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Compliance in the public versus the private realm: Economic preferences, institutional trust and COVID-19 health behaviors

Henrike Sternberg[1,2,3] | **Janina Isabel Steinert**[1,3,4] | **Tim Büthe**[1,2,3,5]

[1]TUM School of Social Sciences and Technology, Technical University of Munich, Munich, Germany

[2]TUM School of Management, Technical University of Munich, Munich, Germany

[3]Munich School of Politics and Public Policy (HfP), Technical University of Munich, Munich, Germany

[4]TUM School of Medicine and Health, Technical University of Munich, Munich, Germany

[5]Sanford School of Public Policy, Duke University, Durham, North Carolina, USA

Correspondence
Henrike Sternberg, Department of Governance, School of Social Sciences and Technology, Technical University of Munich, Richard-Wagner-Strasse 1, Munich 80333, Germany.
Email: henrike.sternberg@tum.de

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Abstract

To what extent do economic preferences and institutional trust predict compliance with physical distancing rules during the COVID-19 pandemic? We reexamine this question by introducing the theoretical and empirical distinction between individual health behaviors in the public and in the private domain (e.g., keeping a distance from strangers vs. abstaining from private gatherings with friends). Using structural equation modeling to analyze survey data from Germany's second wave of the pandemic (N = 3350), we reveal the following major differences between compliance in both domains: Social preferences, especially (positive) reciprocity, play an essential role in predicting compliance in the public domain but are barely relevant in the private domain. Conversely, individuals' degree of trust in the national government matters predominantly for increasing compliance in the private domain. The clearly strongest predictor in this domain is the perception pandemic-related threats. Our findings encourage tailoring communication strategies to either domain-specific circumstances or factors common across domains. Tailored communication may also help promote compliance with other health-related regulatory policies beyond COVID-19.

KEYWORDS
compliance, COVID-19, economic preferences, health behavior, institutional trust, physical distancing

JEL CLASSIFICATION
D91, H12, H31, I12, I18

1 | INTRODUCTION

What drives individual compliance with norms, standards, and imperfectly monitored laws and regulations? The importance of this question has long been recognized for general public policy contexts such as tax or fare avoidance as well as for health policy contexts such as vaccination mandates. More recently, the question has gained further significance for COVID-19-related physical distancing—a context in which individual behavior has a very high apparent societal relevance, but the individual and collective short-and long-term consequences of non-compliance are relatively uncertain.[1] These characteristics pose a particular challenge for policy makers because they imply that a substantial amount of variance in compliance behaviors may not be exclusively driven by fully informed, rational cost-benefit considerations. Instead, previous research suggests that compliance behavior in such contexts is shaped to a significant extent by individuals' economic preferences (i.e., social, risk and time preferences) and their degree of trust in the institutions endorsing the rules (e.g., Bargain & Aminjonov, 2020; Campos-Mercade, Meier, Schneider, Meier, et al., 2021; Campos-Mercade, Meier, Schneider, & Wengström, 2021; Chan, Skali, et al., 2020; Cucciniello et al., 2022; Keser & Rau, 2023; Shim et al., 2012; Sutinen & Kuperan, 1999).

This paper proposes and empirically investigates a heretofore unaddressed implication emerging from the pronounced influence of these factors on compliance patterns: Compliance behavior may systematically vary between the public and the private domain, induced by the differential impact of individuals' economic preferences and institutional trust on compliance in these two domains. This is highly relevant in the context of behavioral stipulations to contain the spread of COVID-19, which have included rules governing people's behavior in public spaces, such as requirements to wear masks and maintain physical distance from others, as well as rules governing relatively private behaviors, such as limits to the number of friends with whom to meet at home. While compliance in both the public and private domain is crucial to achieving the overarching objective of these rules, the two domains differ regarding the audiences who might observe and enforce compliance, suggesting potentially differing incentive structures.

Against this background, we examined whether such a divergence in compliance behavior exists in the context of COVID-19-related physical distancing rules. Compliance in the public domain here comprised acting in conformity with health guidelines intended to govern behaviors that are easily observable by members of the general public, including public authorities. Examples include wearing a facemask or keeping a physical distance from people from other households in public spaces. Compliance in the private domain comprised behavior consistent with health guidelines intended to govern more private decisions about restricting social contacts and mobility altogether, which is to a large extent observed only by those who also fail to comply. Recognizing and examining a potential divergence in compliance between these two domains is important for advancing our theoretical understanding of compliance in general and moreover highly relevant for public policy in the context of COVID-19. Given the lower COVID-19 vaccine access and coverage in countries of the Global South and the prospect of emerging highly contagious virus variants, lockdown and physical distancing mandates remain crucial tools for containing infection rates in such scenarios.

To assess the extent to which economic preferences and institutional trust might differ in their ability to predict health behaviors in the public versus in the private domain, we estimated separate structural equation models (SEMs) of self-reported compliance with nationwide issued physical distancing rules, using original survey data from Germany's second wave of the pandemic in the winter of 2020/21 ($N = 3350$). As for economic preferences, we examined risk aversion, patience, reciprocity, altruism and civic responsibility. As for institutional trust, we considered COVID-19-related trust in the government and in scientific institutions.

Our results confirm that compliance is significantly correlated with individuals' social and risk preferences and their institutional trust. This finding holds when controlling for COVID-19 threat perception, which was revealed as the strongest predictor of compliance in both domains.

More importantly, our survey data revealed that behavioral patterns differ significantly across the two compliance domains in three ways. First, respondents' level of positive reciprocity was of great importance for compliance in the public domain but barely relevant in the private domain. The same (but slightly weaker) domain-specific differences emerged for negative reciprocity. Interestingly, correlations between reciprocity and compliance were positive in the case of positive reciprocity and negative in the case of negative reciprocity. Second, we also found domain-specific patterns for the degree of trust in the national government and trust in scientific institutions: While trust in the government mattered only for increasing compliance in the private domain, trust in scientific institutions was an important factor in both domains, but significantly more so in the public domain. Third and more generally, our results suggest differences across domains in the relative importance of COVID-19 threat perceptions vis-à-vis preferences and trust. Specifically, the dominance of COVID-19 threat perceptions as the primary predictor of compliance was significantly more pronounced in the private domain. In contrast, individuals' social preferences were more strongly associated with compliance in the public domain.

This analysis contributes to the literatures on the predictors of individual-level outside-the-lab rule and norm compliance in economics, law, political science and psychology in a variety of contexts, including health behaviors during epidemics or pandemics (e.g., Algan et al., 2021; Blair et al., 2017; Böhm et al., 2016; Brodeur, Gray, et al., 2021; Galizzi et al., 2022). Furthermore, we contribute to the more specific and recently emerging literature on health behaviors in times of COVID-19. In this literature, social preferences, risk preferences, (to a lesser extent) time preferences, institutional trust, and pandemic-related threat perceptions have been identified both theoretically and empirically as important predictors of various types of compliance behaviors as well as mobility patterns.[2] To the best of our knowledge, this is the first paper to introduce—both in the general as well as in the more specific COVID-19 compliance literature—the conceptual distinction between compliance in the public and the private domain, identify the implications for how compliance might be linked to individuals' economic preferences and institutional trust in distinct ways across the two domains, and systematically examine these potential differences empirically. Our findings suggest that the same individual may exhibit different degrees of compliance across these two domains. They also imply that the effectiveness of policies aimed at spurring compliance will vary across domains—or put differently: distinct policies might be needed to spur compliance in each domain.

These policy implications of our findings are important for health policy well beyond behavioral stipulations during a pandemic, which is the context that allowed us to examine the issue. For instance, communication strategies aimed at improving public health through environmentally conscious consumer behavior might seek to encourage the purchase of products with a low carbon footprint at local stores, which we would classify as compliance in the public domain, because it is easily observed by fellow citizens. Conversely, communication strategies might target consumer behavior with regards to online purchases, which may be classified as compliance in the private domain. Quantifying the extent and analyzing the dynamics of a potential compliance divergence in this context would be highly relevant for designing effective environmental policies.

The remainder of this paper is organized as follows. Section 2 characterizes the two compliance domains and articulates expectations for (differential) impacts of individuals' economic preferences and institutional trust. Section 3 describes the survey design and the empirical strategy, that is, the SEMs. Section 4 presents the main results and robustness checks. Section 5 discusses the broader significance and policy implications.

2 | THEORETICAL CONSIDERATIONS

2.1 | Characterization of compliance domains

The existing literature on (COVID-19-related) compliance does not distinguish between the public and private domain as spurring distinct logics of compliance. We now turn to this distinction.

Physical distancing rules during the COVID-19 pandemic have in numerous countries called for limiting social contacts and mobility in a variety of ways to reduce the risk of spreading the infection. Some of these rules predominantly govern behavior that inherently takes place in the public sphere, such as requirements or norms to, for example, wear a mask or keep a certain distance to persons from other households in public transport, at restaurants, in a public park, etc. Violations of these rules are easily observed (and hence enforceable), including by government authorities and by compliant fellow citizens.

Other rules govern behavior that predominantly takes place in the private sphere, for example, rules asking citizens to restrict private gatherings to a maximum of two households or to only leave the house for necessary daily errands and other urgent reasons. We refer to decisions about complying or violating these rules as compliance in the private domain. Non-compliance with such rules leaving the house to visit friends for fun instead of leaving the house only to get groceries, or attending or hosting a dinner party with friends from 10 different households is not easily observable. Moreover, it is most readily observed by individuals who have also chosen not to comply with the restrictions (the friends who themselves attend the dinner party).

The two domains thus vary in terms of the observability of compliance behaviors to certain audiences. This results in differences with regard to (i) the risk of formal (i.e., state) punishment of non-compliant behavior and (ii) the likelihood of social punishment by fellow citizens. Further, the two domains vary by (iii) the degree of social closeness of the people that seem most immediately affected by (non-)compliance (in terms of the medical risk of getting infected with COVID-19). Importantly, note that although compliance decisions across the two domains may in practice be correlated, they are logically orthogonal in the sense that compliance in any one realm could be practiced regardless of whether one complied with the rules for the respective other domain.

As in (i), the risk of formal punishment, for example, getting fined for non-compliance, was inherently higher in the public than in the private domain. For instance, mask-wearing was in many places monitored through an increased police presence in subways or crowded city centers, whereas larger-than-allowed gatherings in the privacy of a home was subject only to the much smaller risk of reports by proactive neighbors. Thus, while the amount of fines at the time of data collection was higher for non-compliance in the private domain, the risk of actually getting fined was higher in the public domain (see Table A30). To that end, a recent study suggests that the impact of economic preferences may be sensitive to the existence of government enforcement/punishment in the form of fines, which further strengthens the rationale for the suggested public-private distinction (Papanastasiou et al., 2022).

As in (ii), in terms of social punishment by fellow citizens, the type of audience to potentially execute such a punishment differs between both domains. While in the private realm, observable non-compliance is subjected to disapproval by one's close peers, non-compliance in the public realm is widely observed by the general public. One may argue that social incentives to comply in private settings may for this reason be in principle very strong (see also (iii) below). However, as highlighted above, in contrast to the public domain, compliance in the private domain is directly observed mostly by others who are also non-compliant. Consequently, the likelihood (not necessarily the severity) of social punishment is also assumed to be lower in the private than in the public domain.

As in (iii), the degree of social closeness of the people that seem most immediately affected by (non-)compliant behavior (in terms of the risk of an infection) is higher in the private than in the public domain. Of course, a lack of compliance with the rules in either domain can cause a close family member or friend to get infected through virus transmission. However, this risk is much more salient in compliance behaviors in the private domain, where one directly decides about whether to meet with family and friends. Apart from that, this third distinctive characteristic also suggests that the personal dilemma of whether to comply or not is more substantial in the private domain: Complying means protecting one's closest friends/family but also not being able to maintain close social contact and support them.

2.2 | Logics of compliance: Distinctive decision-making logics across domains

In the following, we first present theoretically and empirically informed expectations on how economic preferences and institutional trust may affect COVID-19 compliance overall before we then elaborate on how we expect dynamics to differ across the two compliance domains.

2.2.1 | Civic responsibility

Compliance is likely more pronounced among individuals with a higher sense of civic responsibility, as the act of complying with physical distancing regulations during a pandemic resembles an act of civic responsibility (e.g., Barrios et al., 2021). Regarding differential dynamics across domains, expectations are conflicting: On the one hand, civic responsibility may be a more relevant driver of compliance in the public domain, which is the realm that social or civic duties are mainly associated with. On the other hand, civic responsibility can be viewed as an internalized, intrinsic motivation for compliance, which might thus be more important in the private domain, that is, in the absence of formal enforcement.

2.2.2 | Positive and negative reciprocity

Individuals' level of positive and negative reciprocity may also affect compliance behavior: Specifically, in an environment in which compliance is generally high, a person with higher levels of positive reciprocity (i.e., a stronger willingness to return a favor) should exhibit a higher degree of compliance because compliance by others also protects this person and thus may be perceived as a favor to him or her (e.g., Nikolov et al., 2020). In contrast, negative reciprocity (the willingness to punish antisocial behavior) should in expectation not affect one's own level of compliance, because non-compliance as an attempted punishment would, in the pandemic context, also punish those individuals who contribute to the public good (i.e., compliant individuals). However, one could argue that non-compliant individuals might be punishable to a higher degree by one's own act of non-compliance because compliance also yields self-protection from the virus. This would suggest that individuals with higher levels of negative reciprocity comply relatively less with the imposed rules (e.g., Alfaro et al., 2022). In terms of differential dynamics across the two domains, a person's degree of (positive or negative) reciprocity should matter more for compliance in the public domain. Here, compliance behaviors are much more exposed to and observed by potential reciprocators than in the private domain, that is, whether a person wears a mask on the train or in the supermarket is observed by a higher number of individuals than whether a person stays at home alone and refrains from meeting with friends.

2.2.3 | Altruism

We generally expect individuals with higher levels of altruism to exhibit higher compliance with COVID-19 rules because those rules aim at reducing the spread of harmful infections among fellow citizens (e.g., Nikolov et al., 2020; Quaas et al., 2021). Pure altruism should not have any differential effects across the two compliance domains, since pure altruism refers to intrinsic values and does not include any reciprocated dynamics or incentives. As long as compliance in the public and private domain more or less equally helps to reduce the spread of the virus, higher levels of pure altruism should increase compliance regardless of whether it is relatively easily observed by others or not. However, given the personal dilemma individuals face in terms of compliance in the private domain, altruism could also have opposing effects in this domain: Altruism might not only call for protecting others from the medical consequences of the virus, but also from the social consequences, that is, social isolation.

2.2.4 | Risk preferences

Risk-averse individuals are expected to comply to a larger degree with physical distancing rules than individuals who are more risk-accepting or risk-seeking because higher compliance lowers the risk of getting infected, as well as the risk of getting fined for non-compliance (e.g., Müller & Rau, 2021; Papanastasiou et al., 2022). Regarding differential effects across domains, we do not have strong expectations, given that non-compliance in both domains can be characterized as risky behavior, only concerning differing aspects (e.g., the risk of punishment for non-compliance vs. the risk of passing on an infection to close friends or family members).

2.2.5 | Time preferences

We might expect more patient individuals (i.e., with lower discount rates) to exhibit higher levels of compliance as they are more willing to sacrifice a certain immediate reward (e.g., meeting with friends) for a later larger reward (e.g., the end of contact restrictions altogether) (e.g., Alfaro et al., 2022; Papanastasiou et al., 2022). We do not have strong expectations regarding differential effects across the two domains.

2.2.6 | Institutional trust

The government and scientific institutions acted as key endorsers of the social-distancing rules imposed during the COVID-19 pandemic. Therefore, we expect that higher levels of COVID-19-related trust in governmental or scientific institutions spur compliance with physical distancing rules, which is in line with what recent empirical evidence suggests (e.g., Bargain & Aminjonov, 2020; Brodeur, Grigoryeva, & Kattan, 2021). For trust in the government, conflicting logics make the difference between the public and private realms theoretically indeterminate. On the one hand, trust in the government might have a more pronounced positive effect in the private domain, given that lower levels of monitoring and enforcement by state authorities make trust in the government as an intrinsic motivator more important. On the other hand, an understanding of the private domain as a realm in which the government has inherently no legitimate role to play might make trust in the government less relevant as a predictor. For trust in science, we do not have pronounced differential expectations, though one might argue that its relevance should be stronger in the public domain given the more technical-scientific nature of the stipulations in this realm, for example, wearing a mask or keeping a 1.50 m distance from another.

3 | MATERIAL AND METHODS

3.1 | Study setting and sampling

The study was conducted as an online survey between February 3 and March 3, 2021, during the second nationwide COVID-19 lockdown in Germany, which had begun in November 2020. The only stores fully operating at this time were those for daily necessities and medical supplies, while restaurants, retail stores and the like operated at most on a take-away or delivery basis. Physical distancing rules for the second nationwide lockdown were put in place early and were repeatedly renewed, that is, they remained unchanged during the entire study period and we can expect the vast majority of the population to have been aware of their existence.[3] The national and state governments met to discuss potential changes in the national lockdown strategy on March 3, which marks the end of the data collection.

The sample consisted of 3350 respondents recruited from a German access panel maintained by the survey company Respondi. Individuals were eligible to participate in the study if they were at least 18 years old and reported that they had spent the majority of the last 2 weeks in Germany. Quota sampling was used to obtain a representative sample of the German population with regard to (i) gender, (ii) age group, (iii) education, and (iv) state. Respondents received "mingle points" (worth between three to five Euros) for participating in the study, which they could redeem in the form of cash, vouchers, or donations.

3.2 | Survey design and outcome variables

The survey was designed to collect information on the main variables of interest for this study, namely respondents' compliance with national physical distancing rules in Germany as well as their economic preferences and their level of institutional trust. We also collected information about an alternative highly relevant predictor of compliance, namely COVID-19 threat perception, which has been shown to affect (COVID-19) health behaviors (e.g., Jørgensen et al., 2021; Kluwe-Schiavon et al., 2021; Papanastasiou et al., 2022; Plohl & Musil, 2021), and may be correlated with preferences and trust. The survey moreover collected information on a number of additional explanatory variables, including respondents' demographic and socioeconomic characteristics, political and ideological factors, knowledge about the efficacy of different prevention measures to reduce the spread of COVID-19, and a scale to assess possible social desirability bias (Kemper et al., 2012). Tables A1 and A2 in Appendix A summarize all survey items employed in this paper (Table A21 reveals the exact formulation of the survey items as displayed to respondents, translated from the original German version). The full questionnaire, the pre-analysis plan and the rationale for deviations from the latter can be retrieved from the supplementary material.

3.2.1 | Elicitation of compliance behaviors

Compliance was elicited by asking respondents about their behavior in six situations governed by various physical distancing rules issued by the German national government. In each case, respondents were asked to rate on a scale from 1 to 5 the extent to which their own behavior in the past 2 weeks reflected these behaviors (ranging from never to always).

Following the theoretical considerations above, three questions were intended to primarily elicit information about compliance in the public domain, asking respondents about (i) wearing a mask in public transport or when shopping, (ii) keeping the government-stipulated distance of approximately 1.50 m in public spaces, and (iii) avoiding handshakes when greeting other people. Another three questions were primarily intended to elicit information about compliance in the private domain, asking respondents about (iv) leaving the home only when truly necessary, (v) restricting private meetings to the government-stipulated limit of one person from one other household, and (vi) minimizing interactions with persons from outside one's own households in general.[4] Importantly, the German federal government's stipulations—and hence the requirements for compliant behavior—were equally clear and stable for the private and for the public domain during the data gathering phase.

3.2.2 | Elicitation of economic preferences and institutional trust

With regards to economic preferences, we elicited respondents' level of altruism, positive and negative reciprocity, risk aversion, patience and civic responsibility. To capture institutional trust, we elicited their COVID-19-related trust in the national government and in the Robert-Koch-Institute (RKI), the latter as a proxy for trust in science.

For the majority of these factors (altruism, positive and negative reciprocity, risk aversion, patience), we adapted the items and measurement procedure from the German version of the Global Preference Module (Falk et al., 2022, 2018): We used both (i) attitudinal measures that ask about generally behaving in a certain way, and (ii) actual incentivized choices (such as donation decisions in the case of altruism or lottery participation in the case of risk aversion). These survey items were standardized and then used to construct one final measure for each preference, based on the weights for the survey items that emerged from the experimental validation procedure by Falk et al. (2018, p. 1653).[5] The survey items, weights, final preference measures, and general procedure are summarized in Tables A4–A6 and Figure A5 in Appendix A.[6]

Civic responsibility was measured using (i) respondents' reported voter turn-out in the last national election, (ii) their self-reported tendency (not) to evade fares in public transport, and (iii) their self-reported tendency (not) to litter. Responses to these three items were used to estimate a factor score of respondents' underlying level of civic responsibility, which we assumed to be the primary common factor among these indicators (for a similar approach, see, e.g., Müller and Rau (2021)).

Institutional trust was elicited through questions about respondents' degree of trust in the German national government's and the RKI's ability to manage the pandemic situation. These two institutions were the primary endorsers of physical distancing rules and the main sources of official public health communications during the pandemic in Germany. Throughout the pandemic, the RKI has been the most widely known and recognized German national-level scientific body to conduct epidemiological and medical analyses of COVID-19 and to issue policy recommendations. It thus served as a proxy for trust in science in the German context (Betsch et al., 2021b).

3.2.3 | Elicitation of COVID-19 threat perception

COVID-19 threat perception was captured using a battery of questions about (i) how threatening respondents perceived the COVID-19 pandemic to be in general and (ii) how threatening they perceived it to be with regard to specific aspects of their lives, including their own health or the health of those close to them, their financial situation and their social lives. These items were used to estimate factor scores capturing respondents' underlying COVID-19 threat perceptions to be then employed in the subsequent analysis. The majority of the items were adapted from Betsch et al. (2021a).

3.3 | Data collection and processing

The survey was programmed in German using Qualtrics and piloted with 150 participants. The recruitment for the final survey was conducted by the survey company Bilendi.[7] Analyses were performed in R (version 4.1.0) and STATA17. Informed consent was obtained from all respondents before they were presented with the questionnaire, which they could interrupt or exit at any time. As part of the debriefing upon completion of the survey, participants were provided with a substantive list of resources for help and information sources about the COVID-19 pandemic as well as mental health support services.

3.4 | Empirical strategy

The empirical strategy comprised essentially two steps. First, we examined compliance across the six different physical distancing behaviors to ascertain to what extent there is empirical evidence for the existence of the conceptual distinction between compliance in the private and in the public domain. In view of this, we employed exploratory factor analyses to identify the subsets of physical distancing behaviors that reflect compliance in each domain and then derived initial estimates for compliance in the public and private domain, respectively.

Second, we investigated by means of SEM techniques to what extent compliance patterns are correlated with individuals' economic preferences and institutional trust for each of the two domains of compliance. SEMs help to reduce measurement error in the underlying latent variable(s) of interest—here compliance behavior—by combining path analysis (the structural component of the SEM) with confirmatory factor analysis (the measurement component of the SEM) (Acock, 2013). In our case, the SEM simultaneously (i) fits a confirmatory factor analysis that captures compliance in the public/private domain as a latent variable and (ii) estimates effects of preferences and trust on this latent measure of compliance.

The confirmatory factor analysis (i.e., the measurement component of the SEM) is defined as follows for compliance in each domain d, where $d = \{\text{public, private}\}$.

$$\boldsymbol{y}'_d = \boldsymbol{\lambda}'_d C_d + \boldsymbol{\epsilon}'_d \boldsymbol{\psi}_d, \tag{1}$$

$\boldsymbol{y}'_d$ in Equation (1) denotes a vector of the subset of the six observed compliance items that reflect the respective compliance domain, using the results from the exploratory factor analyses in the first step (see Section 4.1). C_d denotes the identified latent measure of domain-specific compliance (i.e., the common factor within each item subset), and $\boldsymbol{\lambda}'_d$ is a vector of the regression coefficients of the model, that is, the factor pattern coefficients (loadings) of the observed items for their respective compliance domain. $\boldsymbol{\epsilon}'_d$ correspond to the unobserved unique factors of the six compliance items and $\boldsymbol{\psi}_d$ are the coefficients relating the unique factors to the items. The variables of interest here are the factors capturing compliance in both domains, C_d, which are assumed to induce observed responses to the respective subset of the six compliance items. The latter, $\boldsymbol{y}'_d$, are therefore the dependent variables in the measurement model and constitute the reflective indicators of compliance in each domain (Acock, 2013).

The structural component of the SEM regresses compliance behaviors in each domain (i.e., the latent variables of compliance) on economic preferences and institutional trust, and is defined as follows.

$$C_d = \boldsymbol{P}'\boldsymbol{\alpha}_d + \gamma_d T + \boldsymbol{X}'\boldsymbol{\eta}_d + \boldsymbol{Z}'\boldsymbol{\zeta}_d + \upsilon_d \tag{2}$$

$\boldsymbol{P}'$ denotes a vector of the regression coefficients of preferences and trust on the latent measure of domain-specific compliance *(C_d)*. γ_d denotes the regression coefficient of COVID-19 threat perception *(T)* as an alternative predictor of compliance in each domain. $\boldsymbol{X}'$ is a vector of demographic and socioeconomic controls, namely gender, age group, state, education, employment in essential services, household size and income, and $\boldsymbol{Z}'$ is a vector of specific compliance controls, namely knowledge about COVID-19 preventive measures and the degree of social desirability bias. υ_d denotes the error term. Individual subscripts are suppressed for simplicity.

The measurement component and the structural component of the SEM are connected through the latent variable, that is, compliance in the public/private domain, respectively, allowing us to simultaneously estimate the above equations. We estimated the SEM separately for each compliance domain using Diagonal Weighted Least Squares on a polychoric correlation matrix while generating robust standard errors and a corrected test statistic to account for the ordinal and not normally distributed compliance items (e.g., Finney & DiStefano, 2006; Li, 2016).

4 | RESULTS

Overall, 3350 respondents completed the online survey, among which 49.85% were female, 49.91% were male, and 0.24% indicated their gender to be diverse. Respondents were on average 47.83 years old. In terms of age, gender, educational attainment, and state of residence our sample was representative of the German population aged 18–74 (see Table A2 in Appendix A). All six compliance items were non-normally distributed and skewed to the left. This means self-reported compliance was generally high, which could be indicative of some social desirability bias in reporting but is not necessarily surprising given that data was collected in the midst of the quite intense second wave of infections in Germany (for a similar finding at that time, see Betsch et al., 2021b). Histograms and density plots of all six compliance items are presented in Figure A1 in Appendix A. Descriptive statistics for all variables employed in the core analysis are presented in Tables A1, A2[8] and A6 in Appendix A and the screeplots and factor scores of constructing the indexes for COVID-19 threat perception and civic responsibility are shown in Tables A7, A8 and Figures A2–A4 in Appendix A.[9]

4.1 | Uncovering the domains: Compliance dimensionality across imposed rules

We first conducted an exploratory unrotated factor analysis and constructed the corresponding screeplot, without restricting the number of factors, to assess the initial dimensionality of compliance behaviors as measured by means of the six physical distancing rules. The screeplot and the polychoric correlation input matrix are shown in Figure A6 and Table A9 in Appendix A. The screeplot suggests that there is one dominating underlying dimension shared among all six items, whereas a potential second, independent (orthogonal) dimension seems much less relevant. This result should not be surprising, given the expectation that compliance in the public and private domain are likely related. Hence, the nature and relevance of each compliance dimension in terms of the factor-specific percent of shared variance explained and factor loadings would become visible only after allowing obtained factors to be correlated.

In view of this, we re-estimated the factor analysis, specifying a two-factor solution, and performed a promax rotation, which allowed obtained factors to be correlated. The promax-rotated 2-factor solution is presented in Table 1 (see Table A10 in Appendix A for the unrotated solution).

The results suggest a pattern of two underlying factors that are related to each other by a Pearson correlation coefficient of 0.787 and jointly account for more than 70% of the shared variance between all six compliance items. The percent shared variance accounted for is distributed roughly equally between both factors (37.21%; 34.88%). Importantly, each factor seems to relate more strongly to a distinct set of three compliance items. The first factor exhibits strong loadings on the compliance items (i) leaving the home only when absolutely necessary, (ii) restricting private meetings to one person from one other household, and (iii) avoiding other households in general. The second factor exhibits strong loadings on the compliance items (i) wearing a mask in public transport or when shopping, (ii) avoiding handshake greetings and (iii) keeping a distance in public spaces whenever possible. Thus, recalling our theoretical considerations, the first factor seems to reflect compliance in the private domain and the second one compliance in the public domain.

To obtain initial estimates for respondents' level of compliance in the public and private domain, we predicted their factor scores based on the rotated 2-factor solution in Table 1 and additionally constructed summated rating scales using the distinct three-item subset for each compliance domain. A reliability analysis of the constructed scales is presented in Table A11, with Cronbach's α of the scales being as high as 0.797 and 0.780, and α decreasing if any item is removed from the scale (see Figure A7 for an assessment of the monotone homogeneity assumption). As expected, the correlation between the public and private summated rating scale (0.643, see Table A11) was lower than between the factor scores of compliance in both domains (0.787, Table 1), given that each factor here reflects all

TABLE 1 Dimensionality in compliance: Promax-rotated 2-factor solution.

	Factor 1	Factor 2
Compliance in the public domain		
Wearing a mask in public transport/when shopping	−0.104	**0.980**
Keeping a 1.5 m distance in public spaces (whenever possible)	0.249	**0.642**
Avoiding handshake greetings	0.321	**0.633**
Compliance in the private domain		
Leaving the home only when absolutely necessary	**0.649**	0.164
Generally avoiding other households	**0.966**	−0.085
Restricting private meetings to one person from another household	**0.653**	0.100
Eigenvalue	2.232	2.093
Percent shared variance accounted for	37.21	34.88
Multiple R^2 of scores with factors:	0.904	0.913
Correlation between factors: 0.787		
Observations: 3340		

Note: The table shows standardized factor patterns coefficients from a 2-factor solution of the six compliance items, estimated using iterated principal axis factoring, promax rotation and polychoric correlations. Numbers printed in bold indicate the two sets of item triplets, that relate most strongly to each factor.

six items. Density plots and histograms contrasting compliance in the private and public domain as measured by the standardized factor scores and the summated rating scales are shown in Figure 1, with higher scores indicating higher compliance.

These preliminary analyses consistently show that, while sharing the same general pattern, compliance patterns were distributed somewhat differently in the two domains. Specifically, the level of compliance in the private domain was generally lower (see mean values in Table 1) and notably less skewed than that of compliance in the public domain. This suggests that rules governing behavior (and specifically social interactions) in the private realm, such as gatherings with friends in the home, were less complied with than rules governing the public domain. This could be suggestive of a differential nature of individual preferences and trust shaping decision-making in each compliance domain.

4.2 | Decision-making patterns across compliance domains

We estimated, for each domain, the SEM by means of Equation (1) (the measurement component) and Equation (2) (the structural component) to examine compliance behavior across the public and private domain. The measurement component thereby employed the above-identified subsets of items to form both compliance measures. Its results, shown in Table A12 in Appendix A, revealed strong and statistically significant indicator loadings of all items on compliance in their respective domain. The results of the structural component—that is, the results of regressing the domain-specific latent measure of compliance on the hypothesized predictors—are presented in Figure 2 and Table 2.

Table 2 presents a detailed account of the findings by including the different sets of hypothesized predictors one by one (COVID-19 threat perception, social preferences, risk and time preferences, institutional trust) and adding different sets of control variables. Figure 2 visualizes the coefficient estimates of the final models from Table 2 (Columns 8 and 16) for both compliance domains in a joint coefficient plot. Both, Table 2 and Figure 2, indicate whether the differences

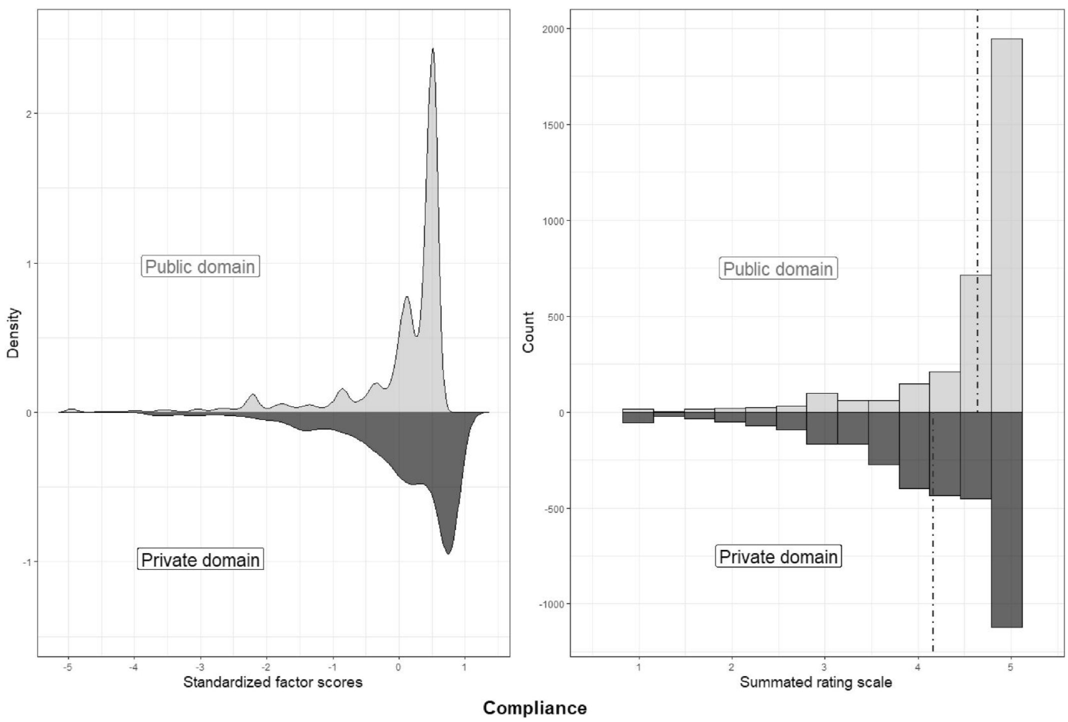

FIGURE 1 Density distributions and histograms of compliance in the public and private domain. This figure shows the distribution of compliance in the public (positive *y*-axis) and private (negative *y*-axis) domain, by means of mirrored density plots of the predicted scores from the factor analysis, left graph (see also Table 1), and mirrored histograms of the constructed summated rating scale, right graph (see also Table A11). Higher scores indicate higher compliance. The factor analysis constructed standardized values, that is, factor scores have a mean of 0 and SD of 1. For the summated rating scale, respondents' answers to the identified compliance item triplets of each domain were summed and then averaged. The *x*-axis thus follows the same scale as the original items, that is, 5 = always complied; 1 = never complied with the respective rules. The dotted lines represent the mean of compliance in each domain.

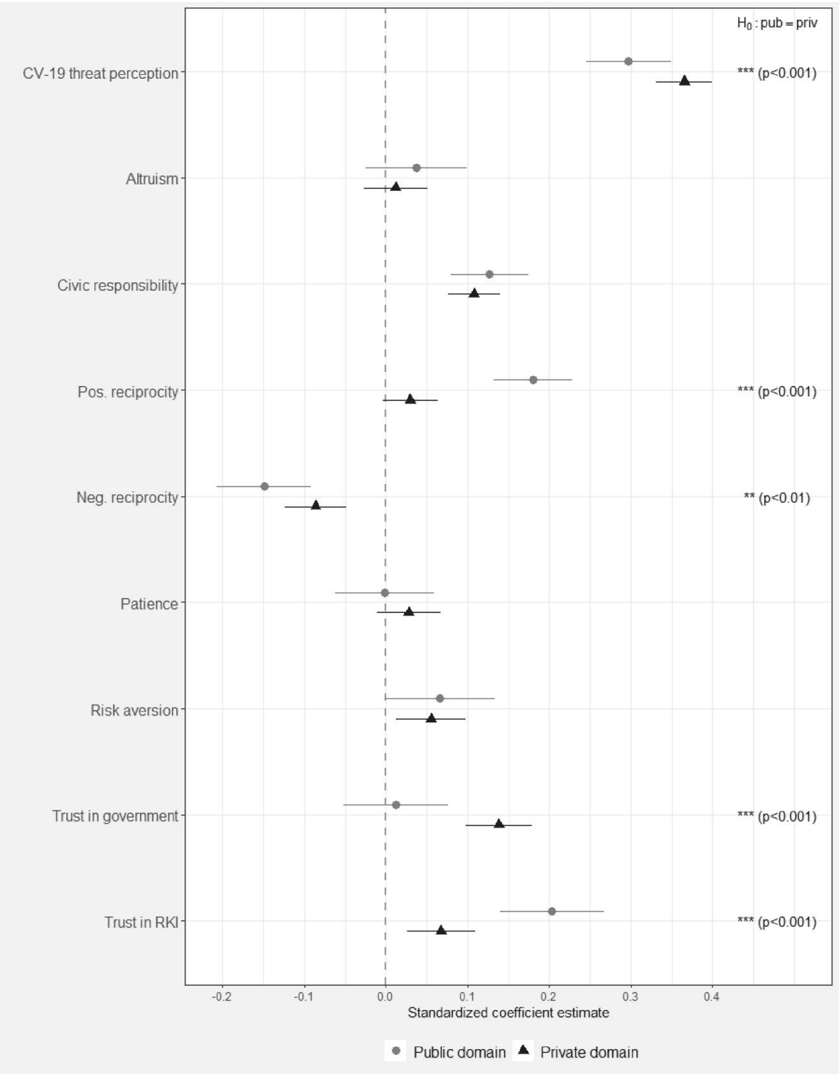

FIGURE 2 Decision-making across compliance domains: Structural equation model (SEM) results (structural component). This figure shows standardized coefficient estimates and 95% confidence intervals for results of the SEMs estimated by means of Equations (1) and (2) (shown are only the structural component results as in Table 2 columns 8 and 16; see Table A12 for the results of the measurement component). The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. Shown are the coefficient estimates for economic preferences, institutional trust and COVID-19 threat perception on compliance in both domains (see Table A13 for full results and precise coefficients). The right column of the figure shows the results of a Wald test for equality of coefficients across the private and public domain (as in Klopp, 2022).

in coefficient estimates between the domains are statistically significant by means of a Wald test for testing the equality of standardized coefficients (as in Klopp, 2022).

The SEM fit statistics were, for both models, good according to common standards, while slightly better for the model of compliance in the private domain (see Table 2). The only statistic that did not meet common standards was the χ^2 test statistic, but this should not be a concern given that its value is inflated by a large sample size and thus extremely sensitive to the model's degrees of freedom, which are quite large in our model.[10] In all figures and tables, we report standardized coefficient estimates.

The findings suggest that respondents' threat perception of the COVID-19 pandemic was overall the most important individual determinant of compliance behavior, both in terms of magnitude and estimated predictive power. Respondents with more pronounced threat perceptions reported on average significantly higher levels of compliance, all else equal. This was the case for compliance in both domains, but to a greater degree for compliance in the private

TABLE 2 Decision-making across compliance domains: Structural equation model (SEM) results by submodel (structural component).

Outcome	Compliance in the public domain (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Compliance in the private domain (9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	Wald-test (8) = (16)
COVID-19 threat perception	0.456***				0.321***	0.304***	0.314***	0.297***	0.486***				0.389***	0.372***	0.382***	0.365***	Stat: 11.95
	(0.020)				(0.025)	(0.026)	(0.025)	(0.026)	(0.015)				(0.017)	(0.017)	(0.017)	(0.017)	$p < 0.001$
Altruism		0.172***			0.061**	0.044	0.054*	0.037		0.133***			0.031	0.017	0.024	0.012	Stat: 1.40
		(0.027)			(0.030)	(0.031)	(0.030)	(0.031)		(0.018)			(0.019)	(0.020)	(0.019)	(0.020)	$p = 0.237$
Civic responsibility		0.200***			0.174***	0.147***	0.152***	0.127***		0.205***			0.169***	0.127***	0.148***	0.108***	Stat: 0.84
		(0.022)			(0.023)	(0.024)	(0.023)	(0.024)		(0.016)			(0.016)	(0.016)	(0.016)	(0.016)	$p = 0.360$
Pos. reciprocity		0.251***			0.217***	0.205***	0.192***	0.180***		0.121***			0.064**	0.056**	0.037	0.030	Stat: 59.55
		(0.021)			(0.023)	(0.024)	(0.024)	(0.024)		(0.016)			(0.017)	(0.017)	(0.017)	(0.017)	$p < 0.001$
Neg. reciprocity		−0.194***			−0.185***	−0.170***	−0.165***	−0.149***		−0.120***			−0.107***	−0.103***	−0.089***	−0.086***	Stat: 9.72
		(0.026)			(0.028)	(0.029)	(0.028)	(0.029)		(0.018)			(0.019)	(0.019)	(0.019)	(0.019)	$p < 0.01$
Risk aversion			0.164***		0.084***	0.066**	0.083***	0.065**			0.162***		0.081***	0.055**	0.081***	0.055**	Stat: 0.23
			(0.030)		(0.033)	(0.034)	(0.033)	(0.034)			(0.021)		(0.021)	(0.022)	(0.021)	(0.022)	$p = 0.630$
Patience			0.148***		−0.012	0.004	−0.018	−0.001			0.118***		0.013	0.032	0.009	0.028	Stat: 1.88
			(0.026)		(0.029)	(0.031)	(0.029)	(0.031)			(0.019)		(0.019)	(0.020)	(0.019)	(0.020)	$p = 0.170$
Trust in RKI				0.396***	0.222***	0.216***	0.209***	0.204***				0.244***	0.085**	0.075**	0.078**	0.068**	Stat: 25.02
				(0.028)	(0.031)	(0.032)	(0.031)	(0.032)				(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	$p < 0.001$
Trust in government				0.015	0.014	0.017	0.009	0.012				0.170***	0.135***	0.145***	0.128***	0.138***	Stat: 19.55
				(0.028)	(0.031)	(0.033)	(0.031)	(0.033)				(0.020)	(0.020)	(0.021)	(0.020)	(0.021)	$p < 0.001$
Demogr. and socioecon. controls	No	No	No	No	No	Yes	No	Yes	No	No	No	No	No	Yes	No	Yes	
Compliance-specific controls	No	No	No	No	No	No	Yes	Yes	No	No	No	No	No	No	Yes	Yes	
R^2	0.208	0.234	0.043	0.166	0.447	0.477	0.464	0.492	0.236	0.121	0.036	0.147	0.365	0.396	0.381	0.411	
Observations	3321	3166	3096	3340	2939	2918	2939	2918	3321	3166	3096	3340	2939	2918	2939	2918	
Full SEM fit statistics (columns 8 | 16)							**Public**								**Private**		
							Robust $\chi^2(66) = 156.55$; $p < 0.001$								Robust $\chi^2(66) = 104.25$; $p < 0.001$		
							Robust RMSEA = 0.022								Robust RMSEA = 0.014		
							Robust TLI = 0.998								Robust TLI = 0.99		
							Robust CFI = 0.959								Robust CFI = 0.987		
							SRMR = 0.017								SRMR = 0.008		

Note: Displayed are standardized coefficient estimates and standard errors in parentheses for the results of the SEM estimated by means of Equations (1) and (2) (shown are only the structural component results, see Table A12 for the results of the measurement component). The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. The far right column shows the results of a Wald test for equality of coefficients across the private and public domain (as in Klopp, 2022). Demographic controls contain respondents' gender, age group and state. Socioeconomic controls include education, employment in essential services, household size and income. Compliance-specific controls contain knowledge about COVID-19 preventive measures and the degree of social desirability bias (factor scores as in Figure A8 and Table A15). Table A13 shows also the coefficients of control variables and Table A14 in the Appendix A repeats the same analyses with the final-model sample of $N = 2918$ throughout.

Abbreviations: CFI, comparative fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual; TLI, Tucker-Lewis index.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

domain ($\beta_{pub} = 0.297$, $\beta_{priv} = 0.365$; p-values < 0.001 each). Respondents' economic preferences and institutional trust played a crucial role for the extent of compliance, revealing a similar directional pattern among the coefficient estimates in both domains.[11] However, while in some cases magnitude and statistical significance of the coefficient estimates were indeed almost identical across domains, they differed substantially and significantly in other cases, according to the results of Wald tests examining the equality of coefficients. In the following, we first report the identified similarities and then turn to the key differences across the two domains.

For civic responsibility, risk aversion, altruism and patience, coefficient estimates did not differ significantly across the two domains (see Table 2, last column). Higher levels of civic responsibility and risk aversion (the former more so than the latter) were correlated with significantly greater compliance to similar extents in both domains (risk aversion: $\beta_{pub} = 0.065$, $p > 0.01$, $\beta_{priv} = 0.055$, p-value < 0.001; civic responsibility: $\beta_{pub} = 0.127$, $\beta_{priv} = 0.108$; p-values < 0.001 each). At the same time, respondents' degree of altruism and patience did not seem to be important potential predictors of compliance behavior in either domain.

Importantly, the results from Figure 2 and Table 2 reveal three major differences between compliance patterns across domains, namely with respect to (i) (especially) positive reciprocity, (ii) trust in institutions and (iii) the relative importance of economic preferences and institutional trust as opposed to individuals' threat perceptions as predictors of compliance behavior.

First, respondents' level of positive reciprocity played a crucial role for compliance only in the public domain, where a one standard deviation increase in positive reciprocity was associated with a 0.18 standard deviation increase in compliance (p-value < 0.001). The coefficient estimate was statistically insignificant and small in the private domain ($\beta_{priv} = 0.030$; p-value $= 0.128$). An additional Wald test revealed that the difference in coefficients between domains was highly statistically significant (Wald test statistic: 59.55, p-value < 0.001). We found the same (but slightly weaker) domain-specific differences for negative reciprocity, only that instead of positive, we reveal negative correlations with compliance behaviors, in line with our theoretical expectations. Specifically, a one standard deviation increase in negative reciprocity was associated with a 0.149 standard deviation decrease in public compliance (p-value < 0.001) and with a 0.086 standard deviation decrease in private compliance (p-value < 0.001) (Wald test statistic: 9.72, p-value < 0.01).

Second, we found opposing patterns for trust in the government and trust in scientific institutions: For compliance in the public domain, trust in the RKI was clearly the dominant determinant in terms of institutional trust. Specifically, a one standard deviation increase in trust in the RKI was associated with a 0.204 standard deviation increase in public compliance (p-value < 0.001), while the coefficient for trust in the government was statistically insignificant and small ($\beta_{pub} = 0.012$, p-value $= 0.681$). In the private domain, however, both trust in the government and trust in the RKI seem to matter for compliance, the former more so than the latter, with estimated effects between 0.068 (trust in the RKI, p-value < 0.01) and 0.138 standard deviations (trust in the government, p-value < 0.001). In line with this interpretation, additional Wald tests reject the equality of coefficients of both types of institutional trust across the two domains, suggesting that trust in the government (trust in science) may be more important as a potential predictor for compliance in the private (public) domain (p-values < 0.001, see Table 2, last column).[12]

Third, and partially resulting from these first two observations, both the absolute and relative importance of COVID-19 threat perceptions in shaping compliance behaviors differed significantly between the public and private domain: A one standard deviation increase in threat perceptions was associated with a 0.297 standard deviation increase in compliance in the public domain and a 0.365 standard deviation increase in the private domain (both p-values < 0.001, Wald test statistic: 11.95, p-value < 0.001). In terms of its relative importance, COVID-19 threat perception was the only determinant of this magnitude for compliance in the private domain—the largest magnitude among the estimated effects of the remaining predictors amounts to just slightly more than a third of this value (trust in the government: $\beta_{priv} = 0.138$). In contrast, the results from the model of compliance in the public domain seem to reflect a different pattern: COVID-19 threat perception also had the largest predicted influence, but respondents' levels of trust in science ($\beta_{pub} = 0.204$) and positive reciprocity ($\beta_{pub} = 0.180$) were of a similar importance in terms of magnitude.

Hence, the relevance of COVID-19 threat perception as the primary predictor appears much more pronounced in the private domain, which results in part from reciprocal preferences being significantly more important in the public domain (Wald test statistic: 56.72, p-value < 0.001; not in table). In line with this, additional Wald tests also reject the hypothesis that the social preferences considered here have the same impact across both domains (Wald test statistic: 55.85, p-value < 0.001; not in table). This interpretation is also reflected in the R^2-values: Regressing compliance in each domain purely on the social preference measures yields an R^2 of 0.234 in the public domain, but only 0.121 in the private domain (see Table 2, Columns 2 and 10).

Finally, our findings suggest that demographic factors were also significant predictors of compliance whose relevance seems to differ across domains. While female and older respondents reported higher compliance in both domains, gender was the dominating factor in the public domain ($\beta_{pub} = 0.117$, p-value < 0.001; $\beta_{priv} = 0.039$, p-value < 0.05; Wald test statistic: 14.088, p-value < 0.001) and age in the private domain ($\beta_{pub} = 0.135$, p-value < 0.001; $\beta_{priv} = 0.057$, p-value < 0.05; Wald test statistic: 11.336, p-value < 0.001) (see Table A13 in Appendix A).[13] Socioeconomic factors, namely educational attainment, employment type, household size and income, do not seem to be relevant predictors of (differential) compliance behaviors.

4.3 | Robustness checks and extensions

4.3.1 | Self-reported compliance measures and observed mobility patterns

The measures of compliance in the public and private domain as identified in the main analysis rely on the truthfulness of respondents' self-reports, which may be subject to social desirability bias in reporting. In light of this concern, we assessed the correlation between the SEM-predicted measures for compliance in each domain and Google mobility statistics. To do so, we employed data from Google's mobility reports, which contain phone-tracking-based changes in mobility in several countries and subregions for various types of locations relative to a baseline period before the pandemic (January 3 to February 6, 2020). Types of locations include retail and recreation, grocery stores and pharmacies, parks, transit stations, workplaces, and private residence (Google LLC, 2021).

We calculated the average mobility change for each German state over a period of 4 weeks (January 20 to February 16, 2021) and correlated these with state-level averages of the SEM-predicted compliance measures from our survey. These 4 weeks correspond to the period on which the majority of our sample was supposed to have based their compliance reports, as 98.5% of observations were collected between February 3 and 16, and respondents had been told to refer to their behavior during the past 2 weeks. For the purpose of this exercise, we focused on mobility changes in retail and recreation, transit stations, workplaces, and private residences, as for parks and grocery/pharmacy visits, the expected relation with our compliance measures is ambiguous.[14]

Figure 3 presents the results of this exercise for each of the compliance measures (public and private) as identified by means of the SEM. Mobility generally decreased in all of the employed location types relative to its baseline level in January/February 2020 (i.e., value changes on the y-axis are negative), except for mobility in residential areas, which increased compared to the baseline (i.e., value changes on the y-axis are positive) and shows that citizens were indeed spending substantially more time in their homes. We found that both compliance measures exhibit the expected relation with changes in observed mobility patterns in the employed location types recorded in the period on which respondents were supposed to base their reports: While standard errors were naturally large given a total number of only 16 federal states in Germany, the Pearson correlation coefficients were clearly positive for residential areas and negative for all other areas. Thus, states with higher reported levels of compliance also showed larger mobility reductions (and vice versa for residential areas). Interestingly, we observed that correlations with compliance in the private domain were in all four types of locations larger in magnitude and showed lower p-values than for compliance in the public domain (the differences in slopes between both domains are, however, not statistically significant). This pattern can be confirmed and becomes even clearer, when instead estimating a regression that includes both compliance measures simultaneously as predictors of mobility changes at the state-level, controlling for population density and whether the state is a city-state (e.g., Berlin, Bremen, Hamburg) (see Tables A26 and A27 in Appendix A).

These findings seem to align with the conceptualization of the two compliance domains: compliance in the private domain would be expected to reduce mobility to a larger extent, given that it relates to people actually reducing their social contacts with other households, and thus, necessarily their movements. In contrast, compliance in the public domain itself would not necessarily relate to mobility changes, as, for example, wearing a mask or keeping a distance can also be practiced while in transit or the like. The findings strengthen the credibility of the self-reported compliance measures examined in this paper as well as the external relevance of the two domains of compliance behaviors emphasized thereby. Note, however, that the relationships captured in Figure 3 were based on state-level rather than individual-level secondary data from Google's mobility reports.

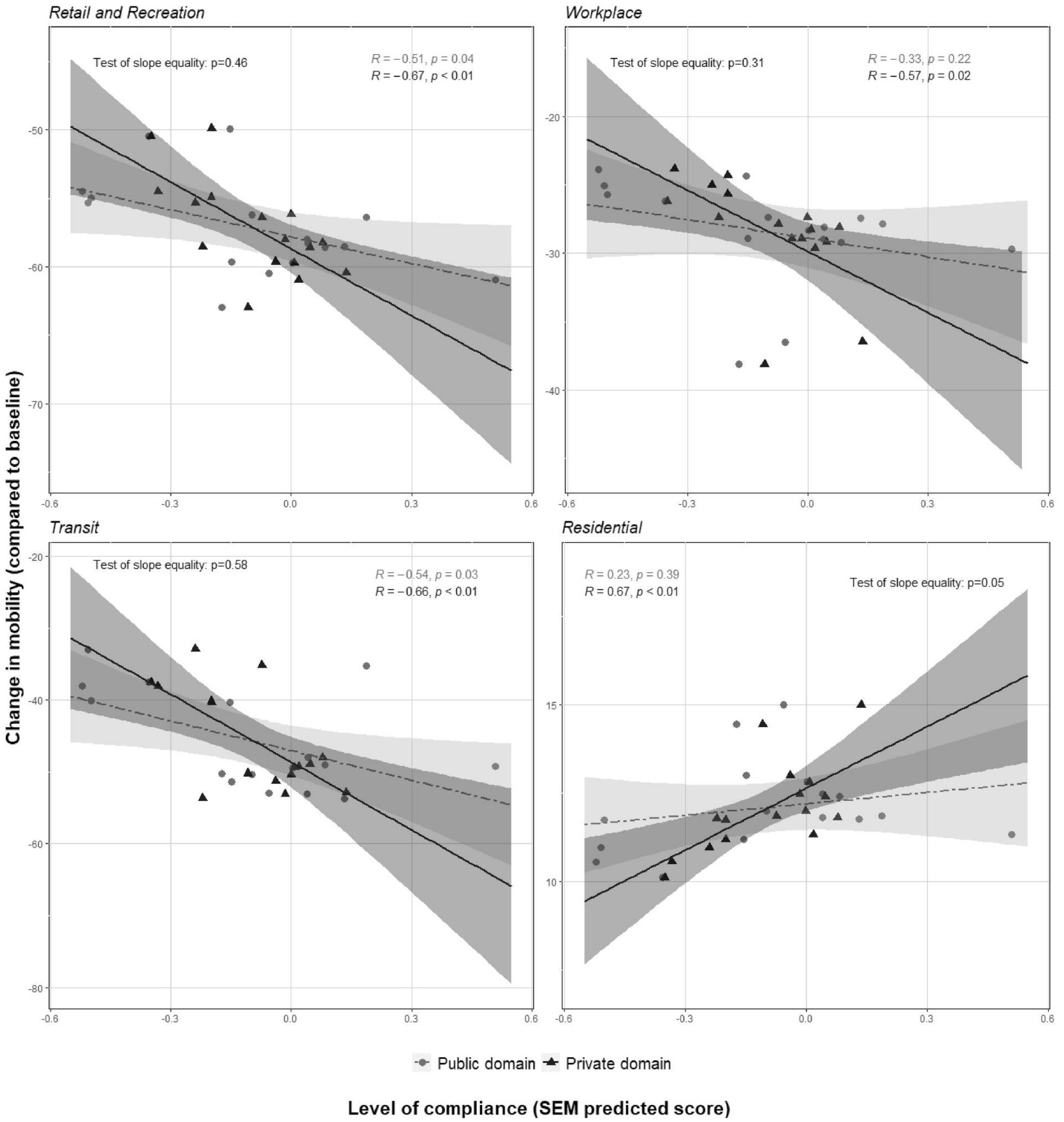

FIGURE 3 External relevance of compliance domains: State-level Google mobility patterns. This figure shows scatter plots, linear (with 95% confidence intervals) regression lines, Pearson correlation coefficients, and *p*-values of (i) compliance in the public and private domain, as predicted from the structural equation model (SEM) by means of Equations (1) and (2) (on the *x*-axis), and (ii) phone-tracking-based changes in mobility according to Google's mobility reports in the areas of Retail and Recreation, Workplace, Transit, and Residential (on the *y*-axis). Higher values of the SEM-predicted compliance measures indicate higher compliance. In the first three graphs, lower values of mobility changes (i.e., more negative values) indicate stronger reductions in mobility relative to the 2020 baseline period (correspondingly for increases in mobility for the case of Retail and Recreation, fourth graph). The unit of analysis are the 16 federal states in Germany, given that this is the lowest level of Google mobility reports available for Germany.

4.3.2 | Additional robustness checks

We conducted a number of additional analyses to assess the robustness of our results by having a closer look at the dependent variable, that is, the compliance measures, as well as at the different hypothesized predictors. For the sake of brevity, this subsection merely summarizes the different approaches and their results briefly, while Appendix B contains a more detailed account of the rationale behind the approaches and of their results.

In terms of the elicitation of compliance, we re-estimated the SEM with an alternative measure of compliance in the private domain (i.e., altering the measurement part of the SEM), which we assume is less susceptible to social desirability bias, but still has the advantage of being available at the respondent level (as opposed to the Google mobility patterns). For this alternative measure of private compliance, we utilized three questions asking respondents about their willingness to participate in concrete social activities (for more details see Appendix B). The results of this exercise reveal estimates that are similar to the previous ones for compliance in the private domain (and that differ from the ones for public compliance in the same crucial instances), thus, strengthening the credibility of the main results. See Tables A17 and A18 and Figures A9 and A10 in Appendix A for the detailed results of the adjusted measurement model and the structural model of the SEM.

In terms of the different hypothesized predictors, we conducted additional analyses to (i) account for potentially mediating effects of respondents' COVID-19 threat perception (see Table A19 and Figure A11), and (ii) control for two more possibly important competing predictors, namely respondents' degree of generalized interpersonal trust and their residence in urban versus rural areas (see Table A22). As in (i), we argue that individual threat perceptions of the COVID-19 pandemic may themselves be affected by economic preferences and institutional trust (Harper et al., 2020; Plohl & Musil, 2021), therefore suggesting not only direct but also indirect effects of preferences and trust through threat perception. In view of this, we re-estimated the SEM by adding our measure of threat perception as a mediator to the structural component of the SEM. The results suggest that the differences across compliance domains predominantly stem from direct effects—thus, reinforcing the core argument and finding of this paper—while the estimated indirect effects were very similar across domains and in most cases also much smaller in magnitude.

As in (ii), we find that our main results are robust to including a respondent's degree of generalized trust—as measured by means of a survey-based item adopted from Falk et al. (2018)—or their rural as opposed to urban place of residence as additional predictors of public and private compliance. Moreover, our results do not suggest that a rural/urban setting plays a statistically significant role for compliance behaviors in either domain (if any, there is a small negative estimated effect of a rural setting on compliance). Interestingly, we find that generalized trust (the degree to which respondents believe other people to generally have good intentions) significantly decreases compliance only in the public domain, while it has no statistically significant estimated effect in the private domain (see Appendix B for a more detailed discussion of this additional finding).

5 | DISCUSSION AND CONCLUSION

Compliance with expert behavioral recommendations and explicit mandates is crucial for a society's ability to achieve a wide range of public health objectives (and public policy objectives in general), ranging from safeguards for patient privacy or vaccination mandates to requirements for COVID-19-related physical distancing. It is especially crucial when the behavioral stipulations or mandates established by such norms, standards or regulations are only imperfectly enforceable, and compliance depends to a greater and substantive degree on individual choices and considerations about whether to comply. Accordingly, previous research has identified economic preferences and institutional trust as important drivers of individual-level compliance (e.g., Algan et al., 2021; Bargain & Aminjonov, 2020; Campos-Mercade, Meier, Schneider, Meier, et al., 2021; Campos-Mercade, Meier, Schneider, & Wengström, 2021; Chan, Skali, et al., 2020; Cucciniello et al., 2022; Keser & Rau, 2023; Papanastasiou et al., 2022; Shim et al., 2012; Sutinen & Kuperan, 1999).

In this paper, we have introduced the conceptual distinction between compliance in the public and the private domain and have explored empirically, in the context of compliance with COVID-19-related physical distancing rules, to what extent its correlations with economic preferences and institutional trust differ across the two domains. Understanding individual-level compliance and recognizing potential differences between the private and public domain remains highly relevant in this context. Even though the immediate urgency of the current pandemic may seem to have passed, an increasing likelihood of novel epidemics and pandemics (e.g., Marani et al., 2021) combined with a significant degree of vaccine hesitancy "especially towards newly developed vaccines" suggests that physical distancing mandates will persist as a crucial part of governments' policy toolkit.

Our fine-grained analysis revealed systematic heterogeneity across the two identified domains, advancing our understanding of compliance and thus providing more tangible grounds for policy interventions. Specifically, while individuals' risk and time preferences appeared to be similarly relevant for compliance across domains, we found significantly different correlations across the two compliance domains in the case of (i) reciprocity (and to some extent also generally for social preferences as a whole), (ii) institutional trust and (iii) COVID-19 threat perception.[15]

First, our empirical analyses suggest that relying on, or appealing to, reciprocal dynamics may only be a promising strategy for compliance in the public domain. These results are in line with our theoretical expectation laid out in Section 2: in the public realm, the reciprocation of compliance behaviors (e.g., in the form of wearing a mask in public or only entering an elevator separately) is more observable and, thus, much more salient in people's minds than in the private domain. Here, compliance occurs in the form of staying at home and isolating, but one does not directly perceive others doing the same—at least not to the extent that it is the case in the public realm. This interpretation is moreover supported by the fact that we observed a substantively and statistically much weaker correlation between compliance in the public domain and altruism, which, in its pure form, we had hypothesized and defined without any reciprocal component.

Second, the results reveal somewhat opposing patterns for trust in the national government and trust in scientific institutions (the RKI). While the former only seems to matter in the private realm, the latter plays a crucial role in both realms but more dominantly in the public domain. For trust in the RKI, we had weak expectations of a stronger relevance in the public domain as a result of the relatively more technical and specific stipulations in this domain, which may, thus, be more saliently perceived as scientifically validated regulations. We found support for this expectation in supplementary analyses, which reveal the exact same pattern for other proxies of trust in scientific institutions, namely, trust in science in general and trust in the World Health Organization (see Table A28 and Appendix B). For trust in the national government, we had indeterminate theoretical expectations. Additional supplementary analyses exploiting respondents' trust in government-related media channels point to a possible explanation of the high relevance of trust in the national government in the private domain (see Table A29 and Appendix B). The observed dynamic could well be a result of the communication strategies employed by the national government over the course of the pandemic and chancellor Angela Merkel's public addresses urging citizens to stay at home and isolate (i.e., using a narrative along the lines of “united in separation”). This communication strategy might have worked against the perception of the private realm as a realm in which the government has no prominent role to play, especially for individuals with high levels of trust in the government.

Finally, our findings suggest that policies which succeed in adequately informing individuals about the threat of (the detrimental consequences of) a COVID-19 infection are likely to be highly effective across compliance domains but to an even greater extent in the private realm. Considering the different theoretically outlined characteristics of the two domains, this finding seems plausible. In the private domain, the perceived risk of passing on an infection to a close family member or friend through non-compliance is much more salient than in the public domain. At the same time, the fear of losing a close family member or friend to COVID-19 was one of the most dominant indicators of our measure for COVID-19 threat perception.

This potential for a varying effectiveness of communication strategies across the compliance domains suggests that policy makers should either tailor communications strategies to the circumstances of each domain or focus on the determinants that are common across domains.

We are cautiously referring to our findings in terms of correlations rather than causal effects, given that gathering the data through a cross-sectional survey in the midst of the pandemic did not allow for ensuring exogeneity by design. However, our results remained stable when controlling for various alternative influences and when performing a number of additional robustness checks (see Section 4). Moreover, previous literature seems to suggest that economic preferences and institutional trust are likely exogenous to the analyses conducted in this paper.[16] In addition, we also acknowledge that our paper only employs self-reported compliance measures and utilizes data from an online survey panel. However, given the various robustness checks conducted to validate the compliance measures and the comparisons of our survey data with other representative non-online surveys, we still believe that our research documents real behavioral mechanisms that can provide useful insights to policy makers. Finally, our paper, strictly speaking, only captures a snapshot of behaviors at the one specific point in the pandemic when the data was collected. Nevertheless, our survey was conducted in the midst of Germany's third wave, and, thus, in the midst of a phase of the pandemic, during which vaccines were not yet available and physical distancing was crucial—which is the exact phase relevant to our research question.

Although we have investigated compliance only in the pandemic context of Germany, the general distinction between compliance in the public and private domain is likely also relevant for other countries that introduced a similar catalog of physical distancing rules. Moreover, the conceptual and empirical contribution of this paper may extend beyond the context of the current and possible future pandemics to other aspects of public policy more generally as well as to health policy in particular. One related example is easily monitorable versus largely unobserved compliance with different types of hygiene regulations by health personnel/professionals. Another, more general example of a contemporary and very pressing regulatory challenge with similar characteristics are policies encouraging environmentally responsible behavior. A public-private compliance divergence in this context may for instance manifest itself in the differential behavioral predictors of environmentally responsible consumer behaviors in supermarkets versus online shopping with a home delivery option. Finally, our approach also has theoretical relevance for research and established findings on regulatory compliance by challenging the way in which compliance is conceptualized.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data available on request from the authors.

ETHICS STATEMENT

Ethics approval for this study was obtained from the committee for human subjects and research ethics review of the medical faculty at the Technical University of Munich (TUM, 20/21 S-SR).

ORCID

Henrike Sternberg https://orcid.org/0000-0001-8539-6478
Janina Isabel Steinert https://orcid.org/0000-0001-7120-0075
Tim Büthe https://orcid.org/0000-0002-4724-5000

ENDNOTES

[1] By uncertainty we mean long tails in the probability distribution, as in what Knight (1921) called "risk".

[2] An extensive, but not complete list of conducted works in this regard include Barrios et al. (2021), Campos-Mercade, Meier, Schneider, and Wengström (2021), Durante et al. (2021), Müller and Rau (2021), Bartscher et al. (2021), Borgonovi and Andrieu (2020), Nikolov et al. (2020), Quaas et al. (2021), Sheth and Wright (2020), and van Hulsen et al. (2020) for various types of social preferences; Papanastasiou et al. (2022), Andersson et al. (2021), Müller and Rau (2021), Schunk and Wagner (2021), Alfaro et al. (2022), Chan, Skali, et al. (2020), Nikolov et al. (2020), Pullano et al. (2020), Xie et al. (2020), and Xu and Cheng (2021) for risk preferences; Fang et al. (2022), Papanastasiou et al. (2022), Andersson et al. (2021), Müller and Rau (2021), Schunk and Wagner (2021), Alfaro et al. (2022), and Nikolov et al. (2020) for time preferences; Brodeur, Grigoryeva, and Kattan (2021), Farzanegan and Hofmann (2022), Fazio et al. (2021), Granados Samayoa et al. (2021), Kazemian et al. (2021), Koetke et al. (2021), Plohl and Musil (2021), Bargain and Aminjonov (2020), Chan, Brumpton, et al. (2020), and Goldstein and Wiedemann (2022) for institutional trust; and Papanastasiou et al. (2022), Algan et al. (2021), Jørgensen et al. (2021), Kluwe-Schiavon et al. (2021), Plohl and Musil (2021), Harper et al. (2020), Vai et al. (2020), and Van Bavel et al. (2020) for COVID-19-related threat perceptions.

[3] In addition to the nationwide rules of interest for this paper, there were some minor differences across the German states in the specific rules and recommendations regarding for example, school/nursery restrictions, contact restrictions for young children and disabled individuals, or the specifics of quarantining after returning from a trip outside Germany (Press and Information Office of the Federal Government, 2021a, 2021b).

[4] The behaviors and the corresponding questions were adapted from Betsch et al. (2021a) and slightly adjusted. See Table A3 in Appendix A for the exact wording. As part of our robustness checks, we consider an alternative way of distinguishing between compliance in the public and the private realm; see Section 4.3.

[5] The experimental validation procedure enabled Falk et al. (2018) to analyze which linear combination of the different survey items performed best in predicting the corresponding behavior in an experimental setting in the lab. We used these same identified weights to form our preference measures. Note that Falk et al. (2018) conducted the validation procedure with a German sample and thus, in the same country context as this study.

[6] For positive reciprocity, we were only able to collect one of the two survey items intended to form the final measure for positive reciprocity. We therefore proceeded with this single item and further assessed the results for robustness when using only a single survey item for all the other preferences as well (selecting the item that had been assigned the highest weight in the experimental validation procedure by Falk et al. (2018)). Our core findings remained robust, see Table A20 and Figure A12 in Appendix A.

[7] Prior to the pilot launch in the field, the survey was moreover piloted and discussed in two research design seminars at the authors' university.

[8] In order to increase the credibility of and validate the main variables of interest for our empirical analysis (i.e., compliance, economic preferences and threat perception), we compare descriptive statistics of our survey data with other representative surveys that collected data on presumably comparable items, specifically data from the COVID-19 Snapshot Monitoring, the World Value Survey (WVS) and the Global Preference Survey. We generally find a high similarity between our survey data and the other datasets (see Tables A24, A25 and Figure A13), while the similarities are highest for our measures of compliance and threat perception and slightly less so for our measures of economic preferences. Specifically, as intuitively to be expected, the similarity in descriptive statistics is slightly lower, the more a measure deviates from those employed by the Global Preference Survey.

[9] We examine, in an additional analysis, to what extent state-level averaged COVID-19 threat perception is correlated with state-level COVID-19 case incidence rates. For this analysis, we employ data about the COVID-19 incidence date by region (number of registered COVID-19 infections in a state within the past 7 days/100,000 inhabitants) from the COVID-19 dataset by the Federal Statistical Office of Germany ("Statistisches Bundesamt"). We find a positive (statistically insignificant) correlation between COVID-19 case incidence during the time of the data collection and average threat perception at the state level (Pearson correlation coefficient: +0.2928). We, moreover, find a negative (statistically insignificant) correlation between state-level threat perception and the average case incidence in a state throughout the infection waves since the start of the pandemic and therefore also prior to the start of our data collection (Pearson correlation coefficient: −0.3847). See Table A23 in Appendix A as well as Appendix B for a detailed summary and interpretation of results.

[10] Degrees of freedom for SEMs are differently calculated (see e.g., Rigdon, 1994).

[11] See Table A16 in Appendix A for the Pearson's correlation matrix of the core explanatory variables, which suggests that we were not facing a case of highly correlated explanatory variables. With the exception of trust in government/trust in the RKI (corr. coeff.: 0.71), all other pairwise correlations were of a low/moderate degree (corr. coeff.:0.01–0.38).

[12] We conduct a number of additional analyses with potential proxies for trust in the RKI (trust in science, trust in WHO) and potential channels for trust in the government (trust in state-level government, trust in established media channels) to better understand the differential effects observed for the institutional trust variables. The results reveal that the estimated effects for trust in the RKI are indeed robust, that is, we observe the same pattern for the utilized proxies: a high, statistically significant relevance in both domains, but more so in the public domain. For trust in the government, the additional analyses seem to suggest that the large, statistically significant estimated effects only in the private domain may be a result of the communication strategy of particularly the national government, whose narrative focused predominantly on the general message to stay at home and isolate (i.e., closely related to our definition of private compliance). See Tables A28 and A29 for details.

[13] Our findings for respondents' age align well with those for COVID-19 threat perceptions, which previous studies have found to be stronger among older citizens: Both factors were a stronger predictor of compliance in the private domain. However, the fact that both variables remain statistically significant when added simultaneously suggests that the age effect captures a dynamic that is somewhat distinct from respondents' pandemic-related threat perceptions (e.g., older people being more rule-compliant in general, especially in private settings, while younger people largely comply only when substantially monitored).

[14] Mobility changes in going to the grocery store/pharmacy are conceptually unrelated to the compliance items in our survey. Mobility changes in parks would be hard to interpret given very different weather conditions throughout weeks of the year, which predominantly determine outside activities in Germany during these months.

[15] Our results are particularly interesting in light of a recent contribution by Papanastasiou et al. (2022): The authors find that economic preferences, specifically, risk and time preferences, become less relevant as predictors of compliance behaviors if respondents are presented with the hypothetical prospect of being fined for non-compliance. While they conducted their data collection at a point in time when fines had not yet been introduced, fines had already come into effect when we conducted our study. The comparison with Papanastasiou et al. (2022) thus seems to permit the following two additional interpretations of our results: First, the fact that we find economic preferences in general to be statistically relevant despite the existence of fees suggests that the estimated effects are rather a lower bound for their relevance in the absence of fees. Second, the finding by Papanastasiou et al. (2022), who examined risk and time preferences in particular, may also serve as a partial explanation for why social preferences as opposed to risk and time preferences are more important for compliance behaviors in our study. This applies especially for compliance in the public realm, which we had not only assigned a larger likelihood of formal (state-) punishment through fines, but also of social punishment to which especially the impacts of social preferences seem to be sensitive.

[16] Betsch et al. (2021b), Drichoutis and Nayga (2021), Shachat et al. (2021), Angrisani et al. (2020), Bu et al. (2020), Ikeda et al. (2023), Lotti and Pethiyagoda (2021), van de Groep et al. (2020), Habibpour et al. (2018), Chuang and Schechter (2015), Meier and Sprenger (2015), Carlsson et al. (2014), Volk et al. (2012), and Andersen et al. (2008), see Appendix B for a structured and more detailed overview of these articles' relevance for our argument.

[17] Data was retrieved from https://www.corona-daten-deutschland.de/dataset/infektionen_bundeslaender.

REFERENCES

Acock, A. C. (2013). *Discovering structural equation modeling using Stata*. Stata Press Books.

Alfaro, L., Faia, E., Lamersdorf, N., & Saidi, F. (2022). Health externalities and policy: The role of social preferences. *Management Science*, *68*(9), 6751–6761. https://doi.org/10.1287/mnsc.2022.4461

Algan, Y., Cohen, D., Davoine, E., Foucault, M., & Stantcheva, S. (2021). Trust in scientists in times of pandemic: Panel evidence from 12 countries. *Proceedings of the National Academy of Sciences*, *118*(40), e2108576118. https://doi.org/10.1073/pnas.2108576118

Andersen, S., Harrison, G. W., Lau, M. I., & Elisabet Rutström, E. (2008). Lost in state space: Are preferences stable? *International Economic Review*, *49*(3), 1091–1112. https://doi.org/10.1111/j.1468-2354.2008.00507.x

Andersson, O., Campos-Mercade, P., Meier, A. N., & Wengström, E. (2021). Anticipation of COVID-19 vaccines reduces willingness to socially distance. *Journal of Health Economics*, *80*, 102530. https://doi.org/10.1016/j.jhealeco.2021.102530

Angrisani, M., Cipriani, M., Guarino, A., Kendall, R., & Ortiz de Zarate, J. (2020). Risk preferences at the time of COVID-19: An experiment with professional traders and students (Federal Reserve Bank of New York Staff Report 927). https://ssrn.com/abstract=3609586

Bargain, O., & Aminjonov, U. (2020). Trust and compliance to public health policies in times of COVID-19. *Journal of Public Economics*, *192*, 104316. https://doi.org/10.1016/j.jpubeco.2020.104316

Barrios, J. M., Benmelech, E., Hochberg, Y. V., Sapienza, P., & Zingales, L. (2021). Civic capital and social distancing during the COVID-19 pandemic. *Journal of Public Economics*, *193*, 104310. https://doi.org/10.1016/j.jpubeco.2020.104310

Bartscher, A. K., Seitz, S., Siegloch, S., Slotwinski, M., & Wehrhöfer, N. (2021). Social capital and the spread of COVID-19: Insights from European countries. *Journal of Health Economics*, *80*, 102531. https://doi.org/10.1016/j.jhealeco.2021.102531

Betsch, C., Wieler, L., Bosnjak, M., Ramharter, M., Stollorz, V., Omer, S., Korn, L., Sprengholz, P., Felgendreff, L., Eitze, S., & Schmid, P. (2021a). Germany COVID-19 Snapshot MOnitoring (COSMO Germany): Monitoring knowledge, risk perceptions, preventive behaviours, and public trust in the current coronavirus outbreak in Germany – Wave 27. Retrieved from https://projekte.uni-erfurt.de/cosmo2020/web/summary/27/

Betsch, C., Wieler, L., Bosnjak, M., Ramharter, M., Stollorz, V., Omer, S., Korn, L., Sprengholz, P., Felgendreff, L., Eitze, S., & Schmid, P. (2021b). Germany COVID-19 Snapshot MOnitoring (COSMO Germany): Monitoring knowledge, risk perceptions, preventive behaviours, and public trust in the current coronavirus outbreak in Germany – Wave 38 summary. Retrieved from https://projekte.uni-erfurt.de/cosmo2020/web/summary/38/

Blair, R. A., Morse, B. S., & Tsai, L. L. (2017). Public health and public trust: Survey evidence from the Ebola Virus Disease epidemic in Liberia. *Social Science & Medicine*, *172*, 89–97. https://doi.org/10.1016/j.socscimed.2016.11.016

Böhm, R., Betsch, C., & Korn, L. (2016). Selfish-rational non-vaccination: Experimental evidence from an interactive vaccination game. *Journal of Economic Behavior & Organization*, *131*, 183–195. https://doi.org/10.1016/j.jebo.2015.11.008

Borgonovi, F., & Andrieu, E. (2020). Bowling together by bowling alone: Social capital and COVID-19. *Social Science & Medicine*, *265*, 113501. https://doi.org/10.1016/j.socscimed.2020.113501

Brodeur, A., Gray, D., Islam, A., & Bhuiyan, S. (2021). A literature review of the economics of COVID-19. *Journal of Economic Surveys*, *35*(4), 1007–1044. https://doi.org/10.1111/joes.12423

Brodeur, A., Grigoryeva, I., & Kattan, L. (2021). Stay-at-home orders, social distancing, and trust. *Journal of Population Economics*, *34*(4), 1–34. https://doi.org/10.1007/s00148-021-00848-z

Bu, D., Hanspal, T., Liao, Y., & Liu, Y. (2020). Risk taking during a global crisis: Evidence from Wuhan. *Covid Economics*, *5*, 106–146.

Campos-Mercade, P., Meier, A. N., Schneider, F. H., Meier, S., Pope, D., & Wengström, E. (2021). Monetary incentives increase COVID-19 vaccinations. *Science*, *374*(6569), 879–882. https://doi.org/10.1126/science.abm0475

Campos-Mercade, P., Meier, A. N., Schneider, F. H., & Wengström, E. (2021). Prosociality predicts health behaviors during the COVID-19 pandemic. *Journal of Public Economics*, *195*, 104367. https://doi.org/10.1016/j.jpubeco.2021.104367

Carlsson, F., Johansson-Stenman, O., & Nam, P. K. (2014). Social preferences are stable over long periods of time. *Journal of Public Economics*, *117*, 104–114. https://doi.org/10.1016/j.jpubeco.2014.05.009

Chan, H. F., Brumpton, M., Macintyre, A., Arapoc, J., Savage, D. A., Skali, A., Stadelmann, D., & Torgler, B. (2020). How confidence in health care systems affects mobility and compliance during the COVID-19 pandemic. *PLoS One*, *15*(10), e0240644. https://doi.org/10.1371/journal.pone.0240644

Chan, H. F., Skali, A., Savage, D. A., Stadelmann, D., & Torgler, B. (2020). Risk attitudes and human mobility during the COVID-19 pandemic. *Scientific Reports*, *10*(1), 1–13. https://doi.org/10.1038/s41598-020-76763-2

Chuang, Y., & Schechter, L. (2015). Stability of experimental and survey measures of risk, time, and social preferences: A review and some new results. *Journal of Development Economics*, *117*, 151–170. https://doi.org/10.1016/j.jdeveco.2015.07.008

Cucciniello, M., Pin, P., Imre, B., Porumbescu, G. A., & Melegaro, A. (2022). Altruism and vaccination intentions: Evidence from behavioral experiments. *Social Science & Medicine*, *292*, 114195. https://doi.org/10.1016/j.socscimed.2021.114195

Destatis Statistisches Bundesamt. (2021). Bevölkerungsstand: Amtliche Einwohnerzahl Deutschlands 2022. [Online]. Retrieved January, 29, 2021 from https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/_inhalt.html

Drichoutis, A. C., & Nayga, R. M. (2021). On the stability of risk and time preferences amid the COVID-19 pandemic. *Experimental Economics*, *25*(3), 1–36. https://doi.org/10.1007/s10683-021-09727-6

Durante, R., Guiso, L., & Gulino, G. (2021). Asocial capital: Civic culture and social distancing during COVID-19. *Journal of Public Economics*, *194*, 104342. https://doi.org/10.1016/j.jpubeco.2020.104342

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., & Sunde, U. (2018). Global evidence on economic preferences. *Quarterly Journal of Economics*, *133*(4), 1645–1692. https://doi.org/10.1093/qje/qjy013

Falk, A., Becker, A., Dohmen, T. J., Huffman, D., & Sunde, U. (2022). The preference survey Module: A validated instrument for measuring risk, time, and social preferences. *Management Science*, *69*(4), 1935–1950. https://doi.org/10.1287/mnsc.2022.4455

Fang, X., Freyer, T., Ho, C. Y., Chen, Z., & Goette, L. (2022). Prosociality predicts individual behavior and collective outcomes in the COVID-19 pandemic. *Social Science & Medicine*, *308*, 115192. https://doi.org/10.1016/j.socscimed.2022.115192

Farzanegan, M. R., & Hofmann, H. P. (2022). A matter of trust? Political trust and the COVID-19 pandemic. *International Journal of Sociology*, *52*(6), 476–499. https://doi.org/10.1080/00207659.2022.2086729

Fazio, R. H., Ruisch, B. C., Moore, C. A., Granados Samayoa, J. A., Boggs, S. T., & Ladanyi, J. T. (2021). Who is (not) complying with the US social distancing directive and why? Testing a general framework of compliance with virtual measures of social distancing. *PLoS One*, *16*(2), e0247520. https://doi.org/10.1371/journal.pone.0247520

Finney, S. J., & DiStefano, C. (2006). Non-normal and categorical data in structural equation modeling. In G. R. Hancock & R. O. Mueller (Eds.), *Structural equation modeling: A second course* (Chap. 9, pp. 269–314). Information Age Publishing.

Galizzi, M. M., W. Lau, K., Miraldo, M., & Hauck, K. (2022). Bandwagoning, free-riding and heterogeneity in influenza vaccine decisions: An online experiment. *Health Economics*, *31*(4), 614–646. https://doi.org/10.1002/hec.4467

Goldstein, D. A., & Wiedemann, J. (2022). Who do you trust? The consequences of political and social trust for public responsiveness to COVID-19 orders. *The Consequences of Political and Social Trust for Public Responsiveness to COVID-19 Orders. Perspectives on Politics*, *20*(2), 412–438. https://doi.org10.1017/S1537592721000049

Google LLC. (2021). Google COVID-19 community mobility reports [online]. Retrieved July 9, 2021, from https://www.google.com/covid19/mobility/

Granados Samayoa, J. A., Ruisch, B. C., Moore, C. A., Boggs, S. T., Ladanyi, J. T., & Fazio, R. H. (2021). When does knowing better mean doing better? Trust in President Trump and in scientists moderates the relation between COVID-19 knowledge and social distancing. *Journal of Elections, Public Opinion, and Parties*, *31*(sup1), 218–231. https://doi.org/10.1080/17457289.2021.1924744

Habibpour, M. M., Peiffer, M., Pepermans, R., & Jegers, M. (2018). How giving affects giving: A long-term analysis of donations. *Applied Economics*, *50*(21), 2402–2413. https://doi.org/10.1080/00036846.2017.1397853

Harper, C. A., Satchell, L. P., Fido, D., & Latzman, R. D. (2020). Functional fear predicts public health compliance in the COVID-19 pandemic. *International Journal of Mental Health and Addiction*, *19*(5), 1–14. https://doi.org/10.1007/s11469-020-00281-5

Ikeda, S., Yamamura, E., & Tsutsui, Y. (2023). COVID-19 Enhanced Diminishing Sensitivity in Prospect-Theory Risk Preferences: A Panel Analysis. *Review of Behavioral Economics*, *10*(4), 287–313.

Jørgensen, F., Bor, A., & Petersen, M. B. (2021). Compliance without fear: Individual-level protective behaviour during the first wave of the COVID-19 pandemic. *British Journal of Health Psychology*, *26*(2), 679–696. https://doi.org/10.1111/bjhp.12519

Kazemian, S., Fuller, S., & Algara, C. (2021). The role of race and scientific trust on support for COVID-19 social distancing measures in the United States. *PLoS One*, *16*(7), e0254127. https://doi.org/10.1371/journal.pone.0254127

Kemper, C. J., Beierlein, C., Bensch, D., Kovaleva, A., & Rammstedt, B. (2012). Eine Kurzskala zur Erfassung des Gamma-Faktors sozial erwünschten Antwortverhaltens: Die Kurzskala Soziale Erwünschtheit-Gamma (KSE-G) (GESIS-Leibniz-Institut für Sozialwissenschaften Working Papers, 2012/25). GESIS - Leibniz-Institut für Sozialwissenschaften.

Keser, C., & Rau, H. A. (2023). Determinants of people's motivations to approach COVID-19 vaccination centers. *Scientific Reports*, *13*(1), 5282. https://doi.org/10.1038/s41598-023-30244-4

Klopp, E. (2022). A tutorial on testing the equality of standardized regression coefficients in structural equation models using Wald tests with lavaan. *The Quantitative Methods for Psychology*, *16*(4), 315–333.

Kluwe-Schiavon, B., Viola, T. W., Bandinelli, L. P., Castro, S. C. C., Kristensen, C. H., Costa da Costa, J., & Grassi-Oliveira, R. (2021). A behavioral economic risk aversion experiment in the context of the COVID-19 pandemic. *PLoS One*, *16*(1), e0245261. https://doi.org/10.1371/journal.pone.0245261

Knight, F. H. (1921). *Risk, uncertainty and profit* (Vol. 31). Houghton Mifflin.

Koetke, J., Schumann, K., & Porter, T. (2021). Trust in science increases conservative support for social distancing. *Group Processes & Intergroup Relations*, *24*(4), 680–697. https://doi.org/10.1177/1368430220985918

Li, C.-H. (2016). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods*, *48*(3), 936–949. https://doi.org/10.3758/s13428-015-0619-7

Lotti, L., & Pethiyagoda, S. (2021). Generosity during COIVID-19: Investigating socioeconomic shocks and game framing. *Humanities and Social Sciences Communications*, *9*(1). https://doi.org/10.1057/s41599-022-01200-w

Marani, M., Katul, G. G., Pan, W. K., & Parolari, A. J. (2021). Intensity and frequency of extreme novel epidemics. *Proceedings of the National Academy of Sciences*, *118*(35), e2105482118. https://doi.org/10.1073/pnas.2105482118

Meier, S., & Sprenger, C. D. (2015). Temporal stability of time preferences. *The Review of Economics and Statistics*, *97*(2), 273–286. https://doi.org/10.1162/rest_a_00433

Merkel, A. (Televised speech). (2020). Fernsehansprache von Angela Merkel (Pressemitteilung 100). [Online]. Retrieved May, 10, 2023, from https://www.bundesregierung.de/breg-de/aktuelles/fernsehansprache-von-bundeskanzlerin-angela-merkel-1732134

Müller, S., & Rau, H. A. (2021). Economic preferences and compliance in the social stress test of the COVID-19 crisis. *Journal of Public Economics*, *194*, 104322. https://doi.org/10.1016/j.jpubeco.2020.104322

Nikolov, P., Pape, A., Tonguc, O., & Williams, C. (2020). *Predictors of social distancing and mask-wearing behavior: Panel survey in seven US states*. Human Capital and Economic Opportunity Working Group.

Papanastasiou, A., Ruffle, B. J., & Zheng, A. (2022). Compliance with social distancing: Theory and empirical evidence from Ontario during COVID-19. *Canadian Journal of Economics/Revue canadienne d'économique*, *55*(S1), 705–734. https://doi.org/10.1111/caje.12565

Plohl, N., & Musil, B. (2021). Modeling compliance with COVID-19 prevention guidelines: The critical role of trust in science. *Psychology Health & Medicine*, *26*(1), 1–12. https://doi.org/10.1080/13548506.2020.1772988

Press and Information Office of the Federal Government. (2021a). Coronavirus in Deutschland [online]. Retrieved September 19, 2021, from https://www.bundesregierung.de/breg-de/themen/coronavirus/corona-diese-regeln-und-einschraenkung-gelten-1734724

Press and Information Office of the Federal Government. (2021b). Regeln in den Bundesländern [online]. Retrieved September 19, 2021, from https://www.bundesregierung.de/breg-de/themen/coronavirus/corona-bundeslaender-1745198

Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., & Colizza, V. (2020). Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: A population-based study. *The Lancet Digital Health*, *2*(12), e638–e649. https://doi.org/10.1016/s2589-7500(20)30243-0

Quaas, M., Meya, J., Schenk, H., Bos, B., Drupp, M. A., & Requate, T. (2021). The social cost of contacts: Theory and evidence for the COVID-19 pandemic in Germany. *PLoS One*, *16*(3), e0248288. https://doi.org/10.1371/journal.pone.0248288

Rigdon, E. E. (1994). Calculating degrees of freedom for a structural equation model. *Structural Equation Modeling: A Multidisciplinary Journal*, *1*(3), 274–278. https://doi.org/10.1080/10705519409539979

Schunk, D., & Wagner, V. (2021). What determines the willingness to sanction violations of newly introduced social norms: Personality traits or economic preferences? Evidence from the COVID-19 crisis. *Journal of Behavioral and Experimental Economics*, *93*, 101716. https://doi.org/10.1016/j.socec.2021.101716

Shachat, J., Walker, M., & Wei, L. (2021). How the onset of the COVID-19 pandemic impacted pro-social behaviour and individual preferences: Experimental evidence from China. *Journal of Economic Behavior & Organization*, *190*, 480–494. https://doi.org/10.1016/j.jebo.2021.08.001

Sheth, K., & Wright, G. C. (2020). The usual suspects: Do risk tolerance, altruism, and health predict the response to COVID-19? *Review of Economics of the Household*, *18*(4), 1041–1052. https://doi.org/10.1007/s11150-020-09515-w

Shim, E., Chapman, G. B., Townsend, J. P., & Galvani, A. P. (2012). The influence of altruism on influenza vaccination decisions. *Journal of The Royal Society Interface*, *9*(74), 2234–2243. https://doi.org/10.1098/rsif.2012.0115

Sutinen, J. G., & Kuperan, K. (1999). A socio-economic theory of regulatory compliance. *International Journal of Social Economics*, *26*(1–2), 174–193. https://doi.org/10.1108/03068299910229569

Vai, B., Cazzetta, S., Ghiglino, D., Parenti, L., Saibene, G., Toti, M., Verga, C., Wykowska, A., & Benedetti, F. (2020). Risk perception and media in shaping protective behaviors: Insights from the early phase of COVID-19 Italian outbreak. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.563426

Van Bavel, J. J., Baicker, K., Boggio, P. S., Capraro, V., Cichocka, A., Cikara, M., Crockett, M. J., Crum, A. J., Douglas, K. M., Druckman, J. N., Drury, J., Dube, O., Ellemers, N., Finkel, E. J., Fowler, J. H., Gelfand, M., Han, S., Haslam, S. A., Jetten, J., … Willer, R. (2020). Using social and behavioural science to support COVID-19 pandemic response. *Nature Human Behaviour*, *4*(5), 460–471. https://doi.org/10.1038/s41562-020-0884-z

van de Groep, S., Zanolie, K., Green, K. H., Sweijen, S. W., & Crone, E. A. (2020). A daily diary study on adolescents' mood, empathy, and prosocial behavior during the COVID-19 pandemic. *PLoS One*, *15*(10), e0240349. https://doi.org/10.1371/journal.pone.0240349

van Hulsen, M., Rohde, K. I., & van Exel, J. (2020). Inter-temporal and social preferences predict compliance in a social dilemma: An application in the context of COVID-19 (Tinbergen Institute Discussion Paper 2020-047/I). Tinbergen Institute. http://hdl.handle.net/10419/229667

Volk, S., Thöni, C., & Ruigrok, W. (2012). Temporal stability and psychological foundations of cooperation preferences. *Journal of Economic Behavior & Organization*, *81*(2), 664–676. https://doi.org/10.1016/j.jebo.2011.10.006

Xie, K., Liang, B., Dulebenets, M. A., & Mei, Y. (2020). The impact of risk perception on social distancing during the COVID-19 pandemic in China. *International Journal of Environmental Research and Public Health*, *17*(17), 6256. https://doi.org/10.3390/ijerph17176256

Xu, P., & Cheng, J. (2021). Individual differences in social distancing and mask-wearing in the pandemic of COVID-19: The role of need for cognition, self-control and risk attitude. *Personality and Individual Differences*, *175*, 110706. https://doi.org/10.1016/j.paid.2021.110706

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APPENDIX A

TABLE A1 Overview and descriptive statistics of survey items.

Variable	Values/description	Mean (SD)	Min	Max	*N*
Female	0: Male (50.03%)	0.499 (0.50)	0	1	3342
	1: Female (49.97%)				
Age group	1: 18–29 (18.99%)	3.12 (1.44)	1	5	3350
	2: 30–39 (17.85%)				
	3: 40–49 (18.06%)				
	4: 50–59 (22.09%)				
	5: 60+ (23.01%)				
Education	1: Low (33.50%)	2.02 (0.83)	1	3	3349
	2: Medium (31.11%)				
	3: High (35.38%)				
Employed in essential services	0: No (78.81%)	0.21 (0.41)	0	1	3350
	1: Yes (21.19%)				
Household income (monthly)	1: Less than 900€ (9.30%)	4.54 (2.06)	1	10	3333
	2: 900–1299€ (10.68%)				
	3: 1300–1699€ (10.56%)				
	4: 1700–2299€ (16.17%)				
	5: 2300–3199€ (20.70%)				
	6: 3200–3999€ (15.39%)				
	7: 4000–4999€ (10.23%)				
	8: 5000–5999€ (3.96%)				
	9: 6000–9999€ (2.61%)				
	10: More than 10,000€ (0.39%)				
Household size	1: Just me (28.90%)	2.06 (0.85)	1	4	3350
	2: 2–3 people (40.15%)				
	3: 3–4 people (26.81%)				
	4: More than 4 people (4.15%)				
Compliance items					
Keeping distance	Scale from 1 (applies never) to 5 (applies always in last 2 weeks)	4.44 (0.87)	1	5	3346
Wearing masks	Scale from 1 (applies never) to 5 (applies always in last 2 weeks)	4.78 (0.71)	1	5	3347
Avoiding handshakes	Scale from 1 (applies never) to 5 (applies always in last 2 weeks)	4.70 (0.79)	1	5	3347
Only leaving home when necessary	Scale from 1 (applies never) to 5 (applies always in last 2 weeks)	4.21 (1.11)	1	5	3346
Avoiding other households	Scale from 1 (applies never) to 5 (applies always in last 2 weeks)	4.15 (1.11)	1	5	3345

(Continues)

TABLE A1 (Continued)

Variable	Values/description	Mean (SD)	Min	Max	*N*
Restricting private meetings	Scale from 1 (applies never) to 5 (applies always in last 2 weeks)	4.14 (1.16)	1	5	3347
Alternative compliance items					
Willingness to join friends' sledding trip next weekend (rev. coded)	Scale from 1 (not at all willing) to 7 (very willing)	2.33 (1.91)	1	7	2742
Willingness to join friends' surprise birthday caroling (rev. coded)	Scale from 1 (not at all willing) to 7 (very willing)	3.32 (2.18)	1	7	3002
Willingness to join friends' dinner/movie night (rev. coded)	Scale from 1 (not at all willing) to 7 (very willing)	2.40 (1.96)	1	7	2944
Economic preference items					
Altruism					
Incentivized donation decision	0–10 (donation from 10€ windfall endowment)	3.88 (3.46)	0	10	3320
Willingness to give to good causes	Scale from 1 (not at all willing) to 11 (very willing)	7.82 (2.82)	1	11	3349
Pos. reciprocity					
Willingness to return a favor	Scale from 1 (not at all willing) to 11 (very willing)	9.44 (1.98)	1	11	3349
Neg. reciprocity					
Willingness to take revenge	Scale from 1 (not at all willing) to 11 (very willing)	3.80 (2.78)	1	11	3348
Willingness to punish unfair behavior toward self	Scale from 1 (not at all willing) to 11 (very willing)	4.88 (2.87)	1	11	3349
Willingness to punish unfair behavior toward others	Scale from 1 (not at all willing) to 11 (very willing)	5.28 (2.83)	1	11	3349
Risk aversion					
Willingness to take risks (rev. coded)	Scale from 1 (not at all willing) to 11 (very willing)	6.45 (2.63)	1	11	3350
Incentivized lottery choice	0: Lottery with 5% chance of 10 Euro payment (54.45%) 1: Guaranteed payment of 0.50 Euro (45.55%)	0.46 (0.50)	0	1	3339
Patience					
Intertemporal choice sequence using staircase method	1–32 (see Figure A5 for details)	17.20 (12.11)	1	32	3111
Willingness to wait	Scale from 1 (not at all willing) to 11 (very willing)	7.53 (2.48)	1	11	3349
Civic responsibility					
Voter turnout	0: Did not vote in the last national election 2017 (14.94%) 1: Voted in the last national election 2017 (85.06%)	0.85 (0.36)	0	1	3200
Frequency to evade fares (rev. coded)	Scale from 1 (never) to 6 (always)	1.71 (0.98)	1	6	3350
Frequency of littering (rev. coded)	Scale from 1 (applies not at all) to 4 (applies always)	1.78 (0.93)	1	4	3350
Institutional trust items					
Trust in RKI	Scale from 1 (very low trust) to 7 (very high trust in this institution)	4.91 (1.91)	1	7	3350
Trust in government	Scale from 1 (very low trust) to 7 (very high trust in this institution)	4.10 (1.90)	1	7	3349

TABLE A1 (Continued)

Variable	Values/description	Mean (SD)	Min	Max	N
CV19 threat perception items					
CV19-Induced anxiety	Scale from 1 (not at all anxious) to 7 (very anxious)	4.49 (1.81)	1	7	3337
CV19-grounded concern	Scale from 1 (not at all concerned) to 7 (very concerned)	5.18 (1.68)	1	7	3343
CV19-occupied thoughts	Scale from 1 to 7 (something I never/always think about)	4.92 (1.59)	1	7	3341
Own health threat	Scale from 1 to 49; severity (1–7) × probability of infection (1–7)	12.72 (9.01)	1	49	3348
Fear of losing a loved one	Scale from 1 (very worried) to 7 (not at all worried)	4.38 (2.05)	1	7	3350
Financial threat	Scale from 1 (very worried) to 7 (not at all worried)	3.25 (2.18)	1	7	3346
Social isolation threat	Scale from 1 (very worried) to 7 (not at all worried)	5.03 (1.78)	1	7	3349
Social desirability bias items					
Unconditional objectivity in disputes	Scale from 1 (does not apply at all) to 4 (fully applies)	2.88 (0.67)	1	4	3349
Unconditional kindness under stress	Scale from 1 (does not apply at all) to 4 (fully applies)	2.95 (0.71)	1	4	3350
Unconditional attention in conversations	Scale from 1 (does not apply at all) to 4 (fully applies)	3.24 (0.64)	1	4	3350
Knowledge preventive measures items					
	Indicator variable formed from the 9 items below				
High knowledge of preventive measures	0: Failed to identify listed prevention measures correctly (53.21%)	0.47 (0.50)	0	1	3349
	1: Identified all listed prevention measures correctly (46.79%)				
Measures that respondents had to assess for their ability to help prevent a COVID-19 infection					
Staying at home when sick (correct)	0: No (4.81%)	0.99 (0.29)	0	2	3349
	1: Yes (91.88%)				
	2: Don't know (3.31%)				
Washing your hands for at least 20 s (correct)	0: No (4.96%)	0.98 (0.29)	0	2	3348
	1: Yes (91.88%)				
	2: Don't know (3.17%)				
Regularly ventilating rooms (correct)	0: No (2.51%)	1.00 (0.23)	0	2	3347
	1: Yes (94.71%)				
	2: Don't know (2.78%)				
Consumption of garlic (false)	0: No (81.70%)	0.30 (0.66)	0	2	3349
	1: Yes (6.87%)				
	2: Don't know (11.44%)				
Keep physical distance from people of other households (correct)	0: No (7.38%)	0.96 (0.33)	0	2	3348
	1: Yes (89.16%)				
	2: Don't know (3.46%)				

(Continues)

TABLE A1 (Continued)

Variable	Values/description	Mean (SD)	Min	Max	*N*
Disinfecting your hands (correct)	0: No (6.81%)	0.97 (0.32)	0	2	3349
	1: Yes (89.82%)				
	2: Don't know (3.37%)				
Taking antibiotics (false)	0: No (85.73%)	0.24 (0.61)	0	2	3349
	1: Yes (4.81%)				
	2: Don't know (9.47%)				
Getting vaccinated against influenza (false)	0: No (68.50%)	0.45 (0.71)	0	2	3349
	1: Yes (18.45%)				
	2: Don't know (13.05%)				
Avoid crowded places and groups of people (correct)	0: No (3.58%)	0.99 (0.25)	0	2	3348
	1: Yes (93.94%)				
	2: Don't know (2.48%)				

Note: This table shows mean, standard deviation, minimum, maximum and the number of observations for each of the raw survey items (except for state of residence, see Table A2 for this). The survey items for civic responsibility, COVID-19 threat perception, social desirability bias were introduced to exploratory factor analyses to then form factor scores to be employed in the final analysis (see Tables A7, A8 and A15 and Figures A2–A4 and A8). The survey items for the remaining economic preferences were formed into the final preference measures by means of the weighting procedure by Falk et al. (2018) (see Tables A4 and A5 and Figure A5). See Table A6 for a summary of all these newly constructed measures employed in the SEM analysis.

TABLE A2 Sample representativeness.

Variable	Proportion in German population	Proportion in study sample
Gender and age		
Female 18–29	9.05%	9.07%
Female 30–39	8.80%	8.83%
Female 40–49	8.45%	9.01%
Female 50–59	11.17%	11.04%
Female 60–74	12.30%	12.03%
Male 18–29	9.87%	9.90%
Male 30–39	9.20%	9.04%
Male 40–49	8.54%	9.04%
Male 50–59	11.27%	11.04%
Male 60–74	11.36%	10.95%
State		
Baden-Württemberg	13.39%	13.05%
Bayern	15.95%	16.13%
Berlin	4.48%	3.95%
Brandenburg	2.98%	2.96%
Bremen	0.82%	0.96%
Hamburg	2.26%	2.09%
Hessen	7.60%	7.96%
Mecklenburg-Vorpommern	1.92%	2.03%
Niedersachsen	9.56%	9.96%

TABLE A2 (Continued)

Variable	Proportion in German population	Proportion in study sample
Nordrhein-Westfalen	21.58%	22.14%
Rheinland-Pfalz	4.95%	5.00%
Saarland	1.20%	0.90%
Sachsen	4.73%	5.00%
Sachsen-Anhalt	2.60%	2.90%
Schleswig-Holstein	3.46%	3.05%
Thüringen	1.31%	1.92%
Education		
Low	34%	33.55%
Medium	31%	31.10%
High	35%	35.35%
Observations	59,931,254 (forward projected census)	3342

Note: This table compares our sample characteristics with the characteristics of the German population. Proportions for the German population refer to 18–74 year old men and women according to the forward projection of the population census (December/2019) retrieved from the GENESIS databank of the German Federal Statistical Office (Destatis Statistisches Bundesamt, 2021). Proportions for our sample are based on the 3342 individuals (out of a total of 3350) who indicated their gender to be male or female. 99.94% of this sample comprised individuals aged 18–74 years, two individuals were older than 74 years.

TABLE A3 Compliance items (initial and translated).

Statement English/*German*
I have worn a mask in public transport or when shopping
Ich habe eine Maske in öffentlichen Verkehrsmitteln und beim Einkaufen getragen
I have kept a distance of at least 1.50 m to other people in public, whenever possible
Ich habe versucht (sofern möglich), in der Öffentlichkeit einen Abstand von 1.50 Metern zu anderen Menschen einzuhalten
I have avoided shaking other people's hands when greeting them
Ich habe Händeschütteln vermieden
I have only left the house when absolutely necessary (such as groceries, medical reasons or sports)
Ich habe nur aus triftigen Gründen das Haus verlassen (z.B. Einkäufe, Arztbesuche oder Sport)
I have restricted private gatherings to only one other person from another household
Ich habe mich privat nur mit höchstens einer anderen Person aus einem anderen Haushalt getroffen
I have deliberately avoided physical contact with people from other households
Ich habe bewusst Kontakte mit Personen aus anderen Haushalten vermieden

Note: This table lists the survey items used to measure compliance behaviors. Prior to this list, participants were asked the following overarching question: "Below, you find a list of behavioral patterns. How well does each statement reflect your behavior in the past 2 weeks?" Response options were "Applied never"; "Applied rarely"; "Applied sometimes"; "Applied often"; "Applied always".

TABLE A4 Applied weights and survey items for preference measures (adapted from Falk et al. (2018)).

Preference	Item description	Weight
Patience	*Intertemporal choice sequence using staircase method*	*0.712*
	Self-assessment: willingness to wait	0.288
Risk taking (RC)	Incentivized lottery choice (guaranteed payment of 0.50 Euro or lottery with 5% chance of 10 Euro payment)	0.473
	Self-assessment: willingness to take risks in general	*0.527*
Positive reciprocity	Self-assessment: willingness to return a favor	1
Negative reciprocity	*Self-assessment: willingness to take revenge*	*0.374*
	Self-assessment: willingness to punish unfair behavior toward self	0.313
	Self-assessment: willingness to punish unfair behavior toward others	0.313
Altruism	*Incentivized donation decision (out of 10 Euro)*	*0.635*
	Self-assessment: willingness to give to good causes	0.365

Note: The table shows the survey items and weights employed in this study, adapted from Falk et al. (2018), to form the final preference measures. The survey items were first standardized and then formed into the final preference measure using the respective weights. Most employed survey items were identical to the items used by Falk et al. (2018) (see Table A5), while two were replaced with very similar items, as we were able to employ incentivized measures in these cases (Altruism, Risk taking/aversion). In one case, we were not able to collect both survey items; specifically, we were not able to include the gift exchange task, which Falk et al. (2018) used as the second survey item for forming the preference measure for positive reciprocity (see Table A5). Thus, we used merely the self-assessment measure in this case, but aim to assess our results for robustness by conducting the same analysis when only using a single survey item for all the other preference measures as well (see Table A20 and Figure A12). For this, we used the respective survey item that has been assigned the higher weight, here marked in italic.

TABLE A5 Weighting procedure and preference measures of the Global Preference Survey (GPS) by Falk et al. (2018).

Preference	Item description	Weight
Patience	Intertemporal choice sequence using staircase method	0.712
	Self-assessment: willingness to wait	0.288
Risk taking (RC)	Lottery choice sequence using staircase method	0.473
	Self-assessment: willingness to take risks in general	0.527
Positive reciprocity	Gift in exchange for help	0.515
	Self-assessment: willingness to return a favor	0.485
Negative reciprocity	Self-assessment: willingness to take revenge	0.374
	Self-assessment: willingness to punish unfair behavior toward self	0.313
	Self-assessment: willingness to punish unfair behavior toward others	0.313
Altruism	Donation decision (out of 1000 Euro)	0.635
	Self-assessment: willingness to give to good causes	0.365

Source: Extracted from Falk et al. (2018), Table 1, p. 1653.

TABLE A6 Overview and descriptive statistics of newly constructed variables (weighted preference measures and variables constructed from factor analyses).

Variable	Source items and procedure	Mean (SD)	Min	Max	*N*
Altruism	Weights from Falk et al. (2018), 2 altruism items (donation decision, willingness to give to good causes; standardized), see Tables A1, A4 and A21	0.00 (0.84)	−1.60	1.53	3311
Negative reciprocity	Weights from Falk et al. (2018), 3 Neg. reciprocity items (willingness to take revenge/punish unfair behavior toward self/others; standardized), see Tables A1, A4 and A21	0.00 (0.83)	−1.27	2.27	3338
Risk aversion	Weights from Falk et al. (2018), 2 risk aversion items (lottery choice, willingness to take risks; standardized), see Tables A1, A4 and A21	0.00 (0.74)	−1.61	1.35	3329
Patience	Weights from Falk et al. (2018), 2 Patience aversion items (stair case method, willingness to wait; standardized), see Tables A1, A4 and A21 and Figure A5	0.01 (0.82)	−1.63	1.35	3102
Civic responsibility	Standardized factor scores from 3 items on voter turnout, fare evasion, littering frequency; see Tables A1, A8 and A21 and Figure A4	0.01 (0.80)	−2.82	0.81	3191
COVID-19 threat perception	Standardized factor scores from 8 items on general and specific CV19 threat perception; see Tables A1, A7 and A21 and Figures A2 and A3	−0.00 (0.97)	−2.53	1.82	3321
Social desirability bias	Standardized factor scores from 3 items on social desirability bias; see Tables A1, A15 and A21 and Figure A8	0.00 (0.89)	−3.42	1.70	3339

Note: This table shows mean, standard deviation, minimum, maximum and the number of observations for those variables, which were newly constructed from the raw survey items before employed in the SEM analysis, that is, variables which were formed from factor analyses or the GPS weighting procedure. For each variable, column 2 of the table refers to the respective Table/Figure, procedure and the raw variables that were used for their formation.

TABLE A7 COVID-19 threat perception: Factor loadings.

	Factor 1
COVID-19 threat perception items	
CV19-induced anxiety	0.909
CV19-grounded concern	0.844
CV19-occupied thoughts	0.705
Own health threat	0.529
Fear of losing a loved one	0.675
Financial threat	0.199
Social isolation threat	0.156
Eigenvalue	2.835
Percent shared variance accounted for	40.50
Multiple R^2 of scores with factors	0.902
Observations: 3321	

Note: The table shows standard factor pattern coefficients from a 1-factor solution of the survey items aimed at capturing COVID-19 threat perception. Estimated using iterated principal axis factoring, no rotation and a mixed correlation matrix (continuous and polychoric).

TABLE A8 Civic responsibility: Factor loadings (reverse coded for analysis).

	Factor 1
Civic responsibility items	
Fare evasion frequency	0.464
Littering behavior	0.743
Voter turnout last national election	−0.148
Eigenvalue	0.789
Percent shared variance accounted for	26.30
Multiple R^2 of scores with factors	0.604
Observations: 3193	

Note: The table shows standardized factor pattern coefficients from a 1-factor solution of the survey items aimed at capturing civic responsibility. Estimated using iterated principal axis factoring, no rotation and polychoric correlations.

TABLE A9 Polychoric correlation input matrix compliance items.

Variables	[Item 1]	[Item 2]	[Item 3]	[Item 4]	[Item 5]	[Item 6]
Wearing a mask in public transport/when shopping [item 1]	1.000					
Keeping a 1.5 m distance in public spaces (whenever possible) [item 2]	0.743	1.000				
Avoiding handshake greetings [item 3]	0.782	0.773	1.000			
Generally avoiding other households [item 4]	0.564	0.662	0.718	1.000		
Restricting private meetings [item 5]	0.531	0.569	0.620	0.655	1.000	
Leaving the home only when absolutely necessary [item 6]	0.580	0.627	0.676	0.692	0.580	1.000

Note: This table shows polychoric correlations for the six survey items aimed to quantify compliance behavior (measured on a 5-point Likert scale, with higher values indicating higher compliance, see Table A3).

TABLE A10 Compliance: Exploratory unrotated factor analysis results.

	Factor 1	Factor 2
Dimension: Compliance in the public domain		
Wearing a mask in public transport/when shopping	0.823	−0.364
Keeping a 1.5 m distance in public spaces (whenever possible)	0.840	−0.138
Avoiding handshake greetings	0.900	−0.113
Dimension: Compliance in the private domain		
Leaving the home only when absolutely necessary	0.770	0.149
Generally avoiding other households	0.837	0.334
Restricting private meetings to 1 person from another household	0.714	0.172
Eigenvalue	3.998	0.327
Percent shared variance accounted for	66.63	5.46
Multiple R^2 of scores with factors	0.944	0.605
Correlation between factors: -		
Observations: 3340		

Note: The table shows standardized factor patterns coefficients from a 2-factor analysis of the six compliance items, estimated using iterated principal axis factoring, no rotation and polychoric correlations.

TABLE A11 Compliance: Summated rating scale reliability analysis.

Item	Cronbach's α	α If item is deleted
Scale: Compliance in the public domain	0.797	
Wearing a mask in crowded places		0.765
Keeping a 1.5 m distance in public spaces (whenever possible)		0.712
Avoiding handshakes		0.693
Scale: Compliance in the private domain	0.780	
Leaving the home only when absolutely necessary		0.709
Generally avoiding other households		0.642
Restricting private meetings to 1 person from another household		0.753
Correlation between scales: 0.643		
Observations: 3340		

Note: The table shows the results of a reliability analysis (i.e., overall Cronbach's α and Cronbach's α when dropping a certain item) of two summated rating scales using the two item triplets as indicated in the table and identified in the exploratory factor analysis in Table 1.

TABLE A12 Structural equation model (SEM) measurement component (confirmatory factor analysis).

Latent variable	Compliance in the public domain	Compliance in the private domain
Wearing a mask in public transport/when shopping	0.892***	
	(0.035)	
Keeping a 1.5 m distance in public spaces (whenever possible)	0.833***	
	(0.027)	
Avoiding handshake greetings	0.886	
	(const.)	
Leaving the home only when absolutely necessary		0.775***
		(0.028)
Generally avoiding other households		0.895***
		(0.038)
Restricting private meetings to 1 person from another household		0.743
		(const.)
Observations = 2922		

Note: The table shows the results purely of the measurement component of the SEM for each compliance domain, as in Equation (1) (but resulting from estimating both equations simultaneously). Coefficient estimates are standardized and estimated using diagonal weighted least squares and a polychoric correlation matrix. See Table 2 for the fit statistics of the full SEM.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A13 Decision-making across compliance domains—extended structural equation model (SEM) results (also showing coefficients for control variables).

Outcome	Compliance in the public domain	Compliance in the private domain
COVID-19 threat perception	0.297***	0.365***
	(0.026)	(0.017)
Altruism	0.037	0.012
	(0.031)	(0.020)

(Continues)

TABLE A13 (Continued)

Outcome	Compliance in the public domain	Compliance in the private domain
Civic responsibility	0.127***	0.108***
	(0.024)	(0.016)
Pos. reciprocity	0.180***	0.030
	(0.024)	(0.017)
Neg. reciprocity	−0.149***	−0.086***
	(0.029)	(0.019)
Risk aversion	0.065**	0.055**
	(0.034)	(0.022)
Patience	−0.001	0.028
	(0.031)	(0.020)
Trust in RKI	0.204***	0.068**
	(0.032)	(0.021)
Trust in government	0.012	0.138***
	(0.033)	(0.021)
Female	0.117***	0.039*
	(0.025)	(0.016)
Age group	0.057*	0.135***
	(0.027)	(0.018)
High education	−0.002	0.019
	(0.030)	(0.020)
Medium education	0.027	0.016
	(0.028)	0.018
Employed essential services	0.020	−0.021
	(0.024)	(0.016)
Household income	0.003	−0.034
	(0.030)	(0.019)
Household size	−0.044	−0.013
	(0.028)	(0.018)
Knowledge preventive measures	0.117***	0.087***
	(0.025)	(0.016)
Social desirability index	0.092***	0.102***
	(0.024)	(0.016)
R^2	0.492	0.411
Observations	2918	2918

Note: Displayed are standardized coefficient estimates and standard errors in parentheses for the results of the SEMs estimated by means of Equations (1) and (2) (shown are only the structural component results, see Table A12 for the results of the measurement component). The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. All estimations moreover control for the respondents' state of residence. Table A14 repeats the same analyses with the final-model sample of $N = 2922$ throughout. See Tables A1, A15 and A21 and Figure A8 for the source survey items and factor scores of the social desirability bias index.

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

TABLE A14 Decision-making across compliance domains—structural equation model (SEM) results (same observations in all submodels).

	Compliance in the public domain								Compliance in the private domain							
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
COVID-19 threat perception	0.464***				0.321***	0.304***	0.314***	0.297***	0.502***				0.387***	0.372***	0.381***	0.365***
	(0.022)				(0.025)	(0.026)	(0.025)	(0.026)	(0.016)				(0.017)	(0.017)	(0.017)	(0.017)
Altruism		0.164***			0.060**	0.044	0.053*	0.037		0.127***			0.030	0.017	0.024	0.012
		(0.028)			(0.030)	(0.031)	(0.030)	(0.031)		(0.019)			(0.019)	(0.020)	(0.019)	(0.020)
Civic responsibility		0.196***			0.172***	0.147***	0.151***	0.127***		0.202***			0.169***	0.127***	0.148***	0.108***
		(0.023)			(0.023)	(0.024)	(0.023)	(0.024)		(0.016)			(0.016)	(0.016)	(0.016)	(0.016)
Pos. reciprocity		0.248***			0.218***	0.205***	0.193***	0.180***		0.115***			0.066**	0.056**	0.039*	0.030
		(0.023)			(0.023)	(0.024)	(0.024)	(0.024)		(0.018)			(0.017)	(0.017)	(0.017)	(0.017)
Neg. reciprocity		−0.193***			−0.184***	−0.170***	−0.165***	−0.149***		−0.125***			−0.109***	−0.103***	−0.092***	−0.086***
		(0.027)			(0.028)	(0.029)	(0.028)	(0.029)		(0.019)			(0.019)	(0.019)	(0.019)	(0.019)
Risk aversion			0.169***		0.085***	0.066**	0.085***	0.065**			0.168***		0.080***	0.055**	0.081***	0.055**
			(0.031)		(0.033)	(0.034)	(0.033)	(0.034)			(0.022)		(0.021)	(0.022)	(0.021)	(0.022)
Patience			0.141***		−0.014	0.004	−0.019	−0.001			0.115***		0.010	0.032	0.006	0.028
			(0.027)		(0.029)	(0.031)	(0.029)	(0.031)			(0.019)		(0.019)	(0.020)	(0.019)	(0.020)
Trust in RKI				0.385***	0.223***	0.216***	0.210***	0.204***				0.239***	0.087**	0.075**	0.079**	0.068**
				(0.030)	(0.031)	(0.032)	(0.031)	(0.032)				(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Trust in government				0.042	0.014	0.017	0.008	0.012				0.186***	0.137***	0.145***	0.129***	0.138***
				(0.031)	(0.031)	(0.033)	(0.031)	(0.033)				(0.022)	(0.020)	(0.021)	(0.020)	(0.021)
Demogr. and socioecon. controls	No	No	No	No	No	Yes	No	Yes	No	No	No	No	No	Yes	No	Yes
Compliance-specific controls	No	No	No	No	No	No	Yes	Yes	No	No	No	No	No	No	Yes	Yes
R^2	0.215	0.222	0.043	0.173	0.448	0.477	0.464	0.492	0.252	0.116	0.037	0.155	0.366	0.396	0.382	0.411
Observations	2918	2918	2918	2918	2918	2918	2918	2918	2918	2918	2918	2918	2918	2918	2918	2918

Note: Displayed are standardized coefficient estimates and standard errors in parentheses for the results of the SEMs estimated by means of Equations (1) and (2) (shown are only the structural component results, see Table A12 for the results of the measurement component), replicating Table 2 but using the same observations for all estimations. The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. Demographic controls contain respondents' gender, age group and state. Socioeconomic controls include education, employment in essential services, household size and income. Compliance-specific controls contain knowledge about COVID-19 preventive measures and the degree of social desirability bias (factor scores as in Figure A8 and Table A15).

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A15 Social desirability: Factor loadings.

	Factor 1
Social desirability items (positive)	
Unconditional objectivity in disputes	0.658
Unconditional kindness under stress	0.772
Unconditional attention in conversations	0.564
Eigenvalue	1.347
Percent shared variance accounted for	44.90
Multiple R^2 of scores with factors	0.730
Observations: 3339	

Note: The table shows standardized factor pattern coefficients from a 1-factor solution of the survey items aimed at capturing social desirability bias (exaggerating positive characteristics). Estimated using iterated principal axis factoring, no rotation and polychoric correlations.

TABLE A16 Correlation matrix of core explanatory variables.

	CV19-threat	Pos. Reci.	Neg. Reci.	Altruism	Civ. Resp.	Risk aversion	Patience	Trust (RKI)	Trust (Govt.)
CV19-threat	1.00								
Pos. Reci.	0.16***	1.00							
Neg. Reci.	0.02	−0.03	1.00						
Altruism	0.18***	0.24***	−0.03	1.00					
Civ. Resp.	0.08***	0.13***	−0.19***	0.12***	1.00				
Risk aversion	0.08***	−0.05**	−0.21***	−0.12***	0.12***	1.00			
Patience	0.06**	0.14***	0.02	0.22***	0.05**	−0.11***	1.00		
Trust (RKI)	0.38***	0.14***	−0.04*	0.23***	0.10***	−0.00	0.20***	1.00	
Trust (Govt.)	0.33***	0.06***	−0.03	0.21***	0.06**	−0.02	0.20***	0.71***	1.00

Source: Shown are Pearson correlations between the main explanatory variables of the SEM, that is, the final preference measures as well as the COVID-19 threat perception measure.

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

TABLE A17 Alternative compliance measure: Structural equation model (SEM) measurement component (confirmatory factor analysis).

Latent variable	Alternative compliance measure
Sledding trip (reverse coded)	0.896
	(const.)
Surprise birthday caroling (reverse coded)	0.830***
	(0.018)
Dinner or movie night (reverse coded)	0.932***
	(0.024)
Observations = 2141	

Note: The table purely shows the results of the measurement component of the SEM, as in Equation (1) (but resulting from estimating both equations simultaneously). However, instead of the initial compliance items, we used three alternative survey items as reflective indicators, as displayed in the table (see Section 4.3 and Tables A1 and A21 for detailed descriptions). Coefficient estimates are standardized and estimated using diagonal weighted least squares and a polychoric correlation matrix.

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

TABLE A18 Robustness: Decision-making across compliance domains—structural equation model (SEM) results with alternative compliance measure.

Outcome: Compliance (alternative measure)	
COVID-19 threat perception	0.319***
	(0.025)
Altruism	0.025
	(0.030)
Civic responsibility	0.173***
	(0.024)
Pos. reciprocity	−0.053*
	(0.026)
Neg. reciprocity	−0.164***
	(0.028)
Risk aversion	0.099***
	(0.031)
Patience	0.010
	(0.030)
Trust in RKI	0.156***
	(0.033)
Trust in government	0.079**
	(0.034)
Female	−0.034
	(0.023)
Age group	0.207***
	(0.026)
High education	0.013
	(0.029)
Medium education	0.009
	(0.027)
Employed essential services	−0.040*
	(0.022)
Household income	0.014
	(0.029)
Household size	0.008
	(0.026)
Knowledge preventive measures	0.073***
	(0.023)
Social desirability index	−0.014
	(0.023)

(Continues)

TABLE A18 (Continued)

Outcome: Compliance (alternative measure)	
R^2	0.469
Fit statistics (full SEM)	
Robust $\chi^2(66) = 126.907$; $p < 0.001$	
Robust RMSEA = 0.021	
Robust TLI = 0.999	
Robust CFI = 0.987	
SRMR = 0.007	
$R^2 = 0.469$	
Observations = 2141	

Note: Displayed are standardized coefficient estimates and standard errors in parentheses for the results of the SEM estimated by means of Equations (1) and (2) (shown are only the structural component results, see Table A17 for the results of the measurement component) and fit statistics for the full SEM. However, instead of the initial compliance items, we used three alternative survey items as reflective indicators (see Section 4.3 and Tables A1 and A21 for detailed descriptions). The SEM was estimated using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. All estimations moreover control for the respondents' state of residence. See Tables A1, A15 and A21 and Figure A8 for the source survey items and factor scores of the social desirability bias index.

Abbreviations: CFI, comparative fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual; TLI, Tucker-Lewis index.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A19 Robustness: Decision-making across compliance domains—structural equation model (SEM) results with mediation.

	Compliance in the public domain			Compliance in the private domain		
Model	**Direct effect**	**Indirect effect**	**Total effect**	**Direct effect**	**Indirect effect**	**Total effect**
COVID-19 threat perception	0.286***	-	0.286***	0.359***	-	0.359***
	(0.021)		(0.021)	(0.017)		(0.017)
Altruism	0.044	0.019***	0.063**	0.013	0.024***	0.037
	(0.031)	(0.007)	(0.031)	(0.024)	(0.008)	(0.026)
Civic responsibility	0.121***	−0.004	0.105***	0.110***	−0.005	0.100***
	(0.024)	(0.006)	(0.024)	(0.019)	(0.007)	(0.021)
Pos. reciprocity	0.172***	0.021***	0.193***	0.027	0.026***	0.053*
	(0.024)	(0.006)	(0.025)	(0.021)	(0.007)	(0.022)
Neg. reciprocity	−0.142***	0.020***	−0.122***	−0.085***	0.025***	−0.060**
	(0.028)	(0.007)	(0.029)	(0.023)	(0.008)	(0.025)
Risk aversion	0.069**	0.028***	0.097***	0.056**	0.035***	0.092***
	(0.033)	(0.008)	(0.034)	(0.026)	(0.009)	(0.028)
Patience	0.003	−0.003	0.000	0.029	−0.004	0.025
	(0.030)	(0.007)	(0.031)	(0.024)	(0.008)	(0.026)
Trust in RKI	0.201***	0.068***	0.270***	0.069**	0.086***	0.156***
	(0.031)	(0.009)	(0.032)	(0.026)	(0.009)	(0.027)
Trust in government	0.031	0.038***	0.069*	0.144***	0.047***	0.192***
	(0.032)	(0.008)	(0.033)	(0.026)	(0.009)	(0.027)

TABLE A19 (Continued)

Model	Compliance in the public domain: Direct effect	Indirect effect	Total effect	Compliance in the private domain: Direct effect	Indirect effect	Total effect
Female	0.116***	0.031***	0.147***	0.039*	0.039***	0.078***
	(0.024)	(0.006)	(0.025)	(0.020)	(0.007)	(0.021)
Age group	0.057*	0.020***	0.078**	0.138***	0.026***	0.163***
	(0.027)	(0.006)	(0.027)	(0.021)	(0.007)	(0.023)
High education	−0.003	−0.011	−0.014	0.020	−0.013	0.007
	(0.030)	(0.007)	(0.030)	(0.024)	(0.008)	(0.026)
Medium education	0.023	−0.002	0.021	0.016	−0.003	0.013
	(0.027)	(0.006)	(0.028)	(0.022)	(0.007)	(0.024)
Employed essential services	0.019	−0.016**	0.003	−0.020	−0.020**	−0.040*
	(0.023)	(0.006)	(0.024)	(0.020)	(0.007)	(0.021)
Household income	0.009	−0.005	0.004	−0.033	−0.007	−0.039
	(0.029)	(0.007)	(0.030)	(0.024)	(0.008)	(0.025)
Household size	−0.046	0.015**	−0.030	−0.015	0.019	0.004
	(0.027)	(0.006)	(0.028)	(0.022)	(0.008)	(0.024)
Knowledge measures	0.130***	-	0.130***	0.102***	-	0.102***
	(0.025)	-	(0.025)	(0.021)	-	(0.021)
Social desirability index	0.099***		0.099***	0.110***	-	0.110***
	(0.024)	-	(0.024)	(0.021)	-	(0.021)

Fit statistics (full SEM)	Public	Private
	Robust $\chi^2(68) = 167.704$; $p < 0.001$	Robust $\chi^2(68) = 116.578$; $p < 0.001$
	Robust RMSEA = 0.022	Robust RMSEA = 0.016
	Robust TLI = 0.997	Robust TLI = 0.999
	Robust CFI = 0.965	Robust CFI = 0.988
	SRMR = 0.025	SRMR = 0.013
	$R^2 = 0.487$	$R^2 = 0.412$
	Observations = 2918	Observations = 2918

Note: Displayed are standardized coefficient estimates and standard errors in parentheses of estimating the SEMs by means of Equations (1) and (2), and additionally allowing for a mediating effect of COVID-19 threat perceptions. Shown are the resulting estimated direct, indirect and indirect effects (i.e., the results of the structural component) as well as fit statistics of the full SEM. The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. All estimations moreover control for the respondents' state of residence. See Tables A1, A15 and A21 and Figure A8 for the source survey items and factor scores of the social desirability bias index.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A20 Robustness: Decision-making across compliance domains—structural equation model (SEM) results using single-item preference measures.

Outcome	Compliance in the public domain	Compliance in the private domain
COVID-19 threat perception	0.290***	0.361***
	(0.026)	(0.018)
Altruism	0.026	0.006
	(0.025)	(0.016)
Civic responsibility	0.122***	0.104***
	(0.024)	(0.016)
Pos. reciprocity	0.179***	0.032
	(0.024)	(0.017)
Neg. reciprocity	−0.155***	−0.088***
	(0.024)	(0.016)
Risk aversion	0.094***	0.081***
	(0.026)	(0.017)
Patience	−0.033	−0.010
	(0.025)	(0.016)
Trust in RKI	0.200***	0.066**
	(0.032)	(0.021)
Trust in government	0.016	0.144***
	(0.033)	(0.021)
Female	0.110***	0.032
	(0.025)	(0.016)
Age group	0.050*	0.128***
	(0.027)	(0.018)
High education	0.003	0.028
	(0.030)	(0.020)
Medium education	0.023	0.017
	(0.028)	(0.018)
Employed essential services	0.020	−0.019
	(0.024)	(0.016)
Household income	0.016	−0.024
	(0.029)	(0.019)
Household size	−0.048	−0.014
	(0.028)	(0.018)
Knowledge preventive measures	0.114***	0.084***
	(0.025)	(0.016)
Social desirability index	0.086***	0.098***
	(0.024)	(0.016)

TABLE A20 (Continued)

Outcome	Compliance in the public domain	Compliance in the private domain
R^2	0.500	0.414
Observations	2918	2918
Fit statistics (full SEM)	**Public**	**Private**
	Robust $\chi^2(66) = 160.35$; $p < 0.001$	Robust $\chi^2(66) = 114.982$; $p < 0.001$
	Robust RMSEA = 0.022	Robust RMSEA = 0.016
	Robust TLI = 0.998	Robust TLI = 0.999
	Robust CFI = 0.956	Robust CFI = 0.983
	SRMR = 0.019	SRMR = 0.009

Note: Displayed are standardized coefficient estimates and standard errors in parentheses for the results of the SEMs estimated by means of Equations (1) and (2) (shown are only the structural component results) and fit statistics for each SEM. However, instead of the initially constructed preference measures, we used only a single survey item for each type of preference to assess the robustness of the singular survey item of positive reciprocity. For each preference type, we used the survey item with the highest weight in the experimental validation procedure developed by Falk et al. (2018). See Table A4 for these items, the respective items are marked in italic font. The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. All estimations moreover control for the respondents state of residence. See Tables A1, A15 and A21 and Figure A8 for the source survey items and factor scores of the social desirability bias index.

Abbreviations: CFI, comparative fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual; TLI, Tucker-Lewis index.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A21 Questionnaire items (translated from original German version).

Question (*Variable name as in* Table A1)	Response options
Compliance	
Below you find a list of behavioral patterns. How well does each reflect your behavior in the past 2 weeks? All information you provide in the questionnaire will be treated anonymously and cannot be linked to your identity.	
I have kept a distance of at least 1.50 m to other people in public, whenever possible. *(Keeping distance)*	1: Applied never; 2: Applied rarely; 3: Applied sometimes; 4: Applied often; 5: Applied always
I have worn a mask in public transport or when shopping. *(Wearing masks)*	1: Applied never; 2: Applied rarely; 3: Applied sometimes; 4: Applied often; 5: Applied always
I have only left the house when absolutely necessary (such as groceries, medical reasons or sports). *(Only leaving home when necessary)*	1: Applied never; 2: Applied rarely; 3: Applied sometimes; 4: Applied often; 5: Applied always
I have deliberately avoided physical contact with people from other households. *(Avoiding other households)*	1: Applied never; 2: Applied rarely; 3: Applied sometimes; 4: Applied often; 5: Applied always
I have restricted private gatherings to only one other person from another household. *(Restricting private meetings)*	1: Applied never; 2: Applied rarely; 3: Applied sometimes; 4: Applied often; 5: Applied always
I have avoided shaking other people's hands when greeting them. *(Avoiding handshakes)*	1: Applied never; 2: Applied rarely; 3: Applied sometimes; 4: Applied often; 5: Applied always
Compliance (alternative measures)	
When answering the next questions, please remember that all the information you provide in the questionnaire will be treated anonymously by us and cannot be linked to your identity. How would you act in the following situations?	
If it snows heavily next weekend and some friends of yours organize a sledding trip (there is still room for you on their	Scale from 1 (Definitely not) to 7 (Certainly); 99 (I am generally not very enthusiastic about this type of activity.)

(Continues)

TABLE A21 (Continued)

Question (*Variable name as in* Table A1)	Response options
sleds), would you join them? *(Willingness to join sledding trip with friends next weekend)*	
If a friend invited you to have dinner with three other friends next weekend and then watch soccer or a movie, would you accept the invitation? *(Willingness to join surprise birthday caroling for a friend)*	Scale from 1 (Definitely not) to 7 (Certainly); 99 (I am generally not very enthusiastic about this type of activity.)
Suppose one or more of your best friends has a birthday next week. A group of friends is planning to get together in the morning to serenade the birthday girl or boy at the door or under the window. Will you join them? *(Willingness to join a dinner/movie night at friends' house)*	Scale from 1 (Definitely not) to 7 (Certainly); 99 (I am generally not very enthusiastic about this type of activity.)
Economic preferences	
We now ask for your willingness to act in a certain way in different areas. Please indicate your answer on a scale from 0 to 10, where 0 means you are "completely unwilling to do so" and a 10 means you are "very willing to do so".	
How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future? *(Willingness to wait)*	Scale from 0 (completely unwilling to do so) to 10 (very willing to do so)
How willing are you to punish someone who treats you unfairly, even if there may be costs for you? *(Willingness to punish unfair behavior toward self)*	Scale from 0 (completely unwilling to do so) to 10 (very willing to do so)
How willing are you to punish someone who treats others unfairly, even if there may be costs for you? *(Willingness to punish unfair behavior toward others)*	Scale from 0 (completely unwilling to do so) to 10 (very willing to do so)
How willing are you to give to good causes without expecting anything in return? *(Willingness to give to good causes)*	Scale from 0 (completely unwilling to do so) to 10 (very willing to do so)
How well do the following statements describe you as a person? Please indicate your answer on a scale from 0 to 10. A 0 means "does not describe me at all" and a 10 means "describes me perfectly".	
When someone does me a favor, I am willing to return it. *(Willingness to return a favor)*	Scale from 0 (does not describe me at all) to 10 (describes me perfectly)
If I am treated very unjustly, I will take revenge at the very first occasion, even if there is a cost to do so. *(Willingness to take revenge)*	Scale from 0 (does not describe me at all) to 10 (describes me perfectly)
In general, how willing or unwilling you are to take risks? Please use a scale from 0 to 10, where 0 means you are "completely unwilling to take risks" and a 10 means you are "very willing to take risks". *(Willingness to take risks)*	Scale from 0 (completely unwilling to take risks) to 10 (very willing to take risks)
By answering the following questions, you have the chance to win a bonus payment of 10 euros. After completing the survey, 5% of the participants (i.e., 1 out of 20) will be randomly selected to receive this bonus payment of 10 euros.	
You have the option to donate any portion of the bonus payment to a charitable organization, while you would receive the remaining amount from Respondi. If you decide to make a donation, we will do so after the survey is	

TABLE A21 (Continued)

Question (*Variable name as in* Table A1)	Response options
completed. You can select the non-profit organization that would receive your donation below.	
Please indicate how much of your bonus payment you would like to donate if you were randomly selected as a winner. *(Incentivized donation decision)*	Scale from 0 (I do not want to donate anything) to 10 (10 Euro); 1 Euro-steps each
To which organization would you like to donate the money? (Filter, if donation ! = 0)	1 = United Nations Children's Fund (UNICEF); 2 = Greenpeace; 3 = United Nations High Commissioner for Refugees (UNHCR); 4 = United Nations World Food Program (WFP)
Suppose you were given the choice between receiving a payment today or a payment in 12 months. We will now present to you 5 situations. The payment today is the same in each of these situations. The payment in 12 months is different in every situation. For each of these situations we would like to know which you would choose. Please assume there is no inflation, that is, future prices are the same as today's prices.	
Please consider the following: would you rather receive 100 Euro today or 154 Euro in 12 months? *(Intertemporal choice sequence using staircase method)*	1 = 100 Euro today; 2 = 154 Euro in 12 months; 3 = Don't know/Don't want to specify
(Rest of intertemporal choice sequence using staircase method, see Figure A5)	
You can receive a further bonus payment for completing the questionnaire in full, which will also be sent to you by Respondi after the survey has been completed. You have the following choice:	
Do you prefer to receive a guaranteed bonus payment of 0.50 Euro OR instead participate in a lottery where you can receive a bonus payment of 10 euros with a probability of 5% (i.e., 1 out of 20 participants wins)? *(Incentivized lottery choice)*	0 = Guaranteed bonus payment of 0.50 Euro; 1 = Participate in lottery (5% chance of winning a bonus payment of 10 Euro)
Which of the following parties did you vote for in the last election (Bundestag elections)? *(Voter turnout)*	1 = CDU/CSU; 2 = SPD; 3 = AfD; 4 = FDP; 5 = Die Linke; 6 = Bündnis 90/Die Grünen; 7 = Other (please specify); 8 = I did not vote (Voting turnout: 0 = 8; 1 = 1–7)
When answering the next questions, please remember that all the information you provide in the questionnaire will be treated anonymously by us and cannot be linked to your identity.	
How often have you used public transport, for example, tram, metro, bus, or train etc., without a valid ticket? *(Frequency to evade fares)*	1 = Never; 2 = Rarely; 3 = Sometimes; 4 = Often; 5 = Very often; 6 = Always
How much does the following statement apply to you?	
I have thrown trash into the landscape or onto the street in the past. *(Frequency of littering)*	1 = Does not apply at all; 2 = does somewhat not apply; 3 = Somewhat applies; 4 = Fully applies
Institutional trust	
Think about the groups of people and organizations listed below. How much confidence do you have in each of the groups of people and organizations to deal well and properly with COVID-19 and the pandemic situation?	
Robert Koch Institute (RKI) *(Trust in RKI)*	Scale from 1 (very little confidence) to 7 (very much confidence)
Federal government *(Trust in government)*	Scale from 1 (very little confidence) to 7 (very much confidence)

(Continues)

TABLE A21 (Continued)

Question (*Variable name as in* Table A1)	Response options
COVID-19 threat perception	
How would you assess the probability that you will be infected with COVID-19 in the next 4 weeks? *(Perceived probability of getting infected)*	Scale from 1 (very unlikely) to 7 (very likely)
How would you assess the medical consequences if you yourself got infected with COVID-19? *(Perceived severity of infection)*	Scale from 1 (completely harmless) to 7 (very severe)
Based on the current pandemic situation, how much do you worry about...	
...Losing someone you love? *(Fear of losing a loved one)*	Scale from 1 (not at all worried) to 7 (very worried)
...Getting into financial difficulties because of a loss of income? *(Financial threat)*	Scale from 1 (not at all worried) to 7 (very worried)
...Social life/activities being limited in the long-term? *(Social isolation threat)*	Scale from 1 (not at all worried) to 7 (very worried)
How have you perceived the COVID-19 pandemic situation? The coronavirus is for me...	
(CV19-occupied thoughts)	Scale from 1 (something I almost never think about) to 7 (something I think about all the time)
(CV19-induced anxiety)	Scale from 1 (not frightening) to 7 (frightening)
(CV19-grounded concern)	Scale from 1 (not worrisome) to 7 (worrisome)
Demographics and socioeconomics	
What is your gender? *(Female)*	1 = Male; 2 = Female; 3 = Diverse
In what year were you born? *(Age group)*	Scale from 1920 to 2003 (Age group: 1 = 18–29; 2 = 30–39; 3 = 40–49; 4 = 50–59; 5 = above 60)
What is your highest educational degree? *(Education)*	1 = No school-leaving qualification; 2 = Primary school certificate without completed apprenticeship; 3 = Primary school certificate with completed apprenticeship; 4 = Secondary school certificate; 5 = Technical college entrance qualification; 6 = Abitur (general university entrance qualification); 7 = University of applied sciences or university degree (Bachelor, Master, Magister, Diploma or Staatsexamen); 8 = Doctorate (Low education: 1–3; Medium education: 4; High education: 5–8)
In which federal state do you live? *(Federal state)*	1 = Baden-Württemberg; 2 = Bavaria; 3 = Berlin; 4 = Brandenburg; 5 = Bremen; 6 = Hamburg; 7 = Hesse; 8 = Lower Saxony; 9 = Mecklenburg-Western Pomerania; 10 = North Rhine-Westphalia; 11 = Rhineland-Palatinate; 12 = Saarland; 13 = Saxony; 14 = Saxony-Anhalt; 15 = Schleswig-Holstein; 16 = Thuringia
Do you work in essential services (e.g., as a cashier, pharmacist, nurse, doctor, mail carrier, etc.)? *(Employed in essential services)*	0 = Yes; 1 = No
How many people live permanently in your household, including yourself? To the household belong all those people who live there together. Please also consider all children living in the household. *(Household size)*	1 = Just me; 2 = 2 persons; 3 = 3 persons; 4 = more than 4 persons
If you take all the incomes together: What is the current monthly household income of all household members? Please add regular payments received such as pensions, housing allowance, child benefit, BAföG, alimony	1 = Below 900 Euro; 2 = 900 up until below 1300 Euro; 3 = 1300 up until below 1700 Euro; 4 = 1700 up until below 2300 Euro; 5 = 2300 up until below 3200 Euro; 6 = 3200 up until below 4000 Euro; 7 = 4000

TABLE A21 (Continued)

Question (*Variable name as in* Table A1)	Response options
payments, etc. Please state the monthly net amount, that is, after deduction of taxes and social security contributions. If you do not know exactly, please estimate the monthly amount. *(Household income)*	up until below 5000 Euro; 8 = 5000 up until below 6000 Euro; 9 = 6000 up until below 10,000 Euro; 10 = 10,000 Euro and above
Knowledge about preventive measures	
Which of the following are effective preventive measures to prevent the spread of and infection with COVID-19? Please rate all of the measures below. *(High knowledge of preventive measures)*	
Staying at home when you are sick (for example, if you have a cold)	0 = No; 1 = Yes; 2 = Don't know
Washing your hands for 20 s	0 = No; 1 = Yes; 2 = Don't know
Airing rooms regularly	0 = No; 1 = Yes; 2 = Don't know
Eating garlic	0 = No; 1 = Yes; 2 = Don't know
Contact with people from other households only with sufficient distance	0 = No; 1 = Yes; 2 = Don't know
Cleaning hands with disinfectant	0 = No; 1 = Yes; 2 = Don't know
Taking antibiotics	0 = No; 1 = Yes; 2 = Don't know
The traditional flu vaccination	0 = No; 1 = Yes; 2 = Don't know
Avoid groups and crowds with many people in one place	0 = No; 1 = Yes; 2 = Don't know
Social desirability bias	
How much do the following statements apply to you?	
In an argument, I always remain factual and objective. *(Unconditional objectivity in disputes)*	1 = Does not apply at all; 2 = Does somewhat not apply; 3 = Somewhat applies; 4 = Fully applies
Even when I am stressed myself, I always treat others in a friendly and courteous manner. *(Unconditional kindness under stress)*	1 = Does not apply at all; 2 = Does somewhat not apply; 3 = Somewhat applies; 4 = Fully applies
When I talk to someone, I always listen to them carefully. *(Unconditional attention in conversations)*	1 = Does not apply at all; 2 = Does somewhat not apply; 3 = Somewhat applies; 4 = Fully applies

Abbreviations: AfD, Alternative für Deutschland; CDU/CSU, Christlich Demokratische Union/Christlich-Soziale Union; FDP, Freie Demokratische Partei; SPD, Sozialdemokratische Partei Deutschlands.

TABLE A22 Robustness: Decision-making across compliance domains—structural equation model (SEM) results with additional competing predictors (rural setting, generalized trust).

	Compliance in the public domain			Compliance in the private domain			
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**Wald-test (2) = (5) and (3) = (6)**
COVID-19 threat perception	0.297***	0.301***	0.297***	0.365***	0.366***	0.364***	Same as in Table 2
	(0.026)	(0.027)	(0.027)	(0.017)	(0.018)	(0.018)	
Altruism	0.037	0.050*	0.037	0.012	0.012	0.011	Same as in Table 2
	(0.031)	(0.032)	(0.031)	(0.020)	(0.020)	(0.020)	
Civic responsibility	0.127***	0.119***	0.127***	0.108***	0.108***	0.109***	Same as in Table 2
	(0.024)	(0.031)	(0.031)	(0.016)	(0.020)	(0.020)	
Pos. reciprocity	0.180***	0.174***	0.180***	0.030	0.030	0.030	Same as in Table 2
	(0.024)	(0.012)	(0.012)	(0.017)	(0.009)	(0.009)	
Neg. reciprocity	−0.149***	−0.148***	−0.149***	−0.086***	−0.086***	−0.087***	Same as in Table 2
	(0.029)	(0.029)	(0.029)	(0.019)	(0.019)	(0.019)	
Risk aversion	0.065**	0.059**	0.066**	0.055**	0.055**	0.056**	Same as in Table 2
	(0.034)	(0.034)	(0.034)	(0.022)	(0.022)	(0.022)	
Patience	−0.001	0.005	−0.001	0.028	0.028	0.028	Same as in Table 2
	(0.031)	(0.031)	(0.031)	(0.020)	(0.020)	(0.020)	
Trust in RKI	0.204***	0.204***	0.204***	0.068**	0.068**	0.069**	Same as in Table 2
	(0.032)	(0.017)	(0.017)	(0.021)	(0.011)	(0.011)	
Trust in government	0.012	0.034	0.012	0.138***	0.139***	0.138***	Same as in Table 2
	(0.033)	(0.017)	(0.017)	(0.021)	(0.011)	(0.011)	
Generalized trust		−0.098***			−0.002		Stat: 22.938
		(0.009)			(0.006)		$p < 0.001$
Rural (≤20,000 inhabitants)			−0.009			−0.029	Stat: 0.974
			(0.051)			(0.033)	$p = 0.324$
Demogr. and socioecon. controls	Yes	Yes	Yes	Yes	Yes	Yes	
Compliance-specific controls	Yes	Yes	Yes	Yes	Yes	Yes	
R^2	0.492	0.497	0.492	0.411	0.411	0.412	
Observations	2918	2918	2918	2918	2918	2918	

Full SEM fit statistics (columns 1 | 4)	**Public**	**Private**
	Robust $\chi^2(66) = 156.55$; $p < 0.001$	Robust $\chi^2(66) = 104.25$; $p < 0.001$
	Robust RMSEA = 0.022	Robust RMSEA = 0.014
	Robust TLI = 0.998	Robust TLI = 0.999
	Robust CFI = 0.959	Robust CFI = 0.987
	SRMR = 0.017	SRMR = 0.008

Note: Displayed are standardized coefficient estimates and standard errors in parentheses for the results of the SEM estimated by means of Equations (1) and (2) (shown are only the structural component results, see Table A12 for the results of the measurement component). The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. The far right column shows the results of a Wald test for equality of coefficients across the private and public domain (as in Klopp, 2022). Demographic controls contain respondents' gender, age group and state. Socioeconomic controls include education, employment in essential services, household size and income. Compliance-specific controls contain knowledge about COVID-19 preventive measures and the degree of social desirability bias (factor scores as in Figure A8 and Table A15).

Abbreviations: CFI, comparative fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual; TLI, Tucker-Lewis index.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A23 Correlation between COVID-19 threat perception and case incidence rate by region.

	State-level CV-19 threat perception										
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
State case incidence (during data collection)	0.003	0.003	0.003	0.003	0.004						0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)						(0.002)
State case incidence (prior infection waves)						−0.003	−0.003	−0.003	−0.003	−0.003	−0.003
						(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Population density (inhabitants/km)		0.000			−0.000		0.000			−0.000	0.000
		(0.000)			(0.000)		(0.000)			(0.000)	(0.000)
Stadtstaat			0.109		0.174			0.109		0.141	0.128
			(0.075)		(0.198)			(0.071)		(0.192)	(0.187)
Share of German population				0.176	0.519				0.172	0.476	0.597
				(0.550)	(0.587)				(0.527)	(0.558)	(0.552)
Constant	−0.206	−0.272	−0.252	−0.228	−0.316	0.154	0.155	0.146	0.148	0.127	−0.125
	(0.179)	(0.182)	(0.175)	(0.198)	(0.206)	(0.105)	(0.102)	(0.101)	(0.110)	(0.110)	(0.226)
R^2	0.086	0.189	0.214	0.093	0.266	0.148	0.264	0.277	0.155	0.323	0.417
Observations	16	16	16	16	16	16	16	16	16	16	16

Note: Shown are the results of regressing our measure of COVID-19 threat perception, averaged at state level, on the state-level COVID-19 case incidence rate (number of registered COVID-19 cases in past 7 days/100,000 people). Data about case incidence level were retrieved from https://www.corona-daten-deutschland.de/dataset/infektionen_bundeslaender. The Pearson correlation coefficient of the state case incidence rate during the data collection (in the infection waves prior to the data collection) and state-level threat perception is +0.2928 (−0.3847), but not statistically significant.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A24 Cross-check of descriptive statistics with other representative surveys I.

Variable	**Our survey data**	**COSMO survey**	**World value survey**	**Notes**
Compliance behaviors (Proportion stating often or always)				
Wearing a mask in crowded places	93.47%	93%		
Keeping a 1.5 m distance in public spaces (whenever possible)	88.39%	90%		
Avoid handshakes	91.85%	92%		
Leaving the home only when absolutely necessary	78.54%	85%		COSMO survey refers only to “Staying at home when sick”
Restricting private meetings to 1 person from another household	77.18%	84%		
Generally avoiding other households	77.52%	83%		
COVID-19 threat perception (all: Scale 1–7)				
Worry long-term social restrictions	Mean: 5.03	Mean: 5.19		
Worry own financial difficulties	Mean: 3.25	Mean: 3.61		
Worry loosing a loved one	Mean: 4.39	Mean: 4.93		
Severity of own infection	Mean: 4.32	Mean: 4.26		
Probability of own infection	Mean: 2.76	Mean: 3.69		

(Continues)

TABLE A24 (Continued)

Variable	Our survey data	COSMO survey	World value survey	Notes
General CV19-induced anxiety (Proportions: Low (1–3), Medium (4), High (5–7))	Low: 26.54%	Low: 29.2%		
	Medium: 20.65%	Medium: 20.4%		
	High: 52.81%	High: 50.4%		
General CV19-induced concern (Proportions: Low (1–3), Medium (4), High (5–7))	Low: 14.19%	Low: 20.00%		
	Medium: 16.14%	Medium: 16.60%		
	High: 69.66%	High: 63.50%		
General CV19-induced thoughts (Proportions: Low (1–3), Medium (4), High (5–7))	Low: 16.57%	Low: 30.10%		
	Medium: 20.74%	Medium: 24.10%		
	High: 62.69%	High: 45.8%		
Institutional trust (all: Scale 1–7)				
Trust in the government	Mean: 4.09	Mean: 3.96		
Trust in the RKI	Mean: 4.91	Mean: 4.76		
Civic responsibility				
Never avoided public transport fares	51.92%		68.00%	WVS refers to justification of fare avoidance not actual behaviors
Voted in 2017 national election	85.08%		83.37%	WVS asks whether respondents generally vote in national elections
Observations	3340	1021	1528	

Note: This table compares our descriptive statistics for the core variables employed in the empirical analysis with the descriptive statistics of the COSMO survey in the case of compliance, threat perceptions and institutional trust and with the descriptive statistics of the World Value Survey for the case of civic responsibility. For economic preferences, we compare our descriptive statistics with the Global Preference Survey Module (Falk et al., 2018); these results are depicted separately in Figure A13 and Table A25. The data from the COSMO survey comes from wave 35, conducted between February 9 and 10, 2021, and is drawn from the summary of wave 35 and the summaries by themes both of which can be retrieved from https://projekte.uni-erfurt.de/cosmo2020/web/. Data from the World Value Survey stems from wave 7, conducted in 2018 for the German sample, and be retrieved from https://www.worldvaluessurvey.org/WVSDocumentationWV7.jsp.

Abbreviation: COSMO, COVID-19 Snapshot Monitoring.

TABLE A25 Cross-check of descriptive statistics with other representative surveys II.

	Pos. Reci.	Neg. Reci.	Altruism	Risk aversion	Patience
Pos. Reci.	1.00				
Neg. Reci.	0.10**	1.00			
	[−0.03]				
Altruism	0.26***	0.04	1.00		
	[0.24***]	[−0.03]			
Risk aversion	−0.02	−0.11***	−0.01	1.00	
	[−0.05**]	[−0.21***]	[−0.11***]		
Patience	0.11***	0.06	0.09***	−0.08*	1.00
	[0.14***]	[0.02]	[0.22***]	[−0.11***]	

Source: Shown are Pearson correlation coefficients between the GPS measures for economic preferences for the German sample retrieved from https://www.briq-institute.org/global-preferences/downloads (Falk et al., 2018). The respective Pearson correlation coefficients of our data are shown in square brackets below (see also Table A16).

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A26 Robustness check Google mobility patterns: Retail and recreation and transit.

	Retail and recreation areas				Transit areas			
Outcome: Mobility changes in	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Private compliance	−16.058**		−14.030*	−10.410	−31.044**		−24.835	−21.600
	(4.772)		(6.348)	(5.331)	(9.540)		(12.523)	(12.965)
Public compliance		−6.807*	−1.797	−2.769		−14.370*	−5.502	−7.957
		(3.118)	(3.571)	(3.095)		(5.986)	(7.044)	(7.527)
Population density (inhabitants/km)				−0.003				−0.004
				(0.001)				(0.003)
Stadtstaat				3.193				8.649
				(3.817)				(9.283)
Constant	−46.774***	−45.191***	−44.924***	−44.375***	−25.619**	−20.430	−19.958	−16.525
	(3.165)	(5.545)	(4.908)	(4.45349)	(6.328)	(10.644)	(9.681)	(10.832)
Adj. R^2	0.408	0.201	0.374	0.584	0.584	0.241	0.373	0.366
Observations	16	16	16	16	16	16	16	16

Note: Shown are the results of regressing (i) state-level phone-tracking-based changes in mobility according to Google's mobility reports in the areas of Retail and Recreation (columns 2–5) and Transit (columns 6–9) and on (ii) state-level averages of our measures of compliance in the public and private domain, as predicted from the SEM by means of Equations (1) and (2) (controlling for a state's population density and whether the state is a city state, i.e., Hamburg, Berlin and Bremen). Mobility data retrieved from Google LLC (2021). Changes in mobility refer to the 2020 baseline period before the start of the pandemic.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A27 Robustness check Google mobility patterns: Workplace and residential.

	Workplace areas				Residential areas			
Outcome: Mobility changes in	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Private compliance	−14.731*		−15.859	−9.420**	5.756**		7.613**	6.109***
	(5.726)		(7.675)	(1.723)		(2.167)	(1.374)	
Public compliance		−4.664	0.999	0.083		1.073	−1.645	−1.134
		(3.705)	(4.318)	(1.570)		(1.267)	(1.219)	(0.798)
Population density (inhabitants/km)				−0.004***				0.001**
				(0.001)				(0.000)
Stadtstaat				2.711				−1.721
				(1.936)				(0.984)
Constant	−18.931*	−20.261**	−19.959**	−20.490***	8.366***	10.204***	10.059***	9.631***
	(3.798)	(6.588)	(5.934)	(2.259)	(1.143)	(2.253)	(1.675)	(1.148)
Adj. R^2	0.273	0.038	0.220	0.909	0.404	−0.019	0.437	0.787
Observations	16	16	16	16	16	16	16	16

Note: Shown are the results of regressing (i) state-level phone-tracking-based changes in mobility according to Google's mobility reports in the areas of Workplace (columns 2–5) and Residential (columns 6–9) and on (ii) state-level averages of our measures of compliance in the public and private domain, as predicted from the SEM by means of Equations (1) and (2) (controlling for a state's population density and whether the state is a city state, i.e., Hamburg, Berlin and Bremen). Mobility data retrieved from Google LLC (2021). Changes in mobility refer to the 2020 baseline period before the start of the pandemic.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A28 Extension institutional trust: Proxies for trust in Robert Koch Institute (RKI).

	Public compliance			Private compliance		
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Trust in RKI	0.204***			0.068**		
	(0.032)			(0.021)		
Trust in science		0.182***			0.053*	
		(0.018)			0.012	
Trust in WHO			0.165***			0.055*
			(0.018)			(0.011)
Trust in government	0.012	0.050	0.044	0.138***	0.153***	0.147***
	(0.033)	(0.016)	(0.017)	(0.021)	(0.010)	(0.011)
Other main behavioral predictors	Yes	Yes	Yes	Yes	Yes	Yes
Demogr. and socioecon. controls	Yes	Yes	Yes	Yes	Yes	Yes
Compliance-specific controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.492	0.493	0.490	0.411	0.411	0.410
Observations	2918	2918	2918	2918	2918	2918

Note: Displayed are standardized coefficient estimates and standard errors in parentheses for the institutional trust variables of the SEM, as estimated by means of Equations (1) and (2) (shown are only the structural component results). Columns 1 and 4 therefore merely repeat the results from Table 2. The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. Other main behavioral predictors contain COVID19 threat perception, pos. and neg. reciprocity, altruism, civic responsibility, risk aversion and patience. Demographic controls contain respondents' gender, age group and state. Socioeconomic controls include education, employment in essential services, household size and income. Compliance-specific controls contain knowledge about COVID-19 preventive measures and the degree of social desirability bias (factor scores as in Figure A8 and Table A15).

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A29 Extension institutional trust: Understanding effects of trust in government.

	Public compliance					Private compliance				
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Trust in government	0.012		−0.007		0.030	0.138***		0.145***		0.118***
	(0.033)		(0.021)		(0.019)	(0.021)		(0.013)		(0.012)
Trust in state govt.		0.031	0.034				0.070**	−0.010		
		(0.017)	(0.022)				(0.011)	(0.013)		
Trust in estab. media				−0.017	−0.026				0.081***	0.045*
				(0.017)	(0.019)				(0.010)	(0.011)
Trust in RKI	0.204***	0.190***	0.194***	0.219***	0.207***	0.068**	0.112***	0.124***	0.070**	0.062*
	(0.032)	(0.017)	(0.018)	(0.015)	(0.017)	(0.021)	(0.011)	(0.010)	(0.012)	(0.011)
Other main behavioral predictors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demogr. and socioecon. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Compliance-specific controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.492	0.490	0.491	0.492	0.494	0.411	0.406	0.413	0.407	0.413
Observations	2918	2917	2917	2918	2918	2918	2917	2917	2918	2918

Note: Displayed are standardized coefficient estimates and standard errors in parentheses for the institutional trust variables of the SEM, as estimated by means of Equations (1) and (2) (shown are only the structural component results). Columns 1 and 6 therefore merely repeat the results from Table 2. The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. Other main behavioral predictors contain COVID-19 threat perception, pos. and neg. reciprocity, altruism, civic responsibility, risk aversion and patience. Demographic controls contain respondents' gender, age group and state. Socioeconomic controls include education, employment in essential services, household size and income. Compliance-specific controls contain knowledge about COVID-19 preventive measures and the degree of social desirability bias (factor scores as in Figure A8 and Table A15).

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE A30 Fines for non-compliance across German states.

State	Behavior: Not wearing a face-mask	Not keeping distance of 1.50 m	Meeting with more than allowed number of people	Hosting an illegal gathering	Date of regulations	Source
Baden-Württemberg	50–250 Euro	n.a.	n.a.	100–1000 Euro	September 15, 2021	https://www.bussgeldkatalog.org/corona-baden-wuerttemberg/
Bayern	250 Euro	150 Euro	150 Euro	5000 Euro	November 20, 2020	https://www.bussgeldkatalog.org/corona-bayern/
Berlin	50–500 Euro	100–500 Euro	25–500 Euro	n.a.	November 20, 2020	https://www.bussgeldkatalog.org/corona-berlin/
Brandenburg	50–250 Euro	n.a.	50–250 Euro	1000–5000 Euro	August 25, 2020	https://www.bussgeldkatalog.org/corona-brandenburg/
Bremen	n.a.	n.a.	50–250 Euro	250–2500 Euro	November 23, 2020	https://www.bussgeldkatalog.org/corona-bremen/
Hamburg	150 Euro	150 Euro	150–500 Euro	1000 Euro	November 23, 2020	https://www.bussgeldkatalog.org/corona-hamburg/
Hessen	200 Euro	n.a.	200 Euro	500–1000 Euro	April 20, 2020	https://www.bussgeldkatalog.org/corona-hessen/
Mecklenburg-Vorpommern	50–150 Euro	n.a.	50–500 Euro	n.a.	November 23, 2020	https://www.bussgeldkatalog.org/corona-mecklenburg-vorpommern/
Niedersachsen	100–150 Euro	100–400 Euro	150–400 Euro	300–3000 Euro	November 23, 2020	https://www.bussgeldkatalog.org/corona-niedersachsen/
Nordrhein-Westfalen	50–150 Euro	n.a.	250 Euro	1000–5000 Euro	September 6, 2020	https://www.bussgeldkatalog.org/corona-nrw/
Rheinland-Pfalz	50 Euro	50 Euro	100 Euro	500 Euro	November 23, 2020	https://www.bussgeldkatalog.org/corona-rheinland-pfalz/

(Continues)

TABLE A30 (Continued)

State	Behavior: Not wearing a face-mask	Not keeping distance of 1.50 m	Meeting with more than allowed number of people	Hosting an illegal gathering	Date of regulations	Source
Saarland	50–100 Euro	n.a.	200 Euro	1000–4000 Euro	November 23, 2020	https://www.bussgeldkatalog.org/corona-saarland/
Sachsen	60 Euro	150 Euro	150 Euro	5000 Euro	November 23, 2020	https://www.bussgeldkatalog.org/corona-sachsen/
Sachsen-Anhalt	50–75 Euro	n.a.	50 Euro	1000 Euro	September 14, 2021	https://www.bussgeldkatalog.org/corona-sachsen-anhalt/
Schleswig-Holstein	150 Euro	150 Euro	150 Euro	1000–2000 Euro	November 23, 2020	https://www.bussgeldkatalog.org/corona-schleswig-holstein/
Thüringen	60 Euro	100 Euro	n.a.	1000–3000 Euro	November 20, 2020	https://www.bussgeldkatalog.org/corona-thueringen/

Note: The table shows fines for non-compliance with COVID-19 regulations across federal states in Germany. Note that the time at which regulations came into place differ across states, for example, in Baden-Württemberg and Sachsen-Anhalt, we were only able to obtain information about the regulations at the later stages in the pandemic, such that they did not anymore include fines for most rules that were relevant during our survey data collection. "n.a." indicates that we were not able to obtain information about the amount of the specific fine in this state, given the dynamically changing conditions during the pandemic and difficulties to find information about regulations that are no longer in place. Coherently, an "n.a." entry does *not* mean that there was no fine for the respective behavior.

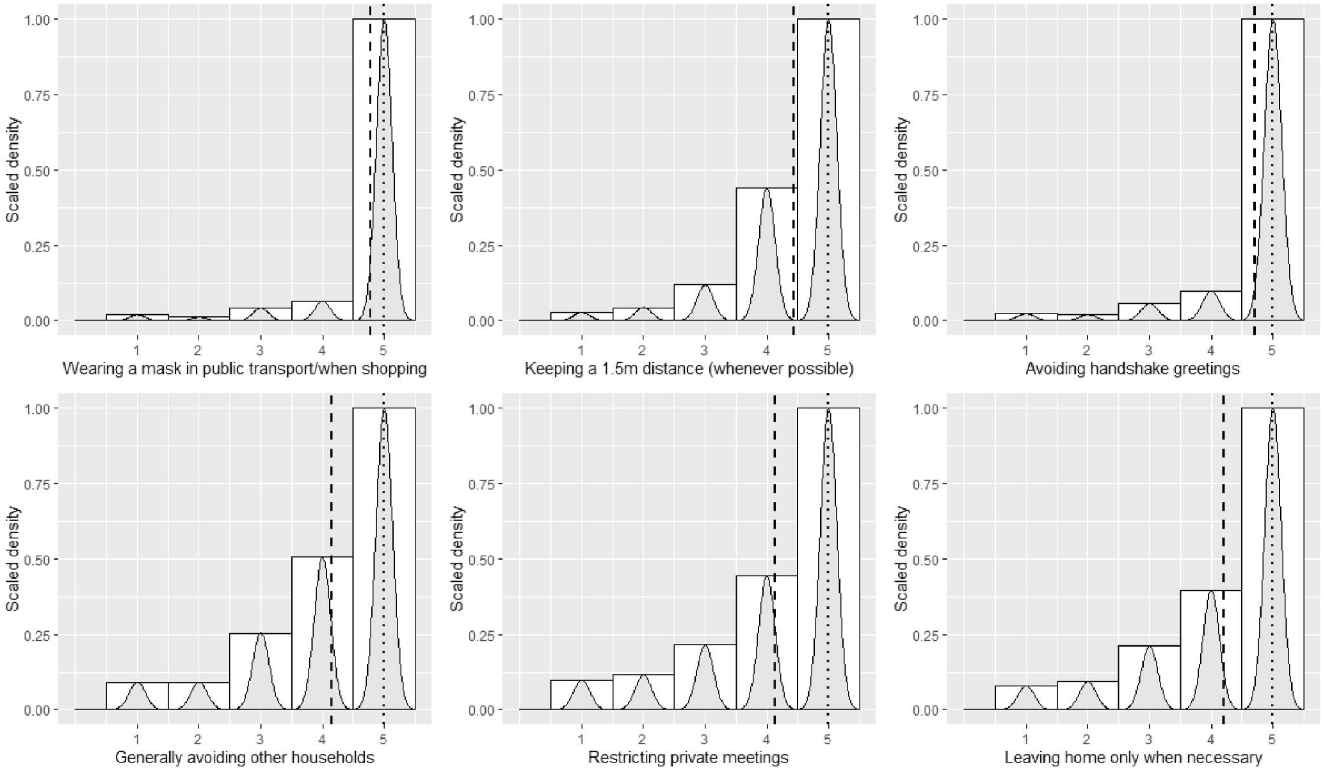


FIGURE A1 Distribution of self-reported compliance items. This figure shows the scaled density distribution of each of the six survey items aimed to quantify compliance behavior. The bold line indicates the mean and the non-bold line the median in each case. Participants were asked the following question: "Below you find a list of behavioral patterns. How well does each reflect your behavior in the past 2 weeks?" Response options were 1 = "Applied never"; 2 = "Applied rarely"; 3 = "Applied sometimes"; 4 = "Applied often"; 5 = "Applied always".

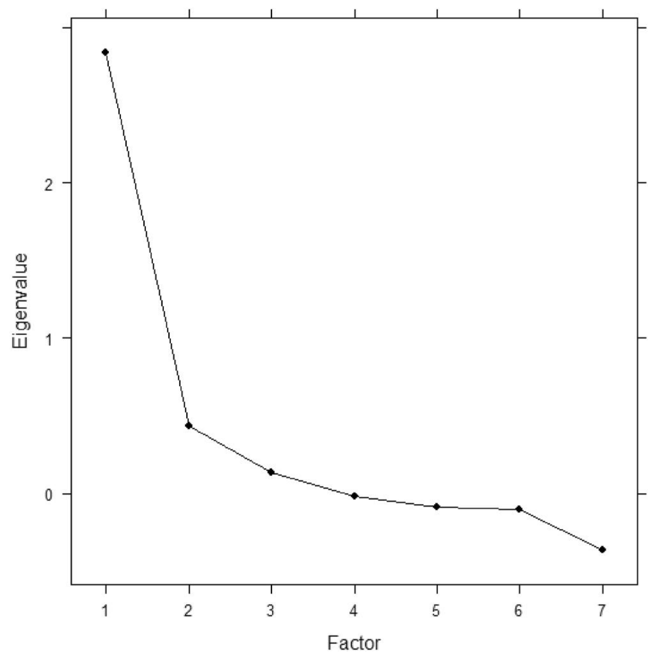


FIGURE A2 COVID-19 threat perception: screeplot factor analysis. This figure shows a screeplot of an exploratory factor analysis of the 8 survey items aimed at capturing COVID-19 threat perception (see Tables A1, A6 and A21 for the items and procedure), with Eigenvalues of factors on the *y*-axis and the identified factors on the *x*-axis. The factor analysis was performed using iterated principal axis factoring, no rotation, and a mixed correlation matrix (continuous and polychoric).

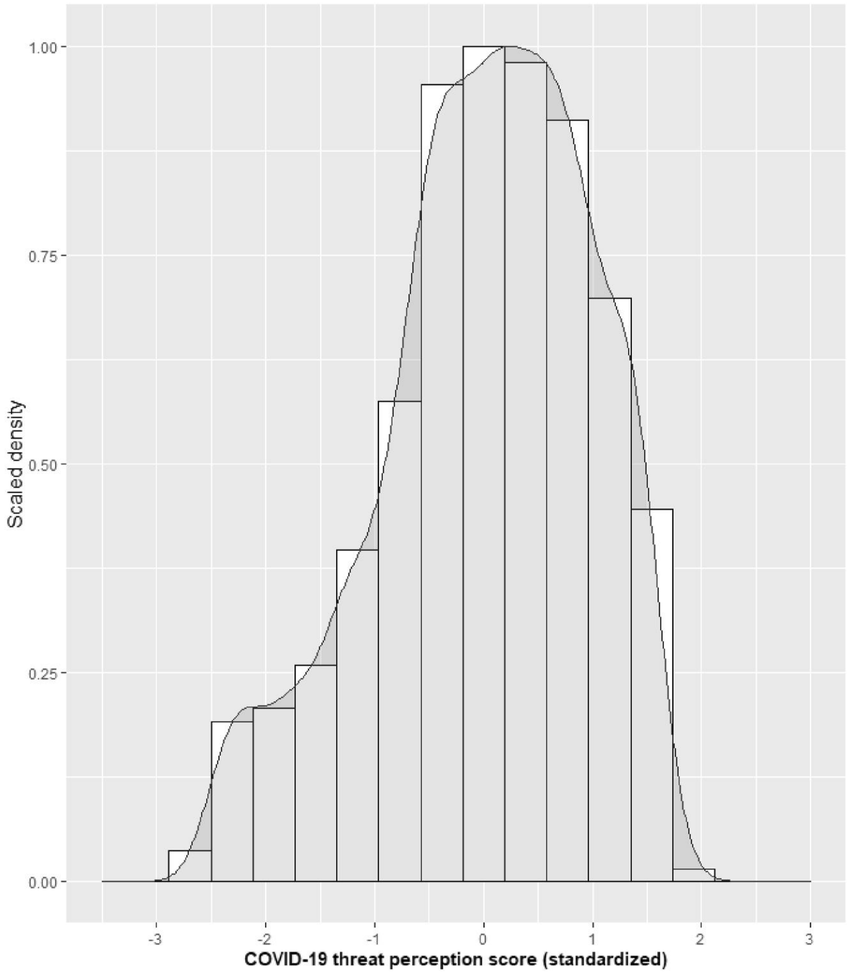


FIGURE A3 Distribution of COVID-19 threat perception factor scores. This figure shows a scaled density and histogram of the factor scores capturing COVID-19 threat perception, as in Table A7.

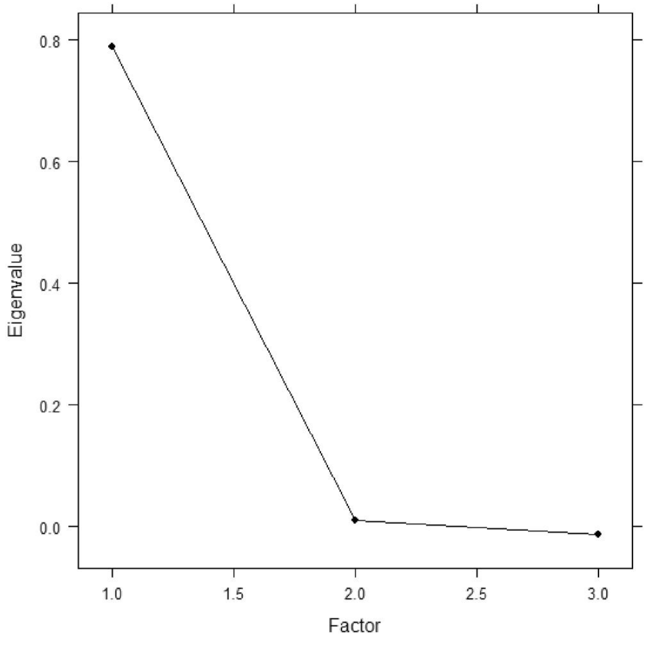
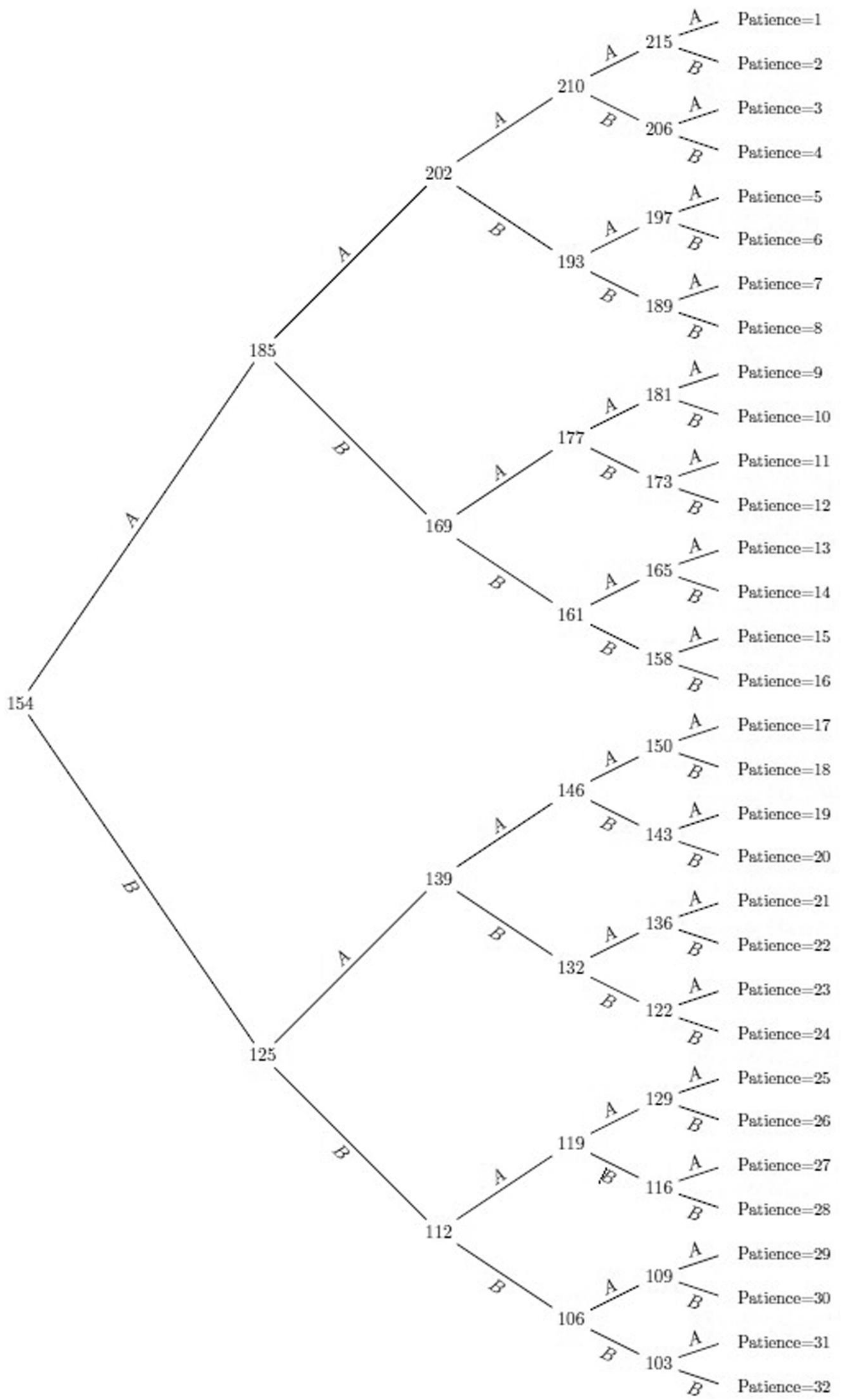


FIGURE A4 Civic responsibility: screeplot factor analysis. This figure shows a screeplot of an exploratory factor analysis of the 3 survey items aimed at capturing civic responsibility (see Tables A1, A6 and A21 for the items and procedure), with Eigenvalues of factors on the *y*-axis and the identified factors on the *x*-axis. The factor analysis was performed using iterated principal axis factoring, no rotation, and a polychoric correlation matrix.

FIGURE A5 Tree for the staircase time task (extracted from Falk et al. (2022), p. 66). This figure shows the intertemporal choice sequence of the staircase method in detail, as developed by Falk et al. (2022), and employed in this paper as part of the preference measure for patience. The numbers indicate the payment in 12 months, "A" denotes the respondent's choice of "100 euros today," while "B" denotes the respondent's choice of "x euros in 12 months". All respondents start with the left-most decision, the remaining intertemporal choice sequence is revealed by going from left to right through the tree.



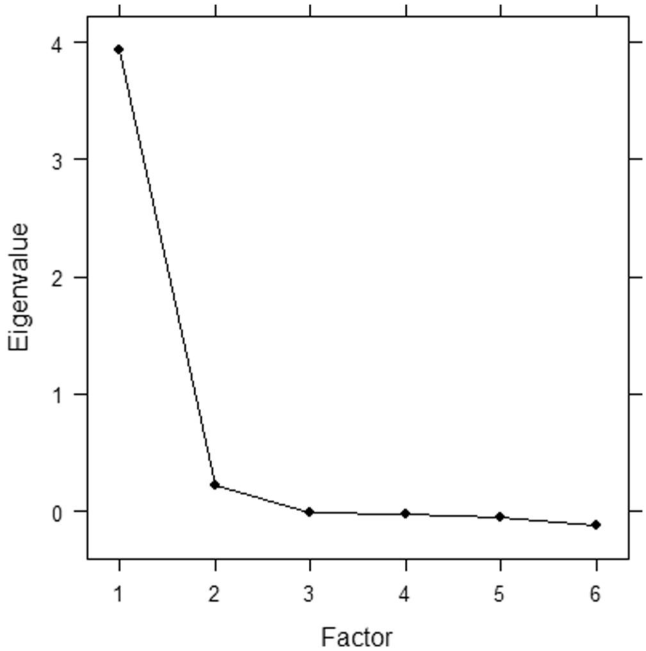


FIGURE A6 Compliance: screeplot exploratory unrotated factor analysis. This figure shows a screeplot of an exploratory factor analysis of the 6 survey items aimed at capturing compliance behavior (see Tables A1, A3 and A21 for the items), with Eigenvalues of factors on the *y*-axis and the identified factors on the *x*-axis. The factor analysis was performed using iterated principal axis factoring, no rotation, and a polychoric correlation matrix.

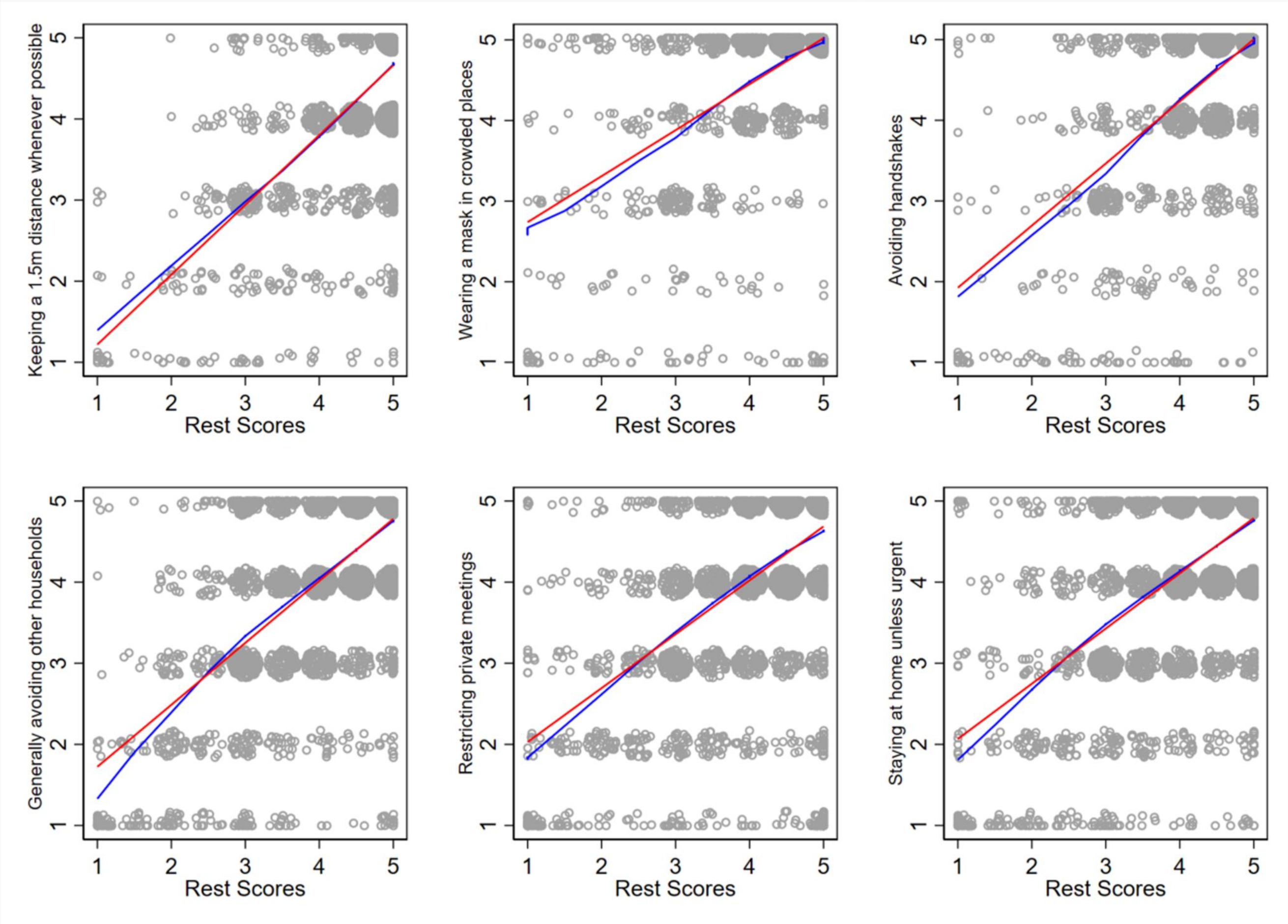


FIGURE A7 Compliance: summated rating scale monotone homogeneity assumption. This figure illustrates an assessment of the monotone homogeneity assumption of the two summated rating scales for compliance in the public (first row of graphs) and private (second row of graphs) domain, as in Table A11. Plotted are rest scores on the x-axis (i.e., the public/private scale score if dropping one of the items) and the value of the respective dropped item on the y-axis. The monotone homogeneity assumption thereby requires expected responses to each of the three items of compliance in the public (private) domain to be increasing/decreasing as the true dimension of compliance in the public (private) domain also increases/decreases (i.e., the rest scores). This increase/decrease has to be of a monotone nature, which here seems to be the case (all lines are monotonously increasing). The red line shows a linear fit, the blue line a smoothed fit. [Colour figure can be viewed at wileyonlinelibrary.com]

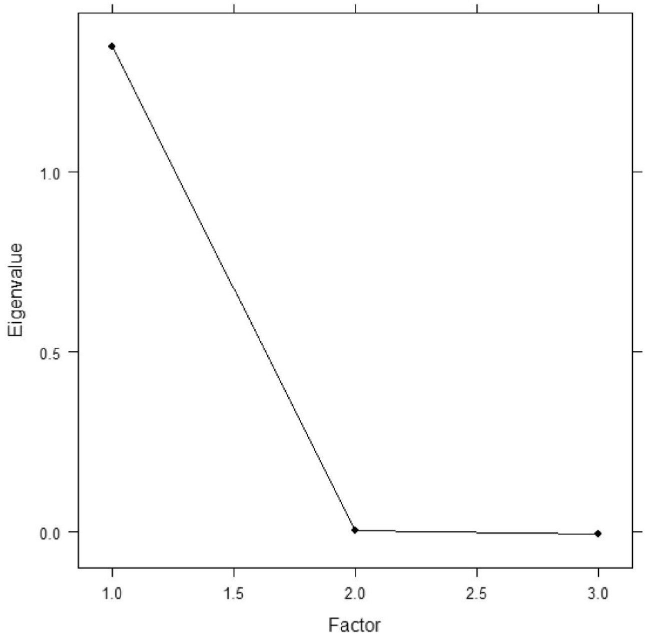


FIGURE A8 Social desirability: screeplot factor analysis. This figure shows a screeplot of an exploratory factor analysis of the 3 survey items aimed at capturing social desirability bias (exaggerating positive characteristics) (see Tables A1, A6 and A21 for the items and procedure), with Eigenvalues of factors on the y-axis and the identified factors on the x-axis. The factor analysis was performed using iterated principal axis factoring, no rotation, and a polychoric correlation matrix.

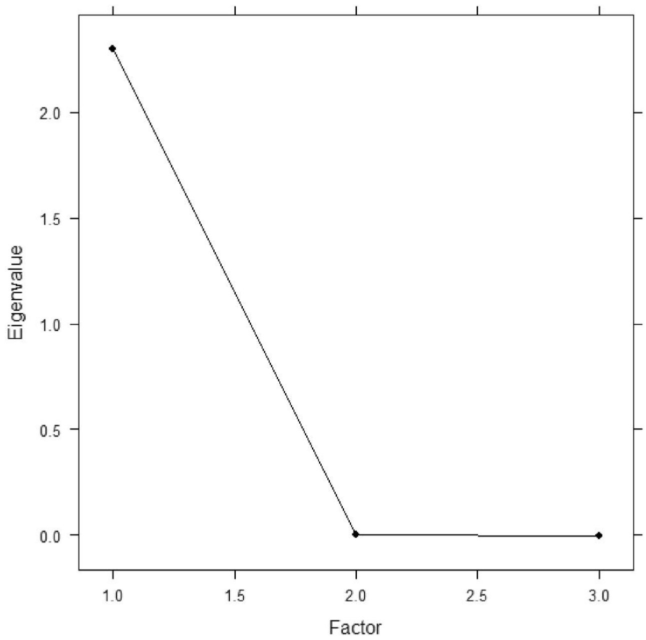


FIGURE A9 Alternative compliance measure: screeplot factor analysis. This figure shows a screeplot of an exploratory factor analysis of 3 alternative survey items aimed at capturing compliance behavior (see Tables A1 and A21 for the items), with Eigenvalues of factors on the y-axis and the identified factors on the x-axis. The factor analysis was performed using iterated principal axis factoring, no rotation, and a polychoric correlation matrix.

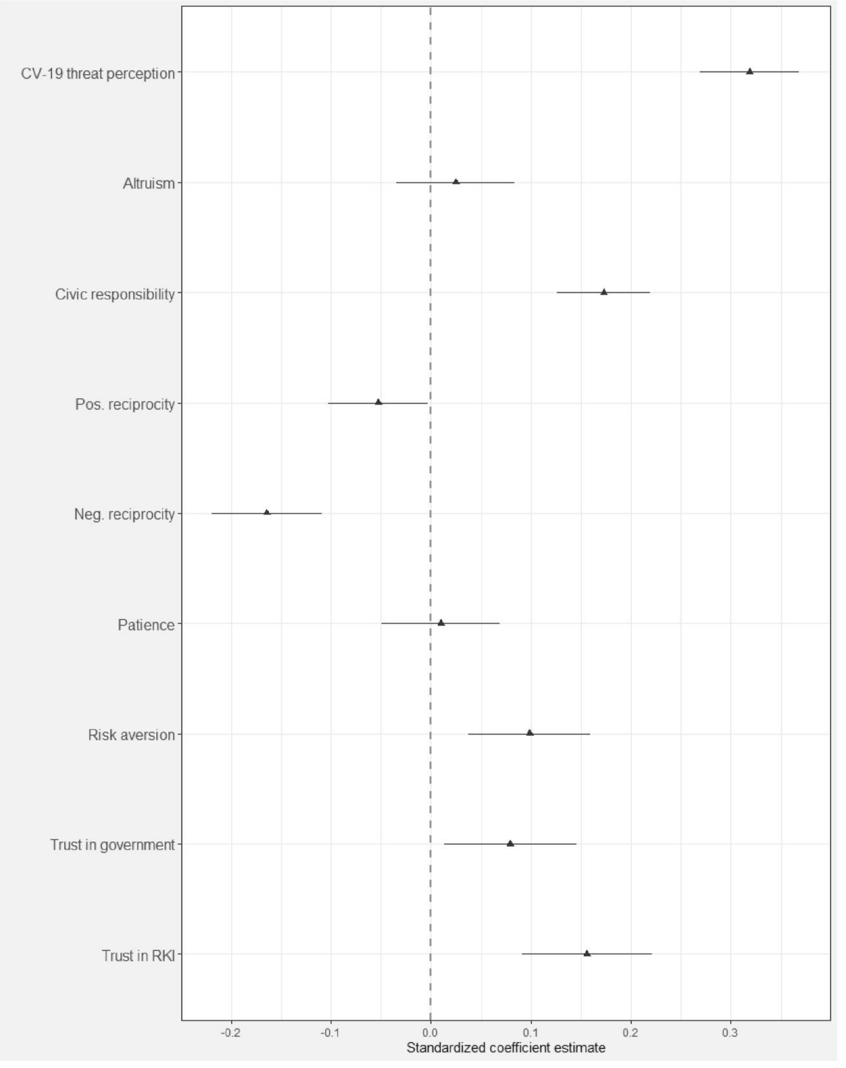


FIGURE A10 Robustness: decision-making across compliance domains (alternative compliance measures). This figure shows standardized coefficient estimates and 95% confidence intervals for the structural component of the structural equation model as in Equation (2) (but resulting from estimating both equations simultaneously). However, instead of the initial compliance items, we used three alternative survey items as reflective indicators (see Section 4.3 and Tables A1 and A21 for detailed descriptions). The SEM was estimated using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. Shown are estimates for economic preferences, institutional trust and COVID-19 threat perception, but estimations were conducted with demographic, socioeconomic and compliance-specific controls (not shown here). See Table A18 for the precise coefficients, including those for control variables.

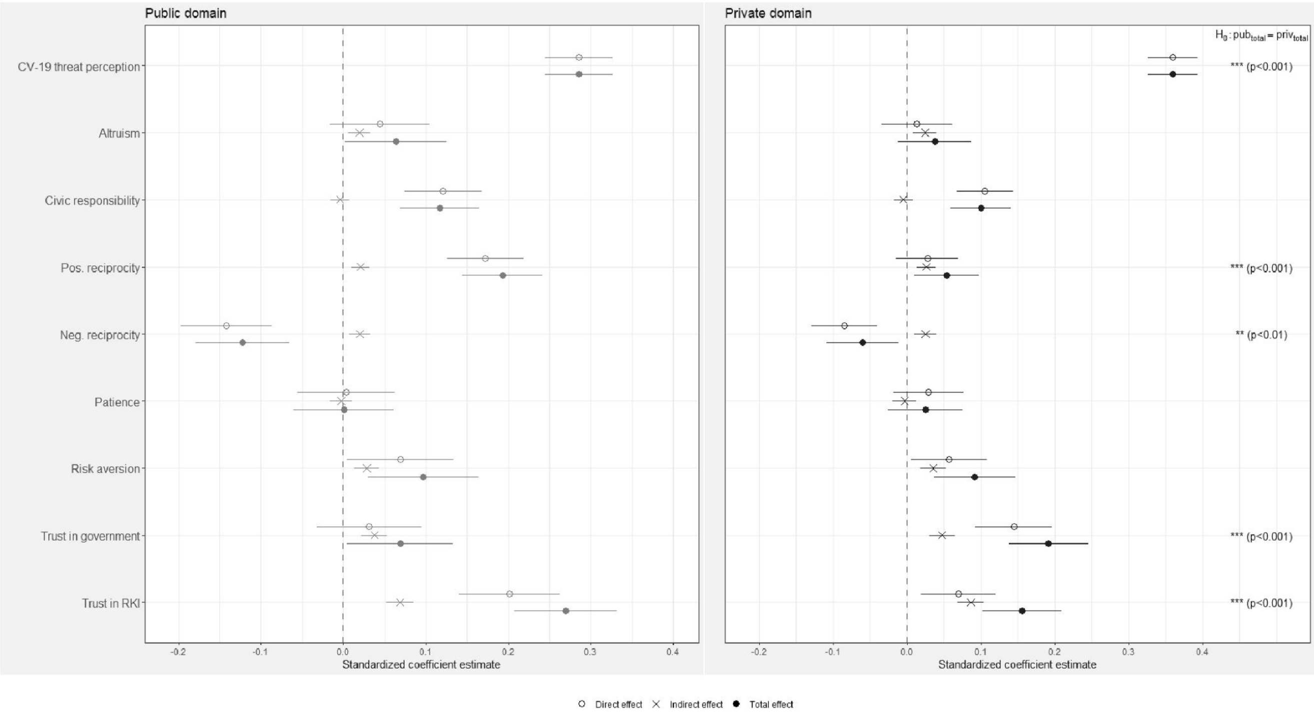


FIGURE A11 Robustness: decision-making across compliance domains (threat perception mediation). This figure shows standardized coefficient estimates and 95% confidence intervals for estimating the structural equation models by means of Equations (1) and (2), and additionally allowing for a mediating effect of COVID-19 threat perceptions. Shown are the resulting estimated direct, indirect and indirect effects (i.e., the results of the structural component). The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. Shown are estimates for economic preferences, institutional trust and COVID-19 threat perception, but estimations were conducted with demographic, socioeconomic and compliance-specific controls (not shown here). See Table A19 for the precise coefficients, including those for control variables. The right column of the figure shows the results of a Wald test for equality of coefficients across the private and public domain (as in Klopp, 2022).

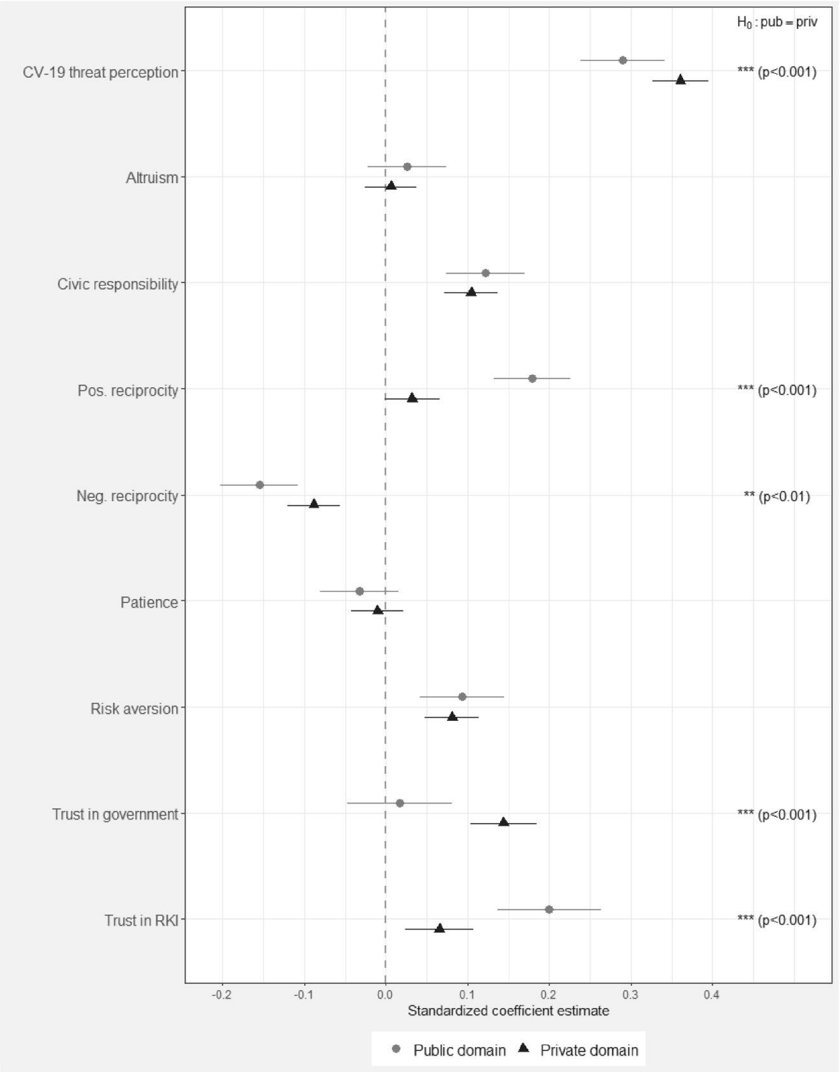


FIGURE A12 Robustness: decision-making across compliance domains (single-item preference measures). This figure shows standardized coefficient estimates and 95% confidence intervals for the structural component of the structural equation model as in Equation (2) (but resulting from estimating both equations simultaneously). However, instead of the initially constructed preference measures, we used only a single survey item for each type of preference to assess the robustness of the singular survey item of positive reciprocity. For each preference type, we used the survey item with the highest weight in the experimental validation procedure developed by Falk et al. (2018). See Table A4 for these items, the respective items are marked in italic font. The SEM was estimated separately for each compliance domain, using Diagonal Weighted Least Squares, a polychoric correlation matrix, robust standard errors and a corrected test statistic. Shown are estimates for economic preferences, institutional trust and COVID-19 threat perception, but estimations were conducted with demographic, socioeconomic and compliance-specific controls (not shown here). See Table A20 for the precise coefficients, including those for control variables. The right column of the figure shows the results of a Wald test for equality of coefficients across the private and public domain (as in Klopp, 2022).

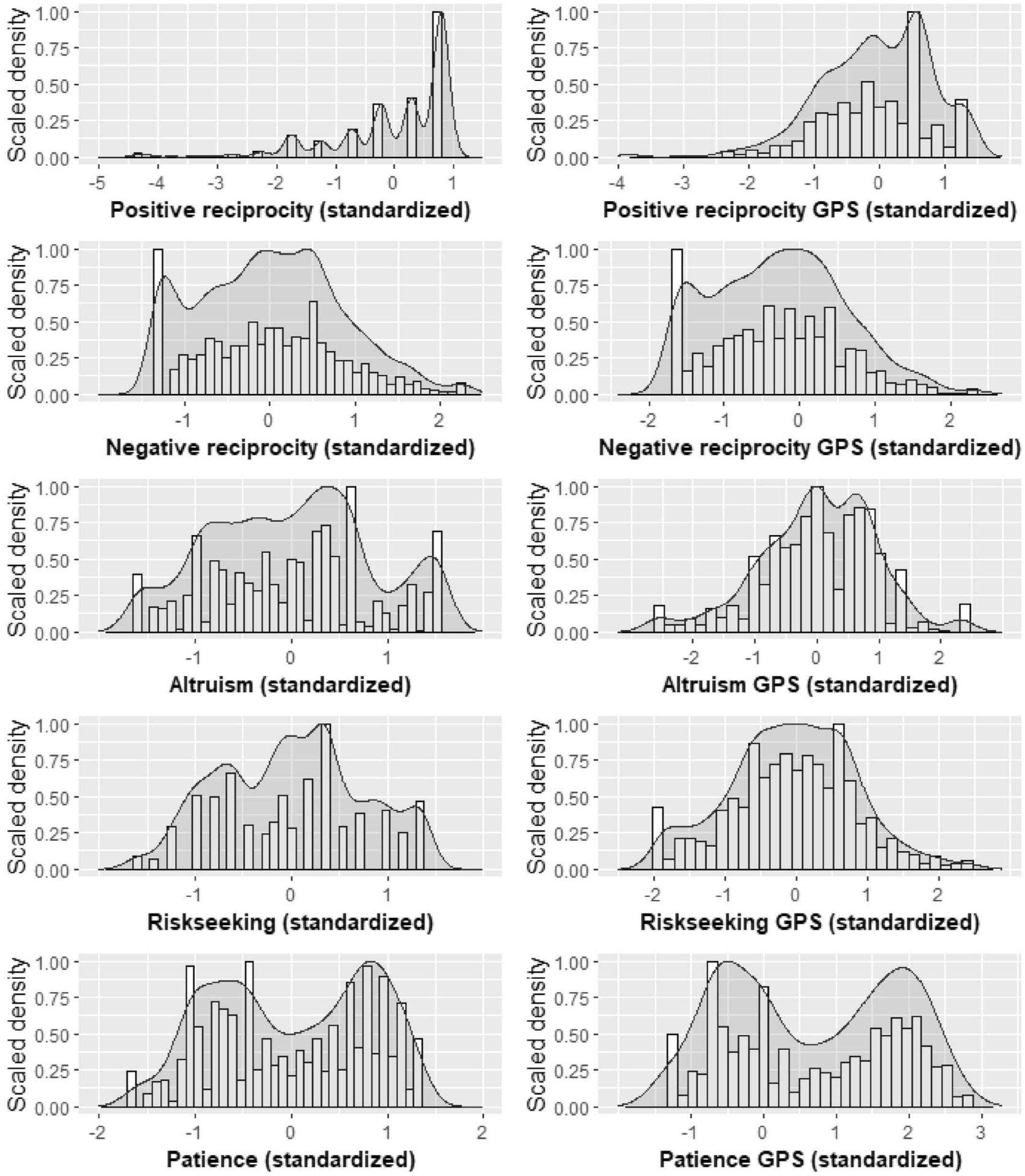


FIGURE A13 Density plots for preference measures: our data versus the Global Preference Survey (GPS). The figure shows scaled density plots for positive reciprocity, negative reciprocity, altruism, risk taking and patience for our survey data (left column) and for the German survey data from the GPS retrieved from https://www.briq-institute.org/global-preferences/downloads (Falk et al., 2018) (right column). The GPS data for Germany consists of approximately 1000 observations. For the purpose of this figure (i.e., to be able to make comparisons between our data and the GPS data), our initial survey items for risk aversion were reverse coded before the final measure with the GPS weights was calculated (see Table A6), since the GPS reports risk taking (rather than risk aversion). Our measures for patience and negative reciprocity employed the exact same survey items as the GPS. Our measures for risk taking and altruism employed similar survey items as the GPS measures in the sense that we use the same non-experimental survey item as the GPS survey, but a slightly different experimental item. Our measure of positive reciprocity only consists of a single survey item (the non-experimental/non-behavioral item from the GPS), while the GPS employs two items. See Table A6 for details.

APPENDIX B

Stability of economic preferences and institutional trust over time and during the COVID-19 pandemic

For risk and time preferences in the context of COVID-19, several studies have found that preferences remained largely stable during the COVID-19 pandemic (Angrisani et al., 2020; Drichoutis & Nayga, 2021). Changes were only detected during the very early stages of the pandemic, with somewhat ambiguous findings across studies (Bu et al., 2020; Ikeda et al., 2023; Shachat et al., 2021). Early-stage, ambiguous changes were also detected for social preferences during the first weeks of the pandemic (Lotti, 2021; Shachat et al., 2021; van de Groep et al., 2020), but so far no studies have been reported that looked at longer or later periods of time during the pandemic. For all types of economic preferences, a large body of literature suggests that they are generally very stable over longer periods of time (e.g., Andersen et al., 2008; Carlsson et al., 2014; Habibpour et al., 2018; Meier & Sprenger, 2015; Volk et al., 2012), and that this is even more so the case for survey-based measures than it is for experimental measures (Chuang & Schechter, 2015). Our study uses largely survey-based measures, collected 11 months after the onset of the pandemic in Germany.

In terms of institutional trust, the German COVID-19 Snapshot Monitoring has observed survey-based measures for trust in the Robert-Koch-Institute (RKI) and trust in the government (largely identical to ours) in multiple waves over the entire pandemic. In the time period from the onset of the pandemic in Germany until the end of our data collection, they found both measures to be largely stable, with an overall slight downward trend that seems unrelated to infection wave dynamics (Betsch et al., 2021b).

Bonus payments and donations from experimental preference measures

The incentivized preference measures yielded total amounts of 2089.95 Euro in bonus payments paid to respondents and 1294.05 Euro in donations paid to charities. This corresponds to 6.75% of the amounts of donations and to 6.94% of the amounts of bonus payments that would have been carried out if the entire sample had received real payouts in the respective incentivized survey questions, and not just a randomly selected 5%.

Alternative measure of compliance in the private domain

We re-estimated the structural equation model (SEM) with alternative measures of compliance in the private domain (i.e., altering the measurement part of the SEM). This allows us to assess the robustness of the baseline results specifically regarding their differences across the two compliance domains. The alternative measure of compliance was based on three questions asking respondents about their willingness to participate in concrete social activities, namely a dinner and movie night with a group of friends, a surprise birthday caroling at a friend's doorstep, and a sledding trip with friends. These questions were used as reflective indicators in the measurement model to form the alternative compliance measure (see Figure A9 for a screeplot and Table A17 for the results of the measurement model).

This alternative measure of compliance was expected to be more closely related to the private than to the public compliance domain, given that the three scenarios were designed such that the activity would take place among personal friends and in such a way that the non-compliance would be largely observable only to the participants of the activity themselves. Moreover, this measure may have the additional advantage of being less susceptible to social desirability biases than the initial compliance items. Specifically, the scenarios given do not explicitly mention the existing physical distancing rules (e.g., the exact number of people from other households one is allowed to meet). Instead, the activities themselves, as described in this alternative measure, effectively constitute non-compliance with public health rules governing the private domain.

The results of estimating the SEM with the alternative compliance measure are shown in Table A18 and Figure A10 in Appendix A. COVID-19 threat perception, civic responsibility, risk aversion and trust in the RKI, which in the main analysis had been important for spurring compliance in both domains, were here, too, statistically significant correlates of compliance (estimated effects were even slightly larger). Beyond those three variables, the coefficients more closely resembled the previous estimates for compliance in the private domain, as (i) respondents' level of positive reciprocity was not statistically relevant, (ii) their degree of trust in government was significantly associated with higher levels of compliance, and (iii) COVID-19 threat perception clearly exhibited the largest standardized coefficient among all potential predictors. These findings strengthen the credibility of the main results, especially those regarding the two different compliance domains.

Mediating effects of COVID-19 threat perceptions

Recent evidence suggests that individual threat perceptions of the COVID-19 pandemic may themselves be affected by economic preferences and institutional trust (Harper et al., 2020; Plohl & Musil, 2021), thus making threat perceptions a potential mediator when assessing the impact of preferences and trust on compliance.

Tables A19 and Figure A11 in Appendix A report the results of including this mediation into the structural component of the SEM. The results suggest that the differences across compliance domains predominantly stemmed from direct effects, while the estimated indirect effects were very similar across domains and, beyond that, in most cases much smaller in magnitude. The estimates for the direct effects were almost identical to the patterns in Table 2, and thus, reinforce the paper's core findings regarding the differences and similarities across the two domains. That said, we found supportive evidence of a more general relevance of the indirect channel, corroborating previous evidence (Harper et al., 2020; Plohl & Musil, 2021) emphasizing that preferences and trust may indeed play an important role in shaping individuals' threat perceptions of the pandemic. Specifically, almost all coefficients for indirect effects of preferences and trust were highly statistically significant, even though small in their effect size. The most substantial estimated indirect effects were those for the institutional trust measures, suggesting that especially the interlinkages between institutional trust, threat perceptions and compliance might be of a high relevance.

Additional competing predictors of compliance: Generalized trust

Besides institutional trust, interpersonal generalized trust may also predict individuals' compliance behaviors during the pandemic and contribute to the outlined divergence in compliance across the private and the public domain. Most studies conducted so far look at citizens' trust in certain scientific institutions, individual politicians, or (a specific branch of) the government (see e.g., Bargain & Aminjonov, 2020; Brodeur, Grigoryeva, & Kattan, 2021; Farzanegan & Hofmann, 2022; Granados Samayoa et al., 2021). These studies largely find a strong and statistically significant (sometimes causal) relation between such measures of trust and different types of physical distancing compliance. Interpersonal, generalized trust—that is, to what extent individuals generally have confidence in the good intentions of others—could play a role for compliance behaviors since trust here refers to a *belief about the behavior of others*, and, thus, also about their behavior during the COVID-19 pandemic.

On the one hand, we might expect individuals with a high degree of trust in others to exhibit relatively higher levels of physical distancing because their trust could reflect the belief of a generally compliant public, which could in turn positively affect individuals' own degree of compliance. On the other hand, the expectation of a generally compliant public could also have a harmful effect on compliance behaviors: If individuals believe others to be generally highly compliant with the rules, it might cause them to think that their *own behavior* is less relevant, in the sense that the risk of infection is kept rather low since everyone else is complying with the rules, for example, in the form of wearing a mask or keeping a distance. If so, higher degrees of generalized trust would be associated with lower levels of compliance (similar to the mechanism demonstrated by Keser and Rau (2023) in terms of generalized trust and vaccination decisions). Both of these theoretical expectations seem a priori more relevant in the public than in the private domain due to the facilitated observability of compliance of others.

We examine the potential importance of individuals' generalized trust as an additional predictor for compliance in the public and private domain by using a survey-based measure of generalized trust adopted from Falk et al. (2018). Specifically, as part of our questionnaire, we measured respondents' agreement with the statement "People only have the best intentions." on a scale from 0 to 10. Table A22 (Columns 2 and 5) presents the results of including this measure of generalized trust as an additional predictor in the full model of compliance in the public and private domain, respectively. We find evidence supporting the second above-outlined theoretical expectation: Generalized trust is strongly and significantly associated with lower degrees of compliance in the public domain ($\beta_{\text{pub}} = -0.098$, p-value < 0.001), while there is no statistically significant relation between trust and compliance in the private domain ($\beta_{\text{priv}} = -0.002$, p-value $= 0.927$). A Wald-test confirms the higher statistical relevance of generalized trust in the public domain (Wald test statistic: 22.938, p-value < 0.001). Finally and importantly, the main results in terms of our previously examined core predictors (economic preferences, institutional trust, threat perception) remain stable when including generalized trust as an additional predictor.

Additional competing predictors of compliance: Rural versus urban setting

Besides controlling for respondents' state of residence to account for varying pandemic situations within Germany, also their residence in urban versus rural areas may play a role for compliance behaviors as well as for the outlined public-private compliance divergence. While, on the one hand, we may expect compliance in urban settings to be generally higher due to the higher density and observability of the behavior of others, this line of argument may be even more relevant for the private domain given the contrast between crowded living situations in the city and the much more spaced, rural housing. On the other hand, one could argue that residents in smaller towns know each other (and especially their neighbors) substantially better and are less anonymous than those living in a larger city. In that case, our expectations would suggest the opposite, that is, (private) compliance being higher in the rural context.

We examine the potential importance of respondents' residence in rural versus urban settings as an additional predictor for compliance in the public and private domain by using a survey-based measure of the size of the community a respondent lives in. Specifically, as part of our survey, we asked respondents how many inhabitants live in their community/municipality, with response options being "below 5000," "5001–20,000," "20,001–100,000," "100,001–500,000," "above 500,000." Based on this question, we constructed an indicator variable that takes on the value of 1 if a respondent reported living in a municipality with less than or equal to 20,000 inhabitants and that takes on the value of 0 if (s)he reported living in a municipality with more than 20,000 inhabitants. We chose this definition of the variable because, in Germany, municipalities with less than 20,000 inhabitants are counted as "Kleinstädte," that is, small towns/villages.

Table A22 (Columns 3 and 6) presents the results of including this measure of rural/urban residence setting as an additional predictor in the full model of compliance in the public and private domain, respectively. We find a negative, but no statistically significant association between a respondent living in a rural as opposed to a more urban setting and their degree of compliance in the public/private domain. However, in terms of magnitude, the effect size of the coefficient is much larger for compliance in the private than in the public domain (though this difference is also not statistically significant according to a Wald test testing for the equality of coefficients). Thus, the direction and pattern of this finding is generally in line with the first theoretical expectation outlined above, even though they lack statistical significance. Finally and importantly, the main results in terms of our previously examined core predictors (economic preferences, institutional trust, threat perception) remain stable when including respondents' urban/rural residence setting as an additional predictor.

Correlation between regional CV-19 threat perception and case incidence rate

We examine the relation between our measure of respondents' COVID-19 threat perception and the incidence rate of COVID-19 cases, using data from the Federal Statistical Office of Germany ("Statistisches Bundesamt") about the number of registered COVID-19 cases in the past 7 days per 100 people.[17] To do so, we employ federal state level averages of our threat perception measure and the state level averaged COVID-19 case incidence (i) across the time period of the data collection (February 2021) and (ii) across all previous infection waves (i.e., from the beginning of the pandemic until the start of the data collection). We chose to examine the case incidence level during both of these time periods because it seems likely that, if individuals' threat perceptions are indeed related to the actual number of cases, both, the trajectory and intensity of previous infection waves as well as the severity of the infection wave in the midst of our data collection, play a role (in potentially opposing ways). In addition to reporting Pearson correlation coefficients, we also show the results of regressing state level threat perception on state level case incidence rates while controlling for possible confounders at the state level (population density, share of the German population living in this state, the state being a Stadtstaat, i.e., one of the three German cities that are also a federal state).

The results of this exercise are shown in Table A23 in Appendix A. We find that neither the average COVID-19 case incidence during the data collection nor the case incidence during the prior infection waves are significantly related to respondents' COVID-19 threat perception at the state level. However, the findings do reveal a pattern with respect to the direction of the correlations: While there is a small, positive correlation between respondents' threat perception and the case incidence rate *during our data collection period*, its correlation with the case incidence rate *during prior infection waves* is slightly negative.

We, first, interpret the former result as providing some form of validation for our threat perception measure. Second, in combination, these findings interestingly also suggest that individuals' threat perception may be, on the one hand, highly dependent on the *immediate* pandemic situation, and, on the other hand, particularly sensitive to *retrospective adjustments*. Specifically, we observe that respondents who experienced higher case numbers in the first waves of the pandemic actually reported a slightly lower fear of COVID-19 during our survey data collection, while those that experienced higher case incidence levels during the data collection also revealed a slightly higher perceived threat. To that end, these findings moreover confirm the conceptualization of our measure of threat perception as a not necessarily rationally or objectively informed concept, but rather as a subjective account of how threatening respondents perceived the COVID-19 pandemic to be in general and how threatening they perceived it to be with regard to specific aspects of their lives (health, financial, social; see also the factor scores we used to construct the threat perception measure). This conceptualization of threat perception may also contribute to explaining why it appears to play such a crucial role for individuals' compliance behaviors during the pandemic, as identified in the main analysis.

Finally, we remain, for the following reasons, cautious not to overstate or over-interpret the outlined correlations between our measure of threat perception and COVID-19 case incidence rates—neither in terms of the absence of statistical significance nor in terms of the mere directions of the correlations. First, the analysis was conducted at the state-level and is, thus, based on $N = 16$. It is therefore statistically underpowered. Second, during the pandemic there was a lot of variation within federal states themselves and it is likely that living in a large city within a certain state as opposed to living in a rural area within a certain state plays a crucial role for the correlation between case numbers and threat perception. A more thorough analysis would therefore be to go even lower than state-level. Unfortunately, we did not ask respondents about the specific district they live in and, thus, could not conduct such an analysis. Third, and relatedly, patterns at individual level and the aggregate level can differ.

Additional analyses for the institutional trust variables

To better understand the differential observed dynamics for trust in the RKI and trust in the government across the two domains, we conducted a number of supplementary analyses that exploit additional information collected in our survey.

In terms of trust in the RKI, we had, in our theory section, argued that we would, if any, expect a larger impact on compliance in the public domain given the more technical stipulations in this realm, for example, wearing a mask or keeping a 1.50 m distance from another as opposed to the general recommendation of "staying at home" in the private domain. Recall that we had chosen trust in the RKI as a measure of trust in scientific institutions in the German case, because in Germany the RKI was the dominant scientific institution that was heavily involved in policy consultation and communication with regards to the COVID-19 pandemic. In line with our theoretical expectations, our core results suggest that trust in the RKI, indeed, plays a stronger role for public compliance than for private compliance, though its estimated effects are statistically significant in both realms. Thus, to assess whether the above explanation is plausible, we draw on two alternative proxies for trust in scientific institutions, namely (i) trust in science (in general) and (ii) trust in the WHO and examine whether the observed pattern holds. Table A28 in Appendix A reports the results of this exercise. Estimating the SEM with trust in science and trust in the WHO, respectively, instead of trust in the RKI as a predictor of public and private compliance (all other variables remaining as in the main specification) reveals the same pattern, which we also observed for trust in the RKI: Both proxies reveal statistically significant correlations with compliance in the two domains, but much larger estimated effects in the public domain. The magnitudes and levels of statistical significance are strikingly similar to those of trust in the RKI (trust in science: $\beta_{pub} = 0.182$, p-value < 0.001; $\beta_{priv} = 0.053$, p-value < 0.05; trust in the WHO: $\beta_{pub} = 0.165$, p-value < 0.001; $\beta_{priv} = 0.055$, p-value < 0.05). Moreover, including trust in science and trust in the WHO did not change the pattern identified for trust in the government (or any of the other core predictors) substantially.

In terms of trust in the national government, we had, in our theory section hypothesized conflicting logics: On the one hand, the absence of formal monitoring by state authorities in the private realm might make trust as an intrinsic motivator more important. On the other hand, the private realm may be understood as a realm in which the government has inherently no legitimate role to play. Our results revealed that trust in the government is only significantly correlated with compliance in the private domain, not with compliance in the public domain. To examine this finding further and understand how it relates to our initial expectations, we utilize two additional institutional trust variables, which aim at quantifying trust in institutions or actors that are related to the German government, but in different ways: First, we repeat the main SEM specification, but replace trust in the government with trust in the state-level government. We use this variable since they allow us to investigate whether the observed pattern is a general pattern for government-related institutions or whether it is a specific pattern of citizens' trust in the national government in particular. The results of this exercise are reported in Table A29 (Columns 2, 3, 7 and 8) in Appendix A. For trust in the state-level government, we initially find a similar pattern as for trust in the (national) government, that is, there is only a significant correlation with compliance in the private, but not in the public domain. However, the estimated effects are smaller and also slightly less statistically meaningful ($\beta_{pub} = 0.031$, p-value $= 0.267$; $\beta_{priv} = 0.070$, p-value < 0.01). Moreover, when adding both, trust in the state-level government and trust in the national government, simultaneously, the statistical significance of the estimated effects for trust in the state-level government disappears, while those for trust in the national government remains (see Columns 3 and 8). These findings suggest that the pattern observed in our main analysis may be specific to and driven by trust in the national government ("Bundesregierung").

Given these findings, we propose an alternative explanation for the observed dynamics, which we aim to investigate by repeating the above exercise but instead including trust in Germany's established media channels as a predictor in the model. Specifically, we argue that the high relevance of trust in the national government for citizens' compliance in the private realm could be a result of the specific policy communication and messaging campaigns issued during the pandemic in Germany. For instance, the narratives of the regular public addresses by Chancellor Angela Merkel to the German population were much more focused on the general aspect of staying at home (i.e., along the lines of being united in isolation), which is closely related to our definition of private compliance, and less so on the more technical rules of mask-wearing or avoiding handshakes (i.e., our definition of public compliance) (see e.g., Angela Merkel, televised speech, 2020). Thus, it may be that, as a result of such communication strategies throughout the entire pandemic, the view of the private realm as a realm in which the government has no prominent role to play was somewhat loosened, especially for individuals with a high level of trust in the national government. We try to assess the plausibility of this alternative interpretation by drawing on another variable, namely trust in established media channels, which are widely broadcasted and supported the mentioned public addresses by Angela Merkel. Thus, if the observed patterns are a result of policy communication during the pandemic, we should observe a very similar pattern for citizens' trust in the said government-related media channels—which is what we indeed observe: The estimated coefficients of citizens' trust in established media channels show the same pattern as those for trust in the national government, that is, they are statistically significant for compliance the private realm, but not for compliance in the public realm ($\beta_{\text{pub}} = -0.017$, p-value $= 0.499$; $\beta_{\text{priv}} = 0.081$, p-value < 0.001). Moreover, while the coefficients are smaller in magnitude, they are, unlike the coefficients of trust in the state-level government, robust to a simultaneous estimation together with trust in the national government (see Columns 4, 5, 9 and 10 of Table A29). We therefore interpret these findings as support for the alternative explanation outlined above. Finally, it is noteworthy that including the mentioned additional variables did not change the patterns identified for trust in the RKI (or any of the other core predictors) substantially.