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Prosociality Predicts Individual Behavior and Collective Outcomes in the COVID-19 Pandemic

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Prosociality predicts individual behavior and collective outcomes in the COVID-19 pandemic*

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Abstract

The COVID-19 pandemic induces a typical social dilemma situation, as engaging in preventive behaviors such as social distancing is costly for individuals, but generates benefits that accrue to society at large. The extent to which individuals internalize the social impact of their actions may depend on their (pro-)social preferences. We leverage a nationally representative survey in Germany (n = 5,843), conducted during the second coronavirus wave, to investigate the role of prosociality in reducing the spread of COVID-19. At the individual level, higher prosociality is strongly positively related to compliance with recommended public health behaviors. At the regional (NUTS-2) level, higher average prosociality is associated with significantly lower incidence and growth rates of COVID-19 infections. This association is robust to controlling for a host of regional socio-economic factors, and mediated by stronger average compliance with public health measures. Our correlational results thus confirm the notion that voluntary behavioral change due to prosocial motivations can play an important role in the pandemic.

JEL Classification: D64, I12, I18, H41

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1. Introduction

To curb the COVID-19 pandemic, individuals have to engage in costly preventive behaviors such as reducing social contacts, wearing face masks, or using contact tracing apps. The benefits from lower transmission, however, accrue to society at large and thus constitute a public good. This results in a social dilemma situation, as individuals have little incentive to take the benefit of their actions on society into account, which potentially leads to collectively inefficient outcomes — e.g. unnecesssarily wide spread of COVID-19, with its resulting hospitalizations and deaths. In this sense, the pandemic is comparable to other collective action problems such as civic engagement or the fight against climate change.

Which factors determine the success of groups or societies in overcoming collective action problems has been a long-standing question in the social sciences. One plausible determinant is the extent to which individual members are prosocial, i.e. how willing they are to behave in a way that mostly benefits other people or society at large. Previous studies have documented associations between (pro-)social preferences and, amongst others, pro-environmental behavior (Fuhrmann-Riebel, D'Exelle and Verschoor, 2021; Lades, Laffan and Weber, 2021; Andre et al., 2021), donation and volunteering decisions (Falk et al., 2018), redistributive voting (Epper, Fehr and Senn, 2020), as well as labor market outcomes (Dohmen et al., 2008; Kosse and Tincani, 2020). Prosocial individuals may help their groups in achieving more beneficial outcomes in the face of social dilemmas, both by contributing more to a common cause themselves, and also by increasing cooperation rates among other members — for example through establishing and enforcing corresponding social norms (Fehr and Gächter, 2002; Fehr and Fischbacher, 2003; Fischbacher and Gächter, 2010; Albrecht, Kube and Traxler, 2018; Fehr and Schurtenberger, 2018).

In this study, we examine the relationship between prosociality and individual behavior as well as collective health outcomes in the context of the COVID-19 pandemic. When fighting the pandemic, governments and public health experts have recurringly appealed to people's altruistic motivations for protecting others from getting infected. Generally, more prosocial individuals might have a stronger inclination to internalize the health externalities that their behavior imposes on others; consistent with this, previous studies have found that more prosocial individuals tend to follow social distancing and hygiene guidelines more stringently (Campos-Mercade et al., 2021; Müller and Rau, 2021). One implication is that regions with higher average levels of prosociality might be more successful in slowing the spread of the virus (Farboodi, Jarosch and Shimer, 2020; Quaas et al., 2020; Alfaro et al., 2020). Indeed, there is some evidence that proxies for social (or civic) capital are related to mobility flows and COVID-19 incidence rates at the subnational level (Barrios et al., 2021; Bartscher et al., 2020; Borgonovi and Andrieu, 2020; Durante, Guiso and Gulino, 2021; Makridis and Wu, 2021), but these studies cannot link their regional measures to individual-level data.

We study the role of prosociality in the pandemic by employing data from a large-scale online survey in Germany ($n = 5,843$) that is nationally representative of the population aged 18 to 65. The survey was conducted between mid-November to mid-December 2020, thus falling into the second coronavirus wave in Germany, in a period that was characterized by steeply increasing incidence rates and a relatively lenient "lockdown light". To measure individuals' public health behavior (PHB) during that time, we included a series of questions about the extent to which they engage in physical distancing, mask-wearing, precautionary hygiene measures, self-quarantining, etc., which we then combine into a single index variable. Although imperfect, self-reported PHB measures such as ours have been shown to be good indicators of actual behavior in the pandemic (Jensen, 2020; Gollwitzer et al., 2021). We further elicited individuals' prosociality based on experimentally validated survey measures of altruism, trust, positive reciprocity, and indirect (negative) reciprocity (Falk et al., 2016, 2018). Our data confirms that prosociality is strongly positively related to compliance with recommended social distancing and hygiene measures. Due to the relatively large sample size, we can further aggregate our survey measures to regional-level averages across NUTS-2 regions in Germany and link them to official statistical data on Covid-19 infections and deaths. Our focus on within-country variation has the advantage that policy mandates and regulations in response to the pandemic remain largely similar. We are thus able to investigate whether the individual-level relation between prosociality and PHB also translates into slower spread of Sars-CoV-2 in regions where average prosociality in the population is high.

2. Individual-level prosociality and public health behavior

We begin by establishing a robust positive relationship between prosociality and PHB at the individual level. Table 1 presents results from ordinary least squares (OLS) regressions using data from our representative online sample. Column 1 shows that prosociality strongly predicts individual behavior in the pandemic conditional on time and risk preferences — a one standard deviation (SD) increase in prosociality is associated with a one third SD increase in PHB. As would be expected, more patient and more risk averse individuals are also more likely to adhere to social distancing and hygiene measures.

People who are more prosocial also differ along other characteristics that may be associated with differential costs and benefits of adhering to recommended PHBs. For example, infection risk and disease severity vary with demographic factors, such as age or gender, whereas economic factors, such as occupation, income, or household situation could determine the costs of complying with certain preventive measures. Regional differences in current and past infection rates could further influence individual behaviour, e.g., if regions hit more severely have stricter policy measures in place, or have developed stricter norms in enforcing such measures. In general, all these factors tend to be corre-

Table 1: Individual-level association between preferences and PHB

	Public Health Behavior (PHB)				
	(1)	(2)	(3)	(4)	(5)
Prosociality	0.3356***	0.3059***	0.3115***	0.2216***	0.1625***
	(0.0162)	(0.0165)	(0.0168)	(0.0173)	(0.0148)
Patience	0.1983***	0.1969***	0.1858***	0.1633***	0.0777***
	(0.0150)	(0.0151)	(0.0155)	(0.0155)	(0.0131)
Risk-taking	-0.2095***	-0.1710***	-0.1722***	-0.1683***	-0.0790***
	(0.0141)	(0.0144)	(0.0148)	(0.0141)	(0.0110)
Socio-demographic factors	*No*	*Yes*	*Yes*	*Yes*	*Yes*
County FEs	*No*	*No*	*Yes*	*Yes*	*Yes*
Big Five	*No*	*No*	*No*	*Yes*	*Yes*
COVID-19 Perceptions	*No*	*No*	*No*	*No*	*Yes*
Observations	5843	5660	5653	5653	5653
Clusters	397	396	389	389	389
R^2	0.209	0.234	0.293	0.345	0.529

Notes. In the interest of brevity, we report only the coefficients on economic preference variables here; Table A2 reports estimates on other variables included in each specification. SEs (in parentheses) are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

lated with prosociality and could thus act as confounders (Falk et al., 2018). However, columns 2 and 3 of Table 1 show that the estimated coefficient for prosociality remains stable and highly statistically significant when controlling for socio-demographic characteristics (e.g. age, gender, education, income) and county fixed effects.

Apart from economic preferences, certain psychological personality traits such as agreeableness and openness have also been linked with stronger adherence to PH measures in the COVID-19 pandemic (Nikolov et al., 2020; Zettler et al., 2021). However, as the estimates in column 4 of Table 1 show, differences in Big-5 personality does not drive the association between prosociality and PHB.[1] We also investigate to which degree the role of prosociality can be explained by individuals' perceptions, assessments, and attitudes regarding the COVID-19 pandemic (Table 1 column 5). However, even controlling for these potentially mediating factors again leaves a strong association between prosociality and PHB intact.

[1]In general, personality traits and economic preferences seem to be partially distinct concepts (Becker et al., 2012; **?**) and both retain explanatory value for individual behavior in the pandemic (see Table A2, SI Appendix). For example, while prosociality and agreeableness may seem similar at first glance, the former is largely defined by concern towards the welfare of others, whereas the latter also encompasses conformity and traditional values (Roccas et al., 2002). Correspondingly, agreeableness is much less predictive of one's attitudes towards the pandemic and how much one worries about others getting infected compared to prosociality (SI Appendix Table A4).

3. Regional-level prosociality and collective health outcomes

3.1. Descriptive overview

In the next step, we examine how regional variation in prosociality across Germany relates to public health outcomes during the COVID-19 pandemic. For this purpose, we construct regional averages of our prosociality and PHB measures by aggregating individual survey responses at NUTS-2 level ("Regierungsbezirk"), using sampling weights to improve regional representativeness by age, gender, and education.[2]

We document meaningful variation in prosociality across regions in Germany, as illustrated by the map in Figure 1a. Average prosociality ranges from -0.37 to 0.42 across NUTS-2 regions, thus spanning about 80% of an individual-level standard deviation.[3] These cross-regional differences in prosociality are further related to commonly used proxies for social (or civic) capital (Putnam, 2000; Guiso, Sapienza and Zingales, 2011; Bartscher et al., 2020), see SI Appendix Table A6. For example, higher average prosociality in a region is associated with higher voter turnout in the 2019 EU election ($\varrho = 0.3098$, $p < 0.05$) and larger density of civic associations in 2008 ($\varrho = 0.1394$, $p < 0.1$).

Moreover, Figure 1b shows that average prosociality is also closely linked with average PHB in the pandemic at the regional level. In fact, the regional-level correlation ($\varrho = 0.5795$, $p < 0.001$) is substantially stronger than what would have been predicted solely based on the unconditional individual-level correlation ($\varrho = 0.3503$, $p < 0.001$), suggesting that prosocial individuals may also raise public health compliance indirectly through social influence on others.[4] This amplification effect is consistent with previous evidence on spillovers of prosocial behavior — e.g. through conditional cooperation or through establishment and enforcement of social norms for cooperation — documented both in laboratory studies (Fehr and Fischbacher, 2003; Weber and Murnighan, 2008; Fowler and Christakis, 2010; Gächter, Nosenzo and Sefton, 2013; Albrecht, Kube and Traxler, 2018) and field settings (Frey and Meier, 2004; Chen et al., 2010; Rustagi, Engel and Kosfeld, 2010; Kessler, 2017).

Figure 1c plots the evolution of COVID-19 infections per 100,000 population in Germany (as reported by the RKI) over the course of the pandemic, split by regions with above-median and below-median prosociality. Incidence rates in high-prosociality re-

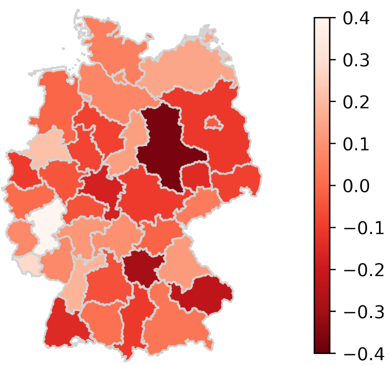
[2]See SI Appendix for more details. The median sample size per region is 124. We calculate sampling weights to match the regional age and gender distribution as well as the share of population with a university degree, but all results are very similar when using an unweighted sample. To validate the regional representativeness of our sample, we compare vote shares of the main political parties in the 2019 election with the implied vote shares in our survey based on self-reported party preferences (SI Appendix, Table A1). The regional correlations are extremely high — ρ between 0.76 and 0.86 — for all parties with the exception of the FDP, the German liberal party ($\rho = 0.29$).

[3]While measurement error could certainly lead to an exaggeration in regional differences, we can statistically reject the null-hypothesis of zero cross-regional variation at the 5% level, both when controlling and when not controlling for socio-demographic variables.

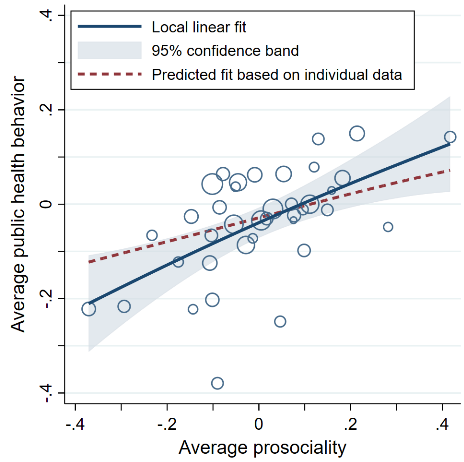
[4]A placebo test that randomly permutates individual-to-region assignments confirms that this result is not driven by reduction in measurement error through (random) grouping. See SI Appendix.

Figure 1: Prosociality, public health behavior, and COVID-19 incidence rates

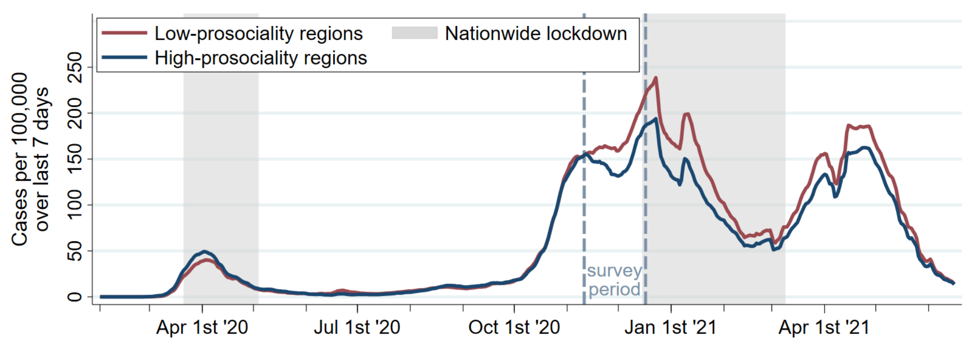
(a) Regional variation in prosociality



(b) Prosociality and PHB at NUTS-2 level



(c) COVID-19 infections per 100.000 population reported in the last 7 days



Panel (a): Map of the 38 NUTS-2 regions in Germany, with color intensity indicating average level of prosociality based on our survey measures. The unit is individual-level SDs. Panel (b): Relation between average prosociality and average PHB on NUTS-2 level, both expressed in terms of individual-level SDs. The solid fitted line is constructed from an unweighted local linear regression (Gaussian kernel, bandwidth = 0.3) of average PHB on average prosociality at NUTS-2 region level (N = 38). The dashed line shows the association between average prosociality and the average fitted values from an individual-level regression of PHB on prosociality and prosociality-squared. Bubbles indicate NUTS-2 regions, with the depicted bubble area being proportional to the population size. Panel (c): Official number of COVID-19 infections reported by RKI between Feb 1, 2020, and Jun 15, 2021. Grey shaded areas indicate time periods of strict nationwide lockdowns in Germany (as of March 8, 2021, restrictions were tied to the regional incidence rate, although the lockdown formally remained in place).

gions dropped persistently below those in low-prosociality regions starting from around Nov 2020, in the period of the so-called "lockdown light", which was in place at the beginning of the second wave in Germany and had the goal of reducing social contacts while avoiding a complete economic standstill. At the height of the second wave, high-prosociality regions experienced around 15-25% lower incidence rates and 20-30% fewer COVID-19 deaths; this gap in health outcomes is accompanied and preceded by a gap in mobility patterns based on mobile phone data (see SI Appendix, Figure A1). These observations suggest a meaningful role of prosociality in determining how well a region can slow the spread of the virus and protect vulnerable groups. However, regions with different levels of prosociality also differ by other characteristics that could influence the spread of the virus, e.g. population density and socio-economic factors. Therefore, we will now move on to our formal statistical analyses.

3.2. Association between prosociality and COVID-19 incidence rates

Our main outcome variable is the official number of new COVID-19 infections per 100,000 population that is reported by the RKI for each county in Germany. In the SI Appendix, we also present results using COVID-19 deaths as outcome variable, which are in general very similar. We mostly focus on the time period in which we conducted the survey, because this is when our information on PHB is the most applicable. As the effects of changes in behavior (or policies) will only manifest themselves with a delay, we analyze health outcomes of the two-month period from Nov 16 to Jan 17 — also to take into account reporting delays by local health authorities due to Christmas and New Year.[5] We use the log of the incidence rate as the dependent variable, to better capture the potentially exponential effects from differences in behavior on the spread of infections.

Table 2 presents the baseline results. For ease of interpretation, we standardize prosociality to mean 0 and standard deviation 1 across regions. To adjust for the highly dynamic nature of the pandemic, all specifications include week fixed effects. Column 1 shows that, when not controlling for other county characteristics, our estimates imply that a one SD higher prosociality is associated with a 13% lower weekly incidence rate in the time period between Nov 16, 2020, and Jan 17, 2021 — an effect that is both quantitatively sizeable and statistically significant ($p < 0.01$). The estimated coefficient remains robust to including regional-level time and risk preferences as regressors (column 2), although its precision decreases. In contrast, the estimates for average patience and risk taking are small and insignificant.

Importantly, we verify whether the association between prosociality and COVID-19 incidence rates is robust to controlling for other demographic and socio-economic county characteristics that could influence the regional spread of the virus. In column 3, we therefore include a host of control variables, among others for population density, employment shares, education level, and GDP per capita. We further allow the effects of these county controls to differ by week. Another potential concern is that regional differences in severity of the pandemic experienced during the first wave may have had an impact on the level of prosociality, but simultaneously also on other factors like general attitudes or local government preparedness. To flexibly account for this, we further add control variables for counties' first wave outcomes in column 4, namely the overall number of infections per population, its square, and the case fatality rate. This may also to some degree control for certain time-invariant county characteristics that affect infection rates both in the first and second wave of the pandemic, although coming at the risk of

[5] Our results are not sensitive to the exact specification of the time period of analysis, see SI Appendix.

Table 2: Weekly incidence at the time of the survey

	$y_{c,t} = \log(cases_{c,t})$ in county c and week t				
	(1)	(2)	(3)	(4)	(5)
Prosociality	-0.1384 ***	-0.1266 *	-0.1234 **	-0.1179 **	0.0190
	[-0.283, -0.060]	[-0.303, 0.011]	[-0.296, -0.020]	[-0.245, -0.032]	[-0.089, 0.107]
Patience	–	-0.0281	0.0028	-0.0055	0.0601
		[-0.212, 0.134]	[-0.116, 0.181]	[-0.111, 0.129]	[-0.019, 0.189]
Risk taking	–	0.0105	-0.0379	-0.0453	-0.0813 *
		[-0.107, 0.126]	[-0.154, 0.092]	[-0.137, 0.072]	[-0.149, 0.005]
Public health behavior	–	–	–	–	-0.2991 ***
					[-0.444, -0.157]
Wave 1 severity	*No*	*No*	*No*	*Yes*	*Yes*
County controls × Week	*No*	*No*	*Yes*	*Yes*	*Yes*
Week fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3609	3609	3609	3609	3609
Spatial units (counties)	401	401	401	401	401
Clusters	38	38	38	38	38
R^2	0.116	0.117	0.357	0.414	0.480

Notes. Bootstrapped 95%-confidence-intervals in brackets (clustered at NUTS-2 level), obtained using wild bootstrapping with Rademacher-weights and 9,999 simulations. The time period of analysis ranges from Nov 16, 2020, until Jan 17, 2021. County controls include log population density, log GDP per capita, log average income per capita, share of college graduates, employment share, share of non-German residents, share of workers in the service sector, share of population below age 18, share of population age 65 or above, and border county dummies for each neighboring country of Germany. Controls for wave 1 severity include the log of aggregate case numbers, its square, and case fatality rate in the time period from the first confirmed infection until May 17th, 2020.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

overcontrolling, since average prosociality can also be related to first wave outcomes (see Discussion). After including this rich set of control variables (Table 2, columns 3 and 4), the explanatory power of the regression increases drastically by a factor of more than three. Crucially, the coefficient for prosociality remains nearly unchanged, with a one SD increase being associated with 11-12% lower weekly incidence rates ($p < 0.05$).

Why is the number of new infections lower in regions with higher prosociality? Our individual-level results show that prosociality predicts self-reported PHB conditional on a person's age, education, income, county of residence, and so on; the relationship between prosociality and PHB tends to be even stronger at the regional level. Hence, we hypothesize that the effect of prosociality is mediated by higher compliance with recommended or mandatory social distancing and hygiene measures. Indeed, a mediation analysis in column 5 shows that when adding average PHB in a region as regressor, the coefficient size for prosociality is reduced by 84% to almost zero. Hence, virtually the entire effect of prosociality can be explained by differences in behavior across regions. The association between self-reported behavior and incidence rates is remarkably strong: a one SD increase in average PHB is associated with a 26% decrease in the number of weekly infections per 100,000 population.[6]

[6] Interestingly, risk taking has a weakly significant negative effect on infections after controlling for PHB, which could potentially be explained with higher willingness to experiment with new strategies or to adopt new technologies against the spread of the virus.

Table 3: Weekly growth rate of infections at the time of the survey

	$y_{c,t} = \log(cases_{c,t}) - \log(cases_{c,t-1})$			
	(1)	(2)	(3)	(4)
Prosociality	-0.0093 **	-0.0101 *	-0.0218 ***	-0.0075
	[-0.019, -0.001]	[-0.023, 0.002]	[-0.037, -0.011]	[-0.025, 0.007]
Patience	-0.0011	-0.0015	-0.0011	0.0061
	[-0.014, 0.007]	[-0.015, 0.009]	[-0.011, 0.014]	[-0.008, 0.026]
Risk taking	0.0001	0.0003	-0.0044	-0.0091
	[-0.012, 0.013]	[-0.012, 0.012]	[-0.016, 0.010]	[-0.026, 0.007]
Public health behavior	–	0.0018	–	-0.0333 **
		[-0.021, 0.022]		[-0.065, -0.006]
$\log(cases_{c,t-2})$	–	–	-0.1080 ***	-0.1205 ***
			[-0.125, -0.093]	[-0.145, -0.097]
Policy stringency$_{c,t-2}$	–	–	-0.2361	-0.2017
			[-0.848, 0.287]	[-0.758, 0.227]
Wave 1 severity	*Yes*	*Yes*	*Yes*	*Yes*
County controls × Week	*Yes*	*Yes*	*Yes*	*Yes*
Week fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3609	3609	3609	3609
R^2	0.292	0.292	0.313	0.315

Notes. Bootstrapped 95%-confidence-intervals in brackets (clustered at NUTS-2 level), obtained using wild bootstrapping with Rademacher-weights and 9,999 simulations. The outcome variable is the log of weekly infections per capita in a county, ranging from Nov 16th 2020 until Jan 17th 2021. County controls include log population density, log GDP per capita, log average income per capita, share of college graduates, employment share, share of non-German residents, share of workers in the service sector, share of population below age 18, share of population age 65 or above, and border county dummies for each neighboring country of Germany. Controls for wave 1 severity include the log of aggregate case numbers, its square, and case fatality rate in the time period from the first confirmed infection until May 17th, 2020.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Although we have controlled for a number of demographic and socio-economic county characteristics, there could still be other, possibly unobserved factors that lead to generally lower levels of infections in a county, while also being positively correlated with prosociality and PHB. A more stringent test is thus whether regions with higher prosociality also exhibit lower growth rates of new infections, given the previous number of infected people. In a next step, we therefore evaluate the effect of prosociality on the weekly growth rate of new cases, approximated by the change in log incidence $\Delta \log(cases_{c,t}) = \log(cases_{c,t}) - \log(cases_{c,t-1})$ in county c and week t (see Table 3). We include the full set of previously used control variables in all specifications.

Although high- and low-prosociality regions start from roughly similar levels of infections at the beginning of the second wave (see Figure A1), differences in the growth rate would gradually drive infection levels apart over time, eventually resulting in large cumulative differences. Indeed, our baseline specification in Table 3 shows that, in the time period we study, the growth rate of new infections was about 1%p lower in regions with a one SD higher prosociality ($p < 0.05$). We find no evidence for mediation through

PHB in column 2 yet. However, the estimated effects of prosociality and social distancing might be attenuated due to dynamic interactions between infection rates, behavior, and policy responses that push towards regional convergence. For example, in regions with higher incidence, the population may endogenously reduce their contacts in response to higher infection risks, and local governments will respond with stricter curtailment measures. More prosocial regions could thus, in some sense, become the victims of their own success. For this reason, we further add the 2-week lagged incidence rate $\log(cases_{c,t-2})$ as well as the 2-week lag of local policy stringency as regressors.[7] After including these lagged variables, the coefficient size for prosociality more than doubles, implying a 2%p lower weekly growth rate per SD increase ($p < 0.01$). In the mediation analysis presented in column 4, prosociality becomes insignificant after adding average PHB, further lending support to the hypothesis that better compliance with social distancing and hygiene measures mediate the effect of higher prosociality on collective health outcomes during the pandemic.

4. Discussion

How well a group of individuals succeeds in achieving desirable collective outcomes in the face of social dilemma depends, amongst other things, on how willingly individual members engage in actions that incur personal costs but that benefit the group as a whole. We have provided suggestive evidence that, in the context of the COVID-19 pandemic, individuals who are more prosocial are significantly more willing to engage in public health behaviors (e.g. physical distancing and mask wearing) aimed at slowing the spread of the virus, and that in turn, regions in Germany with higher average prosociality in the population also tend to experience a lower incidence of COVID-19 cases and deaths. The estimated (conditional) correlations are quantitatively sizeable: a 1 SD higher average prosociality in a region is associated with around 10% lower cumulative numbers of COVID-19 infections and deaths per capita (see Figure A3, SI Appendix).

The interpretation of our results needs to take into account the broader context in which our study is embedded, as the role of prosociality may be moderated, among others, by the stage of the pandemic, the regional severity of the outbreak, and the stringency of government-mandated restrictions and policy measures. Our survey was conducted in the late fall of 2020, before the peak of the second wave in Germany, during the so-called lockdown light. In contrast, the vast majority of related studies examining determinants of PHB was conducted in the first wave of the pandemic, when there was more fear and uncertainty revolving around the disease and the spread of the virus (Harper et al., 2020). Thus, we confirm previous results on the importance of prosociality (Campos-Mercade et al., 2021; Müller and Rau, 2021) also for later stages of the pandemic, when

[7] We construct the local policy measure stringency index using data obtained from infas360 (`https://www.corona-datenplattform.de/dataset/massnahmen_oberkategorien_kreise`).

people had became more accustomed to (but also more weary of) the situation. In Table A8 of the SI Appendix, we compare predictors of regional incidence rates in the first and the second COVID-19 in Germany and observe that the same set of demographic and socio-economic county characteristics (e.g. population density, employment share) has much higher explanatory value in the first wave ($R^2 = 0.497$) than in the second wave ($R^2 = 0.265$), possibly because behavioral responses in the population were more homogeneous early on in the pandemic.[8]

The quickly rising case numbers at the time period of our survey might have further driven attitudes and behavioral responses apart for people in different regions and with different individual characteristics, as protecting those who are vulnerable to the disease becomes especially relevant when the risk of infection and transmission is high. In contrast, private gatherings may not be considered as irresponsible acts of selfishness in periods of low incidence such as the summer of 2020 in Germany. Another potentially amplifying factor for the role of prosociality in our context may be that the lockdown light in Germany left plenty of wiggle room in the extent of social distancing behavior within the limits of what was allowed, thereby putting considerable weight on voluntary reduction of social contacts. In general, voluntary behavior shifts and government-mandated restrictions can be thought of as substitutes for each other (Alfaro et al., 2020; Yan et al., 2021). On the other hand, perfect monitoring and enforcement of compliance is hardly feasible, and drastic government measures can also influence public perceptions of social norms and the severity of the situation (Casoria, Galeotti and Villeval, 2020; Galbiati et al., 2020). Thus, prosociality can affect behavioral responses and collective health outcomes even under more stringent lockdown regimes.

Finally, a natural question in our context is to which extent the conditional correlations we find in our empirical analyses can be interpreted as causal. There are several potential concerns against such a causal interpretation. First, our sample may not be regionally representative due to self-selection into completing the survey. While such selection effects are hard to rule out, they could only explain our results if systematically more prosocial individuals respond to our survey in regions with lower incidence rates, which seems implausible. Second, one might worry that our measures of prosociality and economic preferences are themselves affected by the COVID-19 pandemic (Alsharawy et al., 2021; Branas-Garza et al., 2020; Cappelen et al., 2021; Frondel, Osberghaus and Sommer, 2021; Shachat, Walker and Wei, 2020). If any influence on individuals' survey responses reflect true changes in preferences and attitudes, our measures remain internally valid for the time period around which we conducted the survey. On the other hand, we might overestimate the role of prosociality if respondents' answers to broadly framed questions overreflected their behavior during the pandemic, e.g. due to availability bias (Tversky and Kahneman, 1973). We cannot directly investigate this issue with our cross-sectional

[8]In support of this hypothesis, the cross-county variance of mobility flows was generally lower during the first wave of the pandemic compared to later stages, see SI appendix.

survey data, but note that regional prosociality in our data correlates with pre-pandemic outcomes such as election turnout, and that our results are robust to controlling for severity of the pandemic in the first wave. Moreover, there is evidence that individual health behavior during the pandemic is predicted by prosociality measured before the COVID-19 outbreak (Campos-Mercade et al., 2021), which is consistent with the notion that individual's (social) preferences are fairly stable in general (Carlsson, Johansson-Stenman and Nam, 2014; **?**). A third concern is reverse causality, because regional incidence rates may also have an influence on PHB and its relation to prosociality. This might actually lead to an underestimation, since lower incidence rates allow residents and policy makers to become more lenient in their responses. Consistent with this convergence effect, we have shown in Table 3 that the estimated association between average prosociality and weekly infection growth rate doubles in magnitude when controlling for lagged incidence levels.

The fourth and arguably most important concern is omitted variable bias. At the individual level, it seems unlikely that the relation between prosociality and PHB is entirely driven by some unobserved factor, as we control for a host of demographic and socio-economic characteristics, and further confirm robustness to including personality factors and political attitudes as regressors. At the regional level, we control for a variety of relevant county characteristics, but it is difficult to rule out all potentially confounding factors, e.g. stringency of local implementation and enforcement of containment measures, contact tracing efficiency, etc., which may themselves also be partly a function of prosociality in the population. Eventually, our empirical investigation must inevitably remain of correlational nature, since the distribution of (pro-)social preferences, values, norms, and beliefs is inherently endogenous to a myriad of social, cultural, political, and institutional factors that are imperfectly observable and whose causal relationships are highly complex and interdependent.

Our paper is inspired by a number of previous studies that measure individual and geographical variation of (pro-)social behavior and preferences in order to advance our understanding of how collective societal outcomes may be shaped by the prevalent values, norms and preferences in the population, and vice versa, how individual dispositions may vary due to ecological, cultural, or socio-economic factors (Henrich et al., 2006; Herrmann, Thöni and Gächter, 2008; Wilson, O'Brien and Sesma, 2009; Nettle, Colléony and Cockerill, 2011; Falk et al., 2018; Cohn et al., 2019; Barsbai, Lukas and Pondorfer, 2021; Caicedo, Dohmen and Pondorfer, 2021). Recent experimental evidence further highlights the malleability of prosociality by documenting the role of a person's socialization and the social interactions he or she experiences during childhood (Kosse et al., 2020). Our hypothesis that a higher share of prosocial individuals may help in overcoming collective action problems implies that policies that foster prosociality in the population would hold beneficial consequences other challenges that society is facing, such as, e.g., the mitigation of global warming. Yet, individuals' actions cannot be understood without taking into account the nexus of values and norms in which they are embedded, as well as the dynamics of social reinforcement. Thus, future research on this topic could further shed light on how the distribution and network structure of prosociality in a group affects individual and collective cooperation behavior in social dilemma situations.

Materials and Methods

Survey data. To obtain the survey data, we partnered with the online market research firm Dynata to recruit a target sample of 6000 German participants. The survey was conducted between 11 November to 17 December 2020. Participants were sampled using demographic quotas on age, gender, and state to achieve national-level representativeness. Our final analysis sample consists of 5,843 responses that fulfilled the quality criteria for inclusion in the analysis, which included a minimum response duration, passing an attention check, no inconsistencies in responses to demographic questions, and no excessive straightlining.

We elicited subjects' time, risk, and social preferences using experimentally validated measures (Falk et al., 2016, 2018), see SI Appendix for more details. To construct an individual-level measure of prosociality, we combine several facets of prosocial preferences and beliefs — altruism, trust, positive reciprocity, and indirect (negative) reciprocity — into one index variable by extracting their first principal component (eigenvalue = 1.789). To measure public health behavior in the pandemic, we construct an index from responses (on a 7-point Likert scale) to ten questions with regard to subjects' social distancing, hygiene behavior, etc., using a factor analysis. We further collected information on demographic characteristics, education, income, Big 5 personality factors (15-item BFI-S), political attitudes, beliefs and attitudes towards the COVID-19 pandemic, news consumption, and conspiracy mentality. For the purposes of another study, we also included information and several questions about subjects' attitudes towards the Corona-Warn-App, the official German digital contact tracing app.

Regional-level data. For regional-level analyses, we aggregate our survey measures at NUTS-2 level in Germany (38 regions in Germany) by calculating the average of all respondents who currently live in that region. The sample size per region ranges from 46 to 427 (mean 154, median 124). We use sampling weights from a raking procedure to improve regional representativeness by age and gender (age above/below 40 $\times$ gender) as well as the share of adults with a college degree. Demographic and socio-economic information for different regions in Germany are collected from the joint database of the statistical offices of the German states (Regionaldatenbank: `https://www.regionalstatistik.de/genesis/online`) and infas360.

We further obtain information on the official daily number of reported COVID-19 cases and deaths on the county-level from the Robert-Koch-Institut (RKI), the federal government agency and research institute responsible for disease control and prevention in Germany. County-level measures of change in mobility flows (compared to the same month in 2019) based on smartphone data is publicly available on the OpenScience-Framework repository (Schlosser et al., 2021), by courtesy of Frank Schlosser. Finally, we use data obtained from infas360 (`https://www.corona-datenplattform.de/dataset/massnahmen_oberkategorien_kreise`) to construct a local policy stringency index by summing up a total of 23 indicator variables for whether local mandates in a certain category (e.g. curfew, school closure, ...) were in place. We normalize this index to range between 0 (no restriction) and 100 (full restriction).

Estimation. For the individual-level analyses, the outcome of interest is the PHB index explained above. We regress this PHB variable on our measures of prosociality, as well as time and risk preferences and a number of controls, using ordinary least squares (OLS). The statistical model underlying the results in Table 1 is

$$PHB_{ic} = \alpha + \beta_1 \cdot Prosocial_i + \beta_2 \cdot Patience_i + \beta_3 \cdot RiskTak_i + \gamma' \boldsymbol{x}_{ic} + \varepsilon_{ic}\,, \tag{1}$$

where PHB_{ic} is the public health behavior factor for individual i (living in county c), $Prosocial_i$ is his or her level of prosociality, $Patience_i$ and $RiskTak_i$ denote her level of patience and risk taking, respectively, and $\boldsymbol{x}_{ic}$ is a vector of control variables. Depending on the specification, $\boldsymbol{x}_{ic}$ includes socio-demographic characteristics (age, age squared, gender, education level, household income, ...), county fixed effects, Big 5 personality factors, and general attitudes towards and beliefs about the COVID-19 pandemic. Standard errors are always clustered at the county level.

In Figure 1b we show the regional-level correlation between the regional averages of PHB and prosociality. The fitted line comes from a local linear regression using the Gaussian kernel and a bandwidth of 0.3. The dashed line shows the predicted fit based on the individual-level association between prosociality and PHB, obtained from averaging the predicted values of PHB based on the regression of PHB on prosociality and prosociality square, using sampling weights for regional representativeness.

When analysing the relationship between regional incidence rates and prosociality in Table 2, we use the following statistical model:

$$\log(cases_{crt}) = \alpha_t + \beta_1 \cdot \overline{Prosocial}_r + \beta_2 \cdot \overline{Patience}_r + \beta_3 \cdot \overline{RiskTak}_r + \gamma_t' \boldsymbol{x}_c + \boldsymbol{\delta}' \boldsymbol{w}_c + \varepsilon_{crt} \,. \tag{2}$$

y_{crt} is the COVID-19 incidence rate, i.e. number of new infections per 100,000 population, in county c (NUTS-3 level) and time period t. Our main regressor of interest is $\overline{Prosocial}_r$, which is the average prosociality in region r (NUTS-2 level). Similarly, $\overline{Patience}_r$ and $\overline{RiskTak}_i$ denote the average level of patience and risk taking, respectively. $\boldsymbol{x}_c$ is a vector of pre-pandemic county characteristics, including log population density, log GDP per capita, log average income per capita, share of college graduates, employment share, share of non-German residents, share of workers in the service sector, share of population below age 18, share of population age 65 or above, and border county dummies for each neighboring country of Germany. We allow the coefficient vector γ_t to vary across different time periods. $\boldsymbol{w}_c$ is a vector of controls for wave 1 severity, including the log of aggregate case numbers, its square, and case fatality rate in the time period from the first confirmed infection until May 17th. Statistical inference is robust to clustering at the NUTS-2 region level. Due to the relatively low number of clusters (38 regions), we report confidence intervals based on a wild cluster bootstrap-t procedure that has been shown to be more reliable than standard inference based on asymptotic approximation (Cameron, Gelbach and Miller, 2008), implemented using the boottest package in Stata (Roodman et al., 2019). The basic regression equation is the same for the results in Table A8, with the only difference that t is defined as the entire wave 1 period (Jan 1 until May 17, 2020) or wave 2 period (Sep 28, 2020, until Feb 28, 2021), respectively.

When analysing the infection growth rate in Table 3, the statistical model is

$$\begin{aligned} \log(cases_{crt}) - \log(cases_{crt-1}) = \alpha_t &+ \beta_1 \cdot \overline{Prosocial}_r + \beta_2 \cdot \overline{Patience}_r + \beta_3 \cdot \overline{RiskTak}_r \\ &+ \theta' \boldsymbol{l}_{crt-2} + \gamma_t' \boldsymbol{x}_c + \boldsymbol{\delta}' \boldsymbol{w}_c + \varepsilon_{crt} \,, \end{aligned} \tag{3}$$

where everything is defined in the same way as above, but the outcome variable is now the log weekly change in incidence. In some specifications, we add a vector of lagged variables $\boldsymbol{l}_{crt-2}$ that includes the two-week lagged incidence rate $\log(cases_{crt-2})$ and the two-week lagged local policy stringency index.

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Supplementary Information

Appendix A Supplementary figures and tables

Table A1: Correlation matrix of prosociality components

	Altruism	Positive reciprocity	Trust	Indirect neg. reciprocity
Altruism	1			
Positive reciprocity	0.3344	1		
Trust	0.2591	0.1503	1	
Indirect neg. reciprocity	0.2574	0.1705	0.1488	1
Observations		5949		

Notes. Pearson correlation coefficients of altruism, positive reciprocity, trust, and indirect (negative) reciprocity across individual survey respondents.

Table A2: Individual-level association between preferences and PHB

	Public Health Behavior (PHB)				
	(1)	(2)	(3)	(4)	(5)
Prosociality	0.3356***	0.3059***	0.3115***	0.2216***	0.1625***
	(0.0162)	(0.0165)	(0.0168)	(0.0173)	(0.0148)
Patience	0.1983***	0.1969***	0.1858***	0.1633***	0.0777***
	(0.0150)	(0.0151)	(0.0155)	(0.0155)	(0.0131)
Risk-taking	-0.2095***	-0.1710***	-0.1722***	-0.1683***	-0.0790***
	(0.0141)	(0.0144)	(0.0148)	(0.0141)	(0.0110)
Negative reciprocity (Direct)	-0.1231***	-0.1078***	-0.1075***	-0.0662***	-0.0184
	(0.0141)	(0.0145)	(0.0151)	(0.0156)	(0.0127)
Female		0.1546***	0.1542***	0.0895***	0.0800***
		(0.0267)	(0.0269)	(0.0266)	(0.0225)
Age		0.0146*	0.0141*	0.0084	0.0127*
		(0.0083)	(0.0085)	(0.0081)	(0.0070)
Age^2		-0.0000	-0.0000	0.0000	-0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Big 5: Openness				0.0578***	0.0423***
				(0.0135)	(0.0116)
Big 5: Conscientiousness				0.1596***	0.1577***
				(0.0157)	(0.0129)
Big 5: Extraversion				0.0192	0.0070
				(0.0135)	(0.0114)
Big 5: Agreeableness				0.1186***	0.1055***
				(0.0162)	(0.0137)
Big 5: Neuroticism				0.0418***	-0.0121
				(0.0136)	(0.0116)
Affected by pandemic					0.0252**
					(0.0121)
Take pandemic seriously					0.2974***
					(0.0157)
Worry: Self					0.0211**
					(0.0084)
Worry: Family & Friends					0.0761***
					(0.0107)
Worry: Others					0.0557***
					(0.0101)
Socio-demographic factors	*No*	*Yes*	*Yes*	*Yes*	*Yes*
County FEs	*No*	*No*	*Yes*	*Yes*	*Yes*
Big Five	*No*	*No*	*No*	*Yes*	*Yes*
COVID-19 Perceptions	*No*	*No*	*No*	*No*	*Yes*
Observations	5843	5660	5653	5653	5653
Clusters	397	396	389	389	389
R^2	0.209	0.234	0.293	0.345	0.529

Notes. This table estimates the same specifications as in Table 1, but reports additional estimates that might be of interest to the reader. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Individual-level association between preferences and individual PHB survey items

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prosociality	0.2928***	0.3807***	0.2893***	0.3562***	0.3749***	0.4040***	0.3317***	0.3647***	0.2626***	0.3738***
	(0.0224)	(0.0268)	(0.0236)	(0.0240)	(0.0366)	(0.0301)	(0.0285)	(0.0241)	(0.0295)	(0.0244)
Patience	0.2112***	0.2257***	0.2339***	0.1562***	0.2061***	0.1473***	0.2299***	0.1531***	0.2824***	0.1608***
	(0.0223)	(0.0247)	(0.0254)	(0.0217)	(0.0353)	(0.0275)	(0.0279)	(0.0245)	(0.0277)	(0.0202)
Risk-taking	-0.1870***	-0.2419***	-0.1546***	-0.1429***	-0.1728***	-0.1473***	-0.1993***	-0.1189***	-0.3499***	-0.1206***
	(0.0208)	(0.0236)	(0.0252)	(0.0217)	(0.0350)	(0.0244)	(0.0244)	(0.0243)	(0.0248)	(0.0179)
Negative reciprocity (Direct)	-0.0835***	-0.1463***	-0.0436*	-0.1407***	-0.0766**	-0.1922***	-0.1085***	-0.1322***	-0.0569**	-0.1762***
	(0.0235)	(0.0258)	(0.0260)	(0.0224)	(0.0389)	(0.0269)	(0.0228)	(0.0248)	(0.0278)	(0.0212)
Observations	5653	5653	5653	5653	5653	5653	5653	5653	5653	5653
R^2	0.206	0.215	0.199	0.204	0.184	0.179	0.198	0.197	0.198	0.233
Clusters	389	389	389	389	389	389	389	389	389	389

Notes. This table estimates the specification (3) of Table 1, but using individual survey items of the PHB index as dependent variables. The columns are defined as follows: 1) Social distancing of 1.5 meters 2) Self-quarantining in the case of risky contact 3) Keeping onself informed about the pandemic 4) Washing and disinfecting hands 5) Willingness to get vaccinated 6) Sneezing and coughing into elbow 7) Wearing mask 8) Ventilating when indoors 9) Avoiding social contacts 10) Informing others if infected. Each survey item is measured on a 7-point scale, with 1 indicating "Do not agree" and 7 indicating "Agree completely". * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Economic preferences, personality traits and COVID-19 perceptions

	(1) Pandemic serious	(2) Worry: Family & Friends	(3) Worry: Others
Prosociality	0.1059***	0.1875***	0.2682***
	(0.0192)	(0.0362)	(0.0329)
Patience	0.1838***	0.2446***	0.1765***
	(0.0168)	(0.0310)	(0.0313)
Risk-taking	-0.1962***	-0.2275***	-0.1954***
	(0.0181)	(0.0349)	(0.0292)
Negative reciprocity (Direct)	-0.1429***	-0.0558	-0.0932***
	(0.0177)	(0.0349)	(0.0332)
Big 5: Openness	-0.0016	0.0814***	0.0981***
	(0.0164)	(0.0309)	(0.0279)
Big 5: Conscientiousness	-0.0116	0.0311	-0.0237
	(0.0190)	(0.0303)	(0.0294)
Big 5: Extraversion	-0.0204	0.1032***	0.1500***
	(0.0164)	(0.0325)	(0.0269)
Big 5: Agreeableness	0.0042	0.1136***	0.0518
	(0.0180)	(0.0304)	(0.0318)
Big 5: Neuroticism	-0.0144	0.3725***	0.3351***
	(0.0148)	(0.0299)	(0.0295)
Observations	5653	5653	5653
R^2	0.190	0.200	0.192
Clusters	389	389	389

Notes. Pandemic serious is a factor comprised of two survey items measuring (on a 5-point scale) how much the respondent disagrees with the statements that the media takes the pandemic too seriously, and that government measures are too strict. Worry: Family & Friends and Worry: Others measure (on a 7-point scale) how much the respondent worries about their family and friends, and others around them, respectively. All specifications include socio-demographic controls and county FEs. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Regional correlations of vote shares for the major political parties

	Regional correlation with 2019 election outcome					
	CDU/CSU	SPD	Grüne	FDP	Die Linke	AfD
Survey vote shares	0.808***	0.854***	0.757***	0.290*	0.861***	0.784***
2017 election outcomes	0.904***	0.923***	0.844***	0.763***	0.980***	0.970***
Observations	38	38	38	38	38	38
Overall 2019 vote share [%]	22.6	15.8	20.5	5.4	5.5	11.0

Notes. The first row shows the Pearson's correlation coefficients of 2019 election vote shares with the implied vote shares from our survey on NUTS-2 region level. For comparison, the second rows shows the correlation of 2019 election outcomes with 2017 election outcomes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

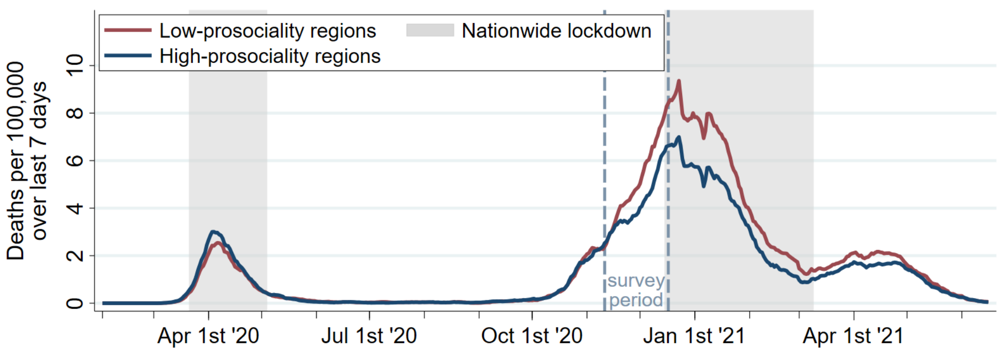
Table A6: Prosociality and measures of social capital

	Turnout in 2019 election [%]			Civic associations per 100k pop. in 2008		
	(1)	(2)	(3)	(4)	(5)	(6)
Prosociality	1.52 **	1.57 **	1.51 ***	14.63 *	10.79 *	10.92
	[0.37, 2.51]	[0.36, 2.93]	[0.56, 2.55]	[-1.06, 23.85]	[-1.91, 19.16]	[-7.49, 24.83]
Patience	–	-0.46	-0.26	–	12.62 *	12.78
		[-1.93, 0.58]	[-1.40, 0.79]		[-1.57, 30.41]	[-12.39, 40.19]
Risk taking	–	0.74	0.36	–	-10.75	-16.82 **
		[-0.50, 1.74]	[-1.15, 1.75]		[-24.60, 3.87]	[-30.38, -1.64]
County controls	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Population mean	61.37	61.37	61.37	280.82	280.82	280.82
Observations	401	401	401	401	401	401
Clusters	38	38	38	38	38	38
R^2	0.096	0.117	0.542	0.019	0.035	0.415

Notes. Bootstrapped 95%-confidence-intervals in brackets (clustered at NUTS-2 level), obtained using wild bootstrapping with Rademacher-weights and 9,999 simulations. Control variables include log GDP per capita, log average income per capita, share of college graduates, share of non-German residents, share of population below age 18, share of population age 65 or above, and indicators for the degree of urbanization. Under civic associations, we include (non-profit) organizations focused on social and economic welfare, political asssociations, and interest groups, following a classification by Franzen and Botzen (2011).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: The COVID-19 pandemic in Germany

(a) COVID-19 deaths per 100.000 population in 7 days (by date of infection)



(b) Change in mobility [%] compared to 2019 (7-day moving average)

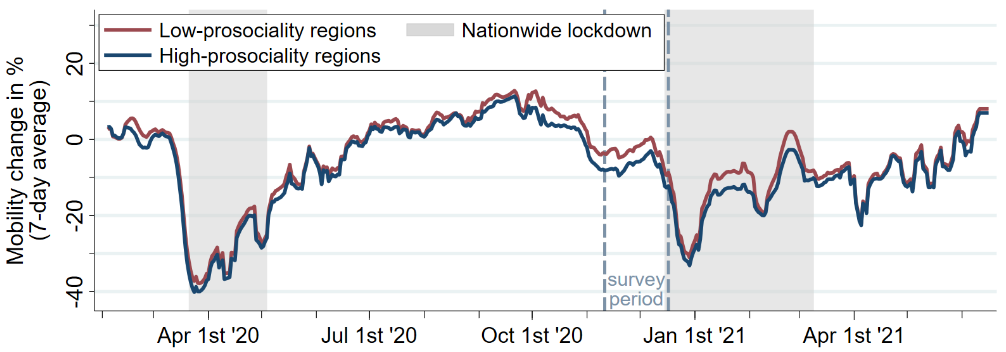


Figure Notes. The time labels in figure A1a refer to the day the coronavirus infection of the deceased person was first reported to the RKI, not the day of death. Grey shaded areas indicate time periods of strict nationwide lockdowns in Germany (as of March 8, 2021, restrictions were tied to the regional incidence rate, although the lockdown formally remained in place).

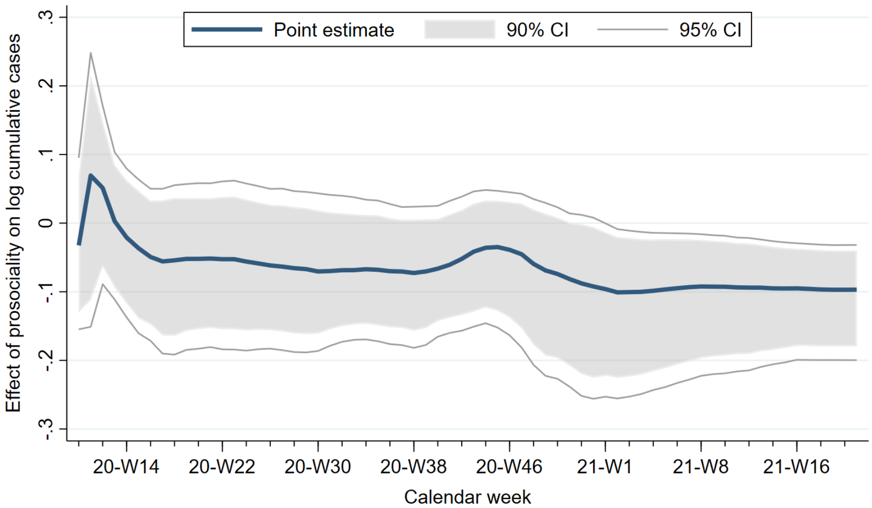
Table A7: Effect of preferences and behavior on weekly deaths

	$y = \log\, deaths_t$			$y = \log\, deaths_t - \log\, deaths_{t-1}$	
	(1)	(2)	(3)	(4)	(5)
Prosociality	-0.1272 *	-0.1241 *	0.0488	-0.0134 *	-0.0051
	[-0.315, 0.009]	[-0.288, 0.007]	[-0.089, 0.176]	[-0.033, 0.000]	[-0.035, 0.019]
Patience	-0.0095	-0.0163	0.0678	-0.0010	0.0032
	[-0.174, 0.207]	[-0.180, 0.180]	[-0.051, 0.222]	[-0.015, 0.020]	[-0.013, 0.024]
Risk taking	-0.0271	-0.0307	-0.0852	-0.0147	-0.0181
	[-0.139, 0.110]	[-0.134, 0.107]	[-0.196, 0.022]	[-0.048, 0.013]	[-0.053, 0.016]
Public health behavior			-0.3851 ***		-0.0197
			[-0.520, -0.240]		[-0.056, 0.022]
$\log cases_{t-2}$				-0.1476 ***	-0.1549 ***
				[-0.195, -0.103]	[-0.211, -0.101]
Policy measures$_{t-2}$				-0.2032	-0.1806
				[-1.079, 0.321]	[-0.948, 0.299]
Wave 1 severity		*Yes*	*Yes*	*Yes*	*Yes*
County controls × Week	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Week fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3395	3395	3395	3213	3213
Spatial units (counties)	401	401	401	401	401
Clusters	38	38	38	38	38
R^2	0.249	0.257	0.299	0.090	0.090

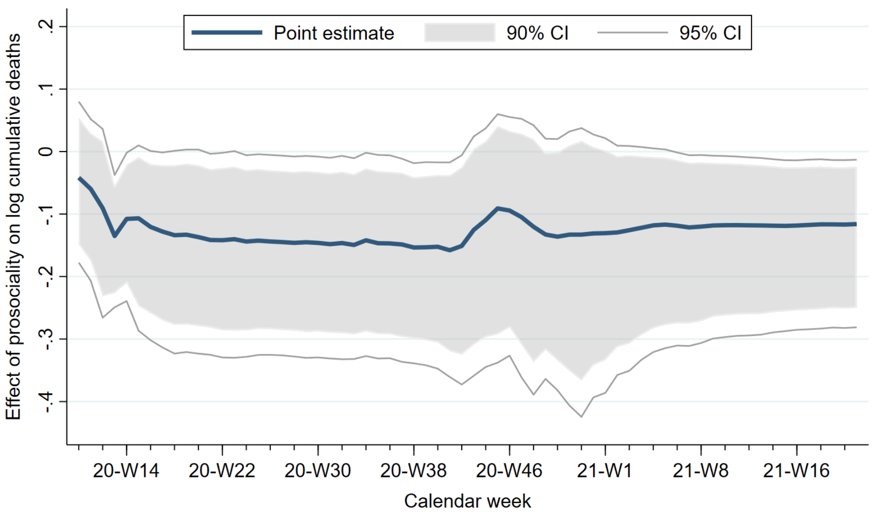
Notes. Bootstrapped 95%-confidence-intervals in brackets (clustered at NUTS-2 level), obtained using wild bootstrapping with Rademacher-weights and 9,999 simulations. The outcome variable is the log of weekly deaths per 100000 population in a county, ranging from Nov 11th 2020 until Jan 17th 2021. Controls for wave 1 severity include the log of aggregate case numbers, its square, and case fatality rate in the time period from the first confirmed infection until May 17th, 2020. County controls include log population density, log GDP per capita, log average income per capita, share of college graduates, employment share, share of non-German residents, share of workers in the service sector, share of population below age 18, share of population age 65 or above, and border county dummies for each neighboring country of Germany.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A3: Estimated effect of prosociality on cumulative cases and deaths

(a) log cumulative cases per population



(b) log cumulative deaths per population



Confidence-intervals are obtained using the wild bootstrap (9,999 simulations) with clustering on NUTS-2 region level and Rademacher-weights. The time labels in Panel (b) refer to the day the coronavirus infection of the deceased person was first reported to the RKI, not the day of death.

Table A8: Overall number of infections in first and second wave

	y_i = *log overall infections per 100000 population in county i*			
	"first wave"		"second wave"	
	(1)	(2)	(3)	(4)
Prosociality	–	-0.0546	–	-0.0913 **
		[-0.186, 0.053]		[-0.231, -0.011]
Patience	–	0.0113	–	0.0025
		[-0.110, 0.182]		[-0.092, 0.146]
Risk taking	–	0.0938	–	-0.0238
		[-0.017, 0.212]		[-0.124, 0.089]
log population density	0.4055 **	0.4142 **	0.0634	0.0847
	[0.045, 0.738]	[0.047, 0.757]	[-0.192, 0.347]	[-0.151, 0.341]
Employed / population	3.5720 ***	3.6969 ***	1.5709 *	1.4675 *
	[2.072, 5.091]	[2.150, 5.276]	[-0.056, 3.428]	[-0.156, 3.458]
Share of jobs in service sector	-3.1460 ***	-3.0334 ***	-1.4531 *	-1.4196 *
	[-4.694, -1.551]	[-4.559, -1.429]	[-3.077, 0.086]	[-3.052, 0.078]
Further county characteristics	*Yes*	*Yes*	*Yes*	*Yes*
Observations	401	401	401	401
Clusters	38	38	38	38
R^2	0.497	0.509	0.265	0.323

Notes. Bootstrapped 95%-confidence-intervals in brackets (clustered at NUTS-2 level), obtained using wild bootstrapping with Rademacher-weights and 9,999 simulations. The "first wave" is defined as the time period until May 17th, 2020; the "second wave" is defined as time period between Sep 28th 2020 and Feb 28th 2021. Further regressors include log GDP per capita, log average income per capita, share of college graduates, share of non-German residents, share of population below age 18, share of population age 65 or above, and border county dummies for each neighboring country of Germany.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Aggregate number of deaths in first and second wave

	y_i = *log COVID-19 deaths per 100000 population in county i*			
	"First wave"		"Second wave"	
	(1)	(2)	(3)	(4)
Prosociality	–	-0.1835 ** [-0.373, -0.043]	–	-0.1157 * [-0.312, 0.003]
Patience	–	0.0571 [-0.106, 0.261]	–	-0.0345 [-0.157, 0.185]
Risk taking	–	0.2022 *** [0.066, 0.376]	–	-0.0254 [-0.144, 0.101]
log population density	0.2898 [-0.175, 0.786]	0.3214 [-0.147, 0.789]	0.0433 [-0.256, 0.378]	0.0686 [-0.200, 0.353]
Employed / population	5.1239 *** [2.655, 7.635]	5.4715 *** [2.984, 7.960]	1.1927 [-0.743, 3.316]	0.9480 [-1.224, 3.444]
Share of jobs in service sector	-4.1070 *** [-6.428, -1.782]	-3.8792 *** [-6.176, -1.563]	-1.1468 [-3.186, 0.791]	-1.0467 [-3.141, 0.904]
Further county controls	*Yes*	*Yes*	*Yes*	*Yes*
Observations	381	381	401	401
Clusters	38	38	38	38
R^2	0.288	0.322	0.272	0.321

Notes. Bootstrapped 95%-confidence-intervals in brackets (clustered at NUTS-2 level), obtained using wild bootstrapping with Rademacher-weights and 9,999 simulations. The "first wave" is defined as the time period until May 17th, 2020; the "second wave" is defined as time period between Sep 28th 2020 and Feb 28th 2021. Further controls include log average income per capita, share of college graduates, share of non-German residents, share of population below age 18, share of population age 65 or above, and border county dummies for each neighboring country of Germany.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Aggregate number of cases and deaths in third wave

	"Third wave": starting from March 1st, 2021			
	log cumulative cases		log cumulative deaths	
	(1)	(2)	(3)	(4)
Prosociality	–	-0.1020 ***	–	-0.0947 **
		[-0.186, -0.049]		[-0.240, -0.004]
Patience	–	0.0106	–	-0.0257
		[-0.064, 0.121]		[-0.134, 0.163]
Risk taking	–	0.0220	–	-0.0097
		[-0.036, 0.106]		[-0.110, 0.113]
log population density	0.0973	0.1196	0.0773	0.0977
	[-0.072, 0.258]	[-0.030, 0.266]	[-0.259, 0.389]	[-0.230, 0.410]
log GDP per capita	-0.0826 **	-0.1105 **	-0.4362 ***	-0.4030 ***
	[0.489, 9.790]	[0.237, 9.521]	[3.679, 12.716]	[3.037, 12.165]
Employed / population	2.3504 ***	2.3284 ***	2.0686	1.8922
	[0.731, 4.251]	[0.676, 4.329]	[-0.514, 4.643]	[-0.962, 4.837]
Share of jobs in service sector	-2.3614 ***	-2.2861 ***	-2.3779 *	-2.2885 *
	[-4.179, -0.668]	[-4.092, -0.604]	[-4.840, 0.099]	[-4.825, 0.192]
Population share age 65 or above	5.3880	5.0146	11.4636	10.9036
	[-0.412, 0.301]	[-0.415, 0.236]	[-0.516, 0.549]	[-0.517, 0.579]
Further county controls	*Yes*	*Yes*	*Yes*	*Yes*
Observations	401	401	401	401
Clusters	38	38	38	38
R^2	0.305	0.365	0.319	0.346

Notes. Bootstrapped 95%-confidence-intervals in brackets (clustered at NUTS-2 level), obtained using wild bootstrapping with Rademacher-weights and 9,999 simulations. Dependent variables are log cumulative cases (deaths) per 100000 population. The time period of analysis goes until July 8, 2021. Further controls include log average income per capita, share of college graduates, share of non-German residents, share of population below age 18, share of population age 65 or above, and border county dummies for each neighboring country of Germany.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix B Survey measures

In this section, we list the survey questions used to elicit subjects' preferences and pandemic-related behavior. All questions used to elicit preferences prompted subjects to indicate their self-assessment on a ten-point Likert scale. We indicate alongside each question the corresponding preference (not displayed in the survey). Note that there are two questions regarding direct negative reciprocity; we give each of them equal weight to obtain a single measure for this preference. The questions used to elicit pandemic-related behavior prompted subjects to indicate their self-assessment on a seven-point Likert scale.

B.1 Preferences

Risk taking: In general, are you trying to avoid risk, or are you generally a risk-taking person? Please rate yourself personally on a scale from 0 to 10. The value 0 means: not at all willing to take risks. The value 10 means: very willing to take risks.

We are now asking you about your willingness to behave in a certain way. Please use a scale from 0 to 10 again. The value 0 means: not at all willing to do it. The value 10 means: very willing to do it.

Patience: How willing would you be to forgo something that is of benefit to you today in order to benefit more in the future?

Negative reciprocity (direct): How willing would you be to punish someone who treats you unfairly, even if it had negative consequences for you?

Negative reciprocity (indirect): How willing would you be to punish someone who treats others unfairly, even if it cost you to do so?

Altruism: How willing would you be to give to a good cause without expecting anything in return?

How well does each of the following statements describe you as a person? Please use a scale from 0 to 10 again. The value 0 means: does not describe me at all. The value 10 means: describes me perfectly.

Positive reciprocity: When someone does me a favor, I am ready to return it.

Negative reciprocity (direct): If I am treated very unfairly, I will take revenge at the first opportunity, even if there is a cost to do so.

Trust: I suspect people have only the best of intentions.

B.2 Pandemic-related behavior

To what extent do the following statements apply to your own behavior? Please rate again on a scale from 1 to 7. The value 1 means: does not apply at all. The value 7 means: applies completely.

I keep a distance of at least 1.5 meters from other people.

I will isolate myself socially if I have had contact with an infected person.

I always keep myself up to date with news about the corona pandemic.

I wash and disinfect my hands regularly.

I will get vaccinated against the coronavirus when a vaccine becomes available.

I cough and sneeze into the crook of my elbow.

I wear mouth and nose protection in public.

I ventilate regularly when several people are using a room.

I avoid social contacts as much as possible.

I will inform other people if I have been infected with the coronavirus.