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

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ABSTRACT

The COVID-19 pandemic induces a social dilemma: engaging in preventive health behaviors is costly for individuals but generates benefits that also accrue to society at large. The extent to which individuals internalize the social impact of their actions may depend on their prosociality, i.e. the willingness to behave in a way that mostly benefits other people. We conduct a nationally representative online survey in Germany (n = 5843) to investigate the role of prosociality in reducing the spread of COVID-19 during the second coronavirus wave. At the individual level, higher prosociality is strongly positively related to compliance with public health behaviors such as mask wearing and social distancing. A one standard deviation (SD) increase in prosociality is associated with a 0.3 SD increase in compliance ($p < 0.01$). At the regional (NUTS-2) level, a one SD higher average prosociality is associated with an 11% lower weekly incidence rate ($p < 0.01$), and a 2%p lower weekly growth rate ($p < 0.01$) of COVID-19 cases, controlling for a host of demographic and socio-economic factors. This association is driven by higher compliance with public health behaviors in regions with higher prosociality. Our correlational results thus support the common notion that voluntary behavioral change plays a vital role in fighting the pandemic and, more generally, that social preferences may determine collective action outcomes of a society.

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. However, the benefits from a lower rate of transmission accrue to society at large and thus constitute a public good. This results in a social dilemma, where "the maximization of short-term self-interest yields outcomes leaving all participants worse off than feasible alternatives." (Ostrom, 1998, p.1). 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 primarily benefits other people or society at large. 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 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 et al., 2018; Fehr and Schurtenberger, 2018). Previous studies have documented associations between (pro-)social preferences and, amongst others, pro-environmental behavior (Fuhrmann-Riebel et al., 2021; Lades et al., 2021; Andre et al., 2021), donation and volunteering decisions (Falk et al., 2018), redistributive voting (Epper et al., 2020), as well as labor market outcomes (Burks et al., 2009; Dohmen et al., 2008; Kosse and Tincani, 2020). However, combining data of both individual- and group-level behavior and outcomes under collective action problems in real-world contexts remains challenging.

In this paper, 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 recurrently appealed to people's altruistic motivations to protect others from getting infected by embracing

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voluntary behavioral changes. More prosocial individuals may be more likely to respond to (and propagate) such norms and appeals, and they may generally be more inclined to internalize the health externalities that their behavior imposes on others. Consistent with this, studies have found that more prosocial individuals tend to follow social distancing and hygiene guidelines more stringently (van Hulsen et al., 2020; Campos-Mercade et al., 2021; Müller and Rau, 2021). One implication is that regions with higher average levels of prosociality in the population might be more successful in slowing the spread of the virus. This is also proposed theoretically in recent susceptible-infected-recovered (SIR) models with endogeneous behavior (Alfaro et al., 2021b; Farboodi et al., 2021; Quaas et al., 2021). Indeed, some empirical studies provide 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; Alfaro et al., 2021a; Durante et al., 2021; Makridis and Wu, 2021), but they do not combine regional-level associations with individual-level data.

We study the role of prosociality in the COVID-19 pandemic by employing data from a representative online survey in Germany ($n = 5843$) that we conducted during the second coronavirus wave, between mid-November and mid-December 2020. This period 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 of PHB by means of a factor analysis. 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 use experimentally-validated survey measures by Falk et al. (2016) to elicit different components of individuals' prosocial preferences and beliefs — altruism, trust, positive reciprocity, and indirect (negative) reciprocity — and collapse them into a single summary measure of "prosociality".

Our data confirms that prosociality is strongly positively related to compliance with recommended social distancing and hygiene measures. Due to the 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 incidence and deaths reported by the Robert-Koch-Institut (RKI), the federal government agency and research institute responsible for disease control and prevention in Germany. Our focus on within-country variation has the advantage that policy mandates and regulations in response to the pandemic remain largely similar. We find that the individual-level relation between prosociality and PHB translates into better health outcomes at the regional level — the spread of Sars-CoV-2 is slower in regions where average prosociality in the population is high. This relationship is mediated by compliance with public health measures, which supports our suggested pathway of prosociality leading to greater PH compliance, which in turn leads to lower incidence rates.

2. Theoretical predictions

The rates of social contact and disease transmission are key parameters in epidemiological models, namely the susceptible-infected-recovered (SIR) model and its various modifications (Kermack and McKendrick, 1927; Keeling and Rohani, 2011), but they are typically determined exogenously and do not respond to voluntary behavioral adaptation by individuals in a pandemic.

Canonical SIR models can be extended by endogenizing behavioral responses of forward-looking agents who face a trade-off between utility from social contacts and disutility from increased risk of getting infected (e.g., Bauch and Earn, 2004; Fenichel et al., 2011; Jones et al., 2021). To protect themselves, individuals may choose to engage in preventive health behaviors even in the absence of government restrictions. However, individuals' actions also impose health externalities on others, and

social costs of infections can exceed private costs significantly — e.g., for young and healthy individuals in the COVID-19 pandemic. Hence, behavioral adaption due to purely self-interested motives (i.e., avoiding to get infected) only flattens the infection trajectory to a limited extent.

Recent theoretical studies have explicitly incorporated prosocial motives in SIR models with endogenous behavior (Alfaro et al., 2021a; Quaas et al., 2021; Farboodi et al., 2021). Agents in these models are not only concerned about their own health, but also about other people's health. Thus, they partially internalize the health risks that their own behavior imposes on susceptible individuals around them. This is particularly relevant for people who are uncertain about whether they are susceptible or infectious (e.g., due to asymptomatic cases and limited testing capacitites), which applies to the majority of the population during our study period, since most people in Germany had not experienced a COVID-19 infection yet. To prevent that they unknowingly spread the virus, prosocial agents endogenously engage in lower levels of (risky) social activity.

While prosocial engagement in social distancing follows from an assumption on exogenously given preferences in these models, it can also be derived more explicitly from theories of human behavior that take a stance on where preferences to behave prosocially come from (e. g., Batson and Powell, 2003). For example, as an anonymous referee pointed out to us, a link between individuals' prosociality and their public health behavior can be explained by different variants of consistency theory (Festinger, 1957; Heider, 1958; Abelson et al., 1968). Specifically, individuals who hold strong prosocial values and attitudes may experience cognitive dissonance if they do not adjust their behavior in the pandemic accordingly.

In this empirical study, we consider several distinct elements of prosociality that all reflect a positive disposition towards others: altruism, positive reciprocity, trust, and indirect (negative) reciprocity. Altruism constitutes a direct concern for others' well-being and links most closely to the above-mentioned models. Positive reciprocity is the tendency to return favors, which can facilitate norms of conditional cooperation (Bowles and Gintis, 2011). Trust is a composite trait reflecting preferences as well as beliefs about whether other people in general hold good intentions; higher generalized trust may encourage individuals to behave more prosocially towards friends and strangers alike. Indirect negative reciprocity describes the willingness to punish those who treat others unfairly and act detrimentally to the group. In the context of the pandemic, this could for example entail confronting others who disregard rules or norms regarding mask wearing and social distancing. This sort of third-party punishment can deter norm violation and free-riding and is therefore considered to be prosocial (Fehr and Gächter, 2002; Albrecht et al., 2018). In summary, as illustrated in Fig. 1, individuals' prosocial attitudes can positively affect compliance with health measures both directly, out of concern for not (unintentionally) infecting others, as well as indirectly, through the social dynamics of cooperation and norm adoption. Thus, our first prediction is that more prosocial individuals are more likely to engage in preventive health measures in the pandemic.

Through the lens of an SIR model with endogenous behavior, increased compliance due to higher prosociality leads to a lower rate of disease transmission and thus fewer infections in the population, all else equal. In a dynamic setting, this positive effect is dampened, as lower incidence rates will reduce perceived infection risks and thus subsequent readjustment towards more social interactions. However, it can be shown that higher prosociality will still lead to a flatter infection curve in equilibrium (Alfaro et al., 2021b; Quaas et al., 2021; Farboodi et al., 2021). Thus, our second predictions is that infection rates will tend to be lower in regions with more prosocial individuals.

There are many other determinants of health behavior that are not considered in Fig. 1. Importantly, the models highlight that behavior should adapt strongly to the perceived threat of COVID-19, which can vary based on the contemporaneous regional incidence rates and based on heterogeneity in expected health/mortality risks, e.g. due to age.
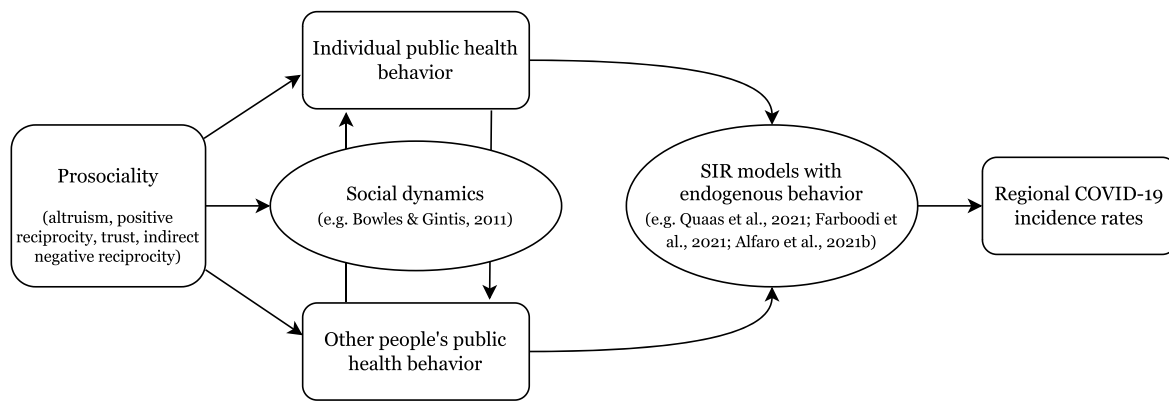
Fig. 1. Framework.

Furthermore, time and risk preferences also play a role, as more patient individuals place a higher weight on future risks of infection (relative to immediate utility from social interactions) and more risk averse individuals shy away from uncertain consequences of a potential infection. Indeed, previous empirical studies have found positive associations of patience and risk aversion with better health behaviors and outcomes both in the COVID-19 pandemic (e.g., Chan et al., 2020; Alfaro et al., 2021b) and in other health-related domains such as smoking or obesity (e.g., Khwaja et al., 2006; Burks et al., 2012; Sutter et al., 2013; de Oliveira et al., 2016).

3. Data and measurements

3.1. Survey data

We partnered with the market research firm Dynata to recruit a target sample of 6000 German participants and conducted our web-based survey between November 11 to December 17, 2020. Participants were invited via email and sampled using demographic quotas on age, gender, and state, to achieve national-level representativeness of the population aged 18 to 65. Our final analysis sample consists of 5843 responses that fulfilled the quality criteria for inclusion in the analysis: a minimum response duration, passing an attention check, no inconsistencies in demographic information, and no excessive straightlining.

To measure health behavior in the pandemic, we obtain responses (on a 7-point Likert scale) to ten questions about subjects' social distancing, hygiene behavior, etc. These questions were selected based on public health guidelines in Germany at that time. Using responses to these questions, we then construct an index by factor analysis. This index is our main measure of compliance to PHB. The eigenvalue of the first factor is 4.47 (0.25 for the second factor), which points towards a single underlying factor driving adherence to different PH measures. The Cronbach's α is 0.87, indicating that the different aspects of PHB are strongly interrelated.

We elicited subjects' time, risk, and social preferences using experimentally validated measures that have been employed in a large-scale representative global survey (Falk et al., 2016, 2018). Although the validation was conducted in a German student sample, it is plausible that the measures remain informative in our context, as language and culture are constant and there is no evidence that insights from student experiments fundamentally misrepresent behavior in the general population (Exadaktylos et al., 2013; Falk et al., 2013). To construct an individual-level measure of prosociality, we follow Falk et al. (2018) and Kosse and Tincani (2020) and combine several facets of social preferences and beliefs — altruism, trust, positive reciprocity, and indirect (negative) reciprocity — into one index variable by extracting their first principal component (eigenvalue = 1.789). This component places positive weight on all input variables and is thus congruent with the common notion of prosociality. We deviate from previous studies by also including indirect negative reciprocity, which reflects altruistic punishment and is positively correlated with our measure of altruism ($\rho = 0.257$, see Appendix Table A1).

We further collected information on demographic characteristics, education, income, political attitudes, beliefs and attitudes towards the COVID-19 pandemic, news consumption, conspiracy mentality, and Big Five personality factors. We construct the Big Five personality traits of openness, conscientiousness, neuroticism, agreeableness, and extraversion using the 15-item BFI–S scale by Gerlitz and Schupp (2005). See Appendix B for a detailed description of all survey questions and variables.

3.2. Regional-level aggregation

For regional-level analyses, we aggregate our survey measures at the administrative NUTS-2 region level in Germany (38 regions; visit https://ec.europa.eu/eurostat/web/nuts/background for information on the NUTS classification system) 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 (Battaglia et al., 2009) to improve regional representativeness by age and gender (age above/below 40 × gender) as well as the share of adults with a college degree. 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 (Appendix, Table A7). The regional correlations are extremely high — ρ between 0.76 and 0.86 — for all parties except for the FDP, the German liberal party ($\rho = 0.29$).

We further obtain information on the official daily number of confirmed COVID-19 cases and deaths at the county-level (NUTS-3 region) reported by the Robert-Koch-Institut (RKI), the federal government agency and research institute responsible for disease control and prevention in Germany. We use data obtained from infas360 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). Finally, we collect a host of demographic information and socio-economic indicators for each county in Germany from the joint database of the statistical offices of the German states. See Appendix C for detailed descriptions of regional-level data.

4. Individual-level prosociality and public health behavior

We begin by establishing a robust positive relationship between prosociality and PHB at the individual level using data from our representative online sample. To do so, we regress the PHB variable on our

measures of prosociality, time and risk preferences and a number of controls, using ordinary least squares (OLS). The statistical model is

$$PHB_{ic} = \alpha + \beta_1 \cdot Prosocial_i + \beta_2 \cdot Patience_i + \beta_3 \cdot RiskT_i + \gamma' x_{ic} + \varepsilon_{ic} \quad (1)$$

where PHB_{ic} is the public health behavior factor for individual i (living in county c) and $Prosocial_i$ is his or her level of prosociality. $Patience_i$ and $RiskT_i$ denote her level of patience and risk-taking, respectively, which we include as these are generally correlated with prosociality (Falk et al., 2016) and may also have an influence on individual's willingness to engage in preventive health measures. x_{ic} is a vector of control variables that differ by specifications. Standard errors are always clustered at the county level.

Table 1 presents the regression estimates from the baseline specification in equation (1) without additional control variables. Column 1 shows that prosociality strongly predicts individual behavior in the pandemic, with a one SD increase in prosociality being associated with a one third SD increase in PHB ($p < 0.001$). Additionally, we find that more patient and less risk-tolerant individuals are also more likely to adhere to social distancing and hygiene measures. These results are consistent with our theoretical predictions from Section 2.

People who are more prosocial also tend to differ with regard to 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 behavior, 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 correlated 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 demographic and socio-economic characteristics as well as region fixed effects.

Apart from economic preferences, certain psychological personality traits such as agreeableness and openness from the Big Five inventory have also been linked with stronger adherence to PH measures in the COVID-19 pandemic (Nikolov et al., 2020; Zettler et al., 2022) and are also correlated with prosociality to some degree (see e.g. Appendix Table A6). However, as the estimates in column 4 of Table 1 show, differences in Big Five personality traits do not drive the association between prosociality and PHB. This squares with the general observation that personality traits and economic preferences seem to be partially distinct concepts (Becker et al., 2012; Jagelka, 2020), and both

retain explanatory value for individual behavior in the pandemic (see Appendix Table A2).

Finally, we also investigate to which degree the role of prosociality can be explained by individuals' perceptions and attitudes regarding the COVID-19 pandemic (Table 1 column 5). However, even controlling for these factors leaves a strong association between prosociality and PHB intact.

5. Regional-level prosociality and collective health outcomes

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") as described in section 3.

5.1. Descriptive overview

We document substantial variation in our measure of prosociality within Germany, as illustrated by the map in Fig. 2a. Average prosociality ranges from -0.37 to 0.42 across NUTS-2 regions, thus spanning about 80% of an individual-level standard deviation. These regional differences are statistically significant ($p < 0.05$) and explain about 50% additional variation in individual-level prosociality compared to other socio-demographic variables alone (Appendix Table A8). Moreover, regional prosociality patterns are related to commonly used proxies for social (or civic) capital: higher average prosociality is associated with higher voter turnout in the 2019 EU election ($\varrho = 0.3098$, $p = 0.0169$) and larger density of civic associations in 2008 ($\varrho = 0.1394$, $p = 0.0657$), see Appendix Table A9. Thus, our measure seems to capture stable and meaningful variation.

Fig. 2b shows that average prosociality is 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 general health compliance indirectly through social influence and normative channels.

Fig. 2c plots the evolution of COVID-19 cases per 100,000 population in Germany over the course of the pandemic, split by regions with above-median and below-median prosociality. Incidence rates in high-prosociality regions 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

Table 1
Individual-level association between preferences and public health behavior.

	Public Health Behavior (PHB)				
	(1)	(2)	(3)	(4)	(5)
Prosociality	0.3356*** (0.0162)	0.3059*** (0.0165)	0.3071*** (0.0167)	0.2182*** (0.0173)	0.1611*** (0.0144)
Patience	0.1983*** (0.0150)	0.1969*** (0.0151)	0.1921*** (0.0150)	0.1689*** (0.0149)	0.0809*** (0.0126)
Risk-taking	−0.2095*** (0.0141)	−0.1710*** (0.0144)	−0.1725*** (0.0143)	−0.1715*** (0.0138)	−0.0785*** (0.0107)
Socio-demographic controls	No	Yes	Yes	Yes	Yes
NUTS-2 region FEs	No	No	Yes	Yes	Yes
Big 5 personality traits	No	No	No	Yes	Yes
COVID-19 perceptions	No	No	No	No	Yes
Observations	5843	5660	5660	5660	5660
Clusters (counties)	397	396	396	396	396
R2	0.209	0.234	0.242	0.298	0.495

Notes. In the interest of brevity, we report only the coefficients on economic preference variables here; Appendix Table A2 reports estimates on other variables included in each specification. Socio-demographic controls include age and age-squared, gender, education, income, employment status, household size, number of children, and an indicator for having children below age 16. COVID-19 perceptions include general attitudes towards the pandemic, infection experiences, and worrying about oneself, family members, and others being infected. Standard errors (in parentheses) are clustered at the county level. See Appendix Tables A3 and A4 for detailed results using individual elements of prosociality or PHB.

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

(a) Regional variation in prosociality

(b) Prosociality and PHB at NUTS-2 level

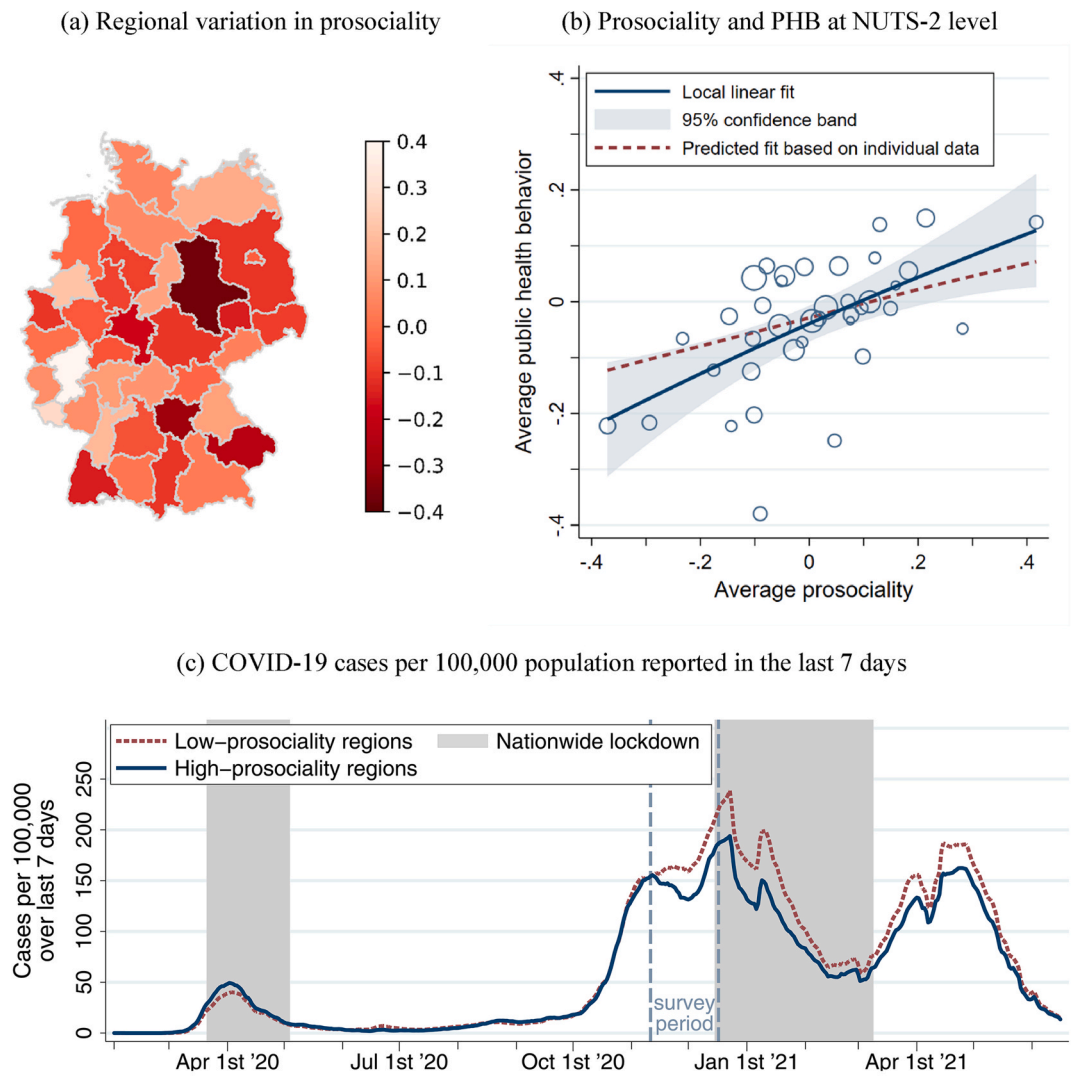(c) COVID-19 cases per 100,000 population reported in the last 7 days

Fig. 2. Prosociality, public health behavior, and COVID-19 incidence rates. 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 and are proportional to population size. Panel (c): Official number of COVID-19 cases 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). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

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 (see Appendix Figure A2, which also shows differential mobility patterns during the second wave). These descriptive observations hint at 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 such as population density and socio-economic factors. Therefore, we will now move on to our formal statistical analyses.

5.2. Association between prosociality and COVID-19 incidence rates

Our main outcome variable is the weekly COVID-19 incidence rate, i. e., the confirmed number of new cases per 100,000 population within 7 days, as reported by the RKI for each county in Germany. We additionally take the logarithm of the incidence rate to capture the exponential nature of infectious disease dynamics. Results for COVID-19

deaths are reported in the Appendix and in general very similar. As a first step in examining the relation between regional incidence rates and prosociality, we use OLS to estimate the following statistical model:

$$\log(cases_{crt}) = \alpha_t + \beta_1 \cdot \overline{Prosocial}_r + \beta_2 \cdot \overline{Patience}_r + \beta_3 \cdot \overline{RiskT}_r + \gamma_t' x_c + \varepsilon_{crt} \tag{2}$$

where $\log(cases_{crt})$ is the log COVID-19 incidence rate in county c (NUTS-3 level) and week t. Our main regressor of interest is $\overline{Prosocial}_r$ which is the average prosociality in NUTS-2 region r. $\overline{Patience}_r$ and $\overline{RiskT}_r$ denote the average level of patience and risk-taking, respectively. For ease of interpretation, we standardize these three preference measures to mean 0 and standard deviation 1 across regions. x_c is a vector of pre-pandemic county characteristics, which we interact with week dummies to allow the coefficient vector γ_t to change over time. To account for the highly dynamic nature of the pandemic, all specifications include week fixed effects α_t. We focus our analysis on the two-month period from Nov 16 to Jan 17, around the peak of the second wave in Germany, because this is

when our survey measures are most applicable. Note that we include an additional month of data from the end our survey onwards, as the effects of changes in behavior or policies will only manifest themselves with a delay, which is exacerbated by reporting lags by local health authorities during Christmas and New Year. Statistical inference is robust to clustering at the NUTS-2 region level. Due to the relatively low number of clusters (38), we report confidence intervals based on a wild cluster bootstrap-t procedure (Cameron et al., 2008; Roodman et al., 2019).

Table 2 presents the baseline results, which indicate a robust association between regional incidence rates and prosociality. The estimated coefficient in column 1 shows that, without controlling for any other county characteristics, a one SD higher prosociality is associated with a 13% lower weekly incidence rate in the time period we study. This effect is both statistically significant ($p < 0.001$) and quantitatively sizeable, corresponding to about 8% of the region-week SD in incidence rates (see Appendix Table A16). This association remains robust to including regional-level time and risk preferences as regressors (column 2), although its precision decreases due to the covariates being correlated with each other. The estimated coefficients for 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

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	−0.1391 ***	−0.1270 *	−0.1241 **	−0.1189 **	0.0183
	[-0.283, −0.061]	[-0.303, 0.010]	[-0.296, −0.021]	[-0.246, −0.033]	[-0.088, 0.106]
Patience		−0.02286	0.0024	−0.0054	0.0602
		[-0.211, 0.133]	[-0.117, 0.181]	[-0.111, 0.129]	[-0.019, 0.188]
Risk taking		0.0106	−0.0377	−0.0454	−0.0814 *
		[-0.107, 0.126]	[-0.154, 0.092]	[-0.137, 0.072]	[-0.149, 0.005]
Public health behavior					−0.2996 ***
					[-0.443, −0.158]
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 (NUTS-2 regions)	38	38	38	38	38
R^2	0.116	0.118	0.357	0.415	0.481

Notes. Bootstrapped 95%-confidence-intervals in brackets (clustered at NUTS-2 level), obtained using wild bootstrapping with Rademacher-weights and 9999 simulations. The outcome variable is the log weekly incidence rate by county, ranging from Nov 16, 2020, until Jan 17, 2021 (9 weeks). County controls include 18 variables: 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 country 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. See Appendix Table A10 for results with the individual elements of prosociality. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

influence the regional spread of the virus. In column 3, we therefore add pre-pandemic county characteristics (x_c) and allow their effect to vary by week. The vector of county controls consists of log population density, log GDP per capita, log average income per capita, share of college graduates, employment share, share of workers in the service sector, 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. 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 (February–May) infection outcomes in another specification.

After including this rich set of control variables in columns 3–4 of Table 2, 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 incidence rate lower in regions with higher prosociality? Our theoretical considerations suggest that more prosocial individuals should be more willing to comply with recommended or mandatory social distancing and hygiene measures, which is confirmed empirically by our individual-level results. The models discussed in Section 2 would then predict that stricter engagement in preventive health behaviors leads to a lower contact and transmission rate, and thus eventually to a lower COVID-19 incidence rate in high-prosociality regions. To test this mediating role of behavior, we include our measure of average PHB as additional regressor in column 5 of Table 2 (Baron and Kenny, 1986). Upon doing so, the coefficient size for prosociality is reduced by 85% to almost zero, whereas we observe a remarkably strong relation between self-reported PHB and incidence rates: a one SD increase in PHB is associated with a 26% decrease in the weekly number of cases per 100, 000 population. This is consistent with the hypothesis that the effect of prosociality is mediated by differences in PHB across regions. Interestingly, risk-taking has a weakly significant negative effect conditional on PHB, which could potentially be explained with a higher willingness to experiment with new strategies or to adopt new technologies.

Although we have controlled for a host of demographic and socio-economic county characteristics, there could still be other, unobserved factors that lead to generally lower levels of infections in a county, while also being positively correlated with prosociality and PHB. To circumvent this issue, we test whether regions with higher prosociality also exhibit lower growth rates of new cases, as this partials out any time-invariant differences across counties that can affect absolute levels of infection rates in the pandemic. We approximate growth rates by the weekly change in log incidence rates $\Delta log(cases_{crt}) = log(cases_{cr,t}) - log(cases_{cr,t-1})$ in county c and week t and estimate the following statistical model:

$$\Delta log(cases_{crt}) = \alpha_t + \beta_1 \cdot \overline{Prosocial}_r + \beta_2 \cdot \overline{Patience}_r + \beta_3 \cdot \overline{RiskT}_r + \gamma_t' x_c + \delta' w_c + \varepsilon_{crt}$$

(3)

where everything is defined as in equation (2). We include the full set of previously used control variables in all specifications, including the vector of controls for wave 1 severity w_c.

Although high- and low-prosociality regions start from roughly similar levels of incidence at the beginning of the second wave (see Fig. 2c), differences in the growth rate would gradually drive incidence 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 cases 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

Table 3
Weekly growth rate of confirmed cases at the time of the survey.

	$y_{crt} = log(cases_{cr,t}) - log(cases_{cr,t-1})$			
	(1)	(2)	(3)	(4)
Prosociality	−0.0091 **	−0.0097	−0.0218 ***	−0.0072
	[−0.018, −0.001]	[−0.022, 0.002]	[−0.037, −0.011]	[−0.025, 0.008]
Patience	−0.0012	−0.0015	−0.0012	0.0062
	[−0.014, 0.007]	[−0.015, 0.009]	[−0.011, 0.014]	[−0.008, 0.026]
Risk taking	0.0002	0.0003	−0.0044	−0.0092
	[−0.012, 0.013]	[−0.012, 0.012]	[−0.016, 0.010]	[−0.026, 0.007]
Public health behavior		0.0012		−0.0340 **
		[−0.021, 0.022]		[−0.066, −0.006]
$log(cases_{c,t-2})$			−0.1081 ***	−0.1209 ***
			[−0.126, −0.093]	[−0.146, −0.096]
$Policy\ stringency_{c,t-2}$			−0.2403	−0.2050
			[−0.857, 0.289]	[−0.765, 0.228]
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
Spatial units (counties)	401	401	401	401
Clusters (NUTS-2 regions)	38	38	38	38
R^2	0.293	0.293	0.315	0.317

Notes. Bootstrapped 95%-confidence-intervals in brackets (clustered at NUTS-2 level), obtained using wild bootstrapping with Rademacher-weights and 9999 simulations. The outcome variable is the change in log weekly incidence rate in a county, ranging from Nov 16th, 2020 until Jan 17th, 2021 (9 weeks). All control variables are defined as in Table 2. See Appendix Table A11 for results with the individual elements of prosociality. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

might be attenuated due to dynamic interactions between incidence rates, behavior, and policy responses that push towards regional convergence. For one, the share of susceptibles in the population is naturally higher in regions with fewer past infections, although this effect may have been negligible at that stage of the pandemic. Moreover, SIR models with endogenous behavior predict that in regions with lower incidence rates, people may endogenously reengage in more social contacts in response to reduced infection risks. Local governments could also feel encouraged to partially lift curtailment measures. Thus, more prosocial regions could 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 a 2-week lagged local policy stringency index (see Section 3.2) as covariates in equation (3). After including these lagged variables, the coefficient size for prosociality more than doubles, implying a 2%p lower weekly growth rate per SD increase ($p < 0.01$) – this corresponds to about 3% of a region-week SD in incidence growth rates (see Appendix Table A17). This is a sizeable effect given that small differences in growth rates accumulate to large absolute differences over time. In column 4, prosociality becomes insignificant after adding average PHB, further supporting the hypothesis that better compliance with social distancing and hygiene measures mediates the effect of higher prosociality on collective health outcomes during the pandemic.

Finally, we check whether our results are influenced by comparisons between West Germany and East Germany, as previous studies document that historical institutional differences between these two regions before the German reunification still have a persistent effect on preferences, norms, and outcomes (Torgler, 2002; Alesina and Fuchs-Schündeln, 2007; Brosig-Koch et al., 2011; Becker et al., 2020). Therefore, we rerun our analyses adding an East-Germany dummy as

control variable, and further interacting it with our measure of average prosociality (Appendix Tables A13-A15). The results show that the estimated coefficients for prosociality remain robust, and that there is no evidence for a differential association between higher prosociality and lower COVID-19 incidence rates in East and West Germany, although the low number of regional units in the East precludes any conclusive statement.

6. 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, more prosocial individuals 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. We further presented evidence 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 11% lower COVID19 incidence rates and 2%p lower incidence growth rates.

6.1. Role of the study context

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, most related studies examining determinants of PHB were conducted in the first wave of the pandemic, when more fear and uncertainty was 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 people had become more accustomed to and more weary of the situation (Petherick et al., 2021). In Table A16 of the Appendix, we compare predictors of regional incidence rates in the first and the second COVID-19 wave in Germany. We 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.

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 vulnerable to the disease becomes especially relevant when the risk of infection and transmission is high. In contrast, private gatherings may not be considered 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. Although, voluntary adaptions and government-mandated restrictions can be partly substitutable (Alfaro et al., 2021b), prosociality may affect health behaviors and outcomes even under more stringent lockdown regimes, as perfect monitoring and enforcement of compliance are infeasible, and drastic government measures can also influence public perceptions of severity and social norms (Casoria et al., 2021; Galbiati et al., 2021).

6.2. Potential endogeneity concerns

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 (Bauer et al., 2016; Branas-Garza et al., 2020; Cappelen et al., 2021; Frondel et al., 2021; Shachat et al., 2021). If any influence on individuals' survey responses reflects 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 over-reflected 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 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 first-wave severity of the pandemic. Moreover, Campos-Mercade et al., 2021 provide evidence that individual health behavior during the pandemic is predicted by prosociality measured before the COVID-19 outbreak, which is consistent with the notion that individual's (social) preferences are fairly stable in general (Volk et al., 2012; Carlsson et al., 2014). A third concern is reverse causality, because regional incidence rates may also influence PHB and its relation to prosociality. However, this would presumably lead to an underestimation of the true effect since lower incidence rates allow residents and policymakers 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 incidence 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. However, it is difficult to rule out all potentially confounding factors, e.g., the stringency of local implementation and enforcement of containment measures, contact tracing efficiency, etc., which may themselves be a function of prosociality in the population. Most notably, the distribution of (pro-)social preferences, values, norms, and beliefs is inherently endogenous to social, cultural, political, and institutional factors. Because these factors are imperfectly observable and the underlying causal relationships highly complex and interdependent, our empirical investigation must inevitably remain correlational.

6.3. Concluding remarks

Our paper is inspired by several 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; Nettle et al., 2011; Falk et al., 2018; Cohn et al., 2019; Barsbai et al., 2021; Caicedo et al., 2021). Recent experimental evidence further highlights the malleability of prosociality by documenting the importance of socialization and role models (Kosse et al., 2020). Cultivating prosocial values and norms within a society may strengthen its

capacity to face challenges such as pandemics or global warming that require widespread cooperation and collective action.

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