Navigating Uncertainty: Do Communicable Diseases Influence Risk Preferences?

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June 28, 2024

Abstract

This paper explores the effect of COVID-19 infection rates on individuals' risk preferences using the Socio-Economic Panel (SOEP). Our findings show that the spread of COVID-19 does not significantly alter risk preferences. This zero effect is remarkably stable across subgroups of the population, although we do find that individuals with prior cardiovascular diseases reduce their preference for risk-taking. We further identify financial worries, satisfaction with family life, and emotions as mediators of the effect of COVID-19 infection rates on individuals' risk preferences.

Keywords: Risk preferences, COVID-19, infection rate.
JEL codes: D81,I10,I12.

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1. Introduction

Risk preferences guide many important individual decisions that are associated with uncertainty, ranging from investment and savings, labor supply and business decisions, insurance and health behaviors. Thus, risk preferences have a substantial impact on economic prosperity and individual well-being. Traditional economic theories consider risk preferences to be a stable individual characteristic. i.e., a deep parameter. However, a growing economic literature investigates the variability of risk preferences (e.g. Avdeenko and Eryilmaz 2021; Brown et al. 2019; Cameron and Shah 2015; Eckel et al. 2009; Jakiela and Ozier 2019; Sakha 2019). Foremost, the interest in the variability of risk preferences is steered by economists' urge to understand the determinants of economic decision-making. But variability in risk preferences can also help understand various phenomena that are important for economic policy. One such example is large health crises that are caused by communicable diseases, such as the COVID-19 pandemic. In fact, in such settings, almost all actions are associated with a non-zero probability of getting infected.

Research question. The goal of this paper is to contribute to this literature by analyzing the impact of regional exposure to COVID-19 on risk preferences. This case is interesting because the pandemic is a natural disaster that involves severe health risks as well as a sizeable (macro)economic shock. Thus, this analysis contributes to a better understanding of the intertemporal variability of risk preferences, which is an important component for researchers and politicians aiming at understanding the pandemic's gross impact on the economy. For instance, increased risk aversion could, among other things, reduce investments and consumption, thus delaying economic recovery after the pandemic. In addition, risk preferences are an important factor for health behavior during the pandemic, i.e., the demand for self-protection as a function of the prevalence of a communicable disease. Therefore, our results also provide important information on how to effectively design policy measures to combat pandemics in general. By addressing these aspects, our paper also contributes to the literature on the economic impact of the COVID-19 pandemic (Alon et al. 2020; Aucejo et al. 2020; Binder 2020; Deb et al. 2020; Fetzer et al. 2020; Forsythe et al. 2020).

Data. In order to estimate the causal effect of the COVID-19 incidence on individuals' risk preferences, we use data from the Socio-Economic Panel (SOEP; Goebel et al. 2019). The SOEP is a representative panel of German households, which started in 1984. As of today, it surveys more than 30,000 individuals in 15,000 households on a yearly basis. The SOEP surveys its respondents on a wide range of topics, such as the individuals' childhood, their education, labor market experience, and attitudes.

Importantly, the SOEP includes a well-established and experimentally validated measure of risk preferences (Dohmen et al. 2011). Individuals' risk preferences are inferred from responses to the single-item question: "Are you generally a person who is willing to take risks or do you try to avoid taking risks?" Responses are given on an 11-point Likert scale ranging from "not at all willing to take risks" to "very willing to take risks". Stated risk preferences have been shown to have high predictive validity for paid lottery choices, as well as for domain-specific risky behavior, such as holding stocks, smoking, mental health, migration, or occupational choice (e.g. Akgüç et al. 2016; Caliendo et al. 2010, 2009; Cobb-Clark et al. 2020a; Dohmen et al. 2011; Dustmann et al. 2020; Murray et al. 2023; Serra-Garcia 2021; Skriabikova et al. 2014; Vieider et al. 2015). In fact, it has been argued that stated risk preferences can predict actual risk-taking even better than experimental measures (Lönnqvist et al. 2015).

Empirical strategy. The longitudinal design as well as the geospatial information of the SOEP enables us to estimate the effect of the COVID-19 pandemic on individuals' risk preferences. In particular, we estimate the effect of the state-level number of COVID-19 cases on individuals' risk preferences using a difference-in-differences (DiD) approach. Under the assumption of common trends, the DiD specification allows us to recover the effect of the regional number of COVID-19 cases on risk preferences, accounting for yearly macro shocks as well as time-invariant confounders at the individual level.

Results. Our results show that, on average, there is no effect of the regional number of COVID-19 cases on individuals' risk preferences. In our preferred specification, the point estimate suggests that a one standard deviation increase of the state-level number of COVID-19 cases decreases risk preferences by an effect as small as 0.8% of a standard deviation. but this effect is not statistically significant at any conventional level of significance. Moreover, the estimates suggest that we can rule out effects larger than 2.8% or smaller than -1.2% of a standard deviation with 95% certainty.

While this zero effect is remarkably stable across subgroups of the population, we do detect some heterogeneity: for individuals that were diagnosed with a cardiovascular disease prior to the COVID-19 pandemic, a one standard deviation increase in the number of COVID-19 cases decreases their willingness to take risks by about 3.9% of a standard deviation. For individuals that have not been diagnosed with cardiovascular diseases prior to the COVID-19 pandemic, there is no effect.

To further advance the literature on the malleability of economic preferences in response to catastrophes in general, and deadly communicable diseases in particular, we also shed light on potential mediators of the relationship between risk preferences and the spread of COVID-19. The absence of an average effect does not imply the absence of any indirect effects of the incidence of the COVID-19 pandemic on individuals' risk preferences. In our mediation analysis, we test whether economic consequences of the crisis, one's own health status, worries, life satisfaction, and domain satisfactions, such as satisfaction with leisure, family life, and sleep, or emotions are mediators of the effect of regional exposure to COVID-19 cases and individuals' willingness to take risks.

Our mediation analysis proceeds in two steps. First, we employ our DiD strategy on the potential mediators. Second, we explore how these mediators are associated with changes in the willingness to take risks. The overall effect then informs us about the direction and magnitude of the contribution of the respective mediator. Our results reveal that worries about one's own financial situation, satisfaction with life in general, with leisure and with family life, as well as feeling anxiety and happiness, are important mediators of the relationship between exposure to COVID-19 and risk preferences. This has not been shown in the literature so far and contributes to the literature on (health) crises and preference formation. However, the fact that the implied contributions of these mediators point towards a negative relationship leads us to conclude that there must exist additional unobserved mediators offsetting the implied negative effect of the exposure to the number of COVID-19 cases on individuals' risk preferences.

Literature & contribution. Our study relates to contemporaneous research on risk preferences and health in relation to the COVID-19 pandemic. For instance, Bu et al. (2021) study risk-taking behavior of Wuhan students located in areas with different levels of COVID-19 prevalence at the onset of the pandemic in China. Students quarantined in the strongly affected city of Wuhan display a lower willingness to take risks in a lottery, showcase reduced planned risk-taking, but no difference in stated willingness to take risks compared to students located further away from Wuhan. Similarly, Shachat et al. (2021) study the evolution of risk preferences via lottery choice tasks in the gain and loss domains in a repeated cross-section of Wuhan students at the onset of the pandemic in China. They find an increase in risk tolerance in the gain domain and a decrease in risk tolerance in the loss domain. Another experimental study on risk preferences during the early stages of the COVID-19 pandemic among students in China was conducted by Lohmann et al. (2023). Their study permits a generalized DiD design, relating the city-level prevalence of COVID-19 to choices in lottery tasks. They find no significant changes in risk preferences. Angrisani et al. (2020) analyze the inter-temporal changes in risk preferences of undergraduate students and financial traders from the U.K. using a "Bomb Risk Elicitation Task" and, on average, do not find any changes in risk preferences. Furthermore, Ikeda et al. (2020) elicit risk preferences in a five-wave internet survey in Japan by means of lottery choice tasks during three months of the COVID-19 pandemic, starting in mid-March. Ikeda et al. (2020) find a decrease in risk premiums, i.e., an increase in the individuals' willingness to take risks associated with the spread of COVID-19 in Japan. The authors argue that their finding of a negative relationship between risk preferences and the pandemic, which contradicts previous studies, including Bu et al. (2021), could partially stem from their focus on the loss rather than the gain domain. Lastly, they contrast the observed changes in risk preferences to pre-pandemic data in a comparable internet survey, thus providing indirect evidence that the observed increase in risk preferences reflects the influence of the pandemic. Drichoutis and Nayga (2020) investigate the evolution of risk preferences, elicited by lottery choices, among students from Athens, Greece, between January and May 2020. They do not find any variation of risk preferences during this time. Lastly. Adema et al. (2022) investigate the changes in risk preferences as a response to the crises among university students in four countries, including Germany, in a before and after comparison. They find that elicited willingness to take risks increases, whereas the stated willingness to take risks decreases. Adema et al. (2022) suggest that those differences are explained by the domain specificity of the two measures.

Our study extends this literature on the evolution of risk preferences during the early stages of the COVID-19 pandemic along two important dimensions: First, with the exception of Ikeda et al. (2020), all of the surveyed studies above are limited to standard subject pools, i.e., students. Student samples are typically very homogeneous in age or socio-economic status. Importantly, students, who are typically young and highly educated, face very different economic and health risks in this pandemic from people who are of older age or less educated. Thus, it is difficult to draw generalizable conclusions from these findings. More generally, the effect of the COVID-19 pandemic on risk preferences likely varies along dimensions such as age, pre-pandemic health, socio-economic status or household context. While Ikeda et al. (2020) consider differences along the dimensions of gender and income, none of the studies surveyed has the depth of data at their disposal which would allow for a detailed heterogeneity analysis. Such information is rarely available in experimental studies. Second, we establish causality by exploiting variation in regional exposure to COVID-19 and compare the same individuals before and after the outbreak of the pandemic. From the previously mentioned studies, Lohmann et al. (2023) most closely relates to ours. Lohmann et al. (2023) exploit within-variation in individual-level changes in preferences and variation in exposure to the virus across 183 cities. The authors recruited their sample from Bejing universities and use the fact that most students from outside Bejing had already left the city in January to celebrate the Spring Festival in their respective hometowns, providing the authors with variation in local exposure to the virus. We believe it is a major strength of our study that we can combine both: a longitudinal, nationally representative sample and a framework that allows for causal identification of the effect of the pandemic on risk preferences.

We also add to an active literature studying the stability of risk attitudes (e.g. Zeisberger et al. 2012). This literature can be divided into three main strands analyzing the impacts of different types of events on risk preferences: (i) natural disasters, crime, or violence (Avdeenko and Eryilmaz 2021; Brown et al. 2019; Cameron and Shah 2015; Eckel et al. 2009; Jakiela and Ozier 2019; Sakha 2019); (ii) macroeconomic shocks and the business cycle (Cohn et al. 2015; Fagereng et al. 2017; Koenig-Kersting and Trautmann 2018; Malmendier and Nagel 2011); and (iii) individual shocks, such as unemployment or divorce (Brunnermeier and Nagel 2008; Chiappori and Paiella 2011; Sahm 2012). While individual shocks and natural disasters appear to have mixed impacts on risk preferences, there is clear evidence that macroeconomic shocks and recessions decrease risk tolerance. This counter-cyclical risk aversion explains several puzzling phenomena, among them the high volatility of asset prices (Barberis et al. 2001; Campbell and Cochrane 1999).

Notably, we also add to the literature investigating the effect of health shocks on risk preferences. For instance, Decker and Schmitz (2016) find significant effects of physical health shocks on individuals' risk preferences. Similarly, Rice and Robone (2022) investigate the effect of health shocks on financial risk-taking. Lastly, Cobb-Clark et al. (2020b) provide evidence that being at risk of a depression decreases individuals' willingness to take risks. We contribute to these strands of the literature by analysing the effect of exposure to a communicable disease on individuals' risk preferences.

2. Theory

This section discusses potential channels through which the regional exposure to COVID-19 cases could impact individuals' risk preferences. A formal mediation analysis in Section 6 then tests these mechanisms.

Health channel. Previous studies have shown that physical and mental health are determinants of risk preferences (Cobb-Clark et al. 2020b; Courbage et al. 2018; Decker and Schmitz 2016; Rice and Robone 2022). Therefore, we hypothesize that changes in the prevalence of COVID-19 can influence individuals' risk preferences through their impact on health. For example, individuals' preferences might be contingent on their health status, meaning that the shape of their utility function could depend on their health (Andersen et al. 2008; Finkelstein et al. 2009, 2013). This, in turn, could lead to changes in their risk preferences as a result of potential infections.

This effect is not necessarily driven by actually contracting COVID-19. The immediate threat of exposure alone can cause individuals' risk preferences to change (Guiso et al. 2018; Meier 2019). Additionally, changes in mental health have been closely linked to alterations in individuals' risk preferences (Cobb-Clark et al. 2020b). All of these factors can potentially be magnified by individuals' pre-existing medical conditions.

Economic channel. The magnitude of the COVID-19 shock did not only negatively affect people's incomes (Adams-Prassl et al. 2020; Graeber et al. 2020; Schröder et al. 2020), but also their economic concerns (Binder 2020; Fetzer et al. 2020; Schröder et al. 2020).

Therefore, we hypothesize that economic considerations mediate the relationship between the regional number of COVID-19 cases and individuals' risk preferences. The strength of this relationship depends on the extent to which a potential decrease in income or an increase in uncertainty about future income is associated with increased risk aversion (e.g. Guiso and Paiella 2008). This aligns with standard economic theory, in which the attractiveness of "lotteries" diminishes as the variance associated with potential outcomes in hypothetical future states of the world increases, while holding the mean constant. Since this change doesn't necessarily require individuals to be affected directly, we argue that worries provide important information about this perceived change in economic risks. This is motivated by the forward-looking nature of worries.

Emotions and satisfaction channel. Emotions and feelings play a crucial role in individuals' perception of their environment and appraisal of their actions (Lerner et al. 2015; Loewenstein 2000; Meier 2022).

Empirical studies have consistently demonstrated that emotions such as happiness, sadness, and fear can affect an individual's risk preferences (Campos-Vazquez and Cuilty 2014; Cohn et al. 2015; Heilman et al. 2010; Lerner and Keltner 2000; Meier 2022; Nguyen and Noussair 2014). Similarly, satisfaction, which includes both cognitive and emotional evaluations, has been shown to be associated with risk preferences (Delis and Mylonidis 2015; Dickason-Koekemoer and Ferreira 2019; Dohmen et al. 2011; Goudie et al. 2014; Music et al. 2013). Therefore, we hypothesize that well-being, emotions, and satisfaction act as mediators through which the spread of COVID-19 influences risk preferences.

3. Empirical Strategy

Empirical model. We employ a generalized DiD framework to estimate the effect of the regional incidence of COVID-19 on risk preferences. Exploiting the panel structure of our data, we regress individuals' risk preferences on the state-level COVID-19 infection rates. This allows us to account for individual, regional, and time-fixed effects that could otherwise bias our estimates. Formally, we estimate the following empirical model:

$$WTR_{istd} = \beta_0 + \beta_1 \text{COVID-19}_{std} + \zeta_i + \theta_{2020} + \kappa_d + \eta_s + \varepsilon_{istd}, \tag{1}$$

In this model, WTR_{istd} denotes the individual i's risk preferences, residing in federal state s, in year $t \in \{2019, 2020\}$, and interviewed in week d. COVID-19$_{std}$ denotes the standardized number of COVID-19 cases per 100,000 residents within the seven days preceding the interview. In our application, WTR_{istd} and COVID-19$_{std}$ are standardized to have a mean of zero and a standard deviation of one. For individuals willingness to take risks, this standard deviation and mean are measured in 2019, and for the COVID-19 infection rates, mean and standard deviation are computed in 2020 (see Table A.1).

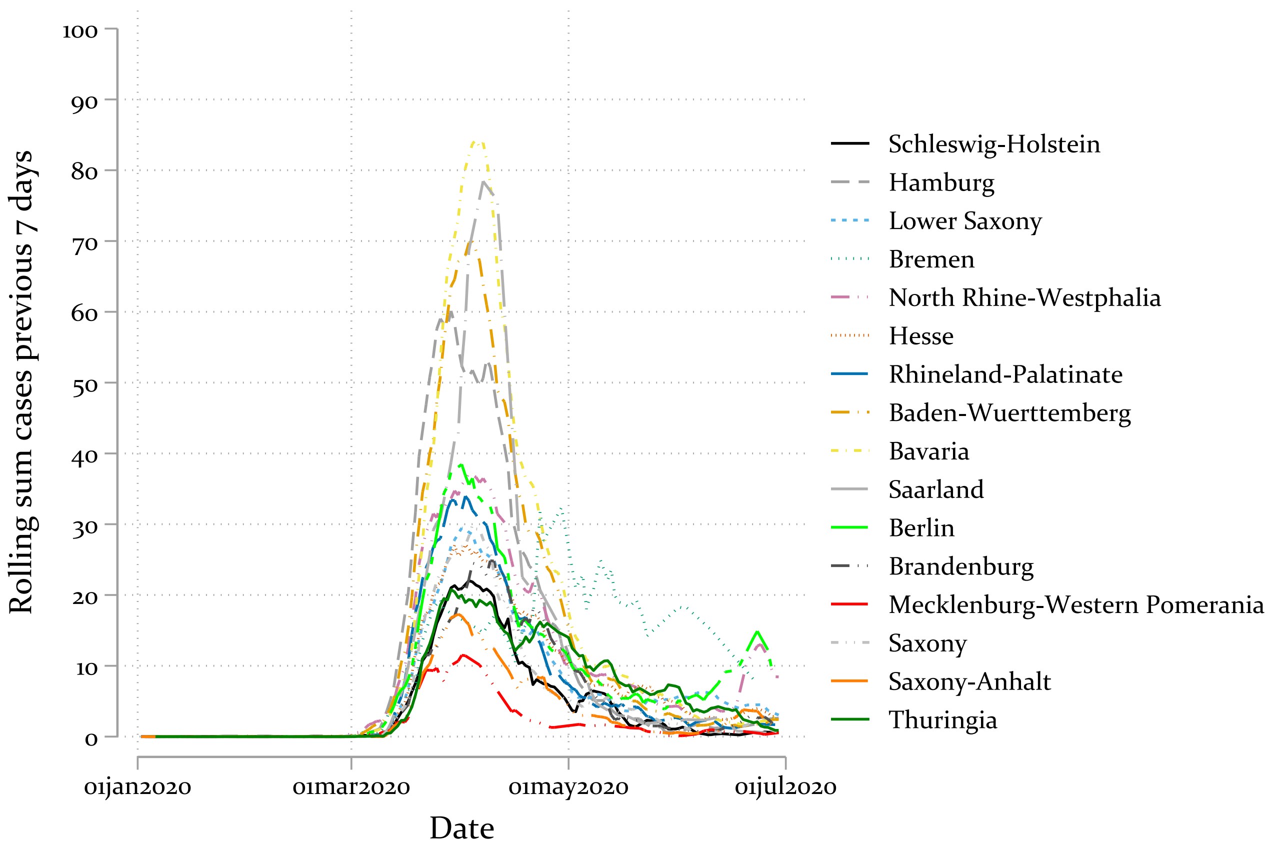
The COVID-19 pandemic is a macro shock affecting everyone. To purge our estimate of interest, $\hat{\beta}_1$, of shocks common to all individuals, we include a set of indicators to account for year and week of interview fixed effects, θ_{2020} and κ_d. Thus, $\hat{\beta}_1$ corresponds to the effect of COVID-19 exposure on individuals' willingness to take risks that goes beyond the common macro shock and relates to variation in state-level infection rates. Therefore, our main estimate is likely a lower-bound estimate of the "true" effect of the pandemic on individuals' willingness to take risks. While the estimate of the common macro shock is likely in part causally related to the pandemic, the potentially causal portion thereof cannot be identified. For this reason we focus on the estimate of β_1.

We include individual fixed effects ζ_i to control for time-invariant and predetermined characteristics at the individual level, which could correlate with exposure to COVID-19 and individuals' willingness to take risks. Similarly, the state fixed effects, η_s , account for observed and unobserved time-invariant state-level confounders, such as population density, the proportion of the elderly population, openness or exposure to international trade, or quality of local healthcare, among others. Lastly, ε_{istd} is the unobserved error term. We cluster standard errors at the state level.[1]

Identification. Identifying the effect of COVID-19 infection rates on individuals' risk preferences relies on variation in state-level COVID-19 rates over time. This approach capitalizes on the fact that individuals were interviewed both in the year preceding the pandemic and over the course of several months in 2020, that is, at different stages of the pandemic. In Figure 1, we illustrate this variation and display the number of COVID-19 infections per 100,000 residents within the past seven days preceding the respective interview day for each state over time. Clearly, there are substantial differences in both the intertemporal evolution and levels of regional COVID-19 infection rates, which we exploit to establish the causal link between the pandemic and risk attitudes.

[1] Since we only have 16 clusters, the 16 federal states, conventional clustered standard errors may potentially be inconsistent (Cameron et al. 2008; Cameron and Miller 2015). For this reason, we also present p-values based on Wild-Cluster bootstrap procedures in the robustness section, using Rademacher weights and 999 repetitions. For this, we employ the Stata module **boottest** authored by Roodman et al. (2019).

FIGURE 1. COVID-19 Infection Rates by State and Over Time



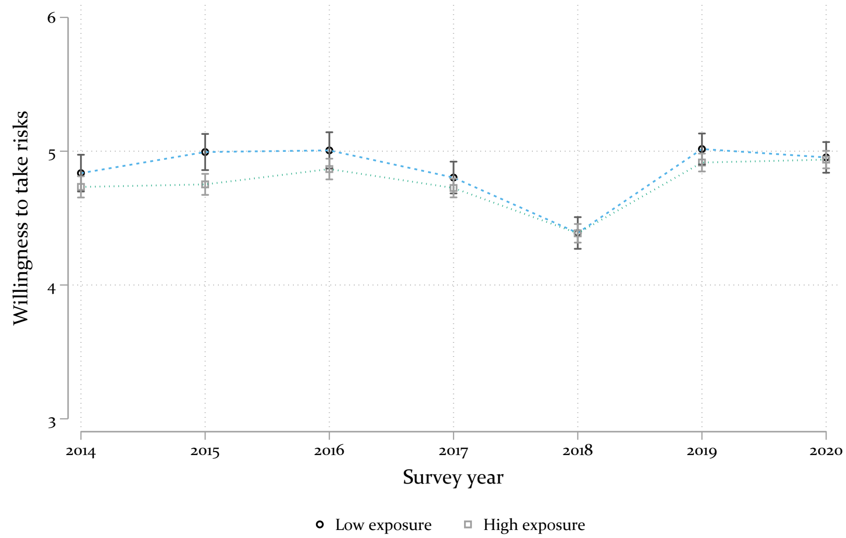
Note: Figure 1 displays the rolling 7-day sum of COVID-19 infections per 100,000 inhabitants within the past seven days for each state over time. Data source: Robert Koch Institute (RKI).

For the estimate of β_1 to be consistent, the trend of individuals' risk preferences would have to remain the same across states in the absence of COVID-19. This counterfactual situation is unobserved. However, we provide suggestive evidence for the validity of the common trend assumption by comparing the evolution of the average risk preferences between high- and low-exposure states in the years before 2020.

Figure 2 suggests that the common trend assumption holds. The figure compares the time series of the average risk preferences of the three states with the highest number of COVID-19 cases per capita in the first half of 2020 (Bavaria, Baden-Wuerttemberg, Hamburg) with those with the fewest cases per capita (Saxony-Anhalt, Schleswig-Holstein, Saxony). That is, we compare the trend in individual risk preferences in regions with high and low rates of exposure to COVID-19.[2] The average risk preferences move parallel over time between high- and low-exposure states. The observed trend provides no evidence against the assumption that the average risk preferences would have evolved similarly in high and low-exposure states in the absence of the COVID-19 pandemic. Additionally, the average risk preferences appear to be very similar in the states with high and low exposure in the pre-pandemic years.

[2] Note that we take the cumulative sum of COVID-19 cases over the entire sample period and then divide the number of cases by the population size. Based on this, we then split the sample into high- and low-exposure states.

FIGURE 2. Common Trend in WTR



Note: Figure 2 displays the average risk preferences per year for high- and low-exposure states from 2014 to 2020. The figure compares the average risk preferences of the three states with the highest number of COVID-19 cases per capita in the observation period (Bavaria, Baden-Wuerttemberg, Hamburg) to those with the fewest cases (Schleswig-Holstein, Saxony-Anhalt, Mecklenburg-Western Pomerania). Vertical bars display 95% confidence intervals associated with the average risk preferences.

A potential concern could be that differential timing in the policy measures potentially confounds our results. However, especially in the early months of the pandemic, policies differed little between the states. Instead, most states implemented policy measures in a coordinated effort one week *prior* to our period of observation. This also marks the time of the strongest variation in the stringency of policy measures (Steinmetz et al. 2020). Thereafter, as our observation period begins, changes in the stringency of the policy measures remain similar across states and, thus, are captured by the inclusion of week fixed effects. Another source of policy variation could be permanent differences in the stringency between states, i.e., unobserved and time-invariant propensity of states to implement stringent policy measures. These are captured by the state fixed effects. Lastly, in a robustness check, we also include week-x-state fixed effects to account for differential policy responses of states across time.

4. Data

The SOEP is a representative longitudinal household survey in Germany.[3] As of 2021, it includes approximately 20,000 households with more than 30,000 adult household members, and it provides, among others, extensive information on the household's and each individual household member's financial situation, education, health, preferences, and attitudes (Goebel et al. 2019).

Dependent variable. Since 2004, the SOEP includes an item measuring individuals' willingness to take risks. These risk preferences are inferred by the answer to the single item question "Are you generally a person who is willing to take risks, or do you try to avoid taking risks?" Answers are provided on an 11-point Likert scale ranging from 0 ("not at all willing to take risks") to 10 ("very willing to take risks"). Responses to this item have proven to be strong predictors of paid lottery choices, and for risk-taking behavior in various life domains, including stock-holding, smoking, marital stability, migration decisions, and occupational choice (e.g. Akgüç et al. 2016; Caliendo et al. 2010; Dohmen et al. 2011; Serra-Garcia 2021; Skriabikova et al. 2014; Vieider et al. 2015).

Explanatory variable. We link the SOEP data to state-level COVID-19 infection rates from the Robert Koch Institute (RKI), the central scientific public health institution of the German government. The RKI provides daily updates on the number of diagnosed COVID-19 cases and deaths.[4] The county-level data contains the number of reported COVID-19 cases on a daily basis.[5] We normalize the number of COVID-19 infections within the seven days preceding the personal interviews for our observations by the respective population size,

[3] We use the SOEPv.37eu (DOI: 10.5684/soep.core.v37eu).

[4] To access the data, see https://www.arcgis.com.

[5] Under the Infection Protection Law (*"Infektionsschutzgesetz"*), Germany's counties are required to report the number of diagnosed COVID-19 cases.

measured in 100,000s.[6] This is our proxy for the number of active cases, given the time required for testing and reporting. We argue that this is a sensible proxy for the number of currently infected individuals and, thus, for the potential relevance of adjustments in respondents' risk preferences. We use 7-day moving averages since the daily reported numbers fluctuate for technical reasons, i.e., delayed reports from health offices, especially over the weekends.[7]

Changes in individuals' risk preferences due to changes in COVID-19 infection rate are driven, presumably, by the information to which they are exposed in the media. Since the onset of the pandemic, the RKI had held daily briefings along with the federal government, informing the public about the latest developments. This information was then disseminated through the media, both national and local. Especially in the early stages of the pandemic, reporting was predominantly focused on the national and state levels. A more granular breakdown of case numbers became more relevant later during the pandemic, when the reporting procedures from local health authorities were better established. Since most of our data originates from the early months of the pandemic, we argue that the state is the relevant unit of reference for individuals. However, in Section 5.2, we demonstrate that our results are robust to using the number of infections at the county level rather than the state level.

Other variables. In our heterogeneity analysis, we test whether individuals who are part of the at-risk group, i.e., individuals with medical conditions, and individuals of different socio-economic backgrounds, respond differently to COVID-19 infection rates. We use the health diagnoses reported by respondents in the last survey year before the pandemic. Thus, these measures are predetermined. While only limited information on the COVID-19 disease was available, initial data suggests that certain characteristics and pre-existing conditions

[6]We use the most recent population information from 2018, as reported by Germany's Federal Statistical Office. See: https://www-genesis.destatis.de/genesis/online.

[7]Many health offices refrain from reporting case numbers on weekends. These numbers are typically reported at the beginning of the following week along with the daily cases.

are associated with a more severe progression of the disease.[8] In 2019, SOEP respondents provided information on whether they have ever been diagnosed with one or more of a collection of potential diagnoses. We use diagnoses on obesity, asthma, diabetes, or heart diseases. For each of these diagnoses, we construct indicators on whether individuals have been diagnosed with the respective disease or not. In 2018, respondents reported their height and weight, which we use to construct an indicator for whether individuals suffer from severe obesity, defined as a body mass index (BMI) of 40 or above, or not. Lastly, we generate an indicator reflecting whether an individual is 65 years of age or older. Together, the indicators on the medical diagnoses, the age indicator, and the indicator for obesity mark individuals as being at risk of a severe disease progression in our heterogeneity analysis.

Moreover, we study effect heterogeneities with respect to sociodemographic dimensions. To ensure that these measures are predetermined and not confounded by the pandemic itself, we use information from 2019, i.e., before the outbreak of the pandemic in Germany. We construct an indicator for gender, for whether an individual has a tertiary education, for whether the equivalence household net equivalence income is above the median, for the presence of children under age 16 in the household, for whether individuals themselves or at least one parent migrated to Germany, for whether individuals are (self-)employed, and for whether individuals are married.

In our mediation analysis, we use information on the individual's employment status, their concerns, satisfaction with various domains, and emotions. The employment status is captured by an indicator that is equal to one if the individuals are employed and zero otherwise. Note that non-employment also includes individuals in education or retirement. Overall health is captured by the self-rated health status of respondents, which is inferred from responses to the item "How would you describe your current health?" Responses are given on a five-point Likert scale ranging from 1 "Very good" to 5 "Bad". We invert the scale

[8]For an overview of the conditions that place individuals at a higher risk of severe progression, please refer to Centers for Disease Control and Prevention (2020) or Robert Koch Institut (2020).

such that higher values indicate better health. We standardize the self-rated health status to have a mean of zero and a standard deviation of one, whereas the standard deviation and the mean are measured pre-treatment. Concerns are inferred from responses to the single item question “How concerned are you about the following issues?” Potential responses are “Very concerned”, “Somewhat concerned", and “Not concerned at all”. In our analysis, higher values indicate more concerns. Again, we standardize these mediators to have a mean of zero and a standard deviation of one with respect to 2019. We focus on concerns about one’s health, the economy in general, one’s financial situation, as well as the social cohesion in society.

For measuring the potential mediator satisfaction, we use the single item inferring the respondents’ satisfaction with life as follows: “In conclusion, we would like to ask you about your satisfaction with your life in general." Answers to this item are given on an 11-point Likert scale with potential responses ranging from 0 “completely dissatisfied" to 10“completely satisfied". Domain satisfaction is captured by responses to the items “How satisfied are you today with the following areas of your life? How satisfied are you with . . . " We focus on satisfaction with health, sleep, family life, and leisure time. The responses to this item are provided on an 11-point Likert scale with potential responses ranging from 0 “completely dissatisfied" to 10 “completely satisfied". We standardize responses to these items to have a mean of zero and a standard deviation of one, with both measured in the year before the pandemic.

Lastly, we consider emotions as potential mediators. Emotions are measured via answers to the item “I will now read to you a number of feelings. Indicate for each feeling how often or rarely you experienced it in the last four weeks." The feelings included are: anger, being worried, sadness and happiness. Responses to this item are provided on a five-point Likert scale, ranging from 1 “Very rarely" to 5 “Very often". Again, we standardize these items to have a mean of zero and a standard deviation of one, using the mean and standard deviation from the pre-treatment year.

Note that we restrict our period of analysis to 2019 and the first half of 2020. This decision is based on the progression of the pandemic, which suggests that different periods can be characterized as different regimes. Additionally, the field phase of the survey is such that the second half of each year consists mainly of migrants, rendering the sample non-representative of the underlying population if intra-year developments later in the year are considered. Our final sample comprises 18,881 individuals observed in both years, 2019 and 2020. We display the descriptive statistics for our sample in the Appendix, Table A.1.

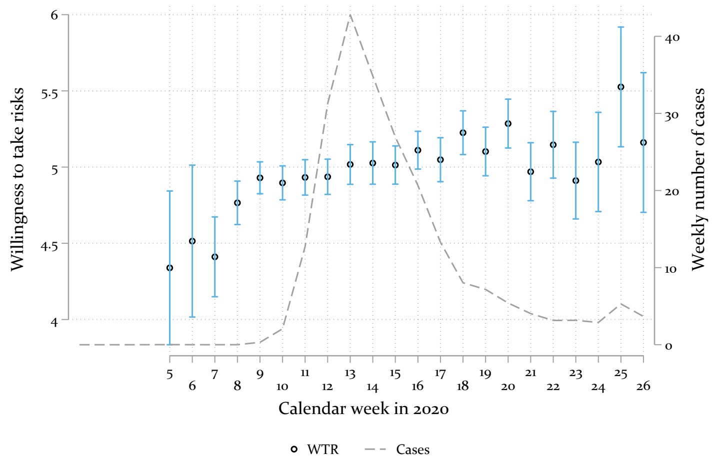
5. Results

5.1. Main Results

Our empirical strategy utilizes both the cross-sectional and longitudinal elements of our data to accurately portray the dynamics of the COVID-19 pandemic and its impact on risk preferences.

Figure 3 shows the weekly average risk preferences in 2020 (black circles), along with the number of new confirmed COVID-19 cases for each week in the first half of the year 2020 (dashed grey line). Notably, the time series does not imply strong co-movements between the average willingness to take risks and the weekly confirmed cases. While the number of confirmed cases decreases after week 14, the average risk preferences do not.

FIGURE 3. Risk Preferences Over Time



Note: Figure 3 displays the average risk preferences per calendar week in 2020 along with the number of new confirmed COVID-19 cases per 100,000 inhabitants in a given week. Vertical bars display 95% confidence intervals associated with the average risk preferences.

Table 1 presents our estimates from Equation 1 for five model specifications. Column (1) shows results for a specification without controls. Column (2) adds year fixed effects; column (3) includes individual fixed effects; column (4) adds year and week of the interview fixed effects, but excludes individual fixed effects; and column (5) includes the full set of controls.

Our results indicate that the number of regional COVID-19 cases does not affect individuals' risk preferences. While columns (1) and (2) suggest that a one standard deviation increase in the number of regional COVID-19 cases increases individuals' risk preferences by approximately 2.7 to 3.6% of a standard deviation, this effect dissipates once we consider individual fixed effects (column (3)), indicating that time-invariant, individual-level confounders imply an overestimation of the effect. Including week fixed effects (column (4)) confirms the null effect, so does our main specification in column (5): An one standard deviation increase in the number of COVID-19 cases implies a rather small and statistically insignificant increase on individual's risk preferences by approximately 0.8% of a standard deviation. Furthermore, the associated confidence intervals suggest that we can rule out

TABLE 1. The effect of the COVID-19 infection rate on individuals' willingness to take risks.

	(1)	(2)	(3)	(4)	(5)
COVID-19 infection rate	0.027**	0.036**	0.006	0.003	0.008
	(0.009)	(0.014)	(0.006)	(0.008)	(0.010)
Individual FE	✗	✗	✓	✗	✓
Year FE	✗	✓	✓	✓	✓
Week FE	✗	✗	✗	✓	✓
Region FE	✗	✗	✗	✗	✓
2020 year effect		-0.036**	-0.015	0.007	-0.007
		(0.015)	(0.013)	(0.014)	(0.009)
Observations	37,762	37,762	37,762	37,762	37,762
Individuals	18,881	18,881	18,881	18,881	18,881

Note: Table 1 displays results for a regression of the standardized willingness to take risks on the COVID-19 infection rate within the seven days preceding the interview date per 100,000 inhabitants, normalized to have mean zero and standard deviation one. Column (1) includes no controls, column (2) includes year fixed effects only, column (3) includes year and individual fixed effects, column (4) includes year and week of interview fixed effects and column (5) includes individual, region, year and week of interview fixed effects. Robust standard errors, clustered at the state level, are in parentheses. P-values are based on a Student's t-distribution with 15 degrees of freedom and read * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

effects larger than 2.8% or smaller than -1.2% of a standard deviation with 95% certainty.

5.2. Robustness

Inference. We exploit variation in COVID-19 infection rates over time across Germany's 16 federal states and cluster standard errors at the state level. The asymptotic theory for clustered variance-covariance matrices relies on the number of clusters converging to infinity (Cameron and Miller 2015). With only 16 clusters, our estimate of the variance-covariance matrix might be inconsistent. As a remedy, we compute Wild-cluster bootstrap p-values. Wild-cluster bootstrap procedures are useful in such situations due to their asymptotic refinement (Cameron et al. 2008). That is, the estimated variance-covariance matrix converges faster to its probability limit. We calculate Wild-cluster bootstrap p-values with 999 repetitions and Rademacher weights. The results are displayed in the second row of Table A.2 and do not alter our conclusions. Specifically, the Wild-cluster bootstrap procedure returns a p-value of 0.43, as shown in square brackets in Table A.2.

Placebo regression. Figure 2 shows that the average risk preferences follow a common trend in both high- and low-exposure states, providing no evidence against the assumption that risk preferences would have evolved similarly in these states absent variation in COVID-19 infection rates. As an additional check for the validity of the common trend assumption, we perform a placebo regression of individuals' risk preferences on the one period lead of the COVID-19 infection rates in 2018 and 2019. A significant effect on the coefficient for the COVID-19 infection rate would indicate a violation of our identifying assumption. As shown in the third row of Table A.2, the estimated effect of -0.008 is small and not statistically significant.

Scale. Our measures of risk preferences is an ordinal outcome. The implied assumption is that the categories correspond to intervals along a latent continuous distribution of risk preferences. However, ordinally scaled variables allow for monotonically increasing transformations and this might change the regression results (Bond and Lang 2019; Schröder and Yitzhaki 2017). As a remedy, we construct an indicator that equals one for the five highest categories on the willingness to take risks scale, and zero otherwise. We use the indicator as the dependent variable in Equation 1. Thus, results obtained from this regression are insensitive to monotonic transformations of the dependent variable. The results, displayed in the fourth row of Table A.2, also suggest no effect of the regional number of COVID-19 cases on individuals' willingness to take risks.

Flexible time trends. Another concern, as discussed in Section 3, could be that states implemented different policy measures at different times in an attempt to contain the COVID-19 pandemic. According to German law, containing infectious diseases is the responsibility of both states and counties. However, the majority of policy measures in Germany were implemented in a coordinated effort at the federal level before our observational period. This should limit the potential bias induced by differential responses of states over time. Our results would be confounded if, for instance, the state-level implementation of measures aimed at containing the spread of COVID-19 were associated with individuals' risk preferences and state-level COVID-19 infection rates. To address this concern, we re-estimate Equation 1, interacting calendar weeks and states to account for time-varying heterogeneity at the state level. The main estimate, displayed in the fifth row of Table A.2, is practically zero and indicates the absence of any effect of the number of COVID-19 cases.

County-level infection rates. In Section 4 we argue that the state level is the appropriate level of aggregation for our analysis. The main reason is that in the early stages of the pandemic, where most of our data is concentrated, public attention was largely focused on the national and the state level. Nevertheless, individuals might have tracked the developments of the pandemic at a more granular level, i.e., counties. To accommodate this, we repeat our analyses using variation in infection rates at the county level instead of the state level. Again, our conclusions are not altered by this change in our specification, as shown in the sixth row of Table A.2. The effect size is small and not statistically significant.

6. Heterogeneous effects across population subgroups & mechanisms

6.1. Heterogeneous effects

The previous section showed that COVID-19 infection rates do not affect individual risk preferences, *on average*. Here, we study possible effect heterogeneities across population subgroups. We focus on characteristics that are relevant from a medical point of view, as well as characteristics deemed important in the economic literature. To account for heterogeneities in effect sizes, we re-estimate Equation 1 with the full set of controls and include an interaction term between the COVID-19 infection rate and an indicator for the group under consideration. The results are shown in Table 2. In each column, the first estimate corresponds to the coefficient estimate for the reference group, while the second entry reflects the differential response associated with belonging to the respective group of interest.

Preexisting medical conditions. Our analyses concerning health differences are displayed in column (1) to (5). Individuals diagnosed with heart disease show a stronger decrease in risk preferences in response to a higher state-level COVID-19 infection rate than individuals without such a disease. We do not find any evidence of differential effects for obese individuals, individuals who had asthma, diabetes or are above the age of 64. By contrast, while individuals never diagnosed with a heart disease do not respond to the number of COVID-19 cases, we find a significantly more negative effect for individuals diagnosed with a heart disease. This is displayed in column (4) of Table 2. Moreover, the linear combination suggests that the effect for individuals with a heart disease corresponds to -3.9% of a standard deviation.

Socio-demographics. The results for gender, presence of a child in the household, migration background, working status, and marital status, are displayed in columns (6) to (10) of Table 2. We do not find any (differential) effects for individuals with a child living in the household, for migrants, nor for employment or marital status. While we find virtually no effect for men, we find a small effect for women. The point estimates suggest that a one standard deviation increase of the number of COVID-19 cases increases women's risk preferences by about 1.5% of a standard deviation. However, this effect is not statistically significant either.

Socio-economic status. We analyze differential effects for different income and educational levels in column (11) and (12) of Table 2, respectively. An one standard deviation increase in the number of COVID-19 cases increases risk preferences of individuals with a non-tertiary education by about 1.5% of a standard deviation. For individuals with a tertiary education, this effect is about 1.2% of a standard deviation smaller. The p-value associated with the corresponding linear combination suggests that we cannot reject the null-hypothesis of no effect for individuals with a tertiary education. Similarly, along the income dimension, effect differences are statistically insignificant.

TABLE 2. Heterogenous effect of the COVID-19 infection rate on individuals' willingness to take risks.

	(1) BMI $\geq$ 40	(2) Asthma	(3) Diabetes	(4) Heart disease	(5) Age $\geq$ 65	(6) Female
COVID-19 rate	0.004	0.005	0.006	0.009	0.007	0.000
	(0.013)	(0.011)	(0.009)	(0.010)	(0.011)	(0.009)
Interaction	-0.025	0.008	0.005	-0.048**	0.003	0.015
	(0.042)	(0.025)	(0.029)	(0.020)	(0.011)	(0.013)
P-value linear combination	0.636	0.629	0.772	0.105	0.346	0.25
Observations	32,046	37,038	37,038	37,038	37,762	37,710
Individuals	16,024	18,519	18,519	18,519	18,881	18,855
	(7) Child $\leq$ 16	(8) Migration background	(9) Working	(10) Married	(11) Tertiary education	(12) High income
COVID-19 rate	0.004	0.003	0.012	0.013	0.015*	0.023
	(0.008)	(0.007)	(0.011)	(0.012)	(0.009)	(0.017)
Interaction	0.006	0.017	-0.005	-0.010	-0.012	-0.020
	(0.011)	(0.013)	(0.015)	(0.013)	(0.007)	(0.012)
P-value linear combination	0.558	0.289	0.601	0.848	0.764	0.12
Observations	37,034	37,762	37,762	37,024	36,798	35,836
Individuals	18,517	18,881	18,881	18,512	18,399	17,918

Note: Table 2 displays results for a regression of the standardized willingness to take risks on the standardized COVID-19 infection rate within the seven days preceding the interview date per 100,000 inhabitants and the respective interaction terms. All regressions control for individual, state and time fixed effects. Robust standard errors, clustered at the state level, are in parentheses. P-values are based on a Student's t-distribution with 15 degrees of freedom and read * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.2. Potential mechanisms

Our estimate of the effect of COVID-19 on risk preferences represents a gross effect of the regional number of COVID-19 cases on risk preferences. While the exposure to COVID-19 might have a direct effect on risk preferences, it is very likely that potential effects operate via mediators. If many mediators with different effects are present, they could cancel each other out. This could in turn cause the average effect of the exposure to COVID-19 on risk preferences to be equal to zero. Thus, the role of mediators of the relationship between the regional number of COVID-19 cases and individuals' risk preferences is informative for the effect the prevalence of communicable diseases has on risk preferences.

In our mediation analysis, we proceed in two steps:

1. We re-estimate Equation 1 using the mediators as the dependent variable. That is, we study whether a change in the regional COVID-19 rate also translates into a change in the respective mediator.

2. Second, we replace our explanatory variable in Equation 1 with our respective mediator to study whether changes in the mediating variable are (conditionally) correlated with changes in risk preferences.

For a causal pathway to exist, we would expect that COVID-19 infection rates directly impact the mediator, which in turn affects the change in risk preferences between 2019 and 2020.

Turning to step 1, Table 3, indicates that higher COVID-19 exposure leads to a significant increase in economic concerns, consistent with previous studies by Binder (2020) and Fetzer et al. (2020). A one standard deviation increase in the number of COVID-19 cases increases individuals' worries about the economy by about 5.9% of a standard deviation. Similarly, worries about one's financial situation increase by about 1.4% of a standard deviation. Additionally, a one standard deviation increase in the number of COVID-19 cases decreases worries about social cohesion by about 4.8% of a standard deviation.

We also find that the exposure to the number of COVID-19 cases decreases individuals overall satisfaction, satisfaction with family life, and satisfaction with leisure. In particular, a one standard deviation increase in the number of COVID-19 cases decreases general satisfaction with life by about 3.5% of a standard deviation, satisfaction with leisure by about 2% of a standard deviation, and satisfaction with family life by about 4.2% of a standard deviation.

Lastly, emotions are also heavily affected by the exposure to COVID-19. Columns (13) to (15) show that a one standard deviation increase in the number of COVID-19 cases increases the frequency at which individuals feel anxious by about 11.9%, decreases the frequency at which individuals feel happy by about 3.1% and increases the frequency at which individuals feel sad by about 3.6% of a standard deviation.

Turning to step 2, the results in Table 4 suggest that financial worries, satisfaction with life, satisfaction with leisure, with family life, as well as the emotions anxiety and happiness are relevant mediators since they are both impacted by the pandemic and correlated with changes in risk preferences. A one standard deviation increase in one's own financial situation is associated with a 5.8% standard deviation decrease in one's risk preferences. A one standard deviation increase in satisfaction with life, satisfaction with leisure, and satisfaction with family life is associated with an increase in individuals' risk preferences of 4.6%, 3.7%, and 4.3% of a standard deviation, respectively. Lastly, a one standard deviation increase in anxiety and happiness is associated with a decrease in individuals' by about 2.3% and 3.4% of a standard deviation, respectively.

Average Controlled Direct Effect. To complement our mediation analysis, we resort to the mediation analysis technique introduced by Acharya et al. (2016). Their method, which builds on the Average Controlled Direct Effect (ACDE), allows us to assess how much the of the effect of COVID-19 exposure on risk preferences can be attributed to the respective mediators. The ACDE accounts for unobserved confounders that could otherwise introduce collider biases, thus, invalidating any mediation analysis (Acharya et al. 2016). Specifically, we focus on the difference between the ACDE and our main effect to understand the relevance of various mechanisms. The results are displayed in Table B.3. The first row shows the main effect after netting out the effect of the respective mediator, while the second row displays the difference between this de-mediated main effect and the main effect in column (5) of Table 1. Thus, this difference indicates how much of estimated main effect can be explained away by the respective mediator under consideration.[9] Overall, this analysis confirms our previous results: worries about individuals' own financial situation, satisfaction with life, satisfaction with leisure, satisfaction with family life as well as anxiety and happiness are mediators in the relationship of interest. As shown in the previous analysis, the implied contribution of all mediators to the overall effect is negative. The only additional mediator suggested by this analysis is the frequency at which individuals feel sadness.

[9]Details are displayed in Section B in the Appendix.

TABLE 3. The effect of the COVID-19 infection rate on potential mediators.

	A: Employment and health		B: Worries			
	(1)	(2)	(3)	(4)	(5)	(6)
	Working	Health	Economy	Fin. situation	Health	Society
COVID-19 rate	0.001	0.012	0.076***	0.018***	0.003	-0.061*
	(0.003)	(0.011)	(0.023)	(0.002)	(0.004)	(0.029)
Observations	37,762	37,696	36,802	37,582	37,554	36,736
Individuals	18,881	18,848	18,401	18,791	18,777	18,368

	C: Satisfaction					*D: Emotions*			
	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Overall	Leisure	Family	Health	Sleep	Anger	Anxiety	Happiness	Sadness
COVID-19 rate	-0.035***	-0.020**	-0.042***	0.006	0.002	0.000	0.119***	-0.031**	0.036***
	(0.009)	(0.009)	(0.007)	(0.015)	(0.009)	(0.009)	(0.028)	(0.012)	(0.010)
Observations	37,622	36,830	36,190	37,722	37,008	36,990	36,948	36,968	36,966
Individuals	18,811	18,415	18,095	18,861	18,504	18,495	18,474	18,484	18,483

Note: Table 3 displays results for a regression of potential mediators on the COVID-19 infection rate within the seven days preceding the interview date per 100,000 inhabitants, normalized to have mean zero and standard deviation one. All regressions include week of the interview, year, individual and state fixed effects. Robust standard errors, clustered on the state level, are in parentheses. P-values are based on a Student's t-distribution with 15 degrees of freedom. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4. Correlations of mediators with changes in risk aversion.

	(1) Correlation	(2) Observations
Panel A: Employment and health status		
Working	0.055**	37,762
	(0.023)	
Health	0.029***	37,696
	(0.008)	
Panel B: Worries		
Economy	-0.008	36,802
	(0.013)	
Own financial situation	-0.058***	37,582
	(0.020)	
Health	-0.010	37,554
	(0.018)	
Social cohesion	0.002	36,736
	(0.006)	
Panel C: Satisfaction		
Overall	0.046***	37,622
	(0.008)	
Leisure	0.037***	36,830
	(0.007)	
Family	0.043***	36,190
	(0.007)	
Health	0.044***	37,722
	(0.008)	
Sleep	0.028***	37,008
	(0.008)	
Panel D: Emotions		
Anger	-0.002	36,990
	(0.006)	
Anxiety	-0.023***	36,948
	(0.006)	
Happiness	0.034***	36,968
	(0.007)	
Sadness	-0.002	36,966
	(0.006)	

Note: Table 4 displays correlations of potential mediators with the willingness to take risks. All regressions include week of the interview, year and individual fixed effects. Robust standard errors, clustered on the individual level, are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7. Conclusions

Our study contributes to the new economic literature on the effect of communicable diseases on individuals' risk preferences by analyzing the impact of regional exposure to a communicable disease, COVID-19, on individuals' risk preferences in Germany. It provides new insights into the time variability of risk aversion and its dependence on external shocks.

We find that, on average, regional exposure to COVID-19 does not change individuals' risk preferences. This adds to the existing literature on this topic, which presents mixed results. One explanation for this heterogeneity in findings could be the fact that the treatment varies widely across studies. This variation in turn influences the interpretation of the treatment and the associated effects on risk preferences across studies. Most notably, the work of Bu et al. (2021) relies on exogenous intertemporal and regional variation in participating students' distance to Wuhan, the city of the first documented SARS-CoV-2 outbreak. While this undoubtedly relates to the degree of exposure to the disease itself, the city was also subject to a robust policy response by government authorities in China, including strict curfews.

The majority of studies in this literature, reviewed in Section 1, relies on student samples or other very specific groups, such as professional investors. The only exception is Ikeda et al. (2020), who have access to a representative sample in Japan. Thus, results from studies using representative samples, like ours, is vitally important. Student samples likely differ from the general population, which undermines the extrapolation of results from these studies to the general populace.

While we find the average effect of the spread of COVID-19 on risk preferences to be zero, our findings indicate that individuals with a diagnosed heart disease display a reduced risk preferences in response to a higher exposure to the number of COVID-19 cases. This seems like a rational response since these individuals are likely predisposed to a severe progression of COVID-19 and thus have a good reason to shield themselves against a transmission of SARS-CoV-2.

Our extensive data also allows for investigating a wide range of potential mediators, which enhances the literature on the impact of communicable diseases and crises on risk preferences more generally. The mediating channels include concerns about one's own financial situation, satisfaction with life in general, with leisure and family life, as well as emotions such as anxiety and happiness. Importantly, since most of these relationships suggest a negative correlation between exposure to COVID-19 and risk preferences, we conclude that there must be other unobserved factors offsetting this negative gross effect induced by the mediators under consideration.

Acknowledgements

The authors acknowledge valuable feedback from seminar participants at the DIW Berlin. The authors declare they have no conflict of interest. Daniel Graeber and Carsten Schröder acknowledge funding by Deutsche Forschungsgemeinschaft for the project „The consequences of SARS-CoV-2 for societal inequalities“ (contract number: SCHR 1498/7-1).

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Appendix A. Tables and Figures

Table A.1. Summary statistics.

	(1) Mean	(2) S.D.	(3) Observations
Willingness to take risks (2019)	5.059	2.394	18,881
Willingness to take risks (2020)	5.031	2.331	18,881
COVID-19 infection rate (2020)	12.033	17.746	18,881
Predetermined characteristics:			
Age	51.967	17.141	37,762
Female	0.519	0.500	37,710
Children under 16 in HH	0.292	0.455	37,034
Migration background	0.219	0.414	37,762
Working	0.630	0.483	37,762
Married	0.613	0.487	37,024
Education:			
Primary or none	0.284	0.451	36,798
Secondary	0.418	0.493	36,798
Tertiary	0.298	0.457	36,798
Household income (in Euros)	0	0	36,798
Risk groups:			
BMI $\geq$ 40	0.021	0.143	32,048
Asthma	0.071	0.258	37,038
Diabetes	0.082	0.274	37,038
Heart disease	0.097	0.296	37,038
Age $\geq$ 65	0.255	0.436	37,762

Note: Table A.1 displays the mean, standard deviations and the number of observations of our sample. For household income we use the equivalized disposable income, which is defined as the total income of a household, after tax and social security contributions, divided by the square root of the number of household members.

TABLE A.2. The effect of the COVID-19 infection rate on individuals' willingness to take risks.

	(1) Coefficient estimate	(2) Observations	(3) Individuals
1st Main result	0.008	37,762	18,881
	(0.010)		
2nd Inference	0.008	37,762	18,881
	[0.43]		
3rd Placebo test	-0.008	32,516	16,258
	(0.007)		
4th Scale of the outcome	0.003	37,762	18,881
	(0.005)		
5th Flexible trend	0.000	37,762	18,881
	(0.000)		
6th County-level infections	0.009	35,824	17,912
	(0.010)		

Note: Table A.2 displays results for our robustness checks. The 1st row replicates our main result. The 2nd row displays our main estimate with the WC-bootstrap equaltail p-value (in square brackets) based on 999 replications and Rademacher weights. The 3rd row displays the result if we date our treatment back, i.e. act as if individuals are exposed to the COVID-19 prevalence they experienced in 2020 in 2019. The 4th row displays our results if we scale or outcome such that those individuals who have a WTR above 5 score a 1 and 0 otherwise. The 5th row displays our results with more flexible trends as controls. Robust standard errors, clustered at the state level, are in parentheses. Significance stars are based on a Student's t-statistic with 15 degress of freedom. The 6th row displays the results for our main analysis when we use county-level infection rates instead. Robust standard errors, clustered at the county level, are in parentheses. Significance stars are based on a Student's t-statistic with 398 degrees of freedom. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B. Average controlled direct effect

Acharya et al. (2016) describe the Average Controlled Direct Effect (ACDE) and illustrate a two-step procedure that, under certain conditions, allows for consistent estimation of the Average Controlled Direct Effect (ACDE).[10] The basic idea is to gain a sense of how much of the main effect can be explained away by the respective mediator. Formally, the ACDE is defined as follows:

$$\begin{aligned} E[WTR_{istd}(a,0) - WTR_i(0,0)|X_{istd} = x] = E[WTR_{istd} - \gamma(a, M_{istd}, x)|COVID-19_{std} = a, x] \\ -E[WTR_{istd} - \gamma(0, M_{istd}, x)|COVID-19_{std} = 0, x]. \end{aligned} \tag{A1}$$

In Equation A1, a and x correspond to the realization of $COVID-19_{std}$ and X_{istd}, respectively. In our case, X_{istd} includes the individual, region, and time fixed effects. $WTR_{istd}(COVID-19, M)$ denotes the outcome in potential outcomes notation, e.g., the realization of the outcome under different realisations of the exposure to COVID-19 and the mediator under consideration M. The function γ is the demediation function and defined as follows:

$$\gamma(a, m, x) = E[WTR_i(a, m) - WTR_i(a, 0)|X_i = x]. \tag{A2}$$

The demediation function indicates the average change in the outcome if one switches the level of the mediator from some level m to 0. To quantify the contribution of the mediators to the effect of interest, we proceed along the following steps:

1. The demediation function can be estimated by a regression of the outcome on the variables in the demediation function (M_{istd}) plus the intermediate confounders (Z_{istd}, all the other mediators not under consideration), treatment ($COVID-19_{istd}$), and baseline

[10] For other applications of this approach see, for instance, Brown et al. (2019); Moya (2018).

confounders (X_{istd}; individual, region, and time fixed effects in our case).

2. The demediated outcome is estimated as follows:

$$\tilde{WTR}_{istd} = WTR_{istd} - \widehat{\gamma}(COVID-19_{istd}, M_{istd}, X_{istd}). \tag{A3}$$

3. The estimate of the ACDE then corresponds to the estimate of the coefficient α_1 in the following regression:

$$E[\tilde{WTR}_{istd}|COVID-19, X_{istd}] = \alpha_0 + \alpha_1 COVID-19_{std} + \omega_i + \lambda_{2020} + \upsilon_d + \psi_{istd}, \tag{A4}$$

The contribution of the mediator to the effect of interest is then defined as $\Delta = \beta_1 - \beta_m$. If the overall contribution is negative, i.e., if the effect would be larger if we held the variation of the mediator fixed, Δ is negative. If the contribution is positive, so is Δ. The estimated Δ are displayed in Table B.3, together with bootstrapped standard errors, clustered at the state level.

TABLE B.3. Mediation analysis.

	A: Employment and health		B: Worries			
	(1)	(2)	(3)	(4)	(5)	(6)
	Working	Health	Economy	Fin. situation	Health	Society
COVID-19 rate	0.00301	0.00298	0.00289	0.00385	0.00301	0.00333
	(0.00760)	(0.00761)	(0.00768)	(0.00764)	(0.00761)	(0.00767)
$\Delta = \beta_1 - \beta_m$	0.00005	0.00008	0.00017	-0.00079*	0.00005	-0.00027
	(0.00011)	(0.00012)	(0.00101)	(0.00041)	(0.00010)	(0.00037)

	C: Satisfaction					*D: Emotions*			
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
	Overall	Leisure	Family	Health	Sleep	Anger	Anxiety	Happiness	Sadness
COVID-19 rate	0.00399	0.00352	0.00416	0.00289	0.00306	0.00309	0.00480	0.00370	0.00248
	(0.00757)	(0.00760)	(0.00757)	(0.00759)	(0.00760)	(0.00760)	(0.00765)	(0.00760)	(0.00760)
$\Delta = \beta_1 - \beta_m$	-0.00093**	-0.00045*	-0.00109**	0.00018	0.00000	-0.00002	-0.00173**	-0.00063**	0.00059**
	(0.00036)	(0.00027)	(0.00044)	(0.00021)	(0.00007)	(0.00010)	(0.00084)	(0.00031)	(0.00029)
Observations	35,234	35,234	35,234	35,234	35,234	35,234	35,234	35,234	35,234
Individuals	17,617	17,617	17,617	17,617	17,617	17,617	17,617	17,617	17,617

Note: Table B.3 displays results for a mediation analysis adopting the procedure of Archaya et al. (2016). All regressions include week of the interview, year, individual and state fixed effects. Standard errors are estimated with a boostrapping procedure using 500 replications and clustered at the state level. * p < 0.1, ** p < 0.05, *** p < 0.01.