CESifo WORKING PAPERS

10387
2023

April 2023

Financial Risk-Taking under Health Risk

Björn Bos, Moritz A. Drupp, Jasper N. Meya, Martin F. Quaas

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 10387*

Financial Risk-Taking under Health Risk

Abstract

We study how background health risk affects financial risk-taking. We elicit financial risk-taking behavior of a representative sample of more than 5,000 Germans in five panel waves during the COVID-19 pandemic. Exploiting variation in local infections across time and space, we find that an increase in infections affecting background health risk translates into higher levels of self-reported fear and decreases financial investments in a risky asset. Once vaccines become available as a self-insurance device, the tempering effect on investments ceases. Our results provide evidence that non-financial background risks affect financial risk-taking, and for the alleviating effect of self-insurance devices.

JEL-Codes: D140, D910, G110, G410, G510.

Björn Bos
Department of Economics
University of Hamburg / Germany
bjoern.bos@uni-hamburg.de

Moritz A. Drupp
Department of Economics
University of Hamburg / Germany
moritz.drupp@uni-hamburg.de

Jasper N. Meya
Department of Economics
University of Leipzig / Germany
jasper.meya@idiv.de

Martin F. Quaas
Department of Economics
University of Leipzig / Germany
martin.quaas@idiv.de

April 17, 2023
We thank Mickael Beaud, Andreas Fagereng, Jan Marcus and Petra Steinorth as well as seminar audiences at Esbjerg, Hamburg, Leipzig, and Maastricht for helpful comments, and are grateful to Alexander Mahler and Fabian Marder for excellent research assistance. We acknowledge funding by the German Federal Ministry of Education and Research (BMBF) under grant number 01LC1826E. BB, JM and MQ acknowledge the support of iDiv funded by the German Research Foundation (DFG-FZT 118, 202548816); MQ acknowledges funding by the German Research Foundation in project CRAMORES (QU 357/14-1). Parts of this study were pre-registered at the AEA RCT Registry under AEARCTR-0005573 and the initial study design was approved by the WiSo Research Laboratories Hamburg at the University of Hamburg in March 2020.

1 Introduction

How do background risks affect financial risk-taking? Economic theory suggests that individuals who face financial background risk are expected to take less financial risk if they exhibit decreasing absolute risk aversion or are characterised by risk-vulnerability (Eeckhoudt et al., 1996; Gollier and Pratt, 1996). Yet, the effects of background risks are challenging to identify in the field, and empirical approaches have so-far focused predominantly on financial background risks, such as uninsurable wage risk (e.g., Fagereng et al., 2018), or have resorted to laboratory experiments (e.g., Beaud and Willinger, 2015) or surveys (e.g., Bacon et al., 2020; Guiso and Paiella, 2008). Evidence suggests that many individuals are risk averse and risk vulnerable, but that the effect of financial background risk on risk-taking is modest in magnitude, for instance because uninsurable wage risk is small (Fagereng et al., 2018).

Individuals may also face sizable non-financial background risks, which can impact financial risk-taking via two channels. An extra risk on a non-financial asset, such as health, decreases the expected value of this asset and the financial absolute risk aversion may decrease with expected non-financial wealth (decreasing absolute risk aversion across domains; short cross-DARA). Moreover, an extra risk on a non-financial asset increases uncertainty about future non-financial wealth, which may affect financial risk taking if financial decision-makers are characterized by cross-risk vulnerability (Malevergne and Rey, 2009). For instance, public health risks caused by communicable diseases, like seasonal influenza, AIDS, and malaria, made up 18 percent of all deaths in 2019 (Vos et al., 2020), and these health risks are expected to intensify (e.g., Baker, 2020; Haines et al., 2006; Lindgren et al., 2012; O'Neill, 2016; Jones et al., 2008). This makes it increasingly important to better understand the effects of background health risks on risk-taking.

In this article, we study how background health risk affects financial risk-taking. We consider the COVID-19 pandemic as a natural experiment that creates substantial variation in background health risk over time and space that is largely exogenous to an individual's behavior. During the pandemic, we conduct a panel experiment that repeatedly elicits financial risk-taking behavior of a representative sample of more than 5,000 participants from the German population. Our strategy of combining a panel experiment, featuring an incentivized risky investment task (cf. Gneezy and Potters, 1997; Cohn et al., 2015, 2017), with administrative data on local pandemic prevalence, which captures exogenous variation in background health risk, allows us to overcome key identification challenges. First, the panel structure allows us to eliminate subject-specific effects, which would otherwise cause an omitted variable bias. Second, we keep the risk profile of the investment task constant over time and independent of pandemic prevalence or the state of the economy. Third, we exploit the exogenous variation in the local pandemic prevalence over space and time, which allows us to isolate the causal effect of infection risk on financial risk-taking.

Our main analysis on health risk builds on three data collection periods during the early phase of the COVID-19 pandemic in March, August and December 2020, when no vaccine was available in Germany against COVID. We estimate the effect of the local coronavirus infections—and pandemic induced deaths as an alternative measure—on financial risk-taking with a fixed effects estimation. Next, we exploit within-subject variation in the amount of endowment invested in the risky lottery. We control for income changes, a linear time trend to capture experience effects with the pandemic over time, and eliminate any time-invariant factors with individual-specific fixed effects. We attribute the remaining variation in portfolio choices to changes in the background health risk caused by the pandemic. We contrast the analysis on health risk with results from two additional data collections in 2021, when vaccines were available. Vaccination provides self-insurance against COVID-19, as it significantly reduces the severity of the disease, but not a self-protection, as the likelihood of an infection is not substantially lowered. This allows us to discern the impact of health risks with and without this self-insurance on financial risk-taking.

Our results suggest that background health risk has a negative effect on financial risk-taking and decreases investments in a risky asset. Specifically, we find that an increase of 1 percentage point in the current number of local infections leads to an average reduction of investments into the risky asset by 0.22 percentage points, as long as a vaccine is not available. Given the substantial spatial and temporal pandemic dynamics, this may have sizable implications for portfolio choices. With the availability of vaccines, people can self-insure against this health risk and, indeed, we do not find anymore that pandemic prevalence negatively affects financial risk-taking at that time.

Exploring mechanisms that may explain the impact of background health risks on risk-taking, we identify fear induced by the pandemic as a key channel. This is in line with experimental studies on financial risk-taking (e.g. Cohn et al., 2015; Guiso et al., 2018) and studies highlighting the role of fear for macroeconomic expectations (e.g. Binder, 2020; Fetzer et al., 2020) and economic decline (e.g. Goolsbee and Syverson, 2021). When we isolate the share of fear that is driven by the local infections with an instrumental variable approach, we even find a much stronger effect. Finally, we observe that most of the variation in fear levels is directly driven by local infections, rather than by changes in incomes, income expectations or local restrictions. Consistent with our main effect of how uninsurable health risk decreases risky investments but insurable health risk does not, fear levels are not impacted anymore by pandemic prevalence after vaccines become available.

Our paper relates most closely to studies documenting empirical evidence on the role of background risk for financial risk-taking.[1] Previous studies document how background risk in labor income (Fagereng et al., 2018; Guiso et al., 1996; Guiso and Paiella, 2008; Heaton and Lucas, 2000), in entrepreneurial income (Heaton and Lucas, 2000), in illiquid assets (Palia et al., 2014), and from environmental conditions or climate change (Kleemann and Riekhof, 2022; Howden and Levin, 2022;

[1]Related studies on COVID-19 focused on the role of infections for asset prices (e.g., Hong et al., 2021), consumption choices (Eichenbaum et al., 2023), and risk-taking (Angrisani et al., 2020; Bu et al., 2021; Drichoutis and Nayga, 2021; Huber et al., 2021). Harrison et al. (2022) conduct repeated monthly cross-sectional samples of around 600 undergraduate students between May and November 2020. They find an increase in risk aversion compared to pre-pandemic experiments according to rank-dependent utility theory. Graeber et al. (2020) and Frondel et al. (2021) study the *stated* willingness to take risk in general by representative sample in Germany in the years before the pandemic and during the first epidemic wave until July 2020. In contrast, we focus on *incentivized, financial* risk-taking behavior throughout the pandemic, building on unique panel data following the same individuals in five waves over almost two years.

Ilhan, 2020) impact risky decision making. Fagereng et al. (2018), for instance, find that the overall effect of uninsurable wage risk on portfolio choice is limited: While marginal effects are large, uninsurable wage risk itself is small in absolute terms. In contrast, we find modest infection-investment elasticities that can, however, lead to sizable shifts in risk-taking due to the substantial variation in pandemic prevalence.

All of these studies focus on background risks primarily in the financial domain. In contrast, we focus on how non-financial background risk affects financial risk-taking. While evidence suggests that, for instance, poor health reduces financial investments and makes people prefer safer assets (Døskeland and Kvaerner, 2022; Edwards, 2008; Rosen and Wu, 2004), empirical evidence on how (background) health risk affects financial risk-taking is very scarce.[2] Courbage et al. (2018) use survey data from Europeans aged 50 or older on financial and health risks and find evidence pointing towards both risk vulnerability and cross-risk vulnerability. Baranov and Kohler (2018) use survey data from Malawi to show that health risk matters for investment decisions. They find that the local availability of an AIDS treatment increases stated savings and educational investments in children of HIV-negative individuals through a reduction in perceived mortality risk. In contrast to existing studies using survey data, we conduct an incentivized panel experiment and draw on the unique natural experiment posed by the COVID-19 pandemic to estimate within-subject changes induced by changes in uninsurable background health risk due to exogenous variations in pandemic prevalence. We show that background health risk decreases financial risk taking, which is consistent with the hypotheses of cross-DARA and cross-risk vulnerability (Beaud and Willinger, 2015; Eeckhoudt et al., 1996; Gollier and Pratt, 1996; Malevergne and Rey, 2009). The theory that we develop as the basis shows that our empirical results can be uniquely interpreted as evidence for cross-DARA.

[2] A large literature focuses on risk preferences in the aftermath of health shocks (e.g., Decker and Schmitz, 2016), or key life events like violent conflicts, natural catastrophes, economic crises, or the death of family members (e.g., Kettlewell, 2019; Malmendier and Nagel, 2011; Meier, 2022; Schildberg-Hörisch, 2018). In contrast to a focus on health status and investments in health (e.g., Hugonnier et al., 2013), we examine the *risk* of a health shock—rather than its occurrence—and its impacts on risk-taking.

Additional data collections after vaccines became available allow us to shed light on the importance of self-insurance, which leads the previously negative effect of pandemic prevalence on individual fear levels and risk-taking to vanish. As such, our paper contributes to the literature on the stability of risk preferences (e.g. Schildberg-Hörisch, 2018) by documenting how risk-taking changes during the course of a global health crisis, depending on the extent of background health risk and on the availability of vaccines that offer self-insurance against hitherto uninsurable health risks.

2 Experimental Design

We conducted an online panel survey experiment with around 5,700 Germans starting in spring 2020 during the outbreak of COVID-19 pandemic. Data was collected in five periods in March, August, and December 2020, and in June–July and December 2021. During the first three data collections, no vaccines have been available. With the availability of vaccines from early 2021, the health risk became insurable, as a vaccination strongly reduced the health consequences of a corona infection. We recruited a representative sample of the German population in terms of gender, age, education, and income via the market research company *respondi*. To compensate for attrition, we added refreshment samples with new participants from the second data collection onward.[3]

Our panel survey includes an incentivized financial investment task (Gneezy and Potters, 1997; Cohn et al., 2015, 2017).[4] Participants receive an endowment of 1 EUR which they can fully or partly invest into a risky lottery, while keeping the rest for sure. The amount invested in the risky lottery in each of the five data collection period was either multiplied by a factor of 2.5 or lost with equal probabilities, depending on a public lottery draw after each data collection period, and

[3]We present descriptive statistics on our participants sample in Table A1 in the Appendix and provide further information on our data collection in Appendix B.2.

[4]Besides an additional experimental coin-tossing task, we included a number of survey questions about household income, income loss, fear levels, compliance with regulations and stated preference measures.

paid out by respondi shortly thereafter.[5] The online format allows us to repeatedly recruit a representative sample independent of governmental regulations like stay-at-home orders. Crucially, it also avoids that participants would have to leave their home and take health risks to participate. Thus, we avoid any priming of risk-taking or selection bias.

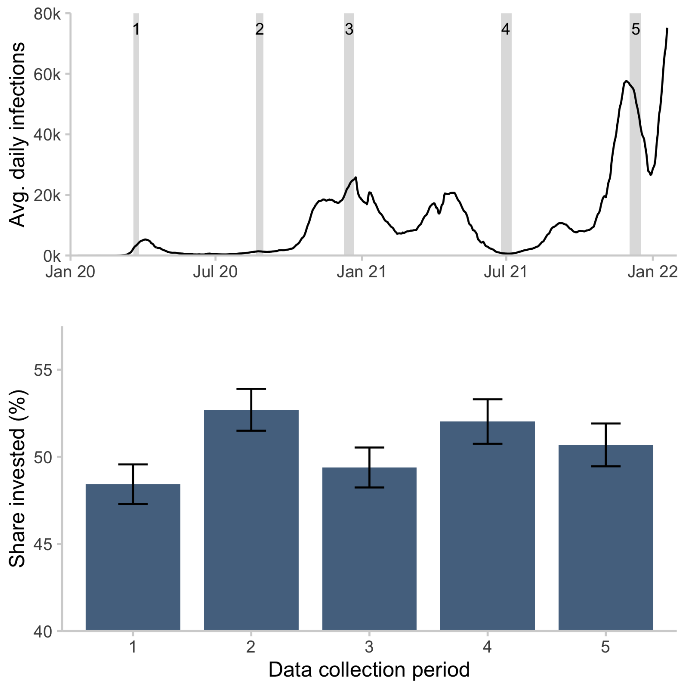
Figure 1 illustrates our data collection periods and the mean investment decisions in light of the coronavirus infections. During our first data collection period, the first infection wave of the SARS-CoV-2 virus hit Germany.[6] During our second data collection period, in contrast, infections were at a relatively low level. Finally, we ran a third data collection when the second infection wave hit, leading to a much higher peak in the number of infections. These three waves represent our main sample for examining the effect of background health risk on financial risk-taking, as no vaccine or cure was yet available. Two further data collections took place when infections were low during summer 2021 and high in winter 2021, at times when vaccines were available. The bottom panel of Figure 1 shows the average investments into the risky lottery for each data collection period. Over time, we observe a striking pattern between the pandemic prevalence and financial risk-taking: When infection rates are high (data collection periods 1, 3, and 5), participants invest substantially less money compared to periods when infection rates are low (data collection periods 2 and 4). This pattern suggests a negative correlation between background health risk and risk-taking, but it does not account for other factors that co-varied over time such as fluctuations in (labor) income, for example.

A reasonable concern is that changes in financial risk-taking over the pandemic are rather due to labor income shocks than due to background health risk. While much of the previous literature has focused on abor income risk only (Fagereng et al., 2018; Guiso et al., 1996; Guiso and Paiella, 2008; Heaton and Lucas, 2000), we focus primarily on the

[5]Please refer to Appendix B.3 for the experimental instructions.

[6]The survey of our first data collection period included an unrelated information treatment about the expected severity of the COVID-19 pandemic before the investment task and another information treatment with moral appeals after the investment task (Bos et al., 2020). In line with our pre-registered hypotheses, Table A5 in the Appendix shows that neither had an effect on the incentivized investment task.

Figure 1: Infections and financial risk-taking over time in Germany.



Notes: The top panel shows the 7-day average in the daily number of infections with SARS-CoV-2 in Germany. The gray areas indicate the time of our five data collection periods. The bottom panel shows the mean investments with two standard errors from the risk-taking task in our survey experiment during the respective data collection period. For the spatial distribution of infections and investments across counties and data collection periods see Figure A1 in the Appendix, and for the cumulative distribution of investments across respondents and data collection periods see Figure A2 in the Appendix.

role of health risk. There is no doubt that the COVID-19 pandemic caused risk of income losses for many households. In our survey, for example, participants reported a mean reduction of 7.72 [9.96] percent in their monthly household income for August [November] 2020, and for Germany as a whole, the average loss of income was 5.1% in 2020, all relative to 2019 (German Council of Economic Experts, 2021).[7]

Despite these income uncertainties, however, we expect that most changes in financial risk-taking are due to background health risk in-

[7]Likewise, capital income losses have been likely when using the volatility of the German stock market index as a risk indicator.

stead of income risk in our setting. During a pandemic, income risk is ultimately driven by health risk. As we show in a conceptual causal diagram in Figure A1 in the Appendix, businesses had to restrict their operations and introduce short-time work only due to the pandemic prevalence and local infection risks. In previous studies, the source of labor income risk is often not systematic or correlated between individuals. Individuals, for example, may face a high labor income risk due to the profitability of their employer (Fagereng et al., 2018) or due to their engagement in entrepreneurial ventures (Heaton and Lucas, 2000). In other studies, labor income risk is measured through variations in local GDP levels (Guiso and Paiella, 2008) or through stated subjective expectations (Guiso et al., 1996). In each of these studies, the underlying source of variation in labor income could be manifold. Yet, during the COVID-19 pandemic, the majority of income losses can be attributed directly to the pandemic and its associated health risks. Thus, we consider the income risk as a moderator instead of the cause in portfolio shifts in our field setting.

3 Estimation Strategy

To guide our estimation strategy and the interpretation of our empirical results, we formulate a theory that describes the individual behavior in the experiment. In particular, we try to understand how the background risk η on the respondents' health h affects their investment x in the lottery. For each cent invested in the experiment, the lottery pays out 2.5 cents with a probability of 0.5, and nothing with probability of 0.5. Any money not invested in the lottery will be payed out for sure and added to the overall income y. For concreteness, we assume that a respondent chooses an investment level x which maximizes the expected utility derived from monetary income and health,

$$\max_x \mathbb{E}_\eta \Big[0.5\, u\left(y + 1.5\, x, h - \eta\right) + 0.5\, u\left(y - x, h - \eta\right) \Big], \tag{1}$$

under uncertainty about the payoff of the lottery in the experiment (the probabilities 0.5 and 0.5 for the two outcomes are explicitly written out in equation (1)), as well as background risk on health (the expectation $\mathbb{E}_\eta$ over the background risk η). The first-order condition for the optimal investment reads

$$\mathbb{E}_\eta \Big[0.75\, u_y \left(y + 1.5\, x, h - \eta\right) - 0.5\, u_y \left(y - x, h - \eta\right) \Big] = 0, \tag{2}$$

where u_y denotes the partial derivative of utility with respect to income. Optimal investment balances expected gain (i.e. the expected marginal utility in case the respondent wins) and expected loss (i.e. the expected marginal utility in case of a loss). Given that the stakes in the experimental lottery are rather small compared to respondents' overall income, the first-order condition can be reformulated as follows:[8]

$$x = \frac{0.4}{r}, \tag{3}$$

where

$$r := -\frac{\mathbb{E}_\eta \Big[u_{yy} \left(y, h - \eta\right) \Big]}{\mathbb{E}_\eta \Big[u_y \left(y, h - \eta\right) \Big]} \tag{4}$$

is the index of absolute risk aversion with respect to income, which depends on (i) income, (ii) health level and health risk, and (iii) risk preferences (Eeckhoudt et al., 1996). Equation (3) shows that the experiment directly allows us to observe the index of absolute income risk aversion.

It seems plausible that the absolute risk aversion r decreases with the level of income and we find evidence for this in our data (cf. Figure A3 in the Appendix). So we expect *ceteris paribus* that investments

[8] Approximating (2) by a first-order Taylor series around $x = 0$, we get:

$$\mathbb{E}_\eta \Big[0.25\, u_y \left(y, h - \eta\right) + 0.625\, u_{yy} \left(y, h - \eta\right)\, x \Big] = 0. \text{ Rearranging gives (3).}$$

become larger when individuals get richer. In this paper, however, we are primarily interested in how the absolute risk aversion r depends on health risk. To answer this question, we exploit the risk of a corona infection as a salient health risk. Using p to denote the probability of a reduction in health by $\eta > 0$ due to an infection, the index of absolute income risk aversion can be expressed as

$$r = -\frac{p\, u_{yy}\left(y, h-\eta\right) + (1-p)\, u_{yy}\left(y, h\right)}{p\, u_y\left(y, h-\eta\right) + (1-p)\, u_y\left(y, h\right)}. \tag{5}$$

Given that the risk of an infection is relatively small, we use a first-order Taylor-series expansion around $p = 0$. Applying the logarithm to both sides of (5), using a first-order Taylor series expansion around $p = 0$ on the right-hand-side, and inserting (3), we obtain

$$\ln(x) = \underbrace{\ln(0.4) - \ln(r_0)}_{\text{fixed effect}} - \underbrace{\frac{\left.\frac{\partial r}{\partial p}\right|_{p=0}}{r_0}}_{\text{estimated coefficient}} p, \tag{6}$$

where $r_0 := -\frac{u_{yy}(y,h)}{u_y(y,h)}$ is the absolute income risk aversion without health risk in a state of health. We further use $r_1 := -\frac{u_{yy}(y,h-\eta)}{u_y(y,h-\eta)}$ to denote the absolute income risk aversion for an individual who got infected.

We find that absolute risk aversion r is increasing with the probability of an infection, p, if and only if there is cross-DARA, i.e. if and only if the coefficient for absolute income risk aversion is larger in case of an infection than without an infection, i.e. if and only if $r_1 > r_0$, as

$$\frac{\partial r}{\partial p} = \frac{u_y\left(y, h\right)\; u_y\left(y, h-\eta\right)}{\left(p\, u_y\left(y, h-\eta\right) + (1-p)\, u_y\left(y, h\right)\right)^2} \left(r_1 - r_0\right). \tag{7}$$

This holds in particular also true for a small risk, i.e. when letting $p \to 0$ in equation (7). We thus formulate the following result:

Proposition 1. *Absolute income risk aversion is increasing with the probability of an infection if and only if absolute income risk aversion is decreasing with the actual health status, i.e. if there is cross-DARA.*

Cross-DARA can be empirically tested by bringing the Model (6) to the data and testing the sign of the coefficient for the probability p of an infection. Allowing for some noise in the form of a normally distributed error term ε_i, we estimate Equation (6) with an ordinary least squares regression. Thus we estimate by how many percentage points, on average, the absolute risk aversion increases if the probability of an infection increases by one percentage point.[9] In further specifications, we model the relative change in risk aversion as a linear function of n observable socio-demographic characteristics X_i of individual i:

$$\frac{\left.\frac{\partial r}{\partial p}\right|_{p=0}}{r_0} = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ji}. \tag{8}$$

The corresponding empirical model reads

$$\log(x_{ict}) = \beta_0 + \alpha_i + \beta_1 p_{ct} + \beta_2 \text{Inc}_{it} \times p_{ct} + \delta \, \text{Time}_t + \epsilon_{ict} \tag{9}$$

where x_{ict} is the share of endowment invested in the risky lottery of subject i, living in county c, at time t. p_{ct} represents the probability to get infected in county c, measured by the local number of new infected persons per 1,000 residents in county c at the day of participation t.

As many employees received short-term allowance or became unemployed in response to the pandemic outbreak, we control for the change in household income with Inc_{it}, reflecting the percentage point change in households' income relative to February 2020. As motivated by our theory and given by equations (6) and (8), we interact this covariate with p_{ct}. Figure A4 in the Appendix shows almost identical results when we omit this interaction and just control for income. Any time-invariant factors like age, gender, and pre-existing health issues are absorbed by individual fixed effects α_i. Finally, we include a linear time trend with Time_t to capture experience effects over time as society learned about the pandemic, weekday fixed effects, and we use robust standard errors.

[9] As we measure the probability of an infection with the local number of infected persons per 1,000 residents, such a one percentage point increase would reflect an increase of 10 infections per 1,000 residents.

4 Results

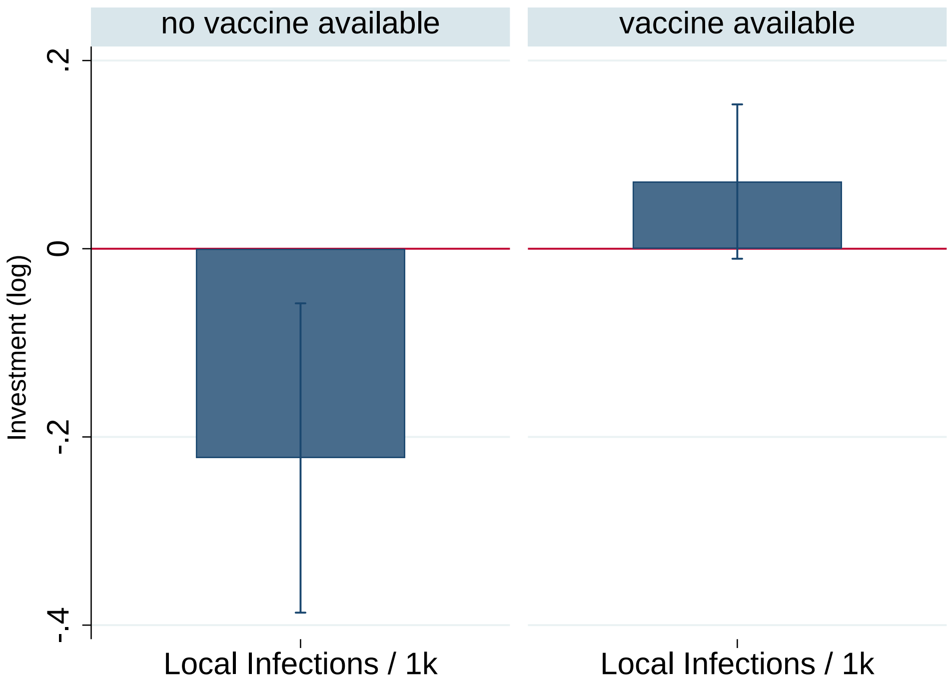
4.1 Health risk and risk-taking with and without availability of vaccination as self-insurance

We show our main result on how health risk, as measured by local coronavirus infections, affects financial risk-taking in Figure 2. First, in the left panel of Figure 2, we show that background health risk, as measured by local coronavirus infections, reduced financial risk-taking during the first three data collections, i.e. for the time when no vaccines were available. Under background health risk without vaccination as a self-insurance device, a 1 percentage point increase in the local number of infections per 1,000 residents on the day of participation decreases investments in our experiment c.p. by 0.22 percentage points. Following the intuition of our theory, we interpret these coefficients as the relative change in absolute risk aversion due to background health risk.

While the marginal effect size is modest, it translates into substantial overall effects. As the average number of infections decreased by almost a factor of four between our first and second data collection period, it increased by a factor of almost 20 between the second and third period. Similarly, we also observe strong variation across space with a 6-fold [12-fold; 3-fold] gap in local infections between the bottom 10% and top 10% of participants during the first [second; third] data collection period. In contrast to the risks associated with pandemic prevalence, we held the risk profile of the investment task constant over time.

In early 2021, vaccinations became available at scale, making health risks (partially) self-insurable. Accordingly, one would expect an alleviated background risk which translates into a reduced risk vulnerability as compared to our result from the first three rounds of data collection. Indeed, once people could self-insure against the severe health risk posed by COVID-19 via vaccines in later data collection periods, higher local coronavirus infections did not translate into reduced risk-taking anymore, as shown in the right panel of Figure 2. This highlights how self-insurance options can alleviate cross-DARA or cross-vulnerability of financial risk-taking to non-financial risks.

Figure 2: Effect of background health risk on risk-taking.



Notes: This figure shows the estimated effect of background health risk on financial risk-taking with and without availability of vaccination as self-insurance. It is based on the fixed-effects estimation described in Equation 9. N = 8,041 for the effect in data of our first three data collections and N = 3,658 for the effect during our last two data collections, when vaccination was available. Bars represent the coefficient β_1 capturing the effect of the number of reported infections in participants' counties per 1,000 residents at the day of participation in our survey on the investment level into the risky asset in our experiment. We provide more detailed results in Table A2 in the Appendix. Error bars represent 95 percent confidence intervals.

4.2 Mechanisms

Our main analysis builds on the direct link between pandemic prevalence inducing health risks and its effect on financial risk-taking. As we illustrate in a conceptual causal diagram in Figure A1 in the Appendix, pandemic prevalence may also affect risk-taking, for instance, through the effects of the pandemic on income losses and background income risks, as well as through fear. In this section, we first explore the income channel by examining how pandemic prevalence affects individuals who could more or less easily self-protect against background health risks as well as background income risks by being able to work from home. We then explore a key channel through which background risks affect financial risk-taking that has been identified in the literature: fear (Cohn et al., 2015; Guiso et al., 2018). Subsequently, we study the relative strength of background health risk and background income risk on fear levels and isolate the effect of fear on financial risk-taking. Again, we do this separately for data from our first three data collection periods when the pandemic-induced health risk was not self-insurable, and for the last two data collection periods when health risks became insurable via vaccines.

Income channel

Already during the first three data collection periods, people could partially protect against income shocks by working from home. Being able to work from home not only reduces the risk of getting infected, but it also protects employees from short-time work and associated income effects (Alipour et al., 2021). Choosing a job that can be done from home can thereby serve as a protection device against negative (income) shocks during a global health crisis. As a result, we would expect a lower impact on risk-taking for employees with a high feasibility to work from home. Yet, the issue of self selection into such jobs makes it difficult to clearly identify this effect as people with a low income, less education, and fewer liquid assets are often less likely to work from home (Mongey et al., 2021). Accordingly, in Table 1, we provide suggestive evidence comparing the impact of the local number of infections between participating employees living in a county with a high versus a low feasibility to work from home.[10]

At times when the risk of an coronavirus infection was uninsurable, Table 1 documents an insignificant impact on investments for participating employees living in counties with a low feasibility, but a strong impact for those living in a county with a high feasibility. This contrasts our expectation that a high feasibility to work from home can reduce the

[10] In Table A3 in the Appendix, we provide additional results from further analyses exploring additional measures on the feasibility to work from home and compare employees against retirees.

Table 1: Effect of the feasibility to work from home on risk-taking.

	WFH feasibility (no vaccine available)		WFH feasibility (vaccine available)	
	Low	High	Low	High
Local infections / 1k	-0.0683	-0.646***	0.130**	-0.0382
	(0.135)	(0.216)	(0.065)	(0.088)
Observations	2,413	2,538	1,077	1,111

Notes: This table shows results from fixed effects estimations using a sample of participating employees only. The dependent variable is the logarithmic investment level in our experiment. In Columns (1) and (3), we focus on employees living in a county with a low feasibility to work from home. In Columns (2) and (4), we focus on those living in a county with a high feasibility to work from home. The split is based on the median value and the corresponding data is taken from Alipour et al. (2021). Covariates include an interaction between the change in households income relative to February 2020 with the number of infections, weekday fixed effects, individual fixed effects, and a linear time trend. Robust standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

impact via partial self-protection. Instead, it highlights that personal characteristics and self-selection seem to matter more for changes in financial risk-taking behavior. In the next section, we show that actual and expected income changes have an indirect impact on financial risk-taking by reducing participants' fear level. Yet, we find no evidence that the ability to work from home directly mitigates the impact of the pandemic prevalence on financial risk-taking. When health risks becomes self-insurable, this negative impact within counties with a high feasibility to work from home becomes insignificant and we observe that people living in a county with a low feasibility to even slightly increase their investments from summer 2021 to winter 2021 when infections increased. We also find that particularly those people who live in a county with few employees on short-time work during summer 2021 increase their investments during that time period (cf. Table A4).[11]

[11] We did not expect a positive direction of the effect for people in counties with a high feasibility to work from home under insurable health risk, and can only make ex-post hypotheses about its causes: First, for the period with insurable health risk, we only have data from two periods so that there is less temporal variation and spatial variation is more relevant. Second, local labor market characteristics, a period of economic recovery, and improvements on local labor markets may have led to more infections while simultaneously reducing risk-aversion after vaccines became avail-

Fear channel

Consistent with the literature (Cohn et al., 2015; Guiso et al., 2018), we find that a substantial share of the changes in financial risk-taking is driven by fear, which we elicit on a 7-point Likert scale following (cf. Cohn et al., 2015). We further observe a positive correlation between the self-reported fear level and the local number of infections. When infections peaked in March 2020, most participants reported a high fear level. The average fear level declined with the number of infections in August 2020, and increased again in December 2020 (cf. Table A1 in the Appendix).

In Table 2, we provide evidence on the role of fear for financial risk-taking and differentiate between periods when the health risk was not or was self-insurable by means of the vaccination. In Column (1), we show a significantly negative correlation between participants' fear level and their investments when no vaccine was available. As fear can be driven by various factors, we isolate the share of fear that is driven by local infections in Column (2). We use an instrumental variable approach with the logarithm of the local number of infections as an instrument for the current fear level. In the first stage, we predict the fear level that is driven by the pandemic prevalence and regress this predicted fear level on the investment behavior in the second stage. The two-stage least square estimate suggests that a one percent increase in the self-reported fear level, due to the local pandemic prevalence, reduces investments by almost 0.3 percent. With the availability of vaccines, the negative relationship between infections and fear disappears as shown in Columns (3) and (4). Again, this highlights the role of self-insurance devices which can attenuate the impact of background health risk via fear on financial risk-taking.

Finally, Figure 3 explores the predictors of fear and also differentiates between times when background health risks were or were not self-insurable. When no vaccine is available, we observe that the number of infections increases the self-reported fear level of participants and has

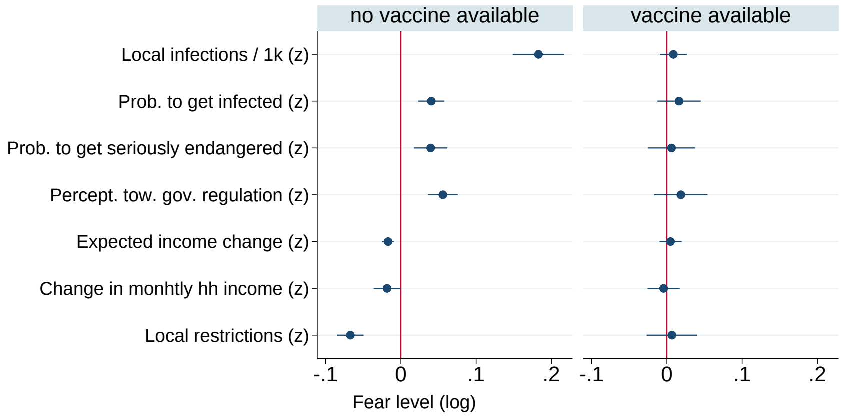
able. This would suggest that people may have started to accept the insurable health risk from an infection in order to satisfy other needs.

Table 2: Fear moderator for financial risk-taking.

	no vaccine available		vaccine available	
	FE	IV	FE	IV
	(1)	(2)	(3)	(4)
Fear level (log)	-0.068***	-0.297***	-0.009	-1.140
	(0.024)	(0.100)	(0.038)	(1.887)
Observations	8,255	4,589	3,801	1,806
F statistic		213.64		0.93
First stage:				
Local infections/1k (log)		0.092***		-0.018
		(0.006)		(0.018)

Notes: This table shows results from fixed effects estimations and instrumental variable estimations. In Columns (1) and (2), we focus on the first three data collection periods when no vaccine was available. In Columns (3) and (4), we focus on the last two data collection periods when vaccines rendered the health risk self-insurable. The dependent variable is the logarithmic investment level in our experiment. The main explanatory variable is the self-reported fear level. In Columns (2) and (4), we instrument the fear level with the logarithm of the local number of infections to isolate the share of fear driven by the pandemic prevalence. Regressions include the change in monthly household income relative to February 2020, individual fixed effects and a constant. Robust standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 3: Predictors of the fear level.



Notes: This figure shows the predicted impact of various factors on the self-reported fear level at times when no vaccine was available (left panel) and with vaccine available (right panel). It is based on fixed effect estimations with the logarithmic fear level as the dependent variable. All potential explanatory variables that are shown have been standardized using their z-scores to compare their magnitude. The perception towards governmental regulation ranges from "[measures] are way too much" to "[measures] are way too little". Due to concerns about multicollinearity, we report separate results on the impact of the number of deaths in Figure A7 in the Appendix.

the strongest effect among all potential drivers considered. Likewise, participants report a higher fear level when they expect a high probability to get infected and to get seriously endangered once they are infected. The perception towards governmental regulation is positively correlated with the fear level meaning that those who think governmental regulations are not enough have a higher fear level. Furthermore, those who expected and got a lower income compared to times prior to the pandemic report a lower fear level. These impacts disappear, however, during later data collection periods when vaccines rendered the health risk self-insurable. None of those previously relevant factors seem to matter anymore. In Figure A7 in the Appendix, we find similar results when we use the number of deaths instead of the infections.

5 Robustness checks

To examine the robustness of our main result on how uninsurable health risk affects financial risk-taking, we carry out several additional analyses. First, we consider an alternative metric for pandemic prevelance: COVID-19 attributed deaths. Subsequently, we investigate, among others, the impact of seasonality, the number of local restrictions to contain the pandemic, and explore effects on the extensive margin, i.e. the decision to make an investment in the first place.

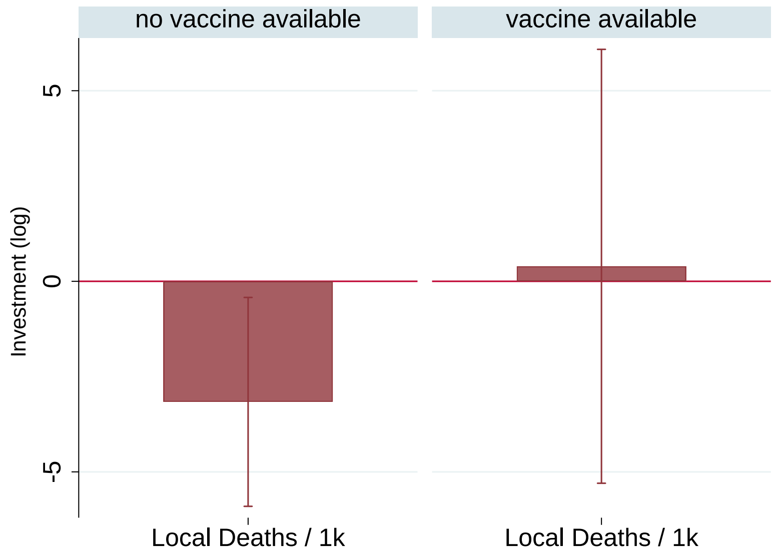
Deaths as alternative proxy for background health risk

In our main analysis, we use the local number of infections on the day of the participant's participation in the panel experiment as a proxy for background health risk. This measure is beneficial as it captures the probability of an infection which can lead to various health outcomes. However, the reported number of infections depends on testing strategies and capacities, which varied over time. As a consequence, the reported number of infections is a lower bound and may not capture infected people that did not get tested due to an asymptomatic infection and those that have not been tested at official test stations. While those factors lead to a downward bias in the reported number of infections, they may attenuate our estimated effects.[12] This means that we might expect even stronger effects if people would had known the actual number of infections at the time of their participation in our experiment, which is likely much higher.

We overcome the issue of testing strategies and capacities by using the number of local deaths that are related to a coronavirus infection as an alternative measure for background health risk. The number of local death related to COVID-19 has therefore more precision and is

[12] Irrespective of measurement error caused by testing strategies and capacities, measurement error can also be caused by the precision of test kits themselves. False-positive test results could lead to an upward bias and false-negatives to a downward bias in the reported number of infections. While test kits usually have lower false-negative rates than false-positive rates (Dinnes et al., 2022), this would imply fewer actual infections. We suspect, however, that testing strategies and capacities had a larger impact on the overall measurement error than the precision of test kits.

Figure 4: Effect of background health risk (for deaths) on risk-taking.



Notes: The figure re-estimates our main specification (9) but using the local number of deaths in participants' counties per 1,000 residents as a measure of health risk. Bars represent the coefficient β_1 that captures the effect of the background health risk. Error bars represent 95 percent confidence intervals.

another key measure that was very salient during our study period and frequently reported in the news. In addition, this measure also directly captures the drastic potential health damages of an infection and allows for better comparisons over time, at least until vaccines and other medical treatments became available, and later mutations of the coronavirus became less severe in terms of their case-fatality rate.

In Figure 4, we replicate our main results using the number of local deaths per 1,000 residents as a proxy for health risk and find consistent results. For the time period without availability of vaccines, an increase in the number of deaths during the past 7 days significantly reduces investments in a risky asset, but this effect becomes insignificant with pharmaceutical interventions to contain the health risk.[13]

[13] The effect of background health risk may also depend on the capacity to get treatment in case of a severe illness and thus on pandemic prevalence in neighboring counties. To explore effects along different spatial bandwidths, we apply a spatial smoothing and attach a positive weight to infections and deaths that occur in neighboring counties (see Appendix B.4 for details). In Figure A6 in the Appendix, we show that the impact of background health risk slightly increases for people who attach a positive weight to their neighboring counties.

Seasonality

As the timing of our data collection periods was determined by the course of the pandemic prevalence, data collection periods usually occurred in different seasons of the year. Seasonality can be problematic as it could affect both infections (e.g., Carleton et al., 2021; Kerr et al., 2021) as well as financial risk-taking. Although there are no systematic studies focusing on how risk preferences change over the seasons, there is some evidence suggesting effects of seasonality and luminosity on economic preferences. For example, seasonal affective disorder (SAD), which is also known as "winter blues" due to fewer hours of sunshine, received much attention in the context of stock market returns (e.g., Kamstra et al., 2003). Evidence on the effect of seasonality, (day-)light or weather on risk-taking from controlled experiments and studies using natural experiments, are, however, scarce. Exemptions are Kramer and Weber (2012), who use a variant of the investment game to study risk-taking of university students (N=331) in July and December 2008 as well as July 2009. They find that individuals who scored higher on a SAD questionnaire exhibited less risk-taking in the winter as compared to the rest of the sample. Bassi et al. (2013) study whether risk-taking of university students (N=208) is affected by weather conditions and find that more sunshine and good weather lead to more risk-taking using a multiple price list design. Finally, contrasting the previous result, Glimcher and Tymula (2017) conduct a much larger but less tightly controlled study with visitors (N=2530) to the National Academy of Sciences Museum in Washington, DC., and find that increased luminosity leads to more not less risk-aversion.

We address the seasonality concern as follows: We elicited if participants are likely to suffer from SAD and compare estimates between those who do and those who do not. To this end, we added a short questionnaire following Rosenthal et al. (1984) to identify subjects that are likely to suffer from SAD in the fifth data collection period. We identified 13 percent of participants who may likely suffer from SAD. For those who suffer from SAD, we would attribute the major share of their changes in financial risk-taking to changes in the seasons, but would not expect that the pandemic prevalence predominantly affects changes in their financial risk-taking between data collection periods. For those who do not suffer from SAD, however, we expect that changes in risk-taking are independent from the seasons.

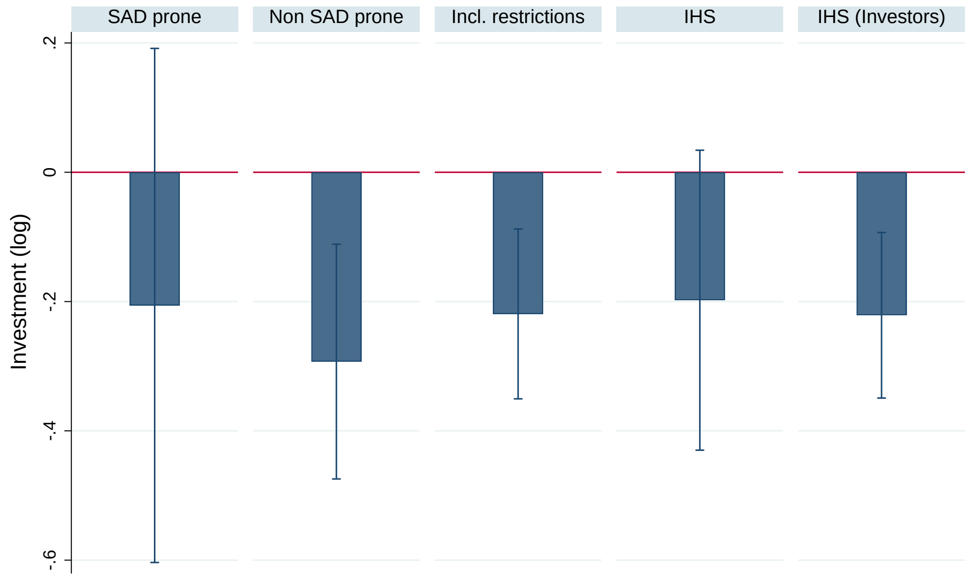
Columns (1) and (2) in Figure 5 shows results consistent with our main results for those that are prone to not suffer from SAD. These subjects reduce their financial investments for reasons that do not seem to be related to the season, suggesting that seasonality may only have a limited effect on the changes in financial risk-taking occurring during the pandemic. Subjects that are prone to suffer from SAD, however, show no reaction to increases in the health risk as seasonality seems to dominate changes in their risk-taking behavior.

Local pandemic politics

To rule out that our results are driven by changes in the local measures to contain the pandemic and by mental health effects associated with it (Ahrens et al., 2021; Bogan and Fertig, 2013), we control for them in another robustness check. To this end we rely on data by infas360 (2023), who indicate for 21 categories if local restrictions to contain the pandemic are in place or not. These categories include restrictions for private and public places, schools, events, restaurants, hospitality, sport activities, and more. For each county and day, we sum up all measures and consider the resulting index M_{ct} as a proxy for local restrictions in county c at time t and add them to our main specification. Column (3) in Figure 5 shows that while the impact of background health risk on risk-taking decreases slightly, we still observe a clear tempering effect of the number of infections and deaths on risk-taking.

Although evidence shows mixed and heterogeneous effects (Ahrens et al., 2021), regulations to contain the pandemic could also have affected the mental health of participants directly so that we cannot rule out that some fraction of the change in risk-taking is due to poorer mental health (cf. Bogan and Fertig, 2013). Brülhart et al. (2021), for instance, find that increased helpline calls during the pandemic were strongly driven by fear and concerns directly linked to the pandemic.

Figure 5: Robustness checks.



Notes: This figure summarizes results from different robustness checks and extensions. It shows the reduction in investments depending on the local number of infections over different variations of our main specification. All regressions are based on the first three data collection periods. Column (1) only includes subjects that are prone to SAD (N = 665), and Column (2) includes only subjects that are not prone to SAD ($N = 4,165$). In Column (3), we control for the number of local restrictions ($N = 8,316$) and in Columns (4) and (5), we transform the level of investments with the inverse hyperbolic sine ($N = 9,732$) and exclude subjects that never made an investment ($N = 8,316$). We replicate these robustness checks also for the number of deaths as a proxy for uninsurable health risk and report their results in Figure A8 in the Appendix. Error bars represent 95 percent confidence intervals.

They show that—conditional on infection rates—suicide-related calls increased when containment policies became more stringent. Pandemic policy stringency might therefore also affect risk-taking via the fear channel examined above. As shown in Figure 3, however, we find that local stringency of pandemic containment policies tend to have reduced fear levels instead of increasing them. We therefore do not find evidence that our main effect may be driven by decreases in mental health due to containment policies.

Extensive margin

Our main results focus on the investment level of participants that made a positive investment. The focus on this intensive margin is given by the logarithmic transformation of the investment level in our theory-led estimation strategy, which excludes around 15 percent of the participants, who did not invest anything of their endowment in one of the data collection periods. To explore effects when including those subjects, i.e. the extensive margin, we re-estimate our main results and use an inverse hyperbolic sine transformation of the investment level (cf., e.g., Baranov and Kohler, 2018).

In Column (4) in Figure 5 we observe that the impact of the local number of infections becomes insignificant while the effect of the local number of deaths becomes stronger. Although we would expect that participants that do not invest in spring 2020 start to invest in summer 2020 when infections and deaths went down, many do not start to invest even at a time with a lower infection risk. As a result, we exclude 416 participants (i.e., 8.6 percent) that never invested anything in another specification. We show those results in Column (5) which are based on participants that invested at least a positive amount once. Those results are similar to our main results. We, therefore, conclude that the observation of a larger standard error for the case of infections Column (4), rendering the main result insignificant, is driven in particular by participants that never invested in the lottery and highlight that our results hold for participants that made at least some positive investment once.

6 Conclusion

We study how background health risk affects financial risk-taking. An extra risk on a non-financial asset decreases the expected value of this asset and the financial absolute risk aversion decreases with expected non-financial wealth if individuals exhibit cross-DARA (Malevergne and Rey, 2009). We are not aware of any plausibly causal estimate of how non-financial background risks impact risk-taking. To fill this gap, we leveraged the COVID-19 pandemic as a natural experiment and repeatedly elicited financial risk-taking behavior of a representative sample of more than 5,000 Germans during the COVID-19 pandemic in a panel experiment over five data collection periods.

Exploiting variation in pandemic prevalence across time and space that is exogenous for an individual, we find that an increase in background health risk decreases investments in a risky asset. Given the substantial spatial and temporal heterogeneity in pandemic prevalence, our findings suggest notable shifts in risk-taking due to background health risk during a major global health crisis. We identify fear as a key mechanism for how background health risk affects financial risk-taking. Furthermore, once vaccines became available as a self-insurance device, infections do not affect fear levels anymore, and the tempering effect on risky investments ceases. Our results provide field experimental evidence for reduced financial risk taking due to non-financial background risks, in particular support for the hypothesis of cross-DARA, and for the alleviating effect of insurance devices.

One feature of our analysis is both a key advantage and limitation. Identifying the effects of background risk, in particular when caused by larger-scale shocks, is complicated by the fact that the source of background risk may not only affect individual risk-taking but also returns on stock and bond markets, for instance. Our approach has the benefit that we can keep the payoff structure of the risky investment task in our panel experiment constant throughout the pandemic. This allows for cleaner identification yet limits the generalizability of our results for actual portfolio choices. Evidence from the field indeed appears to be mixed. While Au et al. (2023), for example, show that fund managers located in or socially connected to COVID-19 hotspots in the United States sold more stock holdings during the initial phase of the pandemic than other investors, Ozik et al. (2021) document an overall increase in market participation and trading activity among retail investors during the pandemic due to better access to financial markets, more savings, and more leisure time. When comparing our experimental results with observational data, one needs to consider that we impose a controlled environment in which we hold the features of the risky asset constant over time and independent from the state of the economy. While Breunig et al. (2021) show that behavior in a stylized portfolio choice problem is predictive for actual stock market participation, household's trading behavior in the field is driven by a host of factors, including stock prices and market liquidity. Here, we can only infere how pandemic prevalence translates into risk-taking in a controlled experimental setting. Thus, while we do not claim that the effects of background health risk directly translate to financial behavior in the field, our results point towards an important role of health risk for financial risk-taking.

Overall, our results provide important insights for delineating factors that affect the stability of risk-taking behavior (Schildberg-Hörisch, 2018), and indicate the magnitude of potential (short-term) distortions of preferences and behavior due to a global health crisis. Importantly, our findings shed light on an additional channel of how background risks affect risk-taking and portfolio choice (e.g. Eeckhoudt et al., 1996; Heaton and Lucas, 2000; Fagereng et al., 2018): in the form of health risk. We further shed light on important mediating factors, such as fear, and alleviating factors, such as vaccines. While Fagereng et al. (2018) find that uninsurable wage risks have only a limited effect on portfolio choice, the modest infection-investment elasticities we observe may have induced sizable shifts in risk-taking due to the substantial variation in pandemic prevalence across time and space. More broadly, our results from the uninsurable phase of the COVID-19 pandemic when vaccines were not available may foreshadow possible effects of future health risks induced by infectious diseases that are projected to increase, among others, due to climate change and biodiversity loss, which may trigger even more sizable health risks in the future (e.g., Baker, 2020;

Haines et al., 2006; Lindgren et al., 2012; O'Neill, 2016; Jones et al., 2008). While our study examines the effects of background risk induced by a global health crisis on risk-taking in a relatively controlled experimental setting, future work should investigate the economic impacts of non-financial risks on financial risk-taking in less tightly controlled settings and on other important economic outcomes, such as human capital investments.

References

Ahrens, K., R. Neumann, B. Kollmann, J. Brokelmann, N. Von Werthern, A. Malyshau, D. Weichert, B. Lutz, C. Fiebach, M. Wessa, et al. (2021). Impact of COVID-19 lockdown on mental health in Germany: longitudinal observation of different mental health trajectories and protective factors. *Translational psychiatry 11*(1), 1–10.

Alipour, J.-V., H. Fadinger, and J. Schymik (2021). My home is my castle – The benefits of working from home during a pandemic crisis. *Journal of Public Economics 196*, 104373.

Angrisani, M., M. Cipriani, A. Guarino, R. Kendall, and J. Ortiz de Zarate (2020). Risk Preferences at the Time of COVID-19: An Experiment with Professional Traders and Students. FRB of New York Staff Report No. 927.

Au, S.-Y., M. Dong, and X. Zhou (2023). Does social interaction spread fear among institutional investors? Evidence from COVID-19. *Management Science*, forthcoming.

Bacon, P. M., A. Conte, and P. G. Moffatt (2020). A test of risk vulnerability in the wider population. *Theory and Decision 88*(1), 37–50.

Baker, R. E. (2020). Climate change drives increase in modeled HIV prevalence. *Climatic Change 163*(1), 237–252.

Baranov, V. and H.-P. Kohler (2018). The Impact of AIDS Treatment on Savings and Human Capital Investment in Malawi. *American Economic Journal: Applied Economics 10*(1), 266–306.

Bassi, A., R. Colacito, and P. Fulghieri (2013). 'O sole mio: An experimental analysis of weather and risk attitudes in financial decisions. *The Review of Financial Studies 26*(7), 1824–1852.

Beaud, M. and M. Willinger (2015). Are People Risk Vulnerable? *Management Science 61*(3), 624–636.

Binder, C. (2020). Coronavirus fears and macroeconomic expectations. *The Review of Economics and Statistics 102*(4), 721–730.

Bogan, V. L. and A. R. Fertig (2013). Portfolio Choice and Mental Health. *Review of Finance 17*(3), 955–992.

Bos, B., M. A. Drupp, J. N. Meya, and M. F. Quaas (2020). Moral Suasion and the Private Provision of Public Goods: Evidence from the COVID-19 Pandemic. *Environmental and Resource Economics 76*(4), 1117–1138.

Breunig, C., S. Huck, T. Schmidt, and G. Weizsäcker (2021). The Standard Portfolio Choice Problem in Germany. *The Economic Journal 131*(638), 2413–2446.

Brülhart, M., V. Klotzbücher, R. Lalive, and S. K. Reich (2021). Mental health concerns during the COVID-19 pandemic as revealed by helpline calls. *Nature 600*(7887), 121–126.

Bu, D., T. Hanspal, Y. Liao, and Y. Liu (2021). Risk Taking, Preferences, and Beliefs: Evidence from Wuhan. SAFE Working Paper No. 301.

Carleton, T., J. Cornetet, P. Huybers, K. C. Meng, and J. Proctor (2021). Global evidence for ultraviolet radiation decreasing COVID-19 growth rates. *Proceedings of the National Academy of Sciences 118*(1).

Cohn, A., J. Engelmann, E. Fehr, and M. A. Maréchal (2015). Evidence for Countercyclical Risk Aversion: An Experiment with Financial Professionals. *American Economic Review 105*(2), 860–885.

Cohn, A., E. Fehr, and M. A. Maréchal (2017). Do Professional Norms in the Banking Industry Favor Risk-taking? *The Review of Financial Studies 30*(11), 3801–3823.

Courbage, C., G. Montoliu-Montes, B. Rey, et al. (2018). How vulnerable is risk aversion to wealth, health and other risks? An empirical analysis for Europe. Technical report.

Decker, S. and H. Schmitz (2016). Health shocks and risk aversion. *Journal of Health Economics 50*, 156–170.

Dinnes, J., P. Sharma, S. Berhane, S. S. van Wyk, N. Nyaaba, J. Domen, M. Taylor, J. Cunningham, C. Davenport, S. Dittrich, D. Emperador,

L. Hooft, M. M. Leeflang, M. D. McInnes, R. Spijker, J. Y. Verbakel, Y. Takwoingi, S. Taylor-Phillips, A. Van den Bruel, J. J. Deeks, and Cochrane COVID-19 Diagnostic Test Accuracy Group (2022). Rapid, point-of-care antigen tests for diagnosis of SARS-CoV-2 infection. *Cochrane Database of Systematic Reviews* (7).

Døskeland, T. and J. S. Kvaerner (2022). Cancer and portfolio choice: Evidence from norwegian register data. *Review of Finance 26*(2), 407–442.

Drichoutis, A. C. and R. M. Nayga (2021). On the stability of risk and time preferences amid the COVID-19 pandemic. *Experimental Economics*, 1–36.

Edwards, R. D. (2008). Health Risk and Portfolio Choice. *Journal of Business & Economic Statistics 26*(4), 472–485.

Eeckhoudt, L., C. Gollier, and H. Schlesinger (1996). Changes in background risk and risk taking behavior. *Econometrica 64*(3), 683–689.

Eichenbaum, M. S., M. G. de Matos, F. Lima, S. Rebelo, and M. Trabandt (2023). Expectations, Infections, and Economic Activity. Working Paper. https://drive.google.com/file/d/14EC9wb2g_XFHr2i3aZn_xH8Q_OGpY9hQ/view.

Fagereng, A., L. Guiso, and L. Pistaferri (2018). Portfolio Choices, Firm Shocks, and Uninsurable Wage Risk. *The Review of Economic Studies 85*(1), 437–474.

Fetzer, T., L. Hensel, J. Hermle, and C. Roth (2020). Coronavirus Perceptions and Economic Anxiety. *The Review of Economics and Statistics*, 1–36.

Frondel, M., D. Osberghaus, and S. Sommer (2021). Corona and the Stability of Personal Traits and Preferences: Evidence From Germany. ZEW Discussion Papers 21-029.

German Council of Economic Experts (2021). Ecomomic Outlook 2021 and 2022. Technical report, Wiesbaden.

Glimcher, P. W. and A. Tymula (2017). Let the sunshine in? The effects of luminance on economic preferences, choice consistency and dominance violations. *PLOS ONE 12*(8), e0181112.

Gneezy, U. and J. Potters (1997). An Experiment on Risk Taking and Evaluation Periods. *The Quarterly Journal of Economics 112*(2), 631–645.

Gollier, C. and J. W. Pratt (1996). Risk Vulnerability and the Tempering Effect of Background Risk. *Econometrica 64*(5), 1109–1123.

Goolsbee, A. and C. Syverson (2021). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *Journal of Public Economics 193*, 104311.

Graeber, D., U. Schmidt, C. Schroeder, and J. Seebauer (2020). The Effect of a Major Pandemic on Risk Preferences - Evidence from Exposure to COVID-19. *SSRN Electronic Journal*.

Guiso, L., T. Jappelli, and D. Terlizzese (1996). Income Risk, Borrowing Constraints, and Portfolio Choice. *The American Economic Review 86*(1), 158–172.

Guiso, L. and M. Paiella (2008). Risk aversion, wealth, and background risk. *Journal of the European Economic Association 6*(6), 1109–1150.

Guiso, L., P. Sapienza, and L. Zingales (2018). Time varying risk aversion. *Journal of Financial Economics 128*(3), 403–421.

Haines, A., R. S. Kovats, D. Campbell-Lendrum, and C. Corvalan (2006). Climate change and human health: Impacts, vulnerability, and mitigation. *The Lancet 367*(9528), 2101–2109.

Harrison, G. W., A. Hofmeyr, H. Kincaid, B. Monroe, D. Ross, M. Schneider, and J. T. Swarthout (2022). Subjective beliefs and economic preferences during the COVID-19 pandemic. *Experimental Economics*, 1–29.

Heaton, J. and D. Lucas (2000). Portfolio Choice and Asset Prices: The Importance of Entrepreneurial Risk. *The Journal of Finance 55*(3), 1163–1198.

Hong, H., N. Wang, and J. Yang (2021). Implications of Stochastic Transmission Rates for Managing Pandemic Risks. *The Review of Financial Studies*.

Howden, W. and R. Levin (2022). The Global Impacts of Climate Change on Risk Preferences. *SSRN Electronic Journal*.

Huber, C., J. Huber, and M. Kirchler (2021). Market shocks and professionals' investment behavior – evidence from the COVID-19 crash. *Journal of Banking & Finance 133*, 106247.

Hugonnier, J., F. Pelgrin, and P. St-Amour (2013). Health and (Other) Asset Holdings. *The Review of Economic Studies 80*(2), 663–710.

Ilhan, E. (2020). Sea Level Rise and Portfolio Choice. Technical report.

infas360 (2023). Corona-Datenplattform – Verordnungen. Accessed on January 17, 2023.

Jones, K. E., N. G. Patel, M. A. Levy, A. Storeygard, D. Balk, J. L. Gittleman, and P. Daszak (2008). Global trends in emerging infectious diseases. *Nature 451*(7181), 990–993.

Kamstra, M. J., L. A. Kramer, and M. D. Levi (2003). Winter blues: A sad stock market cycle. *American Economic Review 93*(1), 324–343.

Kerr, G. H., H. S. Badr, L. M. Gardner, J. Perez-Saez, and B. F. Zaitchik (2021). Associations between meteorology and COVID-19 in early studies: Inconsistencies, uncertainties, and recommendations. *One Health 12*, 100225.

Kettlewell, N. (2019). Risk preference dynamics around life events. *Journal of Economic Behavior & Organization 162*, 66–84.

Kleemann, L. and M.-C. Riekhof (2022). Background risk and risk-taking – evidence from the field. *Environment and Development Economics*, 1–20.

Kramer, L. A. and J. M. Weber (2012). This is your portfolio on winter: Seasonal affective disorder and risk aversion in financial decision making. *Social Psychological and Personality Science 3*(2), 193–199.

Lindgren, E., Y. Andersson, J. E. Suk, B. Sudre, and J. C. Semenza (2012). Monitoring EU Emerging Infectious Disease Risk Due to Climate Change. *Science 336*(6080), 418–419.

Malevergne, Y. and B. Rey (2009). On cross-risk vulnerability. *Insurance: Mathematics and Economics 45*(2), 224–229.

Malmendier, U. and S. Nagel (2011). Depression Babies: Do Macroeconomic Experiences Affect Risk Taking? *The Quarterly Journal of Economics 126*(1), 373–416.

Meier, A. N. (2022). Emotions and Risk Attitudes. *American Economic Journal: Applied Economics 14*(3), 527–58.

Mongey, S., L. Pilossoph, and A. Weinberg (2021). Which workers bear the burden of social distancing? *The Journal of Economic Inequality 19*(3), 509–526.

O'Neill, J. (2016). Tackling drug-resistant infections globally: Final report and recommendations. Review on Antimicrobial Resistance.

Ozik, G., R. Sadka, and S. Shen (2021). Flattening the illiquidity curve: Retail trading during the COVID-19 lockdown. *Journal of Financial and Quantitative Analysis 56*(7), 2356–2388.

Palia, D., Y. Qi, and Y. Wu (2014). Heterogeneous Background Risks and Portfolio Choice: Evidence from Micro-level Data. *Journal of Money, Credit and Banking 46*, 1687–1720.

Rosen, H. S. and S. Wu (2004). Portfolio choice and health status. *Journal of Financial Economics 72*(3), 457–484.

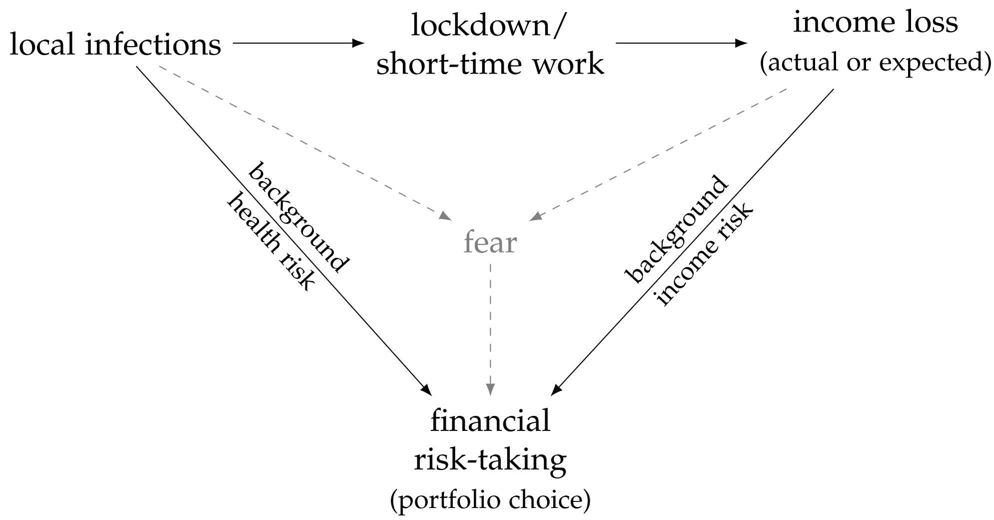
Rosenthal, N., G. Bradt, and T. Wehr (1984). Seasonal pattern assessment questionnaire (spaq). National Institute of Mental Health, Bethesda MD.

Schildberg-Hörisch, H. (2018). Are Risk Preferences Stable? *Journal of Economic Perspectives 32*(2), 135–154.

Vos, T., S. S. Lim, C. Abbafati, and et al. (2020). Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. *The Lancet 396*(10258), 1204–1222.

Appendix A

Figure A1: Conceptual Causal Diagram.

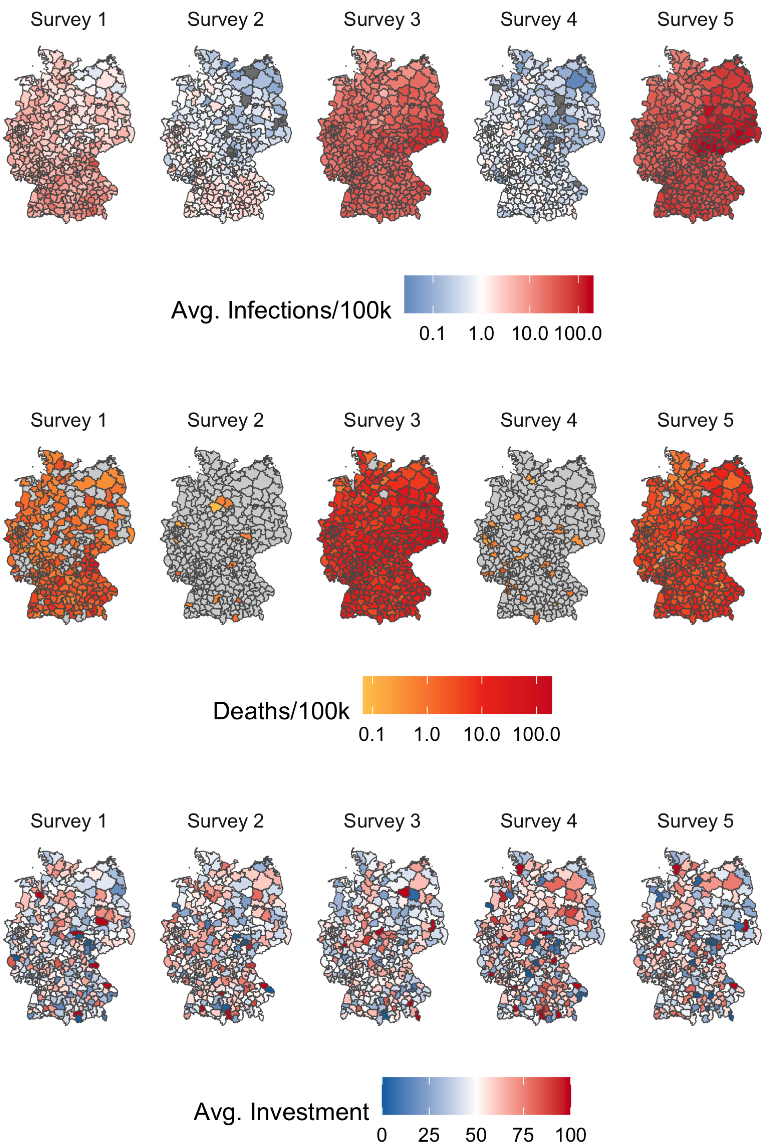


Notes: This figure shows a conceptual causal diagram of how a global health crisis can affect financial risk-taking and portfolio choice. Local infections (or deaths) have a direct impact on risk-taking behavior via background health risk, but they also lead to lockdowns and short-time work so that they can also cause income losses. Compared to previous studies analyzing background risk in income, income shocks are correlated in our setting and ultimately originate from health risks caused by pandemic prevalence, measured by infections or deaths.

Appendix B For Online Publication

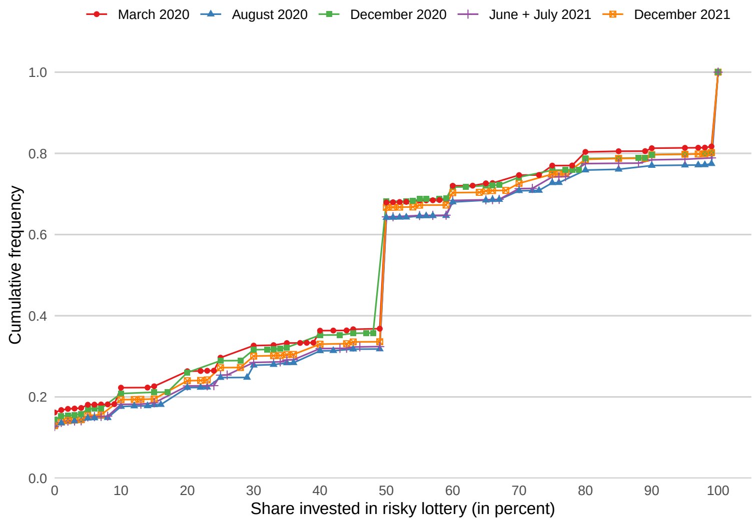
B.1 Additional figures and tables

Figure A1: Infections, deaths and investments per county and data collection period.



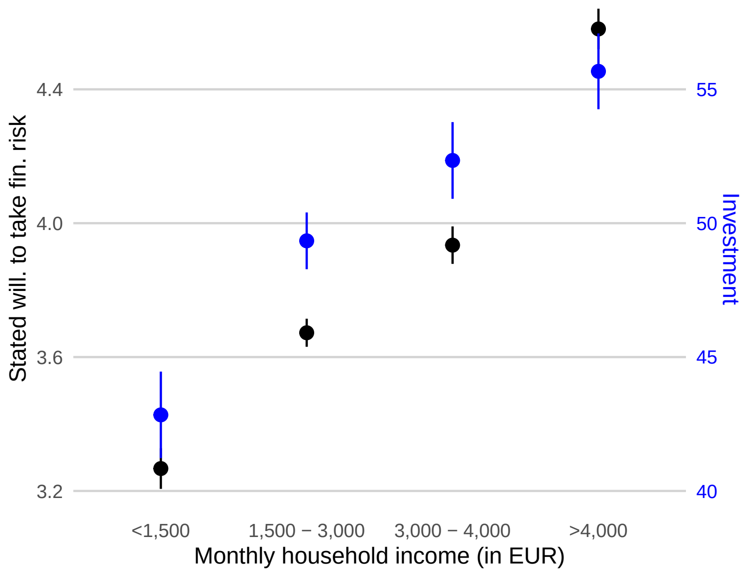
Notes: This figure shows spatially high resolution information on the mean infections with SARS-CoV-2 for each German county in the top panel, the number of deaths related to an coronvirus infection per 100,000 residents, and the mean investments per county in the bottom panel for each data collection. While infections and deaths could have been spatially correlated, we find no evidence for spatial clusters with regard to investments in our experiment.

Figure A2: Distribution of investments.



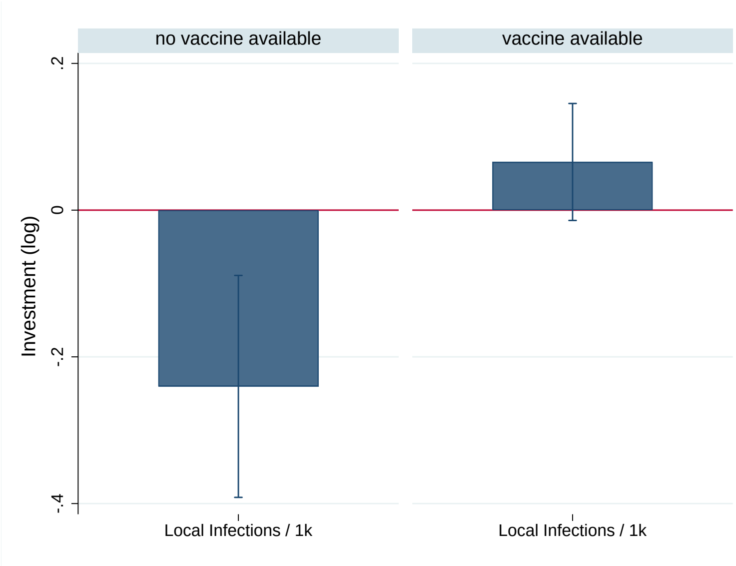
Notes: This figure shows the distribution of investments in our experiment during each data collection period. Across all data collections, the distribution remained fairly similar. However, there are differences in the mean values which we also show in Figure 1. N = 3502 in March 2020, N = 3126 in August 2020, N = 3437 in December 2020, N = 2713 in June and July 2021, and N = 2918 in December 2021.

Figure A3: Relationship between income and risk-taking.



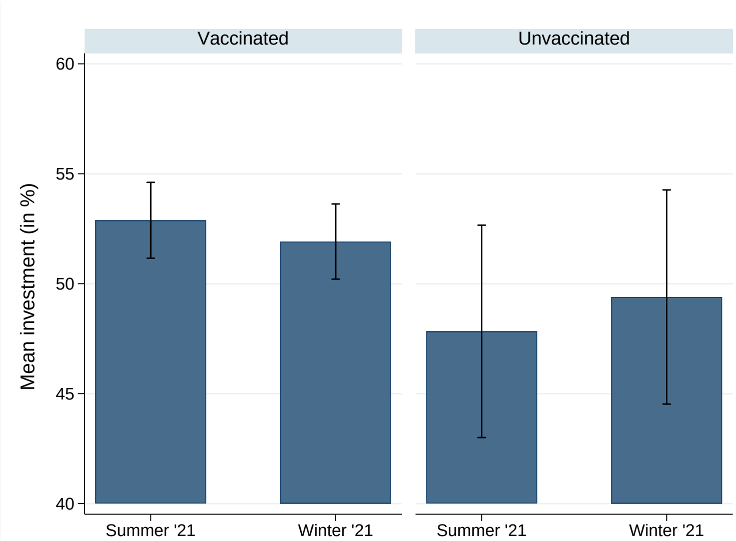
Notes: This figure shows the stated willingness to take financial risk as well as the revealed financial risk-taking from the investments into to the risky asset by household income. We observe that richer households tend to take more financial risks which implies a decreasing risk aversion when income increases. Error lines indicate two standard errors.

Figure A4: Main results without the interaction between income and infections.



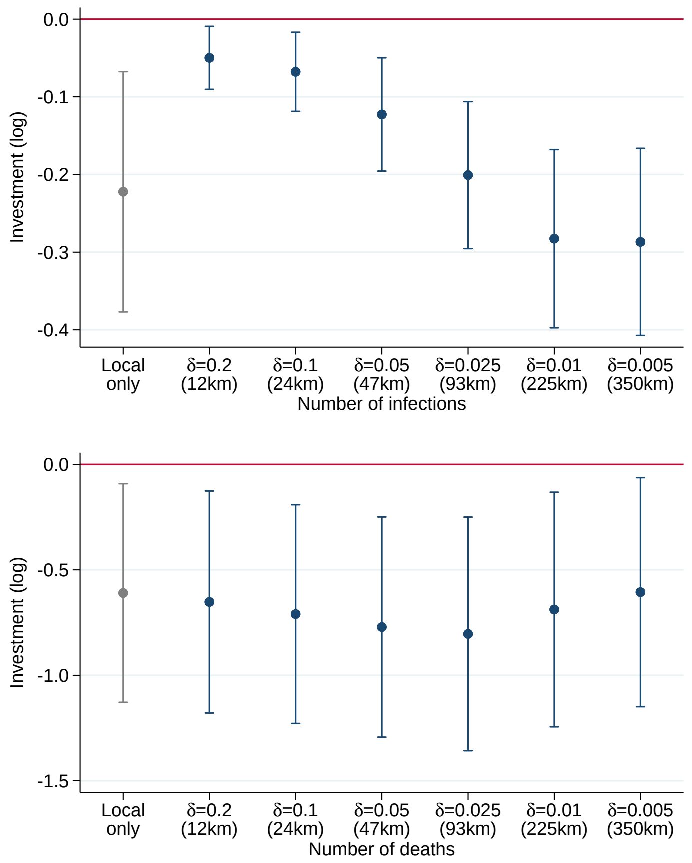
Notes: The figure re-estimates our main specification (9) without the interaction between households' income change and the local infections. Instead, we simply control for changes in household income in the underlying specification of this figure. Bars represent the coefficient β_1 that captures the effect of the background health risk as measured through the number of infections on the investment level in our experiment. Error bars represent 95 percent confidence intervals.

Figure A5: Mean investments by vaccination status.



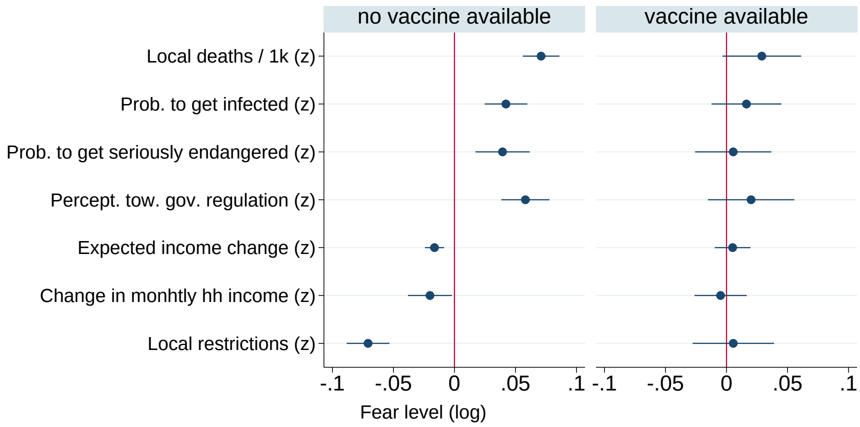
Notes: This figure shows the mean investments during our fourth and fifth data collection period by vaccination status in the respective periods. In this figure, we only compare subjects that have been vaccinated ($N = 1,385$) or unvaccinated ($N = 192$) in both data collection periods.

Figure A6: Effect on risk-taking by spatially smoothed infections and deaths.



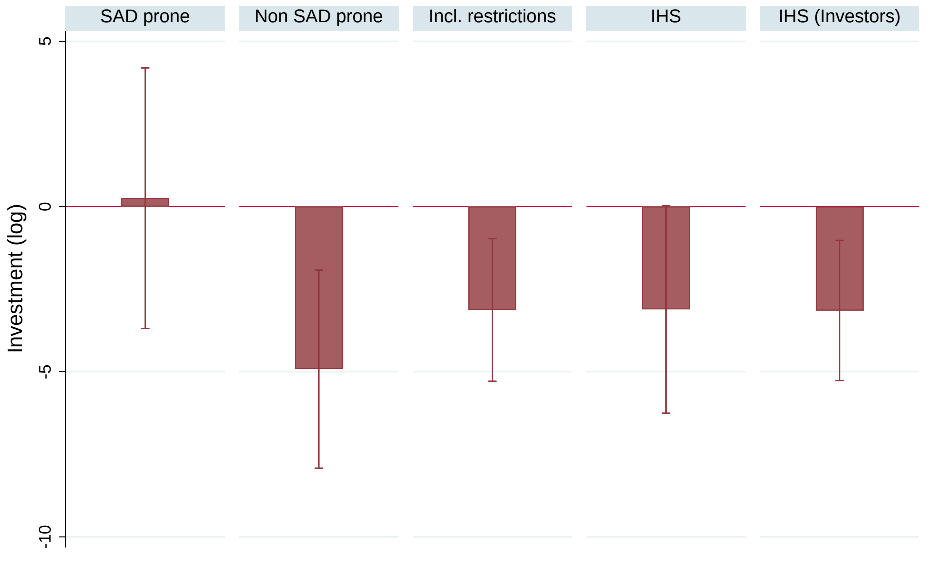
Notes: This figure shows the impact on the investment in our experiment for spatially smoothed infections and deaths. As explained in Appendix B.4, we apply a spatial smoothing and attach a positive weight to infections and deaths in neighboring counties. The weighting parameter δ indicates how much weight is given to neighboring counties. In parentheses, we also indicate the radii in which 90 percent of the weights are given to. This figure shows that the impact of background health risk becomes stronger for participants that also consider the background health risk in neighboring counties.

Figure A7: Predictors of the fear level (II).



Notes: This figure shows the predicted impact of various factors on the self reported fear level at times without vaccine availability (left panel) and with vaccine availability (right panel). This figure is based on fixed effect estimations with the logarithmic fear level as the dependent variable. In contrast to Figure 3 and due to concerns of multicollinearity between infections and deaths, we here consider the number of deaths (as opposed to infections). All potential explanatory variables that are shown have been standardized using their z-scores to compare their magnitude. The perception towards governmental regulation ranges from "[measures] are way too much" to "[measures] are way too little".

Figure A8: Robustness checks with the number of deaths.



Notes: This figure summarizes results from different robustness checks and extensions. It shows the reduction in investments depending on the local number of deaths over different variations of our main specification. All regressions are based on the first three data collection periods. Column (1) only includes subjects that are prone to SAD (N=665), and Column (2) includes only subjects that are not prone to SAD (N=4,165). In Column (3), we control for the number of local restrictions (N=8,316) and in Columns (4) and (5), we transform the level of investments with the inverse hyperbolic sine (N=9,732) and exclude subjects that never made an investment (N=8,316). Error bars represent 95 percent confidence intervals.

Table A1: Descriptive statistics.

	All	Data collection period				
		1	2	3	4	5
Age	51.87	50.07	51.82	52.20	52.74	53.65
	(14.92)	(15.42)	(14.80)	(15.04)	(14.68)	(13.95)
Female	0.47	0.51	0.47	0.45	0.45	0.43
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Education						
University degree	0.21	0.21	0.22	0.21	0.21	0.21
	(0.41)	(0.41)	(0.42)	(0.41)	(0.41)	(0.41)
A-levels / vocational training	0.21	0.19	0.20	0.22	0.23	0.23
	(0.41)	(0.39)	(0.40)	(0.42)	(0.42)	(0.42)
Secondary school	0.34	0.37	0.35	0.32	0.32	0.33
	(0.47)	(0.48)	(0.48)	(0.47)	(0.47)	(0.47)
Secondary general school	0.23	0.23	0.22	0.24	0.24	0.23
	(0.42)	(0.42)	(0.42)	(0.43)	(0.43)	(0.42)
No degree	0.00	0.00	0.00	0.00	0.00	0.00
	(0.06)	(0.07)	(0.05)	(0.07)	(0.06)	(0.06)
Monthly HH income						
< 1,500 EUR	0.17	0.17	0.18	0.21	0.14	0.13
	(0.38)	(0.37)	(0.39)	(0.41)	(0.35)	(0.34)
1,500 – 3,000 EUR	0.39	0.41	0.37	0.39	0.38	0.39
	(0.49)	(0.49)	(0.48)	(0.49)	(0.49)	(0.49)
3,000 - 4,000 EUR	0.21	0.22	0.21	0.20	0.22	0.22
	(0.41)	(0.42)	(0.41)	(0.40)	(0.42)	(0.42)
≥ 4,000 EUR	0.22	0.20	0.23	0.21	0.25	0.25
	(0.42)	(0.40)	(0.42)	(0.40)	(0.43)	(0.44)
Change in HH income to Feb 2020 (%)	-7.00	0.00	-7.72	-9.89	-10.13	-9.96
	(22.98)	(0.00)	(24.68)	(26.35)	(27.10)	(26.59)
Financial risk-taking						
Investment in risky lottery (%)	50.58	48.43	52.70	49.31	51.83	51.54
	(33.46)	(33.56)	(33.53)	(33.61)	(33.35)	(32.78)
Local infections / 1k	0.16	0.05	0.01	0.26	0.01	0.64
	(0.32)	(0.05)	(0.02)	(0.20)	(0.01)	(0.57)
Local deaths / 1k in past 7d	0.02	0.01	0.00	0.07	0.00	0.03
	(0.04)	(0.01)	(0.00)	(0.06)	(0.00)	(0.04)
Local regulations (index)	13.66	10.11	15.87	16.54	10.01	16.47
	(4.91)	(5.24)	(1.91)	(2.58)	(5.43)	(1.84)
Self reported fear level	3.35	4.20	3.07	3.37	2.79	2.97
	(1.76)	(1.65)	(1.68)	(1.71)	(1.67)	(1.68)
Likely suffers from SAD	0.14	0.13	0.13	0.13	0.14	0.14
	(0.34)	(0.34)	(0.34)	(0.34)	(0.35)	(0.35)
Observations	14,078	3,502	3,126	3,096	2,401	1,953

Notes: This table shows mean values and standard deviations in parentheses. The first data collection period took place in March 2020, the second in August 2020, the third in December 2020, the fourth in June and July 2021, and the fifth in December 2021.

Table A2: Effect of background risk on risk-taking.

	no vaccine available (1)	vaccine available (2)
Local infections / 1k	-0.2224***	0.0714*
	(0.084)	(0.042)
Local infections × Change in HH inc.	0.0035	0.0005
	(0.003)	(0.001)
Observations	8,041	3,657
Data collection periods	1-3	4-5
Weekday FE	Yes	Yes
Time trend	Yes	Yes

Notes: This table shows our main results. It is based on the fixed effects estimations described in Equation 9. In Column (1) we restrict our focus to times when no vaccine was available and when infections represented an uninsurable background risk. In Column (2), we show results for data collected when the pandemic represented an insurable background risk. All regressions include weekday fixed effects and a linear time trend. Robust standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Heterogenous effects by income vulnerability.

	WFH occasionally		WFH frequently		Employment Status	
	Low	High	Low	High	Employees	Retirees
Local infections / 1k	-0.095	-0.500***	-0.067	-0.486***	-0.229**	-0.218
	(0.126)	(0.193)	(0.133)	(0.183)	(0.107)	(0.158)
Observations	2,393	2,558	2,407	2,544	4,951	1,650
Mean Investment	60.59	59.18	60.17	59.57	59.86	57.86
F	1.61	2.30	0.78	2.68	2.44	1.12
Adj. R^2	0.003	0.008	0.001	0.011	0.004	0.003

Notes: This table shows results from fixed effects estimations. The dependent variable is the logarithmic investment level in our experiment. In Columns (1) to (4), we explore the effect of background health risk for employees living in counties with different feasibilities to work from home (WFH). Following Alipour et al. (2021), the WFH indices represent the share of employees that occasionally or frequently work from home. We split samples at the median values of those indices. In Columns (5) and (6), we then compare the effect of background health risk on investments between employees and retirees. Following our main specification in Equation 9, all regressions include an interaction between the change in monthly household income relative to February 2020 and the local number of infections, individual fixed effects, a linear time trend, weekday fixed effects, and a constant. Robust standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effect of the local labor market conditions on risk-taking.

	Local short-time work in spring 2020 (no vaccine available)		Local short-time work in summer 2021 (vaccine available)	
	Low	High	Low	High
Local infections / 1k	-0.188	-0.264**	0.138***	0.009
	(0.153)	(0.105)	(0.052)	(0.056)
Observations	3,288	3,389	1,964	1,961

Notes: This table shows results from fixed effects estimations. The dependent variable is the logarithmic investment level in our experiment. In Columns (1) and (3), we focus on people living in a county with a low share of employees on short-time work. In Columns (2) and (4), we focus on those living in a county with a high share of employees on short-time work. The split is based on the median value and the corresponding data is taken from infas360 (2023). Covariates include an interaction between the change in households income relative to February 2020 with the number of infections, weekday fixed effects, individual fixed effects, and a linear time trend. Robust standard errors are shown in parentheses.

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

Table A5: Robustness check regarding information treatments.

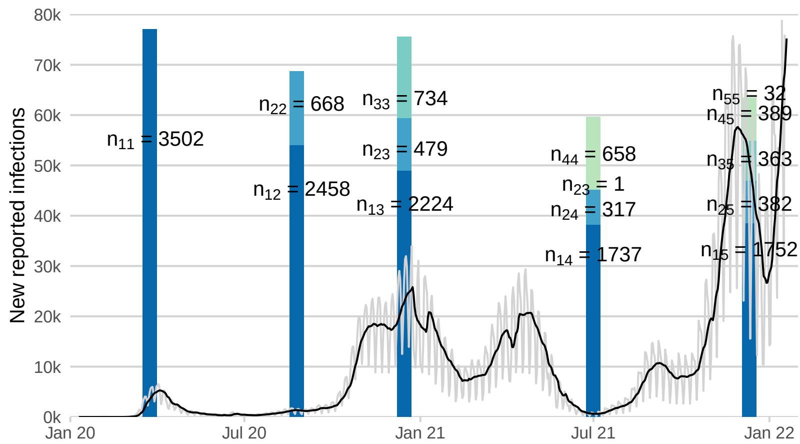
	Investment (linear)		Investment (log)	
	(1)	(2)	(3)	(4)
Panel A: Information treatment regarding risk				
High risk	0.889	0.889	0.049	0.049
	(1.385)	(1.385)	(0.033)	(0.033)
Low risk	0.279	0.279	0.016	0.016
	(1.390)	(1.390)	(0.034)	(0.034)
Observations	3,502	3,502	2,936	2,936
Panel B: Moral appeal treatment				
Deont. appeal	0.823	0.823	0.008	0.008
	(1.423)	(1.423)	(0.035)	(0.035)
Conseq. appeal	1.602	1.602	0.010	0.010
	(1.398)	(1.398)	(0.034)	(0.034)
Observations	3,502	3,502	2,936	2,936

Notes: This table shows OLS estimation using data from the first data collection period. The dependent variable are the investments in our experiment. The information treatment about risk was designed to affect respondents' expectations about the health-related and economic risk of the corona pandemic. It informs about the expected number of infected individuals and reactions of the stock market and economy and differs by its framing. The moral appeals treatment showed participants either a deontological or consequentialistic statement to slow down the pandemic. The role of these treatments on the private privision of public goods are examined in Bos et al. (2020). Both treatments have been assigned independently and randomly. For each treatment, there was a control group with no information or appeal. This control group serves as a baseline. Robust standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.2 Data collection and attrition analysis

We conducted five data collections with more than 5,700 Germans for our online panel survey experiment. In Figure A9, we visualize the timing of our data collection periods, the number of participants, and the background health risk as measured by the number of infections. The data collection periods took place from March 20 – 27, 2020, from August 21 – 30, 2020, from December 09 – 22, 2020, from June 24 – July 8, 2021 and from December 3 – 17, 2021. The German vaccination campaign against SARS-CoV-2 started on December 29, 2020, so that no vaccine was available during our first three data collection periods that we use in the main analysis of this paper. We recruited participants via the company *respondi* that also managed payments.

Figure A9: Sample size per data collection period and COVID-19 infections.



Notes: The figure depicts the number of participants per data collection period as well as the [smoothed] number of COVID-19 infections in Germany during 2020 in gray [black]. n_{jt} indicates the number of participants that were recruited during data collection period j and that participated in data collection period t. For example, n_{12} represents the number of participants that were recruited in the first data collection period and which also participated during the second data collection period. n_{22}, on the other hand, represents the fresh sample of the second data collection period.

The median time to complete the survey was between 11 to 15 minutes. Due to concerns regarding inattention, we excluded observations from respondents that completed the survey in less than 3 or more than 60 minutes. Likewise, we excluded participants that skipped one data collection period. Participants received a fixed participation fee of 0.50 EUR by the recruitment company and earned additional 1.73 [1.15; 1.11; 1.14; 1.10] EUR on average from this task in the first [second; third; fourth; fifth] data collection. Regardless of whether participants invested in the risky lottery or not, they were paid out at the same time after each data collection period. For an unrelated experimental coin-tossing task, they earned additional money with similar amounts.

Due to attrition, we added fresh samples of new participants from the second data collection onwards as specified in our pre-registration at the AEA RCT Registry (`https://doi.org/10.1257/rct.5573-1.1`). In Table A6, we show that attrition was unrelated to local pandemic prevalence, which reinforces the internal validity of our results. On average, older participants where very less likely to drop out of our sample and female participants where more likely to drop out. Participants with a low education dropped out more likely compared to participants with a university degree, and household income seemed to be relevant only in the third data collection period. Those who invested more of their endowment in the risky asset seem more likely to drop out, but this relationship is only weakly significant and whether participants could multiply their investment or not had no effect on attrition. Finally, the local pandemic prevalence seems to matter only after the third data collection period. Therefore, our refreshment samples where drawn from the same pool of participants to ensure representativeness of the general population.

Table A6: Probability to drop out in the next data collection period.

	Data collection			
	1	2	3	4
Age	-0.0051***	-0.0045***	-0.0022***	-0.0036***
	(0.001)	(0.001)	(0.001)	(0.001)
Female	0.0639***	0.0709***	0.0329*	0.0443**
	(0.016)	(0.016)	(0.018)	(0.019)
Education				
University degree	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
A-levels / vocational training	0.0396	0.0091	0.0238	-0.0114
	(0.025)	(0.025)	(0.028)	(0.027)
Secondary school	0.0181	-0.0209	-0.0841***	-0.0024
	(0.021)	(0.021)	(0.025)	(0.026)
Secondary general school	0.0659***	0.0135	0.0170	0.0474*
	(0.024)	(0.024)	(0.028)	(0.029)
No degree	0.2634*	0.1491	0.2097**	0.2539
	(0.143)	(0.166)	(0.088)	(0.162)
Monthly HH income				
$<$ 1,500 EUR	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
1,500 – 3,000 EUR	0.0234	-0.0056	-0.1620***	-0.0520*
	(0.023)	(0.023)	(0.024)	(0.030)
3,000 - 4,000 EUR	0.0096	-0.0235	-0.2294***	-0.0402
	(0.026)	(0.025)	(0.028)	(0.032)
$\geq$ 4,000 EUR	-0.0278	-0.0228	-0.3212***	-0.0570*
	(0.026)	(0.025)	(0.028)	(0.032)
Investment into risky lottery	0.0007**	0.0004*	-0.0001	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)
Won in investment task	-0.0375	-0.0146	0.0084	-0.0247
	(0.028)	(0.016)	(0.018)	(0.019)
Local infections/1k	-0.2021	-0.0957	0.2462***	0.3050
	(0.170)	(0.433)	(0.051)	(0.938)
Local deaths/1k in past 7d	0.1186	-1.6852	-0.5622***	-2.2712
	(0.584)	(5.115)	(0.159)	(6.433)
Observations	3,363	2,992	2,961	2,294

Notes: The dependent variable is a dummy equal to one if a participant drops out of our sample until the next data collection period. Regression also includes a constant. We show robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.3 Experimental instructions

Now we come to a task where you can earn additional money (mingle points). You will receive 100 Euro-Cent from us for this. You can use this money to invest it in a risky lottery. Please decide now which share of it you want to invest in the risky lottery. You will receive the amount that you do not invest for sure.

The risky investment works as follows:

- You have a 50% chance of winning 2.5 times your investment.
- You have a 50% chance of losing your investment.

You win if the super number (between 0 and 9) of the Saturday Lotto drawing on . . . [14] (www.lotto.de) is one of the numbers 0, 1, 2, 3, or 4 [5, 6, 7, 8, or 9][15]. You lose if the super number of this draw is one of the numbers 5, 6, 7, 8, or 9 [0, 1, 2, 3, or 4]. Therefore, the amount you earn by investing in this task is calculated as follows:

- If you win: Payout = 100 Euro-Cent minus investment plus (2.5 x investment)
- If you lose: Payout = 100 Euro-Cent minus investment

How many Euro-Cent would you like to invest (0 - 100)?

[14] 1st wave: April 4, 2020; 2nd wave: September 12, 2020; 3rd wave: December 26, 2020.

[15] We randomized whether the low or high numbers win in the second and third survey wave. In the first survey wave, all subjects could win if the super number was between zero and four.

B.4 Spatial smoothing of infections and deaths

We explore differences in the spatial focus of participants by applying a spatial smoothing to the number of infections and deaths. To this end, we attach a positive weight to infections and deaths that occur in neighboring counties. The weight that a neighboring county receives is given by

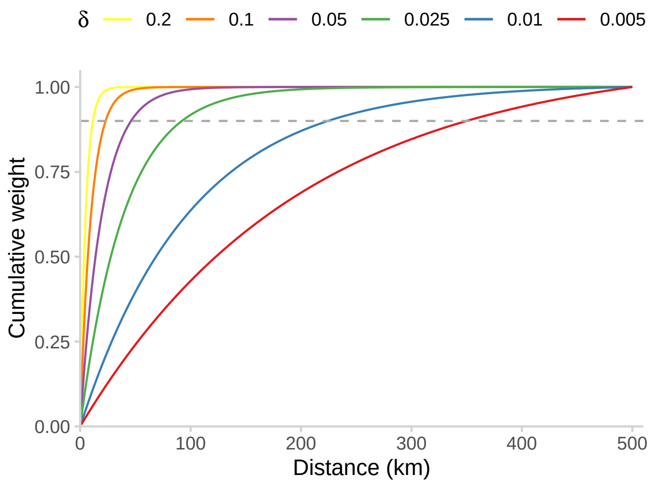
$$\text{weight}_d = \frac{\exp(-\delta \times d)}{\sum_{d=0}^{dlim} \exp(-\delta \times d)},$$

where the weight depends on the distance d to the centroid of a given neighboring county and the weighting parameter $\delta \in (0, 1)$. The weighting parameter δ indicates the weight that is given to neighboring counties. It is low when we attach more weight to other and more distant counties, and high when we attach less weight to them. In Figure A10, we provide some intuition on δ and indicate the cumulative weight given to infections and deaths in a given distance depending on δ. For example, 90 percent of the weight is given to infections and deaths within a radius of 24 km when $\delta = 0.1$. In comparison, 90 percent of the weight is attached to infections and deaths in a radius of up to 225 km for $\delta = 0.01$.

The spatial smoothing increases the perceived background health risk for participants living in counties where surrounding counties have higher infections and deaths. Likewise, it reduces the perceived background health risk for participants living in counties where sourrounding counties have lower infections and deaths. We show the correlation between the actual and reweighted deaths in Figure A11 which reflects that the adjusted death rates can both increase or decrease.

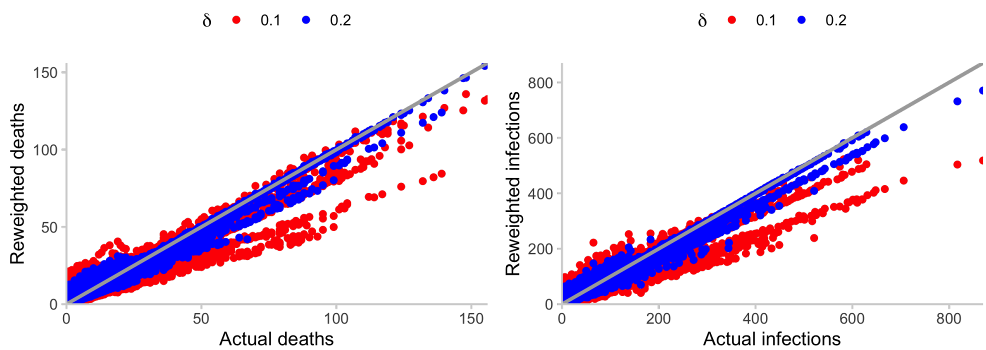
In Figures A6, we observe that the impact of the background health risk slightly increases for people who attach a positive weight to their neighboring counties. In particular, we find the largest impacts for those who attach substantial weights to counties in a radius of 93 km around themselves.

Figure A10: Cumulative spatial weight per distance and δ.



Notes: This figure shows the cumulative weight given to the infections and deaths in a distance around a given county depending on the weighting parameter δ. A high value of δ assigns less weight to neighboring and distant counties. The dashed line represents the 90 percentile and indicates up to which distance most weight is given to.

Figure A11: Correlation between actual and reweighted infections and deaths.



Notes: This figure compares the actual number of deaths with the reweighted deaths for two values of δ. For each color, one dot represents one county. The blue dots represent the actual and adjusted numbers for $\delta = 0.2$ and the red dots represent the death numbers for $\delta = 0.1$.