Disaster Risk and Wealth Inequality

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—Preliminary and Incomplete —

Abstract

The risk of disasters—whether natural, political, or financial—is reflected in GDP tail risk. Based on cross-country data, we first establish a robust link between GDP tail risk and wealth inequality. Next, to explain this pattern, we propose an incomplete markets model in which wealthier households tend to increase their savings in response to heightened tail risk, whereas lower-wealth households save less. This differential savings response exacerbates wealth inequality over time. Finally, using data from a randomized controlled trial (RCT), we corroborate the mechanism at the heart of the model: we establish a causal relationship between tail risk beliefs and household savings behavior, which systematically varies with wealth.

Keywords: Natural disasters, financial crises, geopolitics, GDP tail risk, inequality

JEL-Codes: G51, Q54, E44

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1 Introduction

Disasters and inequality have become increasingly salient over the past one or two decades. We assess whether they are systematically linked. In particular, wealth inequality is a defining issue of our time. In many countries around the world, the richest ten percent of households own about 60% of the society's total wealth. Wealth inequality far exceeds income inequality, especially inequality in labor income. Hence, economic models have to go beyond differences in labor productivity to explain wealth inequality. In this paper, we provide an explanation that hinges on heterogeneous saving behavior in response to disaster risk. We find that, both theoretically and empirically, richer households tend to increase their saving rate by more than poorer households in the face of a heightened risk of a severe adverse wealth shock. We can thus explain higher wealth inequality with a higher risk of a severe economic downturn, a "disaster".

In the first empirical part, we collect observational evidence for our theory. On the macroeconomic level, we combine estimates of country-specific disaster risk with data on wealth inequality. We find a strong positive relationship: a 1pp higher risk of a severe economic downturn is associated with 4-5pp higher Gini coefficient. Disaster risk remains significant in explaining wealth inequality when we control for inequality in labor income. To get at the problem of reverse causality, we also use another approach, where we leverage the spatial variation in natural disaster risk in the U.S. to relate it with estimates of local wealth inequality. We find that, both at state and at commuting zone-level, that a one standard deviation higher exposure to natural disaster risk increases the top 10% wealth share in the region by 0.5-1pp. Higher risk of a natural disaster explains almost 20% of the variation in wealth inequality across U.S. states.

Next, we build an incomplete markets general equilibrium model with uninsurable labor income shocks, and add left-skewed return risk. First, we build intuition for the mechanism with a two period, partial equilibrium version of the model. The heterogeneity we find to be crucial for the effect of disaster risk on inequality is the fraction of expected asset income within total expected income. We find that poorer households, who rely mostly on labor income, reduce their saving in response to higher risk. In contrast, richer households, whose main source of income is the return on their financial wealth, save more. We find that the sign-difference of the savings responses hinges on the households having a sufficiently high relative *prudence* and *temperance* (for the response to third moments). The heterogeneous response to return risk across the wealth distribution causes wealth inequality to increase when return risk increases. The full, general equilibrium model provides us with a tool to quantitatively connect the micro channel—the heterogeneous saving response to aggregate return risk—with the macro prediction of higher wealth inequality. We find that a 1pp higher tail risk increases the wealth Gini by about 1pp in the model.

Finally, in order to understand the relation between disaster risk perceptions and savings behavior on the household level, we use the results of a randomized controlled trial (RCT) within a representative household survey in Germany. To do so, we rely on data from the Bundesbank Online Panel of Households, collected by Beutel and Stockerl (2025) in August 2022. The data not only contains disaster related GDP tail risk expectations of households and employs information treatments within an RCT, but also provides unique granular information on the wealth of households. In an instrumental variable design, following the approach by Coibion et al. (2024), we provide causal evidence on the heterogeneous relation between tail risk and the savings rate. While high wealth households increase their planned savings rate following an increase in their perceived tail risk, due to the information treatments, low wealth survey participants do not. We find that the heterogeneity is strongest for a financial crisis scenario.

The rise in wealth inequality in recent decades has motivated a growing literature to explain this fact. Mian et al. (2020) and Gaillard et al. (2023), among others, argue that the introduction of non-homothetic preferences is needed to explain the "excess" saving of the rich. Moll et al. (2020) and Fernández-Villaverde and Levintal (2024) stress the importance of the "passive" saving of capital gains on the stock market, in expectation of falling future returns, for explaining recent increases in the top wealth share. Benhabib et al. (2015, 2024) and Hubmer et al. (2021) show that the introduction of idiosyncratic return risk can generate a wealth distribution with a fatter right tail. Our paper adds a new potential channel for explaining higher wealth inequality to this literature. In particular, we show that aggregate risk can cause "active" saving rates to diverge across the wealth distribution. We conjecture that this finding can be very complementary to prominent features that we abstract from in our model, in particular to the portfolio choice between assets with different exposure to risk.

The rest of the paper is structured as follows: In section 2, we present evidence for a positive relation between disaster risk and wealth inequality, using variation both across countries, and across regions in the US. In section 3, we show how return risk generates heterogeneous saving rates in a two-period, partial equilibrium model. In section 4, we provide causal evidence from an RCT on the heterogeneous impact of tail risk perceptions on the savings rate. Section 5 concludes.

2 Observational evidence

We follow two approaches to investigate the relation between disaster risk and inequality in available observational data. The first approach relies on cross-country differences in wealth inequality and exposure to disaster risk. We measure disaster risk as tail risk in GDP growth, following the approach by Marfè and Pénasse (2024). We find that risk of a disaster, which in the sample stems mostly from financial crisis risk, is positively related to wealth inequality. The second approach leverages recent advances in measuring spatial wealth inequality within the United States (Suss et al., 2024). Using this imputed data, that links household survey data with Census data, we can investigate the relation between local differences in natural disaster risk with local wealth inequality. We find, both at the state and at the commuting zone-level, a significantly positive relation. In the following, we describe each approach in detail.

2.1 Cross-country evidence

Our sample consists of 42 countries. The World Inequality Database contains data on the wealth share of the highest decile in the wealth distribution at least since 1995 for all countries in our sample. Taking the average over time from 1995 to 2022, we find that wealth inequality varies considerably across countries: while the richest 10 percent own 62% of a country's wealth on average, the cross-country standard deviation of the wealth share is 8pp. The Gini coefficient, which lies between 0 (no inequality) and 1, is another measure for wealth inequality, which represents inequalities also in the middle of the wealth distribution. It paints a similar picture: The average Gini coefficient is 0.77 in our sample, with a standad deviation of 6pp.

Marfè and Pénasse (2024) use panel data of these 42 countries to estimate a time-varying tail risk for each of the countries. Their econometric approach relies on regressing several quantiles τ in the left tail of the three-year output growth distribution on a set of predictor variables $X_{i,t}$:

$$Q_{X_{i,t}}(\tau \mid X_{i,t}) = X_{i,t}B \tag{1}$$

where i denotes a country, and t denotes a year. Crucially, the coefficients in B are assumed to be the same across countries. Thereby, the approach leverages the data's panel dimension. For this, the authors *standardize* each country's three-year output growth time series by its long-run mean and standard deviation.[1] Next, the authors fit a country- and year-specific log-linear function $g_{i,t}(\tau) \approx \hat{Q}_{X_{i,t}}(\tau \mid X_{i,t})$, for a set

[1] For example, three-year output growth in the US, from 1875 to 2016, varies around a mean of 5.9% by a standard deviation of 9.8pp.

of quantiles $\tau \in [0.01, 0.5]$. Evaluating the inverse of g at -2 gives an estimate of the probability in a given year, and for a given country, of three-year output growth being at least two standard deviations lower than the country-average:

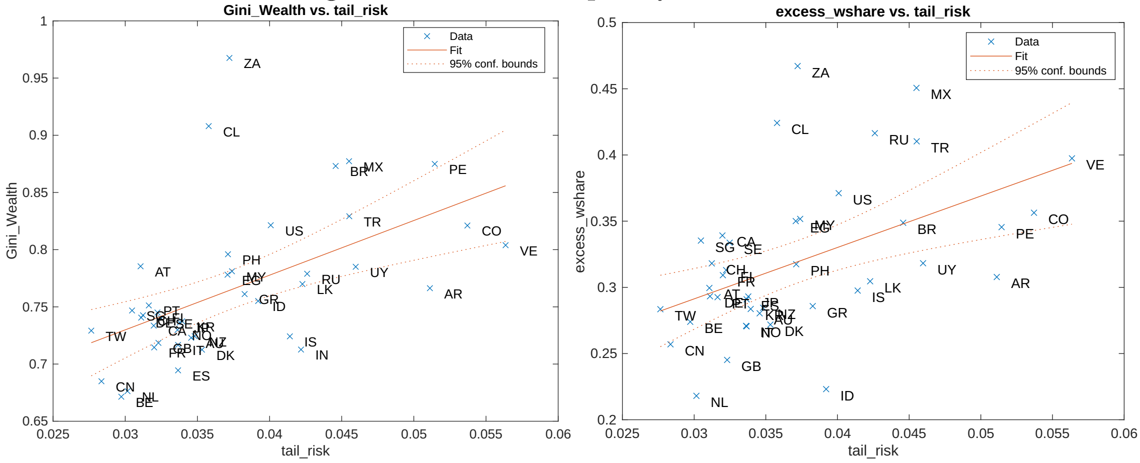
$$\hat{\pi}_{i,t} = g_{i,t}^{-1}(-2) \tag{2}$$

Deviating from the analysis in Marfè and Pénasse (2024), we compute the time-average of tail risk for each country in the sample, $\hat{\pi}_i$. We use the time period from 1987 to 2013 where the estimate of tail risk is available for every country in the sample (when standardizing, using a rolling window approach, we need 25 years of prior data to estimate country-specific mean and standard deviation). We find meaningful variation across countries: the average tail risk of GDP growth in this period is 3.74%, with a standard deviation of 71 basis points. To put this number into perspective, our estimate implies that the average output growth distribution has about a 1.5pp fatter left tail than what would be expected from a normal distribution. What is more, for countries with the highest tail risk in our sample, Colombia and Venezuela, their left tail is almost double the size of the left tail of the countries with the lowest tail risk in our sample, China and Taiwan. This points towards considerable heterogeneity in the left-skewness of the output growth distribution across countries.[2]

Next, we relate a country's disaster risk to the degree of wealth inequality in the country. The theory, as outlined in section 3, predicts a positive relationship. Table 1 shows results of a regression of the wealth Gini on tail risk, with and without controlling for labor income inequality, which we define as the share of labor income obtained by the 10% of households with the highest labor income. We collect the data on labor income inequality from the International Labour Organization, for the years 2004 to 2020 for each country in the sample, and take a time-average. Without outlier India, where the top 10% labor income share is estimated at 62%, the mean labor income share of the top decile is 30%, with a standard deviation of 5pp.

[2]The differences in the left tail could also be explained by differences in the kurtosis of the distributions. To investigate this further, we compare the output growth distributions of the countries with the highest tail risk and those with the lowest tail risk. Note that the empirical distribution only captures *realized* tail risk, not the *predicted* tail risk that we estimate from quantile regressions. Figure 5 in the Appendix shows the result. We find that the distributions of *both* countries with high and with low tail risk feature excess kurtosis, where the distributions of low risk countries are *more* leptokurtic. The difference between low and high tail risk countries is most pronounced in the lower half, where high tail risk countries have more probability mass below -1 SD. This supports our interpretation that high tail risk countries have more negatively skewed output growth distributions than low tail risk countries.

Figure 1: Wealth inequality and tail risk



Notes: Left panel: Wealth Gini and GDP tail risk; Scatter plot and regression line (N=42). Right panel: Excess wealth share, defined as Top 10% Wealth Share - Top 10% Labor Income Share, and GDP tail risk; Scatter plot and regression line (N=41, without outlier India).

Table 1: Wealth inequality and GDP tail risk

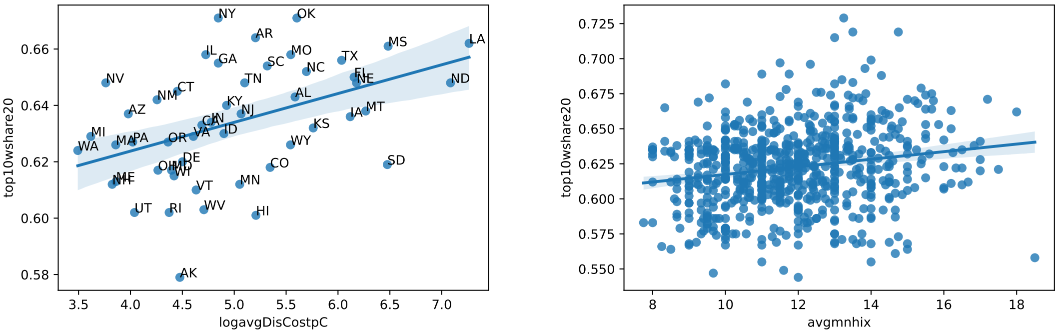
	(1)	(2)
const	0.5865***	0.5511**
	(0.0453)	(0.0504)
Tail risk	4.7793***	4.0772***
	(1.1916)	(1.2615)
Wage inequality		0.1995
		(0.1319)
N	42	41
Adj. R-Squared	0.292	0.269

Note:*p<0.10,**p<0.05,***p<0.01. Standard errors in parenthesis. Dependent variable: Wealth Gini. Wage inequality denotes wage share of highest decile of wage-earners. Specification (2) is without outlier India.

The left panel of Figure 1 shows the scatter plot and regression line for the regression specification (1) in Table 1. We find that tail risk has a statistically and economically significant positive relationship with wealth inequality: A 1pp higher tail risk is associated with a 4-5pp higher wealth Gini. Differences in disaster risk alone can explain about 30% of the variation in wealth inequality across countries. The top 10% labor income share is not significantly related to the wealth Gini.

We run the same regressions with the top 10% wealth share as the dependent variable. Table 2 shows the results. Again, we find that tail risk is a highly significant positive regressor for wealth inequality. Unsurprisingly, the top 10% labor income share also is highly correlated with the top 10% wealth share. Differences in disaster risk together with differences in wage inequality already explain 63% of the cross-country variance. To illustrate this finding, we define the "Excess Wealth Share"

Figure 2: Wealth Inequality and Natural Disaster Risk: U.S.



Notes: Both panels show the scatter plot of a regression with dependent variable given as top 10% wealth share within a region in the U.S., in 2020. Left panel: regressor is the log of the average disaster cost per capita since 1980, per U.S. state (N=50). Right panel: regressor is natural disaster risk-index at commuting zone level (N=722).

as the difference of the top 10% wealth share and the top 10% labor income share, and show the scatter plot and regression line on regressing it on tail risk in the right panel of Figure 1.

Table 2: Wealth inequality and GDP tail risk

	(1)	(2)
Constant	0.3736***	0.1524**
	(0.0576)	(0.0565)
Tail risk	6.6194***	3.5631***
	(1.5149)	(1.2437)
Wage inequality		1.1139***
		(0.1885)
N	42	41
Adj. R^2	0.306	0.631

Note: *p<0.10, **p<0.05, ***p<0.01. Standard errors in parenthesis. Dependent variable: Top 10% wealth share. Wage inequality denotes wage share of highest decile of wage-earners. Specification (2) is without outlier India.

2.2 Natural disaster risk in the U.S.

We now turn to a specific type of tail risk: natural disaster risk. For this, we leverage that natural disaster risk varies significantly across regions in the United States. Together with the spatial wealth inequality data provided by Suss et al. (2024), this gives us the opportunity to investigate our hypothesis in a context where reverse causality is less of a concern. We start with an analysis at the state level. Natural disaster risk varies across U.S. states due to differing vulnerabilities to droughts, floodings, freezes, storms, cyclones, or wildfires. We use the (realized) disaster cost per capita since 1980 as a measure of natural disaster risk, which we take from the National Center for Environmental Information. We regress the top

10% wealth share by U.S. state on the risk of a natural disaster. Specification (1) in Table 3 shows the result. We find that a one standard deviation increase in natural disaster risk increases the regional top 10% wealth share by 0.92pp. The scatter plot in the left panel of Figure 2 illustrates that disaster risk explains a considerable amount of variation in inequality across U.S. states (the R-Squared is 19%).

Next, we go to the commuting zone level in the U.S. For a measure of natural disaster risk, we use the U.S. Natural Hazards Index, provided by the National Center for Disaster Preparedness of Columbia University. For each commuting zone, the index categorizes the risk of a given type of natural disaster as either "None", "Low", "Medium", or "High". We average across types of natural disasters for our measure. Specification (2) in Table 3 shows the result of regressing the top 10% wealth share per commuting zone on this risk index. Again, the relation of wealth inequality to disaster risk is highly significantly positive. We find that a one standard deviation increase in exposure to natural disasters increases the top 10% wealth share by 0.53pp.

Table 3: Wealth inequality and natural disaster risk: U.S.

	(1)	(2)
const	0.6336***	0.6222***
	(0.003)	(0.001)
Avg Disaster Cost	0.0092***	-
	(0.003)	
Natural disaster risk index	-	0.0053***
		(0.001)
N	50	722
Adj. R-Squared	0.188	0.036

Note:*p<0.10,**p<0.05,***p<0.01. Standard errors in parenthesis. Dependent variable: Top 10% wealth share, per region. Avg. Disaster Cost is in logs. Both regressors are standardized.

3 Incomplete markets model

In this section, we present our theory. We model an economy with a continuum of households facing idiosyncratic risk in their human capital, h_t, which they rent out to firms at the wage rate, w_t. Households can self-insure by accumulating non-negative amounts of capital, k_t, which they rent out to firms at gross return R_t. Human capital evolves according to a log-normal AR(1) process. Households enjoy utility from consumption, c_t, and solve the dynamic program:

$$\max_{\{c_t, k_{t+1}\}_{t=0}^{\infty}} \mathbb{E} \sum_{t=0}^{\infty} \beta^t u(c_t) \tag{3}$$

$$\text{s.t. } c_t + k_{t+1} = R_t k_t + h_t w_t \tag{4}$$

$$k_{t+1} \geq 0 \tag{5}$$

Wage w_t and capital rate r_t are given by the marginal products of labor and capital, respectively, where the production function is given by:

$$Y_t = K_t^{\alpha} N^{1-\alpha}, \tag{6}$$

where N is the total amount of human capital supplied by households. We abstract from labor supply choice in our description of the household problem, and normalize $N = 1$. The gross return is composed of $R_t = 1 - \delta + r_t + \nu_t$, where δ denotes capital depreciation. Since $r_t = \alpha \left(N/K_t\right)^{1-\alpha}$ is predetermined by the predetermined capital stock K_t, the shock ν_t is the only source of return risk, and of aggregate risk in the economy. The distribution of ν_t is time-constant, and is characterized by its first three (centralized) moments: $\mathbb{E}_{t-1} \nu_t = 0$, $\mathbb{E}_{t-1} \nu_t^2 =: \sigma_\nu^2$, $\mathbb{E}_{t-1} \nu_t^3 =: \tau_\nu^3$.

3.1 Analysis of two-period problem

In order to provide intuition for the main mechanism, we first discuss the outcome of disaster risk in a two-period version of the model. In this version, a household with available funds a can save in one asset with ex-post gross return R, and receives predetermined labor income $y = wh$. Thus, we abstract from idiosyncratic labor income risk here, which can be seen as an approximation to the full model with a persistent labor-income process. Importantly, however, households are *heterogeneous* in their expected labor income, as well as in their wealth. By virtue of taking a "snapshot" in time, holding everything besides the risk of disaster constant, we are able to describe the problem analytically.

The household chooses the level of saving k s.t.

$$u(a-k) + \beta\,\mathbb{E}[u(Rk+y)] \tag{7}$$

is maximized. For financially unconstrained households, the optimal savings choice is characterized by the first-order condition

$$-u'(a-k) + \beta\,\mathbb{E}[Ru'(Rk+y)] = 0 \tag{8}$$

We follow the seminal approach of Arrow and Pratt in computing changes in the savings response that are caused by a marginal increase in asset return risk, starting from the deterministic case. To this end, we perturb equation (8) with respect to deviations in return risk R.

At first order, $R = R_0 + \epsilon$, and a first-order Taylor expansion of the expectation in (8) around R_0 gives

$$\mathbb{E}[Ru'(Rk+y)] \approx \mathbb{E}[R_0 u'(R_0 k + y) + (u'(R_0 k + y) + R_0 u''(R_0 k + y)k)\epsilon] \tag{9}$$

As $\mathbb{E}[\epsilon] = 0$, this has the well-known implication that up to first order, risk does not have an impact. As certainty equivalence holds, the household is on the Euler equation under deterministic returns:

$$R_0 = \frac{u'(a-k)}{\beta u'(R_0 k + y)} \tag{10}$$

Assuming CRRA preferences, $u'(c) = c^{-\gamma}$, the optimal saving rate k/w equals

$$\frac{k^*}{a} = \frac{(\beta R_0)^{1/\gamma} - y/a}{R_0 + (\beta R_0)^{1/\gamma}} \tag{11}$$

At second order, $R = R_0 + \epsilon + \frac{1}{2}\epsilon^2$, a second-order Taylor expansion adds the following terms to the expectation-term in (9):

$$\mathbb{E}\left[\frac{\epsilon^2}{2}\left\{2ku''(R_0 k + y) + R_0 k^2 u'''(R_0 k + y)\right\}\right] \tag{12}$$

Defining return variance $\sigma^2 = \mathbb{E}[\epsilon^2]$, rearranging adds the following term to the left-hand side of (10):

$$\frac{\gamma\sigma^2\lambda}{2R_0}(\rho\lambda - 2) \tag{13}$$

where we define $\rho := -c\frac{u'''(c)}{u''(c)}$ as the coefficient of relative *prudence*, and $\lambda := \frac{R_0 k}{R_0 k + y}$ as the ratio of expected asset income to total expected income. The richer the household is (in expectation), the higher is λ, which is bounded above by 1.

Accounting for the possibility of $\lambda < 1$ extends the simplified treatment of optimal portfolio choice often found in the finance literature, where financial and human wealth is not distinguished (e.g. Barro (2006)). In fact, this distinction is the focus of the analysis in Angeletos (2007), which is closely related to the mechanism we analyze here: he finds that when the average share of risky over total wealth is less than one, higher investment risk can lead to less saving in the aggregate. The condition on the share of risky wealth (here, λ) and preferences, under which this result holds (see Proposition 3(ii) in Angeletos (2007)), is exactly the one that obtains in equation (13): $\rho\lambda < 2$. Intuitively, as $\rho = 1 + \gamma$, households with a relatively high elasticity of intertemporal substitution, $1/\gamma$, and thus low prudence, substitute a more uncertain future consumption unit for today's save consumption unit, provided that total future income is not too much influenced by the amount of saved assets k (i.e., labor income is high compared to expected asset income).

Our analysis adds to this finding in the literature on two accounts: First, we focus on the effect on inequality, while Angeletos (2007) focuses on the aggregate savings response. By modeling heterogeneity in wealth levels, which implies (together with a persistent labor income process) heterogeneous expected values of λ_i, the model predicts *heterogeneous-sign savings responses* to investment risk *if* $\gamma > 1$: for a given, common level of prudence $\rho > 2$, households with $\lambda_i < 2/\rho$ save less in the face of higher risk, while asset-richer households, with $\lambda_i > 2/\rho$, save *more*. The unambiguous prediction of the model is thus a rise in inequality in the face of higher investment risk.

Second, we extend the analysis of risk to the third order. This allows us to analyze the effect of investment risk with a skewed distribution. At third order, $R = R_0 + \epsilon + \frac{1}{2}\epsilon^2 + \frac{1}{6}\epsilon^3$, a third-order Taylor expansion adds the following terms to the expectation-term in (9):

$$\mathbb{E}\left[\frac{\epsilon^3}{6}(3k^2u'''(Rk+y) + Rk^3u^{IV}(Rk+y))\right] \tag{14}$$

Defining skewness $\varsigma = E[\epsilon^3]/\sigma^3$, we find that accounting for third order risk adds an additional term to the left-hand side of Euler equation (10):

$$\frac{\gamma\rho\varsigma\sigma^3\lambda^2}{6R_0^2}(3 - \kappa\lambda) \tag{15}$$

where we define $\kappa := -c\frac{u^{IV}(c)}{u'''(c)}$ as the coefficient of relative *temperance*. It holds that $\kappa = \gamma + 2$. For temperance above 3, we thus find heterogeneity in the sign of the savings response to skewness: poorer households with $\lambda_i < 3/\kappa$ save less when returns become more negatively skewed, $\varsigma < 0$, while richer households with

Table 4: Model calibration

Parameters		Value	Parameters		Value
β	Discount factor	0.99	σ_ϵ	Std. of log-income shocks	0.18
γ	Rel. risk aversion	2.00	ρ_y	Persistence of log-income	0.88
α	Capital share	0.32	δ	Depreciation rate	0.02
σ_ν	Std. of return risk	0.005	τ_ν	Third mom.$^{1/3}$ of return risk	-0.012

Notes: This table describes the parameter values used in the model calibration.

$\lambda_i > 3/\kappa$ save more in that case. This leads us to the following theoretical result:

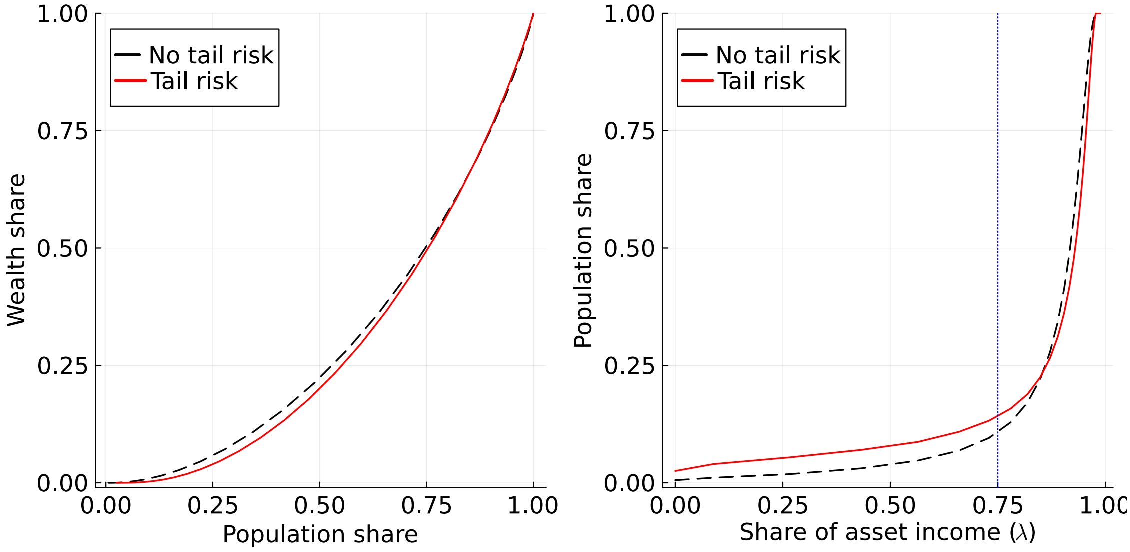
Proposition 1. *Under the assumption of CRRA preferences with a common coefficient of relative risk aversion* γ*, and heterogeneity in* λ_i *as outlined above, there exist thresholds* $\underline{\lambda} \leq \bar{\lambda} < 1$ *such that skewed return risk affects saving rates with heterogeneous signs, i.e. negatively for* $\lambda_i < \underline{\lambda}$ *and positively for* $\lambda_i > \bar{\lambda}$*, iff* $\gamma > 1$.

3.2 Model calibration and solution

Table 3.2 shows the calibration of the full model. A model period is a quarter. The values for the capital share and the depreciation rate are standard in the literature. The calibration of the idiosyncratic human capital risk follows Aiyagari (1994). We assume that the felicity function is of the CRRA form. The values for the time-discount factor and the coefficient of relative risk aversion are standard. We calibrate the higher-order moments of the risky returns to the evidence on tail risk collected in section 2. For this, we follow Levintal (2017) in approximating the binomial distribution of a disaster shock with a continuous distribution that has the same higher-order moments. Agents internalize the positive second moment and negative third moment of the shock, and adjust their response accordingly. Tail risk has two components: the probability of the disaster to materialize, and the expected magnitude. We calibrate the annual probability of a severe disaster with a GDP loss of 9.3% to 2%. This is also broadly in line with the estimates in Barro and Ursúa (2012).

We solve the model using higher-order perturbation, following Bayer et al. (2024). This allows us to directly link the model-implied *risk correction* in the households' optimal savings choices to the micro-level evidence on the effect of disaster risk perception on the saving rate. The risk correction term exactly captures the anticipatory actions of households in response to (higher) return risk. In contrast, a global solution method would yield an optimal policy function that is necessarily influenced by changes to all variables of the ergodic steady state, and in particular by prices which are only perturbed through general equilibrium effects. We do

Figure 3: Effect of tail risk on inequality



Notes: Left panel: Lorenz Curve. Right panel: Plot of cumulative probability weight on λ_i, the ratio of expected asset income over expected total income. Black dashed line: Economy without tail risk. Red solid line: Economy with tail risk. Blue dotted line: Threshold $\bar{\lambda}_3 = 0.75$ at which savings rates switch sign in two-period model.

not expect the household's saving response that we measure in the RCT to include those general equilibrium effects. For this reason, the perturbation solution method appears to be better suited for our goal of bringing together micro- and macro-level evidence on responses to disaster risk.

3.3 Results

In the steady state distribution without disaster risk, the wealth Gini is at 38.97%. Adding disaster risk increases the wealth Gini by 5.6%, to 41.16%. The left panel of Figure 3 illustrates the difference in the two wealth distributions by plotting the share of wealth held by different quantiles of the distribution (the Lorenz curve). Disaster risk increases the curvature of the Lorenz curve especially in the lower 75% of the wealth distribution. Our theoretical result gives us an intuition for why that can happen: since relative risk aversion is above 1, households whose ratio of expected asset income to expected total income is below some threshold $\underline{\lambda}$ save *less* in response to the disaster risk, while households with a ratio above $\bar{\lambda}$ save *more*. We conjecture that the threshold for the third-order response is particularly important, which is given by $\bar{\lambda}_3 = \frac{3}{\kappa}$. For our calibration, relative temperance is 4, so that the two-period analysis would suggest that households that expect to receive less than 75% of their income from capital income save less in response to the skewed return risk. The right panel of Figure 3 tests this theoretical prediction with the response of the full, numerically solved model, by plotting the wealth distribution on the ratios of expected asset income to total expected income, λ_i. λ_i are calculated from the baseline economy without disaster risk. The graph shows that roughly up to $\lambda = \frac{3}{4}$, the wealth distribution in the economy with tail risk is shifted upwards with respect to the wealth distribution without tail risk, by about 3pp. This shows that about 3% of poorer households have less wealth than without the tail risk. On the other side of the threshold $\bar{\lambda}_3$, instead, households are richer than before, as the cumulative distribution function becomes slightly flatter.

Quantitatively, as we calibrate the tail risk in the model to 2% annually, the results imply that in the model, the wealth Gini increases by about 1pp for a 1pp higher tail risk. In terms of order of magnitudes, this is in line with the correlational evidence presented in section 2. In the next section, we empirically test the mechanism that lies behind our theoretical result.

4 Randomized Control Trail

In this section, we provide causal evidence on the heterogeneous role of disaster risk for the savings behavior of households. To do so, we build upon existing data for a randomized control experiment (RCT), conducted by Beutel and Stockerl (2025). The data was collected by the Bundesbank, as part of the Bundesbank Online Panel of Households (BOP-HH) Wave 32, conducted in August 2022. It covers a nationally representative online sample of $N = 8996$ German respondents. Survey weights are utilized to ensure that reported statistics are exactly representative of the German population and to correct for minor sampling biases.

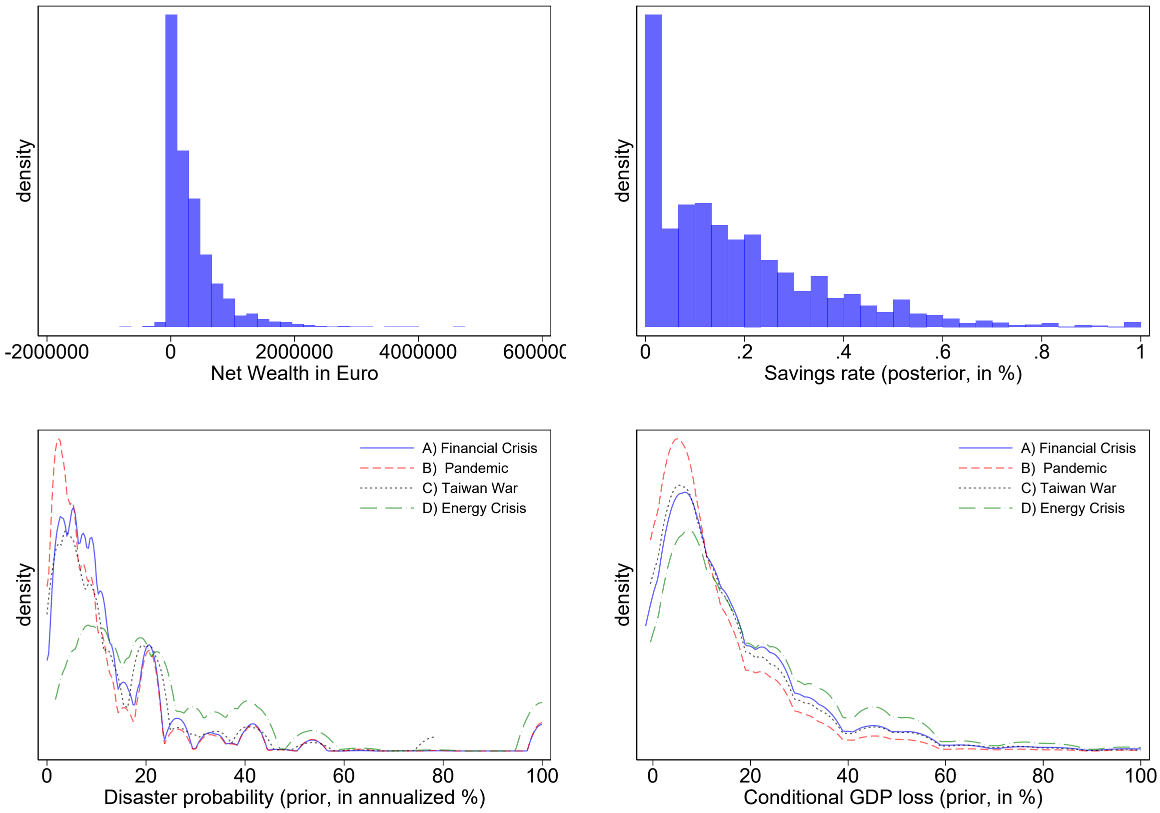
In our analysis, we exploit the causal variation in disaster-related tail risk expectations to understand the heterogeneous effect on respondents planned savings rate. Our analysis closely follows the approach by Coibion et al. (2024).

4.1 Data

The data contains four separate RCT designs that test the impact of information on different disaster types on expectations. Disaster types include a) a financial crisis, b) a new pandemic similar to Covid-19, c) a war between China and Taiwan and d) an energy crisis in Germany. For each disaster type, two treatment groups are defined, each receiving either positive or negative qualitative information on the respective disaster. The control group receives no information. Appendix B lists the relevant survey questions for our analysis, while Bundesbank (2025) gives an overview over the BOP-HH survey in general and the full questionnaire of the respective survey wave.

The structure of the experiment is as follows: First, the survey asks all respondents, irrespective of treatment group about their (prior) expected likelihood that the disaster is realized within the next three years. In addition to the probability, the survey elicits the expected conditional effect of the disasters on GDP. In a second step, respondents receive an information treatment about a particular disaster type; respondents assigned to the control group receive no information. Subsequently, in a third step, the survey asks about the expected likelihood and impact on GDP of the particular disaster type that the respondents' information treatment did refer to. For the control group, the question again asks about all four diaster types. Forth, respondents are asked about their planned average monthly expenditure over the next 12 months, for four categories, "major purchases", "housing", "other living expenses" and "savings". We utilize this information to define the *active savings rate* as the ratio of the "savings" category to total expenses. To reduce noise, we drop respondents for which "major purchases" make up more than 40% of expenses from our sample. This step eliminates respondents where the savings rate is heavily

Figure 4: Survey Data - Description



Notes: Upper left panel: distribution of total wealth in the survey. Upper right panel: distribution of savings rates (on expenditure) in the survey. Lower left panel: prior expectations over likelihood of disasters. Lower right panel: prior expectations over conditional GDP loss from disasters.

biased due to large planned purchases, such as a new car or house.[3] In addition, we drop any respondents that walked away from the survey (i.e., did not finish the survey in one setting on the webpage) and finished at a later point in time, as the effect of the information treatment may be reduced by this.

We annualize the prior (posterior) survey question on the likelihood of the disaster, for ease of interpretation and comparability of results with the model.[4] We then define tail risk as the product between expected disaster probability $p_{i,k}$ and expected conditional GDP loss $\mu_{i,k}$, following a disaster realization, such that $\tau_{i,k} = p_{i,k}\mu_{i,k}$. While we drop the top 5% of disaster tail risk expectations, the savings rate is winsorized at the 2% (top and bottom) level.[5]

At the very end of the survey, granular information on asset holdings of respondents is collected. We define high wealth individuals as those belonging to the top

[3]This is relevant for 6.10% of survey respondents in our sample.

[4]Let p denote the answer to the survey question and $\tilde{p}$ the annualized equivalent. Then, $\tilde{p} = 1 - (1-p)^{1/h}$, where h is the horizon of the survey question.

[5]Effectively this only affects the top 2% of savings rates, as more than 2% report no savings. At the top, this affects savings rates in excess of 65%.

20% for the total net wealth of households. In the survey data, the median wealth of those classified as low wealth (bottom 80% of the wealth distribution) is €79.000, while it is €550.000 for the high wealth individuals (to 20% of the wealth distribution). We use a 20% cutoff for high wealth individuals to strike a balance between capturing the top of the wealth distribution while still being able to maintain a sufficient statistical power in the sample, given a limited overall sample size.

4.2 Direct Treatment Effect

To set the stage, we estimate the *direct* effect of the treatments, relative to the control group, on the planned savings rate of households. Specifically, we estimate the following relationship:

$$s_i^{post} = \alpha_0 + \sum \alpha_j \left[\mathbb{I}(i \in \text{Treat j})\right] + \sum \beta_j \left[\mathbb{I}(i \in \text{Treat j}) \times \mathbb{W}_i\right] + \mathbb{W}_i + D_i + e_{k,i}$$

where s_i^{post} is the posterior planned savings rate, $\mathbb{I}(i \in \text{Treat j})$ and indicator variable equal to 1 if respondent i received treatment k and 0 otherwise. The dummy variable $\mathbb{W}_i$ indicates if respondent i belongs to the high wealth group. D_i is a vector of demographic control variables (age, education, gender, income quintile).

Table 7 in the Appendix displays Huber robust and survey weighted estimation results. The model in column (1) does not control for the interaction with the high wealth individual interaction variable. We find that the respondents receiving a treatment about a potential disaster to German GDP – relative the control group do not have a significantly different savings rate. However, once we split the effect of the treatments along the wealth dimension in column (2), we find that for 6 out of 8 treatments, the planned savings rate is significantly elevated for survey respondents within the high wealth, by up to 7.4pp, relative to the low wealth group.

This result suggests a meaningful heterogeneity in the reaction of individuals' planned savings rate to news about potential disasters: While high wealth individuals tend to *increase* savings, we find no significant effect of the information treatments on the savings rate for low wealth households.

However, the result in Table 7 does not speak to the potential channel through which news about potential disasters affects savings decisions. Thus, in the next section, we will employ an instrumental variable regression to understand the mediating role of perceived tail risk.

Table 5: RCT - First Stage

	(1) τ_i^{post} All	(2) τ_i^{post} Low Wealth	(3) τ_i^{post} High Wealth
τ_i^{pre}	1.248***	1.263***	1.176***
	(51.11)	(52.34)	(19.25)
$\tau_i^{pre} \times \mathbb{I}(i \in \text{T1})$	-0.703***	-0.718***	-0.760***
	(-22.07)	(-21.53)	(-10.21)
$\tau_i^{pre} \times \mathbb{I}(i \in \text{T2})$	-0.466***	-0.486***	-0.201***
	(-13.55)	(-13.63)	(-2.62)
$\tau_i^{pre} \times \mathbb{I}(i \in \text{T3})$	-0.0175	-0.0723	0.225**
	(-0.38)	(-1.44)	(2.57)
$\tau_i^{pre} \times \mathbb{I}(i \in \text{T4})$	0.0795**	0.0506	0.109
	(2.23)	(1.30)	(1.44)
$\tau_i^{pre} \times \mathbb{I}(i \in \text{T5})$	-0.320***	-0.337***	-0.343***
	(-8.18)	(-7.96)	(-4.25)
$\tau_i^{pre} \times \mathbb{I}(i \in \text{T6})$	0.101***	0.0842**	0.145*
	(3.12)	(2.31)	(1.91)
$\tau_i^{pre} \times \mathbb{I}(i \in \text{T7})$	-0.220***	-0.252***	0.0139
	(-7.07)	(-7.69)	(0.21)
$\tau_i^{pre} \times \mathbb{I}(i \in \text{T8})$	-0.160***	-0.191***	-0.159**
	(-5.47)	(-6.17)	(-2.31)
$\mathbb{I}(i \in \text{T1})$	0.243***	0.303***	0.144
	(3.76)	(4.15)	(1.20)
$\mathbb{I}(i \in \text{T2})$	0.204***	0.198***	0.129
	(3.16)	(2.79)	(1.08)
$\mathbb{I}(i \in \text{T3})$	-0.0152	0.00767	-0.194*
	(-0.24)	(0.11)	(-1.79)
$\mathbb{I}(i \in \text{T4})$	0.0574	0.0646	0.0263
	(0.90)	(0.92)	(0.23)
$\mathbb{I}(i \in \text{T5})$	0.0523	0.0890	-0.0568
	(0.80)	(1.19)	(-0.53)
$\mathbb{I}(i \in \text{T6})$	0.124*	0.153*	-0.0610
	(1.83)	(1.96)	(-0.53)
$\mathbb{I}(i \in \text{T7})$	-0.0240	-0.0179	-0.168
	(-0.31)	(-0.20)	(-1.27)
$\mathbb{I}(i \in \text{T8})$	0.103	0.128	0.0420
	(1.31)	(1.32)	(0.35)
N	3876	3127	755
r2	0.878	0.870	0.904

Notes: All regressions rely on Huber robust and survey weights. t-statistics reported in parentheses. *, **,*** denote statistical significance at 1, 5, and 10 percent levels.

4.3 RCT - The role of expected tail risk

We define tail risk as the product between expected disaster probability $p_{i,k}$ and expected conditional GDP loss $\mu_{i,k}$, following a disaster realization, such that $\tau_{i,k} = p_{i,k}\mu_{i,k}$. Specifically, we estimate the effect of a treatment on tail risk as:

$$\begin{aligned} \tau_{i,k}^{post} = \alpha_0 + \beta_0 \tau_{i,k}^{prior} &+ \sum \alpha_j \left[\mathbb{I}(i \in \text{Treat j})\right] \\ &+ \sum \beta_j \left[\mathbb{I}(i \in \text{Treat j}) \times \tau_{i,k}^{prior}\right] = D_i + e_i \end{aligned} \tag{16}$$

Here, $\tau_{i,k}$ represents subjective tail risk perceptions, for disaster type k. The vector D_i collects demographic fixed effects.

Table 5 shows the results for the first stage, for all four disaster types. Following Coibion et al. (2024) and Coibion et al. (2018) we interpret the coefficient α_j as the signal for tail risk from treatment j. In turn, the coefficient on the prior expectation, $(\beta_0 + \beta_j)$ in interpreted as a measure of the informativeness of the signal: The lower $(\beta_0 + \beta_j)$, the more (less) weight do treated respondents assign to the information received (prior belief).

We find that for all respondents, most treatments (with the exception of T3) seem to be informative. However, for most, we do not find a significant signal. Also, once we split the sample by wealth status, significance is reduces, especially for the high wealth group.

In a second step, we estimate the effect of tail risk on the planned savings rate, s_i^{post}, exploiting the exogenous variation from the RCT in an instrumental variable setting:

$$s_i^{post} = \gamma_0 + \gamma_1 \tau_{i,k}^{IV,post} + \gamma_2 \tau_{i,k}^{prior} + D_i + u_i \tag{17}$$

Here, $\tau_{i,k}^{IV,post}$ is the posterior tail risk, instrumented by the RCT, as in equation (16). The coefficient γ_1 captures the causal effect of tail risk on the savings rate. We interpret the coefficient as follows: Assume two identical survey respondents, where one gets treated with some information and revises its tail risk expectations upwards, by 1pp. γ_1 than captures the causal effect of this revision of tail risk expectations on the planned savings rate of that household, relative to an untreated household.

To test for the heterogeneity between the reaction of the savings rate to disaster risk, we estimate the IV regression in equation (17) separately for low and high wealth individuals. We then calculate a p-value for the equality between the coefficients for the causal effect on the savings rate for both groups. This approach for the heterogeneity analysis follows Coibion et al. (2023).

Table 6 displays results, both for high and low wealth individuals. For both GDP tail risk and DAX tail risk, we find a positive reaction of high wealth individuals' savings rate to increased tail risk. At the same time, the coefficient for low wealth individuals is lower. For GDP tail risk, both coefficients differ significantly (p-val< 0.01). For DAX tail risk, we do not find a significant difference.

Table 6: RCT - Second Stage

Dependent variable: posterior savings rate				
	(1)	(2)	(3)	(4)
	GDP tail risk		DAX tail risk	
	Low Wealth	High Wealth	Low Wealth	High Wealth
$\tau_i^{IV,post}$	0.79**	4.99***	-0.25	0.08
	(0.35)	(1.22)	(0.33)	(0.89)
N	3,121	724	3,250	780
R	0.11	0.09	0.12	0.10
F-stat (first stage)	63.25	12.5	34.94	10.69
p-value equality	< 0.01		0.73	

Notes: Dependent variable: savings rate $\times 100$. All instrumental variable regressions rely on Huber robust and survey weights and use a jackknife algorithm to report stable estimates. The jackknife identifies and filters out influential observations. p-value equality shows p-value for the test of equality of estimated coefficients γ_1 in each sample split. Standard errors clustered by respondent. Heteroskedasticity robust standard errors are reported in parentheses, *, **,*** denote statistical significance at 1, 5 and 10 percent levels.

5 Conclusion

Wealth inequality is a prominent characteristic of many economies worldwide, reaching levels that cannot be solely attributed to differences in income. In this paper, we document a significant correlation between wealth inequality and economic tail risk—the likelihood of a severe economic downturn—across an international sample. Our findings indicate that societies facing a higher risk of economic disaster tend to exhibit greater wealth inequality.

To explain this relationship, we propose a theoretical framework based on the differential responses of savings behavior to tail risk across the wealth distribution. Specifically, we show that while high-wealth households tend to increase their savings in response to elevated tail risk, low-wealth consumers do not. We formalize this mechanism within an incomplete markets general equilibrium model featuring heterogeneous agents and uninsurable labor income shocks.

Finally, we provide empirical support for our theory using data from a randomized controlled trial (RCT). The findings confirm a causal link between beliefs about tail risk and household savings behavior, demonstrating that this response systematically varies with wealth.

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A Additional Tables and Figures

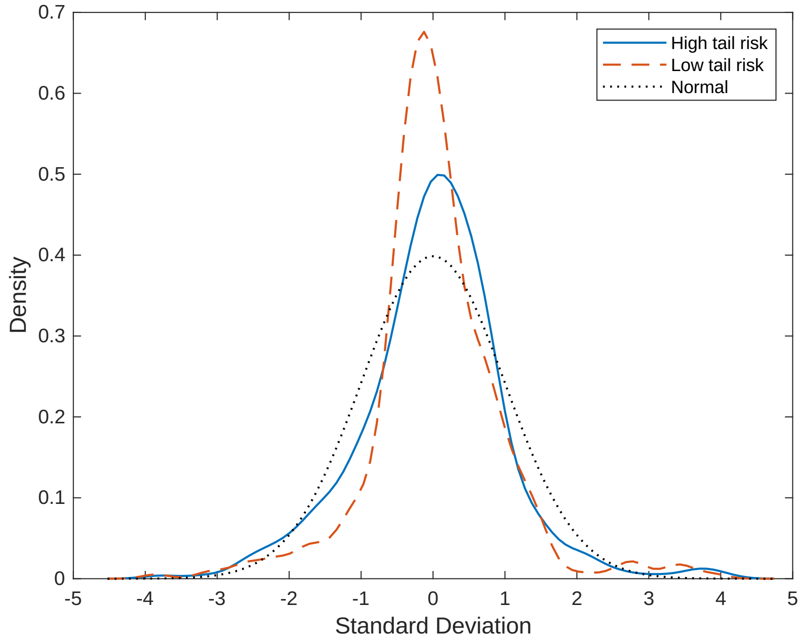

Figure 5: Estimated density from pooled standardized 3-year output growth distributions of countries in two groups: *High tail risk*: Argentina, Colombia, Peru, Venezuela (N=438). *Low tail risk*: Belgium, China, Netherlands, Taiwan (N=412). *Normal* is the standard normal density for comparison.

Table 7: RCT - Direct effect

	(1) s_i^{post}	(2) s_i^{post}
$\mathbb{I}(i \in \text{T1})$	-0.404	-0.293
	(-0.72)	(-0.46)
$\mathbb{I}(i \in \text{T2})$	-0.236	-1.029
	(-0.41)	(-1.59)
$\mathbb{I}(i \in \text{T3})$	-0.129	-0.660
	(-0.23)	(-1.02)
$\mathbb{I}(i \in \text{T4})$	-0.274	-0.604
	(-0.48)	(-0.93)
$\mathbb{I}(i \in \text{T5})$	0.766	0.520
	(1.33)	(0.78)
$\mathbb{I}(i \in \text{T6})$	-0.548	-1.238*
	(-0.96)	(-1.93)
$\mathbb{I}(i \in \text{T7})$	0.00440	0.392
	(0.01)	(0.60)
$\mathbb{I}(i \in \text{T8})$	-0.0204	-0.635
	(-0.04)	(-0.97)
$\mathbb{I}(i \in \text{T1}) \times \mathbb{W}_i$		1.988
		(0.97)
$\mathbb{I}(i \in \text{T2}) \times \mathbb{W}_i$		7.538***
		(3.70)
$\mathbb{I}(i \in \text{T3}) \times \mathbb{W}_i$		6.438***
		(3.25)
$\mathbb{I}(i \in \text{T4}) \times \mathbb{W}_i$		5.173**
		(2.53)
$\mathbb{I}(i \in \text{T5}) \times \mathbb{W}_i$		4.083**
		(2.19)
$\mathbb{I}(i \in \text{T6}) \times \mathbb{W}_i$		5.718***
		(2.90)
$\mathbb{I}(i \in \text{T7}) \times \mathbb{W}_i$		-0.733
		(-0.37)
$\mathbb{I}(i \in \text{T8}) \times \mathbb{W}_i$		7.265***
		(3.61)
$\mathbb{W}$		0.382
		(0.27)
Constant	9.323***	10.07***
	(16.86)	(16.35)
N	7647	6448
r2	0.128	0.157

Notes: All regressions rely on Huber robust and survey weights. t-statistics reported in parentheses. *, **,*** denote statistical significance at 1, 5, and 10 percent levels.

B Survey Appendix

This Appendix lists the most important survey questions from the Bundesbank Online Panel Households, Wave 32.

P3206 *Stellen Sie sich vor, innerhalb der kommenden drei Jahre würde jeweils eines der folgenden Ereignisse eintreten. Was denken Sie, um wieviel Prozent wäre die Wirtschaftsleistung Deutschlands in diesem Fall jeweils geringer?*
Hinweis: Bitte geben Sie an, um wieviel Prozent die Wirtschaftsleistung ein Jahr nach Eintritt des Ereignisses kleiner wäre als ohne Eintritt des Ereignisses. Wenn Sie einen Rückgang erwarten, geben Sie bitte einen Wert größer 0 ein. Wenn Sie keinen Rückgang erwarten, geben Sie bitte einen Wert von Null ein.

1. *Finanzkrise*
2. *Pandemie mit neuem Erreger*
3. *Angriff Chinas auf Taiwan*
4. *Energiekrise*

P3207 *Was denken Sie, wie hoch ist die Wahrscheinlichkeit, dass das jeweilige Ereignis innerhalb der kommenden drei Jahre eintritt?*
Hinweis: Bitte geben Sie jeweils Werte zwischen 0 und 100 ein. 100 bedeutet, dass das Ereignis Ihrer Einschätzung nach vollkommen sicher eintreten wird, 0, dass das Ereignis vollkommen unmöglich ist.[6]

1. *Finanzkrise*
2. *Pandemie mit neuem Erreger*
3. *Angriff Chinas auf Taiwan*
4. *Energiekrise*

Treatment 1 and 2 – Financial crisis

T1: Die Banken sind seit der globalen Finanzkrise von 2008 deutlich widerstandsfähiger geworden. Die Kapitalpuffer, die entscheidend für die Widerstandsfähigkeit der Banken sind, stiegen seitdem um rund 50%. Banken können dadurch leichter durch wirtschaftlich herausfordernde Zeiten kommen, ohne gezwungen zu sein, die Kreditvergabe an Unternehmen und Haushalte einzuschränken.

[6] The stuvey question is displayed to respondents in a way such that an info box linked to GDP *("Wirtschaftsleistung Deutschlands")* is available, stating the following text: *"Die Wirtschaftsleistung wird gewöhnlich durch das Bruttoinlandsprodukt (BIP) gemessen. Das BIP gibt den Gesamtwert aller Waren und Dienstleistungen an, die während eines Jahres innerhalb Deutschlands hergestellt wurden."*

T2: Überbewertete Vermögenswerte, beispielweise Immobilien, stellen eine Verwundbarkeit für das deutsche Finanzsystem dar. Der deutsche Aktienindex (DAX) hat seit Jahresbeginn rund 20 Prozent an Wert verloren. Schätzungen der Bundesbank zufolge sind Immobilienpreise in Deutschland rund 20-35 Prozent überbewertet. Sollten Immobilienpreise plötzlich fallen und zahlreiche Haushalte ihre Kredite nicht mehr bedienen können, drohen Banken erhebliche Verluste.

Treatment 3 and 4 – Pandemic

T3: Um zukünftige Pandemien effektiv zu verhindern oder abzuschwächen, wird mit Hochdruck an einer Reihe von Maßnahmen gearbeitet. Durch die mRNA-Technologie sollen wirksame Impfstoffe schnell verfügbar sein, wirksame Medikamente sollen schnell entwickelt werden können und das Infektionsgeschehen soll besser überwacht werden. Diese und weitere Maßnahmen können dazu beitragen, die Ausbreitung von Krankheitserregern zukünftig frühzeitig einzudämmen.

T4: Experten warnen, dass es jederzeit zu einer neuen Pandemie kommen könnte. So steht etwa die Haltung bestimmter Tierarten in China mit dem SARS-Virus 2002 in Verbindung, und im Mittleren Osten mit dem MERS-Ausbruch 2012. In Europa ist die Massentierhaltung eine potenzielle Brutstätte für neue Erreger. Aufgrund mangelnder Vorbereitung könnten die Folgen ebenso oder noch weitreichender als bei der Covid-19 Pandemie sein.

Treatment 5 and 6 – War between China and Taiwan

T5: Experten gehen davon aus, dass China derzeit nicht zu einer Invasion Taiwans bereit wäre. Im Falle einer möglichen zukünftigen Eskalation würden Bestrebungen in den USA und Europa, unabhängiger von Einfuhren aus Taiwan und China zu werden, die wirtschaftlichen Folgen begrenzen. Hierfür sollen Produktionsstätten in Europa und USA mit jeweils rund 40-50 Milliarden Euro gefördert werden.

T6: Hochrangige US-Militärs warnen, dass eine Invasion Chinas in Taiwan innerhalb der nächsten fünf Jahre droht. Da Taiwan zwei Drittel der weltweiten Halbleiter produziert, könnten die wirtschaftlichen Folgen in Deutschland und weltweit gravierend sein, beispielsweise für die Automobilproduktion. Die Rolle Chinas als Produktionsstandort und Absatzmarkt könnte im Falle von Spannungen zwischen China und den USA sowie möglicher Sanktionen gegenüber China die wirtschaftlichen Auswirkungen verstärken.

Treatment 7 and 8 – Energy supply crisis

T7: Die führenden deutschen Wirtschaftsforschungsinstitute erwarten im Falle *eines sofortigen Gas-Lieferstopps Russlands keine Versorgungslücke beim Gas bis Ende 2023. Der Gasverbrauch deutscher Industrieunternehmen müsste dann nicht begrenzt werden. Die Versorgung privater Haushalte und sozialer Einrichtungen wäre ohnehin nicht gefährdet.*

T8: Der Bundeswirtschaftsminister hat die zweite Krisenstufe im Notfallplan Gas ausgerufen. Grund dafür sei die seit Mitte Juni bestehende Kürzung der russischen Gaslieferungen sowie die hohen Preise am Gasmarkt. Eine Verdreifachung der Gaspreise für Haushalte und Unternehmen sei im Bereich des Möglichen, ebenso Einschränkungen in der Gasversorgung von Industrieunternehmen.

Control Group

T9: [No information]

P3210 *Sie sehen nun nochmal einige Dinge, für die man im Alltag Geld ausgeben kann oder muss. Wieviel planen Sie in den kommenden zwölf Monaten im Durchschnitt pro Monat für die folgenden Dinge jeweils auszugeben?*

1. *größere Anschaffungen (z.B. Auto, Möbel, elektrische Geräte usw.)*
2. *Wohnkosten (z.B. Miete, Hypothekenkredit, Nebenkosten)*
3. *Sonstige Ausgaben (z.B. Einkäufe, Mobilität, Dienstleistungen, Reisen)*
4. *Sparen (z.B. Sparkonto, Aktien, Anleihen)*

Depending on the treatment group, respondents are shown the next questions. The control group (T4) is asked about all four disaster types.

P3211 A-D *Wir möchten nun noch etwas mehr über Ihre Einschätzungen bezüglich der Auswirkungen und der Wahrscheinlichkeit möglicher Krisen erfahren. Es gibt hierbei kein richtig oder falsch, wir sind an Ihrer persönlichen Meinung interessiert. Stellen Sie sich vor, innerhalb der kommenden zwei Jahre würde eine [Finanzkrise/Pandemie mit neuem Erreger/ Angriff Chinas auf Taiwan/Energiekrise] eintreten. Was denken Sie, um wieviel Prozent wäre die Wirtschaftsleistung Deutschlands in diesem Fall geringer?*

P3213 A-D *Was denken Sie, wie hoch ist die Wahrscheinlichkeit, dass innerhalb der kommenden zwei Jahre eine [Finanzkrise/Pandemie mit neuem Erreger/ Angriff Chinas auf Taiwan/Energiekrise] eintritt?*