Article:

Pickard, H., Dohmen, T. and Van Landeghem, B. orcid.org/0000-0001-6759-8893 (2024) Inequality and risk preference. Journal of Risk and Uncertainty, 69. pp. 191-217. ISSN 0895-5646

https://doi.org/10.1007/s11166-024-09440-8

Journal of Risk and Uncertainty
https://doi.org/10.1007/s11166-024-09440-8

Inequality and risk preference

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Accepted: 19 August 2024

Abstract
This paper studies the relationship between income inequality and risk taking. Increased income inequality is likely to enlarge the scope for upward comparisons and, in the presence of reference-dependent preferences, to increase willingness to take risks. Using a globally representative data set on risk preference in 76 countries, we empirically document that the distribution of income in a country has a positive and significant link with the preference for risk. This relationship is remarkably precise and holds across countries and individuals, as well as alternate measures of inequality. We find evidence of a steeper gradient between willingness to take risks and inequality for cognitively more able individuals who likely have a better assessment of inequality and for those who are dissatisfied with their income. We present results in favour of our mechanism, which suggests that falling behind one's reference group increases the appetite for risk taking.

Keywords Income inequality · Risk preference · Risk sensitivity

JEL Classification D91 · O15 · D81 · D01

We have benefited from comments and suggestions from Jytte Nielsen, Nicolas Van de Sijpe and from the participants of research seminars at Sheffield and Newcastle University. Dohmen gratefully acknowledges funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy - EXC 2126/1- 390838866.

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Published online: 17 October 2024

1 Introduction

There is abundant evidence that individuals do not only derive utility from absolute consumption levels or income levels, but also care about consumption and income relative to comparison groups or reference points (Festinger, 1954; Fliessbach et al., 2007; Kuhn et al., 2011; Card et al., 2012). These reference points can be social, i.e., stem from social comparison, or based on private outcomes, i.e., based on comparisons to one's own (lagged) status quo (see, e.g., Loomes and Sugden, 1982, 1986) or expectations (e.g., Kőszegi and Rabin, 2006, 2007, 2009). A widely acknowledged direct consequence of reference-dependent utility is that falling below the reference point is accompanied by a loss of utility that exceeds the pure loss of utility due to reduced consumption possibilities: falling below the reference point can have additional consequences, namely changes in risk appetite. Risk sensitivity theory (RST) as well as prospect theory and its various refinements typically predict increased risk taking below a reference point.[1] For example, individuals whose reference point corresponds to the lagged status quo, will take excessive risks if they fall below their reference point in order to regain their status quo (see, e.g., theoretical accounts of Thaler and Johnson (1990) & Gomes (2005), as well as empirical evidence by Odean (1998)).

Recent evidence from laboratory experiments and survey data confirm the implication of theory that individuals' risk appetite increases when falling behind. Dohmen et al. (2021) document that participants in a laboratory experiment whose expected earnings would fall below the reference point in a risk-free environment behave risk seeking in risky environments. Schwerter (2024) manipulates a social reference point in a laboratory experiment and shows that participants make less risk averse choices when their peers' earnings are larger, arguably to catch up or surpass these peers. Likewise, Mishra et al. (2015) induce random variation in absolute and relative earnings by varying show-up fees in their experiment and show that this leads those with low expected earnings to be more risk taking in lottery choice tasks. Mishra et al. (2012) demonstrate that individuals who were given a high target goal for returns of financial investments made riskier choices than those with a lower target. Fehr and Reichlin (2021) find that lower perceived relative wealth leads to a higher degree of risk taking in monetary incentivized lottery tasks. Panunzi et al. (2021) show that voter behaviour is consistent with the idea that economically disappointed voters become more risk loving, using data from the German Socio economic Panel (SOEP). Similarly, Dohmen et al. (2016) find suggestive evidence that job loss is associated with increases in willingness to take risks.[2]

[1] Reference-dependent risk attitudes are a feature of a wide range of models that depart from expected utility (e.g., Bell, 1985; Loomes & Sugden, 1986; Thaler & Johnson, 1990; Gul, 1991; Gomes, 2005; Kőszegi & Rabin, 2006; Kőszegi & Rabin, 2007, 2009). Disciplines other than economics also have theories that describe similar properties. In evolutionary biology, for example, RST was developed to explain animal foraging behaviour that is (extremely) risky when animals fall short of their daily energy intake but is marked by risk aversion when foragers have met their daily target (Caraco et al., 1980; Stephens, 1981). See also Trautmann and Vieider (2011) for an overview of risk across various disciplines.

[2] A notable exception in this literature is Linde and Sonnemans (2012), who find evidence that individuals make more risk averse choices if they know that only the positive outcome of the riskier choice would bring their earnings up to the level (but never above) of their peer's earnings.

In this paper, we hypothesise that higher income inequality is associated with increased risk lovingness. This is grounded in two principal strands of literature on reference-dependent utility and behaviour. First, our hypothesis is motivated by convincing empirical evidence that social comparison is asymmetric, and that individuals tend to engage disproportionately in upward comparisons (Ferrer-i Carbonell, 2005; Boyce et al., 2010; Card et al., 2012; Payne et al., 2017; Akesaka et al., 2023).[3] An increase in the total income share accrued by those further up the income ranking might create a higher level of aspiration and hence a fall below one's reference point.

Second, there is a literature suggesting that there is a relationship between the level of inequality and the visibility of income differences, status concerns and conspicuous consumption. While it is of course possible to fall below one's peers in an environment of low inequality, larger income differences may be more visible, prompting status concerns that lead to conspicuous consumption, increasing the visibility of income differences and the salience of the reference point. Walasek and Brown (2015, 2016), for example, conclude based on Google Trends data that states or countries with higher inequality also display more status-seeking behaviours on average. Experimental evidence from Nishi et al. (2015) demonstrates that the relationship is bidirectional: if inequality is high and differences in income are visible, there tends to be less cooperation leading to higher inequality in the long run compared to settings with similarly high inequality where differences are not visible. Similarly, survey experiments by Velandia-Morales et al. (2022) suggest that larger income differences increase the consumption of status goods, a relationship which seems to be mediated by increased concerns for status. Using data from 2,425 US counties, Cheung and Lucas (2016) conclude that the relative income effects on subjective well-being are stronger when inequality is high.

Research in the lab has provided some evidence supporting our hypothesis. Payne et al. (2017) show subjects at random one out of three earnings distributions which have different variances but the same mean, and subjects are informed that it is the distribution of earnings of previous players of a gambling game that they are about to play. Being confronted with a more unequal distribution leads to higher risk taking in the gambling game. Müller and Rau (2019) provides a theoretical model and experimental evidence illustrating that people not only have an increased risk appetite when they are behind their reference point, but that this risk appetite is enhanced in settings of high inequality.

However, the hypothesis that income inequality increases risk appetite has not been rigorously scrutinized using comparable data on risk preferences and income inequality across a large sample of countries. In this paper, we endeavour to reduce this gap in the literature, by analyzing the relationship between individual risk attitudes and measures of income inequality within countries. In order to investigate and to provide global evidence on the relationship between a country's income inequality and individuals' risk preferences, we combine data from the Global Preferences Survey on risk preferences in 76 countries with country-level inequality measures constructed

[3] The asymmetry has in fact been validated by Fliessbach et al. (2007) who used an MRI machine to detect that upward comparisons have slightly stronger effects in the brain, i.e., the negative effect in the reward centre triggered by receiving less than a reference person is larger in absolute terms than the positive effect triggered by receiving more than the reference person.

based on data from the Standardized World Income Inequality Database (SWIID) and the World Bank. The Global Preferences Survey was conducted as part of the Gallup World Poll in 2012 and covers 76 countries (Falk et al., 2018). It is representative at the country level with a median sample size of 1,000 respondents per country, whilst covering countries that hold 90% of the world's population and income. In this survey, risk taking was measured through the combination of two survey questions: a qualitative self-assessment and a quantitative series of fixed odds lottery choices. The SWIID constitutes the pre-eminent source of inequality data for cross-national comparisons (Solt, 2020). Our principal measure of inequality is the Gini index of disposable income, which captures the degree of inequality after taxes and transfers have been deducted from income. While the Gini coefficient is a very common and widely-used inequality measure which captures the entire income distribution, the comparison of a Gini of two countries is not always obvious, if for example at quantile 1 the accumulated share of total income for country 1 is lower than for country 2, while the reverse holds at a higher quantile. This is one reason why we will also use four other well-known inequality measures, which only consider part of the income distribution but which might however be more suitable to test whether patterns are in line with our hypothesis. These are: the income share held by the top and bottom 10th percentile, the Palma ratio (the share of income held by top 10th percentile divided by the share held by the bottom 40th) and the 80/20 income share ratio.

We acknowledge that individuals might not be fully aware of the objective level of inequality they face, so that it is likely the *perceived* level of inequality (cf. Brown-Iannuzzi & McKee, 2019) that affects risk-preferences. Norton and Ariely (2011) reveal that participants significantly underestimate how much wealth is owned by the richest quintile in the US and overestimate how much wealth was owned by the poorest two quintiles. This suggests that the participants perceive more equality than what exists in society. This misperception is even present in a more granular context. Jäger et al. (2022) demonstrate that workers misperceive their rank within their firm's pay distribution: beliefs are compressed around the 50th percentile. Perceptions likely deviate from objective reality through a kaleidoscope of individual biases and imperfect information, all of which determine the extent to which we "experience inequality" (Roth & Wohlfart, 2018). One possible explanation for such a divergence is that the very concept of inequality is difficult to grasp (Eriksson & Simpson, 2012); principally because it requires an understanding about the variance, not just the mean levels, of income. Indeed these perceptions and experiences with inequality have real world effects. For instance, Alesina et al. (2018) find that more pessimistic beliefs about the inequality of opportunity increases support for redistribution. To this end, we must consider that the effect of inequality on individuals is by no means homogeneous. We hypothesise that the risk preference of individuals who are better placed to read or interpret the objective degree of inequality should be more affected.

The analysis of our combined data reveals a robust relationship between inequality and the willingness to take risks, across the entire sample and various subsamples. At both the individual and country-level, we find a precise, stable estimate that indicates higher inequality is significantly associated with a greater degree of risk taking. This finding holds after controlling for a host of potential confounding factors and irrespective of the measure of inequality we use. Two complementary instrumental variable approaches indicate a causal link running from inequality to the willingness to take risks. Following Acemoglu et al. (2019) we construct a spatially weighted instrument that exploits the levels of inequality across countries in the same region and with common political histories. We pay specific attention to the identifying assumptions made regarding this instrument and the criticism they have faced recently (Betz et al., 2018). In light of this, we employ a complementary approach that relies on a different set of identifying assumptions: the Bartik-style ‘shift-share’ instrument. Here, we exploit the changes in inequality in a country’s immediate neighbourhood. The resulting estimates from both approaches indicate that higher inequality is causally linked to greater risk taking at both layers of analysis. Since our instruments may not be fully exogenous, we allow for departures from full exogeneity (Conley et al., 2012). We find that the second-stage estimate of inequality is bounded away from zero as long as the direct (endogenous) effect of the instrument on risk preference is not more than 50% of the reduced form effect. We can therefore conclude that the positive effect of inequality on risk preference is robust even under large departures of exogeneity. We also provide novel evidence on our hypothesised mechanism that links changes in inequality to risk taking. Using data from the German Socioeconomic Panel, we are able to show that individuals who fall behind their peer reference group are significantly more willing to take risks.

With our focus on the relationship between country-level inequality and individuals’ willingness to take risks we do not only complement studies based on lab experiments cited above that indicate a link between income inequality and risk taking behaviour, but we also contribute to a better understanding of the sources of risk preferences. This is important as myriad behaviours and outcomes result from decision-making under risk or uncertainty. While a large strand of empirical literature has emerged to study individual determinants of risk preferences,[4] much less is known about the role of macroeconomic conditions and macroeconomic outcomes for individual risk taking behaviour. Bucciol and Miniaci (2018) provided evidence that willingness to take risks varies over the business cycle. Our findings do not only highlight the role of another macroeconomic outcome, namely income inequality, for risk taking behaviour but also indicates that policies that affect the income distribution may also affect risk attitudes.

The remainder of the paper is as follows. In Section 2, we discuss the data and in Section 3, we provide empirical evidence on the global relationship between inequality and risk taking for several subgroups and using various inequality measures. In Section 4, we present the two instrumental variable approaches to argue that there is a causal link going from inequality to risk taking, and Section 5 contains further extensions which explore the importance of perceptions and income satisfaction. Section 6 provides evidence on the falling behind mechanism that underpins our headline finding. Finally, Section 7 offers a concluding discussion.

[4] For example, gender, age, and cognitive ability have been shown to explain differences in risk attitudes across individuals (see, e.g., Croson & Gneezy, 2009; Dohmen et al., 2011; Sahm, 2012; Benjamin et al., 2013; Golsteyn & Schildberg-Hörisch, 2017).

2 Data

2.1 Risk preference

Our analysis uses data from the Global Preferences Survey (GPS), a dataset on economic preferences from representative samples across the globe. The data are collected as part of the 2012 Gallup World Poll in 76 countries that were chosen to be globally representative. The GPS was created by including a set of survey items specifically designed to measure a respondent's economic preferences. For more details on the GPS, see Falk et al. (2018).

There are four key characteristics of this dataset that make it attractive to this study. First, the preference measures have been elicited in a way that is comparable across countries using a standardized protocol. Second, the preferences are representative at the country-level (unlike small or medium-scale experimental work) which allows for across-country inferences about preferences. The median sample size was 1,000 respondents per country and a total of approximately 80,000 individuals in total. Respondents were selected through probability sampling and interviewed face-to-face or via telephone by a professional interviewer. The third factor is that the GPS reflects geographical representativeness. The 76 sampled countries span all continents, cover various cultures and are of differing levels of development. Specifically, our sample includes 15 countries from the Americas, 25 from Europe, 22 from Asia and Pacific, as well as 14 nations in Africa, 11 of which are Sub-Saharan. The countries account for around 90% of the worlds population and global income. Fourth, the preference measures are based on experimentally validated survey items for eliciting preferences. In order to ensure behavioural relevance, the underlying survey items were designed, tested, and selected through an ex-ante experimental validation procedure (see Falk et al., 2023, for more details). In this validation exercise, those survey items were selected that jointly performed best in explaining observed behaviour in standard financially incentivized experimental tasks to elicit preference parameters. In order to make these items cross-culturally applicable: (i) all items were translated back and forth by professionals, (ii) monetary values used in the survey were adjusted based on the median household income for each country, and (iii) pretests were conducted in 22 countries of various cultural heritage to ensure comparability.

Risk preference is derived from the combination of responses to two survey items: one with a qualitative self-assessment format and the other with a quantitative format. The subjective self-assessment question asks for an individual's willingness to take risks: *"Generally speaking, are you a person who is willing to take risks, or are you not willing to do so? Please indicate your answer on a scale from 0 to 10, where a 0 means "not willing to take risks at all" and a 10 means "very willing to take risks". You can also use the values in between to indicate where you fall on the scale."* This question has been shown to be successful in predicting risk taking behaviour in the field in a representative sample (Dohmen et al., 2011) and incentivized experimental risk taking across countries in student samples (Vieider et al., 2015). The quantitative measure consists of a series of five binary lottery choices, which is commonly known as the "staircase procedure". Choices were between a fixed-odds lottery, where the individual

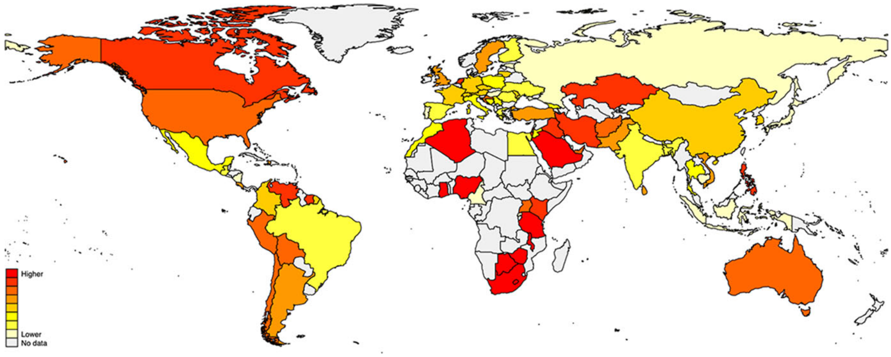

Fig. 1 Risk preference around the globe

has a 50-50 chance to win x or nothing, and a varying guaranteed payment of y. The question is posed as follows: *"Please imagine the following situation. You can choose between a sure payment of a particular amount of money, or a draw, where you would have an equal chance of getting amount x or getting nothing. We will present to you five different situations. What would you prefer: a draw with a 50% chance of receiving amount x, and the same 50% chance of receiving nothing, or the amount of y as a sure payment?"* Selecting the lottery resulted in an increase in the guaranteed payment in the next round, and vice versa. This allows us to "zoom in" on the individual's certainty equivalent. This question elicits risk preference as 1 of 32 ordered outcomes. The two survey items are linearly combined into a single risk preference measure using weights obtained from an experimental validation procedure.[5] The analysis is based on the individual-level risk preference measure that is then standardized, that is, we compute z-scores at the individual-level. We then calculate the country-level risk preference by averaging responses using sampling weights provided by Gallup. The risk preference measure is scaled throughout the paper so that higher values indicate a stronger preference for risk, i.e., the individual is more risk taking. Figure 1 presents the spatial distribution of risk preference across the globe, relative to the world's average individual. Darker (lighter) areas indicate a greater (weaker) preference for risk. A visual inspection of the map reveals that African countries are particularly risk taking, whereas Europeans are typically more risk averse relative to the mean.

2.2 Inequality

Our principal measure of inequality comes from the Standardised World Income Inequality Database by Solt (2020). The SWIID is the pre-eminent source of inequality data for cross-national research and the latest version provides estimates that are more

[5] Responses to both items were standardized (z-score) at the individual-level and then aggregated:

$$\text{Risk preference} = 0.4729985 \times \text{Staircase risk} + 0.5270015 \times \text{Will. to take risks} \,,$$

with weights based on OLS estimates of a regression of observed behaviour in financially incentivized laboratory experiments on the two survey measures. See Falk et al. (2018) for more details.

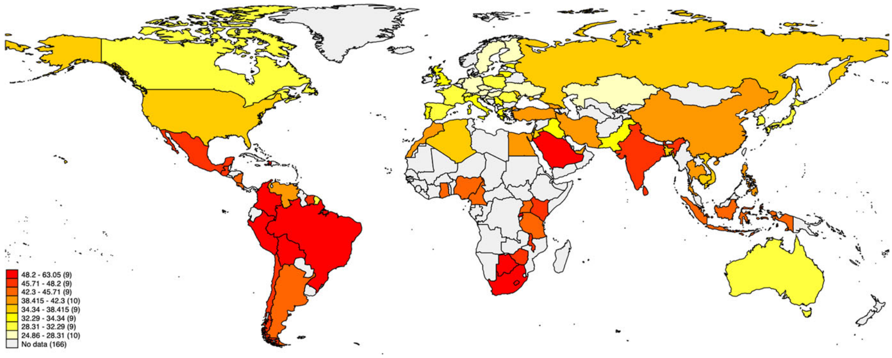

Fig. 2 Inequality around the globe

reliable than previous versions, which is shown via k-fold cross-validation. The SWIID uses the Luxembourg Income Study and the World Inequality Indicators Database in order to construct a comprehensive country-year panel of Gini coefficients that are standardized across sources and measures and has been used in numerous studies (see, e.g., Acemoglu et al., 2015). In order to limit the gaps in the data set, the SWIID uses multiple imputation procedures to recover missing values. Because of this, 100 values of inequality are provided for each country-year cell. Following the standard in the literature, we use the simple mean of these values (see, e.g., Kotschy and Sunde, 2017). Our preferred measure of inequality is the Gini of disposable income, that is, the income that remains after taxes and transfers have been deducted.[6] The Gini index ranges from 0 to 100, where higher values indicate a more unequal income distribution. We aggregate the country-year cells to the country-level average over the 2002 to 2012 period—we stick with this convention wherever we face temporal variation unless stated otherwise. Figure 2 depicts the cross-country variation in the Gini coefficient used in our analysis. We can observe that Latin America and Africa are especially unequal in terms of income, whereas European countries and other developed nations have a relatively more equal distribution of disposable incomes.

We also consider four alternate measures of inequality. These are: the income share held by the top and bottom 10th percentile, the Palma ratio (the share of income held by top 10th percentile divided by the share held by the bottom 40th) and the 80/20 income share ratio. All of which are obtained or derived from the World Bank's Development Indicators. These type of measures are used by Piketty and Saez (2014) to capture income inequality.

3 Inequality and risk: Empirical evidence

As a first step in our analysis, we present associative evidence on the relationship between inequality at two different levels of aggregation: across countries and across

[6] We chose the net Gini rather than the pre-tax and transfers market Gini as it is reasonable that individuals primarily make decisions and form expectations and preferences based on their disposable income (see, e.g., Kerr, 2014).

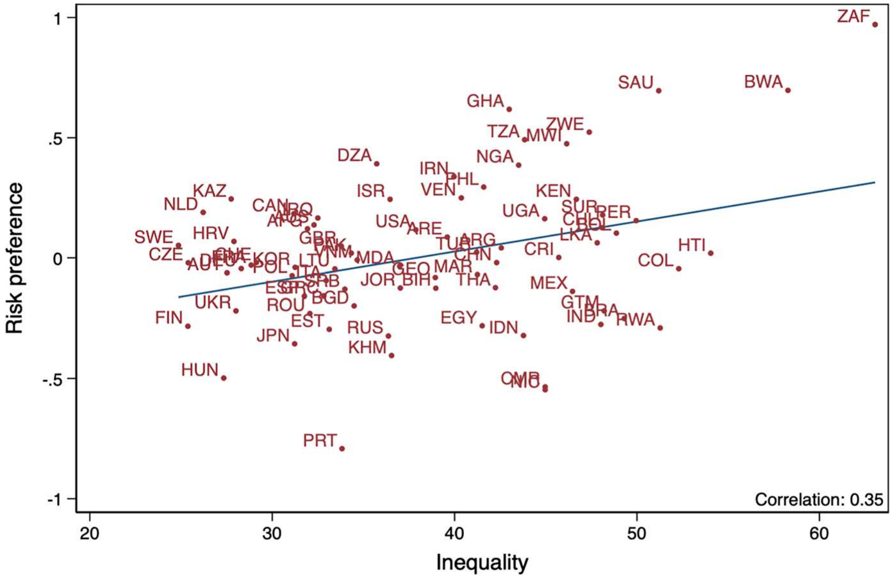

Fig. 3 Inequality and risk preference

individuals.[7] It is worth noting that for the individual-level analysis our measure of inequality remains fixed at the country-level whilst risk preferences vary at the individual-level.

3.1 Cross-country evidence

The raw correlation (ρ) between risk preference and inequality is 0.35 and this relationship is illustrated in Fig. 3. Table 1 presents the results of a set of OLS regressions of risk preference on inequality. Column (1) shows that a 1 standard deviation (approximately 8.49 points) increase in inequality is associated with a 0.12 standard deviation increase in risk preference and is significant at the 5% level. Column (2) to (4) progressively adds economic, climatic, geographic, and political controls. Column (2) introduces GDP per capita. Column (3) contains additional controls for the average precipitation, temperature, ruggedness of the land, distance to the nearest waterway, and whether the country is an island. Finally, column (4) adds a control for whether the country is a democracy. Despite adding a broad set of controls, the coefficient remains remarkably stable across specifications and statistically significant. This gives us confidence that these findings are not driven by unobservables, which would attenuate the inequality coefficient.[8]

[7] We also performed analysis across sub-national regions by aggregating the risk-preference data to this level. To ensure a degree of representativeness at the region-level, we excluded regions with less than 15 respondents and apply techniques used in Chetty and Hendren (2018) by shrinking regional risk preference to the sample mean by its signal-to-noise ratio. Our results, available on request, remain qualitatively the same as the individual and country-level findings.

[8] We provide a formal test of this in the robustness checks section.

Table 1 Inequality and risk preference: country-level

	Risk preference			
	(1)	(2)	(3)	(4)
Inequality	0.012**	0.015***	0.014**	0.013**
	(0.005)	(0.005)	(0.006)	(0.006)
Ln of GDP p/c		0.027	0.038	0.032
		(0.028)	(0.026)	(0.029)
Precipitation			−0.002***	−0.002***
			(0.001)	(0.001)
Temperature			0.008*	0.010*
			(0.005)	(0.006)
Ruggedness			−0.013	−0.009
			(0.027)	(0.029)
Dist. to nearest waterway			0.099	0.127
			(0.085)	(0.090)
Island			0.037	0.047
			(0.105)	(0.107)
Democracy				0.057
				(0.100)
R-squared	0.123	0.136	0.287	0.291
Observations	76	76	76	76

Notes: OLS estimates. The dependent variable is the country-level average of risk preference weighted by sampling weights. Inequality is the Gini index of disposable income averaged over 2002–2012; Ln of GDP p/c is the average natural logarithm of GDP per capita; Precipitation is the average monthly precipitation of a country in millimeters; Temperature is the average monthly temperature of a country in degrees Celsius; Dist. to nearest waterway is the distance, in thousands of kilometers, to the nearest ice-free coastline or sea-navigable river; Ruggedness is the Terrain Ruggedness Index in hundreds of meters; Island is a binary variable denoting whether a country is a island; and Democracy is a binary variable denoting whether a country is a democracy throughout the 2002–2012 period. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

We now examine how our four alternate measures of inequality are associated with risk preference by repeating the specifications used in Table 1. The results are presented in Table 2. Panel A (B) shows the effect of the income share held by the top (bottom) 10 percentile on risk preference. Panel C and D contain the results for the Palma and 80/20 ratio. As with the Gini, we find that more inequality is significantly associated with a greater degree of risk taking, irrespective of the measure.

3.2 Individual-level evidence

Now we consider the relationship between inequality and risk preference at the individual-level. This exercise is particularly important as we are able to control for a huge variety of individual factors that may drive risk preferences, whilst examining the effect of country-level inequality.

Table 2 Income shares and risk preference

	Risk preference			
	(1)	(2)	(3)	(4)
Panel A				
Income share [top 10th pctl.]	0.014**	0.014*	0.016**	0.015*
	(0.007)	(0.008)	(0.007)	(0.008)
R-squared	0.105	0.105	0.258	0.258
Observations	71	71	71	71
Panel B				
Income share [bottom 10th pctl.]	−0.080*	−0.077*	−0.099**	−0.092**
	(0.042)	(0.043)	(0.040)	(0.040)
R-squared	0.055	0.071	0.248	0.250
Observations	71	71	71	71
Panel C				
Palma ratio	0.099***	0.096**	0.099***	0.099***
	(0.035)	(0.037)	(0.032)	(0.037)
R-squared	0.153	0.156	0.296	0.296
Observations	71	71	71	71
Panel D				
80th/20th	0.022**	0.021**	0.023***	0.022**
	(0.009)	(0.009)	(0.008)	(0.009)
R-squared	0.132	0.139	0.288	0.288
Observations	71	71	71	71
Income		✓	✓	✓
Geographic controls			✓	✓
Democracy				✓

Notes: OLS estimates. The dependent variable is the country-level average of risk preference weighted by sampling weights. Income share [top 10th pctl.] is the share of income held by the wealthiest 10th percentile; Income share [bottom 10th pctl.] is the share of income held by the poorest 10th percentile; Palma ratio is the share of income held by wealthiest 10th percentile divided by the share held by the poorest 40th percentile); 80th/20th is the ratio of the share of income held by the wealthiest 20th percentile divided by the share held by the poorest 20th percentile. Control variables refer to those listed in Table 1. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3 presents the results of a set of OLS regressions with the standard error clustered at the country-level. In column (1) we control for GDP per capita and a basic set of individual-level controls: gender, age, age squared, and a set of income quintile dummies. In column (2) we add a comprehensive range of individual covariates: marital status fixed effects, highest education level dummies, an indicator for high self-assessed math skills, religious fixed effects, whether the respondent has children, household size, whether the individual has health problems, whether the individual smokes, and whether they are self-employed. Column (3) adds the remaining country-level variables from Table 1 column (4) instead of the extended individual controls.

Table 3 Inequality and risk preference: individual-level

	Risk preference			
	(1)	(2)	(3)	(4)
Inequality	0.011**	0.013**	0.011*	0.012*
	(0.005)	(0.005)	(0.006)	(0.006)
GDP	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Additional individual controls		✓		✓
Country controls			✓	✓
R-squared	0.086	0.106	0.095	0.117
Observations	79,439	68,415	79,439	68,415

Notes: OLS estimates. The dependent variable is the standardized measure of risk preference. Inequality is the Gini index of disposable income averaged over 2002–2012. GDP refers to Ln of GDP p/c. Individual controls are dummies for income quintiles, gender, age, and age squared. Additional individual controls are dummies for marital status, the level of education attained, high math skills, religious affiliation, having children, is a smoker, reported health problems, self-employment status, and a continuous measure of household size, and Country controls are precipitation, temperature, ruggedness, distance to nearest waterway, island, and democracy. Standard errors, clustered at the country-level are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Lastly, column (4) saturates the regression equation with all possible country- and individual-level information. We find that a 1 unit increase in inequality is associated with an 0.012 standard deviation increase in risk preference. Throughout the table the coefficient for inequality remains stable and statistically significant at the conventional levels. A striking finding here is that the relationship between inequality and risk preference is very similar at the individual and country-level, that is, there are no aggregation effects. This make sense as there are no accumulation or price effects in operation (see, e.g., Sunde et al., 2022, where disagreggation of the time preference leads to attenuation).

3.3 Robustness checks

The key finding that emerges from our analysis thus far is that higher levels of inequality are associated with a higher propensity to take risks. To provide further support for this finding, we perform a series of robustness tests, which are reported in the SI Appendix.

In Table A.2, we include the degree of fiscal redistribution, country size, land suitability for agriculture, and family ties, as motivated by Falk et al. (2018). We also include measures of the rule of law and human capital, as well as accounting for the colonial history of each country. By doing so, our findings are unchanged. In Table A.3, we assess how sensitive the results are to an alternate disposable income Gini index, from the World Bank. The SWIID and World Bank Ginis are quite similar (ρ = 0.87). The coefficient is almost identical despite a reduced sample size and is statistically significant throughout. We explore to what extent our results could be affected by pre-tax and pre-transfers inequality by running a horserace regression. We find a statistically insignificant effect of this type of inequality, whereas our post-taxes and transfers measure remains highly significant. The results are reported in Table

A.4. We also carefully assess the role of outliers in the data in Table A.5 by excluding countries using Cook's distance[9], our result is unaffected. As a final test for outliers, we systematically exclude each country one by one and rerun all the regressions, we consistently observe stable coefficients that are statistically significant in every regression bar one. The results are presented in Fig. A.1. We account for any arbitrary correlation of the error terms by clustering the standard errors at the continent-level, we also use the wild cluster bootstrap method since the number of clusters in our sample is likely to be considered small. Irrespective of how we adjust our standard errors in Table A.6, our results remain unaffected. Whilst we observe that the effect of inequality is stable when further observables are included, we address what role unobservables may play. We employ the method proposed by Oster (2019) to investigate the importance of unobservables. In Table A.7, we reproduce our results for all inequality measures and include the bias adjusted coefficient (the upper bound), where Rmax is 1.3 times the R-squared in the specification that controls for observables. We also present Oster's delta, which indicates the degree of selection on unobservables relative to observables that would be needed to fully explain our results by omitted variable bias. In all cases, the results show very little movement in the coefficients and have delta values that are comfortably above the rule of thumb value 1, which gives us confidence that our result would not be explained away by unobservables.

4 Addressing endogeneity concerns

Our empirical results thus far have an associative interpretation. A causal reading of the results would perhaps be ill-advised given the usual endogeneity concerns. We are not especially concerned about omitted variable bias as we have shown remarkable coefficient stability of inequality across- and within-analysis and passed the Oster test of unobservables, but reverse causality remains an issue. It is entirely plausible that risk taking behaviour may increase the degree of inequality. A simple scenario to illustrate this occurs in capitalist societies; individuals (firm owners) are incentivized to take on risk in order to generate substantial returns for themselves, which, in turn, can exacerbate existing inequalities. In order to alleviate this concern, and any lingering worries about omitted variables, we use an instrumental variable approach to get as close as possible to a causal interpretation.

4.1 Approach

The challenge we face is to find an instrument that is suitably correlated with the level of inequality and also unrelated to risk preference in country i. We take inspiration from Acemoglu et al. (2019) who use the degree of democracy in a country's neighbourhood as a source of exogenous variation for the domestic democratic status. We apply the same rationale to our context. With the GPS data, however, we do not have a temporal dimension to exploit which may lead to a weaker first-stage. We posit that the demand

[9] We exclude observations with a Cook's distance above the common rule-of-thumb threshold: four divided by the number of observations.

for (in)equality in the domestic country is affected by the supply in foreign countries. To illustrate the existence of this concept, Fig. 2 displays a stark spatial correlation of inequality within-regions. Formulaically, we can write that inequality in country i is influenced by inequality in the set of countries:

$$I_i = \{j : j \neq i, R_i = R_j\}, \tag{1}$$

where R denotes the seven regions defined in Acemoglu et al. (2019) in which the countries share a common political history. These regions are Africa, East Asia and the Pacific, Eastern Europe and Central Asia, Western Europe and other developed countries, Latin America and the Caribbean, the Middle East and the North of Africa, and South Asia. Using these sets, we define our instrument as:

$$Z_i = \frac{1}{|I_i|} \frac{\sum_{j \in I_i} \text{Inequality}_j \times W_{ij}}{\sum_{j \in I_i} W_{ij}}, \tag{2}$$

where $Inequality_j$ is the disposable Gini index in foreign country j, and W_{ij} is the inverse distance between country i and j's most populous cities.[10] We apply this inverse distance weighting formula in order to assign a higher weight to inequality in more proximate countries and generate more variation in the instrument for each country. For instance, for the UK, the instrument gives more prominence to inequality in Europe than in North America despite being a member of the same region. It is also important to note that we use a global sample of 178 countries to derive the instrument for the 76 GPS countries. Crucially, the instrument is constructed so that an increase in inequality in the foreign countries increases the value of Z_i, which can influence inequality in the domestic country.[11]

We acknowledge that spatial instruments like this have faced some criticism (Betz et al., 2018). Hence, we also use a complementary Bartik-style 'shift-share' instrument (Bartik, 1991). The intuition here is that countries differ in their current level of inequality, for historical reasons, and these differences can determine the degree to which a country is affected by regional changes in inequality. Specifically, our instrument is constructed as follows:

$$Z_i^{Bartik} = \text{Inequality}_{i,1990-2001} \times g_{t,j \in I_i}, \tag{3}$$

we define the initial level of inequality in country i as the 1990–2001 average and interact this with the growth rate of inequality in country i's region (as defined in

[10] Our results are identical if we use a population weighted measure of distance as the instruments have a correlation coefficient of 0.998.

[11] As in Acemoglu et al. (2019), we construct three related instruments to test the sensitivity of our results to instrument construction: (i) the jackknifed average of inequality in the region, (ii) the jackknifed average of inequality in contiguous countries, and (iii) inequality weighted by proximity for all countries across the globe. The results can be found in Table C.1 and our findings persist irrespective of the instrument used. We also explored robustness to constructing our instrument using the 1990–2000 values of inequality, that is, we used the temporal lag of Z, Z_{t-1}. The results are shown in Table A.8 and our findings remain the same.

Eq. 1), whilst excluding i, from 1990–2001 to 2002–2012 (t). In other words, variation in the instrument comes from the interaction between the initial exposure to inequality (the 'share' term) and the changing pattern of foreign inequality in a given country's region (the 'shift' term). By definition the Bartik-style instrument is a complementary approach to the spatial instrument since we now exploit *changes* in foreign inequality. Specifically, identification in this setting is motivated by exogenous jackknifed regional 'shocks' (changes in the amount of foreign inequality over time), even when exposure shares are assumed to be endogenous (Borusyak et al., 2021). Thus, we continue with the jackknifed (leave-one-out) approach in constructing the growth rates.

4.2 Empirical evidence

We estimate the IV regressions for both the country- and individual-level. Tables 4 and 5 present the results for the country- and individual-level, respectively, and we consider the findings in tandem. The first-stage results are reported at the bottom of

Table 4 Inequality and risk preference: Country-level IV estimates

	Risk preference			
	(1)	(2)	(3)	(4)
Panel A				
Inequality	0.015***	0.020***	0.024***	0.024***
	(0.005)	(0.006)	(0.006)	(0.007)
Income		✓	✓	✓
Geographic controls			✓	✓
Democracy				✓
Z	1.008	1.062	1.069	1.008
Z p-value	0.000	0.000	0.000	0.000
F-stat	186.113	76.658	44.868	46.062
Observations	76	76	76	76
Panel B				
Inequality	0.011**	0.013**	0.013**	0.011*
	(0.005)	(0.006)	(0.006)	(0.006)
Income		✓	✓	✓
Geographic controls			✓	✓
Democracy				✓
Z^{Bartik}	0.969	0.945	0.945	0.945
Z^{Bartik} p-value	0.000	0.000	0.000	0.000
F-stat	1245.862	599.427	423.551	335.556
Observations	72	72	72	72

Notes: IV estimates. The dependent variable is the country-level average of risk preference weighted by sampling weights. Inequality is the Gini index of disposable income averaged over 2002–2012. Control variables refer to those listed in Table 1. F-stat is the Kleibergen-Paap weak instrument statistic. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5 Inequality and risk preference: individual-level IV estimates

	Risk preference			
	(1)	(2)	(3)	(4)
Panel A				
Inequality	0.017***	0.018***	0.024***	0.025***
	(0.006)	(0.005)	(0.009)	(0.008)
GDP	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Additional individual controls		✓		✓
Country controls			✓	✓
Z	1.005	1.024	0.942	0.986
Z p-value	0.000	0.000	0.000	0.000
F-stat	57.568	68.596	31.853	46.306
Observations	79,439	68,415	79,439	68,415
Panel B				
Inequality	0.011*	0.012**	0.010	0.011*
	(0.006)	(0.006)	(0.007)	(0.006)
GDP	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Additional individual controls		✓		✓
Country controls			✓	✓
Z^{Bartik}	0.930	0.933	0.935	0.921
Z^{Bartik} p-value	0.000	0.000	0.000	0.000
F-stat	509.733	580.753	297.307	341.699
Observations	75,450	66,473	75,450	66,473

Notes: IV estimates. The dependent variable is the standardized measure of risk preference. Inequality is the Gini index of disposable income averaged over 2002–2012. Control variables refer to those listed in Table 3. F-stat is the Kleibergen-Paap weak instrument statistic. Standard errors, clustered at the country-level, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

each panel in the tables. As anticipated, the coefficient for *Inequality abroad*, denoted as Z, is positive and highly significant at the 1% level across all specifications. Its value is approximately one, indicating that it effectively predicts domestic inequality, on average. The instrument is strong, as captured by the large KP test statistic values. The second-stage results reported in the Tables once again show a positive effect of inequality on risk preference. The IV estimates of inequality are highly significant and generally not so different from the OLS ones, pointing to the absence of a strong endogeneity bias. As with our OLS estimates, the IV estimates are almost identical between the two layers, which further substantiates that there are no aggregation effects. Turning now to our Bartik-style IV results in Panel B, the instrument performs very well and, in all specifications, we find a positive and significant effect of inequality on risk preference. The smaller sample size is due to the data intensive construction of the instrument, that is, we require full inequality data back to the 1990s. This is likely the reason for a smaller coefficient magnitude.

Overall, the picture is clear: inequality is associated with risk taking and the evidence is in favour of a causal relationship.

4.3 Threats to instrument validity

The key assumption for our spatial instrument to be valid requires that inequality in foreign countries does not affect risk preferences in the domestic country. There are two such channels that may violate this: spillovers and interdependence (Betz et al., 2018).

Interdependence here means that foreign inequality (X_j) could directly affect domestic risk preference (Y_i). The way individuals assess inequality is largely determined by their income relative to others in the same distribution. Therefore, it is difficult to argue that domestic individuals would alter their risk taking preferences due to changes in inequality elsewhere. It is unreasonable that this comparison would be made beyond the level at which policies can affect inequality, i.e., the nation state. However, the scenario in which this may be plausible is when one's network and peers are based outside of their residing country, recent migrants or those wishing to migrate for instance. To this end, we exclude several groups of individuals from the analysis in SI Appendix Tables B.3 and B.4, our results are unchanged.

The more pernicious channel, however, is spillovers. This follows the argument that inequality abroad (X_j) affects foreign risk preference (Y_j), which in turn, has a spillover effect on the domestic risk preference (Y_i). To block this channel, we control for the inverse distance weighted average of risk preference in a country's region. The results are presented in SI Appendix Table A.9 and the effect of inequality reassuringly remains correctly signed and significant throughout.[12]

As we acknowledge, our instrument may not be fully exogenous in the sense that it may have a direct effect on risk preference that does not pass through the level of domestic inequality. We therefore scrutinise the stability of our IV estimates by relaxing the exclusion restriction assumption of the instrument using the union of confidence interval method developed by Conley et al. (2012).[13] Suppose that the instrument may not be fully exogenous, that is, it may have a direct effect on risk preference, with a coefficient of $\gamma \neq 0$. By assuming a range of values for γ over the perfectly exogenous scenario ($\gamma = 0$) and between positive and negative values of reduced form effect, we can derive an interval for the causal effect of inequality that takes into account deviations from exogeneity. This method enables us to determine how large the direct (endogenous) effect would have to be for the coefficient of inequality to include zero or flip the positive sign to a negative one.

[12] As a further check, we verify that our results are not driven by correlated regional shocks to income by adding a control for the inverse distance weighted average of GDP in a country's region. The results are presented in SI Appendix Table A.10 and the effect of inequality remains significant throughout.

[13] This test has recently been used by Alesina et al. (2023); Azar et al. (2022); Meierrieks and Renner (2023), for instance, in various contexts to lend credibility to an instrument that may not be fully exogenous.

We present the bounds on the second-stage effect, assuming varying degrees of endogeneity in the instrument, graphically in Fig. 4. We use the baseline specifications at the country and individual-level (Table 1 column 4 and Table 3 column 4, respectively). Turning first to our preferred spatial instrument in the upper and bottom left panels, the bounds for the second-stage exclude zero as long as the direct of the instrument is smaller than approximately 50% of the reduced form effect when the bias is positive. When γ is negative the coefficient for the instrument is robust to all deviations at least as large as the negative value of the reduced form effect. We can make a similar inference about the Bartik-style instrument, although this is less robust when $\gamma > 0$. We conclude that the positive impact of inequality on risk preference is robust to a large degree of instrument endogeneity. That is, the instrument would have to be highly problematic for the impact of inequality on risk preference to become *negatively* signed or 0.

Finally, we reiterate that our results are robust to the use of a Bartik-style instrument. The jackknifed regional growth rate of inequality circumvents the criticisms of the spatial instrument since we are now relying on *changes* in foreign inequality for identification.

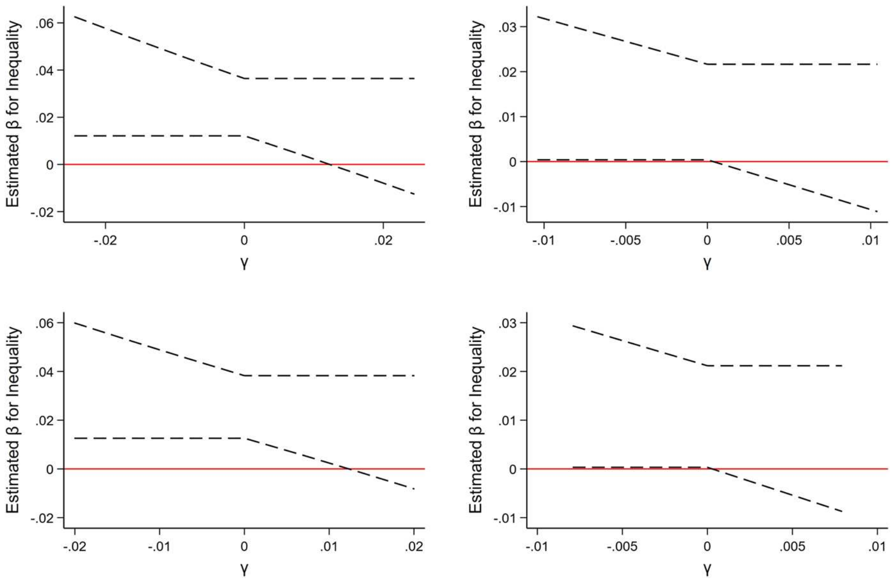

Fig. 4 Plausibly exogenous instrument regressions. *Notes:* The upper and bottom left panels use the spatial instrument for country-level and individual-level analysis, respectively. The upper and bottom right panels use the Bartik-style instrument for country-level and individual-level analysis, respectively. At the country-level, for instance, we consider the following regression in which the instrument is not fully exogenous and therefore enters the second-stage regression: $y_i = \alpha + \beta \text{ Inequality}_i + \gamma Z_i + \theta X_i + \epsilon_i$, where Z_i is our instrumental variable. We implement the plausibly exogenous methodology as follows. We estimate the reduced form effect of our instrument and set $\gamma^{\min}$ and $\gamma^{\max}$ to -/+ values of the reduced form coefficient, respectively. We then compute bounds for Inequality (β) using the union of confidence interval method provided by Conley et al. (2012).

5 Extensions: perceptions and references

In this section we explore two sources of heterogeneity that may ratchet the relationship between inequality and risk preference as predicted in our theoretical framework. We return to our individual-level analysis to provide valuable insights the role of one's reference point and their perception of the level of inequality.[14]

5.1 Perceptions of inequality

Our theoretical framework posits that the effect of inequality on risk preference may vary based on how accurately one perceives the level of inequality in their country. Perceptions can deviate from true inequality levels, as inequality is a measure of variance requiring some numeracy skills to interpret societal signals accurately. To explore this relationship, we use a survey item from the Gallup World Poll that asks respondents about their subjective math skills. Respondents answer on a 11-point scale (0-10), and we create a dichotomous variable for the top 10^{th} percentile (categories 9 and 10) and 0 otherwise.[15] We denote this variable *High math*.

The rationale for using math skills in this context is to proxy for cognitive skills and ability. Evidence suggests that mathematical skills are positively correlated with general cognitive ability (see, e.g., Borghans et al., 2016). Our hypothesis is that individuals with higher cognition are better equipped to perceive the true state of inequality in their country. This aligns with research indicating that more educated people have more accurate perceptions of society, as covered in Lutz and Bitschnau (2023) in the case of immigration misperceptions. We specifically chose mathematical ability as our proxy because it is related to educational attainment (which we control for in our regressions) but more closely linked to understanding measures of dispersion, i.e., inequality. This approach allows us to assess how perception, as approximated by cognitive ability, alters risk preference in the context of inequality. It is important to note that any measure would only serve as a proxy for interpretability quality, as factors such as media consumption or place of residence can also influence perceptions of inequality. Nonetheless, this method provides a valuable insight into the relationship between cognitive skills, inequality perception, and risk preferences.

We estimate the effect of perceptions by interacting the dummy with *Inequality*. The estimates are displayed in Table 6. In the first five columns we proceed as we previously have with model specifications. The final column, however, presents a specification with country fixed effects, which is possible since our interaction term varies within-countries. Throughout the table we observe a positive and statistically significant interaction between inequality and our *High math* proxy of perception. Bear in mind, that the *High math* interaction with inequality is significant even after controlling for the objective level of education. The results support our hypothesis that

[14] In SI Appendix B.2, we implement a machine learning approach, a classification and regression tree (CART), and, fascinatingly, we reach the same conclusions as in this section. We direct the interested reader there for a more detailed explanation.

[15] Our results are robust to using the top 20^{th} percentile, which is categories 8, 9, and 10.

Table 6 Inequality, perceptions and risk preference

	Risk preference				
	(1)	(2)	(3)	(4)	(5)
Inequality	0.011**	0.012**	0.010*	0.011*	
	(0.005)	(0.005)	(0.005)	(0.006)	
High math	−0.055	−0.071	−0.072	−0.071	−0.065
	(0.091)	(0.087)	(0.087)	(0.081)	(0.070)
Inequality × High math	0.006**	0.006**	0.006***	0.006***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GDP	✓	✓	✓	✓	
Individual controls	✓	✓	✓	✓	✓
Additional individual controls		✓		✓	✓
Country controls			✓	✓	
Country FEs					✓
R-squared	0.090	0.106	0.099	0.118	0.172
Observations	79,439	68,415	79,439	68,415	68,415

Notes: OLS estimates. The dependent variable is the standardized measure of risk preference. Inequality is the Gini index of disposable income averaged over 2002–2012. High math takes value 1 if a respondent answers value 9 or 10 on an 11-point Likert-scale, 0 otherwise. Control variables refer to those listed in Table 3. Standard errors, clustered at the country-level, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

when an individual has the ability to better perceive inequity, the effect of inequality is even larger on one's risk preference.

5.2 The role of income satiation

We next investigate what role income plays in determining how inequality can affect risk preferences. Satisfaction with own-income is likely a salient point of reference where individuals react to inequality differently. That is, when an individual is satisfied with their current level of income, we expect changes in the level of inequality to have no effect on their appetite for risk taking. A survey item allows us to create such a measure. We code a binary variable with value 1 if the individual is either finding it *"difficult"* or *"very difficult"* on their current household income, and value 0 if they feel *"comfortable"* or *"getting by"*.

We estimate the role income satiation as a ratcheting factor by interacting the dummy with *Inequality*. The estimates are displayed in Table 7. We follow the same specifications as in the previous subsection. Throughout the table we observe a positive and statistically significant interaction between inequality and income dissatisfaction. We stress that relationship persists even when looking *within* countries in column (5). The interpretation is in line with our hypothesis: when individuals are below their reference point and inequality increases, this is further associated with an increase in one's preference for taking risk. We further unpick this relationship by showing the

Table 7 Inequality, income satiation and risk preference

	Risk preference				
	(1)	(2)	(3)	(4)	(5)
Inequality	0.009*	0.010*	0.007	0.008	
	(0.005)	(0.005)	(0.005)	(0.006)	
Income dissatisfaction	−0.430***	−0.418***	−0.476***	−0.457***	−0.239***
	(0.129)	(0.104)	(0.116)	(0.106)	(0.051)
Inequality × Income dissatisfaction	0.008**	0.009***	0.009***	0.009***	0.004***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
GDP	✓	✓	✓	✓	
Individual controls	✓	✓	✓	✓	✓
Additional individual controls		✓		✓	✓
Country controls			✓	✓	
Country FEs					✓
R-squared	0.092	0.111	0.102	0.124	0.178
Observations	76,285	65,511	76,285	65,511	65,511

Notes: OLS estimates. The dependent variable is the standardized measure of risk preference. Inequality is the Gini index of disposable income averaged over 2002–2012. Income dissatisfaction is a dummy denoting dissatisfaction with current household income, 0 otherwise. Control variables refer to those listed in Table 3. Standard errors, clustered at the country-level, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

effect of *Inequality* over the categories of income dissatisfaction.[16] We display the marginal effects in Fig. 5. We clearly observe that there is only a significant effect when an individual is dissatisfied with their household income.

All in all, this is quite compelling first evidence that reference-dependent risk preferences are important determinants of the relationship studied throughout this paper. We analyse this linkage more closely in the next section.

6 Does falling behind drive risk taking?

Our conceptual framework links inequality to risk taking through changes in individual income relative to the income of some reference group. To shed light on this mechanism, we analyse how falling behind one's occupational peers is related to changes in their willingness to take risks.

To do so, we take advantage of the richly detailed German Socioeconomic Panel, a nationally representative longitudinal study. The SOEP has asked respondents to rate their willingness to take risks in general on a 11-point Likert scale in 2004, 2006 and every year since 2008.[17] The specific questions reads: *"Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?"*, with answers

[16] In SI Appendix Fig. B.1, we show that relationship holds if we use all four survey responses.

[17] The self-assessment is also part of the measure of risk preference in the Preference Module of the Gallup World Poll 2012.

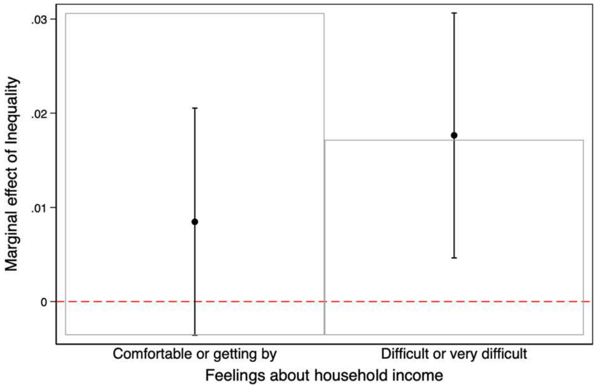

Fig. 5 Inequality, income satiation and risk preference. *Notes:* Marginal effects of the specification from Table 7 column (4). The black whiskers indicate 95% confidence intervals around the point estimate.

ranging from 0 *"unwilling to take risks"* to 10 *"fully prepared to take risk"*.[18] We create a binary measure that takes value 1 for above median responses (5), and value 0 otherwise.[19] Crucially, the SOEP also contains information on renumeration and occupational identifiers. Together, these allow us to get a handle on where a given individual is relative to the earnings of their occupational peers — that is, whether they are striding ahead or falling behind.

We formalise this in the following regression specification:

$$\text{Risk}_{it} = \alpha + \beta \ln(y_{it}) + \left[\beta^{+} \ln\left(\frac{y_{it}}{\bar{y}_{jt}}\right) \times \text{Above}\right] + \left[\beta^{-} \ln\left|\left(\frac{y_{it}}{\bar{y}_{jt}}\right)\right| \times \text{Below}\right] + \gamma \mathbf{X}_{it} + \delta_t + \epsilon_{it}, \tag{4}$$

where Risk_{it} is the binary measure of the willingness to take risks for individual i in wave t, $\ln(y_{it})$ is the natural log of the hourly wage, each individual i is nested within occupation j defined at the 4-digit ISCO-88 level, y_{jt} is the average occupation wage in wave t for which individual i belongs to, $\mathbf{X}_{it}$ is a set of socio-demographic control variables and region fixed effects, δ_t is a wave fixed effect, and ϵ_{it} is the error term. To test for the asymmetric effects of relative income, we introduce two separate terms for an individual being ahead and behind the occupational average. The first $y_{it}/\bar{y}_{jt}$ term is interacted with the dummy variable *Above*, which takes value 1 if $y_{it} > \bar{y}_{jt}$, and 0 otherwise, and the second $y_{it}/\bar{y}_{jt}$ is interacted with the dummy variable *Below*, which takes value 1 if $y_{it} \leq \bar{y}_{jt}$. We use the absolute value of relative wages in the latter case

[18] As in the earlier section, we note that this measure is closely correlated with an experimentally elicited risk taking measure and predictive of risk taking behaviours (Dohmen et al., 2011).

[19] Our results are fully robust to modelling the continuous measure (0-10) using either OLS or an ordered probit in SI Tables B.5 and B.6, respectively.

to make the direction of the coefficients easier to interpret, i.e., falling further behind corresponds to a positive change in taking risks.

Our results are reported in Table 8. In the first three columns, we report estimates from regressions that include only the own- and occupational-wage. Focusing on our preferred specification, column (3), this chimes with the bulk of the literature: higher income is associated with a higher willingness to take risks. The coefficient for occupational-wage is significant and positively signed, which indicates that when the wages of one's occupational peers increase, they are themselves more inclined to take risks. This is some first evidence in favour of our falling behind mechanism. To investigate this further, we estimate Eq. 4 that explicitly distinguishes whether an individual is ahead of or behind their peers. Our first term, β^+, is positive and significant, meaning that those individuals who are further up the wage distribution are more willing to take risks. Turning to our second term, β^-, it is positively signed and statistically significant. This can be interpreted as when an individual falls further behind their occupational average, they become more willing to take risks. The magnitude of the coefficient, interestingly, is significantly larger than β^+—over twice as large in column (4). This implies that individuals are putting more weight on catching up

Table 8 Relative wages and the willingness to take risks

	Willingness to take risks					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Own-wage)	−0.014***	0.013***	0.015***	0.059***	0.051***	0.053***
	(0.003)	(0.004)	(0.004)	(0.006)	(0.007)	(0.007)
ln(Occupational-wage)	0.073***	0.037***	0.037***			
	(0.006)	(0.007)	(0.007)			
Positive gap in relative wage (β^+)				0.050***	0.041***	0.042***
				(0.009)	(0.010)	(0.010)
Abs(Negative gap in relative wage) (β^-)				0.129***	0.077***	0.076***
				(0.007)	(0.007)	(0.007)
Wave FEs	✓	✓	✓	✓	✓	✓
Controls		✓	✓		✓	✓
Region FEs			✓			✓
R-squared	0.014	0.051	0.052	0.017	0.053	0.054
Observations	180,552	174,585	174,585	180,552	174,585	174,585

Notes: LPM estimates. The dependent variable takes value 1 if a respondent answers above the median value (5) on an 11-point Likert scale, 0 otherwise. Hourly own-wage is calculated as the gross monthly individual labour income (capped at 20,000 Euros per month) divided by 4.2 times the reported weekly working hours. Occupational-wage is the average hourly wage for an occupation-year cell. We excluded people younger than 18, older than 65, observations for which the occupation-year cell count is 4 or less, and people with extreme outliers in hourly own-wages. Controls are quadratics in age and years of education, the number of children, and dummies for marital status and gender. Regions are defined as the Bundeslands. Standard errors, clustered at the individual-level, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

when their place in the wage distribution deteriorates, rather than taking more risk whilst ahead. We note that this pattern holds *even after* controlling for own-wage and is robust to various model specifications.

In summary, our correlations provide first evidence in favour of the mechanism that individuals who have fallen behind their reference group, do increase their willingness to take risks. More widely, they also support the idea that preferences are reference-dependent.

7 Concluding discussion

In this paper, we present a global snapshot of the relationship between inequality and risk taking. Using survey data for around 80,000 people across 76 countries representing the global population, we find that there is a strong and robust relationship between a country's measure of post-tax income inequality and experimentally validated measures of willingness to take risks at the individual and country-level. A higher level of inequality in a country relates to a higher willingness-to-take risk both in the raw data and conditional on standard socioeconomic controls. Moreover, two complementary instrumental variable strategies come to the same conclusion that there appears to be a causal relationship running from income inequality to risk preferences, and we provided evidence that reference-dependent utility might be an important driver of this relationship. Furthermore, we presented evidence in favour of the mechanism that links changes in inequality to risk taking, that is, the experience of falling behind one's reference group.

Our baseline measure of inequality is the post-tax Gini coefficient of income inequality. A Gini coefficient summarises the entire income distribution and takes the value of one for the most extreme form of inequality and the value zero for complete equality. We acknowledge that any value in between these extreme outcomes can represent completely different income distributions, but at least in the sampled era it appears that country-level Gini coefficients are highly correlated with income polarisation. That is, in our common sample of 76 countries, the Gini is strongly positively correlated with the total percentage of national income hold by the top 10% earners and strongly negatively correlated with the share of total income hold by the bottom 10% earners. Our empirical models then also lead to similar conclusions when replacing the Gini coefficient with the latter two measures, or alternative measures which do not consider the entire income distribution but which are sensitive to income polarisation.

Our paper uses survey data that were collected in 2012 and inequality data averaged over the period from 2002 to 2012. There is evidence that in the subsequent years, at least in the advanced world, inequality and polarization have further increased or at least, not diminished (Blundell et al., 2018; Hoffmann et al., 2020). Moreover, the recent and on-going shocks to the global economy, are characterised by features such as high inflation, recessions and innovation, which have proven to be potentially important determinants of inequality and polarization. Given the large number of behaviours that risk attitudes can affect, as discussed in the introduction, the results of this paper are of importance to allow policymakers a more complete picture of the costs and benefits of policies related to inequality, or to allow firms and individuals to better assess future macroeconomic and political developments given current levels and predicted trends in inequality.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11166-024-09440-8.

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