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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 dataset 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 that individuals who are more able to understand inequality and individuals who fall behind their inherent point of reference increase their preference for risk. Two complementary instrumental variable approaches support a causal interpretation of our results.

JEL classification: D91; O15; D81; D01
Keywords: Income inequality; risk preference; risk sensitivity

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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 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. However, 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) and 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 (2022) 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. Notably, Linde and Sonnemans (2012) find evidence that individuals make more risk averse

[1] Reference-dependent risk attitudes are a feature of a wide range of models that depart from expected utility (e.g. Bell, 1985; Loomes and Sugden, 1986; Thaler and Johnson, 1990; Gul, 1991; Gomes, 2005; Kőszegi and Rabin, 2006, 2007, 2009).

choices when they cannot surpass their referent even if they win the lottery. 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.

As the perception of falling behind is strongly related to income inequality, these theoretical insights and empirical findings give rise to the conjecture that the distribution of earnings in a country affects risk-taking. We hypothesize that higher income inequality is associated with increased risk lovingness. This hypothesis is not least motivated by convincing empirical evidence that social comparison is asymmetric, and that individuals tend to engage disproportionately in upward comparisons (Boyce et al., 2010; Card et al., 2012; Ferrer-i Carbonell, 2005; Payne et al., 2017).[2] An increase in the total income share accrued by those higher in the income ranking might hence trigger a higher aspiration level and hence a fall below one's reference point.[3] Income inequality may also increase social comparisons by increasing both the frequency and the consequence of comparison, thereby highlighting relative disadvantage (Cheung and Lucas, 2016). Finally, observing a larger discrepancy in upward comparison might increase perceived needs, and according to risk sensitivity theory, increase willingness to take risk. Risk sensitivity theory was developed in evolutionary biology to explain animal foraging behavior that is 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). Notwithstanding, humans have been consistently shown to conform to the predictions of risk sensitivity theory, i.e. when faced with need, via disparity, they will shift their risk preference from aversion to taking.[4] Despite these considerations and

[2]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 center 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.

[3]Some indirect empirical evidence is provided, for example, by Powdthavee et al. (2017) who document a negative relationship between a country's average happiness score and the income share accrued by the richest percentile of its population.

[4]Humans acting in accordance with risk sensitivity theory has been found in a variety of domains (see, e.g., Rode et al., 1999; Ermer et al., 2008; Searcy and Pietras, 2011; Mishra and Fiddick, 2012; Mishra and Lalumière, 2010; Mishra et al., 2014, 2015; Payne et al., 2017; Gonzales et al., 2017).

the empirical findings, 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.[5]

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 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.

[5] Payne et al. (2017) provide some evidence for a relationship between inequality and risk preferences from a laboratory in which subjects are shown at random one out of three earnings distributions which have different variances but the same mean, and 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 higher distribution leads to higher risk-taking in the gambling game.

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 and 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 and Wohlfart, 2018). One possible explanation for such a divergence is that the very concept of inequality is difficult to grasp (Eriksson and 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 risk, 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 risk. 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 '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. These findings become particularly important against the background of rising inequalities in many countries. Blundell et al. (2018), for example, find an increasing gap in labour income for males between the top and bottom decile of the income distribution (an increasing 90/10 ratio) for both the United Kingdom and the United States.[6]

With our focus on the relationship between country-level inequality and individuals' willingness to take risk 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 what individual characteristics determinants of risk preferences[7], 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 reference points. Finally, section 6 offers a concluding discussion.

[6]Note, however, that the 90/10 ratio has been decreasing for family income in the United Kingdom, underlining the significant impact of social policies.

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

2 Data

2.1 Risk preference

Our analysis uses data from the Global Preference 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, 24 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., 2022, 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 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.[8] 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

[8] Responses to both items were standardised (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.

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.

[Figure 1 about here.]

2.2 Inequality

Our principal measure of inequality comes from the Standardised World Income Inequality Database (SWIID) by Solt (2020). The SWIID is the pre-eminent source of inequality for cross-national research and the latest version provides estimates that are more 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.[9] 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.

[Figure 2 about here.]

[9] 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).

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 individuals.[10] 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

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 0.11 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.[11] The raw correlation (ρ) between risk preference and inequality is 0.35 and this relationship is illustrated in Figure 3.

[10] 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.

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

We now examine how our four alternate measures of inequality affect 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.

[Table 1 about here.]

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 inequality at the country-level.

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 maths 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. 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).

[Table 3 about here.]

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 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). By doing so, are findings are not qualitatively affected. 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 ($\rho = 0.87$). The coefficient is almost identical despite a reduced sample size and is statistically significant throughout. The GPS contains information on 5 other preferences: patience; altruism; positive reciprocity; negative reciprocity; and trust. In Table A.4 we repeat our analysis using each of these preferences as the outcome measure and we find no significant relationship with inequality. We also assess the role of outliers in the data by using robust regressions and Cook's distance[12], our result is 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.6, 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.

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

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 the demand for (in)equality in the domestic country is affected by the supply in foreign countries. To illustrate the existence of this concept, Figure 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. 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.[13]

We acknowledge that spatial instruments like this have faced some criticism (Betz et al., 2018). Hence, we also use a complementary Bartik 'shift-share' instrument. 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 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

[13] 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.7 and our findings remain the same.

inequality in a given country's region (the 'shift' term). By definition the Bartik 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. Table 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 each panel in the tables. The coefficient for 'inequality abroad', Z, is positive as expected and significant at the 1% level in all specifications. The instrument is strong, as captured by the 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 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 1990's. 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.

[Table 4 about here.]

[Table 5 about here.]

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). This patently does not make sense. It is difficult to argue that domestic individuals would change their risk taking preferences because of a change in inequality elsewhere. Especially so since individuals very assessment of inequality is based on their income compared to other individuals in the distribution. It is unreasonable that this comparison would be made beyond the level at which policies can affect inequality, i.e. the nation state. The scenario in which this may be plausible is when one's network and peers are based outside of their residing country, recent migrants for instance. To this end, we exclude several groups of individuals from the analysis in 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 Appendix Table A.9 and the effect of inequality reassuringly remains correctly signed and significant throughout.[14]

Finally, we reiterate that our results are robust to the use of a Bartik 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.

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-

[14]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 Appendix Table A.8 and the effect of inequality remains significant throughout.

level analysis to provide valuable insights the role of one's reference point and their perception of the level of inequality.[15]

5.1 Perceptions of inequality

Our theoretical framework outlined the notion that the effect of inequality on risk preference may vary by how accurately one perceives the level of inequality in their country. As we discussed, perceptions may deviate from the true level of inequality given that inequality is a measure of variance and requires some numeracy skils to accurately interpret the signals from society. Indeed, any measure would only be a proxy for interpretability quality since this can affected by media consumption or place of residence, for instance. With this motivation in hand, we exploit a survey item contained in the Gallup World Poll that asks respondents about their subjective math skills to assess how this perception alters risk preference,. Respondents answer on a 11-point scale, and we create a dichotomous variable for the top two categories and 0 otherwise. We denote this variable 'High maths'.

We estimate the effect of perceptions by interacting the dummy with 'Inequality'. The estimates are displayed in Appendix 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 maths' proxy of perception. Bear in mind, that the 'High maths' interaction with inequality is significant even after controlling for the objective level of education. The results support our hypothesis that when an individual has the ability to better perceive inequity, the effect of inequality is even larger on one's risk preference.

[Table 6 about here.]

[15] In 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.

5.2 Reference point

Finally, in accordance with reference dependent utility theories discussed in the introduction, individuals move from a state of risk aversion to one of risk taking when they fall below a reference point.

We estimate the role of the reference point 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. 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.

Our final contribution is to show the effect of 'Inequality' over all categories of income dissatisfaction. We depict the marginal effects in Figure 4. 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 drivers of the relationship studied throughout this paper.

[Table 7 about here.]

[Figure 4 about here.]

6 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 risk 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.

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 zero for the most extreme form of inequality and the value one 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 percent earners and strongly negatively correlated with the share of total income hold by the bottom 10-percent 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 polarisation have further increased or at least, not diminished (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 polarisation. 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.

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Figures and tables

Figure 1: Risk preference around the globe

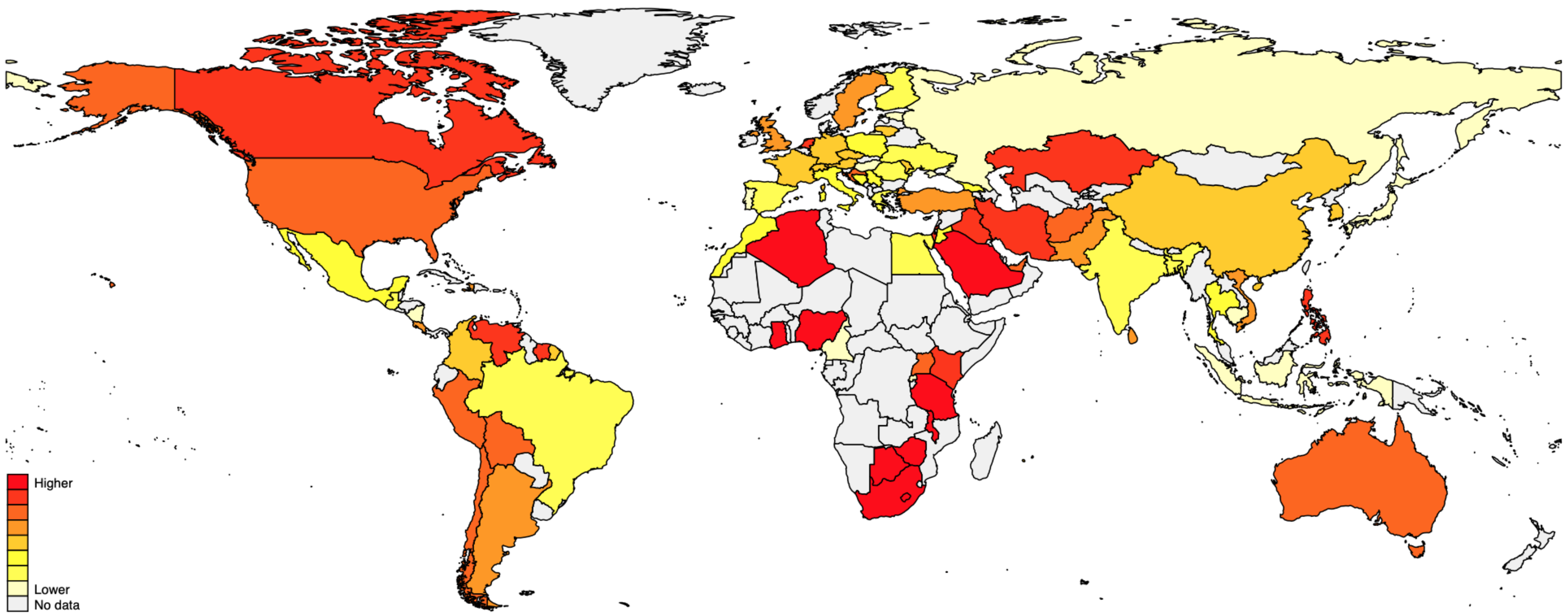


Figure 2: Inequality around the globe

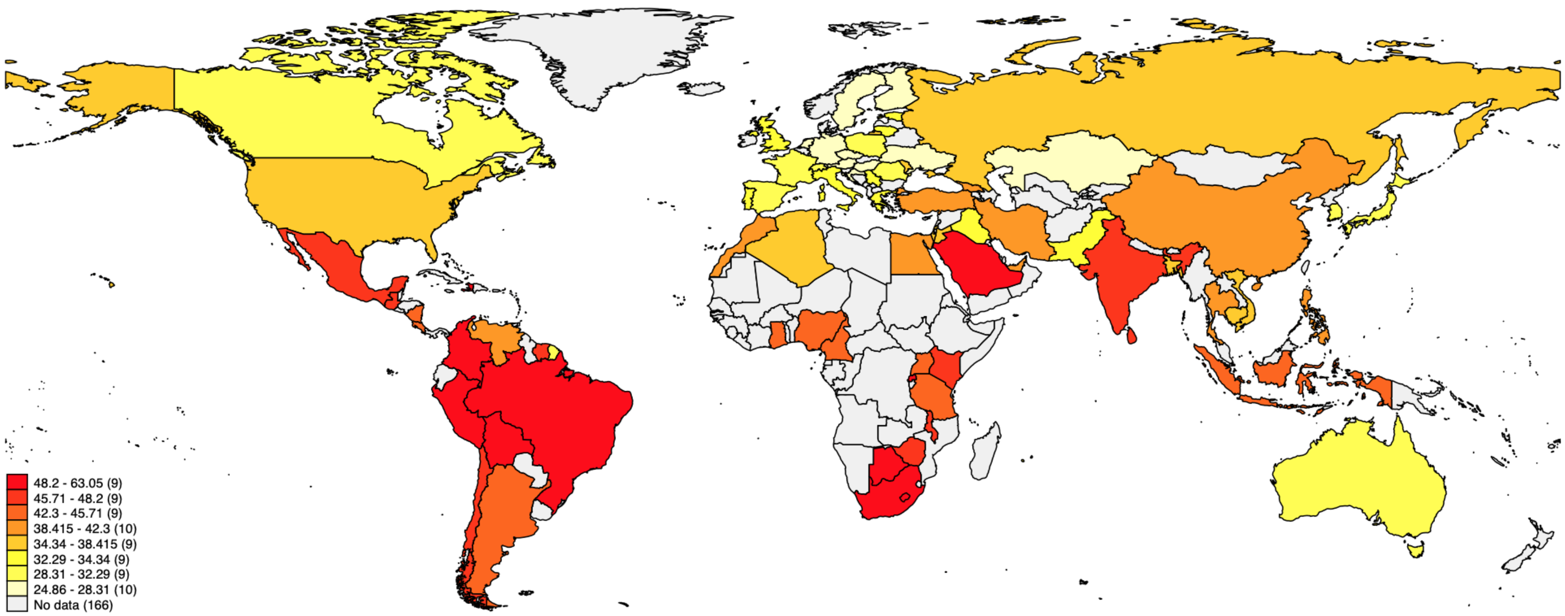


Table 1: Inequality and risk preference: country-level

	Risk preference			
	(1)	(2)	(3)	(4)
Inequality	0.012**	0.015***	0.014**	0.012**
	(0.005)	(0.005)	(0.006)	(0.006)
Ln of GDP p/c		0.027	0.038	0.030
		(0.028)	(0.026)	(0.028)
Precipitation			-0.002***	-0.002***
			(0.001)	(0.001)
Temperature			0.008*	0.012**
			(0.005)	(0.006)
Ruggedness			-0.013	-0.006
			(0.027)	(0.029)
Dist. to nearest waterway			0.099	0.148
			(0.085)	(0.092)
Island			0.037	0.047
			(0.105)	(0.104)
Democracy				0.096
				(0.115)
R-squared	0.123	0.136	0.287	0.296
Observations	76	76	76	76

Notes: Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Figure 3: Inequality and risk preference

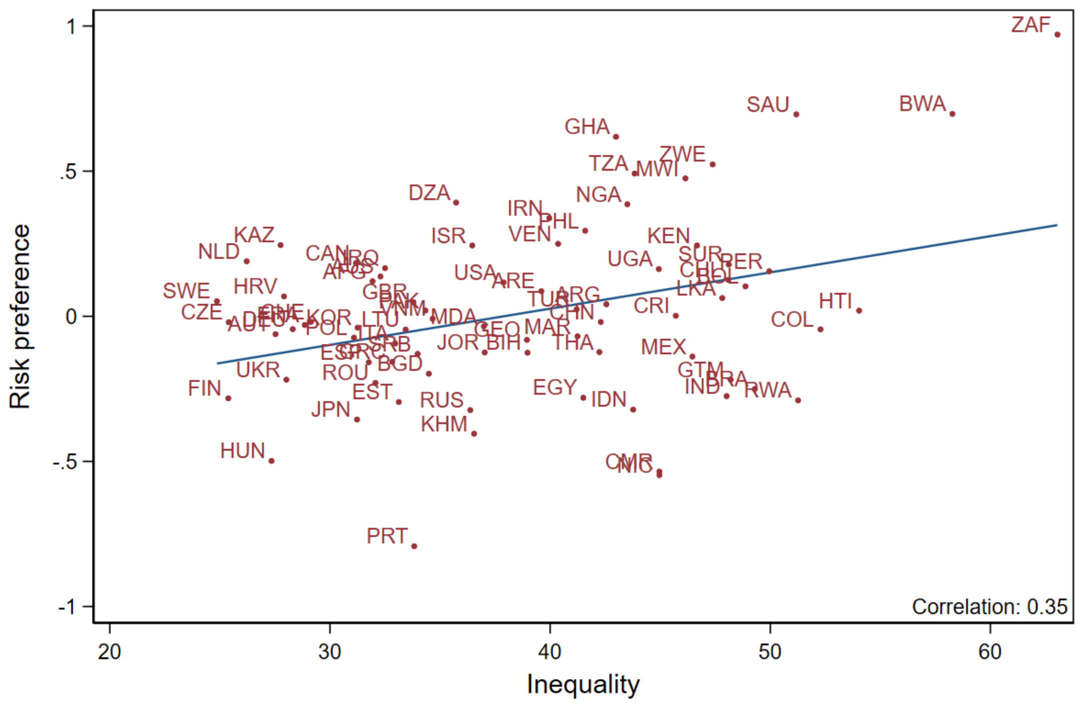


Table 2: Income shares and risk preference

	Risk preference			
	(1)	(2)	(3)	(4)
Panel A				
Income share [top 10%]	0.014**	0.014*	0.016**	0.015*
	(0.007)	(0.008)	(0.007)	(0.008)
Income		✓	✓	✓
Controls			✓	✓
Democracy				✓
R-squared	0.105	0.105	0.258	0.258
Observations	71	71	71	71
Panel B				
Income share [bottom 10%]	-0.080*	-0.077*	-0.099**	-0.092**
	(0.042)	(0.043)	(0.040)	(0.040)
Income		✓	✓	✓
Controls			✓	✓
Democracy				✓
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)
Income		✓	✓	✓
Controls			✓	✓
Democracy				✓
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)
Income		✓	✓	✓
Controls			✓	✓
Democracy				✓
R-squared	0.132	0.139	0.288	0.288
Observations	71	71	71	71

Notes: Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table 3: Inequality and risk preference: individual-level

	Risk preference			
	(1)	(2)	(3)	(4)
Inequality	0.0114**	0.0130**	0.0105*	0.0123*
	(0.005)	(0.005)	(0.006)	(0.006)
Income	✓	✓	✓	✓
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: Standard errors, clustered at the country-level, are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

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		✓	✓	✓
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		✓	✓	✓
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: F-stat is the Kleibergen-Paap weak instrument statistic. Standard errors are in parentheses. ***,**,* Statistically significant 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)
Income	✓	✓	✓	✓
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	75,450	66,473	75,450	66,473
Panel B				
Inequality	0.011*	0.012**	0.010	0.011*
	(0.006)	(0.006)	(0.007)	(0.006)
Income	✓	✓	✓	✓
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: F-stat is the Kleibergen-Paap weak instrument statistic. Standard errors, clustered at the country-level, are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

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 maths	-0.055	-0.071	-0.072	-0.071	-0.065
	(0.091)	(0.087)	(0.087)	(0.081)	(0.070)
Inequality × High maths	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

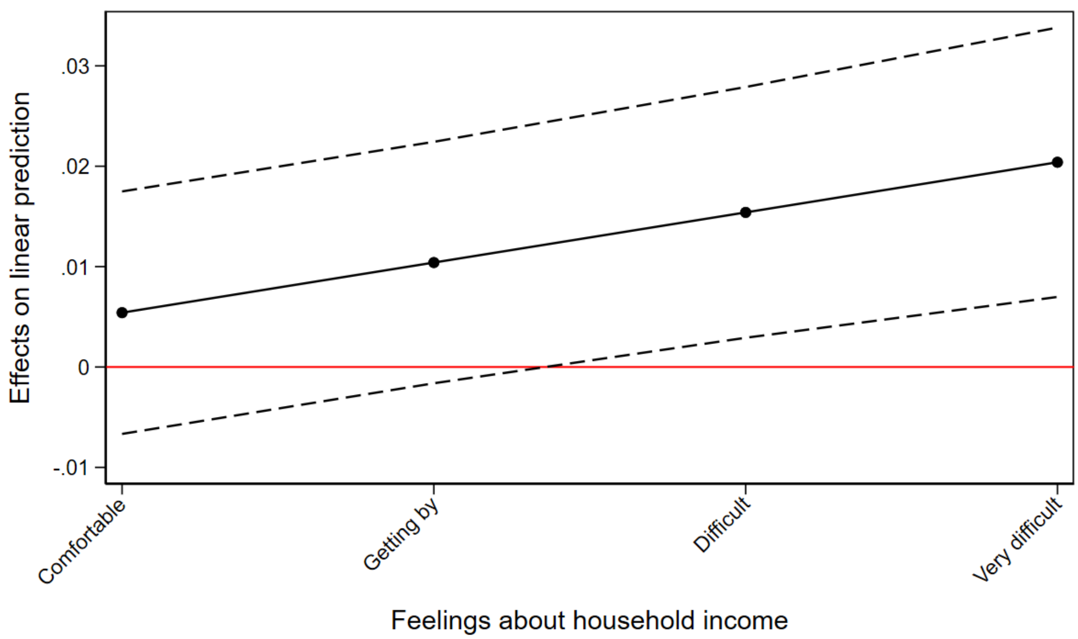
Notes: Standard errors, clustered at the country-level, are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table 7: Inequality, income dissatisfaction 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 $\times$ 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: Standard errors, clustered at the country-level, are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Figure 4: Inequality, the reference point and risk preference



Notes: Dashed lines indicate 95% confidence intervals

Inequality and risk preference

Harry Pickard Thomas Dohmen Bert Van Landeghem

APPENDIX

For Online Publication

A.1 Variable definitions and robustness checks: country-level

- Table A.1 reports summary statistics, notes and the source for each variable used in the country-level analysis.
- Table A.2 shows robustness to the inclusion of a set of extra control variables.
- Table A.3 shows that our findings are robust to using an alternate measure of post-tax and post-transfers inequality from the World Bank.
- Table A.4 shows that there is no significant effect of inequality on the other preferences contained in the GPS.
- We explore to what extent our results could be driven 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 & transfers measure remains highly significant. The results are reported in Table A.5.
- Table A.6 reports the results from the Oster (2019) test of omitted variable bias. The results show that omitted variable bias is not a concern for our findings.
- In Table A.7 we define our instrument as Z_{t-1} by using the 1990-2000 average of inequality to construct the instrument. Our results remain unaffected.
- Table A.8 shows that our IV estimates are robust to the inclusion of the inverse distance weighted GDP per capita in a region as a covariate, thereby controlling for region specific shocks.
- Table A.9 shows that our IV estimates are robust to the inclusion of the inverse distance weighted risk preference in a region as a covariate, thereby controlling for spillover effects.

Table A.1: Country-level summary statistics and definitions

	Mean	Std. Dev.	Min.	Max.	N	Notes & source
Risk preference	0.013	0.302	-0.792	0.971	76	GPS
Inequality	38.905	8.485	24.864	63.045	76	Mean from 2002-2012, SWIID
Inequality (pre-tax & transfers)	46.824	6.935	22.936	71.591	76	Mean from 2002-2012, SWIID
Income share [bottom 10%]	2.494	0.875	0.767	4.050	71	Mean from 2002-2012, WB
Income share [top 10%]	30.538	6.710	21.380	52.267	71	Mean from 2002-2012, WB
Palma ratio	1.998	1.173	0.924	7.127	71	Authors calculation via mean from 2002-2012, WB
80th/20th	8.392	4.913	3.856	27.091	71	Authors calculation via mean from 2002-2012, WB
Ln of GDP p/c	8.735	1.424	6.049	11.190	76	Mean from 2002-2012, WB
Precipitation	84.792	57.749	2.911	241.718	76	Ashraf and Galor (2013)
Temperature	16.313	8.501	-7.929	27.368	76	Ashraf and Galor (2013)
Ruggedness	1.274	0.967	0.037	4.761	76	Nunn and Puga (2012)
Dist. to nearest waterway	0.316	0.437	0.025	2.386	76	Ashraf and Galor (2013)
Island	0.079	0.271	0.000	1.000	76	Spolaore and Wacziarg (2013)
Democracy	0.645	0.482	0.000	1.000	76	Boix et al. (2013)
Redistribution	7.919	7.622	-5.082	24.064	76	SWIID
Ln of area	10.489	1.598	7.680	14.309	76	Nunn and Puga (2012)
Land suitability for agriculture	0.405	0.244	0.003	0.910	75	Ashraf and Galor (2013)
Family ties	-0.006	0.366	-0.998	0.518	49	2005-2009 and 2010-2014 Waves, WVS

Notes: GPS - Global Preference Survey; SWIID - Standardised World Income Inequality Database; WB - World Bank; WVS - World Values Survey

Table A.2: Inequality and risk preference: robustness

	Risk preference					
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality	0.012**	0.012*	0.013**	0.012**	0.016**	0.019**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)
Redistribution		-0.003				0.001
		(0.006)				(0.008)
Ln of area			-0.006			-0.032
			(0.024)			(0.034)
Land suitability for agriculture				-0.049		0.094
				(0.140)		(0.227)
Family ties					0.045	0.055
					(0.135)	(0.142)
All controls	✓	✓	✓	✓	✓	✓
R-squared	0.296	0.298	0.297	0.295	0.381	0.397
Observations	76	76	76	75	49	48

Notes: Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table A.3: Inequality and risk preference: Alternate inequality measure

	Risk preference			
	(1)	(2)	(3)	(4)
Inequality (WB)	0.011**	0.011*	0.013**	0.013**
	(0.005)	(0.006)	(0.005)	(0.006)
Ln of GDP p/c		-0.007	0.015	0.013
		(0.027)	(0.028)	(0.032)
Precipitation			-0.002***	-0.002***
			(0.001)	(0.001)
Temperature			0.010*	0.010*
			(0.005)	(0.005)
Ruggedness			-0.018	-0.016
			(0.029)	(0.031)
Dist. to nearest waterway			0.072	0.082
			(0.083)	(0.094)
Island			0.108	0.109
			(0.093)	(0.094)
Democracy				0.019
				(0.102)
R-squared	0.106	0.107	0.269	0.269
Observations	71	71	71	71

Notes: Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table A.4: Inequality and preferences

	Patience (1)	Risk pref. (2)	Pos. recip. (3)	Neg. recip. (4)	Altruism (5)	Trust (6)
Inequality	-0.005	0.013**	-0.010	-0.006	-0.000	-0.005
	(0.006)	(0.006)	(0.007)	(0.004)	(0.006)	(0.005)
All controls	✓	✓	✓	✓	✓	✓
R-squared	0.436	0.291	0.124	0.151	0.156	0.202
Observations	76	76	76	76	76	76

Notes: Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table A.5: Inequality horserace

	Risk preference			
	(1)	(2)	(3)	(4)
Inequality	0.013***	0.018***	0.015**	0.015**
	(0.005)	(0.005)	(0.007)	(0.007)
Inequality (pre-tax & transfers)	-0.000	-0.005	-0.002	-0.003
	(0.006)	(0.006)	(0.006)	(0.006)
Income		✓	✓	✓
Controls			✓	✓
Democracy				✓
R-squared	0.123	0.142	0.288	0.298
Observations	76	76	76	76

Notes: Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table A.6: Robustness to omitted variable bias

	Risk preference				
	(1)	(2)	(3)	(4)	(5)
Inequality	0.013**				
	(0.006)				
Income share [top 10%]		0.015*			
		(0.008)			
Income share [bottom 10%]			-0.092**		
			(0.040)		
Palma ratio				0.099***	
				(0.037)	
80th/20th					0.022**
					(0.009)
Beta lower bound	0.013	0.015	-0.092	0.099	0.022
Beta upper bound ($\delta = 1$ Rmax=1.3*R)	0.014	0.016	-0.100	0.099	0.023
Treatment effect excludes 0	✓	✓	✓	✓	✓
Delta (Rmax=1.3*R)	1.485	1.736	6.953	1.890	2.236
R-squared	0.291	0.258	0.250	0.296	0.288
Observations	76	71	71	71	71

Notes: Specifications correspond to Table 1 Column (4). Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table A.7: Inequality and risk preference: temporally lagged instrument

	Risk preference			
	(1)	(2)	(3)	(4)
Inequality	0.015***	0.020***	0.015***	0.015***
	(0.005)	(0.006)	(0.005)	(0.005)
Income		✓	✓	✓
Controls			✓	✓
Democracy				✓
Z_{t-1} coef.	0.911	0.937	0.911	0.911
Z_{t-1} p-value	0.000	0.000	0.000	0.000
F-stat	190.592	81.271	190.592	190.592
Observations	76	76	76	76

Notes: F-stat is the Kleibergen-Paap weak instrument statistic. Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table A.8: Inequality and risk preference: IV estimates controlling for a spatial lag of GDP

	Risk preference					
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality	0.021***	0.023***	0.022***	0.021***	0.023***	0.030***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)
Spatial lag of GDP	-0.104**	-0.104**	-0.101**	-0.105**	-0.087	-0.043
	(0.048)	(0.048)	(0.051)	(0.049)	(0.060)	(0.068)
Redistribution		0.003				0.002
		(0.006)				(0.008)
Ln of area			-0.011			-0.040
			(0.027)			(0.033)
Land suitability for agriculture				-0.005		0.146
				(0.147)		(0.247)
Family ties					0.035	0.022
					(0.122)	(0.124)
All controls	✓	✓	✓	✓	✓	✓
Z coef.	0.996	1.013	0.964	0.952	0.910	0.837
Z p-value	0.000	0.000	0.000	0.000	0.000	0.002
F-stat	48.008	34.652	44.169	35.624	22.986	11.568
Observations	76	76	76	75	49	48

Notes: F-stat is the Kleibergen-Paap weak instrument statistic. Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table A.9: Inequality and risk preference: IV estimates controlling for a spatial lag of risk preference

	Risk preference					
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality	0.021**	0.022**	0.023**	0.022**	0.016*	0.022*
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.012)
Spatial lag of risk pref.	0.199	0.188	0.174	0.221	0.590	0.538
	(0.353)	(0.365)	(0.354)	(0.357)	(0.371)	(0.380)
Redistribution		0.001				0.001
		(0.006)				(0.007)
Ln of area			-0.015			-0.035
			(0.024)			(0.031)
Land suitability for agriculture				0.091		0.186
				(0.157)		(0.222)
Family ties					0.028	0.033
					(0.115)	(0.117)
All controls	✓	✓	✓	✓	✓	✓
Z coef.	0.960	0.964	0.920	0.939	0.764	0.747
Z p-value	0.000	0.000	0.000	0.000	0.000	0.000
F-stat	46.680	29.267	40.431	39.997	18.236	15.545
Observations	76	76	76	75	49	48

Notes: F-stat is the Kleibergen-Paap weak instrument statistic. Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

B.1 Variable definitions and robustness checks: individual-level

- Table B.1 presents the full set of coefficients from the baseline specification.
- Table B.2 shows that our individuals level results are, overall, robust to the alternate measure of inequality that we used in the country-level analysis.
- Table B.3 shows that our OLS results are robust to excluding certain groups of individuals. Specifically, we remove the following groups: all 1st generation migrants; migrants who have moved to their host country in the last five years; those who live in large cities; those who have the desire to emigrate; and those who wish to move within their country of residence.
- As above, we repeat the exercise of dropping individual groups except now we show that our instrument variable results are robust to this exercise. Table B.4 shows that this is indeed the case.

B.2 Heterogeneity search and feature importance

Thus far we have imposed a linear functional form on our data and specified the variables to explore heterogeneity across. We now relax this assumption and let the data speak for themselves. By doing so, we are able to explore how important certain variables are in predicting an individual's degree of risk preference. We employ a supervised tree-based ML technique, known as the Classification and Regression Tree (CART) algorithm (Breiman et al., 1984). CART is relatively simple and produces a visual decision tree which is useful for interpretation unlike other ML methods. However, they are typically not competitive with more complex algorithms like Random Forests.

We begin by splitting our data in training and test datasets, 75% and 25%, respectively. We use the full range of individual characteristics, country-level GDP and inequality, i.e. the specification from Table 1 Column (4), as possible predictors of risk preference. The algorithm then grows the classification tree using recursive binary partitioning and we produce an optimal regression tree using cost-complexity pruning, which penalizes overly complex trees, and 10-fold cross validation.

Figure B.1 presents the optimal decision tree. All partitions are obtained using the full sample of individuals and covariates. The structure of the tree shows an initial split at age 52. For those below this age, the next significant circumstance is the level of inequality. Here, we see that inequality is a significant predictor of risk preference, the splitting node is defined by a disposable Gini index of 56. This is especially reassuring for our econometric results given that inequality is retained as a significant predictor of risk preference without any human input. Below this node, we see that subjective math skills is an important predictor of risk preference. Once again, this is inline with theory and empirical results that relate to the perceptions of inequality. Overall, the tree shows important heterogeneity in how inequality affects risk preference.

Table B.1: 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)
Ln of GDP p/c	0.058**	0.021	0.053*	0.028
	(0.028)	(0.031)	(0.030)	(0.031)
Income [2nd quintile]	0.064***	0.046***	0.065***	0.048***
	(0.015)	(0.016)	(0.015)	(0.016)
Income [3rd quintile]	0.103***	0.081***	0.107***	0.081***
	(0.019)	(0.020)	(0.018)	(0.019)
Income [4th quintile]	0.169***	0.122***	0.170***	0.124***
	(0.020)	(0.022)	(0.019)	(0.022)
Income [5th quintile]	0.237***	0.174***	0.237***	0.175***
	(0.020)	(0.022)	(0.019)	(0.021)
Female	-0.210***	-0.160***	-0.203***	-0.154***
	(0.014)	(0.016)	(0.015)	(0.016)
Age	-0.004	0.001	-0.003	0.000
	(0.002)	(0.003)	(0.002)	(0.003)
Age squared	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Married		-0.076***		-0.066***
		(0.024)		(0.021)
Divorced		-0.056*		-0.051*
		(0.031)		(0.027)
Widowed		-0.116***		-0.122***
		(0.031)		(0.026)
Education [medium]		0.141***		0.133***
		(0.030)		(0.026)
Education [High]		0.242***		0.236***
		(0.035)		(0.031)
High math skills		0.166***		0.163***
		(0.022)		(0.021)
Christian		-0.062		-0.051
		(0.044)		(0.045)
Muslim		0.039		-0.054
		(0.079)		(0.066)
Buddhist		-0.165**		-0.129
		(0.082)		(0.094)
Hindu		-0.344***		-0.359***
		(0.087)		(0.090)
Other religion		-0.077		-0.086
		(0.074)		(0.071)
Has children under 15		-0.042**		-0.024
		(0.017)		(0.015)
Household size		0.011**		0.006
		(0.005)		(0.004)
Health problems		-0.063***		-0.068***
		(0.022)		(0.023)
Smoker		0.020		0.044
		(0.061)		(0.054)
Self-employed		0.140***		0.145***
		(0.028)		(0.026)
Precipitation			-0.002***	-0.003***
			(0.001)	(0.001)
Temperature			0.007	0.011
			(0.005)	(0.006)
Ruggedness			0.002	-0.007
			(0.026)	(0.027)
Dist. to nearest waterway			0.071	0.015
			(0.094)	(0.091)
Island			0.087	0.086
			(0.103)	(0.101)
Democracy			0.044	-0.003
			(0.097)	(0.107)
R-squared	0.086	0.106	0.095	0.117
Observations	79,439	68,415	79,439	68,415

Notes: Standard errors, clustered at the country-level, are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.2: Alternate measures of inequality and risk preference: individual-level

	Risk preference			
	(1)	(2)	(3)	(4)
Panel A				
Income share [top 10%]	0.012	0.012	0.014*	0.013
	(0.007)	(0.008)	(0.007)	(0.008)
GDP	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Additional individual controls		✓		✓
Country controls			✓	✓
R-squared	0.085	0.105	0.095	0.118
Observations	74,927	65,962	74,927	65,962
Panel B				
Income share [bottom 10%]	-0.074*	-0.073*	-0.095**	-0.063*
	(0.040)	(0.040)	(0.037)	(0.036)
GDP	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Additional individual controls		✓		✓
Country controls			✓	✓
R-squared	0.085	0.102	0.095	0.116
Observations	74,927	65,962	74,927	65,962
Panel C				
Palma ratio	0.082**	0.089**	0.092***	0.088**
	(0.037)	(0.037)	(0.033)	(0.037)
GDP	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Additional individual controls		✓		✓
Country controls			✓	✓
R-squared	0.089	0.108	0.098	0.120
Observations	74,927	65,962	74,927	65,962
Panel D				
80th/20th	0.018*	0.020**	0.021**	0.019**
	(0.009)	(0.009)	(0.008)	(0.010)
GDP	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Additional individual controls		✓		✓
Country controls			✓	✓
R-squared	0.088	0.107	0.097	0.120
Observations	74,927	65,962	74,927	65,962

Notes: Standard errors, clustered at the country-level, are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.3: Inequality and risk preference: individual-level excluding some individuals

	Risk preference					
Excluded group:	–	1st gen. migrants	Recent migrants	Large cities	Wish to emigrate	Wish to move
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality	0.012*	0.012*	0.012*	0.011*	0.013*	0.013*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
GDP	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓
Additional individual controls	✓	✓	✓	✓	✓	✓
Country controls	✓	✓	✓	✓	✓	✓
R-squared	0.117	0.117	0.117	0.115	0.127	0.132
Observations	68,415	66,297	68,174	62,870	49,272	46,197

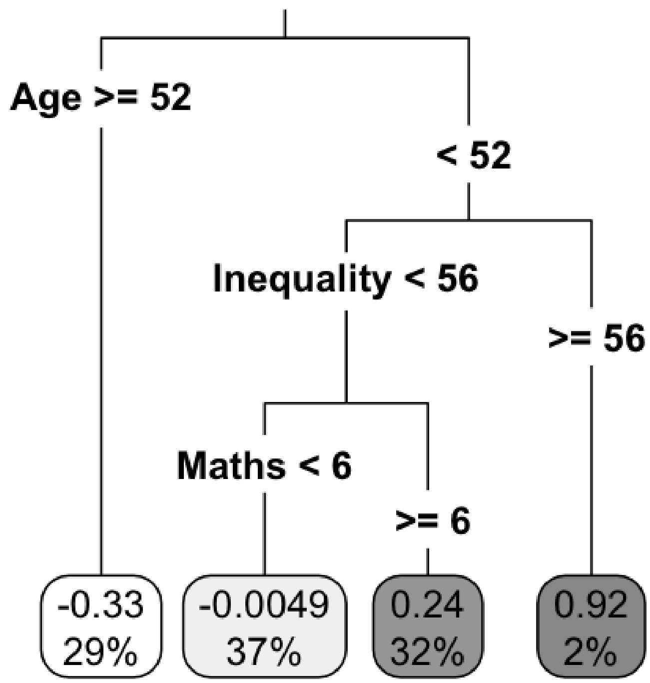
Notes: Standard errors, clustered at the country-level, are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.4: Inequality and risk preference: IV individual-level excluding some individuals

	Risk preference					
Excluded group:	–	1st gen. migrants	Recent migrants	Large cities	Wish to emigrate	Wish to move
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality	0.025***	0.026***	0.025***	0.024***	0.027***	0.027***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
GDP	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓
Additional individual controls	✓	✓	✓	✓	✓	✓
Country controls	✓	✓	✓	✓	✓	✓
Z	0.986	0.987	0.984	0.976	0.976	1.045
Z p-value	0.000	0.000	0.000	0.000	0.000	0.000
F-stat	46.306	46.796	46.429	59.830	38.956	51.912
Observations	68,415	66,297	68,174	62,870	49,272	46,197

Notes: Standard errors, clustered at the country-level, are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Figure B.1: Regression tree



C.1 Alternate instrumental variables

In this section we show robustness to alternate instrument definitions following the approach in Acemoglu et al. (2019). We first algebraically define our alternate instruments and then present results at the country and individual-level, respectively. Finally, we show robustness to using the temporal lag of the spatial instrument.

C.1.1 Instrument definitions

We define 3 alternate instruments as follows:

$$I_{2,i} = \{j : j \neq i, C_i = C_j\}$$

where C denotes whether or not country i and j are contiguous.

$$Z_{2,i} = \frac{1}{|I_{2,i}|} \sum_{j \in I_{2,i}} \text{`Inequality'}_j \tag{C.1}$$

Now, $Z_{2,i}$ is the jackknifed average of democracy in countries that share a border with country i, which leaves out the own-country observation.

$$I_{3,i} = \{j : j \neq i, R_i = R_j\}$$

where R denotes that country i and country j are in the same region.

$$Z_{3,i} = \frac{1}{|I_{3,i}|} \sum_{j \in I_{3,i}} \text{`Inequality'}_j \tag{C.2}$$

Here, $Z_{3,i}$ is the jackknifed average of democracy in countries within the same region as country i, which leaves out the own-country observation.

$$Z_{4,i} = \frac{\sum_{j \neq i} \text{`Inequality'}_j \times W_{ij}}{\sum_{j \neq i} W_{ij}} \tag{C.3}$$

Here, $Z_{4,i}$ is similar to the first instrument except that now all inequality in the world in taken into account, whilst leaving out the own-country observation.

C.1.2 Instrumental variable results: country-level

Table C.1: Inequality and risk preference:
Country-level alternate instruments estimates

	Risk preference			
	(1)	(2)	(3)	(4)
Panel A				
Inequality	0.013**	0.018***	0.023***	0.023***
	(0.005)	(0.006)	(0.007)	(0.008)
Z_2 coef.	1.025	1.073	1.040	0.977
Z_2 p-value	0.000	0.000	0.000	0.000
F-stat	155.747	59.602	34.614	38.174
Observations	76	76	76	76
Panel B				
Inequality	0.017***	0.021***	0.024***	0.025***
	(0.005)	(0.005)	(0.006)	(0.007)
Z_3 coef.	0.928	0.869	0.831	0.783
Z_3 p-value	0.000	0.000	0.000	0.000
F-stat	196.361	97.117	46.025	44.523
Observations	76	76	76	76
Panel C				
Inequality	0.014***	0.017***	0.021***	0.021***
	(0.005)	(0.005)	(0.007)	(0.008)
Z_4 coef.	1.976	1.802	1.819	1.697
Z_4 p-value	0.000	0.000	0.000	0.000
F-stat	154.557	68.861	36.247	36.499
Observations	76	76	76	76
Income		✓	✓	✓
Controls			✓	✓
Democracy				✓

Notes: F-stat is the Kleibergen-Paap weak instrument statistic. Standard errors are in parentheses. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

C.2 References

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