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Does nature shape risk preferences? Evidence from Chile, Norway, and Tanzania

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Abstract

Does exposure to a more risky environment affect risk preferences? Going beyond single-case study evidence, we report results from five surveys conducted in three countries and link this with administrative data to study whether a link between exposure and preferences is detectable and widespread. We find no evidence for endogenous preferences in Norway and Tanzania, but relatively strong evidence in Chile, where differences in risk exposure are most pronounced. Moreover, we make a first pass at disentangling selection from adaptation as potential mechanisms. For Tanzania and Norway, the data speaks for selection, while it speaks for adaptation in Chile.

KEYWORDS
adaptation, endogenous preferences, exposure, selection

JEL CLASSIFICATION
D01, D81, Q22

1 | INTRODUCTION

There is ample evidence of heterogeneity in risk preferences (Dohmen et al., 2011; Falk et al., 2018; Vieider et al., 2015; von Gaudecker et al., 2011). Certainly, not all of it is random. The work of Becker et al. (2020), for example, shows that differences in risk aversion are correlated with the time that elapsed since different populations separated. The longer respective groups have shared common ancestors, the closer are their risk preferences. This suggests that one of the key economic traits may have a genetic component, which is also corroborated by twin studies (Cesarini et al., 2009; Zhong et al., 2009). While risk preferences have—for a long time—been regarded as fixed and stable (Stigler & Becker, 1977),

Abbreviations: CLP, Chilean Pesos; NOK, Norwegian Kroner; TZS, Tanzanian Shilling.
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the view that preferences are in fact endogenous to the socio-cultural environment is becoming more and more established (Bowles, 1998; Cappelen et al., 2020; Di Falco & Vieider, 2022; Schildberg-Hörisch, 2018).

Here, we study the effect of the *natural* environment on risk preferences. Specifically, we report the results from five incentivized surveys among fishers in Chile, Norway, and Tanzania. The effect of the natural environment is particularly direct in fisheries because wind, waves, and biology determine production possibilities. Moreover, the fisheries in the three countries range from artisanal to industrialized and differ strongly in their institutional and economic settings. This provides a unique backdrop to assess whether a link between nature and economic preferences is indeed detectable, and if yes, how widespread it is. The correlational evidence we present here highlights the importance of contextual details that interact with the natural environment.

In each of the three countries, we have selected one fishery that has been described as low-risk and one fishery that has been described as high-risk in the literature. Furthermore, we collected administrative and self-reported data on risk exposure in each fishery. This data is combined with the results from incentivized choice experiments on risk preferences. Because we used the same risk preference elicitation tool across the different contexts, we can standardize outcomes and test whether there is a link between risk exposure and risk preferences that is widespread and detectable across different contexts. This is the prime objective of our paper. In addition, we have information on the length that a participant has worked in the respective fishery and whether he selected into the fishery, so that we can study whether there is an effect of tenure or selection. Finally, a few participants were interviewed twice, so that we can make a first pass at disentangling selection from adaptation as potential mechanisms that make preferences endogenous.

Several studies use large historical and geographical datasets to link heterogeneity in economic preferences to the natural environment. Galor and Özak (2016), for example, argue that pre-industrial agro-climatic characteristics that yield a higher return on investment cause lower discount rates through "a process of selection, adaptation, and learning." Barsbai et al. (2021) show how social behavior among hunters/gatherers and other mammal and bird species alike is influenced by a shared natural environment. Similarly, Buggle (2020) argues that nature has an indirect long-run impact on culture through the mode of production in pre-industrial agriculture. Societies that jointly practiced irrigation in the ancestral past hold more collectivistic, rather than individualistic, norms today.[1] Buggle and Durante (2021) examine the direct effect of climatic risk (inter-annual variability in growing conditions) in the ancestral past on levels of generalized trust today. They find that societies where farmers benefited more from mutual insurance are more likely to have inclusive political institutions early on. A reinforcing feedback loop between social preferences and institutions then means that these societies still display higher levels of trust (as measured by the World Value Survey) and have more inclusive institutions today.

Studies that investigate long-term changes in preferences as a reaction to differing natural environments focus on developments that are encoded in (or transmitted by) institutions. Several studies complement this approach by presenting case-specific evidence for the malleability of preferences over shorter time horizons, for example, as changes over the life-cycle (Dohmen et al., 2017), assimilation among spouses (Di Falco & Vieider, 2018), or transmission from parents to children (Dohmen et al., 2012; Falk et al., 2021).[2]

For example, Gneezy et al. (2016) argue that the way production is organized has an effect on social preferences through adaptation. They compare fishers from a lake in Brazil who work on their own with fishers who fish at sea and work in groups. Fishers at sea are shown to be more pro-social than the fishers at the lake. Importantly, their findings are robust to controlling for selection, and they do not find differences in the pro-sociality of women that do not fish in these two societies. Leibbrandt et al. (2013) use data from the same setting and show that the lake fishers are more competitive than those that fish at the sea. Because this difference is increasing with tenure, Leibbrandt et al. (2013) argue that the competitive attitude is not innate but learned at the workplace. Jang and Lynham (2015) compare Nile perch fishers with Dagaa fishers at Lake Victoria and document significant differences in pro-social behavior across these two groups. Again, they find that the difference between the two groups is stronger for more experienced fishers (captains), suggesting that production specific preferences are malleable at the individual level.

In their seminal contribution, Carpenter and Seki (2011) compare Japanese fishers that either pool their catches or do not, finding that those who pool are more unconditionally cooperative in an incentivized experiment and more productive as evidenced by their actual catch records. Olbrich et al. (2011) find that Namibian farmers who are more risk tolerant occupy riskier farms (consistent with self-selection). Interestingly, farmers who grew up on their own farm are more risk averse if they had been exposed to higher risks at young ages. Working with pastoralists from Namibia, Prediger et al. (2014) compare scarce and abundant areas to show that exposure to greater resource scarcity is related to more anti-social behavior. Nguyen (2011) relies on low labor mobility in rural Vietnam to argue for a nurturing effect of occupational choice, according to which fishers, who are exposed to more risk, are more risk tolerant than farmers, who are exposed to less risk. Di Falco et al. (2019) combine household data from Ethiopian farmers with stated time preferences that are elicited at two points in time to identify the effect of weather. Controlling for wealth and other factors, Di Falco et al. find that households that are exposed to more rainfall are more forward looking. Di Falco and Vieider (2022) relate rainfall shocks and historical rainfall variability to risk tolerance and document that short-term shocks and long-term variability both cause lower risk tolerance, most likely via a drop in consumption. The analysis of their Ethiopian panel improves upon the existing cross-sectional evidence and shows that the environment can causally affect risk preferences.

Taken together, the case studies and the global analyses suggest that there is a role for nature in shaping economic preferences. We add to this literature by reporting survey results from three countries that test the link between risk preferences and exposure to different natural environments by contrasting, in each country, a fishery that has been classified as high-risk with a fishery that has been classified as low-risk. In addition, we construct a data-based measure of risk exposure. We use a unified methodology across surveys, and control for confounding factors such as the general economic situation in the three countries, purchasing power differences of experimental payouts, differences in the way the survey was administered, and other idiosyncratic factors that are common to the fishery by using fixed effects. This then allows us to go beyond single-case evidence and assess whether a link between exposure and preferences is detectable and widespread.

In sum, we find that there is some, but limited evidence that exposure to different environments is related to risk preferences. The evidence is strongest in Chile, where differences in risk are most pronounced and fishers are, globally speaking, neither poor (as in Tanzania) nor rich (as in Norway). Furthermore, using the data from the participants who we observed twice, we document that those participants who work in riskier fisheries become more risk tolerant with time.

To structure our study of fishers' risk preferences in different natural and institutional contexts, it is useful to spell out how we think about the mechanism through which the natural environment shapes risk preferences. We do so in the Section 3, deriving testable hypotheses. Section 2 presents the field settings. Section 4 then explains the data and methods that we use to test these hypotheses and Section 5 presents the results. Section 6 concludes.

2 | FIELD SETTINGS

Figure 1 shows the three countries in which we collected data. We briefly introduce the setting in Chile, Norway and Tanzania. For details on the data collection during our field trips, see Section 4.6.

The coastal waters of Chile are host to a productive and diverse marine ecosystem. The upwelling caused by the Humboldt current brings nutrient rich waters to the surface. This nutrient availability allows for rapid plankton growth, which serves as the primary source of food for many marketable fish species (Gomez et al., 2012). The productivity of this ecosystem supports Chile's status as a top exporter of fish and fish products (FAO, 2020). However, due to natural variability and overfishing, the total catches have fluctuated strongly over the last 10 years. Artisanal fishing vessels, smaller than 18 m, do the majority of fishing in Chile.

In an effort to increase resource sustainability, artisanal fishers have been granted exclusive fishing rights (for pelagic fisheries) and territorial use rights (for benthic fisheries, see Castilla, 2010). The Chilean government distributes these fishing rights to small-scale fisheries organizations, which are founded and managed by the artisanal fishers (Chávez Estrada et al., 2017). The organizations are responsible for the sustainable exploitation of their resources. However, cooperation between fishers within these organizations is necessary to manage these new fishing opportunities successfully. In addition to these rights-based fisheries, a number of species continue to be harvested under de-facto open-access regimes. We distinguish between the benthic fisheries, which are classified as low-risk, and the pelagic fisheries, which are classified as high risk (see next section). Switching between fisheries is difficult in Chile due to high fishery-specific capital investments and the necessity to become a member of the respective fisheries organization.

Norwegian fisheries are among the most valuable fisheries in the world (Gullestad et al., 2014). Annually, about 2.5 million tons of fish, equivalent to a value of 2 billion Euro, are harvested by a highly modern fleet. Two dominant groups can be distinguished: Those boats that harvest pelagic species such as herring and mackerel mainly from Western Norway, and those that harvest demersal species such as cod and haddock. Especially the latter fleet consists largely of relatively small vessels that fish close to the coast in the North. As in Chile, switching between fisheries is relatively uncommon, due to high fishery-specific investments.

FIGURE 1 Map of field sites, showing the landing sites in which we held workshops in Chile and Tanzania. For Norway, municipalities with at least 10 respondents are shown. To avoid clutter some adjacent landing sites have been merged on the map. For a full overview of landings sites and the sample size per site, see Supporting Information S2: Table OA1.

In contrast to the marine fisheries in Chile and Norway, we consider two freshwater fisheries at Lake Victoria in Tanzania. The Lake Victoria region plays a crucial role for the local and regional economy. The lake's fisheries support, directly and indirectly, the livelihood and protein availability for more than 4 million people and its annual economic contribution to the region is estimated to be about 250 million Euro. The sustainability of the Lake Victoria fishery is threatened by climate change, pollution, population pressure, and overfishing (Irvine et al., 2019). Since the laws and regulations that are set in place to protect the lake from being overfished are poorly monitored and enforced, it is especially important to find ways to strengthen cooperation and governance among fishers at Lake Victoria. In contrast to Norway and Chile, switching between fisheries is easier for fishers in Tanzania.

3 | MECHANISMS AND HYPOTHESES

We concentrate on risk preferences as one of the key economic preferences that may be linked to the socio-ecological environment.[3] Fishing is an occupation that is particularly suitable to study the relation between the natural environment and preferences. The level of risk fishers are exposed to differs strongly between fisheries (Pfeiffer &

Gratz, 2016; Sethi, 2010). Exogenous fluctuations in resource abundance are more pronounced, or working conditions are more dangerous in some fisheries than in others. Because a risk tolerant agent has to pay a lower risk premium, she is fitter in a risky fishery than a risk averse agent. We would therefore expect to observe more risk tolerant fishers in riskier fisheries. However, it is an empirical question whether the link between the natural environment and preferences is indeed detectable and strong enough to qualitatively affect outcomes.

Hence, we collect data from three very different countries (Chile, Norway, and Tanzania, see Figure 1), and in each country, we select two fisheries that differ in their risk profile as reported in previous literature. In Chile we compare the low-risk benthic fishery with the high-risk pelagic fishery. In Norway we compare the low-risk demersal fishery in the North to the high-risk pelagic fishery in Western Norway, and in Tanzania, we compare the high-risk Nile perch fishery to the low-risk dagaa fishery (see Table 1 and Section 4.1 for more detail). We use the data from these six fisheries to test the following hypothesis:

Hypothesis 1. Endogenous risk preferences Fishers are more risk tolerant in a more risky fishery.

Two mechanisms can explain this hypotheses: Selection and adaptation. The first mechanism, selection, can only operate if there is occupational choice. If there are always options to choose from, then risk-averse agents will choose low-risk occupations. Conversely, we would expect that risk-tolerant agents benefit from higher expected returns and are more likely to choose high-risk occupations. We hence expect:

Hypothesis 2. Selection We see a stronger link between the natural environment and risk preferences for those fishers who opted into the fishery.

In real life, agents cannot always freely choose their occupations. First, fishing is an occupation where both culture and capital assets are traditionally passed on from one generation to the next (Diekert et al., 2021). Second, many fishing communities around the world are in remote areas where good outside options are rare. Even the fishing activities that are available are determined by the distribution of natural resources. Hence, agents cannot change their exposure to the environment, at least for some period.

This brings us to the second mechanism, adaptation. Adaptation could work through the active process of deliberation. Certainly, agents do not "choose their preferences" in the way one may choose to buy an apple instead of an orange. However, agents may choose to brave a risky situation, and having done so may leave a mark on their future evaluation of risky prospects. Bernheim et al. (2021), for example, develop a model where agents adopt certain "worldviews" that prove to be beneficial in a certain situation and show how these preferences can persist, even after the original situation has changed. Adaptation could also work subconsciously, through a process of habituation (Thompson & Spencer, 1966) or desensitization (Wolpe, 1961). In simple words, this means that agents get used to their environment. As it is the agent's own experience that shapes her preferences, one could call this form of adaptation "experiential learning."

Adaptation could also work through some type of "cultural learning" (Henrich, 2004). There may be peer pressure to act bravely. For example, the popular TV show "Deadliest Catch" documents a culture of risk-taking that is glorified in many fisheries. As an alternative mechanism to behavioral conformity, agents may listen to the reasons of others that, for example, highlight the value of the expected return compared to variance in payout, and afterward change their opinion on the optimal risk-return tradeoff.

Although exposure to the environment may be fixed in a given period, it is not plausible that there are no changes at all over time. For example, the development of the international market for fish meal has increased opportunities in the Chilean pelagic fishery in the 1980s. Similarly, many farmers and traditional dagaa fishers along the shores of Lake Victoria entered the Nile perch fishery during the export boom in the 1990s. Conversely, the discovery of oil in the North Sea opened up massive job opportunities in Norway in the 1970s and many fishers along the coast decided to join the "oil adventure." Hence, selection may not only happen at the beginning of an occupational career but also operate gradually over the course of an agent's life cycle. Both adaptation and gradual selection would lead to the same observation:

Hypothesis 3. Gradual selection or adaptation The link between the natural environment and risk preferences increases with tenure.

While gradual selection can lead to a drift in the average risk preferences in the population of fishers, it is fully consistent with innate and stable preferences at the individual level. Adaptation, in contrast, necessitates preferences that are malleable at the individual level. A significant interaction with tenure is hence not a sufficient condition to identify adaptation. However, observing the same individuals at two points in time, and seeing an increase in the risk preferences of those individuals that are exposed to more risk is evidence for adaptation. Here, we can make use of the fact that we have revisited some communities, and indeed observed a small subsets of the respondents twice, to test our last hypothesis:

Hypothesis 4. Adaptation Risk preferences of fishers in more risky fisheries increase over time.

4 | METHODS AND DATA

We collate the data from five surveys among fishers ($N = 2378$), collected in three countries (see Figure 1), to address the empirical questions of whether there is a detectable link between the natural environment and risk preferences and, if so, how widespread it is.

4.1 | Classification of the fisheries

Together, the fisheries in Chile, Norway, and Tanzania span the range from basic artisanal to highly industrialized industries, from open-access to well-developed institutional systems, and from the tropics to the polar regions. In each of the three countries, we selected two fisheries that contrast in their risk profile based on results reported in the existing literature (see Table 1).

In Chile, we compare benthic to pelagic fishers, where the former fishery is classified as stable, and the latter as risky (Gelcich et al., 2010; Yanez et al., 2001). In Norway, we compare fishers from Northern Norway who are active in the coastal fishery (with cod as the main target species) to fishers from Western Norway, mainly targeting pelagic species such as herring. Our classification is based on Vea (2009), who compares Norwegian cod fishing communities with herring fishing communities in the 19th and 20th century. Purportedly, herring fishers from the West Coast of Norway are more entrepreneurial and risk-tolerant than cod fishers from Northern Norway. Vea (2009) argues that this difference in mentality can be traced back to the fact that the predominant pelagic fishery in the west is volatile and has been risky (as fish are caught offshore), while the predominant cod fishery in the north is relatively stable (the annual spawning migrations bring the resource close to shore and into the fjords). Finally, for Tanzania, we juxtapose the Lake Victoria dagaa fishery with the export oriented Nile perch fishery. Dagaa are attracted with artificial lights on moonless nights and caught by seine nets, while Nile perch are harvested at day, using hook-and-line as well as gillnets. Our classification is based on Eggert and Lokina (2010) and Jang and Lynham (2015), with the inshore dagaa fishery accordingly less risky.

The literature-based classifications shown in Table 1 encompass different dimensions of risk exposure. We complement and cross-validate these measures by a data-based approach that focuses on the observable variability of trip revenue as a specific component of risk exposure. The construction of this measure is described next.

4.2 | Measuring exposure, tenure, and selection

In addition to the ex-ante classification based on the literature, we collect high frequency administrative data of actual variation in landings to estimate the risk exposure of our participants. Specifically, we determine the within-year

TABLE 1 Literature-based classification of fisheries in the three field settings.

Country	Chile		Norway		Tanzania	
Fishery	Benthic	Pelagic	North	West	Dagaa	Nile perch
Risk exposure	(Low)	(High)	(Low)	(High)	(Low)	(High)

variability of daily revenues for a vessel in the relevant fisheries using data from sales slips or landing tickets. We express variability as the coefficient of variation (CoV) in daily revenue. In Chile we calculate the variability of several benthic and pelagic fisheries. As the surveyed Chilean fishers are concentrated in fishing villages (so called *caletas*), we determine variability for each fishery at the village level. In Norway we determine variability for the major gear types used in the Northern and Western fisheries. In Tanzania, administrative data is not available and we therefore develop a self-reported measure. The methods used to determine variability are explained in detail in Supporting Information S2: Online Appendix OA3.

While the literature-based classification captures broad aspects of risk exposure caused by differences in the natural environment (such as health risk, different weather conditions, different production methods, different ownership structures or payment methods), the variation in these measures is limited to the fishery level. Moreover, it is—as the name says—based on the preconceptions found in the literature. Our data-based measure can verify to what extent these classifications correspond to current variability in revenues. Moreover, the data-based measure allows us to have near individual variation in risk exposure. On the downside, this measure of exposure is more narrowly defined as revenue risk.

4.3 | Measuring risk preferences

We elicited risk preferences using an incentivized lottery-choice task. The incentivized lottery-choice task is based on the "Gneezy-Potters method" (Gneezy & Potters, 1997): The participant receives 6 ECU (experimental currency units) and is asked how much to invest in project A and how much to invest in project B. While she obtains 1 ECU for every ECU invested in project A, the outcome of project B is uncertain: With probability $1 - p$, the participant will receive nothing from this investment and with probability p, she will receive k times what she has invested. Say the participant invests x ECU in project B. Her expected payout is then $6 - (1 - pk)x$. A risk-neutral (or risk loving) participant would thus invest all 6 ECU in the risky project if and only if $pk > 1$. As it is standard with this experiment, we select $p = .5$ and $k = 3$. Whether project B pays off will then be determined randomly by a coin-flip at the end of the session (to not contaminate other choices). The "Gneezy-Potters" method has been used widely and is often chosen in field contexts due to its simplicity and robustness (for a review of different risk elicitation methods see Charness et al., 2013 or Crosetto & Filippin, 2016). We used the same setup and illustrations in all three countries.

4.4 | Additional control variables

The set of additional control variables consists of age, comprehension, wealth, tenure and whether the participant has selected into becoming a fisher. Age is elicited as an integer; however, to make it comparable between field surveys, we calculate the z-score for the participant with respect to the other observations in the same country. Comprehension is a dummy variable that equals 1 for respondents who passed all comprehension checks and 0 otherwise.

The wealth variable is constructed differently per field trip: In the first Tanzania and Chile field trips wealth is measured as the number of objects owned by the participant from a predetermined list.[4] For the second field trip to Tanzania, it is based on the average trip revenue as reported by the fisher. For the second field trip to Chile we note whether the fisher is a registered vessel owner, as a proxy of wealth. In Norway, wealth is based on a self-reported assessment of the fishers' financial situation. The wealth variable is z-scored for comparability.

To measure tenure, we asked each fisher how long they have been active as a fisher. For the two surveys in Tanzania and the first survey in Chile, they could choose between the following options: (1) this year only, (2) 2–4 years, (3) 5–10 years, and (4) 11 or more years. In the second Chilean and the Norwegian survey, participants were asked to give the number of years as an integer. Parallel to age, the tenure variable is z-scored.

Lastly, we construct a dummy variable to classify whether a participant has selected into the specific fishery in which they are active now. We classify the participant as having selected into the fishery if one of the following three conditions is true: (1) The participant indicates that fishing was their best option (as opposed to the only option or a family tradition), (2) the participant has moved and lastly, (3) the participant has at some point changed their fishing activity. In Norway the first two conditions are not available; in this case we classify fishers as having selected into the fishery when their parents were not fishers.

We study the cross-correlation of the variables in the dataset (see Supporting Information S2: Online Appendix). We find very little systematic correlation in the Tanzanian sample (except for age and tenure). For Chile, we find that—in addition to age and tenure—our measure of risk exposure is positively correlated with crew size. In Norway, we again find a strong positively correlation between risk exposure and crew size. While age and tenure are positively correlated, we find that tenure is positively correlated with wealth, but age is negatively correlated with wealth.

4.5 | Regression model

Equations (1) and (2) outline our generic statistical model. Here, RP_i refers to the risk preference of agent i (measured so that a higher value means more risk tolerance) and RE_i refers to her risk exposure (also measured positively, i.e. a higher value means exposure to more risk). As age and wealth have been found to be important determinants of risk preferences (Schildberg-Hörisch, 2018), we include them as controls in the regressions. Additionally, we include a measure of participants' comprehension of the experimental preference elicitation task and country-by-year-fixed effects (controlling for the specific survey field trip FT_i). The latter control for the vast differences in the institutional and economic contexts of the three countries.

$$RP_i = \alpha + \beta_1 RE_i + \beta_2 Age_i + \beta_3 Wealth_i + \beta_4 Comprehension_i + \beta_5 FT_i + \varepsilon_i \tag{1}$$

Linking the regression model to the hypotheses discussed above, we see that hypothesis 1 is confirmed when the coefficient β_1 in Equation (1) is positive and significant. We run regression (1) with both our literature-based and our data-based measure of risk exposure. Moreover, we fit the model to the data for each country separately. The pooled regression thus tells us how widespread a link between exposure and preferences might be, while the country-specific regressions allow us to zoom in on one country at a time.

In addition to Equation (1), we also estimate a model that contains interaction effects with the participant's tenure in the fishery and an indicator variable that measures whether a participant has selected into fishing. Regression (2) shows the model for risk preferences and risk exposure.

$$\begin{aligned} RP_i = \alpha &+ \beta_1 RE_i \\ &+ \beta_2 Sel_i + \beta_3 (Sel_i \times RE_i) + \beta_4 Ten_i + \beta_5 (Ten_i \times RE_i) \\ &+ \beta_6 Wealth_i + \beta_7 Comprehension_i + \beta_8 FT_i + \varepsilon_i \end{aligned} \tag{2}$$

A positive coefficient for the effect of selection on its own (β_2 in Equation (2)) means that those fishers who have actively chosen to be fishers are more risk tolerant, confirming hypothesis 2. A positive and significant interaction term (β_3 in Equation (2)) means that this effect is particularly strong for the more risky fishery, speaking toward a relatively strong distinction between fisheries. A positive coefficient on tenure (Ten_i) and on the interaction of tenure and risk exposure could speak to either gradual selection, or adaptation. It means that risk tolerance is higher for participants with longer tenure (and especially so in the high-risk fishery if $\beta_5 > 0$), which could be either due to fishers with low risk tolerance finding other jobs over time (a changing composition of the population), or due to desensitization/cultural learning at the individual level (and an unchanging composition of the population), confirming hypothesis 3. We do not include Age_i in regression (2) because it is strongly correlated with tenure.

To further disentangle the processes of gradual selection and adaptation, we make use of the fact that we happen to have several participants who we observe twice. We can thus build a two-period panel of participants who have stayed in the same fishery. With regression specification 3 we test whether risk preferences increased more in the higher risk fisheries compared to the lower risk fisheries. Here ΔRP_i refers to the change in risk preference between the first and second measurement for participant i. A positive value indicates that the participant has become more risk-tolerant between the measurements. The main variable of interest is risk-exposure (RE_i), and a positive β_1 indicates that fishers in riskier fisheries become relatively more risk-tolerant over time (hypothesis 4).

$$\Delta RP_i = \alpha + \beta_1 RE_i + \beta_2 Age_i + \varepsilon_i \tag{3}$$

By using the within-participant change in preference as the dependent variable, we control for all unobserved time-invariant heterogeneity between participants. We control for age, as the rate of change in preferences would arguably decrease as the participant becomes more experienced or older. The logic is that a first year fisher would likely be affected more by experiencing risk than a fisher who has already been exposed to this risk for several years.

4.6 | Sampling procedures

Fishers in Chile were approached through fisheries organizations by researchers of the Pontificia Universidad Católica de Valparaíso during a round of preparatory visits preceding the two field surveys in 2017 and 2018. When there was interest from a fishery organization to participate, the contact person of this organization was asked to invite participants for the session. If a minimum number of 12 fishers agreed to participate, a workshop was scheduled. We did not have the objective of re-sampling fishers between the first and second field survey in Chile, but we visited some of the same communities, and could identify 75 fishers that participated in both field surveys.

In Tanzania, we conducted two field surveys in close collaboration with the Tanzanian Fisheries Research Institute in 2017 and 2018. We visited the same communities, aiming at a sample size between 500 and 600 participants in each wave. In total, 1038 individual fishers participated in the two surveys. One objective of the second field survey was to re-sample fishers from the first survey wave. This was considerably more difficult than anticipated and we achieved a re-sampling rate of about 24%.

In both Chile and Tanzania, the survey was held in workshop-style sessions in community centers or directly at the landing site. Each session of these field surveys consisted of a series of incentivized preference questions and a demographic survey. At the end of the sessions, one of the preference questions was randomly chosen to be paid out. The preference questions and demographic survey were answered on tablets running either Otree (Chen et al., 2016) or OpenDataKit survey software (Hartung et al., 2010). The sessions lasted between 1.5 and 2 h. Compensation for participating in the survey was equivalent to a day's wage on average (about 5000 TZS in Tanzania and about 18,000 CLP in Chile).

In Norway, it was not possible to conduct workshop-style sessions with a sufficient number of participants due to the thin and dispersed settlement structure along the Norwegian coast. Instead, the Norwegian survey was carried out online. To be sure that participants are sufficiently motivated in this setting, we have slotted the incentivized preference elicitation after the demographic survey, and asked participants to actively opt-in to answering additional questions where they could earn money.[5]

The survey was online in September and October of 2019 (using a survey platform provided by the University of Oslo). We invited respondents to participate through e-mails sent from the Norwegian sales organizations. All ex-vessel sales of fish in Norway must go through one of six sales organizations, which are mandated by law. This means that all fishers are associated with at least one of these sales organizations.

5 | RESULTS

The presentation of the empirical results is structured in the following manner. First, we show how the literature-based classifications for risk exposure relate to the data-based measure. Then, we test whether exposure to more risky fisheries correlates with risk preferences on an aggregate level. Next we discuss country level differences and turn to the country-specific estimates in more detail before exploring the role of selection and tenure. Finally, we make a first pass at disentangling to what extent adaptation or selection might be driving the results by exploiting the fact that we have visited some of the field locations twice, and hence have a panel for a sub-set of participants.

5.1 | Differences in risk exposure across fisheries

The boxplots in Figure 2 show how the literature-based classifications of fisheries compare to the data-based measures. For each fishery classification, we show the distribution of the corresponding CoV in individual trip revenues.

The literature-based classification of differences in exposure to a risky natural environment aligns well with the data-based measure for Chile. Based on the analysis of the landings ticket data, we find that vessels active in benthic

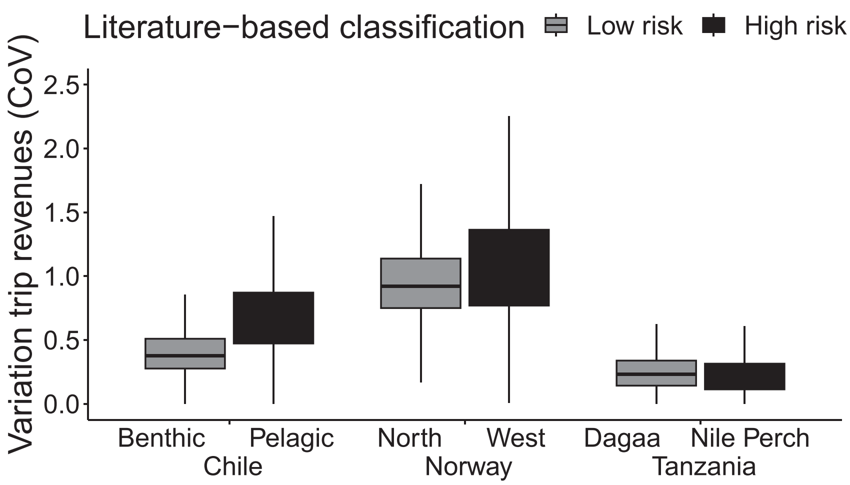

FIGURE 2 Literature-based classifications versus data-based measures of risk exposure. Plot does not show outliers.

fisheries (classified as low-risk) have on average a smaller CoV in trip revenues (from now on, variability) compared to vessels active in the pelagic fisheries (classified as high-risk). The difference is substantial and significant (two-sided *t*-test, $p < .01$). The average vessel active in the benthic fisheries has a variability of 0.43 compared to 0.74 for vessels active in pelagic fisheries. For Norway, the difference in revenue risk between the Northern, primarily demersal, fleet and the Western, primarily pelagic, fleet is smaller: The former has a variability of 0.98 while the latter has a variability of 1.12. This difference is significant (two-sided *t*-test, $p < .01$) and matches the literature-based classification. For Tanzania, finally, we cannot confirm the literature-based risk classification (two-sided *t*-test, $p = .102$). In fact, the data-based variability in the local Dagaa fishery (classified as low-risk in the literature) is higher (0.26) than in the export oriented Nile perch fishery (0.23).

5.2 | Risk exposure is related to risk preferences—Pooled evidence

Table 2 presents the main result of this paper. Our preferred specifications are shown in columns (2) and (4), while columns (1) and (3) show the regression results without control variables for the literature-based classification and the data-based measure of risk exposure, respectively. The estimates from the linear regression model on the pooled sample from all field survey shows that there is a positive, but non-significant, coefficient for the link between the literature-based classification of more risky fisheries and risk preferences (risk tolerance); see column 2. Using the data-based measure of risk exposure, this positive relationship is confirmed (column 4). Here, the coefficient is significant at the 10% level. We find that one standard deviation increase in risk exposure is associated with 0.1 more ECU invested in the lottery task.

While there is weak evidence for a link between risk exposure and risk preferences in the pooled sample, the effect is small in absolute magnitude. It is larger than the effects of age and wealth (which are not significantly different from zero), but smaller than the effect of comprehension: participants who pass all comprehension tests invest about half an ECU less on average.[6]

In particular, the effect is small compared to the country specific fixed effects. Participants in Norway invest 0.8 ECU more and participants in the second Tanzanian survey invest about 0.8 ECU less than participants in the first Chilean survey, the baseline. The point estimate for the first Tanzanian survey is also lower than the baseline value (but not significantly so) and there is no difference between the baseline and the second survey in Chile.

5.3 | Exposure and preferences—Country-specific evidence

Before we delve deeper into the question of whether these relationships between the natural environment and preferences could be caused by a process of selection or a process of adaptation (hypotheses 2–4), we discuss the estimates of

TABLE 2 Main results of linear regression with pooled data of all countries.

	Dependent variable					
	Risk preferences					
	(1)	(2)	(3)	(4)	(5)	(6)
Classification	0.12	0.13				
	(0.13)	(0.12)				
Exposure			0.10	0.10*	0.09	0.12*
			(0.06)	(0.06)	(0.06)	(0.07)
Tenure					0.09*	0.10*
					(0.05)	(0.05)
Selection					0.13	0.13
					(0.08)	(0.08)
Exposure × tenure						−0.03
						(0.06)
Exposure × selection						−0.06
						(0.11)
Age		0.04		0.02		
		(0.05)		(0.05)		
Wealth		−0.05		−0.07	−0.06	−0.06
		(0.05)		(0.05)	(0.05)	(0.05)
Comprehension		−0.48***		−0.41***	−0.36***	−0.36***
		(0.13)		(0.13)	(0.13)	(0.13)
FT-C2	0.11	0.06	0.14	0.09	0.09	0.10
	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.14)
FT-N	0.81***	0.80***	0.77***	0.76***	0.78***	0.77***
	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)
FT-T1	0.01	−0.31	0.05	−0.23	−0.21	−0.22
	(0.18)	(0.21)	(0.19)	(0.22)	(0.22)	(0.22)
FT-T2	−0.59***	−0.82***	−0.61***	−0.80***	−0.80***	−0.80***
	(0.21)	(0.23)	(0.22)	(0.24)	(0.24)	(0.24)
Constant	3.45***	3.93***	3.51***	3.93***	3.81***	3.81***
	(0.12)	(0.18)	(0.11)	(0.17)	(0.17)	(0.17)
Observations	2336	2303	2161	2132	2091	2091
R^2	.05	.06	.05	.06	.06	.06
Adjusted R^2	.05	.06	.05	.06	.06	.06

Note: The dependent variable is the number of ECU (between zero and six) invested in the risky option. Standard errors clustered at the session level in parentheses.

Abbreviation: ECU, experimental currency units.

* $p < .10$, ** $p < .05$, *** $p < .01$.

country-specific regressions given by Equation (1). Figure 3 shows the corresponding coefficient estimates with the 95% confidence intervals for the classification (column 2), and the data-based measure (column 4), respectively. The corresponding Table A2 for Chile, Table A3 for Norway, and Table A4 for Tanzania, are all placed in the Appendix.

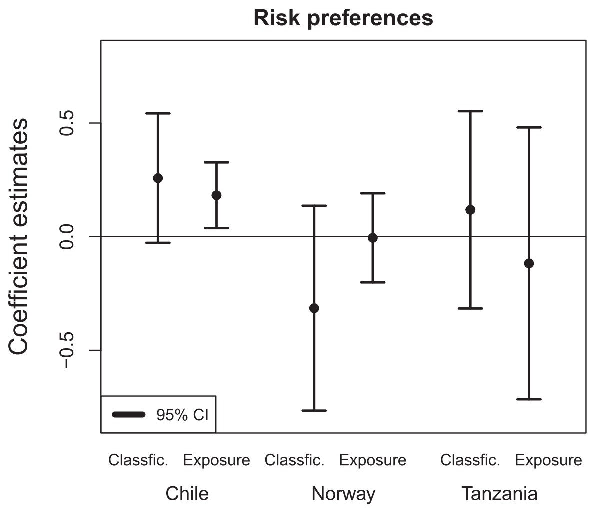

FIGURE 3 Coefficient estimates and confidence intervals of the literature-based classifications and data-based measures of exposure from the country-level regressions. See Tables A2–A4 for full regression results.

For Chile, we find that the effect of exposure to more risk, both when captured by the literature-based classification and when proxied by trip-based revenue volatility, is strongest. Here, a one standard deviation increase in risk exposure is associated with 0.18 more ECU invested in the risky option. The effect is significant at the 2% level. For the country specific regressions for Tanzania and Norway, in contrast, we do not detect a statistically significant effect of risk exposure on risk preferences. For Norway, the effect is nearly zero in absolute terms and much smaller than the effects of age or wealth (neither of which is significant either). In Tanzania, the effects of wealth and comprehension are significant and also larger than the effect of risk exposure.

5.4 | Interactions of exposure with selection or tenure

The regression estimates from the model spelled out in Equation (1) can tell whether there is an overall correlation between exposure and preferences, but do not shed light on the underlying process. Therefore, we formulate the regression model given by Equation (2), where we include an indicator variable for whether respondents have selected into fishing, and a variable that measures their tenure as a fisher (column 5 in Table 2). Positive coefficient estimates for these terms would indicate that being a fisher as such (as opposed to, say, a carpenter) is related to risk preferences. Including interaction terms, then, can tell us whether exposure to a more risky environment has an additional effect on risk preferences (column 6 in Table 2).

Indeed, we find an effect of tenure: Being a fisher for a longer time is related to more risk tolerance. The interaction effect with risk exposure, however, is not significant, indicating that there is no additional effect for being a fisher in a relatively more risky fishery. However, we see that neither selection nor the interaction effect of selection with risk exposure is significant. That is, we find no evidence that selecting into becoming a fisher as such is related to more risk tolerance, nor that having selected into a relatively more risky fishery has an additional effect on risk tolerance. However, the null effect on selection for the pooled sample masks a strong effect of selection for Norway (see column 5 in Table A3). Here we find that those participants who have selected into becoming fishers invest more than half an ECU more in the risk elicitation task (this is in fact the largest effect that we document). There are no differences between the fisheries in Norway either.

Overall, the regression of the model given by Equation (2) does not give us an unequivocal picture of what might be the underlying process leading to the correlation of exposure and preferences. The correlation between tenure and preferences suggests that either adaptation or gradual out-selection has a noticeable impact on the preferences of fishers. However, this empirical strategy cannot detect that either of these processes causes the observed differences between the fisheries.

5.5 | Distinguishing selection from adaptation

In this section, we make use of the fact that we have revisited some of the communities in Chile and in Tanzania twice. This allows us to make an attempt at distinguishing selection from adaptation by conducting two types of analyses.

First, we take a look at the probability that we see the same participant again. That is, some participants in our data were re-sampled when visiting a given community for the second time, while other participants were not re-sampled at our second visit. Comparing re-sampled to not re-sampled participants and finding systematic differences in risk preferences between these two groups would be an indication for gradual (out-) selection as a mechanism that could explain a relationship between risk exposure and risk preferences. Of course, such an analysis can at best be suggestive because there may be many other reasons than leaving the fishery why we would not re-sample a given participant.

The results of this analysis are presented in more detail in Appendix A3. In short, we find no evidence for gradual out-selection in Chile or Tanzania. Interestingly, for Chile, we find that those participants who are exposed to more risk are less likely to be re-sampled and those participants that have selected into fishing in Chile are more likely to be re-sampled.

Second, we can look at within participant changes in risk preferences. Though we are left with only a small sub-sample, this analysis subjects the adaptation hypothesis to a strong test. Provided the method to elicit risk preferences is reliable, a comparatively larger change in risk tolerance in the relatively more risky fishery suggests that an adaptation process takes place within the individual. Due to the small sample size, the results are indicative only. Nevertheless, they are interesting. Table 3 shows the results when regressing our measures of exposure on the difference in risk-preference between the first and the second field surveys.[7] A positive value indicates that the participant has become more risk tolerant after the first field survey and a negative value indicates that the participant has become more risk averse.

Columns 1 and 2 report the results for Chile. We find that the risk preference of Chilean fishers active in the risky fisheries has indeed increased more between field surveys compared to fishers in the less risky fisheries. This effect is significant at the 5% and 1% level for the literature- and data-based measures of risk exposure, respectively.

Turning to the data from Tanzania, we see also see positive point estimates for both measures of risk exposure, but the effects are not significant. Given the negligible differences in actual risk exposure between the fisheries in Tanzania that we have detected in Section 5.1, the fact that we do not find different responses to risk exposure is of course not very surprising.

TABLE 3 Linear estimates of the within participant change in risk preference.

	Dependent variable			
	Δ Risk preferences			
	Chile		**Tanzania**	
	(1)	**(2)**	**(3)**	**(4)**
Classification	0.94**		0.08	
	(0.42)		(0.91)	
Exposure		0.39***		0.48
		(0.10)		(0.80)
Age	0.002	0.003	0.02	0.03
	(0.01)	(0.01)	(0.02)	(0.03)
Constant	−0.54	−0.18	−1.61	−1.53
	(0.57)	(0.64)	(1.13)	(0.97)
Observations	53	53	114	107
Adjusted R^2	.03	.02	−.01	−.01

Note: The sample is subset for those participants who were observed twice, and did not change fisheries in between the field trips. Standard errors clustered on landing site level.

*$p < .10$, **$p < .05$, ***$p < .01$.

6 | DISCUSSION

The natural environment has a direct effect on production in fisheries. Fluctuations in abundance and availability of the resource stock determine how much can be produced and the characteristics of the target species, such as size, habitat, or behavior, determine the mode of production. Here, we study the *indirect* effect that the natural environment may have. The natural environment may shape fishers' risk preferences, and these will in turn affect socio-economic outcomes. We ask whether a correlation between exposure to more risky environments and higher risk tolerance is empirically detectable and widespread.

To put the link to a strong test, we collate data from five surveys conducted in three countries. Specifically, within each country, we contrast a fishery that has been classified as high-risk with a fishery that has been classified as low-risk. In addition to this literature-based measure of risk exposure, we construct a data-based measure of revenue risk and use country fixed effects to control for the institutional setup and the level of development that is vastly different in the three countries. In addition to assessing whether a link between exposure to more risky environment is widespread, we make a first pass at disentangling selection from adaptation as potential mechanisms that make preferences endogenous, using the fact that there are some participants who were interviewed twice.

Overall, we find mixed results. The pooled regressions show a positive, but only weakly significant relationship between exposure and preferences. The link between exposure and preferences is strongest in Chile. Chile is also the country where differences in risk exposure are most pronounced. In fact, the relationship between risk exposure and risk preferences is not significant for Tanzania and Norway. The latter result is maybe not surprising, given the small differences in risk exposure in these countries.

What we do find for Norway and Tanzania is that selection into fishing in general is an important predictor of risk preferences, but we find no differential degree of selection. This result accords well with the development of the fishing sector in the three countries. In Chile, outside opportunities are rare, and many communities are rather isolated. In most communities, however, there is the option to either participate in the pelagic or in the benthic fisheries. Once in a given fishery (and member of the relevant fisheries union), it is uncommon to switch between fisheries. The situation in Tanzania differs: First, capital investments and skills are much less fishery specific, making the boundary between the different fisheries more fluid. Second, both the dagaa and the Nile perch fisheries experienced a boom, so that many farmers decided to become fishers and migrate to the Lake. In Norway, settlement patterns are more stable and the fisheries are also more localized. Relatively large fishery specific investments and a strong tradition for an intergenerational transmission of occupations impede switching between fisheries. All these factors speak for finding a difference in risk preferences across the high-risk and low-risk fisheries in Norway. However, the actual difference in risk level between the Northern and Western fisheries is small and good outside opportunities are plentiful in Norway. These facts may accentuate the difference between fishing and not fishing, and blur the difference between Northern and Western fisheries. Not surprisingly, we find strong differences in the level of risk preferences among Chile, Norway, and Tanzania. Compared to participants in Chile, we find that participants in Norway are more risk tolerant and participants in Tanzania are less risk tolerant.

We have captured risk exposure both based on a broad, literature-based classification and by a data-based measure that we have constructed. This data-based measure of variation in revenues arguably captures more general aspects of risk exposure fairly well. Revenue risk is not only directly linked to what we measure with the elicitation task (the investment decision determines the variation in income from the experiment), but it is also a key determinant of any broader aspect of risk exposure. Mortality risk, for example, is directly linked to the variation in harvest for subsistence fishers. The link is less relevant in developed economies today, where well-functioning social security exists, but it definitely was relevant in the not-so-distant past, and it still is relevant in developing economies where formal insurance markets are largely absent and opportunities for income smoothing are limited (Schaap et al., 2024).

Our study speaks to a growing literature that documents the endogeneity of preferences (Cappelen et al., 2020; Dohmen et al., 2012, 2017; Falk et al., 2021; Schildberg-Hörisch, 2018). A handful of case studies more specifically suggest that the natural environment shapes economic preferences (Di Falco & Vieider, 2022; Gneezy et al., 2016; Jang & Lynham, 2015; Leibbrandt et al., 2013; Nguyen, 2011), thereby complementing global studies that use historical or reconstructed data (Barsbai et al., 2021; Buggle, 2020; Buggle & Durante, 2021; Galor & Özak, 2016).

Combining the virtues of case-study detail with a global scope, we do not find an effect across the board, but we do find that in places with pronounced differences in risk exposure, fishers in more risky fisheries are also more risk tolerant. Our analysis suggests that this could indeed be a causal effect, driven by both selection and adaptation. We find that for a subset of our data, namely those Chilean fishers who we observed twice (hence ruling out selection), we find that risk tolerance increases between field surveys for those fishers that are in the risky fishery, but not for those fishers who are in the more stable fishery.

The sample of participants who we happen to observe twice and are hence available for our within-participant analysis is relatively small. Di Falco and Vieider (2022) present a much larger panel that they match with high resolution rainfall data and thereby provide the first solid causal evidence for a link between the natural environment and risk preferences. They find that Ethiopian farmers from areas with high variability in rainfall are less risk tolerant. Hence, the effect documented in their study goes in the opposite direction than in our study. The difference between their and our study is that Di Falco and Vieider investigate an effect that runs through agricultural yield and household consumption while we are concerned with the effect of exposure to different natural environments. Their theory of change relies on expectations about future consumption possibilities in an environment where subsistence thresholds may become binding. In contrast, our theory of change revolves around selection and adaptation, both by experiential learning and by cultural learning.

The data presented in this paper contrasts, in each of three very different countries, a low-risk fishery with a high-risk fishery. We therefore add to the literature by highlighting the importance of contextual details that interact with the natural environment. That said, there are a number of confounds that deserve to be discussed: First, the data-based measure of risk exposure in Chile and Norway is based on administrative data, while it is based on self-reported data in Tanzania. The latter may be inferior to the administrative data, but it is the only available measure.[8] Second, while we strived to adjust participants' payouts such that they are comparable in terms of the respective opportunity cost of an outside unskilled labor option, differences in purchasing power equivalents will remain. Similarly, differences may be caused by the way the sample was selected and study was administered (see Section 4.6). We used country and field-trip specific fixed effects to absorb these factors in the regression analysis, but ultimately more data and more work would be needed to understand their influence on our findings.

While exposure to the natural environment plays a particularly direct role in fisheries, we believe that our analysis also speaks to other occupations. Farming (especially in settings with little access to financial/insurance markets), for example, could be one such setting where exposure to the natural environment is important. Some farmers, depending on their land and/or their traditional cropping methods, may be more exposed to natural risk than others. It would furthermore be interesting to investigate whether a link between risk exposure and risk preferences is detectable when the risk does not result from the natural environment, but from the social environment.

Furthermore, we conjecture that the dual processes of selection and adaptation that make preferences endogenous operate in many settings. A case in point could be leisure activities: While some choose curling (=low-risk) as a hobby, others choose canyoning (=high-risk). Risk preferences plausibly affect the initial selection of the hobby, but increasing returns to skill and investments in gear present hurdles to switching and potentially lead to an adaptation of participants' risk preferences; they get used to the risk they are exposed to.

Exploring the robustness of our finding, especially those from the within-participant analysis, is but one of several avenues for further research that our study opens. On the one hand, there are several important theoretical questions that arise: How does adaptation work? What role do social processes, such as peer pressure or preferences to conform with the actions of others, play, in contrast to more psychological processes such as desensitization and learning? What distinguishes a process of adaptation from a process of selection, and if there are differences in these processes, do they translate into different socio-ecological outcomes? On the other hand, there are several relevant practical implications: What are the consequences of a link between resource risk and risk preferences for monitoring and enforcement or for capital investments? While the size of the documented effect is modest, could a link between exposure and resource risk still turn into a positive feedback loop, supporting or threatening sustainable management? Should policy makers take endogenous preferences into account when designing welfare programs for fishers?

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DATA AVAILABILITY STATEMENT

Experimental instructions, data, and analysis files to reproduce the results in this paper are publicly available in the WEAI repository at https://doi.org/10.3886/E207909V4 and in the Heidelberg University data repository at https://doi.org/10.11588/data/VO2JGU (Diekert, 2024).

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ENDNOTES

[1] There is a large literature documenting the long-run effect of the mode of production on current outcomes. For example, Alesina et al. (2013) document the relationship between labor intensive shifting cultivation or capital intensive plough cultivation and gender roles. Another example is Bentzen et al. (2017) who show a relationship between irrigation practices in the past and autocratic rule today. The difference of this literature to the studies discussed in the main text is that the latter focus more directly on the underlying economic preferences rather than on their manifestations.

[2] Note that this differs from the literature (e.g., Chuang & Schechter, 2015) that studies the effect of shocks on preferences. Several studies, for example, attempt to estimate the effect of natural disasters such as hurricanes, earthquakes, or mudslides on risk preferences, finding both positive (Eckel et al., 2009; Kahsay & Osberghaus, 2018) and negative effects (Cameron & Shah, 2015; Willinger et al., 2013).

[3] Note that we use the generic term "risk preference" in the more narrow sense of "risk tolerance" in our paper. When we say an agent i has a higher risk preference than another agent j, we therefore mean that she is more tolerant toward risk than agent j.

[4] Tanzania: bike, motorbike, cow, goat, boat, car. Chile: bike, motorbike, TV, house, boat, car.

[5] On average, participants earned about 150 NOK for the 10-minute task; 150 NOK was roughly the hourly wage for unskilled labor at the time of the survey. Hence, the experimental payouts were scaled to the respective opportunity cost of time in terms of unskilled labor in all three countries. Of course, there are vast differences in the general economic situation between Tanzania, Chile, and Norway, which is accounted for in the analysis by using country fixed effects.

[6] Table A1 shows the robustness of our finding when we restrict the sample to those participants that pass all comprehension tests.

[7] The time gap between the surveys is slightly more than a year in Chile and slightly less than a year in Tanzania.

[8] At the end of the day, the administrative dataalso relies on what fishers report on landing tickets.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A

A.1 | Regression results for restricted sample

TABLE A1 Linear regression with pooled data of all countries for restricted sample of those participants that passed all comprehension tests.

	Dependent variable					
	Risk preferences					
	(1)	(2)	(3)	(4)	(5)	(6)
Classification	0.24*	0.26**				
	(0.13)	(0.13)				
Exposure			0.09	0.10*	0.09	0.10
			(0.06)	(0.06)	(0.06)	(0.07)
Tenure					0.11**	0.11**
					(0.06)	(0.06)
Selection					0.18**	0.18*
					(0.09)	(0.09)
Exposure × tenure						0.001
						(0.06)
Exposure × selection						−0.01
						(0.12)
Age		0.07		0.06		
		(0.05)		(0.05)		
Wealth		0.01		0.001	0.01	0.01
		(0.05)		(0.05)	(0.05)	(0.05)
FT-C2	0.14	0.13	0.18	0.17	0.14	0.14
	(0.14)	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)
FT-N	0.86***	0.85***	0.79***	0.77***	0.77***	0.77***
	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)
FT-T1	−0.42*	−0.45*	−0.35	−0.35	−0.40	−0.40
	(0.22)	(0.23)	(0.25)	(0.25)	(0.26)	(0.26)
FT-T2	−0.83***	−0.84***	−0.80***	−0.81***	−0.82***	−0.82***
	(0.24)	(0.24)	(0.26)	(0.26)	(0.27)	(0.27)
Constant	3.38***	3.39***	3.49***	3.51***	3.43***	3.43***
	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)	(0.12)
Observations	1706	1692	1604	1591	1564	1564
R^2	.09	.09	.08	.08	.09	.09
Adjusted R^2	.08	.08	.08	.08	.08	.08

Note: The dependent variable is the number of ECU (between zero and six) invested in the risky option. Standard errors clustered at the session level in parentheses.

Abbreviation: ECU, experimental currency units.

*$p < .10$, **$p < .05$, ***$p < .01$.

A.2 | Country specific regression results

TABLE A2 Country-specific results, Chile.

	Dependent variable					
	Risk preferences					
	(1)	(2)	(3)	(4)	(5)	(6)
Classification	0.24*	0.26*				
	(0.14)	(0.15)				
Exposure			0.17**	0.18**	0.17**	0.14
			(0.07)	(0.07)	(0.07)	(0.09)
Tenure					0.15***	0.15***
					(0.05)	(0.05)
Selection					0.12	0.11
					(0.11)	(0.11)
Exposure × tenure						0.01
						(0.06)
Exposure × selection						0.06
						(0.12)
Age		0.01		0.004		
		(0.01)		(0.005)		
Wealth		0.05		0.06	0.05	0.05
		(0.05)		(0.05)	(0.05)	(0.05)
Comprehension		0.05		0.09	0.18	0.18
		(0.25)		(0.24)	(0.21)	(0.22)
2018 field trip	0.10	0.08	0.14	0.12	0.13	0.13
	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.14)
Constant	3.40***	3.10***	3.51***	3.25***	3.29***	3.28***
	(0.12)	(0.41)	(0.11)	(0.42)	(0.23)	(0.23)
Observations	825	812	812	799	784	784
R^2	.01	.01	.02	.02	.03	.03
Adjusted R^2	.01	.01	.01	.01	.02	.02

Note: Linear estimates of risk exposure on preferences, standard errors clustered at the session level in parentheses.
*$p < .10$, **$p < .05$, ***$p < .01$.

TABLE A3 Country-specific results, Norway.

	Dependent variable					
	Risk preferences					
	(1)	(2)	(3)	(4)	(5)	(6)
Classification	−0.29	−0.31				
	(0.22)	(0.23)				
Exposure			−0.004	−0.01	0.01	0.12
			(0.10)	(0.10)	(0.10)	(0.16)

(Continues)

TABLE A3 (Continued)

	Dependent variable					
	Risk preferences					
	(1)	(2)	(3)	(4)	(5)	(6)
Tenure					0.08	0.07
					(0.09)	(0.09)
Selection					0.52***	0.53***
					(0.20)	(0.20)
Exposure × tenure						−0.04
						(0.10)
Exposure × selection						−0.17
						(0.20)
Age		0.05		0.05		
		(0.09)		(0.09)		
Wealth		0.06		0.03	0.05	0.05
		(0.09)		(0.09)	(0.09)	(0.09)
Constant	4.34***	4.35***	4.28***	4.28***	3.90***	3.89***
	(0.09)	(0.10)	(0.09)	(0.09)	(0.17)	(0.17)
Observations	462	461	459	458	458	458
R^2	.004	.005	.0000	.001	.02	.02
Adjusted R^2	.002	−.002	−.002	−.01	.01	.01

Note: Linear estimates of risk exposure on preferences.
*$p < .10$, **$p < .05$, ***$p < .01$.

TABLE A4 Country-specific results, Tanzania.

	Dependent variable					
	Risk preferences					
	(1)	(2)	(3)	(4)	(5)	(6)
Classification	0.14	0.12				
	(0.23)	(0.22)				
Exposure			−0.07	−0.12	−0.09	0.02
			(0.30)	(0.31)	(0.30)	(0.36)
Tenure					0.01	0.01
					(0.08)	(0.08)
Selection					0.02	0.01
					(0.16)	(0.16)
Exposure × tenure						−0.06
						(0.21)
Exposure × selection						−0.17
						(0.46)

TABLE A4 (Continued)

	Dependent variable					
	Risk preferences					
	(1)	(2)	(3)	(4)	(5)	(6)
Age		0.01		−0.01		
		(0.09)		(0.09)		
Wealth		−0.15**		−0.21***	−0.21**	−0.21**
		(0.07)		(0.08)	(0.08)	(0.08)
Comprehension		−0.58***		−0.53***	−0.51***	−0.51***
		(0.14)		(0.15)	(0.15)	(0.15)
2018 field trip	−0.60***	−0.49**	−0.65***	−0.55**	−0.55**	−0.55**
	(0.22)	(0.22)	(0.25)	(0.25)	(0.25)	(0.25)
Constant	3.45***	3.67***	3.55***	3.73***	3.70***	3.70***
	(0.22)	(0.21)	(0.15)	(0.14)	(0.16)	(0.16)
Observations	1049	1030	890	875	851	851
R^2	.02	.04	.02	.04	.04	.04
Adjusted R^2	.02	.03	.02	.04	.04	.03

Note: Linear estimates of risk exposure on preferences, standard errors clustered at the landing site level in parentheses.
*p < .10, **p < .05, ***p < .01.

A.3 | Robustness check on out-selection

In addition to testing for the effect of *selecting into* a fishery as in specifications (4) and (8) in Table 2 in the main text, we can also test whether less risk tolerant respondents have gradually *selected out* of the fishery. To do so, we can use the fact that we have visited some of the communities twice. That is, in our data there are some respondents who we observe twice (and stayed in the same fishery), and there are respondents who we observe only once (e.g., because they moved, or because they changed their fishery). If the former sample is more risk tolerant than the latter, especially in more risky fisheries, this would be strong evidence for a process based on gradual (out-)selection.

We estimate the probability that a participant is re-sampled using the logistic regression model 4. The variables of interest are the participant's preferences (RP_i) and the interaction coefficient between preferences and exposure ($RE_i \times RP_i$). If the β_2 coefficient is positive it would indicate that risk averse individuals are less likely to be re-sampled. If the coefficient for the interaction effect (β_3) is positive it would indicate that this effect is stronger in high-risk fisheries, which could be evidence for out-selection being a driving mechanism for any differences in preferences found between fisheries.

$$P(Resamp_i = 1) = \alpha + \beta_1 RE_i + \beta_2 RP_i + \beta_3 (RE_i \times RP_i) + \\ + \beta_4 Sel_i + \beta_4 Age_i + \varepsilon_i \tag{A1}$$

This regression obviously only provides a lower bound estimate of out-selection because a fisher that is not observed again in subsequent rounds of data collection might have selected out of the fishery and started a different occupation, but he might also be unavailable for some other reasons (such as visiting relatives).

Table A5 presents the results from a logistic regression where all re-sampled participants are assigned a value of 1 and all participants that we could, but did not re-sample are assigned a value of 0.

The results show that fishers who have been re-sampled, do not significantly differ from those that have not been re-sampled with regard to their risk preferences, regardless of their exposure. Interestingly, we find that for Tanzania, those fishers who are exposed to more revenue risk are less likely to be re-sampled. We also find that those Tanzanian fishers who selected into the fishery are less likely to have stayed. Furthermore, there is a positive interaction between risk exposure and risk preferences. However, the statistical evidence for these correlations is relatively weak.

TABLE A5 Logistic regression coefficients, comparing re-sampled to not re-sampled fishers, standard errors clustered at the landing site level in parentheses.

	Dependent variable	
	Resampled (=1 if yes)	
	Chile (1)	Tanzania (2)
Risk exposure	−0.49	−0.78*
	(0.32)	(0.46)
Risk preference	0.05	−0.06
	(0.14)	(0.04)
Risk exposure × preference	0.05	0.16*
	(0.09)	(0.09)
Selection	0.09	−0.39*
	(0.31)	(0.21)
Age	0.01	0.02**
	(0.01)	(0.01)
Constant	−1.25	−1.42***
	(0.94)	(0.53)
Observations	201	416
Log likelihood	−128.68	−246.02
Akaike inf. crit.	269.37	504.04

*$p < .10$, **$p < .05$, ***$p < .01$.