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Changing background risk and risk-taking – Evidence from the field*

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Abstract

Decisions involving risk are usually taken in the presence of other insurable or non-insurable risks, the latter type called background risk. We examine how changing background risk influences risk-taking based on panel data with monthly observations from Senegalese fishermen. Fishing income is volatile and income risk depends on weather conditions and on technologies employed. To measure risk-taking, we use an incentivized investment task. To measure background risk, we consider long-run wind conditions and a measure based on comparing standardized monthly income deviations from the yearly individual mean. We find that the latter measure that controls for technology choices and thus takes conscious reduction of risk exposure into account has a significant impact when overall fishing income is below average. Then, higher income risk increases risk-taking, suggesting intemperate behavior in low-income situations. This effect is stronger for poorer fishermen, highlighting the need for safety nets.

Keywords: risk-taking, background risk, temperance, investment, fisheries, Senegal

JEL Classification: C93, D81, 012, 013, Q22

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1 Introduction

Most decisions involve some form of risk-taking. While an agent can decide how much risk to take in the current decision, additional unrelated, non- or only partly insurable risks may be present. Exposure to such unavoidable risks—so called background risks (see e.g. Harrison et al. (2007) and Eeckhoudt et al. (1996))—may influence risk-taking in the decision at hand. Examples include portfolio choices when labor income is risky (Guiso and Paiella, 2008) or medical treatment decisions in the presence of other health risks (Bleichrodt et al., 2003). For economic development, the impact of background risk on risk-taking is especially relevant, as investments into the future require risk-taking and formal insurance possibilities are often lacking in low-income countries. Informal insurance may be easier available, but is in many cases limited to traditional occupations (see e.g. Riekhof (2018)).

The theoretical literature examines the role of background risk for risk-taking in the context of higher order risk preferences, i.e. when considering prudence, temperance or edginess. For analyzing the impact of background risk, the relevant concept is temperance. Temperate behavior means that different risks are considered as substitutes (Kimball, 1993) and that exposure to unavoidable risks leads to a reduction in risk-taking in other decisions (Kimball, 1992). In turn, intemperate behavior implies taking different risks as complements, which would be in line with the psychological finding of diminishing sensitivity (see discussion in Harrison et al. (2007)).[1]

Most results from laboratory experiments point towards temperate behavior,[2] although the findings are not as strong as e.g. for prudence (Trautmann and van de Kuilen, 2018). Notable exceptions are the results by Deck and Schlesinger (2010) and Baillon et al. (2018), who find evidence for intemperate behavior. To examine the prevalence of (in)temperate behavior in the field, Noussair et al. (2014) correlate individual lottery choices with behavior in the field and Guiso and Paiella (2008) directly consider labor income risk measured as past economic growth on risk attitudes using cross-sectional data.[3] Neither approach directly measures the impact of background risk on risk-taking in the field.

[1]In the framework of expected utility, temperance is linked to the concavity of the fourth derivative of the utility function and standard utility functions—e.g. with constant relative risk aversion—predict temperate behavior, while intemperance is compatible with prospect theory (Deck and Schlesinger, 2010).

[2]To experimentally examine whether individuals indeed behave temperate, lottery choices (e.g. Harrison et al. (2007), Lusk and Coble (2008), Deck and Schlesinger (2010), Noussair et al. (2014), Beaud and Willinger (2015), Baillon et al. (2018)) or a multiple price list approach (.g. Ebert and Wiesen (2014), Heinrich and Mayrhofer (2018)) have been used, usually based on the model-independent approach by Eeckhoudt and Schlesinger (2006).

[3]Interestingly, when using a subjective measure of earnings uncertainty, Guiso and Paiella (2008) find a positive impact (albeit small and statistically not significant). Baillon et al. (2018) examine higher order ambiguity attitudes in the lab to take into account that objectively known probabilities are often not available in real-life decisions.

In this paper, we examine the impact of real-life background risk on risk-taking. Our study is new in two aspects. First, we consider different types of background risk, i.e. we use two different measures to operationalize background risk in the field to better understand how agents deal with different sources of risks. Second, we examine the occurrence of (in)temperate behavior under different circumstances. To do so, we observe changing background risk over time and connect it to risk-taking, which is measured by an incentiviced investment task that is repeated on a monthly base for over a year.

This work hence makes several contributions. It is the first paper to investigate the impact of background risk on risk-taking in the field using panel data and a repeated incentiviced investment task, allowing to control for unobservables at the individual level. To our knowledge, only Guiso and Paiella (2008) estimate the impact of background risk in the field on risk-taking. They measure background risk—high exogenous labor income risk—by variability of GDP growth in the province of residence using cross-sectional data and a hypothetical question on the willingness to pay for a risky security to measure risk attitudes. Besides using panel data, we compare two different measures of background risk and thereby take a first step to examine the role of chosen exposure to background risk. In laboratory experiments—based on the standard definition of background risk—, actions to reduce the exposure to background risk is usually not possible.

Also, we contribute to the literature on the stability of risk-taking over time. To our knowledge, our data are unique in the sense that they document risk-taking on a high inter-temporal resolution when incomes and environmental conditions are changing. Our work relates to Menkhoff and Sakha (2016) and Chuang and Schechter (2015), the only two studies we know of that assess the stability of risk preferences over time in developing economies (see Chuang and Schechter (2015) for an extensive overview). They look at time steps of several years while we focus on monthly observations. Moreover, we focus on the different roles of anticipated and unanticipated fluctuations in incomes and resulting risks, while Menkhoff and Sakha (2016) and Chuang and Schechter (2015) focus on the impact of shocks. Our results also add to the understanding how to elicit risk preferences in the developing world (see e.g. Charness and Viceisza (2016)) by examining whether short-run fluctuations in risk-taking prevail. Our study further relates more generally to the examination of risk-taking and investment in developing countries, similar to e.g. Kremer et al. (2013) and Cole et al. (2017). It complements this line of literature as we consider how uninsurable risk impacts risk-taking over time.

Background risk in the field may be better referred to as 'background uncertainty' as probabilities are very unlikely to be known. For convention, we stick with the term background risk.

Our study is based on a panel with monthly observations from 134 Senegalese fishermen from April 2015 to August 2016, leading to a sample of over 1500 observations. Risk-taking—apart from dealing with background risk—is measured by a monthly investment task, which was performed at the end of the monthly surveys. The investment task was a portfolio choice task, based on Gneezy and Potters (1997), in which the fishermen received 1200 FCFA[4]. They could decide how much of this amount they wanted to invest, gaining up to 3000 FCFA each month, which equals about half of the average weekly fishing income. The experimental set-up ensures that the risk is independent from all other risk sources, and that no additional variation enters through differences in the investment task. We take the outcome of the investment task as the dependent variable and examine whether it is impacted by background risk related to fishing income.

Fishing is risky (Platteau and Nugent, 1992) and depends on weather conditions, such that monthly income varies during the course of a year. Still, the impact from changing weather conditions may be mitigated by the choice of fishing methods. Accordingly, we employ two measures for background risk that differ in the way they account for risk-exposure. First, we consider 'overall background risk', referring to a risk that the fishermen face caused by uncontrollable factors such as weather. To measure it, we use the long-run average monthly wind speed. Second, we consider 'remaining background risk', the background risk that remains after fishing methods and effort have been adjusted to external circumstances such as local weather conditions. The remaining background risk constitutes the part of variation fishermen cannot or do not want to adapt to. Here, we use a measure based on comparing standardized monthly income deviations from the yearly mean between fishermen.

To measure weather conditions, we took the average monthly wind speed in m/s close to the coast of Senegal, as 64% of the surveyed fishermen state that more wind entails less fish. The wind data are taken from U.S. Department of Commerce, National Oceanic and Atmospheric Administration Earth Systems Research Laboratory[5]. We took the monthly means, as well as the coefficient of variation of the monthly means of daily wind speed for the past years to reflect the overall background risk in a given month.

To create a measure that captures remaining background risk, we face the challenge that our data only covers realized—ex-post—outcomes, e.g. shocks, and not—ex-ante—risks. Based on the idea that a large variation in realized fishing incomes in a given months relates to high risk ex-ante, we construct a measure on an aggregate level that can be taken as exogenous to the individual fisherman.

Our results show that risk-taking is not constant over time. We identify the level of disposable income in one month as an important driver of variations in risk-taking—which suggests that shocks are an important driver of risk-taking. Moreover, wind conditions do not have a significant impact on risk-taking, while our other measure of

[4] Local currency, 'Franc de la Coopération Financière en Afrique Centrale' (FCFA).

[5] See `https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.derived.pressure.html`, last accessed: January, 9th, 2018, as well as Kalnay et al. (1996).

background risk that implicitly controls for technology choices does. In particular for the poorer half of our sample, the uninsurable remaining part of background risk matters for risk-taking, i.e. the risk that remains when fishermen have adapted their production behavior to general weather variability. In months with incomes that lie below the yearly average for most fishermen, we find evidence for intemperate behavior. In months with above-average income, we find no evidence for intemperate behavior. Moreover, we do not observe intemperate behavior in below-average months for wealthier fishermen. This suggests that intemperate behavior occurs in situations with low financial flexibility, different risks become complements. Furthermore, we do not find that the level of disposable income drives variation in risk-taking for the poor. This result could be explained by the fact that disposable income for the poor is always low, i.e. they have to see how they can make ends meet, without much flexibility.

The next section explains the data set we use, including data collection. We also describe the local situation of the Senegalese fishermen. In Section 3, we derive the regression design. In Sections 5 and 6, we present our results, discuss their robustness, and we conclude in the last section.

2 The Data

2.1 Data collection

The data were collected as part of a BMBF[6] funded research project called 'Ecosystem Approach to the Management of Fisheries and the Marine Environment in West African Waters' (AWA) between April 2015 and August 2016. We conducted monthly interviews with fishermen in several of the main fishing ports in Senegal, namely Saint Louis and Kayar, north of Dakar, and Joal and Mbour, south of Dakar (see Figure 1). Four interviewers employed by the Centre de Recherche Océanographique de Dakar-Thiaroye (CRODT) interviewed 134 fishermen once per month, about 35 fishermen per location. The enumerators were selected and trained by the project staff. The sample comprises randomly drawn captains and boat owners (no crew members), as they are the ones deciding on fishing-related investments, as well as on where and when to go fishing.

In total, 1590 interviews were held in the 16 months of the survey period, and for three quarters of all interviewees we have 12 interviews at least.[7] Each questionnaire covers information from the past month, on fishing activities, credit, insurance and

[6]Federal Ministry of Education and Research of Germany.

[7]We dropped 3 interviewees because they only provided one observation. These persons could not be found again for re-interviews by the enumerators. Based on the socio-economic and fishing related data that we collected at the beginning of the survey, these 3 interviewees do not differ significantly in terms of their characteristics. We therefore assume that this did not introduce a systematic bias to our sample.

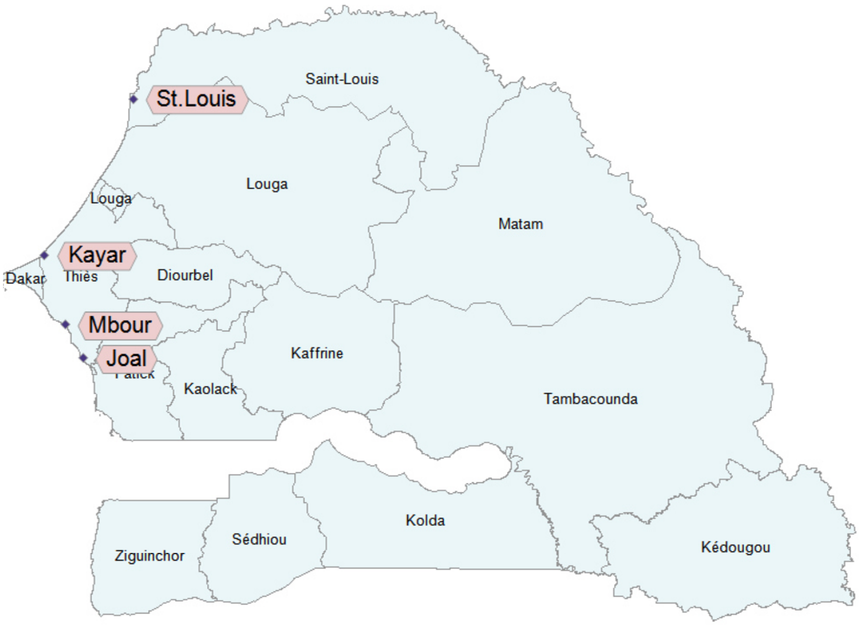

Figure 1: Map of Senegal with interview locations.

credit repayment, income, investment, and social interaction between fishermen. The fishermen also received a fixed amount of money each month that was used to conduct the investment task to measure risk-taking. From the amount received fishermen could invest a variable amount. The invested amount would be increased by a factor 2.5 with 50% probability or lost with a 50% probability.[8] Investing the whole amount would maximize the expected payout. Payouts were made immediately after the task was completed.

Since the fishermen frequently travel or are at sea for long periods of time, some interviews had to be postponed, e.g. the questionnaire for the month August would be filled in September or October. The enumerators were very careful to explain the dates correctly so that, except for potential differences due to recall bias, all interviews should have the same level of validity. To capture remaining differences between 'backdated' and normal interviews, we introduce a dummy in the regressions.

In addition, a separate survey was conducted at the beginning of the interview period. It covers further detailed socio-economic data, climate-change-related aspects and migration activities.

[8] This set-up is based on Gneezy and Potters (1997) and also used by Kremer et al. (2013).

2.2 Data on wind conditions

To measure weather conditions, we take the average monthly wind speed in m/s close to the coast of Senegal.[9] The data are taken from the U.S. Department of Commerce, National Oceanic and Atmospheric Administration Earth Systems Research Laboratory.[10] It indicates the monthly mean wind speed calculated from daily wind speed (from daily vector winds) from 1948/01 to the present. We take the longitude closest to the Senegalese coast and then differentiate between north and south of Dakar for the latitudes. We use the wind speed that prevailed at the surface of the sea (pressure>925). Figure 2 displays the monthly average wind speed north of Dakar (dark line) and south of Dakar (light line). The means for 04/15-07/15 and 04/16-07/16 are more or less identical because compared to the total number of observations per month, the individual point has little influence, and the long-run mean of wind conditions in a given month is relatively stable over time. The data point for the south of Dakar in 04/15 is not depicted, because the first interview there took place in 05/15.

As a measure on the variability of wind speed in a given month over the years, we calculate the coefficient of variations for each month, based on past yearly averages. Overall, the value is 0.111, with a minimum of 0.082 and a maximum of 0.162. A higher value indicates that there has been more variation, implying that a prediction for the month's wind speed base on past experiences is less secure.

2.3 Socio-economic background

With a GDP per capita of 2,420.8 current international dollars (PPP) (World Bank, 2016), Senegal is a lower middle income country. It is also highly dependent on the fishery sector—according to the Fish Dependence Index—and one million people depend directly or indirectly on fisheries (Quaas et al., 2016). Fishing is riskier than agriculture (Platteau and Nugent, 1992), and climate change and overfishing are additional threats to the fishery sector (Quaas et al. (2016); Thiao et al. (2012)).[11]

Our survey only takes into account captains and boat owners, which are, in principle, those who can decide about such investments. By contrast, crew members may not be in the position to take investment decisions. From the survey participants, 62.0 % are captains and vessel owners, while 11.6 % are only captains, and 26.4 % are only vessel owners. The fishing crew consist of 8 members on average, from which, on average, 50 %

[9] Tropical storms are not extremely important in Senegal (see e.g. `http://www.aoml.noaa.gov/hrd/tcfaq/E25.html`, last accessed October 20, 2017.) such that monthly means are a good approximation for wind condition as compared to looking at the number of days with a wind speed above a certain level.

[10] See `https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.derived.pressure.html`, last accessed: January, 9th, 2018, and also Kalnay et al. (1996).

[11] For more details on the Senegalese artisanal fishery, see e.g. Ba et al. (2017).

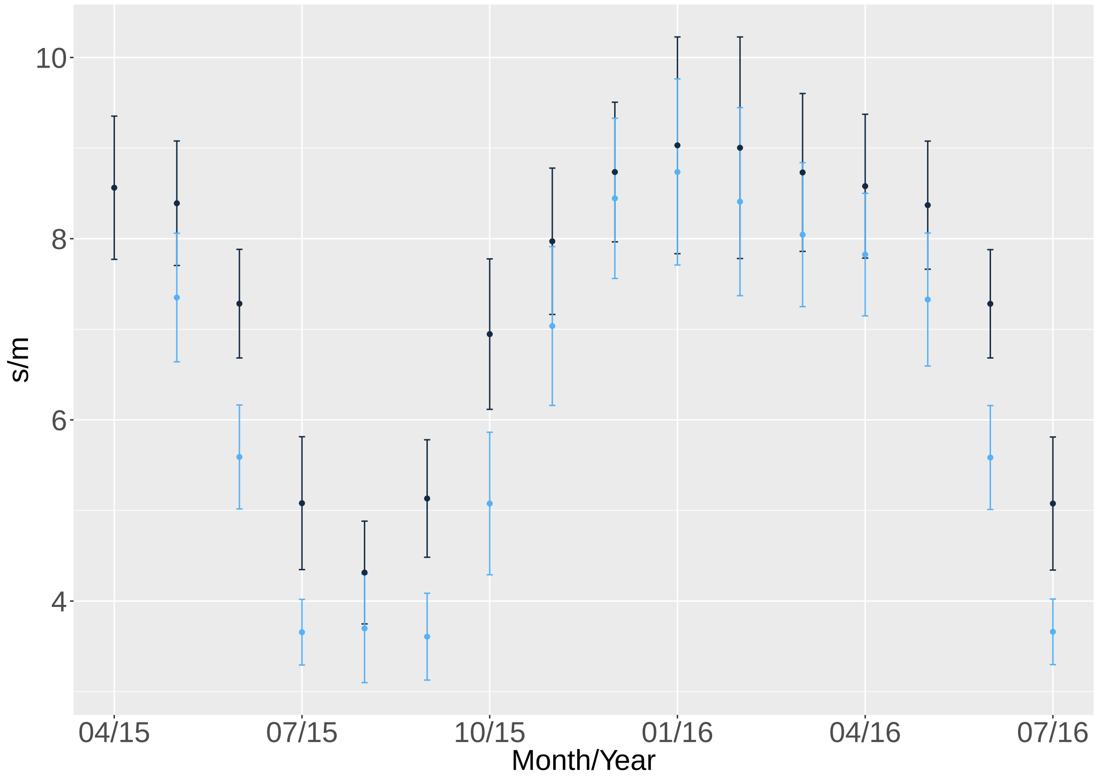

Figure 2: Monthly average of the wind speed north (dark line) and south (light line) of Dakar, with error bars. The average is based on past years, starting with 1948/01.

belong to the family. Usually, only men go fishing. In our sample all participants are male.

From the fishermen in our sample, 41.9 % can read and write, while 14.5 % can only read. The remaining 42.6 % are illiterate. From the 41.0 % that ever had obtained formal education, the majority (71.7 %) only went to primary school, and 15.1 % went to senior secondary school. On average, the fishermen were born 1968, such that they are 48 years old as of 2016.

Most fishermen are married (95 %). On average, the household has 16 members (median 14), not counting the fisherman himself. This high number is explained by the common occurrence of polygamic households.

Living conditions in the fishing villages are simple. Water is accessed through fountain hydrants, with 73.0 % fishermen reporting that they have a private hydrant, while 20.9 % report access to a public hydrant. Most households use wood charcoal for cooking (41.9 %), followed by gas (34.1 %) and wood (24.0 %), while light is usually powered by electricity (94.6 %).

The monthly median income from fishing in our sample is around 150,000 FCFA (about

230 Euros) for the individual fisherman, and fishing is usually their only income source (individually and at household level). Thus, per capita income is considerably lower. Incomes vary seasonally, and so do expenditures for food. Average weekly food expenditure for the whole household and average weekly fishing income are given in Figure 3.[12] We also look at food expenditure per person per month. The average is 554.38 FCFA.

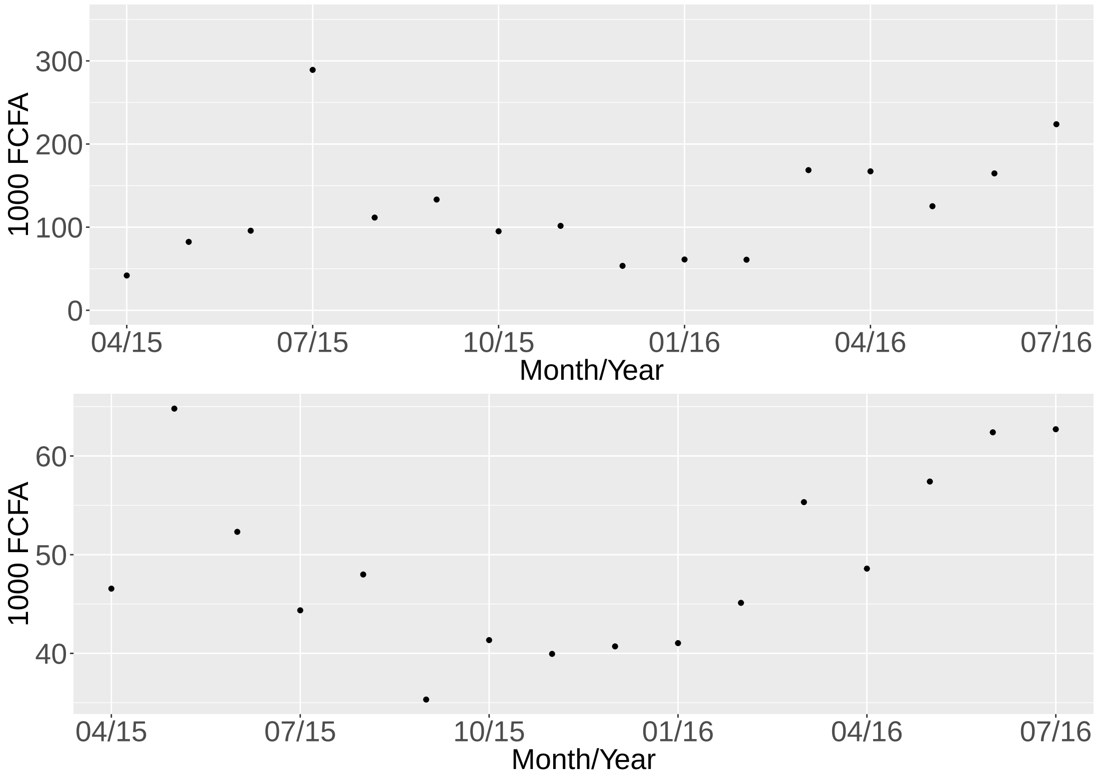

Figure 3: Weekly fishing income (upper graph) and weekly food expenditure (lower graph) over the course of the study period. The graphs depict means over all fishermen.

To obtain a measure for the wealth of the fishermen, we build a wealth index based on Filmer and Pritchett (2001). It is the first component of a principal component analysis including ownership of the accommodation, several vehicle types and telecommunication items. The measure is between -3.600 and 17.167, with an average of -0.085.

2.4 Risk and coping strategies

As discussed above, fishing is risky and income from fishing is volatile (see Figure 3). Part of this volatility stems from weather variability. Weather varies daily and seasonally (see Figure 2 for the monthly variation in average wind). In the detailed survey at

[12]The means of weekly fishing income are calculated based on trimmed data (i.e. the highest and the lowest value are replaced by the median).

the beginning of the study, all fishermen state that variations in weather (wind, rain, temperature, waves, etc.) influence the availability of fish. 64% state that more wind entails less fish (while 22% related more wind to more fish and the remaining either saw no change or changes in species).

To deal with expected risk and volatility ex ante, fishermen can adapt their fishing strategies up to a certain extent by changing fishing effort and fishing gear.[13] They can also take insurance. However, this is not very common among Senegalese fishermen. Only two fishermen have an insurance contract. It is more common to save in order to be able to deal with hard times. Nearly 60% of the fishermen do it, while nearly all of those who do not save state that this is because they do not have enough money to save. Half of the ones that save save for a specific purpose like a wedding or major repairs or gear replacement, and the other half see saving as a general buffer for difficult times.

Taking out a loan is a typical way to react to shocks ex-post. In general, credit is available for Senegalese fishermen. At the time of the initial survey (spring 2015), 39.5% of the fishermen were indebted, with 1.4 loans on average. Additional ways to deal with risks are interlinked loans (see e.g. Riekhof (2018)) or social sharing systems. Both also prevail in some locations on the Senegalese coast.

For dealing with expected risks fishermen influence how much risk they take by choosing between gear and amount of effort (number of fishing days). Accordingly, while fishermen cannot influence weather conditions, they can influence the risk they face from it to some extent. As we use weather conditions to reflect the 'overall' background risk fishermen face, we define 'remaining' background risk as the background risk that remains after fishermen have taken choices that influence their exposure to weather conditions. To capture remaining background risk, we build a new measure. It builds on the following idea: Fishermen form expectations about the weather conditions and resulting income risk in a given month or over the course of the year based on their experience (past seasonal variations).[14] In a 'normal' month—i.e. when conditions are close to the long-run average—, fishermen may thus be successfully buffering part of the background (weather) risk due to their choice of gear and effort, which will result in a certain (normal) variation across incomes. However, if fishing in a given month is more risky than usual, the realized catch and thus the incomes of the fishermen will differ more strongly from each other (some are lucky, others not). Accordingly, the spread in realized incomes will be higher than in a normal month. This means that the differences in the spread of income in a certain month can be used to proxy the level of remaining background risk

[13]Other examples for adaptation to seasonality are given in Noack et al. (2018) for the case of agriculture. Here, households have different income sources, such that large seasonal fluctuations in agricultural income translate in lower seasonal fluctuations in total income .

[14]Note that we cannot distinguish between health risk from bad weather and risk to fishing income from bad weather (fish availability and risk to gear). However, since both risks go into the same direction, i.e. more wind, more risk, we can ignore this difference.

in that month. One challenge of this approach is that if fishermen use different methods, catches may differ in any case. We use a standardization to deal with this problem.

In the following, we explain our approach to calculate the remaining background risk step by step. First, for each fisherman, we take the average catch over the year as a benchmark.[15] Depending on the fishing method used, effort exerted (e.g. number of fishing days) and capital invested, the average catch may either be relatively high or low. Second, we measure the difference between the realized catch of each month and the average catch and divide this difference by the mean (for normalization). For fisherman i in a given month, this would be

$$y_i := \frac{\text{income}_{i,month}\text{-average monthly income}_i}{\text{average monthly income}_i}. \tag{1}$$

A positive value indicates an above-average month in terms of catch, a negative value indicates that catch was below the individual yearly average. The division by the mean makes the measure comparable across fishermen. Third, we compare these deviations across fishermen in a given month. For each month, we calculate the coefficient of variation of these deviations, i.e. of y_i. The idea is that if for all fishermen, the deviations are similar, there is little variation and this was a normal month. If some fishermen are way above their individual mean and others are way below, risk was probably high. The resulting variable which we directly call Remaining background risk is the coefficient of variation of (1) for each month. Figure 4 shows the resulting numbers.

Two remarks on the interpretation of our measure is in order. First, because it is the coefficient of variation—standard deviation over mean—and because the mean over all y_i may be negative, the entire measure may turn out to be negative. While its absolute size measures the volatility, its sign mirrors riskiness in terms of above-or below-average levels. It is thus the interaction of below/above average incomes and background risk. Second, as the measure is based on the comparison of all incomes in a month, it can be taken as exogenous when considering on individual fisherman.

2.5 Investment behavior

The investment task was performed at the end of the interview, so that its outcome would not influence any of the answers. Recall that it was a portfolio choice task in which the fishermen received 1200 FCFA, of which they could decide how much they want to invest in a risky asset. They could gain up to 3000 FCFA each month. This is

[15]The measure depends to a certain extent on the presumption that a smooth fishing income over the year is optimal, as otherwise, deviations from the yearly average are difficult to interpret. Since consumption smoothing possibilities apart from income smoothing are not necessarily available, and since some studies show that effort is often exerted until a certain, pre-defined level is reached (e.g. Camerer et al. (1997); Farber (2008)), we think that using the yearly average as a benchmark is a viable option.

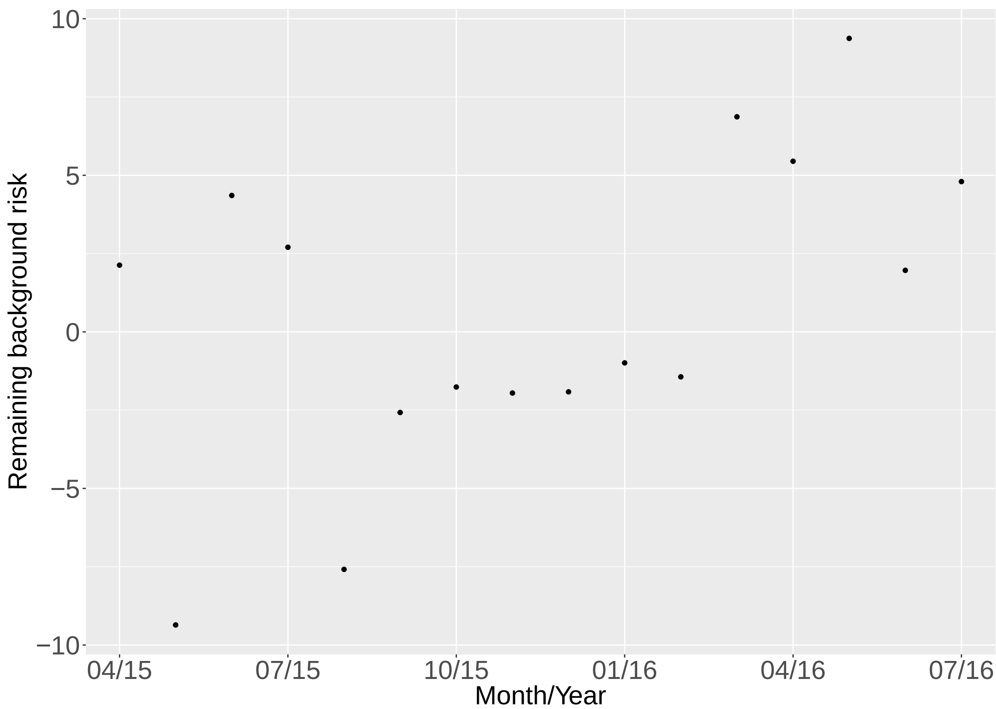

Figure 4: Remaining background risk.

60% of the the median daily fishing income of a fisherman (5000 FCFA, see Section 2.3).

Figure 5 counts mean investments from the investment task per fisherman. Any investment below 1200 FCFA depicts risk-averse behavior, because expected income is maximized when the entire sum is invested. Participants generally behave in a risk-averse way, which is in line with the literature saying that particularly poor individuals will generally behave in this way (see e.g. Kremer et al. (2013)). On average, fishermen invested 60% of the money they received each month.

Results from the investment task show that the risk-taking of the fishermen is not constant over time. We see that investment from the investment task varies considerably from month to month. This is true on average—aggregated, see Figure 6—as well as per fisherman: The difference between the maximum invested and the minimum ever invested was at least 600 FCFA for 68 % of the participants. The mean of the coefficient of variation of the individual participants is 0.3, with a minimum of 0 (always the same investment) and a maximum of 0.8.

The risk associated with the investment opportunity in this task is independent of the other risks the fishermen face (such as market or weather risk). In particular, it is independent of weather risk. In sections three and four, we explore theoretically and empirically which factors drive the instability in risk-taking over time and between fishermen.

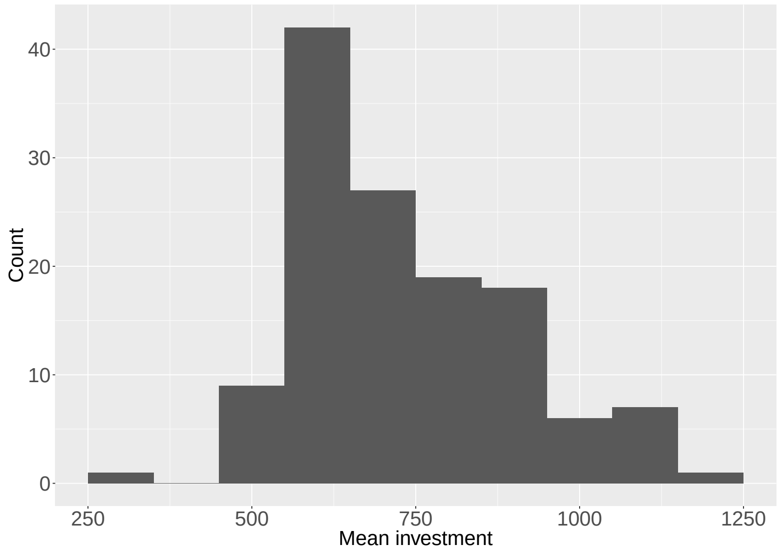

Figure 5: Frequency of mean investment values.

3 Theoretical Background

To guide our empirical set-up, we consider the individual decision problem of a fisherman. The maximization of the expected value or expected utility from the investment task, without considering additional variables, would yield the same optimal investment each month.[16] For the maximization of the expected value, the investment should be 1200 FCFA, i.e. the total amount should be invested. This is, however, not what we observe in the data, as investments differ between fishermen and across time. Being risk-averse and maximizing expected utility would lead to a value below 1200 FCFA, with the value being lower the more risk-averse the decision maker is. Differences between fishermen could be explained by different degrees of risk-aversion, but differences across time would still be difficult to explain. Accordingly, we consider the impact of changing environmental conditions, as in Gollier (2001).

Based on expected utility maximization, an individual considers

$$\begin{aligned} \max_i \quad & Eu(w + \tilde{w} + I(i) + \tilde{I}(i)) \\ \textbf{FOC} \quad & Eu'(w + \tilde{w} + I(i) + \tilde{I}(i))(I'_i + \tilde{I}'_i) = 0, \end{aligned} \tag{2}$$

with utility u derived from income w, with the associated risk $\tilde{w}$, plus the earnings $I(i)$ from investing i, with the associated risk $\tilde{I}(i)$. We divide the income into a level- and a risk-component to be able to discuss both effects in isolation, as in Gollier (2001). The

[16]As solving the decision problem as one interdependent problem requires numerical approaches to find a solution, we do not think that this reflects the way people deal with decisions, so that we consider each investment task individually.

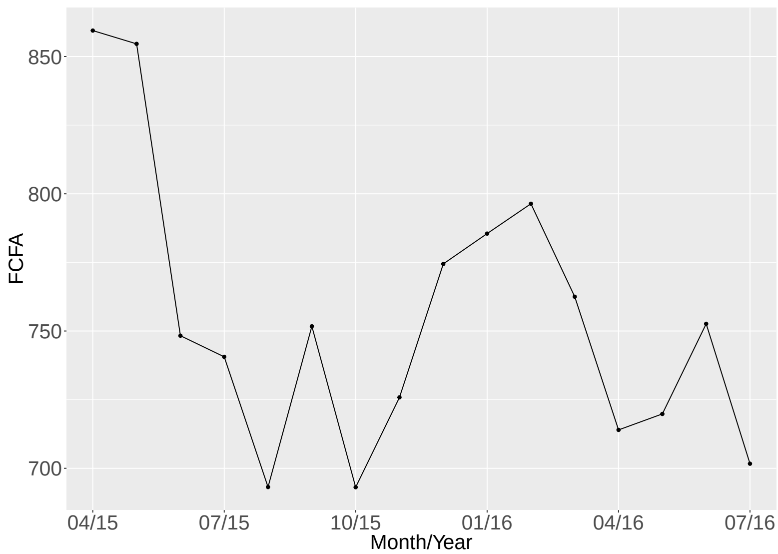

Figure 6: Average investments in the investment task.

two risks are uncorrelated. The symbol E denotes the expectations operator. In the presented set-up, total risk can only be influenced by changes in i.

So-called 'safety first' preferences stress the importance to cover basic needs. This means that individual preferences are shaped in a way that risk is only taken once basic needs are securely covered, i.e. the relevant income for any investment is total income minus basic needs. We write the decision problem as

$$\begin{aligned} \max_{i} \quad & Eu(w + \tilde{w} + I(i) + \tilde{I}(i) - b) \\ \textbf{FOC} \quad & Eu'(w + \tilde{w} + I(i) + \tilde{I}(i) - b)(I'_i + \tilde{I}'_i) = 0, \end{aligned} \tag{3}$$

with b being the expenditures for basic needs.

Last, we take into account that the decision maker may not only be able to influence I and $\tilde{I}$ with the choice of i, but that w and $\tilde{w}$ may also be influenced. Let w and $\tilde{w}$ be a function of d. In this case, risk-substitution between sources becomes possible. Then,

$$\begin{aligned} \max_{i,d} \quad & Eu(w(d) + \tilde{w}(d) + I(i) + \tilde{I}(i) - b) \\ \textbf{FOC I} \quad & Eu'(w(d) + \tilde{w}(d) + I(i) + \tilde{I}(i) - b)(I'_i + \tilde{I}'_i) = 0 \\ \textbf{FOC II} \quad & Eu'(w(d) + \tilde{w}(d) + I(i) + \tilde{I}(i) - b)(w'_d + \tilde{w}'_d) = 0. \end{aligned} \tag{4}$$

For the problem at hand, we assume that the decisions on the number of fishing days (represented by d) and the amount invested in the investment task (represented by i) are not taken simultaneously because the fishermen knew that the interview with the investment task would take place every month, but they did not know the exact date in advance. The reason for this lies in the nature of the fishing activities—fishermen are often gone fishing for several days—, and in the time constraints of the interviewers. As fishing activities depend on weather conditions, which are relatively short-term settings, we argue that the fishermen made the decision on their fishing strategy for a given wind condition in the short-run, without taking the investment task into account. Thus, the conditions (4) change to

$$\begin{aligned} &\textbf{FOC I'} \quad Eu'(w(d^*) + \tilde{w}(d^*) + I(i) + \tilde{I}(i) - b)(I'_i + \tilde{I}'_i) = 0, \\ &\textbf{FOC II'} \quad Eu'(w(d) + \tilde{w} - b)(w'_d + \tilde{w}'_d) = 0, \end{aligned} \tag{5}$$

with d^* indicating the optimal d based on FOC II'.

Let i^* denote the optimal investment implicitly defined by equations (2), (3), and (5). In the first case, it is a function of w and $\tilde{w}$. In the second case, it is also a function of b. In the third case, it is also a function of d^*.

4 Empirical Specification

Our empirical strategy depends on (i) the panel structure of the data and (ii) the exogenous variation in background risk. To examine the influences on the investment decisions—especially from background risk, potentially suggesting temperate or intemperate behavior—, we estimate the following empirical model:

$$I_{it} = \alpha_i + \beta dinc_{i,t} + \delta V_{i,t} + \gamma wind_{i,t} + \lambda CVwind_{i,t} + \Gamma X_t + \epsilon_{it}, \tag{6}$$

with the investment of individual i at time t denoted by $I_{i,t}$, disposable income denoted by $dinc_{i,t}$, remaining background risk denoted by $V_{i,t}$ and two measures of overall background risks by $wind_{i,t}$ and $CVwind_{i,t}$. Household fixed effects—denoted by α_i—control for preferences and other unobservables at the household level that are constant over time. The term X_t collects variables that control for external time varying factors. Let ϵ_{it} denote the error term.

In the following, we describe in more detail how the variables are measured and how they relate to the theoretical considerations. In specification (6), the dependent variable $I_{i,t}$ is the amount invested in FCFA in the investment task. Disposable income relates to $w(d) + \tilde{w}(d) - b_{i,t}$ or $w + \tilde{w} - b_{i,t}$ and is measured in terms of food expenditure per day in logs, with the interpretation that when basic needs are covered, food expenditures go up due to spending on higher quality or more diverse food.[17] We divide the food

[17]This approximation seems reasonable, based on the discussion in Banerjee and Duflo (2007). Also, note that both $w(d) + \tilde{w}(d)$ and $w + \tilde{w}$ are fixed before the decision in the investment task is taken.

expenditure by the household size to take into account that larger households require a higher income to have the same per-person expenditure as smaller households. The resulting variable is 'Log Food Exp pP', which varies between fishermen and over time.

The riskiness of fishing income $\tilde{w}$ is measured by wind speed $wind_{i,t}$ and wind variability $CVwind_{i,t}$, both related to background risk. Wind speed has a direct impact on the riskiness of fishing income in terms of health effects and the availability of fish, while the coefficient of variation measures how reliable past information on the monthly wind speed is. In the estimations, $wind_{i,t}$ and $CVwind_{i,t}$ are called 'Long-run mean wind speed month' and 'Long-run CV wind speed month'. They depict the mean and the coefficient of variation of the monthly averages of wind speed, starting in January 1948 (as described in more detail in Section 2), differentiated according to the two coastlines north and south of Dakar.

The variable Remaining background risk $V_{i,t}$—described in more detail in Section 2—refers to the risk in a situation after fishermen reacted to the situation's riskiness, $\tilde{w}(d^*)$ in terms of the theoretical model. As the variable Remaining background risk can be positive or negative, we also create two variables we term 'Negative remaining background risk' and 'Positive remaining background risk'. These variables are as Remaining background risk except that all positive (negative) values are set to zero. They thus only measure variation when overall incomes are below (above) the average.

Controls include a dummy to control for date differences between when the interview took place and the month it relates to (called 'Backdated')[18], a dummy for the rainy season (June to October, called 'Rainy season') and a dummy for the tabaski 'festival', during which fishermen usually do not go out for fishing (called 'Tabaski'). Also, we include the average fishing income over all fishermen in a month in logs (called 'Log mean fishing income p.month') to control for level effects.[19]

As robustness, we include additional controls, namely a time trend, a dummy whether the household has additional income sources in a given month as well as expected income for the following month, measured as the average fishing income in the ensuing month. The idea is that the average income over all fishermen tells whether it is a good month or bad month in terms of fishing in general. Some further descriptive statistics are in Appendix A.1.

Therefore, disposable income at the time of the investment decision is as described above.

[18]This was needed because enumerators sometimes could not meet each fisherman around the same date each month. In some cases, they went fishing for weeks at a time and were hence not reachable.

[19]We use logs to reduce the impact of outliers and to ease interpretation.

5 Results

Table 1 shows the main results. We use fixed effects with error terms clustered at the household level as preferred specification.[20] As expected, food expenditure is positively and significantly correlated with investment, suggesting that disposable income is relevant for short-term investment. As food covers a basic need, having more of this need covered increases additional risk-taking: A 1 % increase in the food expenditure per person increases the investment in the experiment by approximately 70 FCFA (see Column (1) of Table 1). Negative income shocks would also be reflected in this variable. These are often found to impact risk-taking.

Remaining background risk also has a significant effect. The coefficient is negative, meaning that investment is reduced when fishing incomes are generally above the mean and riskiness increases, and that investment is increased when fishing incomes are generally below the mean and riskiness increases.

Both measures of overall background risk related to wind have no significant impact, which allows to confirm our presumption that background risk related to weather and not taking exposure into account is irrelevant to investment, i.e. additional risks are irrelevant for a decisions as long at they are foreseeable and manageable.

To better understand the results, we run regressions, only including 'Positive remaining background risk' (indicating an above average month in terms of catches) and 'Negative remaining background risk' (indicating a below average month in terms of catches). Interestingly, we find that only negative remaining background risk has an significant impact (see Columns (2) and (3) of Table 1), so this seems to be the driver of the first result.

We then go on to test whether poorer households react differently to changes in Negative remaining background risk by splitting our sample into to the richer and the poorer half of the households in our sample. The idea is to test whether households that are financially very constrained and possibly have no disposable income behave differently from households that are financially less constrained. To run the regressions for the rich and poor separately, we divide the sample according to the median of the wealth index that we described in Section 2.3. We find that Negative remaining background risk only impacts the behavior of the poor (see Columns (4) and (5) of Table 1). The absolute size of the coefficient increases and the sign remains negative. Also, the impact from log food expenditure per person decreases. The reason could be that for the poor, disposable income—the income that can be used for investments after subtracting costs for basic needs—may be close to a lower minimum such that it is comparably stable and

[20]Clustering at household level is preferable because while households live at a particular location which would justify clustering at location level, boats are mobile and hence may move to other fishing grounds temporarily, which will affect our variables of interest, and fishing income, in particular.

Table 1: Main results.

Dependent variable: Investment (in FCFA)	(1) Baseline	(2) Neg. rem. background risk	(3) Pos. rem. background risk Risk	(4) Rich	(5) Poor
Log food exp. pP	60.99***	58.02***	60.45***	82.84***	30.02
	(0.002)	(0.003)	(0.002)	(0.009)	(0.133)
Remaining risk	−3.532**				
	(0.038)				
Long-run mean wind speed p.month	−1.367	2.911	−4.070	21.76	−16.29
	(0.887)	(0.760)	(0.683)	(0.126)	(0.199)
Long-run CV wind speed month	243.9	363.7	295.4	691.6	−13.31
	(0.493)	(0.266)	(0.418)	(0.122)	(0.978)
Tabaski	−8.551	−15.73	−4.252	26.13	−58.44
	(0.765)	(0.593)	(0.881)	(0.568)	(0.113)
Rainy season	−47.18*	−31.06	−56.82**	13.43	−76.35*
	(0.088)	(0.265)	(0.049)	(0.737)	(0.053)
Backdated	30.12	36.31	25.83	169.2	39.54
	(0.526)	(0.448)	(0.584)	(0.125)	(0.423)
Log mean fishing income p.month	−43.45*	−60.74**	−36.56	−57.56	−64.15*
	(0.053)	(0.014)	(0.112)	(0.113)	(0.055)
Negative remaining background risk		−8.604**		−3.624	−14.11***
		(0.012)		(0.473)	(0.001)
Positive remaining background risk			−3.655		
			(0.192)		
Constant	930.9***	1097.8***	872.0***	729.8	1484.9***
	(0.005)	(0.002)	(0.008)	(0.151)	(0.004)
Observations	1523	1523	1523	742	781
Adjusted R^2	0.020	0.023	0.017	0.032	0.028

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

thus exhibits no influence on risk-taking over time. This is consistent with the result that for the rich, the coefficient of log food expenditure per person increases.

The results hence show that the poor increase risk-taking when incomes are below average and background risk is high. Increasing the Negative remaining background risk by one standard deviation— 3.2—, increases investment by 27 FCFA (note that e Negative remaining background risk is negative). This is in line with intemperate behavior of fishermen in situations when income generation is difficult. This result is not in contrast with risk-aversion of the poor—a result often found in the literature, see e.g. Kremer et al. (2013), and also for the Senegalese fishermen (see Section 2.5)—, but with risk-vulnerability or temperance, as these two concepts describe preferences that lead to a reduction in risk-taking when background risk is increased (see e.g. Eeckhoudt et al. (1996), Deck and Schlesinger (2010)).

To test our presumption that fishermen act to reduce overall background risk, we consider the following. One way to reduce background risk—i.e. the riskiness of fishing—is to reduce the number of fishing days. Table 2 shows that both measures for weather-related background risk have a significant negative impact on fishing days, while Negative remaining background risk has no significant influence. We interpret these results as follows: When known environmental risk—measured by wind—increases, fishing days are reduced as a reaction to this increased risk. This suggests that poor fishermen adapt to seasonality and that there is not necessarily any further impact from overall background risk on risk-taking (be it positive or negative). However, an increase in remaining background risk—the part of the background risk that fishermen cannot adapt to—in an already lower-than-usual-income situation, does not lead to a change in fishing days, but to increased risk-taking.

In addition to running the regression with the same explanatory variables as to explain investments before, we also run a regression in which we exclude 'Log food expenditure per person'. The reason is potential reverse causality: Fishing days influence fishing income, which influences food expenditure. The results are robust to the exclusion of the variable.[21]

6 Robustness

To analyze the sensitivity of our results, we implement several robustness checks and additional regressions. We present the most interesting ones below in Table 3. First, we add further controls: A time trend, a dummy whether the household has an additional income source, expected incomes next month, and (not presented in the table) a dummy

[21] As the variables 'Log mean fishing income p. month' and 'Negative remaining background risk' are based on the data from all fishermen in that month, we do not expect reverse causality here.

Table 2: Regression results for fishing days (Poor).

Dependent variable: Fishing days	(1) baseline		(2) without food expenditure	
Log food exp. pP	2.714^{***}	(0.000)		
Negative remaining background risk	-0.0940	(0.383)	-0.0670	(0.538)
Long-run mean wind speed p.month	-0.687^{***}	(0.003)	-0.521^{**}	(0.024)
Long-run CV wind speed p.month	-48.82^{***}	(0.000)	-51.50^{***}	(0.000)
Tabaski	-4.418^{***}	(0.000)	-4.379^{***}	(0.000)
Rainy season	-0.376	(0.607)	0.0722	(0.920)
Backdated	0.183	(0.828)	-0.0268	(0.976)
Log mean fishing income p.month	-2.850^{***}	(0.000)	-2.212^{***}	(0.002)
Constant	45.06^{***}	(0.000)	52.13^{***}	(0.000)
Observations	781		781	
Adjusted R^2	0.085		0.056	

p-values in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$,
with fixed effects and error term clustered at the household level.

whether the household indicated having financial troubles. The time trend picks up potential underlying developments over time. The other variables relate to possible compensating mechanisms for income volatility, a kind of implicit ‘insurance’. Additional income sources may serve as a buffer for low fishing income and thus reduce the overall income risk. A high expected income the ensuing month—measured like the mean fishing income, only for the ensuing month—may also lower the burden of a low current income and make it easier to bear risk, compared to a situation with a low expected income. This, in turn, may then influence risk-taking. The impact from Remaining background risk becomes insignificant (Column (1)), but the impacts from Negative remaining background risk and log food expenditure per person remain significant and of similar size (Column (2)).

In Columns (3) and (4), we split our sample into rich and poor, using alternative criteria to see whether the definition of the poor as owning few assets based on the asset index generates the differing results between ‘rich’ and ‘poor’. We now divide the sample based on median monthly food expenditures per household member for each fisherman. Results are as before.

We then consider only those households that have no additional income sources. These households are more dependent on fishing income and have fewer possibilities to buffer shocks. As expected, we find that the effects for this group of households is as for the poor (see Column (5)).

Next, we drop all backdated interviews to see whether conducting some interviews with larger recall periods affects the results. Results remain the same (see Column (6) of Table 3).

Last, as sensitivity analysis, we use random effects instead of fixed effects. For the random effects, we include the asset index as well as dummies for the different locations.

Column (7) of Table 3 shows that the differences are minimal when using random effects. Across all the alternative specifications, the main results remain remarkably similar. We also tested for serial correlation and unit roots and did not find problems related to either.

7 Discussion and Conclusion

We find that background risk stemming from risky fishing income does not impact risk-taking when it is buffered by changes in the fishing strategy. What influences risk-taking in our case is the remaining background risk that cannot be buffered. This is in line with the interpretation of background risk as a risk that cannot be insured against. Our results suggest that in the field, agents undertake actions to reduce their exposure to uninsurable risk and that only the remaining background risk matters.

The impact of remaining background risk on risk-taking is driven by a stronger reaction of the poorer half of our sample: We show that seasonality in wind conditions has no impact on the poorer fishermen's risk-taking, while uncontrolled risk—i.e. risk that cannot be mitigated by technology choice—does. When the situation is already difficult, as measured by a below average fishing income, an increase in riskiness increases risk-taking. This points towards intemperate behavior. This effect does not exist for the richer part of our sample, or for those with significant additional income sources. Because poorer fishermen react more strongly, our results suggest that different risks become complements in situations with low financial flexibility. Our results further suggest that whether agents behave (in)temperate may depend on the (temporal) circumstances, which could be tested more directly in a laboratory setting.

Our results also complement the existing picture of risk behavior of households in developing countries in several ways, with implications for designing policies as well as investment and insurance products. First, we find that disposable income is an important determinant of risk-taking, but mainly for the richer part in our sample. When it is higher, investment is also increased. Second, we add to the growing evidence on the (in)stability of risk-taking. Specifically, our analysis considers how seasonal variation in background risk affects risky choices.

Climate change increases weather variability and thus increases background risk. If our results allow generalization, they show that there is a direct link between background risk, effort in current occupations (in our case fishing effort) and diversification (in our case risk-taking). While expected and predictable changes in climatic conditions may translate into seasonality and may be buffered by changes in effort and therefore may not impact risk-taking and investment, less predictable changes in weather conditions may be captured as remaining background risk and thus impact the poor's risk-taking.

Table 3: Robustness check regression results.

	(1) add.indicators	(2) Neg. rem. background risk	(3) rich (food)	(4) poor (food)	(5) no add. income	(6) no backdated	(7) Random effects
Log food exp. pP	55.72***	29.40	72.14**	−41.50	60.45***	49.96**	39.26***
	(0.004)	(0.233)	(0.013)	(0.158)	(0.003)	(0.010)	(0.004)
Remaining background risk	−2.803						−3.217**
	(0.120)						(0.021)
Long-run mean wind speed p.month	2.245	9.118	−0.373	1.688	−1.343	13.97	0.0277
	(0.822)	(0.537)	(0.978)	(0.875)	(0.893)	(0.121)	(0.998)
Long-run CV wind speed p.month	360.2	649.3	306.8	27.04	337.7	489.4	176.7
	(0.282)	(0.142)	(0.490)	(0.946)	(0.324)	(0.140)	(0.590)
Tabaski	−0.529	26.09	−44.59	−66.58*	−14.88	33.66	−9.382
	(0.984)	(0.587)	(0.184)	(0.059)	(0.640)	(0.133)	(0.778)
Rainy season	−40.35	−22.12	−28.09	−17.00	−37.48	−13.02	−44.11
	(0.155)	(0.615)	(0.434)	(0.609)	(0.198)	(0.665)	(0.108)
Backdated	40.12	8.492	64.52	92.17*		27.91	16.15
	(0.409)	(0.923)	(0.281)	(0.066)		(0.557)	(0.682)
Time trend	−1.791	0.140	0.115	−3.695			
	(0.507)	(0.973)	(0.979)	(0.206)			
Add. income source	32.60	110.1***	−18.58				
	(0.173)	(0.001)	(0.510)				
Log mean fishing income ensuing month	−31.23	−41.93	−66.83*	−88.56***			
	(0.164)	(0.312)	(0.059)	(0.005)			
Negative remaining background risk		−5.129	−14.02**	−16.71***	−9.505***	−6.639**	
		(0.395)	(0.010)	(0.000)	(0.007)	(0.035)	
Log mean fishing income					−74.08***		−39.17**
					(0.005)		(0.044)
Asset index							0.774
							(0.904)
Location Kayar							202.6***
							(0.000)
Location St Louis							161.5***
							(0.000)
Location Mbour							−41.55
							(0.414)
Observations	1522	752	770	916	1384	1523	1523
Adjusted R^2	0.020	0.027	0.028	0.073	0.024	0.017	

p-values in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, constant terms not reported.

Notably, these sudden extreme weather events that are a main characteristic of climatic change.

Ensuring that investment opportunities in income diversification, modernisation and adaptation to climate change can and will be realized matters for development. Successful investment into adaptation measures—with the accompanying risk-taking—determines how climate change impacts the rural poor in developing economies. We show quite generally that higher disposable incomes increase risk-taking and hence investment in adaptation measures. Hence, raising incomes is an obvious strategy, but often not an easy one to implement. However, our unique data also show that the poor take risks even in difficult environments. While this may seem like good news at first sight, for the very poor, risky investments may have devastating effects if the bad state realizes. For policy makers, this implies that insurance mechanisms for the poor matter. Insurance mechanisms for investments in adaptation or innovations could solve this dilemma, provided that they are credible. In this line, Cole et al. (2017) show that the provision of a rainfall insurance induces farmers to invest more in higher-return but climate-sensitive cash crops. However, the varied experience from weather index insurance (see e.g. Giné and Yang (2009), Karlan et al. (2014)) shows that it is not easy to implement such insurances. A, potentially more costly (Jensen et al., 2017) alternative are cash transfers. Another alternative is a basic-needs social security system, which acts as an insurance against very low income states.

Apart from risk-buffering mechanisms, timing of investment offers may be more relevant than previously supposed. For fishermen, there are better and worse times for risk-taking, which are related to seasonality or weather patterns, translating into differences in disposable income and background risk. If new (fishing) methods are introduced, fishermen may find it easier to experiment with them when background risks are lower or when disposable income is higher. As risk-taking is not stable over time, the right timing of a policy may increase its acceptance and its impact.

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A Appendix

A.1 Descriptive statistics

Table 4: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Investment	748.82	285.88	0	1200	1523
Food expend. p.p.	554.38	1010.34	5.26	16666.67	1523
Log food expend. p.p	5.60	0.68	1.66	9.72	1523
Add. income dummy	0.40	0.49	0	1	1523
Fishing days	14.06	7.79	0	31	1523

Note: Investment and food expenditure both measured in FCFA.

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