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Abstract

Forecast-based Financing (FbF) is a new humanitarian instrument that helps vulnerable households to cope with climate shocks. While economists have posited that ex-post disaster aid decreases households' investment in climate adaptation strategies such as agriculture insurance uptake, the effect of FbF on households' adaptation investments is unknown. In this paper, I use a Randomized Controlled Trial approach to examine the effect of FbF on demand for agriculture insurance among pastoralist households in Mongolia. I find that receiving FbF during an extreme weather event increases the uptake of livestock insurance for the following year, indicating that FbF crowds-in households' investments in climate adaptation. I suggest increased risk awareness through which FbF affects insurance demand.[1]

Keywords: Adaptation, forecast-based financing, index-based agricultural insurance, livestock, charity hazard

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1. Introduction

The increasing frequency and intensity of extreme weather events are predicted to lead to massive economic losses, with poor and vulnerable households being disproportionately affected (Pörtner et al., 2022). There is an urgent need for adaptation measures that help households to cope with climate risks. Forecast-based Financing (FbF) is an ex-ante humanitarian instrument that provides vulnerable households with disaster aid in anticipation of a natural disaster. Based on meteorological forecasts, cash transfers to households are triggered as soon as a pre-determined risk level is reached. In contrast to conventional disaster relief, FbF helps households to invest in measures of preparedness and adaptation (Arnold et al., 2011; German Red Cross, 2017; German Red Cross & Red Cross Red Crescent Climate Centre, 2016). It is hoped that FbF is more effective than other forms of aid by giving households the flexibility to make their own choices on how to use the received money and by providing support at a time when it is most needed to avoid damage (Arnold et al., 2011; European Commission, 2022). Until 2022, FbF programs have been implemented in more than 20 countries, for instance, to assist households to cope with excessive snowfall in Peru, heat waves in Vietnam, hydro-meteorological hazards in Tajikistan, or tropical cyclones in the Philippines (Anticipation Hub, 2022; Red Cross and Red Crescent Societies, 2018).[2] There is a strong intent among international policymakers to scale up FbF. By 2025, the Risk-informed Early Action Partnership initiative (REAP) aims to cover 1 billion people through financing and delivery mechanisms connected to early action plans (REAP Secretariat, 2019). In May 2022, the G7 foreign ministers issued a statement announcing their "commitment to advocate for, scale up and systematically mainstream anticipatory action into the humanitarian system" (German Federal Foreign Office, 2022).

However, disaster aid in the form of cash transfers has been questioned in terms of households' climate adaptation. One issue yet to be resolved is whether the receipt of FbF crowds-out other risk reduction strategies applied by households.

In this paper, I quantify whether the receipt of FbF crowds-in or crowds-out households' investments in climate adaptation. Thefocus is on the uptake of index-based agriculture insurance, a concrete and precisely measurable adaptation strategy. Index-based agriculture insurance has gained traction as an adaptation instrument against extreme weather events where classical indemnity-based insurances are not

[2] For an overview, see Nauman et al. (2021).

feasible (Cai et al., 2020; Fisher et al., 2019; GPFI, 2015; Greatrex et al., 2015; Hazell & Hess, 2017).[3] Index-based insurance relies on a statistical index that is measured at an aggregated geographical level. Policyholders receive insurance payouts whenever the index exceeds or falls short of a predefined threshold at the aggregated level, irrespective of whether a specific policyholder experienced damages (Skees, 2008).

While several theoretical and empirical studies show a negative impact of ex-post disaster aid on insurance uptake (e.g., Landry et al., 2021; Lewis & Nickerson, 1989; Raschky et al., 2013; Raschky & Schwindt, 2016; Sakurai & Reardon, 1997; Tesselaar et al., 2022), the question of whether the provision of FbF encourages charity hazard has not been addressed. Receiving FbF might raise expectations among households to receive again ex-ante or ex-post assistance in case a disaster strikes in the future, which in turn may lower their demand for insurance. In addition, FbF can assist households in investing in preparedness and mitigation measures, thereby reducing households' risk and potentially the perceived utility of purchasing insurance. However, there are multiple reasons to expect a positive effect of FbF on insurance uptake. FbF might increase risk awareness. Studies investigating potential barriers to index insurance uptake identify risk perception as an important predictor for insurance uptake (Gallagher, 2014; Mogge, 2021; Tang et al., 2021). Another reason for households not to purchase insurance is the lack of financial resources (Belissa et al., 2019; Fonta et al., 2018; Giné et al., 2012). Receiving FbF before the insurance sales period can help households to overcome cash constraints. Whether the effect of FbF on the decision to purchase index-based insurance is ambiguous from a theoretical perspective.

In Mongolia, FbF has been implemented by NGOs to assist pastoralist households to cope with extreme winter events leading to massive livestock mortality. Transfers are triggered based on risk maps created by the National Agency for Meteorology and Environmental Monitoring (NAMEM). In winter 2020/21, when NAMEM announced a high risk of an extreme winter event in Western Mongolia, the PIK research team implemented together with the NGO *People in Need* a randomized field experiment, in which early action cash transfers were distributed to randomly chosen households at risk. All households were part of a long-running household panel survey conducted in three Western provinces of Mongolia. Specifically, 965 pastoralist households living in areas with a high or medium forecasted risk of facing extreme winter conditions were assigned to three distinct groups. The first and second groups received an unconditional cash transfer of 250 EUR or 150 EUR, respectively. The third group did not receive a transfer. Treatment and control households were interviewed before and after the cash transfers. The survey recorded the socio-

[3] Compared to conventional indemnity-based insurance schemes, index-based insurance is characterized by generally lower administration costs due to loss verification based on aggregated data (Miranda & Farrin, 2012). Moreover, index-based insurance is by design resistant to adverse selection and moral hazard because policyholders do not gain from individual damage (Barnett & Mahul, 2007; Mahul & Stutley, 2010).

economic characteristics of a household, weather expectations, receipt of aid, and uptake of index-based livestock insurance among others. The self-recorded insurance data were validated with client data from the MongolianReinsurance.

Results show that receiving FbF significantly increases index-based livestock insurance uptake that covers climate risks in the next year. The effect is driven by the group of re-purchasers, namely those households that already did purchase insurance coverage for the 2020/21 winter when FbF cash transfers were provided. I find evidence that FbF has a strong signaling effect on weather expectations for the following winter.

This paper advances the academic literature on the effect of FbF on households' investment in climate adaptation strategies. It is the first study that investigates crowding effects of FbF on insurance uptake. Thereby, this study adds in more general terms to the small knowledge base on the effectiveness of FbF (Gros et al., 2022; Mogge et al., 2022; Pople et al., 2021). In addition, this study is one of the few studies that investigate crowding effects in the light of non-governmental aid in a low-/middle-income country, while existing research has mostly focused on rich countries where governments provide emergency assistance after an extreme weather event occurs.

The remaining paper is organized as follows. The next section outlines the state of knowledge. Section 3 introduces theempirical context. Section 4 describes the experimental framework, followed by an introduction of the data in section 5. Section 6 outlines the estimation strategy. Results and robustness checks are reported in section 7. Section 8 concludes.

2. State of knowledge on the charity hazard

The concept of charity hazard, first introduced by Browne and Hoyt (2000, p. 293) is defined as "the tendency of individuals not to insure themselves against possible natural disasters because they believe help will be available, e.g. from friends, family, the municipality, charities or state emergency programs".[4] According to Mahul and Stutley (2010), charity hazard further increases the problem of adverse selection in insurance uptake since households with low risk that might be only affected by large-scale disasters are unwilling to buy insurance because large-scale events are more likely to trigger governmental disaster aid.

[4] The charity hazard is closely related to the concept of the *Samaritan's dilemma* (Buchanan, 1975). Focusing on governments instead of individuals, the *Samaritan's dilemma* describes how the expectation of official development assistance from foreign donors, in case a disaster strikes, decreases incentives for the recipient government to invest in protective efforts (Gibson et al., 2005; Raschky & Schwindt, 2016).

The theoretical justification for charity hazard based on utility frameworks is well established (e.g., Brunette et al., 2013; Kaplow, 1991; Kelly & Kleffner, 2003; Lewis & Nickerson, 1989; Raschky & Weck-Hannemann, 2007; Robinson et al., 2021; Tesselaar et al., 2022). Taking into account that charity payments are often uncertain and risk exposure varies, Robinson et al. (2021) demonstrate that demand for insurance is higher when the probability of government compensation is ambiguous compared to certain aid. Similarly, Tesselaar et al. (2022) show in their model simulation of European flood insurance markets that the crowding-out effect of governmental aid on demand for insurance is smaller if the compensation of uninsured damage is uncertain and if the regional flood risk is high.

In contrast to the unequivocal conclusions of theoretical studies, empirical research provides ambiguous evidence. Empirical studies in the charity hazard literature almost exclusively explore whether disaster aid crowds out the demand for indemnity-based flood insurance in the Global North. Most studies find evidence in support of the charity hazard hypothesis. For instance, Andor et al. (2020) use cross-sectional data from 6,000 German homeowners suggesting that trust in financial aid from the government reduces the demand for flood insurance among individuals living in flood-prone areas. However, Andor et al. do not find evidence for charity hazard among individuals living in areas with low objective flood risk. Raschky et al. (2013) compare survey data on individuals' stated preferences from Austria, where governmental relief to affected households is certain but incomplete, with data from Germany, where governmental relief is uncertain but more complete. They find supporting evidence for the theoretical assumption that charity hazard is more pronounced when aid payments are certain. Only few studies contradict the hypothesis of a negative relationship between disaster assistance and insurance uptake. Browne and Hoyt (2000) study the effect of disaster grants to households affected by floods provided by the Federal Emergency Management Agency of the United States (FEMA) on the demand for flood insurance in the US applying a fixed effects approach to state panel data spanning the period from 1983-1993. Contrary to their hypothesis of a negative relationship between governmental aid and flood insurance uptake, they find a positive effect, thus no evidence in line with charity hazard. However, Browne and Hoyt caution that their results might be biased due to insufficient control of risk exposure. Davlasheridze and Miao (2019) address this concern by using objective precipitation data to measure risk exposure. Davlasheridze and Miao find a negative impact of the receipt of FEMA grants on flood insurance uptake. Exploiting cross-sectional survey data from property owners, Petrolia et al. (2013) document that households' perceived eligibility for disaster assistance increases the likelihood of holding a flood policy. Using the same dataset, Landry et al. (2021) apply flood damage compensation awarded to the county and the number of regional US Senators that served on Stafford subcommittees as an instrument for the expectation of damage relief. The authors show that coastal households with positive expectations of disaster aid eligibility are 25 to 42 percent less likely to hold flood insurance.

Only a few studies focus on crowding-out effects on insurance in the Global South. Exploiting households panel data from Burkina Faso, Sakurai and Reardon (1997) apply a household fixed effects approach to show that expectations of receiving public food aid decrease investments in informal self-insurance among farmer households. Based on a utility model, the authors find a reduced willingness to pay for hypothetical drought insurance. Using a choice experiment and cross-sectional data from flood-prone Vietnam, Ngoc Que Anh et al. (2019) find no significant negative impact of rice framers' expectation on aid and relief by the government and other organizations for post-flood recovery on their willingness to pay for agricultural flood insurance.

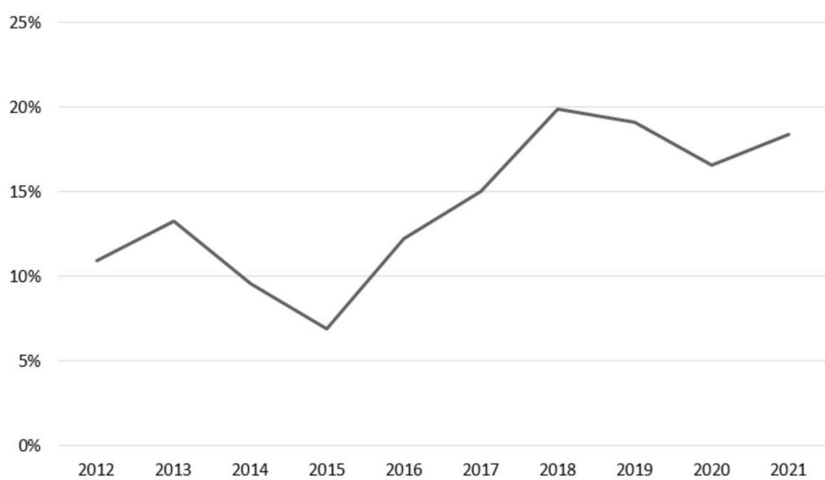
All of the above-mentioned studies have in common that they rely on observational data, using quasi-experimental study designs. This study is the first to study whether the receipt of humanitarian assistance crowds-in or crowds-out households' investment in adaptation strategies based on an RCT design with the advantage that I can make use of a clean control group. It is one of the few studies that investigate charity hazard in the Global South and the first to consider the demand for existing formal agriculture insurance in the Global South.

3. Empirical context: Extreme weather events and adaptation in Mongolia

Mongolia has suffered several extreme winter events in the last decades. Extremely cold and snowy winter conditions following dry summers lead to massive livestock mortality and threaten the livelihood of households involved in animal husbandry (Nandintsetseg et al., 2018). Such extreme winter events have long-lasting welfare-reducing effects on herding households (e.g., Fluhrer & Kraehnert, 2022; Groppo & Kraehnert, 2016, 2017) and lead to massive outmigration from affected areas (Roeckert & Kraehnert, 2022). Many former pastoralists settle in the outskirts of cities where they often live in poverty (Sternberg, 2010). The extreme winter events of 1999/00, 2000/01, and 2001/02 caused the death of over 11 million livestock. During the 2009/10 extreme event, Mongolia's husbandry sector lost 8.5 million livestock, approximately 20% of the country's total livestock population. Additional minor winter disasters occurred in 2015/16, 2017/18, 2019/20 and 2020/21 (European Commission 2010; IFRC, 2020; United Nations Mongolia Country Team, 2010).

In response to the three consecutive extreme winters in 1999-2001, the Mongolian Government developed Index-Based Livestock Insurance (IBLI) with technical support from the World Bank (Mahul & Skees, 2007; World Bank, 2016). Its key objective is "to reduce herders' livelihood vulnerability caused by […] natural disasters" (PIU, 2012). Since 2012, IBLI is offered in all provinces in Mongolia. As of 2020, IBLI is marketed by commercial insurance companies and local banks, with the latter offering policies bundled with loans with reduced interest rates (Mongolian RE, 2021). Policyholders receive IBLI indemnity payments when the district-level livestock mortality rate of a given species exceeds the threshold of 6%, irrespective of whether or not a specific policyholder experienced damage. Herders can purchase IBLI for each of the five commonly held species (sheep, goats, cattle, horses, or camels). They decide on how many animals of each species and for how much of the animals' market value (between 1-100 percent) they wish to purchase IBLI coverage. The sales period is from April to June, at a time when neither herders nor insurance companies can predict conditions in the upcoming winter, which prevents adverse selection. Insurance policies cover livestock losses between December and June of the following year. In case of an extreme weather event, indemnity payments are made to policyholders in August of the following year (Mongolian RE, 2021). In 2021, approximately 18% of all herder households purchased IBLI while some fluctuation exists across years (Fig. 1).

Fig. 1: IBLI uptake among herder households (2012-2021)



Notes: % of herding households purchasing IBLI in a given year out of the total number of herders. Source: National Statistical Office of Mongolia (2022)

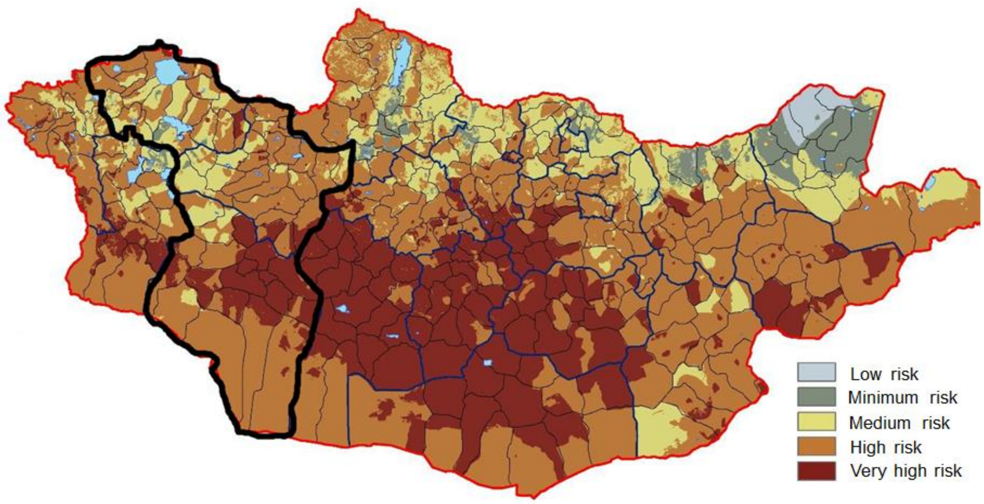
FbF was first introduced in Mongolia in 2017 by the Mongolian Red Cross Society (MRCS). The basis of FbF in Mongolia is dzud risk maps published by the National Agency for Meteorology and Environmental Monitoring (NAMEM) of Mongolia. The maps show the predicted risk of extreme winter conditions (dzud in Mongolian) at a fine spatial resolution. The prediction makes use of 14 indicators, including summer rainfall, forecasted winter temperature, and pasture capacity resulting in 5 different levels of risk (very high, high, normal, low, very low) (IFRC, 2020). In winter 2017/18, the MRCS released 277,000 USD from the IFRC Disaster Relief Emergency Fund (DREF) to assist 2,000 pastoralist households living in areas predicted to be at high or very high risk with emergency supplies, including 100 USD per household (IFRC, 2018). Using the same dzud risk maps, in the winter of 2018/19, an FbF mechanism by

World Vision and Save the Children was triggered. In seven districts in Western Mongolia, a total of 244,720 USD was allocated among herder households with less than 200 livestock. In addition to unconditional cash, households also received hay and fodder for livestock and a booklet on protecting children and family members (Start Network, 2019). In the winter of 2019/20, DREF approved more than 300,000 USD from its Forecast-based Action mechanism for the MRCS to provide unconditional cash transfers and livestock nutrition kits to herder households with up to 400 livestock. FbF was triggered when at least three provinces had very high risk projected in more than 20% of their provincial area according to the risk map published by NAMEM in November (IFRC, 2020). 1000 pastoralist households from 40 districts across 12 provinces received about 90 USD, another 1000 households received livestock nutrition kits.

4. Experimental framework

The PIK research team conducted a randomized field experiment among the sample households of the *Coping with Shocks in Mongolia Household Panel Survey* in Western Mongolia that we implemented in collaboration with the National Statistical Office of Mongolia (NSO) (Kraehnert et al., 2022). The FbF intervention was carried out as a research project by the Potsdam Institute for Climate Impact Research in cooperation with the NGO People in Need (PIN) and NSO, with funding from the Federal Foreign Office of Germany. The RCT was designed to assess the impact of FbF on adaptive behavior and livestock losses as well as the nutritional status and health of humans. For more details on the experiment and results on livestock mortality, see Mogge et al. (2022). Based on the risk map published in December 2020 and updated on January 10, 2021 (Fig. 2), pastoralist households living in areas with medium, high, or very high projected risk of experiencing extreme winter conditions were randomly assigned to the control (N=479 households) or one of two treatment arms (N=373 households). Among households selected for treatment, about half (N=192) received 150 EUR and the other half (N=181) 250 EUR as an unconditional cash transfer. Randomization was carried out at the sub-district level to avoid spillover effects.

Fig. 2: Risk map Mongolia, January 2021

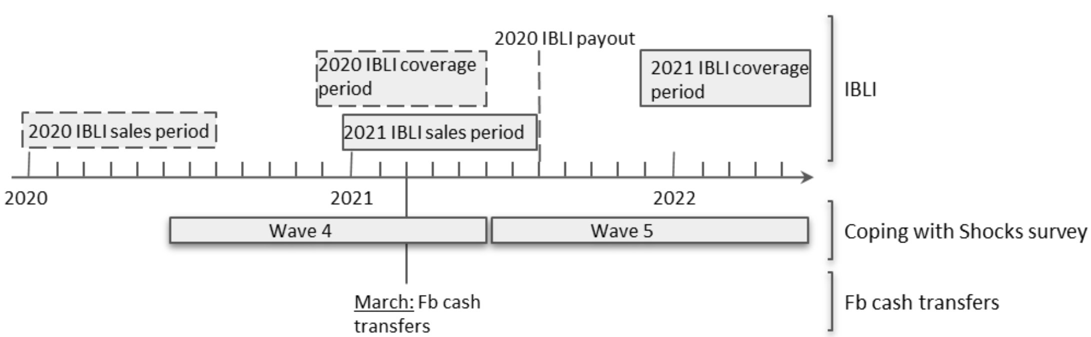


Source: National Agency for Meteorology & Environmental Monitoring of Mongolia, published January 10, 2021. The survey region is bold-rimmed.

The timing of the events was as follows. In March 2021, money was transferred to households' bank accounts. In April 2021, treated households were asked in phone interviews conducted by PIN whether the money was received and for what purpose it was used.

The sale period for index-based livestock insurance covering the following winter started in January 2021 and lasted until June (see Fig. 3). Since the sales period started up to three months before FbF was received, I cannot rule out that some households might have bought IBLI that would not have bought insurance after treatment. In case a payout-triggering disaster strikes, IBLI payouts are made in August of the following year.

Fig. 3: Timeline of data collection, Forecast-based cash transfers and insurance seasons



In the survey region, the realized livestock mortality as a consequence of the extreme winter event 2020/21 varied between 0 and 26 percent among all sub-districts with projected medium, high, or very high risk of extreme winter conditions. Treated as well as non-treated sub-districts were affected by the extreme weather event (Table 1).[5]

Table 1: Predicted risk and realized livestock mortality among treatment and control groups

	Treatment group high (250€)	Treatment group low (150€)	Control group	All groups
Avg. realized livestock mortality in sub-districts with predicted medium risk (%)	0.6	0.4	0.9	0.6
Avg. realized livestock mortality in sub-districts with predicted high or very high risk (%)	5.6	6.3	4.4	5.1
Avg. realized livestock mortality in all sub-districts (%)	3.9	3.7	3	

Source: Coping with Shocks in Mongolia Household Panel Survey (wave 5), National Agency for Meteorology & Environmental Monitoring of Mongolia, Mongolian Statistical Information Service, Mongolia Livestock Census.

5. Data and summary statistics

5.1 Data and measures

The empirical analysis is based on household data from the *Coping with Shocks in Mongolia Household Panel Survey*. The survey comprises five annual panel waves that were collected in the three neighboring provinces of Uvs, Zavkhan, and Govi-Altai in western Mongolia (Fig. A1 in the Appendix). The first three waves were collected between 2012 and 2015. Wave four and wave five, the database of this study, were collected between 06/2020-05/2021 and 06/2021-05/2022, respectively. The sample was drawn using a stratified three-stage design and is representative of the population in rural and urban areas in each of the three provinces as of 2010. Sample households are located in 49 out of the 61 districts and in 108 out of the 289 sub-districts of the survey provinces. Each months, survey interviews are conducted across the whole survey area, making the data roughly representative across seasons. Survey attrition is very low by international standards. In wave 5, 1,629 of the 1,649 households interviewed in wave 4 were successfully re-interviewed resulting in an attrition rate of 1.2% between waves 4 and 5. 852 of the households

[5] See spatial variation maps Fig. A2 and Fig. A3 in the Appendix.

interviewed in wave 5 were livestock-owning households living in medium, high risk or very high risk areas. I excluded from the sample 37 households with missing values in covariates.

The survey questionnaire records detailed information about socio-demographic characteristics of the household, expectations of an extreme winter event, receipt of humanitarian aid, and households' purchase of IBLI, among other things. The uptake of index insurance, the dependent variable, is measured as an indicator variable that takes the value one if a household purchased index insurance in the sales period between January and August 2021. To validate the self-reported data, I merged the household panel survey data with the customer database of MongolianRe, the national reinsurance company. More specifically, the variables whether a household had purchased IBLI in 2021, 2020, and before were drawn from the customer database. The merging exercise was successfully completed for 740 out of 815 livestock-owning households.[6] For the remaining 75 households, I can solely rely on self-reported data on insurance uptake recorded in the *Coping with Shocks in Mongolia Household Panel Survey*.

Another questionnaire module of the *Coping with Shocks in Mongolia Survey* records whether a household received any humanitarian aid during the 2020/21 winter. Both the mode of aid and the aid organization is recorded, which allows us to identify spillover effects from other programs. Households assigned to be in the control group but that received similar cash transfers from another program reduce the likelihood of identifying an effect of the treatment even if there was an impact on insurance uptake. We, therefore, exclude five households from the sample that received a cash transfer from another organization. The module asking about the receipt of emergency aid and the phone interviews conducted by PIN following the intervention also allow us to validate that those households intended for treatment are actual recipients of the cash transfer. Two households that were not assigned to the treatment group but indicated that they received a cash transfer from PIN were dropped from the sample.

The Coping with Shocks survey also records respondents' expectations for weather conditions in the upcoming winter, a variable I consider as a potential channel through which the treatment affects insurance uptake. Respondents were asked to indicate their expectations on a Likert-type scale from 0 to 10, with 0 indicating a harsh and 10 indicating a mild winter. In the model, I transform the expectations measure into an indicator variable that takes the value one if respondents expect the upcoming winter to be harsh (values 0-5). As a second channel, I consider cash constraints that I measure with two different proxies. First, a variable that indicates how likely the respondent thinks that the household would have bought (more)

[6] Matching was done on the basis of the national ID of the head of the household. The ID was not recorded in the Coping with Shocks survey itself but retrospectively assigned to survey households by the NSO based on names and addresses. This exercise could not be completed for some households.

insurance coverage if they had more cash during the previous sales period on a scale from 0 (very unlikely) to 10 (very likely). Second, total annual income measured in Mongolian Tugrik (MNT), which consists of agricultural income, non-agricultural income and transfer income. Agricultural income comprises income from the sale of living and slaughtered livestock, the value of animal byproducts produced by the household (wool, skins and hides, milk), and the value of farming produce. Non-agricultural income includes income from wage work and non-agricultural businesses. Transfer income comprises state benefits, remittances, and other income, including inheritance and property rent. I corrected outliers by replacing prices received for byproducts and livestock below the 1st or above the 95th percentile of the distribution with the price at the threshold. Wage incomes above the 99th percentile were replaced by values at the 99th percentile. Twelve households have missing values in the income variable. In the analysis, total annual income is log-transformed.

5.2 Sample characteristics and balance check

Table 2 compares the mean value of household baseline characteristics across treatment and control groups (for summary statistics see Table A1 in the Appendix).

The relevant sample consists of herder households, with approximately half of them following a nomadic lifestyle. At baseline, the head of household was on average 49 years old, male and married. In most of the households, the head has at least primary education, while less than 15 percent have no formal education. The herd size is measured in sheep forage units (SFUs).[7] On average, households own about 500 animals measured in SFUs. The self-reported risk preference of the head of the household was measured on a scale from 0 (not at all willing to take risks) to 10 (very willing to take risks). The average risk preference score is 4.17. Close to 60 percent of the sample households took up a loan in the past 12 months. Of the sample households interviewed before December 2020, 55 percent expected the winter of 2020/21 to be harsh. 19 percent of the sample households purchased IBLI in 2020, while 60 percent of the sample have ever purchased IBLI since its introduction in 2012, but only 15 percent have received IBLI payouts in response to an extreme winter event.

In the last column, I report the normalized difference as proposed by Imbens and Rubin (2015).[8] The random assignment should lead to a balance across treatments on observables and unobservables. Results from the t-tests on differences in means show that the samples are balanced across all the observed

[7] One horse, cow, camel, and goat is equivalent to 7, 6, 6, and 0.9 SFU, respectively.

[8] The normalized difference is defined as the difference in means, divided by the square root of half the sum of treatment and control group variances (Imbens & Rubin, 2015). Using propensity score matching, Imbens and Rubin show that normalized differences of 0.25 or less are well balanced in terms of experimental results.

baseline household characteristics. This is also true for the realized livestock mortality of winter 2020/21 at sub-district level calculated from livestock census data, which was collected in December 2021 after the randomization took place.

Table 2: Balance tests

	(1) Control Mean/SE	(2) Treatment Mean/SE	(3) Difference (1)-(2)	(4) Normalized difference (1)-(2)
Head of household characteristics				
Age	49.531 [0.693]	48.839 [0.649]	0.474	0.058
Female head	0.116 [0.016]	0.156 [0.019]	0.113	-0.116
Head is married	0.824 [0.018]	0.831 [0.019]	0.779	-0.020
Head has no education	0.118 [0.017]	0.142 [0.022]	0.402	-0.070
Head has primary education	0.589 [0.027]	0.592 [0.027]	0.951	-0.005
Head has secondary or higher education	0.292 [0.027]	0.267 [0.029]	0.508	0.057
Risk preference of head (0-10)	4.147 [0.163]	4.197 [0.208]	0.846	-0.018
Household characteristics				
Number of children (< 10 years)	0.720 [0.053]	0.752 [0.059]	0.686	-0.031
Herd size (in SFU)	503.266 [27.419]	492.523 [35.659]	0.813	0.025
Nomadic household	0.602 [0.054]	0.606 [0.054]	0.960	-0.008
Living in province Zavkhan	0.350 [0.070]	0.331 [0.072]	0.840	0.042
Living in province Gobi-Altai	0.315 [0.067]	0.347 [0.073]	0.737	-0.069
Living in province Uvs	0.335 [0.068]	0.322 [0.075]	0.899	0.027
Living in province center	0.144 [0.041]	0.079 [0.036]	0.238	0.205
Living in district center	0.174 [0.028]	0.203 [0.039]	0.542	-0.073
Living in rural area	0.681 [0.048]	0.718 [0.049]	0.586	-0.081
Received information treatment	0.558 [0.065]	0.675 [0.066]	0.209	-0.240
Loan uptake (in the past 12 months)	0.572 [0.028]	0.607 [0.035]	0.428	-0.072
Expectation harsh winter 2020	0.578 [0.053]	0.526 [0.058]	0.052	0.104
Cash constraints	4.189 [0.092]	4.204 [0.141]	-0.015	-0.010
Hh annual income (in 1,000 Tugrik)	19130.549 [770.396]	19062.944 [1019.903]	0.958	0.005
IBLI uptake in 2020	0.176 [0.021]	0.203 [0.026]	0.421	-0.068
IBLI uptake ever	0.592 [0.036]	0.622 [0.037]	0.549	-0.063
Ever received IBLI payouts	0.152 [0.036]	0.142 [0.033]	0.837	0.029
Sub-district characteristics				
Total livestock mortality (sub-district level) in winter 2020/21	0.034 [0.008]	0.034 [0.007]	0.980	0.005
F-test of joint significance (F-stat)			1.235	
F-test, number of observations			808	

Note: Column 3 displays the differences in means across the groups. Standard errors are clustered at the sub-district level. P-values are reported in parentheses. Column 4 reports the normalized difference between the treatment and control group means, following Imbens and Rubin (2015). The sample size is N=448 households in the control group and N=360 households in the treatment group. Exceptions are the sample size of the variable expectation for winter 2020 which was only collected from N=218 control and N=192 treated households that were interviewed before December 2020, of the variable cash constraints which was only collected from N=212 control and N=211 treated households that have ever purchased IBLI and of the variable household annual income which is only available from N=439 control and N=357 treated households. Sources: Coping with Shocks in Mongolia Household Panel Survey (wave 4), Mongolia Livestock Census and MongolianReinsurance database.

6. Empirical approach

My identification strategy is based on random assignment of households to the treatment group. I estimate

$$IBLI_h = \beta_0 + \beta_1 treatment_h + \beta_2 X_{h,s} + \delta_m + \varepsilon_{hsm} \quad (1)$$

Where $IBLI_h$ is equal to one if a household purchased index-based livestock insurance in the selling period of January to August 2021 providing coverage for the 2021/22 winter, $treatment_h$ indicates whether household h was selected to receive an unconditional cash transfer of either 150€ or 250€ and $X_{h,s}$ is a vector of household and sub-district level controls. Including control variables can help to adjust for pre-selection imbalances and to reduce error variance, leading to more precise parameter estimates. The equation contains interview month fixed effects δ_m and a stochastic error term ε_{hsm}. Due to the dichotomous nature of the outcome, I estimate equation (1) with a multivariate logistic model. Standard errors are clustered at the level of randomization, the sub-district, as the treatment assignment is correlated within the clusters. The estimated coefficient β_1 measures the causal impact of cash transfers on IBLI uptake.

The vector of household level controls comprises of variables that the literature has shown to influence uptake of agriculture index insurances. I include two variables capturing households' insurance history: Insurance payouts and insurance uptake in the preceding sales period. The payout variable indicates whether a household has ever received an IBLI payout in the past.[9] The indicator variable for insurance uptake is equal to 1 if the household purchased IBLI in 2020. While the literature investigating determinants of index-insurance uptake identifies previously received payouts as a strong predictor of future uptake (e.g., Cai et al., 2020; Hill et al., 2016; Stein, 2018; Stoeffler et al., 2022), there is no empirical evidence suggesting that purchasing index-based insurance *per se* increases the likelihood of re-purchase (Cai et al., 2020; Hill et al.,

[9] As a robustness check, I include alternatively whether a household has received payouts in the preceding year. All baseline results are qualitatively similar to the main specification.

2016). I further include an indicator variable measuring if a household took up a loan in the past 12 months.[10] Bundling index-based insurance with credits for smallholder farmers, as promoted by the World Bank (2016), increasingly contributes to insurance uptake in Mongolia. Local banks offer loans with lower interest rates when bundled with IBLI (Mongolian RE, 2021). I account for the livestock mortality at the sub-district level given that households living in areas that experience high livestock mortality in the 2020/21 winter are more likely to expect harsh conditions in the following winter.[11] As a robustness test, I exploit livestock mortality data at the next higher aggregation level, the district, to take into account that total livestock mortality at the sub-district level might be influenced by the FbF treatment.[12] Lastly, I include an indicator variable that equals one if the household received an information treatment[13] that was part of another randomized experiment conducted among the survey population. Interview month fixed effects δ_m adjust for differences due to the time of the interview.

I test for liquidity constraints and weather expectations as potential channels through which FbF may affect insurance uptake. I estimate the effect of FbF on expectations for winter 2021/22. This information is only available for households that were interviewed before December 2021. I test the effect of FbF on liquidity constraints by making use of the variable measuring whether the household would have purchased (more) insurance if more cash had been available and the total annual household income.

7. Results

7.1 Main results

Results on the effect of FbF on insurance uptake obtained from Logit estimation are shown in Table 3.[14] Average marginal effects of the main variables of interest are displayed. Table A2 in the Appendix reports estimated coefficients of the complete set of control variables. Column 1 reports results from the

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[10] As a robustness check, I use the loan uptake variable from the fourth wave for households that were interviewed for the first time in April, May or June 2021 in the fourth wave, after the IBLI sales period had started, to take into account that their insurance decision might lie in the 12-months period of the fourth wave. All baseline results are qualitatively similar to the main specification.

[11] For the relationship between previous exposure and the purchase of insurance, see e.g., Bjerge and Trifkovic (2018), Doherty et al. (2021), Karlan et al. (2014).

[12] In 2020, sub-districts in the survey area had an average size of 1072 km2 and an average population of 200 households, of which 40 to 340 were pastoralist households (National Statistical Office of Mongolia, 2022).

[13] A graph displaying historic livestock mortality per district was shown to a random sample of pastoralist households.

[14] As a robustness check, I repeat all baseline estimation with probit regressions. Results are qualitatively similar.

estimation without any covariates. Columns 2-5 include controls that are deemed likely to affect insurance uptake.

The receipt of cash transfers increases the demand for index insurance in the following season. The treatment coefficient is significant at the 10% level when controlling for determinants of insurance uptake. The likelihood of purchasing IBLI increases on average by 4.8 percent points when receiving FbF, holding all other variables constant. Distinguishing between households who received the high amount (250 EUR) versus those that received the low amount (150 EUR) of cash transfers, I find that the impact only remains significant at conventional levels for the high amount treatment group, while the p-value of the low treatment coefficient turns insignificant at any conventional levels (column 3). This suggests that the size of FbF cash transfers is crucial to observe a positive effect of FbF on the demand for index insurance.

In the next step, I investigate whether the observed treatment effect is driven by a subset of households characterized by common traits. I include an interaction term between FbF treatment and insurance uptake in the previous year (2020). The coefficient of the interaction term is large and highly significant, while the effect of the treatment alone turns insignificant at conventional levels (column 4). Thus, the positive effect of the treatment on the demand for index insurance is driven by the group of re-purchasers. The receipt of FbF increases the likelihood of purchasing IBLI on average by 16 percent points among households that had already purchased IBLI in the preceding year compared to treated households that have not purchased IBLI in the preceding year, holding all other variables constant. Lastly, I explore whether the receipt of FbF cash transfers had similar effects for households living in areas with different realized risk. The best measure available to capture realized risk is livestock mortality at the sub-district level, calculated from the Mongolia Livestock Census. The coefficient is negative and not significant at any conventional levels. This suggests that both households living in sub-districts with high livestock mortality and households living in sub-districts with low livestock mortality are more likely to purchase IBLI when receiving FbF cash transfers. Nevertheless, I caution that aggregated livestock mortality is the best available, but not ideal measure of realized risk.

Table 3: The effects of cash transfers on insurance uptake, marginal effects (Logit)

Variables	IBLI uptake 2021 (1)	IBLI uptake 2021 (2)	IBLI uptake 2021 (3)	IBLI uptake 2021 (4)	IBLI uptake 2021 (5)
Treatment (receipt of cash transfers)	0.038	0.048*		-0.008	0.065**
	(0.036)	(0.028)		(0.031)	(0.033)
High treatment (250€)			0.061*		
			(0.036)		
Low treatment (150€)			0.033		
			(0.032)		
Treatment * IBLI uptake in 2020				0.162***	
				(0.046)	
Treatment * Ls mortality (sub-district)					-0.359
					(0.412)
IBLI uptake in 2020		0.198***	0.199***	0.119***	0.194***
		(0.025)	(0.025)	(0.031)	(0.024)
Ls mortality 2020/21(sub-district)		0.856	0.038	0.044	0.029
		(0.200)	(0.036)	(0.035)	(0.037)
Covariates	NO	YES	YES	YES	YES
Constant	-1.764***	-2.735***	-2.728***	-2.520***	-2.809***
	(0.191)	(0.529)	(0.527)	(0.461)	(0.521)
Adjusted R-squared	0.01	0.19	0.19	0.21	0.19
Observations	808	808	808	808	808

Note: Average marginal effects from logit regressions with standard errors, clustered at the sub-district level and reported in parentheses with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Coping with Shocks in Mongolia Household Panel Survey (waves 4-5), Mongolia Livestock Census and MongolianReinsurance database.

7.2 Mechanisms

I investigate two potential mechanisms through which the receipt of FbF cash transfers might affect households' insurance uptake: risk awareness and financial liquidity (Table 4). Risk awareness is proxied by households' expectation of harsh conditions in the 2021/22 winter (column 1).[15] I hypothesize that receiving FbF increases households' risk awareness of an extreme winter event since cash transfers make the risk of potential economic losses concrete. To analyze the effect of FbF cash transfers on households' expectation of harsh conditions in the upcoming winter, I limit the sample to households that were interviewed before December 2021. I find a large positive and statistically significant effect of FbF on the expectation of harsh conditions in the 2021/22 winter. Computing the average marginal effects, the probability of expecting harsh winter conditions increases by 11 percent points among treated households compared to the control group, holding all other variables constant.

I proxy financial liquidity with the self-reported probability that the household would have purchased (more) insurance if more cash had been available (column 2) and the total annual household income (column 3). In column 2, I estimate the model for a sample of households who have heard of IBLI and were interviewed after the end of the sales period in August 2021, which leaves us with a sample size of N=129. I would expect that households who received FbF cash transfers at the beginning of the IBLI

[15] I find a positive, at the five percent level significant correlation between the expectation of a harsh winter and insurance uptake.

sales period, report a lower probability that they would have bought (more) insurance coverage if they had more cash during the previous sales period. The coefficient is positive but not significant at any conventional levels. This is also true when looking at the second proxy for financial liquidity, total annual income. The coefficient of the treatment is positive but I do not find a statistically significant impact.

Table 4: Mechanisms of the effect of FbF on insurance uptake

Variables	Logit (marginal effect) Harsh winter (1)	OLS Cash constraints (2)	OLS Total income (log) (3)
Treatment (FbF)	0.109**	0.426	-0.011
	(0.054)	(0.336)	(0.060)
Covariates	YES	YES	YES
Constant	-0.860	3.983***	9.528***
	(0.924)	(0.559)	(0.116)
Adjusted R-squared	0.32	0.12	0.07
Observations	496	129	796

Note: Column 1 shows the average marginal effect obtained from logit regression. Standard errors are clustered at the sub-district level and reported in parentheses with * p < 0.1, ** p < 0.05, *** p < 0.01. Source: Coping with Shocks in Mongolia Household Panel Survey (waves 4-5), Mongolia Livestock Census and MongolianReinsurance database.

7.3 Robustness tests

Table 5 displays results from various robustness tests. As elaborated in Section 3, several banks offer loans bundled with IBLI. One potential concern is that the increase in IBLI uptake is only a side effect of households taking up a loan in response to the receipt of FbF. To test for this possibility, I employ an indicator variable measuring whether any member of the household has took up a loan in the past 12 months as an alternative outcome. If the receipt of FbF led to an increase in loan uptake and, therefore, only indirectly to an increase in the demand for IBLI, I would expect the coefficient to be significantly positive. A significantly negative coefficient could mean that the receipt of FbF reduces the need for loan uptake and at the same time decreases the number of insurance policies that are bought in exchange for reduced interest rates. I find the coefficient to be negative but not significant at any conventional level (column 1).

Next, I drop from the sample those treated households that did not confirm in the post-treatment phone interview that the FbF cash transfer was received (column 2). In column 3, I reduce the sample to households that were able to correctly identify in the following survey interview how much cash they received.[16] Both tests make sure that households who were intended to treat received the treatment and are aware of it. Moreover, it gives us insights into households' comprehension and precision in answering the survey questions. The effect size remains qualitatively similar and significant at the 10 percent level in the specification (2). In column 4, I reduce the sample to only households whose insurance purchase records

[16] Taking inflation into account, I consider as correct 500 000 - 550 000 Tugrik for 150€ and 800 000 - 850 000 for 250€, respectively.

could be successfully validated with official data from the MongolianReinsurance. The effect remains positive but is not significant anymore (p-value=0.13). In columns 5-8, I use different measures of livestock mortality to address the potential concern that the variation of sub-district livestock mortality is explained by the treatment variable. Column 5 shows the results when controlling for district total livestock mortality instead of sub-district mortality. While this measure is arguably less influenced by the treatment, it is also less precise due to variation within districts. I find a positive effect of FbF on insurance uptake (p-value=0.18). While I treated all animals as equal so far, in column 6, I use livestock mortality at the sub-district level measured in SFUs and, in column 7, I only take mortality of sheep and goats, the most common species, into account. Results are qualitatively similar. Lastly, I run the analysis without controlling for livestock mortality at the aggregated level to address the potential concern that FbF affects households' demand for insurance through its effect on livestock mortality (column 8). The coefficient of interest remains positive but is not significant at the 10 percent level anymore (p-value=0.12).

Table 5: Robustness checks, marginal effects (Logit)

	Relationship IBLI – loan uptake	Confirmed receipt via phone	Correctly recalled the amount of cash	Sample matched with MongolianRE database	District total livestock mortality	Livestock mortality in SFU	Livestock mortality in small animals	No control livestock mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Loan uptake	IBLI uptake	IBLI uptake	IBLI uptake	IBLI uptake	IBLI uptake	IBLI uptake	IBLI uptake
Treatment (FbF)	-0.021	0.050*	0.051	0.046	0.037	0.047*	0.049*	0.045
	(0.042)	(0.029)	(0.032)	(0.031)	(0.027)	(0.028)	(0.028)	(0.029)
Ls mortality (district)					1.161***			
					(0.232)			
Ls mortality in sfu (sub-district)						0.870***		
						(0.217)		
Mortality small animals (sub-district)							0.852***	
							(0.197)	
Covariates	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.189	-2.723***	-2.885***	-2.669***	-3.004***	-2.695***	-2.744***	-2.238***
	(0.434)	(0.526)	(0.514)	(0.524)	(0.477)	(0.539)	(0.527)	(0.697)
Adjusted R-squared	0.06	0.19	0.17	0.19	0.20	0.19	0.19	0.17
Observations	808	802	682	720	808	808	808	808

Note: Standard errors are clustered at the sub-district level and reported in parentheses with * p<0.1, ** p<0.05, *** p<0.01. Source: Coping with Shocks in Mongolia Household Panel Survey (waves 4-5), Mongolia Livestock Census and MongolianReinsurance database.

8. Conclusion

Among practitioners and policymakers Forecast-based Financing is widely considered an effective tool to assist vulnerable households in coping with extreme weather events. Yet, the empirical evidence on the effectiveness of FbF in general and on the interdependencies of FbF with households' adaptation strategies is scarce. Literature on crowding-out effects of conventional disaster aid suggests that the expectation and the receipt of disaster aid after an extreme weather event leads to a decrease in households' demand for insurance - a phenomenon called charity hazard. This study is the first to address the question whether Forecast-based humanitarian aid crowds-out households' investment in adaptation strategies. Exploiting a randomized experiment, I investigate how the receipt of FbF cash transfers influences the demand for index-based livestock insurance in Mongolia. I make use of two waves of household panel data collected before and after the field experiment. I complement the household survey data with customer data from the national reinsurance company.

Results show that the receipt of FbF cash transfers increases households' demand for index insurance in the following sales period. Thus, this study is one of the few studies that show that the receipt of aid can lead to crowding-in for insurance uptake. The results are robust to controlling for objective risk exposure and households' insurance history in contrast to earlier studies focusing on crowding-in effects of conventional disaster aid (Browne & Hoyt, 2000; Petrolia et al., 2013). Distinguishing between households who received a 250 EUR and a 150 EUR cash transfer, I find a positive effect only for those that received the higher treatment. Moreover, I show that the effect is driven by treated household who have already purchased index insurance in the preceding year. Those households' probability of re-purchasing IBLI increases by 16% compared to treated households who have not been insured in the preceding year.

I contribute to the debate on the crowding-in and crowding-out effects of aid by testing for mechanisms that drive the observed effects. First, I find that households that received FbF are significantly more likely to expect the upcoming winter to be harsh. Second, I focus on financial liquidity as a potential mechanism for increased uptake. I proxy financial liquidity with the self-reported probability that the household would have purchased (more) insurance if more cash had been available and the total annual household income. I do not find any significant effects of FbF on the proxies for financial liquidity. Results suggest that the risk-signaling effect of FbF outweighs the crowding-out effect of expecting aid in the future. Notably, FbF provided by international donors is incomplete and very uncertain, characteristics that reduce the likelihood of charity hazard (Raschky et al., 2013; Robinson et al., 2021; Tesselaar et al., 2022). Moreover, due to the design of index insurance, the disincentivizing effect of disaster aid on insurance uptake is assumedly smaller since policyholders receive payouts regardless of their own losses. Further research is needed to identify whether FbF can also lead to an increase in demand for conventional indemnity-based insurances.

The study's empirical context and experimental design is a rare opportunity to inform policymakers, international aid organizations and insurance providers about the interaction effects between two innovative shock coping instruments. My results suggest that FbF can boost insurance as a risk-managing tool. Thus, a wisely chosen combination of different adaptation strategies can lead to positive synergies.

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10. Appendix

Fig. A1: Map of Mongolia, survey provinces are darkly shaded

Fig. A2: Spatial variation in FbF treatment across survey sub-districts

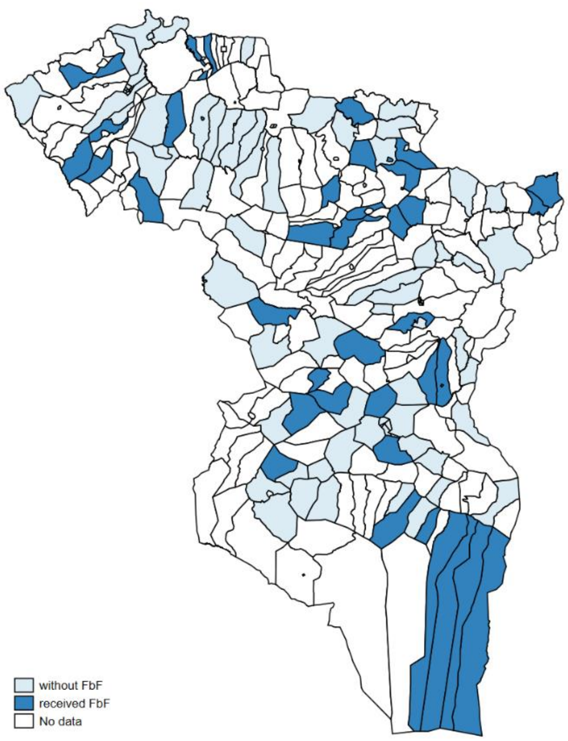
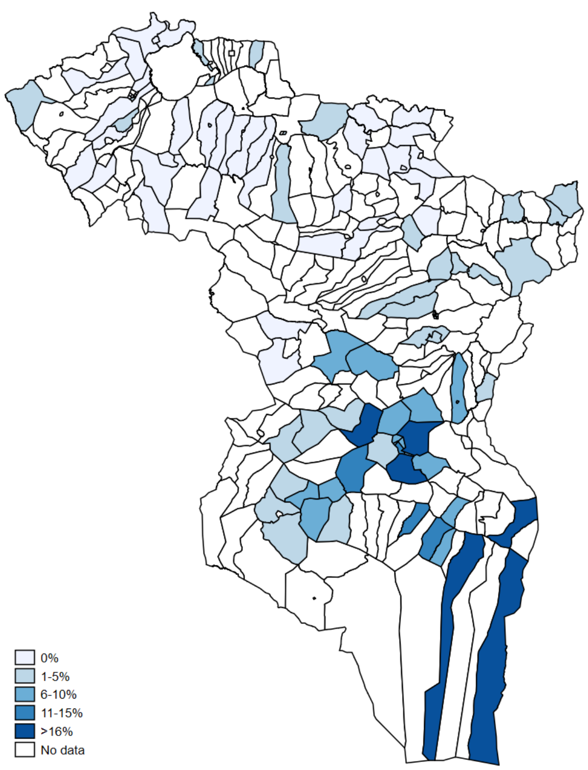


Fig. A3: Spatial variation in total livestock mortality across survey sub-districts



Sources: Mongolia Livestock Census

Table A1: Summary statistics

Name	Mean	S.D.	Min	Max	N
Age head	49.22	11.94	4	89	808
Female head	0.13	0.34	0	1	808
Head is married	0.83	0.38	0	1	808
Number of children (<10years)	0.73	1.06	0	5	808
Head has no education	0.13	0.34	0	1	808
Head has primary education	0.59	0.49	0	1	808
Head has secondary or higher education	0.28	0.45	0	1	808
Herd size (in SFU)	498.48	428.24	9	2,620	808
Nomadic household	0.60	0.49	0	1	808
Risk preference of head	4.17	2.89	0	10	808
Living in province Zavkhan	0.34	0.47	0	1	808
Living in province Gobi-Altai	0.33	0.47	0	1	808
Living in province Uvs	0.33	0.47	0	1	808
Living in province center	0.12	0.32	0	1	808
Living in district center	0.19	0.39	0	1	808
Living in rural area	0.70	0.46	0	1	808
Received information treatment	0.61	0.49	0	1	808
Loan uptake (in the past 12 months)	0.59	0.49	0	1	808
Harsh winter expectation 2020	0.55	0.50	0	1	410
Cash constraints	4.20	2.11	0	10	219
Total annual income	15,102.21	12,897.10	100	127,152	797
Insurance uptake in 2020	0.19	0.39	0	1	808
Insurance uptake ever	0.61	0.49	0	1	808
Ever received insurance payouts	0.15	0.35	0	1	808
Total livestock mortality (sub-district level) in winter 2020/21	0.03	0.05	0	0.26	808

Note: Winter expectation of 2020 is only reported for households that were interviewed before December 2020. Sources: Coping with Shocks in Mongolia Household Panel Survey (wave 4), Mongolia Livestock Census and MongolianReinsurance database.

Table A2: The effect of FbF on insurance uptake, marginal effects (Logit)

Variables	(1) IBLI uptake	(2) IBLI uptake	(3) IBLI uptake	(4) IBLI uptake	(5) IBLI uptake
Treatment (FbF)	0.038	0.048*		-0.008	0.065**
	(0.036)	(0.028)		(0.031)	(0.033)
High treatment (FbF)			0.061*		
			(0.036)		
Low treatment (FbF)			0.033		
			(0.032)		
Treatment (FbF) * IBLI uptake in 2020				0.162***	
				(0.046)	
Treatment (FbF) * Ls mortality (sub-district)					-0.359
					(0.412)
IBLI uptake in 2020		0.198***	0.198***	0.117***	0.199***
		(0.025)	(0.025)	(0.031)	(0.024)
Ls mortality (sub-district)		0.856***	0.858***	0.851***	1.001***
		(0.200)	(0.200)	(0.189)	(0.292)
Ever received insurance payouts		0.041	0.039	0.045	0.040
		(0.037)	(0.037)	(0.035)	(0.037)
Loan uptake (in the past 12 months)		0.041	0.041	0.047*	0.042
		(0.026)	(0.026)	(0.026)	(0.027)
Received information treatment		-0.054*	-0.054*	-0.053*	-0.056*
		(0.033)	(0.032)	(0.032)	(0.032)
Interview month=2		0.066	-0.070	-0.077	0.064
		(0.074)	(0.063)	(0.055)	(0.071)
Interview month=3		-0.047	0.009	0.012	-0.044
		(0.064)	(0.073)	(0.067)	(0.062)
Interview month=4		0.087	0.053	0.053	0.086
		(0.070)	(0.081)	(0.072)	(0.068)
Interview month=5		-0.093	-0.090	-0.093*	-0.094
		(0.080)	(0.059)	(0.053)	(0.078)
Interview month=6		0.049	-0.006	-0.013	0.047
		(0.069)	(0.078)	(0.075)	(0.068)
Interview month=7		-0.071	0.052	0.038	-0.073
		(0.064)	(0.068)	(0.059)	(0.061)
Interview month=8		0.012	0.060	0.061	0.018
		(0.073)	(0.071)	(0.070)	(0.071)
Interview month=9		0.048	-0.044	-0.055	0.050
		(0.080)	(0.064)	(0.057)	(0.079)
Interview month=10		-0.089	0.085	0.085	-0.087
		(0.060)	(0.070)	(0.067)	(0.058)
Interview month=11		-0.004	-0.089	-0.104	-0.003
		(0.081)	(0.083)	(0.072)	(0.079)
Interview month=12		0.044	0.048	0.040	0.045
		(0.067)	(0.069)	(0.062)	(0.065)
Constant	-1.764***	-2.735***	-2.728***	-2.520***	-2.809***
	(0.191)	(0.529)	(0.527)	(0.461)	(0.521)
Adjusted R-squared	0.01	0.19	0.19	0.21	0.19
Observations	808	808	808	808	808

Note: Standard errors are clustered at the sub-district level and reported in parentheses with * p<0.1, ** p<0.05, *** p<0.01. Excluded category is interview month 1. Source: Coping with Shocks in Mongolia Household Panel Survey (waves 4-5), Mongolia Livestock Census and MongolianReinsurance database.