RUHR
ECONOMIC PAPERS

Charity hazard in climate adaptation: The effect of anticipatory cash transfers on demand for weather insurance

Julian Roeckert, Lukas Mogge, Svenja Fluhrer, and Kati Kraehnert

RUHR UNIVERSITÄT BOCHUM RUB

rwi

#1201

Imprint

Ruhr Economic Papers

Ruhr Economic Paper #1201 “Charity hazard in climate adaptation:
The effect of anticipatory cash transfers on demand for weather insurance”
Responsible Editor: Prof. Dr. Manuel Frondel, RWI

Jointly published by

RWI – Leibniz-Institut für Wirtschaftsforschung e.V.
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Bergische Universität Wuppertal, Schumpeter School of Business and Economics
Gaußstraße 20, 42119 Wuppertal, Germany

Series Coordination:
RWI Press Office, presse@rwi-essen.de, phone +49 (0) 201 8149-213
RWI – Leibniz Institute for Economic Research, Hohenzollernstr. 1–3, 45128 Essen, Germany
www.rwi-essen.de

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.
The Institute has the legal form of a registered association; Vereinsregister, Amtsgericht Essen VR 1784

ISSN 1864-4872 (online)
ISBN 978-3-96973-386-8
DOI https://dx.doi.org/10.4419/96973386

Charity hazard in climate adaptation: The effect of anticipatory cash transfers on demand for weather insurance

Julian Roeckert[a*], Lukas Mogge[a], Svenja Fluhrer[b] & Kati Kraehnert[ab]

[a] RWI – Leibniz Institute for Economic Research, Economic Policy Lab Climate, Migration and Development, P.O. Box 10 30 54, 45030 Essen, Germany

[b] Ruhr University Bochum, Faculty of Management and Economics, Universitätsstr. 150, 44801 Bochum, Germany

** Corresponding author, roeckert@rwi-essen.de*

February 27, 2026

Abstract

This study examines whether receiving anticipatory cash transfers during an extreme winter affects households' demand for index-based livestock insurance. We exploit a randomized field experiment conducted during the 2020/21 winter disaster in western Mongolia and combine household panel survey data with administrative insurance records. We do not find evidence of charity hazard: the estimated effect of anticipatory cash transfers on insurance uptake is small and statistically indistinguishable from zero. The 95% confidence interval rules out large crowding-out effects but remains consistent with small negative effects of up to 2 percentage points. Treatment effects are heterogeneous: among households with prior insurance experience, estimated effects are positive and statistically significant, while effects among previously uninsured households are statistically indistinguishable from zero. These findings suggest that, in contexts where assistance is incomplete and index insurance is well-established, anticipatory assistance does not need to undermine insurance demand.

Keywords: Anticipatory humanitarian assistance, extreme weather events, impact evaluation, index-based insurance, randomized controlled trial, Mongolia

JEL codes: ***G22, H84, Q12, Q54***

Acknowledgments

We are grateful to our colleagues at People in Need Mongolia for making this project possible and to the National Statistics Office Mongolia for conducting household interviews despite extreme winter conditions and a global pandemic. We thank Alexandra Avdeenko, Bernd Beber, Banzragch Nandintsetseg and Maximiliane Sievert for helpful comments. The study also benefited from comments provided by participants of the 2023 International Conference on Inclusive Insurance, the 2024 Nordic Conference in Development Economics, the XXIII AISSEC Scientific Conference, the 2024 Annual Conference of the German Economic Association, the 2024 Finance and Development Workshop at Heidelberg University, the 2024 Leibniz Environment and Development Symposium, the 2024 Workshop of the Development Economics Network Berlin, as well as seminars at Kiel University and RWI. The research was generously funded by the German Federal Foreign Office (grant S08-60 321.50 ALL 04/21). The data collection was approved by the Board of the National Statistics Office Mongolia Chairperson on May 5, 2020 (wave 4) and April 7, 2021 (wave 5). The ethical review for the distribution of cash transfers was undertaken by People in Need's Relief and Development Department (project ID "CashEval'20"). The randomized trial is registered in the American Economic Association RCT Registry (RCT ID AEARCTTR-0012880).

1. Introduction

The increasing frequency and intensity of extreme weather events are projected to cause substantial economic losses, disproportionately affecting households in low- and middle-income countries (LMICs) (Pörtner, et al., 2022). In response, policymakers have introduced a range of new instruments designed to support households manage climate risks. In practice, however, households are often targeted by multiple instruments that address the same risks. This coexistence raises critical questions about how these instruments interact and influence household behavior.

This paper studies the interaction between two instruments that are becoming increasingly important for managing climate risks: index-based weather insurance and anticipatory humanitarian assistance. Separate strands of the literature have studied the effectiveness of index-based weather insurance (e.g., Bertram-Huemmer and Kraehnert, 2018, Carter, et al., 2016, Cole, et al., 2017, Hill, et al., 2019, Janzen and Carter, 2019, Stoeffler, et al., 2022) and anticipatory humanitarian assistance in the context of weather disasters (e.g., Christian, et al., 2025, Gros, et al., 2019, Gros, et al., 2022, Mogge, et al., 2025, Pople, et al., 2024). Much less is known about how these instruments interact. We contribute to the evidence base by examining whether the receipt of anticipatory humanitarian assistance during an extreme weather event affects households' demand for index-based insurance covering future weather risks.

We analyze data from a randomized field experiment implemented in western Mongolia, in which households received anticipatory cash transfers to mitigate the impact of an extreme winter event (Mogge, et al., 2025). Mongolia offers a particularly well-suited setting for studying how humanitarian assistance affects private investments in risk management. It was among the earliest adopters of both index-based livestock insurance (IBLI), introduced in 2006, and forecast-based anticipatory humanitarian assistance, first implemented in 2017. The coexistence of these instruments, combined with the randomized distribution of anticipatory cash transfers, allows us to test whether public humanitarian assistance crowds out, crowds in, or leaves unaffected households' demand for private insurance.

Anticipatory humanitarian assistance is provided by governments and humanitarian organizations and delivered to households before a disaster occurs or reaches its peak, often in the form of cash transfers (Arnold, et al., 2011, German Red Cross, 2017, German Red Cross and Red Cross Red Crescent Climate Centre, 2016). These transfers are designed to trigger automatically when risk forecasts exceed predefined thresholds, with the aim of preventing or reducing humanitarian needs before they fully materialize. In contrast, index-based weather insurance is a market-based instrument that households must proactively purchase to protect themselves against future weather-related risks (Cai, et al., 2020, Fisher, et al., 2019, GPFI, 2015, Greatrex, et al., 2015, Hazell and Hess, 2017, Skees, 2008). Insurance payouts are determined by an objective index, calculated at an aggregate geographical level. Once the index exceeds or falls short of a predefined threshold, insured households receive payouts, regardless of whether they incurred individual losses. By avoiding loss verification, index insurance offers a relatively low-cost approach to risk transfer for agricultural households (Cai, et al., 2020, Fisher, et al., 2019, GPFI, 2015, Greatrex, et al., 2015, Hazell and Hess, 2017).[1]

While both instruments aim to mitigate the socioeconomic impacts of weather disasters, their coexistence may have unintended consequences if anticipatory assistance reduces demand for insurance. If households expect to receive public assistance during future disasters, they may be less likely to purchase insurance coverage, a phenomenon commonly referred to as charity hazard (Browne and Hoyt, 2000). This crowding out of private risk management is well established in economic theory (e.g., Brunette, et al., 2013, Kaplow, 1991, Kelly and Kleffner, 2003, Lewis and Nickerson, 1989, Philippi and Schiller, 2024, Raschky and Weck-Hannemann, 2007, Robinson, et al., 2021, Tesselaar, et al., 2022).[2] However, empirical evidence on the existence of charity hazard remains scarce. At the same time, index-based weather insurance itself has struggled to achieve widespread adoption, despite significant policy attention and investment (Binswanger-Mkhize 2012; Carter et al. 2017; Jensen & Barrett 2017). Understanding how anticipatory humanitarian assistance affects the demand for weather insurance is thus a key question for the effective design of both instruments.

Our study builds on a randomized field experiment conducted among households participating in the *Coping with Shocks in Mongolia Household Panel Survey*, a long-running panel

---

1 Compared to conventional indemnity-based insurance schemes, index-based insurance is characterized by generally lower administration costs (Miranda and Farrin, 2012). Moreover, index-based insurance is by design resistant to adverse selection and moral hazard because insured households do not gain from individual damage (Barnett and Mahul, 2007, Mahul and Stutley, 2010).

2 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 receiving official development assistance from foreign donors in the event of a disaster decreases the recipient government's incentive to invest in protective efforts (Gibson, et al., 2005, Raschky and Schwindt, 2016).

survey that is representative of the population in three provinces in western Mongolia. During the 2020/21 winter, pastoralist households living in areas projected to be at risk of facing a winter disaster were randomly selected to receive unconditional cash transfers of 236 USD on average from the NGO People in Need (PIN). We combine the household-level panel survey data with the IBLI customer database, which contains detailed information on insurance purchases. The temporal overlap between the cash transfer intervention and the insurance sales period enables us to identify the effect of anticipatory assistance on households' demand for insurance coverage for the subsequent winter.

We find no evidence of charity hazard. The estimated intention-to-treat effect of receiving an anticipatory cash transfer on insurance uptake during the 2021 sales period is statistically indistinguishable from zero. The 95 percent confidence interval rules out large negative effects, though small reductions in uptake of up to 2 percentage points remain consistent with the data. Allowing for heterogeneity by prior insurance experience, we find a more positive treatment effect for households that had previously purchased insurance. Among households without previous IBLI purchase, the effect of receiving the cash transfer is statistically indistinguishable from zero. For previously insured households, receiving a cash transfer increases the likelihood of repurchasing insurance during the 2021 sales period. These findings suggest that, in our context, anticipatory assistance does not need to crowd out insurance demand and may reinforce participation among households already engaged with the product.

Our analysis contributes to the literature in several ways. First, we extend the literature on charity hazard in disaster assistance. While theory posits that individuals' expectations of public disaster assistance reduce incentives for private risk management, empirical findings remain inconsistent. Existing research documents negative effects of disaster assistance on insurance demand in the US (Davlasheridze and Miao, 2019, Deryugina and Kirwan, 2018, Landry, et al., 2021, Robinson, et al., 2021), the Netherlands (van Asseldonk, et al., 2002), Italy (Miglietta, et al., 2020), Germany (Andor, et al., 2020), and Austria (Raschky, et al., 2013), but finds no effects in Vietnam (Ngoc Que Anh, et al., 2019) and even positive effects in Germany (Philippi and Schiller, 2024) and the US (Bhattacharyya, et al., 2024, Petrolia, et al., 2013). This heterogeneity may reflect differences across studies in the type of insurance considered (hypothetical versus market-based products), the measurement of insurance uptake (willingness-to-pay versus realized purchases), and the unit of analysis (from the household to regional level). Moreover, Andor, et al. (2020) and

Tesselaar, et al. (2022) emphasize the importance of policy context: both the predictability of public disaster support and the requirements for minimum insurance coverage as a precondition for assistance vary substantially across countries. Finally, the identification of causal effects is challenging. While prior studies rely on quasi-experimental designs, our study is the first to examine the presence of charity hazard with a randomized experiment.

Second, we contribute to the literature on demand for index-based weather insurance. Prior studies show that alleviating liquidity constraints can increase insurance demand (Cole, et al., 2013, Hill, et al., 2016, Karlan, et al., 2014, Matsuda, et al., 2019). We extend this literature by focusing on a particular type of cash assistance, i.e. anticipatory cash transfers delivered during a weather disaster. This setting allows us to examine how insurance demand responds to an independently implemented program that targets the same climate risk as the insurance product itself. Furthermore, while a substantial literature has examined determinants of initial adoption of index insurance, there is little evidence on insurance demand in more mature markets. Leveraging insurance records spanning up to nine years prior to the intervention, we examine how an exogenous income shock during a climate disaster affects repurchase decisions. Our results highlight that responses to assistance can differ by prior insurance experience, with suggestive evidence that cash transfers increase demand for insurance among households that have already engaged with the insurance product. These findings underscore the importance of distinguishing between initial uptake and renewal when evaluating insurance demand.

Third, this study contributes to the emerging literature on the effectiveness of anticipatory humanitarian assistance. Existing research documents its impacts on welfare outcomes, including household assets, food consumption, and mental health (Gros, et al., 2019, Gros, et al., 2022, Mogge, et al., 2025, Pople, et al., 2024, Pople, et al., 2025). We extend this literature by providing results on how anticipatory humanitarian assistance influences households' private investments in climate risk management through insurance.

2. Winter disasters and climate adaptation in Mongolia

Mongolia is increasingly affected by extreme weather events. Extremely cold and snowy winters following dry summers cause massive livestock mortality and threaten the livelihoods of households involved in animal husbandry (Nandintsetseg, et al., 2018). The extreme winters of1999/00, 2000/01, and 2001/02 resulted in the deaths of over 11 million livestock. Similarly, the

2009/10 winter led to the loss of around 10 million livestock, equivalent to approximately 23% of the country's total livestock population (UNDP, 2025). More recently, the 2023/24 winter caused the loss of around 8 million livestock and a 27% decline in agricultural GDP (ibid.). Less severe or more localized winter disasters occurred in 2015/16, 2017/18, 2019/20, 2020/21, and 2022/23. Extreme winter events have been shown to negatively impact the well-being of households that rely on herding (e.g., Fluhrer and Kraehnert, 2022, Groppo and Kraehnert, 2016, 2017) and contribute to outmigration from affected areas (Roeckert and Kraehnert, 2022).

Over the past twenty years, Mongolia has been a leader in piloting and scaling instruments for managing climate risk. Following the series of extreme winters in the early 2000s, the Mongolian Government developed the index-based livestock insurance with technical support from the World Bank (World Bank, 2016). IBLI was scaled up to the national level in 2012 and has since been available in all 339 districts. IBLI policies are sold by commercial insurance companies and, since 2017, also by two commercial banks. IBLI covers the risk of livestock losses occurring during the winter season. The index is district-level livestock mortality, calculated using data from the annual Mongolian Livestock Census conducted in December and a mid-year livestock survey conducted in June. An insured household receives an indemnity payment if the mortality rate of the insured species in its district exceeds a predefined threshold of 5% or 6%, regardless of whether the insured household incurred any losses. Insurance coverage can be purchased for each of the five commonly held species: sheep, goats, cattle, horses, and camels. Households choose the number of animals to insure and the share of the animal's market value to be covered, ranging from 1% to 100%.[3] IBLI policies are sold between January and June, when neither herders nor insurance companies and banks can predict weather conditions for the upcoming winter, thereby limiting adverse selection. Indemnity payments are made to insured households in August of the following year. Between 2012 and 2023, annual uptake of IBLI among pastoralist households in the three surveyed provinces in western Mongolia ranged from 6.8% to 20.3% (Fig. A1, Panel A in the Appendix).

Mongolia is also among the global pioneers in the adoption of anticipatory humanitarian assistance. It was one of the first countries where forecast-based risk projections triggered

[3] See Mogge and Kraehnert (2025) for details on the IBLI rollout, the calculation of premiums and payouts, and the data used to calculate the index.

assistance to households during the extreme winter of 2017/18 (IFRC, 2020). In Mongolia, anticipatory assistance is based on risk projections generated by the Information and Research Institute of Meteorology, Hydrology, and Environment (IRIMHE) and Nagoya University (Nandintsetseg, et al., 2018). These projections categorize the risk of extreme winter conditions into five levels, ranging from very low to very high, at a fine spatial resolution. They are based on 14 indicators, including forecasted winter temperature, snow depth, and rainfall during the previous summer. Risk projections are published as maps at the beginning of each winter, in November, and are updated throughout the winter season. Government agencies and humanitarian organizations use these projections for guiding their anticipatory programming. Based on the projected risk levels, anticipatory assistance for pastoralist households was triggered in the winters of 2017/18 (provided by the International Federation of Red Cross and Red Crescent Societies (IFRC) and FAO), 2018/19 (provided by World Vision and Save the Children), 2019/20 (provided by IFRC and FAO), 2022/23 (provided by World Vision and IFRC), and 2023/24 (provided by World Vision, IFRC, and FAO).[4]

In 2020/21, the winter of interest in this study, IRIMHE's risk projections indicated a high risk of extreme winter conditions for several regions of Mongolia. The risk map published on November 20, 2020, classified 85% of the country as being at risk, with particularly high risk in the central and western regions (IRIMHE, 2021). An updated risk map published on January 10, 2021, showed a further increase in projected risk levels. In response, three organizations – IFRC, FAO, and World Vision – implemented anticipatory humanitarian assistance programs in Mongolia during the 2020/21 winter.

3. Empirical approach

Experimental design

This study is based on a randomized field experiment that we conducted during the 2020/21 winter disaster in western Mongolia, previously analyzed in Mogge, et al. (2025). The intervention was part of an evaluation project funded by the German Federal Foreign Office that aimed to study the impact of anticipatory cash transfers distributed by PIN on household welfare. The impact evaluation study revealed that the receipt of anticipatory cash transfers significantly improved the

[4] For details on the number of recipients targeted and the type of assistance provided, see Mogge, et al. (2025).

wellbeing of poorer households that owned less than 300 animals before the disaster (ibid.). For this socioeconomic group, the receipt of cash transfers increased their post-disaster herd sizes, herd-related investments, and home consumption of livestock. No significant impacts were detected when analyzing the full sample, which included wealthier pastoralists with larger herds.

Building on the same field experiment, this study investigates whether the receipt of anticipatory humanitarian assistance affects households' demand for index-based livestock insurance. The randomized anticipatory cash transfer intervention targeted households that met three eligibility criteria. (1) Each household was required to participate in the *Coping with Shocks Survey* (see description below). (2) Each household was required to reside in areas classified as facing very high, high, or medium risk of extreme winter conditions, according to the IRIMHE risk projection published on January 10, 2021. All survey households fulfilled this criterion. (3) Each household was required to own livestock, as the intervention specifically targeted pastoralist livelihoods.

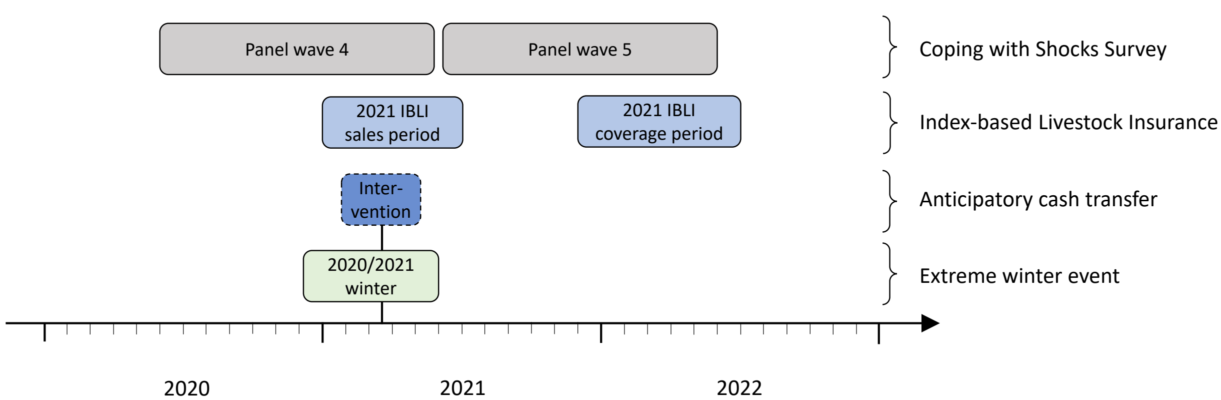
In the first week of February 2021, randomization was carried out. At that time, wave 4 of the *Coping with Shocks Survey* was still ongoing, and data were available for approximately half of the sample. For the remaining households, data from wave 3 were used to determine eligibility. In total, 925 households fulfilled all three eligibility criteria. Of these, 421 were randomly assigned to the treatment group and 504 to the control group. Randomization was conducted at the sub-district level. Households in the treatment group were designated to receive an unconditional anticipatory cash transfer with an average value of USD 238. For comparison, the average IBLI premium paid in 2020 by purchasing households in western Mongolia was approximately USD 37.

Between February 15 and March 1, 2021, the NSO conducted a short pre-intervention survey among households selected for treatment. Enumerators successfully located and surveyed 381 out of the 421 households selected for treatment. The survey collected bank account information and assessed potential obstacles to accessing the local bank branch. All surveyed households reported owning a bank account and indicated that they did not require assistance in accessing their bank branch. All treatment households consented to participate in the study. Enumerators informed them that they had been randomly selected to receive a cash transfer from PIN within the next weeks.

On March 15, 2021, PIN transferred the cash assistance to the bank accounts of the 381 recipient households. Households were subsequently notified by phone call or text message that the transfers had been completed.[5]

The timing of the intervention coincided with the 2021 IBLI sales period, which lasted from January 1 to June 30 (Fig. 1). During this period, households decided whether to purchase insurance coverage for potential livestock losses in the next winter season, from December 2021 to June 2022. Most households tend purchase IBLI policies toward the end of the sales period: Between 2017 and 2021, 46% and 23% of policies in western Mongolia were purchased in June and May, respectively, according to IBLI customer data. The overlap between the 2021 IBLI sales period and the randomized distribution of the cash transfers allows us to estimate the effect of anticipatory cash transfers provided in response to the 2020/21 winter risk on households' subsequent demand for insurance covering risks in the 2021/22 winter.

Fig. 1: Timeline of data collection, insurance season, extreme winter event and anticipatory cash transfer intervention



Source: The authors.

[5] For a detailed description of the experiment and the definition of the sample, see Mogge, et al. (2025).

Data

This study integrates four distinct data sources, described in detail below. First, the *Coping with Shocks in Mongolia Household Panel Survey* is the foundational dataset, as the cash transfer intervention was randomized among sampled households. Second, the IBLI customer database provides the key outcome variable, insurance uptake, for households in the survey sample. Third, the Mongolian Livestock Census is utilized to construct a measure of the realized severity of the 2020/21 winter. Fourth, official projections from IRIMHE on the risk of extreme winter conditions during the 2020/21 season are used as measure of ex ante risk.

The *Coping with Shocks Survey* was implemented by the authors in collaboration with the National Statistical Office of Mongolia (NSO) (Kraehnert, et al., 2022). The panel survey comprises five waves collected in the neighboring western Mongolian provinces of Govi-Altai, Zavkhan, and Uvs. Within these provinces, household survey data were collected in 49 of 63 districts. The sample was drawn using a stratified three-stage design based on the 2010 Population and Housing Census. The resulting sample of 1,768 households in wave 1 is representative of both the rural and urban populations in each of the three survey provinces.[6] The first three waves were collected between 2012 and 2015, the fourth between June 2020 and May 2021, and the fifth between June 2021 and May 2022. The survey follows a rolling design, with one-twelfth of the sample interviewed each month to ensure seasonal coverage. In each wave, households were surveyed in the same calendar month. We construct several household-level control variables from the survey data, which are described at the end of this section.

The outcome of interest is whether households in the *Coping with Shocks* sample purchased IBLI during the 2021 sales period, from January to June 2021. This coverage insured households against weather-related livestock losses occurring between December 2021 and June 2022. Administrative data on annual insurance purchases were obtained from the IBLI customer database, maintained by MongolianRe. The database contains policy-level records of all insurance contracts issued each year, including the timing of the purchase and the policyholder's unique national identification number. The NSO matched these records to the *Coping with Shocks Survey*

[6] See Mogge, et al. (2025) for details on the sampling.

data using the national identification number of the survey household heads in 2021.[7] Merging these two data sources yields comprehensive and reliable information on the insurance history of sample households from 2012 to 2021. Unlike existing studies, which typically rely on self-reported insurance purchase information collected in household surveys (e.g., Andor, et al., 2020, Hill, et al., 2016), our study is based on administrative records and is therefore not subject to recall error or misreporting.

To approximate the realized intensity of the 2021/22 winter, we use data from the Mongolian Livestock Census. Conducted annually in December by the NSO, the census collects species-specific information from all livestock-owning households on current herd sizes and the number of animals that died during the preceding 12 months due to unnatural causes. We first convert livestock holdings and losses into sheep forage units (SFUs), a standardized measure commonly used in Mongolia to aggregate different livestock species into a comparable metric.[8] Then, we calculate district-level livestock mortality in 2021 (in SFU) as a percentage of the number of adult animals that died due to unnatural causes relative to the 2020 stock of livestock.[9]

Lastly, we draw on IRIMHE's risk projection for extreme winter conditions, published on January 10, 2021, to construct a district-level measure of predicted risk. Districts are classified as having a medium, high, or very high projected risk based on the risk category that covers the largest share of their area.

Sample definition

Once complete wave 4 data became available, we verified the eligibility of households to the intervention ex post and restricted the sample slightly (Table A1 in the Appendix). Of the 925 households initially identified as eligible at the time of randomization, 95 were found to have

---

7 We define a household as having purchased insurance in a given year if the registry ID of the survey household head (as recorded in 2021) appears in the administrative records for that year. Households without a corresponding match in the customer database are coded as non-purchasers in our data.

8 Sheep forage units provide a standardized way to compare the annual feeding needs of various livestock, using the requirement of one sheep as the baseline (365 kg of forage per year). One sheep is equivalent to one SFU; one goat to 0.9 SFUs; one cow to six SFUs; one horse to seven SFUs; and one camel to five SFUs.

9 When calculating the district-level mortality rate, we excluded the sub-district in which a sample household resides to prevent the measure from being influenced by sample households.

been misclassified: they either no longer owned livestock, had moved outside the survey area, or had attrited from the survey. These households are therefore excluded from the analysis.

In addition, we excluded 20 households that purchased insurance in the 2021 IBLI sales period prior to receiving anticipatory cash transfers, as the intervention could not have influenced their purchase decisions.[10] The final sample used in the analyses presented below includes 368 households selected for treatment living in 50 sub-districts and 442 control households living in 58 sub-districts. In the robustness section below, we assess the sensitivity of our results to alternative sample restrictions.

Descriptive statistics

Table 1 presents summary statistics for the outcome variable, indicators for households' previous experience with IBLI, and measures of predicted and realized winter intensity for the final sample of 810 households used in the main analysis. During the 2021 IBLI sales period, approximately 18% of sample households purchased IBLI, the outcome of interest. This is similar to the 19% who purchased coverage in 2020, the year before the intervention. Between 2012 and 2020, about 47% of households in the sample purchased IBLI at least once. On average, households purchased IBLI in 1.39 years over this period, and less than 1% purchased IBLI in every year from 2012 to 2020. On average, households in the sample received an insurance payout 0.17 times during the 2013-2020 period. Most sample households (about 61%) lived in districts with high projected risk levels for the 2020/21 winter, while 20% lived in areas projected to be at very high risk. Actual livestock mortality per district in 2021, our preferred measure of realized risk, indicates strong spatial variation in realized winter intensity, ranging from 0% to 20.3%.

Next, we examine the persistence of annual IBLI uptake over the 2012-2021 period in our sample (Table A2). The data reveal a moderate and statistically significant positive correlation between insurance purchase in one year and uptake in the subsequent year, with correlation coefficients exceeding 0.32. To further explore this pattern, Table A3 presents the conditional probability of IBLI uptake in 2021 and 2020, given uptake in the previous year. Specifically, 44% of households that purchased IBLI in 2020 repurchased it in 2021 (Panel A), while 52% of those who purchased in 2019 did so again in 2020 (Panel B). We find that 44% of households that

[10] If households purchased multiple policies at different times, we consider the date of the first purchase.

purchased IBLI in 2020 repurchased it in 2021 (Panel A), and 52% of those who purchased in 2019 did so again in 2020 (Panel B). These patterns indicate substantial persistence in insurance participation.

Table A4 in the Appendix assesses balance between treatment and control groups with respect to experience with IBLI, household characteristics, and risk exposure. While the two groups are generally well balanced, four variables exhibit notable differences. First, conventional hypothesis tests reveal statistically significant differences in the gender of the household head and household size. Second, normalized differences in means (Imbens and Rubin, 2015) identify two further imbalances: treatment households are less likely to live in a provincial center and more likely to reside in districts with medium projected risk levels, both exceeding the 0.2 threshold. To account for these imbalances, we include these four variables as controls in our regression analyses. A joint F-test across all variables included in the balance assessment is significant at the 1% level. However, when variables controlled for in the empirical analysis are excluded, the F-statistic falls to 0.55 and is no longer significant at conventional levels. This pattern suggests that the detected imbalances are concentrated among covariates that enter directly as controls in the regression and are thus accounted for in the analysis.

Fig. A1 in the Appendix compares the share of pastoralist households that purchased IBLI over time in different data sources: Panel A displays data on the whole population of pastoralist households in western Mongolia, calculated from the Mongolian Livestock Census. Panel B displays data on the sample of pastoralist households included in the *Coping with Shocks Survey*. Both figures display comparable trends in IBLI uptake over time, even when considering each of the three western Mongolian provinces separately. We take this as supportive evidence that the *Coping with Shocks Survey* provides a reasonable representation of the population of pastoralists living in western Mongolia.

Table 1: Summary statistics

	Mean	Std. dev.	Min	Max	N
Outcome					
Household purchased insurance in 2021 sales period	0.18	0.38	0	1	810
Experience					
Household purchased insurance in 2020 sales period	0.19	0.39	0	1	810
Number of years in which household purchased insurance between 2012-2020	1.39	1.90	0	9	810
Household received insurance payout in August 2020	0.01	0.11	0	1	810
Number of years in which household received insurance payout between 2013-2020	0.17	0.46	0	2	810
Winter intensity					
Livestock mortality rate in district in 2021 (%)	3.05	4.37	0	20.30	810
Predicted risk of extreme winter conditions in district in 2021: very high (0-1)	0.20	0.40	0	1	810
Predicted risk of extreme winter conditions in district in 2021: high (0-1)	0.61	0.49	0	1	810
Predicted risk of extreme winter conditions in district in 2021: medium (0-1)	0.19	0.39	0	1	810

Source: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Empirical specification

To examine the impact of anticipatory cash transfers on insurance uptake, we estimate:

$$IBLI_{hsd,2021} = \beta_0 + \beta_1 treatment_{hsd} + \beta_2 experience_{hsd} + \beta_3 realized\ risk_d + \beta_4 X_{hsd} + \varphi_p + \varepsilon_{hsd} \quad (1)$$

where $IBLI_{hsd,2021}$ is an indicator equal to one if household h, residing in sub-district s and district d, purchased index-based livestock insurance during the 2021 sales period (covering risks in the winter of 2021/22). $Treatment_{hsd}$ indicates whether the household was randomly assigned to receive an anticipatory cash transfer in March 2021. The coefficient of interest, β_1, captures the intention-to-treat (ITT) effect.[11] Under the charity hazard hypothesis, we would expect $\beta_1 < 0$, indicating that humanitarian assistance crowds out insurance demand.

$Experience_{hsd}$ captures households' prior insurance purchases. In our baseline specification, we proxy experience with an indicator for IBLI uptake in the 2020 sales period, the year preceding the intervention. $Realized\ risk_d$ measures the severity of the 2020/21 winter event, proxied by district-level livestock mortality (in SFU). The vector X_{hsd} includes household and district characteristics that are unbalanced between treatment and control groups: female headship, household size, whether the household lives in the province center, and the projected winter risk at the district level. Province fixed effects, φ_p, absorb time-invariant provincial characteristics. Standard errors are clustered at the sub-district level, the unit of randomization.

To test for heterogeneous treatment effects by prior experience, we augment equation (1) with an interaction between treatment assignment and prior experience:

$$IBLI_{hsd} = \beta_0 + \beta_1 treatment_{hsd} + \beta_2 experience_{hsd} + \beta_3 (treatment_{hsd} * experience_{hsd}) + \beta_4 realized\ risk_d + \beta_5 X_{hsd} + \varphi_p + \varepsilon_{hsd} \quad (2)$$

The interaction coefficient β_3 captures whether the treatment effect differs between households with and without prior insurance experience. We provide results for an extended set of

[11] Of the 368 households selected for treatment in the analysis sample, 359 (98%) received the cash transfer. Given this high compliance rate, we solely focus on intention-to-treat estimates.

alternative definitions of $experience_{hsd}$. In addition to considering uptake in 2020, we define experience as an indicator equal to one if the household purchased IBLI at least once during progressively longer pre-intervention windows, beginning with 2019–2020 and extending back to 2012–2020, when IBLI was scaled up nationally. We also consider a continuous measure equal to the number of years in which a household purchased IBLI between 2012 and 2020. These measures capture both recent exposure and longer-term engagement with the product.

4. Results

Table 2 reports ITT estimates of how anticipatory cash transfers (received in March 2021) influenced the uptake of index-based livestock insurance during the 2021 sales period. All specifications are estimated using OLS. Column 1 presents results from a specification that only includes province fixed effects. Column 2 adds controls for households' prior experience with IBLI (uptake in 2020). Column 3 further controls for realized risk, while col. 4 additionally includes controls for unbalanced covariates.

The ITT effect of anticipatory cash transfers on insurance demand is small and not statistically significant across specifications. In our preferred specification (col. 4), the point estimate is 0.04, with a 95% confidence interval (CI) ranging from -0.02 to 0.10. Thus, we cannot reject the null hypothesis of no effect on insurance demand. The lower bound of the CI excludes crowding-out effects larger than 2 percentage points while the upper bound includes increases in uptake of up to 10 percentage points. The data are therefore consistent with both small negative and modest positive effects, reflecting limited statistical precision. Results are robust to alternative definitions of prior insurance experience (Table A5).

Table 3 presents the ITT estimates from specifications that allow the treatment effect to vary by prior insurance experience, as outlined in equation (2). Each column reports results from a specification that interacts treatment assignment with a different measure of prior experience. Column 1 defines experience, as before, as having purchased IBLI in 2020; cols. 2–9 use progressively longer time windows (2019–2020 through 2012–2020); and col. 10 uses the number of years a household purchased IBLI prior to the intervention. All specifications include the full set of controls and province fixed effects.

Among households that had not purchased insurance in 2020, the estimated effect of anticipatory cash transfers on insurance demand is close to zero and not statistically significant, with the 95% CI ranging from -0.05 to 0.06 (col. 1). This pattern is consistent across all alternative measures of insurance experience (cols. 2–10), with estimated treatment effects statistically indistinguishable from zero.

In contrast, among households with prior insurance experience, the estimated treatment effects are substantially larger and statistically significant. For households that purchased IBLI in 2020, the total treatment effect – the sum of the main effect and interaction term in col. 1 – is 0.17, significant at the 5% level (95% CI: [0.00, 0.34]). This pattern of significant differences between households with and without prior experience, and positive treatment effects among experienced households, holds across alternative definitions of prior insurance experience. The coefficients of the interaction term between treatment and prior experience range from 0.11 to 0.16 for binary measures (cols. 2–9), all statistically significant at the 10% or 5% level. For the continuous measure (col. 10), each additional year of prior IBLI experience is associated with a 3 percentage point larger treatment effect, significant at the 10% level. While these results consistently point to a positive response among households that had previously purchased insurance, the estimates are imprecise, so we abstain from further interpreting their magnitude.

Overall, our results do not provide evidence consistent with the charity hazard hypothesis, which predicts that anticipatory cash transfers reduce insurance demand. We find no evidence of crowding-out, even though the imprecision of our estimates means we cannot rule out small negative effects. When distinguishing by prior insurance experience, the treatment effect is statistically indistinguishable from zero for households without prior experience but positive and significant for those with prior experience, suggesting possible crowding-in among this subgroup. Confidence intervals remain wide across subgroups.

Table 2: Effects of anticipatory cash transfers on insurance uptake (OLS)

Dependent variable:	IBLI uptake in 2021			
	(1)	(2)	(3)	(4)
Selected for treatment	0.05 (0.03)	0.05 (0.03)	0.04 (0.03)	0.04 (0.03)
IBLI uptake in 2020		0.31*** (0.04)	0.31*** (0.04)	0.29*** (0.04)
Livestock mortality in district in 2021			0.01 (0.01)	0.01 (0.01)
Female-headed household				-0.06* (0.03)
Number of household members				0.01 (0.01)
Household lives in province center				0.01 (0.04)
High predicted risk in district in 2021				-0.09** (0.05)
Very high predicted risk in district in 2021				-0.06 (0.06)
Constant	0.08*** (0.02)	0.05** (0.02)	0.04* (0.02)	0.09 (0.05)
Province FE	Yes	Yes	Yes	Yes
R-squared	0.04	0.14	0.14	0.16
Observations	810	810	810	810
IBLI uptake in 2021 in control group	0.15	0.15	0.15	0.15
95% CI: selected for treatment	[-0.02, 0.12]	[-0.01, 0.11]	[-0.02, 0.10]	[-0.02, 0.10]

Notes: Effects from OLS regressions with standard errors clustered at the sub-district level and reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Table 3: Effects of anticipatory cash transfers on insurance uptake, by insurance experience (OLS)

Dependent variable:	IBLI uptake in 2021									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Experience defined as:	IBLI uptake in 2020	IBLI uptake in 2019-20	IBLI uptake in 2018-20	IBLI uptake in 2017-20	IBLI uptake in 2016-20	IBLI uptake in 2015-20	IBLI uptake in 2014-20	IBLI uptake in 2013-20	IBLI uptake in 2012-20	Number of years with IBLI uptake 2012-20
Selected for treatment	0.00 (0.03)	-0.02 (0.03)	-0.03 (0.02)	-0.03 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.02 (0.02)	-0.02 (0.03)	-0.01 (0.03)
Experience	0.21*** (0.06)	0.21*** (0.04)	0.20*** (0.04)	0.19*** (0.03)	0.21*** (0.04)	0.20*** (0.03)	0.20*** (0.03)	0.18*** (0.03)	0.18*** (0.03)	0.05*** (0.01)
Selected for treatment × experience	0.17* (0.09)	0.16** (0.06)	0.16** (0.06)	0.14** (0.05)	0.11* (0.06)	0.11** (0.06)	0.11** (0.05)	0.13*** (0.05)	0.12** (0.05)	0.03* (0.02)
Constant	0.10* (0.05)	0.08 (0.05)	0.05 (0.05)	0.03 (0.05)	0.02 (0.05)	0.02 (0.06)	0.01 (0.06)	0.00 (0.06)	-0.01 (0.06)	0.05 (0.06)
Controls and province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.17	0.19	0.19	0.18	0.18	0.18	0.18	0.17	0.16	0.17
Observations	810	810	810	810	810	810	810	810	810	810
95% CI: select. for treat.	[-0.05, 0.06]	[-0.07, 0.04]	[-0.08, 0.02]	[-0.07, 0.02]	[-0.06, 0.04]	[-0.06, 0.03]	[-0.06, 0.04]	[-0.07, 0.03]	[-0.08, 0.03]	[-0.06, 0.05]
95% CI: select. for treat. × experience	[-0.00, 0.34]	[0.03, 0.29]	[0.04, 0.28]	[0.03, 0.25]	[-0.00, 0.22]	[0.00, 0.22]	[0.00, 0.21]	[0.03, 0.23]	[0.02, 0.22]	[-0.00, 0.07]
Selected for treatment if experience=1	0.17** (0.09)	0.14** (0.06)	0.12** (0.06)	0.11** (0.05)	0.10* (0.05)	0.10* (0.05)	0.10* (0.05)	0.11** (0.05)	0.10** (0.05)	
95% CI: select. for treat. if experience=1	[0.00, 0.34]	[0.02, 0.27]	[0.01, 0.24]	[0.00, 0.22]	[-0.01, 0.20]	[-0.01, 0.21]	[-0.01, 0.20]	[0.01, 0.21]	[0.00, 0.19]	
Share of experienced households	0.19	0.29	0.36	0.41	0.44	0.45	0.48	0.50	0.52	
IBLI uptake in 2021 in control group if experience =1	0.35	0.31	0.29	0.28	0.27	0.27	0.26	0.25	0.24	
IBLI uptake in 2021 in control group if experience =0	0.11	0.09	0.08	0.07	0.06	0.06	0.05	0.05	0.05	

Notes: Effects from OLS regressions with standard errors clustered at the sub-district level and reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Robustness

We conduct a series of robustness checks to assess the stability of our main findings, with attention to (i) inference with limited number of clusters, (ii) pre-treatment balance and placebo tests, (iii) post-treatment persistence, and (iv) alternative sample restrictions.

Treatment is assigned at the sub-district level and our main specifications cluster standard errors accordingly. To address potential finite-sample concerns with cluster-robust inference, Table A6 reports wild cluster bootstrap p-values and confidence intervals based on 10,000 replications with Rademacher weights (Roodman, et al., 2019). Wild bootstrap inference yields results consistent with our main findings: the ITT estimate in the non-interacted model remains insignificant (p-value: 0.24, 95% CI: [-0.02, 0.10]), while the interaction effects are significant at the 5% or 10% level across specifications. Furthermore, we examine the sensitivity of the main results to potential outliers at the cluster level, by re-estimating the main specifications 108 times, each time excluding one sub-district. The range of leave-one-cluster-out (LOCO) results for the main ITT effect (Fig. A2) and interaction effect (Fig. A3) supports our main findings. The LOCO-ITT effects for our main specifications range from 0.02 to 0.04 and are not significant at conventional levels (Fig. A2). The LOCO interaction effects are positive and significant at the 5% or 10% level across alternative definitions of experience (Fig. A3).[12] These exercises suggest that our findings are not driven by inference concerns due to the limited number of clusters or influential sub-districts.

Next, we investigate pre-treatment balance with placebo tests using data on pre-treatment uptake decisions as outcomes. We estimate our main specifications for IBLI uptake in each year from 2012 through 2020 and report results in Fig. A4. If treatment assignment were correlated with pre-existing purchasing trends or household characteristics, we would expect to find spurious placebo "treatment" effects in these pre-treatment years. Panel A shows that placebo treatment effects from the baseline specification (corresponding to Table 2, col. 4) are not statistically significant at conventional levels, although we observe marginally significant coefficients for 2018 (0.05; p-value: 0.10) and 2019 (0.04; p-value: 0.15). Panel B differentiates these placebo estimates by 2020 experience status (corresponding to Table 3, col. 1). The results reveal that these patterns

[12] For the 2016–2020 binary experience measure, two of 108 re-estimations yield p-values ≥ 0.10; for the continuous experience measure, four of 108 re-estimations yield p-values in the same range.

are concentrated among specific subgroups: treatment households not purchasing in 2020 exhibit somewhat higher insurance uptake in 2018 than comparable control households (0.06, p-value: 0.09), while treatment households that buy in 2020 also purchase more insurance in 2019 than comparable control households (0.11, p-value: 0.19).

To address concerns that these pre-treatment imbalances may confound our 2021 estimates, we re-estimate our main specifications with additional controls for prior IBLI uptake. Table A7 shows results controlling for: (i) 2019 uptake only, (ii) 2019 and 2018 uptake, and (iii) all years 2012–2019 individually. The main effect remains of similar magnitude as in our baseline specification, ranging from 0.02 to 0.03 with 95% Cis ranging between -0.03 and 0.09. The interaction effects range between 0.15 and 0.16 and remain significant at the 10% level, providing reassurance that our findings are unlikely to be driven by pre-existing imbalances.

Figure A4 also reports estimates for insurance uptake in the 2022 and 2023 sales periods, extending the analysis beyond the intervention year. These post-intervention estimates should be interpreted cautiously. First, unlike the 2021 specification, we cannot control for lagged insurance uptake without introducing post-treatment endogeneity, leaving the 2022 and 2023 models less tightly specified. Second, sample composition may change over time. Household-level IBLI purchase data come from administrative records, where non-appearance could reflect either non-purchase or exit from herding. Some sample households may have exited herding following the 2020/21 winter disaster, for whom IBLI is no longer a relevant investment. Because wave 5 of the *Coping with Shocks Survey* ended in June 2022, we lack information on livestock ownership during the 2023 IBLI sales period. Moreover, suggestive evidence in Mogge, et al. (2025) indicates that anticipatory cash transfers reduced the likelihood of households exiting herding during the 2021/22 winter disaster. Third, matching between survey households and the IBLI customer database was conducted only through 2021, making information on purchases in 2022 and 2023 less precise if heads of households change. Finally, another high-intensity winter occurred during the 2022/23 season,[13] overlapping with the 2023 sales period, which may further confound estimates if disaster intensity varied across treatment and control groups or by prior insurance experience.

[13] During the 2022/23 winter, national livestock mortality reached 4.9 million animals, equivalent to 7% of the national herd (UNDP, 2025). By February 2023, 191,000 pastoralist households were reported to be affected by adverse winter conditions (United Nations Resident Coordinator for Mongolia, 2023).

With these limitations in mind, Fig. A4 shows no statistically significant effects of cash transfers on insurance uptake in 2022 (Panel A) and no systematic heterogeneous effects with respect to prior insurance experience (Panel B). Results for 2023 are more heterogeneous. We again do not see statistically significant effects of cash transfers on overall insurance uptake. However, in the interacted specification, we find a significantly lower insurance uptake among treated households without prior insurance experience. We view these results as suggestive of potential longer-run dynamics but focus our conclusions on the 2021 estimates, where identification is cleanest.

Finally, we examine the robustness of results to alternative sample definitions. In Table A8, we re-estimate our main specifications in an increased sample where we add the eight households that purchased insurance after the pre-intervention survey but before the disbursement of cash transfers. In Table A9, we estimate the main specifications using the full set of households meeting the eligibility criteria based on completed wave 4 data from the *Coping with Shocks Survey*, thereby including an additional 20 households that purchased IBLI during the 2021 sales period prior to receiving the anticipatory cash transfers. Third, in Table A10, we employ information from endline interviews and exclude households that attrited between waves 4 and 5 (N=15), as well as those who, according to wave 5 interviews, no longer engaged in herding (N=39). Across all specifications with the above-described sample restrictions, the results remain qualitatively unchanged relative to the main analysis.

Spatial heterogeneity by historical risk

The preceding analysis examined household-level responses to anticipatory cash transfers. Here, we shift our focus to the implications for the insurance pool. For insurers, the sustainability of index insurance depends on the risk composition of the pool of insured households. If treatment effects vary systematically with historical exposure to weather risk, the intervention may alter the risk profile of the insurance pool. Differences in historical risk exposure may have influenced households' perceptions of risk and the perceived value of insurance coverage. In particular, a higher record of insurance payouts following extreme winters could have built trust in the insurance product. These factors may generate spatial heterogeneity in how households utilize anticipatory cash transfers. Theoretically, such transfers could disproportionately increase insurance uptake in high-risk districts – raising concerns about adverse spatial selection – or in low-risk districts, which would diversify the pool and reduce risk concentration. To investigate these dynamics, we estimate the following model:

$$IBLI_{hsd} = \beta_0 + \beta_1 treatment_{hsd} + \beta_2 historic\ risk_d + \beta_3 (treatment_{hsd} * historical\ risk_d) + \beta_4 experience_{hsd} + \beta_5 realized\ risk_d + \beta_6 X_{hsdt} + \varphi_p + \varepsilon_{hsd} \quad (3)$$

We measure historical risk at the district level using three proxies: mean livestock mortality over two periods (2000-2020 and 2012-2020) and the number of years in which the IBLI payout trigger was met in a household's district of residence in the 2013-2020 period. Table 4 presents the results. Across all specifications, the estimated coefficients for the interaction between historical risk and treatment are consistently small and statistically indistinguishable from zero. Hence, there is no evidence that the cash transfer differentially increased insurance uptake in districts with higher historical livestock mortality or more frequent payout-triggering events. From the perspective of the insurer, the intervention appears not to have systematically altered the spatial risk composition of the insured pool in the short run.

Table 4: Effects of anticipatory cash transfers on insurance uptake, by historical risk (OLS)

Dependent variable:	IBLI uptake in 2021					
	(1)	(2)	(3)	(4)	(5)	(6)
Historical risk defined as:	Mean livestock mortality in district (2000-2020)		Mean livestock mortality in district (2012-2020)		Number of years with IBLI payouts in district (2013-2020)	
Selected for treatment	0.04 (0.03)	0.03 (0.03)	0.05 (0.03)	0.03 (0.03)	0.04 (0.03)	0.03 (0.03)
Historical risk (centered)	0.02 (0.01)	0.01 (0.01)	0.02 (0.02)	0.00 (0.02)	0.03 (0.02)	0.02 (0.02)
Selected for treatment × historical weather risk (centered)	0.04 (0.03)	0.04 (0.03)	0.04 (0.05)	0.04 (0.04)	0.05 (0.04)	0.04 (0.03)
IBLI uptake in 2020		0.28*** (0.04)		0.29*** (0.04)		0.28*** (0.05)
Livestock mortality in district		0.01 (0.01)		0.01* (0.01)		0.01* (0.01)
Constant	0.06*** (0.02)	0.04 (0.06)	0.07*** (0.02)	0.08 (0.05)	0.07*** (0.02)	0.07 (0.05)
Controls	No	Yes	No	Yes	No	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.06	0.17	0.05	0.16	0.06	0.17
Observations	810	810	810	810	810	810
95% CI: selected for treatment	[-0.02, 0.11]	[-0.03, 0.09]	[-0.02, 0.12]	[-0.03, 0.09]	[-0.02, 0.11]	[-0.03, 0.09]
95% CI: selected for treatment × historical risk	[-0.01, 0.10]	[-0.02, 0.09]	[-0.05, 0.13]	[-0.04, 0.13]	[-0.02, 0.12]	[-0.03, 0.11]

Note: Effects from OLS regressions with standard errors clustered at the sub-district level and reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The three measures of historical risk are centered around their respective sample means. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

5. Discussion

Our findings should be interpreted in light of several considerations: the specific context of Mongolia, the constraints of the survey data and research design, and the time horizon of the analysis.

Several features of Mongolia's institutional and risk environment likely shaped the observed results. First, disaster assistance, whether anticipatory or ex post, remains incomplete and uncertain in Mongolia. This unpredictability may limit crowding-out effects, as households cannot form strong expectations of guaranteed compensation, a key assumption of the charity hazard concept (Raschky, et al., 2013, Robinson, et al., 2021, Tesselaar, et al., 2022). Second, the design of IBLI is critical: because payouts are triggered by district-level indices, compensation is not contingent on individual losses. This feature may reduce the perceived substitutability between humanitarian assistance and index insurance compared to indemnity-based insurance. Third, IBLI has been available nationwide for over a decade, with stable delivery channels and intensive marketing. In this institutional setting, anticipatory cash transfers may have reinforced households' perceived value of formal risk management rather than substituted for it. These conditions, however, may not generalize beyond Mongolia. In contexts where climate risks are less immediate, index insurance products are newly introduced, or trust in insurers is low, the interaction between humanitarian assistance and insurance demand could differ. Likewise, in contexts where public disaster assistance is institutionalized, predictable, and perceived as comprehensive, the incentives for private risk management could evolve differently.

The available data and research design impose two main limitations on interpretation. First, we lack detailed measures to investigate potential channels that could explain the observed relationship between receiving anticipatory cash transfers and insurance uptake. Anticipatory cash transfers may have raised households' expectations about future disaster assistance, as predicted by the charity hazard hypothesis. At the same time, the transfers may have relaxed short-term liquidity constraints during the sales period or increased the salience of winter risk following the disaster, thereby positively affecting demand. Because we lack detailed measures of households' expectations about future disaster assistance, liquidity constraints, or perceived climate risk, we cannot distinguish between these mechanisms and can only assess the net effect on insurance demand. Accordingly, the heterogeneous patterns should be interpreted as consistent with differential behavioral responses to assistance across groups with different levels of experience, rather than as evidence on a specific mechanism. Second, treatment assignment at the sub-district level (N=108 clusters) affects inference, precision, and power. To address inference concerns, we complement clustered standard errors with wild cluster bootstraps and leave-one-cluster-out analyses, all of which yield results consistent with our main findings. We also emphasize the range of effects implied by our confidence intervals and avoid overinterpreting the magnitude of the point estimates.

The analysis primarily focuses on short-run effects, identifying impacts for the insurance sales period that overlaps with the intervention. While we examine insurance uptake for the 2022 and 2023 sales periods, these specifications are less tightly identified due to post-treatment dynamics and data constraints. Our results therefore speak most clearly to short-run responses to a single anticipatory assistance episode, leaving open the possibility of longer-run behavioral adjustments or effects that emerge only after repeated exposure to disaster assistance.

6. Conclusion

Among practitioners and policymakers, anticipatory humanitarian assistance and index-based weather insurance are widely promoted as tools to help households in LMICs manage climate risk. Yet evidence on how these instruments interact when they coexist in the same setting is scarce. To our knowledge, this is the first study to examine the effect of anticipatory humanitarian assistance on demand for index insurance in a randomized setting.

We exploit a randomized distribution of anticipatory cash transfers to at-risk pastoralist households during the 2020/21 winter in western Mongolia to assess whether receiving anticipatory humanitarian assistance affects demand for index-based livestock insurance. Combining household panel survey data with insurance customer records allows us to precisely measure insurance uptake. The temporal overlap between the anticipatory cash transfers and the 2021 insurance sales season enables us to estimate its effect on insurance purchases covering weather risk in the subsequent winter.

We find no evidence of charity hazard. Although the results cannot rule out small negative effects (up to 2 percentage points), they are inconsistent with large crowding-out effects that would raise substantive concerns about the interaction between humanitarian assistance programs and private risk management through IBLI. Results suggest that the treatment effects are heterogenous: among households with prior IBLI experience, estimated effects are positive, while among previously uninsured households they are statistically indistinguishable from zero. We also do not find evidence that the intervention affected the spatial risk composition of the insured pool.

Taken together, the findings suggest that, in this context, where humanitarian assistance is incomplete and index insurance is well-established, anticipatory assistance does not need to undermine insurance demand and may reinforce participation among previously insured households. To what extent this pattern generalizes beyond our setting remains an open question. Results may differ in environments with less mature insurance markets, more institutionalized and predictable disaster assistance, or different types of climate risk.

Future research should examine how instruments that aim to support households in managing similar climate risks interact across contexts and longer time horizons. Larger samples are required to estimate effects with greater precision. Extended panels with repeated exposure to disaster assistance will be needed to study medium and long-term effects on insurance demand and portfolio composition, outcomes directly relevant for actuarial sustainability. Household-level data on perceived weather risk and expectations to receive disaster assistance would allow the identification of underlying mechanisms.

Understanding how public and market-based risk management tools interact remains central for climate adaptation policy. Designing systems that are both effective for households and institutionally sustainable will require careful attention to these interactions, particularly as climate risks intensify and humanitarian budgets tighten.

7. References

Andor, Mark A, Daniel Osberghaus, and Michael Simora. 2020. Natural disasters and governmental aid: Is there a charity hazard? *Ecological Economics* 169:106534.

Arnold, Catherine, Tim Conway, and Matthew Greenslade. Cash transfers literature review. Department for International Development.

Barnett, Barry J, and Olivier Mahul. 2007. Weather index insurance for agriculture and rural areas in lower-income countries. *American Journal of Agricultural Economics* 89:1241–1247.

Bertram-Huemmer, Veronika, and Kati Kraehnert. 2018. Does index insurance help households recover from disaster? Evidence from IBLI Mongolia. *American Journal of Agricultural Economics* 100:145–171.

Bhattacharyya, Arkaprabha, Holly H. Wang, and Makarand Hastak. 2024. Impact of post-disaster federal assistance on the national flood insurance program. *International Journal of Disaster Risk Reduction* 102:104290.

Browne, Mark J., and Robert E. Hoyt. 2000. The Demand for Flood Insurance: Empirical Evidence. *Journal of Risk and Uncertainty* 20:291–306.

Brunette, Marielle, Laure Cabantous, Stéphane Couture, and Anne Stenger. 2013. The impact of governmental assistance on insurance demand under ambiguity: a theoretical model and an experimental test. *Theory and Decision* 75:153–174.

Buchanan, J. M. (1975) The Samaritan's dilemma. In E.S. Phelps ed. *Altruism, morality, and economic theory.* New York, USA, Russell Sage Foundation, pp. 71–89.

Cai, Jing, Alain De Janvry, and Elisabeth Sadoulet. 2020. Subsidy policies and insurance demand. *American Economic Review* 110:2422–2453.

Carter, Michael R., Lan Cheng, and Alexandros Sarris. 2016. Where and how index insurance can boost the adoption of improved agricultural technologies. *Journal of Development Economics* 118:59–71.

Christian, Paul J., Felipe A. Dunsch, Jonas Heirman, Erin M. Kelley, Florence Kondylis, Gregory Lane, Jennifer Waidler, Nidhila Adusumalli, Odbayar Batmunkh, and Kriti Malhotra. 2025. Fast Action for Floods: RCT Evidence on Forecast-based Cash Transfers from Bangladesh and Nepal. *NBER Working Paper* 34414.

Cole, Shawn, Xavier Gine, Jeremy Tobacman, R. Townsend, P. Topalova, and J. Vickery. 2013. Barriers to Household Risk Management: Evidence from India. *American Economic Journal: Applied Economics* 5:104–135.

Cole, Shawn, Xavier Giné, and James Vickery. 2017. How does risk management influence production decisions? Evidence from a field experiment. *The Review of Financial Studies* 30:1935–1970.

Davlasheridze, Meri, and Qing Miao. 2019. Does governmental assistance affect private decisions to insure? An empirical analysis of flood insurance purchases. *Land Economics* 95:124–145.

Deryugina, Tatyana, and Barrett Kirwan. 2018. Does the samaritan's dilemma matter? Evidence from U.S. agriculture. *Economic Inquiry* 56:983–1006.

Fisher, Eleanor, Jon Hellin, Helen Greatrex, and Nathaniel Jensen. 2019. Index insurance and climate risk management: Addressing social equity. *Development Policy Review* 37:581–602.

Fluhrer, Svenja, and Kati Kraehnert. 2022. Sitting in the same boat: Subjective well-being and social comparison after an extreme weather event. *Ecological Economics* 195:107388.

G20 Global Partnership for Financial Inclusion. 2015. *New trends in agricultural finance*. Antalya: G20 Global Partnership for Financial Inclusion.

German Red Cross. 2017. *Forecast-based Financing - A policy overview*. Berlin: German Red Cross.

German Red Cross, and Red Cross Red Crescent Climate Centre. 2016. *Manual for Forecast-based Financing*. Berlin: German Red Cross.

Gibson, Clark C, Krister Andersson, and Sujai Shivakumar. 2005. *The Samaritan's dilemma: the political economy of development aid*. New York, NY: Oxford University Press.

Greatrex, Helen, James Hansen, Samantha Garvin, Rahel Diro, Margot Le Guen, Sari Blakeley, Kolli Rao, and Daniel Osgood. 2015. Scaling up index insurance for smallholder farmers: Recent evidence and insights. *CCAFS Report*.

Groppo, Valeria, and Kati Kraehnert. 2016. Extreme weather events and child height: evidence from Mongolia. *World Development* 86:59–78.

---. 2017. The impact of extreme weather events on education. *Journal of Population Economics* 30:433–472.

Gros, Clemens, Meghan Bailey, Saroja Schwager, Ahmadul Hassan, Raymond Zingg, Muhammad Mamtaz Uddin, Mohammad Shahjahan, Hasibul Islam, Stefanie Lux, Catalina Jaime, and Erin Coughlan de Perez. 2019. Household-level effects of providing forecast-based cash in anticipation of extreme weather events: Quasi-experimental evidence from humanitarian interventions in the 2017 floods in Bangladesh. *International Journal of Disaster Risk Reduction* 41.

Gros, Clemens, Evan Easton-Calabria, Meghan Bailey, Kadirbyek Dagys, Erin Coughlan de Perez, Munguntuya Sharavnyambuu, and Andrew Kruczkiewicz. 2022. The effectiveness of forecast-based humanitarian assistance in anticipation of extreme winters: a case study of vulnerable herders in Mongolia. *Disasters* 46:95–118.

Hazell, Peter, and Ulrich Hess (2017) Beyond hype: Another look at index-based agricultural insurance. In P. Pingali, and G. Feder eds. *Agriculture and Rural Development in a Globalizing World.* London, Routledge, pp. 211–226.

Hill, Ruth Vargas, N. Kumar, N. Magnan, S. Makhija, F. de Nicola, D. J. Spielman, and P. S. Ward. 2019. Ex ante and ex post effects of hybrid index insurance in Bangladesh. *Journal of Development Economics* 136:1–17.

Hill, Ruth Vargas, Miguel Robles, and Francisco Ceballos. 2016. Demand for a simple weather insurance product in India: theory and evidence. *American Journal of Agricultural Economics* 98:1250–1270.

IFRC (International Federation of Red Cross and Red Crescent Societies). 2020. *World disasters report 2020: Come heat or high water*. Geneva: International Federation of Red Cross and Red Crescent Societies.

Imbens, Guido W., and Donald B. Rubin. 2015. *Causal inference in statistics, social, and biomedical sciences*. New York City: Cambridge University Press.

IRIMHE (Information and Research Institute of Meteorology, Hydrology and Environment) (2021) Immediate risk notice (as of January 10, 2021). In.

Janzen, Sarah A., and Michael R. Carter. 2019. After the Drought: The Impact of Microinsurance on Consumption Smoothing and Asset Protection. *American Journal of Agricultural Economics* 101:651–671.

Kaplow, Louis. 1991. Incentives and government relief for risk. *Journal of Risk and Uncertainty* 4:167–175.

Karlan, Dean, Robert Osei, Isaac Osei-Akoto, and Christopher Udry. 2014. Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics* 129:597–652.

Kelly, Mary, and Anne E Kleffner. 2003. Optimal loss mitigation and contract design. *Journal of Risk and Insurance* 70:53–72.

Kraehnert, Kati, Katharina Lehmann-Uschner, Valeria Groppo, Veronika Bertram-Huemmer, Svenja Fluhrer, Lukas Mogge, Julian Roeckert, and Aleksandra Wojewska. 2022. Coping with Shocks in Mongolia Household Panel Survey, Waves 1-5. Version 2.0. Potsdam Institute for Climate Impact Research,German Institute for Economic Research, and National Statistical Office of Mongolia. Last accessed.

Landry, Craig E, Dylan Turner, and Daniel Petrolia. 2021. Flood insurance market penetration and expectations of disaster assistance. *Environmental and Resource Economics* 79:357–386.

Lewis, Tracy, and David Nickerson. 1989. Self-insurance against natural disasters. *Journal of Environmental Economics and Management* 16:209–223.

Mahul, Olivier, and Charles J Stutley. 2010. *Government support to agricultural insurance: challenges and options for developing countries*. Washington: World Bank.

Matsuda, Ayako, Kazushi Takahashi, and Munenobu Ikegami. 2019. Direct and indirect impact of index-based livestock insurance in Southern Ethiopia. *The Geneva Papers on Risk and Insurance - Issues and Practice* 44:481–502.

Miglietta, Pier Paolo, Donatella Porrini, Giulio Fusco, and Fabian Capitanio. 2020. Crowding out agricultural insurance and the subsidy system in Italy: empirical evidence of the charity hazard phenomenon. *Agricultural Finance Review* 81:237–249.

Miranda, Mario J, and Katie Farrin. 2012. Index insurance for developing countries. *Applied Economic Perspectives and Policy* 34:391–427.

Mogge, Lukas, and Kati Kraehnert. 2025. Perception and protection: The effect of risk exposure on demand for index insurance in Mongolia. *Journal of Environmental Economics and Management* 130:103113.

Mogge, Lukas, Julian Roeckert, and Kati Kraehnert. 2025. Anticipatory Cash Transfers in the Context of Weather Disasters. *Journal of the Association of Environmental and Resource Economists* 12:1819–1857.

Nandintsetseg, Banzragch, Masato Shinoda, Chunling Du, and Erdenebadrakh Munkhjargal. 2018. Cold-season disasters on the Eurasian steppes: Climate-driven or man-made. *Scientific Reports* 8:1–9.

Nandintsetseg, Banzragch, Masato Shinoda, and Baasandai Erdenetsetseg. 2018. *DRR in action case study: Developing an early warning system of dzud (cold-season disaster) in Mongolia*. Ulaanbaatar: International Federation of Red Cross and Red Crescent Societies.

Ngoc Que Anh, Nguyen, Phung Thanh Binh, and Truong Dang Thuy. 2019. Willingness to pay for agricultural flood insurance in the Mekong River Delta. *Environmental Hazards* 18:212–227.

Petrolia, Daniel R, Craig E Landry, and Keith H Coble. 2013. Risk preferences, risk perceptions, and flood insurance. *Land Economics* 89:227–245.

Philippi, Tim, and Jörg Schiller. 2024. Abandoning disaster relief and stimulating insurance demand through premium subsidies. *Journal of Risk and Insurance* 91:339–382.

Pople, Ashley, Ruth Hill, Stefan Dercon, and Ben Brunckhorst. 2024. The Importance of Being Early: Anticipatory Cash Transfers for Flood-Affected Households. *CSAE Working Paper Series* 2021-07-02.

Pople, Ashley, Patrick Premand, Stefan Dercon, Margaux Vinez, and Stephanie Brunelin. 2025. The Earlier the Better? Cash Transfers for Drought Response in Niger. *World Bank Policy Research Working Paper* 11138.

Pörtner, H.O., D.C. Roberts, H. Adams, C. Adler, P. Aldunce, E. Ali, (...), and Z.Z. Ibrahim (2022) Technical Summary. In H.O. Pörtner,D.C. Roberts,E.S. Poloczanska,K. Mintenbeck,M. Tignor,A. Alegría,(...), and A. Okem eds. *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, Cambridge University Press, pp. 40–82.

Raschky, Paul A, Reimund Schwarze, Manijeh Schwindt, and Ferdinand Zahn. 2013. Uncertainty of governmental relief and the crowding out of flood insurance. *Environmental and Resource Economics* 54:179–200.

Raschky, Paul A, and Manijeh Schwindt. 2016. Aid, catastrophes and the Samaritan's dilemma. *Economica* 83:624–645.

Raschky, Paul A, and Hannelore Weck-Hannemann. 2007. Charity hazard—A real hazard to natural disaster insurance? *Environmental Hazards* 7:321–329.

Robinson, Peter John, WJ Botzen, and Fujin Zhou. 2021. An experimental study of charity hazard: The effect of risky and ambiguous government compensation on flood insurance demand. *Journal of Risk and Uncertainty*:1–44.

Roeckert, Julian, and Kati Kraehnert. 2022. Extreme Weather Events and Internal Migration: Evidence from Mongolia. *Economics of Disasters and Climate Change* 6:95–128.

Roodman, David, Morten Ørregaard Nielsen, James G. MacKinnon, and Matthew D. Webb. 2019. Fast and wild: Bootstrap inference in Stata using boottest. *The Stata Journal* 19:4–60.

Skees, Jerry R. 2008. Innovations in index insurance for the poor in lower income countries. *Agricultural and Resource Economics Review* 37:1–15.

Stoeffler, Quentin, Michael Carter, Catherine Guirkinger, and Wouter Gelade. 2022. The spillover impact of index insurance on agricultural investment by cotton farmers in Burkina Faso. *The World Bank Economic Review* 36:114–140.

Tesselaar, Max, WJ Wouter Botzen, Peter J Robinson, Jeroen CJH Aerts, and Fujin Zhou. 2022. Charity hazard and the flood insurance protection gap: An EU scale assessment under climate change. *Ecological Economics* 193:107289.

UNDP. 2025. *Socio-economic Impact Assessment of Dzud 2023-2024: Dzud Resilience Strategy Policy Recommendations*. Ulaanbaatar: UNDP Mongolia.

United Nations Resident Coordinator for Mongolia. 2023. *2023 Dzud early action & response plan: Mongolia*. Ulaanbaatar: United Nations.

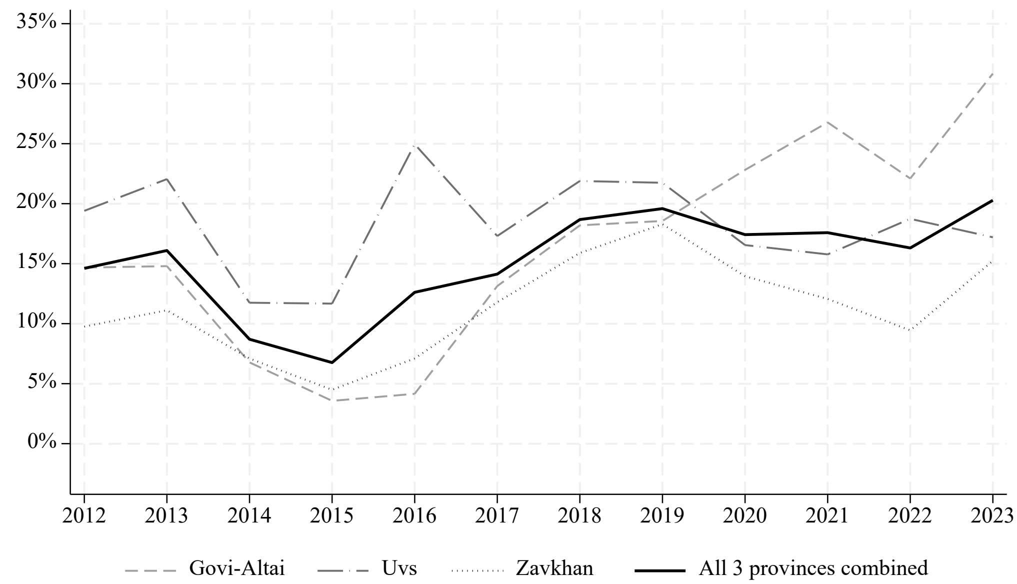
van Asseldonk, Marcel A. P. M., Miranda Huirne, P. M., and Ruud Huirne, B. M. . 2002. Belief in Disaster Relief and the Demand for a Public-Private Insurance Program. *Review of Agricultural Economics* 24:196–207.

World Bank. Mongolia - Index-Based Livestock Insurance Project. Implementation Completation and Results Report ICR00002949. The World Bank.

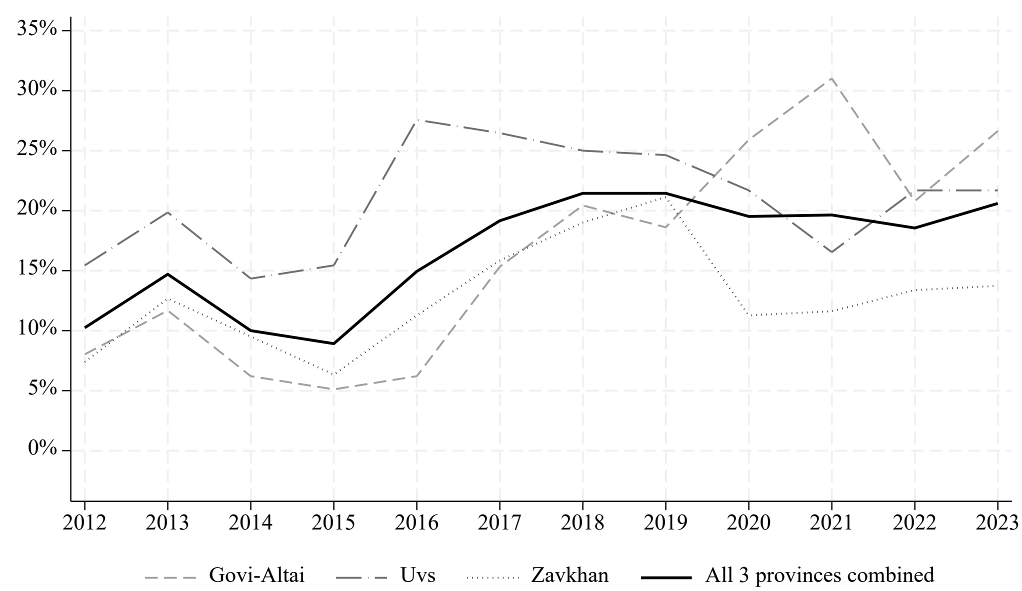
8. Appendix

Fig A1: Annual IBLI uptake rates over time in western Mongolia, by province

Panel A: Share of pastoralist households purchasing IBLI in the whole population of pastoralist households, by province

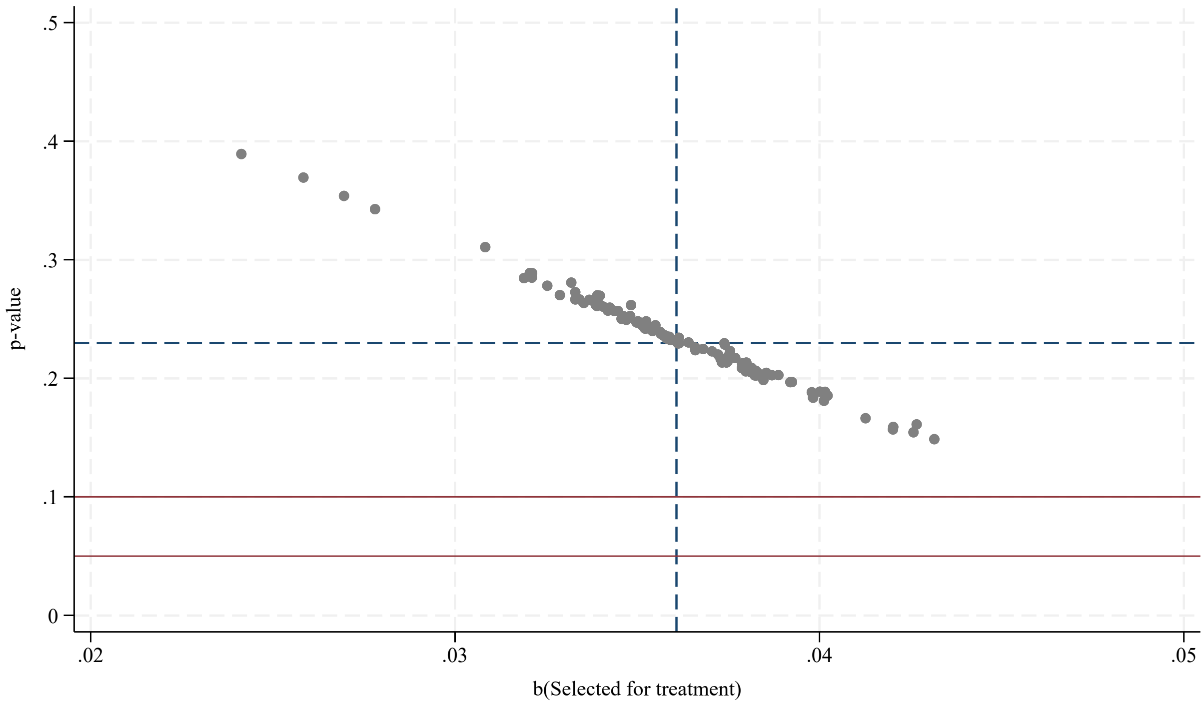


Panel B: Share of pastoralist households purchasing IBLI that are surveyed in main sample, by province



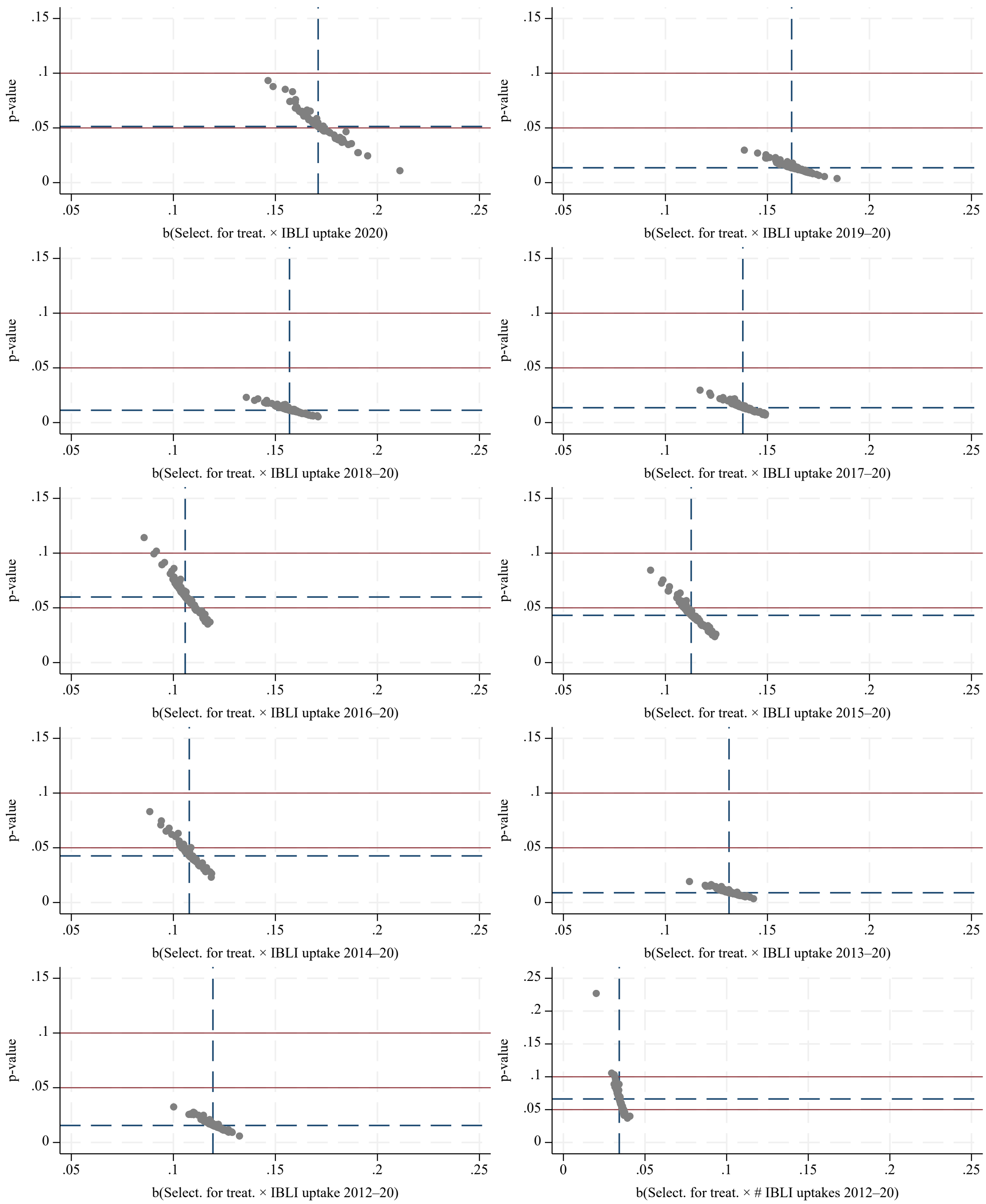
Sources: In Panel A, the number of insured and the number pastoralist households are obtained from the Mongolian Livestock Census. In Panel B, the number of insured households is obtained from the IBLI customer database and the number of sample households from the Coping with Shocks in Mongolia Household Panel Survey.

Fig A2: Leave-one-cluster-out estimates of the ITT effect



Notes: The figure reports results from a leave-one-out robustness analysis for the results displayed in Table 2, col 4. Each dot represents the estimated ITT coefficient alongside its p-value from a regression excluding one sub-district. The blue lines indicate the full-sample ITT estimate and p-value, and the red horizontal red lines indicate the 5% and 10% significance thresholds. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

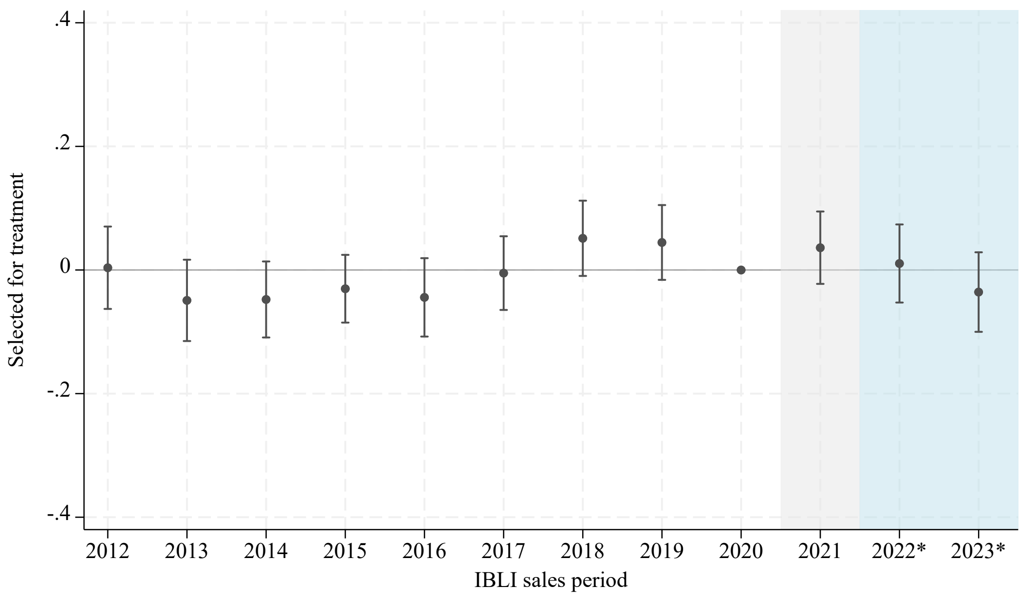
Fig A3: Leave-one-cluster-out estimates of interaction effects



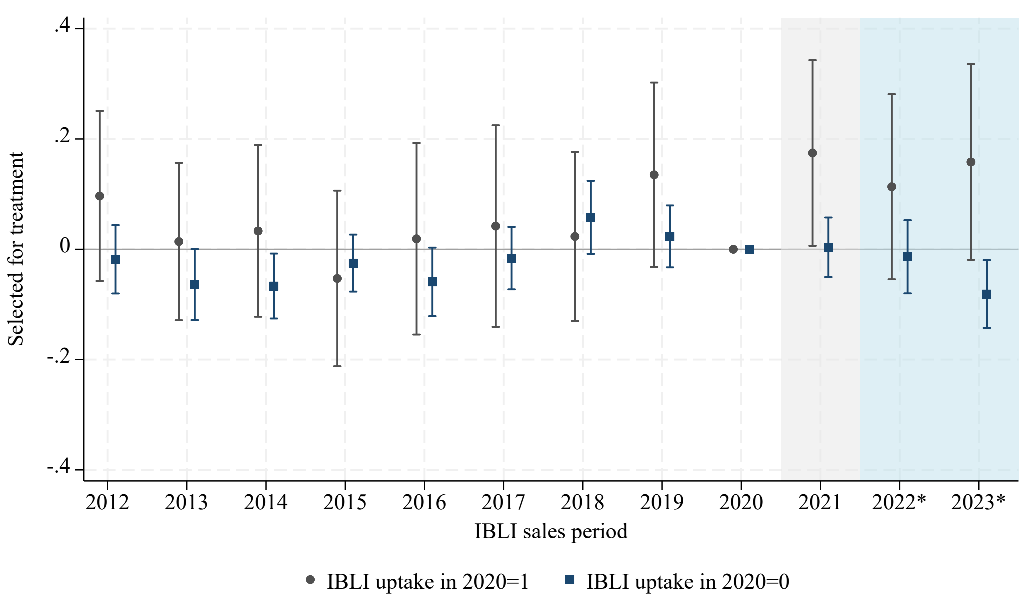
Notes: Each panel reports results from leave-one-out analyses for the results displayed in Table 3 with alternative measures of insurance experience. Each dot represents the estimated coefficient alongside its p-value for the interaction between treatment assignment and insurance experience from a regression excluding one sub-district. The blue lines indicate the full-sample ITT estimates and p-values, and the red horizontal red lines indicate the 5% and 10% significance thresholds. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Fig A4: Placebo test and persistence of treatment effect on insurance uptake over time

Panel A: Baseline specification (insurance uptake in 2020 as experience measure)



Panel B: Interaction specification (treatment × insurance uptake in 2020)



Notes: Each panel shows estimated treatment effects from separate OLS regressions, with IBLI uptake in a given sales period between 2012 and 2013 as the outcome. Bars indicate 95% CIs. Panel A reports estimates from the baseline specification with the full set of controls (Table 2, col. 4), while Panel B reports estimates from the interaction specification (Table 3, col. 1). For all years, insurance experience is measured as having purchased insurance in the 2020 sales period. Sources: Coping with Shocks in Mongolia Household Panel Survey (waves 4–5), IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Table A1: Sample

	Treatment	Control	Total
Number of households meeting the eligibility criteria, based on data available in February 2021	421 (45.5%)	504 (54.5%)	925
Number of households meeting the eligibility criteria, based on complete wave 4 data	378 (45.5%)	452 (54.5%)	830
Number of households receiving AHA cash transfers in March 2021	381 (100%)	-	381
Number of eligible households that did not purchase insurance before the treatment (sample used in analysis)	368 (45.4%)	442 (54.6%)	810
Number of sub-districts in which eligible households reside (sample used in analysis)	50 (46.3%)	58 (53.7%)	108

Source: Coping with Shocks in Mongolia Household Panel Survey.

Table A2: Correlation of IBLI uptake over time, 2012-2021

IBLI uptake in:	2021	2020	2019	2018	2017	2016	2015	2014	2013	2012
2021	1.00									
2020	0.33***	1.00								
2019	0.29***	0.45***	1.00							
2018	0.25***	0.30***	0.39***	1.00						
2017	0.19***	0.21***	0.38***	0.35***	1.00					
2016	0.15***	0.21***	0.31***	0.25***	0.35***	1.00				
2015	0.10***	0.18***	0.14***	0.19***	0.23***	0.39***	1.00			
2014	0.12***	0.10***	0.16***	0.20***	0.21***	0.29***	0.45***	1.00		
2013	0.08**	0.16***	0.19***	0.16***	0.20***	0.31***	0.39***	0.44***	1.00	
2012	0.07**	0.13***	0.21***	0.20***	0.20***	0.32***	0.32***	0.32***	0.44***	1.00

Notes: Pearson correlation coefficients. The sample consists of 810 households used in the main analysis (see Table A1); * p < 0.10, ** p < 0.05, *** p < 0.01. Sources: Coping with Shocks in Mongolia Household Panel Survey and IBLI customer database.

Table A3: IBLI uptake in 2021 and 2020, by previous year's uptake

Panel A: Uptake in 2021 conditional on uptake in 2020

	IBLI uptake in 2021 = 0	IBLI uptake in 2021 = 1	Total
IBLI uptake in 2020 = 0	88% (N=582)	12% (N=76)	100% (N=658)
IBLI uptake in 2020 = 1	56% (N=85)	44% (N=67)	100% (N=152)
Total	82% (N=667)	18% (N=143)	100% (N=810)

Panel B: Uptake in 2020 conditional on uptake in 2019

	IBLI uptake in 2020 = 0	IBLI uptake in 2020 = 1	Total
IBLI uptake in 2019 = 0	90% (N=578)	10% (N=62)	100% (N=640)
IBLI uptake in 2019 = 1	47% (N=80)	52% (N=90)	100% (N=170)
Total	81% (N=658)	19% (N=152)	100% (N=810)

Sources: Coping with Shocks in Mongolia Household Panel Survey and IBLI customer database.

Table A4: Balance tests

	Mean values, treatment group (N=368)	Mean values, control group (N=442)	P-value	Normalized difference
	(1)	(2)	(3)	(4)
Experience				
Household purchased insurance in 2020 sales period	0.20	0.18	0.58	-0.06
Number of times household purchased insurance between 2012-2020	1.43	1.36	0.74	-0.04
Household received insurance payout in August 2020	0.01	0.01	0.80	-0.02
Household received insurance payout in any year from 2013-2020	0.18	0.16	0.69	-0.05
Household characteristics				
Female head of household (0-1)	0.16	0.12	0.05**	-0.13
Age of head of household	48.96	49.77	0.39	0.07
Education of head of household: none (0-1)	0.15	0.12	0.23	-0.09
Education of head of household: primary (0-1)	0.26	0.24	0.41	-0.07
Education of head of household: above primary (0-1)	0.59	0.65	0.14	0.12
Household size	4.12	3.91	0.07*	-0.12
Household lives in province center (0-1)	0.14	0.23	0.22	0.23
Winter intensity				
Livestock mortality rate in district 2021 (%)	3.52	2.66	0.31	-0.20
Predicted risk of extreme winter conditions in district in 2021: very high (0-1)	0.18	0.22	0.38	0.08
Predicted risk of extreme winter conditions in district in 2021: high (0-1)	0.58	0.64	0.73	0.12
Predicted risk of extreme winter conditions in district in 2021: medium (0-1)	0.24	0.14	0.25	-0.24
Past risk				
Number of years in which insurance payouts were triggered in district from 2013-2020	1.76	1.68	0.53	-0.10
Mean livestock mortality rate in district from 2012-2020 (%)	1.02	0.89	0.37	-0.14
F-test of joint significance (F-stat)			2.25***	
F-test, number of observations			810	

Notes: Col. 3 displays the p-value from OLS regressions of each variable on the indicator for treatment, controlling for province fixed effects and clustering standard errors at the sub-district level. Col. 4 reports the normalized difference between the treatment and control group means; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Table A5: Effects of anticipatory cash transfers on insurance uptake with alternative definitions of insurance experience (OLS)

Dependent variable:	IBLI uptake in 2021								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Experience defined as	IBLI uptake in 2019-20	IBLI uptake in 2018-20	IBLI uptake in 2017-20	IBLI uptake in 2016-20	IBLI uptake in 2015-20	IBLI uptake in 2014-20	IBLI uptake in 2013-20	IBLI uptake in 2012-20	Number of years with IBLI uptake 2012-20
Selected for treatment	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)
Experience	0.29*** (0.03)	0.28*** (0.03)	0.26*** (0.03)	0.25*** (0.03)	0.25*** (0.03)	0.25*** (0.03)	0.24*** (0.03)	0.23*** (0.03)	0.06*** (0.01)
Constant	0.06 (0.05)	0.03 (0.05)	0.01 (0.05)	0.00 (0.06)	0.00 (0.06)	-0.01 (0.06)	-0.02 (0.06)	-0.03 (0.06)	0.03 (0.06)
Controls and province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.18	0.18	0.17	0.17	0.17	0.17	0.16	0.16	0.16
Observations	810	810	810	810	810	810	810	810	810
95% CI: select. for treat.	[-0.03, 0.09]	[-0.03, 0.08]	[-0.03, 0.09]	[-0.02, 0.10]	[-0.02, 0.10]	[-0.02, 0.10]	[-0.02, 0.11]	[-0.02, 0.10]	[-0.02, 0.10]
Share of experienced households	0.29	0.36	0.41	0.44	0.45	0.48	0.50	0.52	

Notes: Effects from OLS regressions with standard errors clustered at the sub-district level and reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Table A6: Effects of anticipatory cash transfers on insurance uptake with wild cluster bootstrap p-values and confidence intervals (OLS)

Dependent variable:	IBLI uptake in 2021										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Experience defined as	IBLI uptake in 2020		IBLI uptake in 2019-20	IBLI uptake in 2018-20	IBLI uptake in 2017-20	IBLI uptake in 2016-20	IBLI uptake in 2015-20	IBLI uptake in 2014-20	IBLI uptake in 2013-20	IBLI uptake in 2012-20	Number of years with IBLI uptake 2012-20
Selected for treatment	0.04 (0.03)	0.00 (0.03)	-0.02 (0.03)	-0.03 (0.02)	-0.03 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.02 (0.02)	-0.02 (0.03)	-0.01 (0.03)
Experience	0.29*** (0.04)	0.21*** (0.06)	0.21*** (0.04)	0.20*** (0.04)	0.19*** (0.03)	0.21*** (0.04)	0.20*** (0.03)	0.20*** (0.03)	0.18*** (0.03)	0.18*** (0.03)	0.05*** (0.01)
Selected for treatment × experience		0.17* (0.09)	0.16** (0.06)	0.16** (0.06)	0.14** (0.05)	0.11* (0.06)	0.11** (0.06)	0.11** (0.05)	0.13*** (0.05)	0.12** (0.05)	0.03* (0.02)
Constant	0.09 (0.05)	0.10* (0.05)	0.08 (0.05)	0.05 (0.05)	0.03 (0.05)	0.02 (0.05)	0.02 (0.06)	0.01 (0.06)	0.00 (0.06)	-0.01 (0.06)	0.05 (0.06)
Controls and province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.16	0.17	0.19	0.19	0.18	0.18	0.18	0.18	0.17	0.16	0.17
Observations	810	810	810	810	810	810	810	810	810	810	810
WCB p-value: selected for treatment	0.24	0.89	0.52	0.21	0.31	0.68	0.56	0.64	0.41	0.38	0.80
WCB 95% CI: selected for treatment	[-0.02, 0.10]	[-0.05, 0.06]	[-0.07, 0.04]	[-0.08, 0.02]	[-0.07, 0.02]	[-0.06, 0.04]	[-0.06, 0.04]	[-0.06, 0.04]	[-0.07, 0.03]	[-0.08, 0.03]	[-0.06, 0.05]
WCB p-value: selected for treatment × experience		0.06	0.02	0.01	0.02	0.07	0.05	0.04	0.01	0.02	0.10
WCB 95% CI: selected for treatment × experience		[-0.01, 0.35]	[0.03, 0.29]	[0.03, 0.28]	[0.02, 0.25]	[-0.01, 0.22]	[0.00, 0.22]	[0.00, 0.21]	[0.03, 0.23]	[0.02, 0.22]	[-0.01, 0.08]

Notes: Effects from OLS regressions with standard errors clustered at the sub-district level and reported in parentheses. The last four lines report wild cluster bootstrap p-values and CIs; * p < 0.1, ** p < 0.05, *** p < 0.01. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Table A7: Effects of anticipatory cash transfers on insurance uptake with additional controls for previous IBLI uptake (OLS)

Dependent variable:	IBLI uptake in 2021					
	(1)	(2)	(3)	(4)	(5)	(6)
Selected for treatment	0.03 (0.03)	-0.00 (0.03)	0.02 (0.03)	-0.01 (0.03)	0.03 (0.03)	0.00 (0.03)
IBLI uptake in 2020	0.21*** (0.05)	0.14** (0.06)	0.20*** (0.05)	0.12* (0.06)	0.19*** (0.05)	0.12* (0.06)
Selected for treatment × IBLI uptake in 2020		0.15* (0.09)		0.16* (0.09)		0.15* (0.09)
IBLI uptake in 2019	0.17*** (0.05)	0.17*** (0.04)	0.14*** (0.05)	0.13*** (0.05)	0.12** (0.05)	0.11** (0.05)
IBLI uptake in 2018			0.12** (0.04)	0.12*** (0.04)	0.09** (0.05)	0.10** (0.05)
IBLI uptake in 2017					0.05 (0.05)	0.05 (0.05)
IBLI uptake in 2016					0.06 (0.05)	0.06 (0.05)
IBLI uptake in 2015					0.01 (0.06)	0.02 (0.06)
IBLI uptake in 2014					0.08 (0.05)	0.08 (0.05)
IBLI uptake in 2013					-0.03 (0.05)	-0.04 (0.05)
IBLI uptake in 2012					-0.04 (0.05)	-0.04 (0.05)
Constant	0.08 (0.05)	0.09* (0.05)	0.06 (0.05)	0.07 (0.05)	0.04 (0.06)	0.06 (0.05)
Controls and province FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.18	0.19	0.20	0.20	0.21	0.21
Observations	810	810	810	810	810	810
95% CI: selected for treatment	[-0.03, 0.09]	[-0.05, 0.05]	[-0.03, 0.08]	[-0.06, 0.04]	[-0.02, 0.09]	[-0.05, 0.05]
95% CI: selected for treatment × IBLI uptake in 2020		[-0.02, 0.33]		[-0.01, 0.33]		[-0.02, 0.33]
Selected for treatment if IBLI uptake in 2020=1		0.15* (0.09)		0.15* (0.09)		0.16* (0.09)
95% CI: select. for treat. if IBLI uptake in 2020=1		[-0.02, 0.33]		[-0.02, 0.33]		[-0.02, 0.33]

Notes: Effects from OLS regressions with standard errors clustered at the sub-district level and reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Table A8: The effects of cash transfers on insurance uptake in 2021, including households that purchased insurance after pre-treatment survey (OLS)

Dependent variable:	IBLI uptake in 2021										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Experience defined as	IBLI uptake in 2020		IBLI uptake in 2019-20	IBLI uptake in 2018-20	IBLI uptake in 2017-20	IBLI uptake in 2016-20	IBLI uptake in 2015-20	IBLI uptake in 2014-20	IBLI uptake in 2013-20	IBLI uptake in 2012-20	Number of years with IBLI uptake 2012-20
Selected for treatment	0.04 (0.03)	0.00 (0.03)	-0.02 (0.03)	-0.03 (0.02)	-0.03 (0.02)	-0.01 (0.02)	-0.02 (0.02)	-0.01 (0.02)	-0.02 (0.02)	-0.02 (0.03)	-0.00 (0.03)
Experience	0.30*** (0.05)	0.21*** (0.06)	0.21*** (0.05)	0.21*** (0.04)	0.19*** (0.03)	0.21*** (0.04)	0.20*** (0.04)	0.21*** (0.03)	0.19*** (0.03)	0.18*** (0.03)	0.05*** (0.01)
Selected for treatment × experience		0.18** (0.09)	0.17** (0.07)	0.15** (0.06)	0.14** (0.06)	0.11* (0.06)	0.12** (0.06)	0.11* (0.06)	0.13** (0.05)	0.12** (0.05)	0.03* (0.02)
Constant	0.08 (0.06)	0.10* (0.06)	0.08 (0.05)	0.05 (0.06)	0.03 (0.06)	0.02 (0.06)	0.02 (0.06)	0.00 (0.06)	-0.00 (0.06)	-0.01 (0.06)	0.05 (0.06)
Controls and province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.16	0.17	0.19	0.20	0.19	0.18	0.18	0.18	0.18	0.17	0.18
Observations	818	818	818	818	818	818	818	818	818	818	818
95% CI: select. for treat.	[-0.02,0.10]	[-0.05,0.06]	[-0.07,0.04]	[-0.08,0.02]	[-0.08,0.02]	[-0.06,0.04]	[-0.06,0.03]	[-0.05,0.04]	[-0.07,0.03]	[-0.07,0.03]	[-0.06,0.05]
95% CI: select. for treat. × experience		[0.00,0.36]	[0.03,0.30]	[0.02,0.28]	[0.03,0.26]	[-0.00,0.23]	[0.00,0.23]	[-0.00,0.22]	[0.03,0.23]	[0.02,0.22]	[-0.00,0.07]
Selected for treatment if experience=1		0.18** (0.09)	0.15** (0.07)	0.12** (0.06)	0.12** (0.06)	0.10* (0.06)	0.10* (0.06)	0.10* (0.06)	0.11** (0.05)	0.10* (0.05)	
95% CI: select. for treat. if experience=1		[0.00,0.36]	[0.02,0.28]	[0.00,0.25]	[0.00,0.23]	[-0.01,0.21]	[-0.01,0.22]	[-0.01,0.21]	[0.01,0.21]	[-0.00,0.20]	

Notes: Effects from OLS regressions with standard errors clustered at the sub-district level and reported in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Table A9: The effects of cash transfers on insurance uptake in 2021 among all households meeting the eligibility criteria, based on complete wave 4 data (OLS)

Dependent variable:	IBLI uptake in 2021										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Experience defined as	IBLI uptake in 2020		IBLI uptake in 2019-20	IBLI uptake in 2018-20	IBLI uptake in 2017-20	IBLI uptake in 2016-20	IBLI uptake in 2015-20	IBLI uptake in 2014-20	IBLI uptake in 2013-20	IBLI uptake in 2012-20	Number of years with IBLI uptake 2012-20
Selected for treatment	0.04 (0.03)	0.00 (0.03)	-0.02 (0.03)	-0.03 (0.03)	-0.03 (0.03)	-0.01 (0.03)	-0.02 (0.03)	-0.01 (0.03)	-0.02 (0.03)	-0.02 (0.03)	-0.01 (0.03)
Experience	0.31*** (0.05)	0.23*** (0.06)	0.23*** (0.04)	0.23*** (0.04)	0.21*** (0.04)	0.22*** (0.04)	0.22*** (0.04)	0.22*** (0.04)	0.20*** (0.04)	0.20*** (0.04)	0.05*** (0.02)
Selected for treatment × experience		0.16* (0.09)	0.16** (0.07)	0.14** (0.06)	0.14** (0.06)	0.11* (0.06)	0.11** (0.06)	0.10* (0.06)	0.13** (0.05)	0.11** (0.05)	0.03 (0.02)
Constant	0.09 (0.06)	0.11* (0.06)	0.08 (0.06)	0.06 (0.06)	0.04 (0.06)	0.02 (0.06)	0.02 (0.06)	0.01 (0.06)	0.00 (0.06)	-0.01 (0.07)	0.05 (0.06)
Controls and province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.17	0.17	0.20	0.20	0.19	0.19	0.19	0.19	0.18	0.17	0.18
Observations	830	830	830	830	830	830	830	830	830	830	830
95% CI: select. for treat.	[-0.03,0.10]	[-0.05,0.06]	[-0.07,0.04]	[-0.08,0.02]	[-0.08,0.02]	[-0.07,0.04]	[-0.07,0.03]	[-0.06,0.04]	[-0.07,0.03]	[-0.08,0.03]	[-0.06,0.05]
95% CI: select. for treat. × experience		[-0.02,0.34]	[0.02,0.29]	[0.02,0.27]	[0.02,0.25]	[-0.01,0.22]	[0.00,0.23]	[-0.01,0.21]	[0.02,0.23]	[0.01,0.22]	[-0.01,0.07]
Selected for treatment if experience=1		0.16* (0.09)	0.14** (0.06)	0.12* (0.06)	0.11* (0.06)	0.09 (0.06)	0.10* (0.06)	0.09* (0.05)	0.11** (0.05)	0.09* (0.05)	
95% CI: select. for treat. if experience=1		[-0.01,0.34]	[0.01,0.26]	[-0.01,0.24]	[-0.00,0.22]	[-0.02,0.21]	[-0.01,0.21]	[-0.02,0.20]	[0.00,0.21]	[-0.01,0.19]	

Notes: Effects from OLS regressions with standard errors clustered at the sub-district level and reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).

Table A10: The effects of cash transfers on insurance uptake in 2021, excluding households that are not participating in wave 5 or that are not herders in wave 5 of Coping with Shocks in Mongolia Household Panel Survey (OLS)

Dependent variable:	IBLI uptake in 2021										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Experience defined as	IBLI uptake in 2020		IBLI uptake in 2019-20	IBLI uptake in 2018-20	IBLI uptake in 2017-20	IBLI uptake in 2016-20	IBLI uptake in 2015-20	IBLI uptake in 2014-20	IBLI uptake in 2013-20	IBLI uptake in 2012-20	Number of years with IBLI uptake 2012-20
Selected for treatment	0.03 (0.03)	0.00 (0.03)	-0.02 (0.03)	-0.03 (0.03)	-0.03 (0.03)	-0.01 (0.03)	-0.02 (0.03)	-0.01 (0.02)	-0.02 (0.03)	-0.03 (0.03)	-0.01 (0.03)
Experience	0.27*** (0.05)	0.20*** (0.06)	0.19*** (0.05)	0.19*** (0.04)	0.18*** (0.04)	0.19*** (0.04)	0.19*** (0.04)	0.19*** (0.03)	0.17*** (0.03)	0.16*** (0.03)	0.04*** (0.01)
Selected for treatment × experience		0.15* (0.09)	0.16** (0.07)	0.15** (0.06)	0.13** (0.06)	0.10* (0.06)	0.11* (0.06)	0.10* (0.05)	0.13** (0.05)	0.12** (0.05)	0.03* (0.02)
Constant	0.09 (0.06)	0.10* (0.06)	0.08 (0.05)	0.05 (0.06)	0.04 (0.06)	0.03 (0.06)	0.03 (0.06)	0.01 (0.06)	0.01 (0.06)	0.01 (0.06)	0.05 (0.06)
Controls and province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.15	0.16	0.18	0.19	0.18	0.17	0.17	0.17	0.17	0.16	0.17
Observations	758	758	758	758	758	758	758	758	758	758	758
95% CI: select. for treat.	[-0.03,0.10]	[-0.05,0.06]	[-0.07,0.04]	[-0.09,0.02]	[-0.08,0.02]	[-0.06,0.04]	[-0.07,0.03]	[-0.06,0.04]	[-0.08,0.03]	[-0.08,0.03]	[-0.06,0.05]
95% CI: select. for treat. × experience		[-0.02,0.33]	[0.03,0.29]	[0.03,0.27]	[0.02,0.24]	[-0.01,0.21]	[-0.00,0.22]	[-0.00,0.21]	[0.03,0.23]	[0.02,0.22]	[-0.00,0.07]
Selected for treatment if experience=1		0.16* (0.09)	0.14** (0.06)	0.12** (0.06)	0.10* (0.06)	0.09 (0.06)	0.09* (0.05)	0.09* (0.05)	0.10** (0.05)	0.09* (0.05)	
95% CI: select. for treat. if experience=1		[-0.02,0.33]	[0.01,0.27]	[0.00,0.24]	[-0.01,0.21]	[-0.02,0.20]	[-0.02,0.20]	[-0.02,0.20]	[0.01,0.20]	[-0.00,0.19]	

Notes: Effects from OLS regressions with standard errors clustered at the sub-district level and reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sources: Coping with Shocks in Mongolia Household Panel Survey, IBLI customer database, Mongolia Livestock Census, and IRIMHE (2021).