

When Do Realised Losses Become Subjective Economic Insecurity? Evidence from Cyclone Ana in Malawi

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Abstract

Economic insecurity is measured either objectively, from realised adverse events, or subjectively, from perceptions of downside risk. I study the relationship between the two using Tropical Cyclone Ana, which struck southern Malawi in January 2022, as a plausibly exogenous shock to realised losses. Combining the Malawi High-Frequency Phone Survey with district-level records of pre-cyclone humanitarian activity, I find that households in severely affected districts were 12 to 15 percentage points more likely to report a farm income loss, while business and total income moved little. Farm losses predict worse current financial assessments and greater perceived climate risk, whereas business losses predict expected future deterioration. Exposure alone predicts none of these. Pre-cyclone humanitarian capacity does not reduce losses, but it weakens the association between realised losses and expected deterioration by 7 to 9 percentage points.

JEL codes: Q54, O12, I38, C23

1. Introduction

Low-income households do not experience climate change only as a gradual rise in average temperatures. They experience it as a cyclone that arrives in the middle of the growing season, destroys the harvest, and leaves them unsure whether they will recover. How well the institutions of a low-income country protect its people against such shocks has become a central question of development policy, since extreme weather is among the main forces pushing vulnerable households into poverty and holding them there (Hallegatte and Rozenberg, 2017; Dang et al., 2024), and uninsured risk is itself a mechanism of poverty. Households that face downside risk without insurance smooth income rather than consumption, choosing safer crops and activities with lower average returns, so that the threat of loss depresses incomes before any loss occurs (Morduch, 1995).

Designing protection against this kind of risk requires measuring the welfare cost of exposure to it. This is the agenda of the economic insecurity literature, which the Stiglitz–Sen–Fitoussi Commission placed on the measurement-of-progress agenda alongside income and material deprivation (Stiglitz et al., 2009). In the literature economic insecurity is measured in two ways, objectively, from the size and probability of adverse economic events such as income loss and unemployment risk, and subjectively, from individuals' own perceptions of downside risk and expectations of financial deterioration. The two are usually treated as alternative measurement strategies for the same underlying concept (Rohde and Tang, 2018; Osberg, 2018). Nearly all work on economic insecurity concerns high-income countries. Prieto (2022) brought this research agenda to a middle-income country, building a multidimensional insecurity index for Chile. For low-income countries where formal insurance and safety nets are less common, studying economic insecurity becomes central.

This paper studies how a major climate shock becomes economic insecurity in a low-income setting. Malawi is an instructive setting in which to study what existing protection achieves in terms of economic insecurity mitigation, because (i) livelihoods depend overwhelmingly on rain-fed agriculture; (ii) cyclone

exposure is recent and rising, as storms that once spent themselves on the Mozambican coast increasingly reach inland districts (Bhatia et al., 2022; Kunze, 2021). Therefore, I ask two questions. When an observed adverse event such as an income loss occurs, does it translate into subjective economic insecurity? And does available humanitarian aid at the district level weaken this translation?

I follow Bossert and D'Ambrosio (2013) in defining economic insecurity as “the anxiety produced by the possible exposure to adverse events and by the anticipation of the difficulty to recover from them.” Because it captures past, present, and future dimensions of welfare at once, economic insecurity has been linked to outcomes well beyond income, including voting behaviour, fertility and marriage decisions, and mental health (Rohde et al., 2016; Clark, D'Ambrosio and Lepinteur, 2023; Clark and Lepinteur, 2022; Bossert et al., 2023).

Answering these questions requires variation in realised adverse events that is not driven by how people already feel about their finances, and a way of relating that variation to subjective assessments. Cyclone Ana provides the first, an exogenous shock. For the second, I follow Clark and D'Ambrosio (2018), who show that current and future life evaluations do not respond to the same objective resource gaps in the same way. I bring that logic to disaster economics by relating a household's own realised income loss to its subjective economic insecurity, split into a current and a forward-looking assessment, and asking whether pre-Ana humanitarian aid capacity moderates the two differently.

I combine the Malawi High-Frequency Phone Survey with UN and UNICEF situation reports identifying the districts most affected by Cyclone Ana, and with district-level records of humanitarian, social-protection, food-security, and disaster-preparedness aid activity from the International Aid Transparency Initiative and the Humanitarian Data Exchange. For objective economic insecurity, measured through reported total income losses and their farm and business components, I use a difference-in-differences design comparing individuals in severely affected districts with those elsewhere, before and after the cyclone. Subjective economic insecurity was collected only once, in the round after the cyclone, so no pre-period exists for a second such design. Instead, I relate the objective losses to what individuals report about their financial situation and expectations four months after the cyclone, and test whether pre-cyclone capacity changes that relationship. The second part of the paper is therefore associational, a limitation imposed by the data.

There are three main findings. First, individuals in districts affected by Cyclone Ana were 12–15 percentage points more likely to report a farming income loss after the shock, an approximate 28–36% increase over the pre-shock mean. Business and total income show no comparable change. The shock reached households mainly through agriculture, the income source most directly tied to the weather.

Second, farm income losses are the objective channel most closely tied to subjective insecurity. Households which report a farm income loss are 11 percentage points more likely to say their finances are worse than a year ago and to view extreme weather as a threat to their finances, after accounting for a wide set of pre-cyclone characteristics. However, living in an affected district alone, without

conditioning on the loss, does not predict subjective economic insecurity measured either by the current or future perceptions.

Third, pre-cyclone humanitarian and resilience capacity does not prevent the initial farm income loss. Districts with more pre-Ana aid activity were no less likely to see farm incomes fall. Capacity matters further down the chain, where among households reporting a loss, those in districts with more pre-Ana humanitarian aid activity are less likely to expect their finances to keep worsening over the following year, by 7 to 9 percentage points.

This paper makes three contributions. First, it connects the objective and subjective sides of the economic insecurity literature by framing the analysis explicitly as a contrast between realised and perceived outcomes, rather than treating the two as independent strands of the concept (Rohde and Tang, 2018). Existing work shows that climate shocks affect food security, mental health, and income (Li et al., 2024, Kunze, 2021; Diwakar and Lacroix, 2021; Dasgupta and Robinson, 2022), and survey-based work documents economic sentiment in the region (Wollburg et al., 2023). However, the link between a household's realised loss and its perceived financial security is less commonly drawn, and rarer still is asking whether that link differs between a current and a forward-looking assessment. Second, it extends the economic insecurity literature from the rich countries where it was developed, and the middle-income setting where Prieto (2022) applied it, to a low-income country and provides micro-level causal evidence on a tropical cyclone in a landlocked setting covered by far fewer household-level studies than coastal ones. Third, it measures pre-shock humanitarian and resilience capacity from administrative records of aid activity. Measuring the available safety nets independently of who reports having benefited from them is what allows me to ask whether the aid infrastructure in place before the cyclone, on its own, changes how objective losses are perceived.

Section 2 sets out how economic insecurity is measured. Section 3 introduces the data and empirical strategy. Section 4 presents the results, Section 5 reports robustness checks, and Section 6 concludes.

2. Measuring Economic Insecurity: Objective and Subjective Survey Measures

Economic insecurity has been defined and measured in different ways, both theoretically and empirically (Rohde and Tang, 2018; Osberg, 2018). Hacker et al. (2014) define an individual as economically insecure when income falls by at least 25%. Bossert et al. (2023) build a multiyear, loss-weighted sum of past income changes to capture persistent income instability, and other works define insecurity through an inadequate wealth buffer (Bossert and D'Ambrosio, 2013) or through subjective concerns such as the fear of becoming unemployed (Greenhalgh and Rosenblatt, 1984). What most of these measures share is a forward-looking concept, one that deals with expectations that are unobservable, subjective, and idiosyncratic by nature (Rohde and Tang, 2018). That concept is captured in one of two ways, through realised outcomes such as income, wealth, and employment losses, or through survey questions that elicit individuals' own perceptions of their economic well-being.

This paper uses both realised income losses and individuals' perceptions of their finances, and explores the relationship between these two ways of measuring economic insecurity. The objective measure relies on the survey question, "Since this month, has income (total/farming/business) increased (1), stayed the same (2), or decreased (3)?", which I recode into a dummy equal to 1 if income decreased and 0 otherwise. This question is in the spirit of the economic insecurity measure of Hacker et al. (2014) and is treated as the objective side of economic insecurity, since it reflects a realised loss experienced by the head of the household. Prieto (2022) likewise uses a similar question to capture objective economic insecurity, asking about unexpected losses in household income during the last 12 months.

The subjective side is captured through three questions on financial perceptions and expectations. The respondent is again the household head, so the objective and subjective measures refer to the same household throughout. The first asks, "Would you say that you and your household are financially better off (1), the same (2) or worse off than you were a year ago (3)?", recoded into a dummy equal to 1 if the household reports being worse off. The second asks the same comparison looking ahead one year, recoded in the same way. Espinosa et al. (2014) use closely related questions on households' subjective financial position, in Mexico and Chile, precisely as measures of economic insecurity. This motivates their use here, since each is tied to a financial change or expectation. The third asks how likely it is that extreme weather events such as drought, delayed rains, floods, heatwaves, will negatively affect the household financially during the next 12 months, on a five-point scale from extremely likely (1) to extremely unlikely (5). This question captures forward-looking insecurity tied directly to the hazard under study. I recode it into a dummy for the two most likely categories and, as a stricter version, a dummy for the single extreme category. Respondents who see extreme weather as a likely threat are also asked which type of event they have in mind, which I use descriptively.

3. Data and Empirical Strategy

3.1 Data

I use the High-Frequency Phone Survey (HFPS) (Malawi National Statistical Office, 2020), a follow-up of the Integrated Household Panel Survey (IHPS) collected during the COVID-19 pandemic. The IHPS is a nationally representative household panel run by the Malawian National Statistical Office since 2010, sampled with probability proportional to population size across enumeration areas. Of the 3,178 households in the 2019 wave, 2,337 (73%) provided a phone number; 1,729 of these (74%) completed the HFPS baseline interview and formed the sample followed in subsequent rounds. The HFPS covers urban and rural areas and collects information on household composition, education, income volatility, food security, and mental health. It ran from 2020 to 2024 over 21 rounds with the first 12 collected monthly, the remaining nine every three months.

I use HFPS rounds 7, 9, and 11 as the pre-Cyclone Ana period and rounds 13 and 14 as the post-shock period. Round selection reflects the availability of outcome variables, as some measures drop out in intermediate rounds while others appear only later (Fig. 1). Round 7 (January–February 2021) anchors

the pre-period, isolating the sample from earlier cyclones and establishing a clean baseline for post-Ana comparisons. Table 1 shows the number of individuals interviewed in each round. To check whether attrition could bias the results, I test for systematic differences in dropout between rounds by shock exposure (Table A1) and find no differences significant at the 5% level.

Table 1
Survey Rounds: Dates, Households Interviewed, and Share of Sample

Round	Dates	Households	Share of pooled selected-round observations (%)
<i>Pre-shock rounds</i>			
7	January 20 – February 6, 2021	1,555	20.9
9	April 7 – April 23, 2021	1,537	20.6
11	May 26 – June 9, 2021	1,532	20.5
<i>Post-shock rounds</i>			
13	February 3 – February 20, 2022	1,430	19.2
14	May 8 – May 28, 2022	1,403	18.8
Notes: Malawi High-Frequency Phone Survey. Cyclone Ana made landfall on 24 January 2022, between rounds 11 and 13.			

The subjective outcomes were collected only in round 14, so this part of the analysis uses a cross-section of the 1,403 respondents interviewed in that round. Item non-response leaves 1,401 observations for the current-assessment question, 1,244 for the forward-looking question and 1,377 for the weather-risk question. The controls are drawn from earlier rounds and requiring them to be observed leaves the estimation sample smaller than the total individuals interviewed. The retained sample is less rural and more educated than the excluded sample but is similar in age, household size, employment and female headship (Table A2). The two groups do not differ in cyclone exposure, and exposure does not predict retention.

Table 2 reports descriptive statistics by affected status for rounds 11 and 13, with two-sample t-tests of equality of means within each round. In round 11, before the shock, affected households already have less education and are substantially more likely to work in agriculture and to be employed, while farming and business income loss, age, gender of the household head, and household size do not differ significantly. In round 13, after the shock, affected households report significantly higher farming income losses and a higher share of female-headed households. Affected households therefore differ from non-affected households on several socioeconomic dimensions before the shock which are handled by using a difference-in-differences design.

Table 2
Mean Differences by Affected Status and Survey Round

<i>Panel A: Round 11 (pre-cyclone)</i>	Not affected	Affected	t-test
Farming income loss	0.419	0.373	1.28
Business income loss	0.406	0.440	-0.70
Age	43.29	42.02	1.50
Female head (no spouse)	0.187	0.201	-0.61
Education	1.128	0.712	5.81***
Household size	5.08	5.03	0.33
Rural	0.539	0.934	-14.26***
Agriculture	0.214	0.382	-6.45***
Employment	0.829	0.897	-3.05***
<i>Panel B: Round 13 (post-cyclone)</i>			
Farming income loss	0.584	0.714	-3.31***
Business income loss	0.602	0.653	-1.03
Age	43.40	42.91	0.57
Female head (no spouse)	0.168	0.216	-1.97**
Education	1.160	0.742	5.52***
Household size	5.59	5.71	-0.80
Rural	0.532	0.931	-13.77***
Agriculture	0.210	0.351	-5.25***
Employment	0.872	0.893	-1.02
Notes: Entries are group means by affected status within each survey round. The final column reports t-statistics from two-sample t-tests of equality of means. *** p < 0.01, ** p < 0.05, * p < 0.10.			

3.2 Pre-Ana humanitarian and resilience capacity

I complement the survey data with district-level records of aid activity from the International Aid Transparency Initiative (IATI) and the Humanitarian Data Exchange (HDX), restricted to activities classified as humanitarian, social protection, food security, disaster preparedness, resilience, or climate adaptation. From these records I build three district-level measures of capacity in place before Cyclone Ana, (1) the stock of such activities active when the cyclone struck; (2) the number of project-months of

such activity over the five years before Ana; and (3) the number of project-months over the full pre-Ana period for which records exist. All three enter the analysis in logs, as $\ln(1 + x)$, and are centred at their sample mean when used in interactions.

3.3 Exposure to the cyclone

Defining exposure to a climate shock such as Cyclone Ana is not straightforward, as impacts vary within administrative units and reach households through direct damage as well as disruption of markets, infrastructure, and services. The HFPS does not provide geolocated household coordinates, which limits the analysis to districts instead of more granular measures of proximity or intensity.

I classify individuals as treated if they reside in districts that UNICEF or the UN situation reports list as severely affected, or with more than 40,000 people affected (Malawi Tropical Storm Ana Flash Appeal, 2022; Tropical Storm Ana Situation Report, 2022). This definition yields an intent-to-treat comparison of individuals in severely affected districts with those elsewhere, regardless of whether a given household was directly damaged. The treated districts are Dedza, Mangochi, Machinga, Chiradzulu, Mulanje, Phalombe, Chikwawa, Nsanje, and Balaka. I use alternative thresholds (10,000 and 120,000 affected people) and a continuous treatment measure in robustness checks.

3.4 Identification strategy

Cyclone Ana provides quasi-random spatial variation in exposure across Malawian districts: its timing and path were not determined by household characteristics, which allows a credible comparison between individuals in more and less affected areas. I use two strategies, one for each layer of the analysis: a difference-in-differences design for objective economic insecurity, and an associational specification, moderated by pre-Ana capacity, for subjective economic insecurity.

3.4.1 Objective economic insecurity

I estimate the causal effect of Cyclone Ana on objective economic insecurity with an event-study difference-in-differences design, treating the cyclone as a stochastic exogenous shock (de Chaisemartin and d'Haultfoeuille, 2026):

$$Y_{it} = \alpha_i + \gamma_t + \sum_{r \neq 11} \beta_r (Affected_i \times 1\{Round_t = r\}) + \theta' X_{it} + \varepsilon_{it} \quad (1)$$

where Y is farm, business, or total income loss, α are individual fixed effects, γ are survey-round fixed effects, and X is a vector of time-varying controls (household size, employment history). Round 11, the last pre-Ana round, is the omitted reference period, so each β gives the gap between affected and unaffected individuals in round r relative to that baseline; the coefficient reported as “Effect of exposure” is the round-13 interaction, the first post-Ana interview. In specifications without individual fixed effects, the controls are education, age, region, a rural dummy, working in agriculture, and gender. I cluster standard errors at the district level, the unit of treatment assignment (Bertrand et al., 2004), computed with HC2 and the Bell and McCaffrey (2002) degrees-of-freedom adjustment given the low number of

clusters (31 districts). I estimate the model without survey weights, with weights from the last survey round (which adjust for attrition), and with inverse probability weights that adjust for observable confounders.

3.4.2 Subjective economic insecurity

For subjective economic insecurity I do not build a second causal design: round 14 is the only round in which these questions were collected, so there is no pre-shock baseline. Instead, I use the round-13 income-loss measures as regressors and estimate, separately for each subjective outcome S of individual i in district d :

$$S_{id} = \delta Loss_{id} + \lambda Capacity_d + \rho(Loss_{id} \times Capacity_d) + \varphi'X_i + \eta_r + u_{id} \quad (2)$$

where $Loss$ is the farm income loss dummy, the business income loss dummy, or a count of the two (0, 1, or 2); $Capacity$ is one of the three district-level pre-Ana capacity measures; η are region fixed effects; and X is a fixed, pre-specified set of pre-cyclone covariates (gender and education of the household head, household size, mental health, food security, past employment variation, credit access from the last pre-shock survey round available). I estimate linear probability models with district-clustered HC2 standard errors and the Bell–McCaffrey adjustment, matching the inference used for objective insecurity. I also estimate the same specification with cyclone exposure in place of the loss and without the capacity interaction, to describe how exposure alone relates to these outcomes.

I read δ and ρ as evidence on how the shock is transmitted from realised losses to perceptions, not as causal estimates of Cyclone Ana's effect on subjective insecurity. Reporting an income loss is not randomly assigned as it reflects, among other things, whether a household has a given income source and how that source was affected by the season more broadly. These regressions show which losses move together with worse financial perceptions, and whether that co-movement is weaker where pre-shock capacity was higher. They do not isolate the loss as a cause of the perception in the way the difference-in-differences design isolates the cyclone as a cause of the loss.

4. Results

4.1 Objective economic insecurity

The results section sets the scene by analysing first the effect of Cyclone Ana on the objective side of economic insecurity. Figure 2 plots the average of individuals who reported farming income losses according to treatment status in the survey rounds. In 2021, both affected and unaffected groups followed the expected seasonal pattern with higher income losses in the lean season months of January and March, followed by recovery after the May harvest. In February 2022 (round 13), unaffected individuals again exhibited this seasonal return, resembling the 2021 pattern. Figure 3 shows the trends in business income for affected and unaffected individuals. Differently from the farm income evolution,

both groups evolve in a similar way, without major differences in the periods before and after Cyclone Ana.

Table 3 reports estimates of Eq. (1) with an indicator for a loss of total household income as the dependent variable. The post-Ana interaction is 0.064 in the unweighted specification, 0.068 with survey weights and 0.019 with inverse probability weights. None is statistically significant. A joint test of the pre-shock interactions rejects the parallel-trends restriction for total income ($F(2,30) = 4.95$, $p = 0.014$), so the aggregate does not satisfy the identifying assumption of the design since individuals were already diverging in total income trends before the Cyclone Ana. Since no effect is found when looking at total income, a next step would be to look at the specific sources of income the head of the household reports.

Table 3
Effect of Cyclone Exposure on Total Income Loss

Affected district ($\geq 40,000$) $\times$ post-Ana	(1) Household FE	(2) FE, survey weights	(3) FE, inverse probability weights
	0.064	0.071	0.019
	(0.069)	(0.090)	(0.047)
Observations	6,054	5,563	5,819
Notes: District-clustered HC2 standard errors with the Bell–McCaffrey adjustment in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.			

Tables 4 and 5 report those estimates for farming and non-farm business income respectively.^[1] Individuals living in a district which was affected by Cyclone Ana increase the probability of a farming income loss by 11.8 percentage points without survey weights, 15.4 points with survey weights and 13.4 points with inverse probability weights.^[2] Relative to the round-11 mean among unaffected households, these correspond to increases of 28 to 36 per cent. These results are consistent with the existing evidence on weather shocks in the region, for example, McCarthy et al. (2021) find that droughts and floods reduce agricultural production in Malawi by 32 to 48 per cent. Similarly, Kunze (2021) estimates that cyclone damage lowers agricultural sector growth globally by approximately 2.6 percentage points.

Table 4
Effect of Cyclone Exposure on Farming Income Loss

Affected district ($\geq 40,000$) × post-Ana	(1) Household FE	(2) FE, survey weights	(3) FE, inverse probability weights
	0.118*	0.154**	0.134**
	(0.055)	(0.070)	(0.057)
Observations	3,837	3,482	3,681
Notes: District-clustered HC2 standard errors with the Bell–McCaffrey adjustment in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.			

Table 5
Effect of Cyclone Exposure on Business Income Loss

Affected district ($\geq 40,000$) × post-Ana	(1) Household FE	(2) FE, survey weights	(3) FE, inverse probability weights
	0.006	-0.042	-0.052
	(0.107)	(0.088)	(0.212)
Observations	2,792	2,619	2,703
Notes: District-clustered HC2 standard errors with the Bell–McCaffrey adjustment in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.			

The corresponding estimates for business income are 0.006, – 0.030 and – 0.052, none of which is statistically significant. The cyclone therefore operated through agricultural income, the source most directly exposed to weather, and the principal source of livelihood for rural households in the sample which therefore indicates that those households are the ones experiencing a rise in economic insecurity following a cyclone shock while others which have their main source of income coming from business activities are more protected.

To complement the analysis on income sources which is conditional on the household having any of them and answer a potential question that may rise that individuals that rely solely on farming income might be by design different in several socioeconomic characteristics than those holding only business income, I run the same models displayed above but only for households on which both of the income sources are available.

Of 6,054 person-round observations, 2,191 report farm income only, 1,146 report business income only, and 1,646 report both (Table A3). As mentioned above, farm-only and business-only households differ significantly in rural residence, agricultural employment and exposure (Table A4). Within this sample, in which location and exposure are held fixed, farming income loss rises by 15.3 percentage points after Ana while the total and business income coefficients are statistically insignificant (Table 6). Therefore,

the evidence supports that the rise in the probability of reporting farming income loss and the null effect on business income loss is not driven by compositional differences of whom holds each income source.

Table 6
Farm and Business Income Loss Within Dual-Income Households

Affected district ($\geq 40,000$) $\times$ post-Ana	Farming income loss	Business income loss
	0.153**	0.040
	(0.065)	(0.097)
Observations	1,646	1,646
Notes: Sample restricted to the 1,646 person-round observations (774 households) reporting both farm and business income, so that both outcomes are estimated on the same households and location and exposure are held fixed. District-clustered HC2 (Bell–McCaffrey) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.		

4.2 Subjective economic insecurity

Figure 4 shows the round-14 subjective measures by objective loss profile. Households reporting a farming loss are more likely to say they are worse off than a year ago, 81 per cent against 70 per cent among households reporting no loss, while those reporting only a business loss are close to the no-loss group at 72 per cent. The forward-looking measure is similar across all four profiles, between 50 and 54 per cent.

4.2.1 Subjective economic insecurity and exposure to Cyclone Ana

The first block of analysis on subjective economic insecurity starts by using district level exposure to Cyclone Ana as a predictor of current and future financial perceptions as well as climate risks expectations on household finances. Table 7 reports the outcomes regressed on district exposure. The coefficients are 0.065 on the current assessment and 0.078 on the forward-looking assessment, both insignificant. Thus, living in a district where Cyclone Ana has struck, is not by itself a predictor of negative views about household finances or the potential future impact of climate risks on their economic well-being.

Table 7
Cyclone Exposure and Round-14 Subjective Outcomes

Affected district ($\geq 40,000$)	Worse now	Worse in a year	Climate risk likely	Climate risk extremely likely
	0.072	0.087	0.023	-0.005
	(0.041)	(0.055)	(0.038)	(0.049)
Observations	1,273	1,125	1,249	1,249
Notes: Linear probability models on round-14 respondents, with the pre-specified control set and region fixed effects; district-clustered HC2 standard errors with the Bell–McCaffrey adjustment in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.				

4.2.2 Association of realised losses and subjective economic insecurity

Table 8 distinguishes between indicators for holding farm or business income sources and recording no loss against households possessing no such source. The loss indicators measure the increment attributable to having a loss, conditional on holding the source. For a household that both held a source and lost income the relevant interpretation is therefore the sum of the two coefficients.

Table 8
Objective Income Losses and Round-14 Subjective Outcomes

Farming income loss	Worse now	Worse in a year	Climate risk likely	Climate risk extremely likely
	0.127***	0.023	0.066**	0.074*
	(0.034)	(0.059)	(0.032)	(0.041)
Business income loss	0.069*	0.078*	0.015	-0.058
	(0.035)	(0.038)	(0.042)	(0.056)
Has farm income source	-0.057*	-0.037	0.036	0.016
	(0.031)	(0.045)	(0.028)	(0.042)
Has business income source	-0.059*	-0.104**	-0.033	0.065
	(0.032)	(0.041)	(0.031)	(0.047)
Observations	1,227	1,082	1,203	1,203
Notes: District-clustered HC2 (Bell–McCaffrey) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.				

An income source that did not experience a loss is associated with lower insecurity with households that hold farm income without a recorded loss are 5.7 percentage points less likely to report a worse current situation, and households holding business income without a loss are 5.9 points less likely. The protection is most pronounced prospectively for business income, where no loss was experienced, holding this income source reduces the probability of expecting deterioration over the coming year by 10.4 points.

Realised losses reverse this protection, and they do so on different horizons according to the source. A farming loss raises the probability of reporting a worse current situation by 12.7 percentage points, sufficient to overturn the protection conferred by holding the source, so that a farming household that lost income remains 7.0 points more insecure than a household with no farm income at all. The same loss carries no association with expectations one year ahead. A business loss displays the opposite, as its association with the current assessment is weaker at 6.9 points, while its association with expectations is larger at 7.8 points.

The asymmetry could be assigned to the production structures underlying the two sources. Agricultural income in Malawi is organised around a single growing season, and a cyclone arriving in January destroys a standing crop without necessarily impairing the land or the labour that will produce the following one. The loss is severe, immediate and understood by the household to be bound in time. A business loss more plausibly entails the destruction of working capital, stock or premises, together with the interruption of trading relationships, none of which the next season restores. Households appear to draw this distinction, treating the agricultural loss as a shock to present circumstances and the business loss as information about a persistently lower income path.

The climate risk outcomes corroborate this reading and identify agriculture as the channel through which realised losses are translated into revised beliefs about environmental exposure. A farming loss raises the probability of climate risk as likely by 6.6 percentage points, and relative to a household with no farm income the combined association reaches 10.2 points. A business loss produces no such revision, with coefficients being statistically insignificant. Households attribute agricultural losses to weather and adjust their assessment of climatic exposure accordingly.

4.3 The role of pre-Ana humanitarian and resilience capacity

Table 9 reports the association between realised income losses and subjective insecurity, allowing that association to vary with the level of humanitarian capacity present in the district before the cyclone. Columns 1 to 3 measure capacity as the volume of project months accumulated over the five years preceding Ana. Columns 4 to 6 measure it as the stock of activities in operation when the storm arrived. Both enter in logarithms and are centred at the sample mean, so that the coefficient on the loss count represents the association for a household resident in a district of average capacity.

Table 9
Objective Loss Count and Pre-Ana Humanitarian Capacity

	<i>Five-year project-months</i>			<i>Stock active at Ana</i>		
	Worse now	Worse in a year	Climate risk	Worse now	Worse in a year	Climate risk
Objective EI count	0.098***	0.044	0.047*	0.098***	0.044	0.045*
	(0.022)	(0.034)	(0.024)	(0.022)	(0.033)	(0.024)
EI count × capacity	-0.016	-0.071*	0.003	-0.022	-0.088**	-0.004
	(0.014)	(0.023)	(0.028)	(0.016)	(0.027)	(0.021)
Capacity	0.024	0.024	-0.015	0.039	0.037	-0.019
	(0.031)	(0.052)	(0.017)	(0.042)	(0.062)	(0.020)
Observations	1,227	1,082	1,203	1,227	1,082	1,203
Notes: Columns 1–3 use accumulated project-months over the five years before Ana; columns 4–6 the stock of activities running when the storm arrived. Both enter in logs, centred at the sample mean.						

The estimates indicate that capacity conditions the relationship between realised losses and expectations. For the outcome recording whether a household expects its financial position to deteriorate over the coming year, the interaction term is – 0.071 under the cumulative measure and – 0.088 under the stock measure, significant at the ten and five per cent levels respectively. Evaluated at one log point below mean capacity, an additional realised loss corresponds to an increase of 11.5 percentage points in the probability of expecting deterioration. At the mean the estimate falls to 4.4 percentage points and is no longer statistically distinguishable from zero. The transmission from realised loss to anticipated deterioration is therefore concentrated in districts where humanitarian presence is limited.

No comparable moderation is evident for the remaining outcomes. An additional loss raises the probability that a household reports a worse current situation by 9.9 percentage points, and the corresponding interaction terms are small and imprecise, at – 0.016 and – 0.022. Losses likewise raise the probability that a household considers climate risk as high, by approximately 4.5 percentage points, and humanitarian aid capacity again exerts no moderating influence, with interaction terms of 0.003 and – 0.004.

That the moderation is confined to expectations bears directly on how the result should be interpreted. Districts with greater humanitarian activity before the cyclone are plausibly wealthier, better connected to markets and to administration, or more accustomed to recurrent shocks. Each of these characteristics would be expected to attenuate the association between losses and the assessment of current

circumstances, and equally to attenuate the association between losses and perceived exposure to climate risk, but neither attenuation is observed.

One possible interpretation is that humanitarian capacity substitutes for insurance at the community level, which is least effective when a shock affects an entire district and mutual assistance among neighbours is therefore unavailable. An alternative interpretation is that households in districts of greater capacity anticipate the arrival of assistance, in which case the mechanism operates through beliefs rather than through any transfer of resources. The present data do not permit these interpretations to be distinguished. The composition of the capacity measure, which comprises humanitarian, food security and disaster preparedness activities, is consistent with either account.

5. Robustness Analysis

5.1 Objective economic insecurity

Table 10 columns (1) to (4) report the farm income estimate under alternative definitions of exposure. Lowering the threshold to 10,000 affected people gives a coefficient of 0.107 and raising it to 120,000 gives 0.053, significant at five and ten percentage levels respectively. Including an indicator for the two survey rounds falling within the growing season, since Ana made landfall when farm income is seasonally low, gives 0.136. Restricting the control group to unaffected central and southern districts gives 0.109. Column (5) provides a placebo test where households living in an unaffected district are assigned as treated. The result is close to zero and statistically insignificant.

Table 10
Robustness Tests for the Effect of Cyclone Exposure on Farming Income Loss

Affected district × post-Ana	≥ 10,000 threshold	≥ 120,000 threshold	Seasonality control	Central/Southern only	Placebo
	0.107**	0.053**	0.136*	0.109*	-0.050
	(0.050)	(0.025)	(0.070)	(0.054)	(0.072)
Observations	3,837	3,837	3,837	3,280	3837
Notes: District-clustered HC2 (Bell–McCaffrey) standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.					

Table 11 replaces the binary indicator with the size of the affected population, scaled per 100,000 people. The post-Ana effect on farming income loss is 0.229 (p = 0.042; bootstrap 0.022); the coefficients for business and total income are insignificant, and the pre-period interactions are jointly insignificant. The estimated effect increases with the severity of exposure, which the binary threshold does not capture. Because the measure takes the lower bound of each severity band, and the most severely affected district is coded at 120,000 against a higher recorded figure, this specification understates the gradient.

Table 11
Continuous Affected Population and Income Loss

Affected population (per 100,000) × post-Ana	Farming income loss	Business income loss	Total income loss
	0.229**	0.022	0.073
	(0.094)	(0.144)	(0.086)
Observations	3,837	2,792	6,054
Notes: District-clustered HC2 (Bell–McCaffrey) standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.			

Triple interactions between exposure, survey round and, in turn, a female household head, the bottom three wealth quintiles and a household head under 30 are reported in Table A5. None is statistically significant.

5.2 Sample composition

Since the income-loss outcomes are conditional on holding the corresponding source, the estimates could in principle reflect a change in the composition of source-holders. Table A6 shows that exposure does not alter the probability of holding a farm or business source, so the denominator is stable. The only change is that, after the cyclone, there is an increase of wage source reporting.

Table A7 runs Eq. (1) on each time-varying household characteristic, to see if there is any composition change related to Cyclone Ana exposure that is not captured by fixed effects and the difference-in-differences design. The results show no significant effect of living in an affected district on the household size, number of children or employment.

5.3 Subjective economic insecurity

The subjective specifications condition on a set of controls measured before the cyclone and held fixed across outcomes. Table A8 reports estimates in which the controls are instead selected by a partialling-out LASSO with a cross-validated penalty, drawing on a high-dimensional candidate set that adds health, food-security, mental-health, income-variation, credit and safety-net variables not only from the last survey round before Cyclone Ana but from all the available rounds used in this study (see Fig. 1), together with region fixed effects and district-clustered standard errors.

The estimates on district exposure are 0.054, 0.019 and 0.040 across the three outcomes, none of them significant. Experiencing a farm income loss still positively associated with worse current insecurity, holding business income source remains negatively associated with forward-looking insecurity (– 0.083, significant at the 10 per cent level), and holding a farm income source remains positively associated with perceived climate risk (0.067, significant at 5 per cent).

6. Conclusion

I have used Cyclone Ana, which struck southern Malawi in January 2022, to ask how a realised economic loss becomes a subjective sense of insecurity, and whether the humanitarian capacity already established in a district alters that translation. The cyclone reached households almost entirely through agriculture, raising the probability of a reported farm income loss by 12 to 15 percentage points while leaving business and total income untouched, a contrast that survives within the households holding both sources and therefore reflects the sensitivity of the income sources rather than who happens to hold them. What follows from a loss then depends on where the loss came from. A farm loss is associated with reporting a worse position than a year earlier and with greater concern that weather will damage the household's finances (agriculture being the channel through which weather is experienced at all), while it is business losses that are associated with expecting the coming year to be worse. Holding an income source that survived the storm is associated with lower insecurity throughout, and a loss reverses that advantage, in the case of business income completely.

The measurement literature in economic insecurity treats realised losses and stated perceptions as alternative routes to a single concept, and these results suggest they are not. The two respond to different shocks and at different horizons within the same households. This matters because the concept being measured is anticipatory while almost every applied instrument is retrospective, assembled from income volatility, unemployment spells and asset depletion. An index of that kind records the damage a household has already absorbed. Whether it also captures what the household expects, and therefore the component the development literature holds responsible for depressed investment and for safer choices with lower average returns (Morduch, 1995), is what these results call into question.

Humanitarian aid capacity in place before the cyclone is associated with none of the losses and with neither retrospective assessment. Its association is with expectations, where the link between a realised loss and the anticipation of further deterioration is weaker in districts carrying more prior activity. Two interpretations are possible, which with my current analysis I am unable to distinguish. First, an insurance reading, in which organised assistance substitutes for the mutual help that fails when a whole district is struck at once, and second an expectation reading, in which households anticipate that assistance will arrive. Both interpretations are suitable and separating them would require knowing what households believe about their entitlement, which the survey does not ask.

My analysis has used one cross-section of the subjective questions, taken after the storm, however, a useful extension would be to ask them before a shock as well, in order to move from a short-term associational analysis towards a causal and long-term one.

Declarations

Disclosure Statement on AI

The use of LLM (Anthropic/Claude, 2026) tool was restricted to proof-reading of the manuscript. Specifically, these tools were employed to assist with (a) language corrections and (b) stylistic

improvements of draft sections. All outputs were critically reviewed and, where necessary, revised by the author to ensure accuracy. Any remaining errors are my own.

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Author Contribution

Single author paper.

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I thank Philippe Van Kerm and Anthony Lepinteur for their comments and guidance. I am grateful to participants at the 2026 CSAE Conference and at the World Inequality Lab Conference for helpful discussion. The use of LLM tools was restricted to proof-reading of the manuscript. Any remaining errors are my own

Data Availability

The Malawi High-Frequency Phone Survey data that support the findings of this study are publicly available from the World Bank Microdata Library. District-level aid-activity records are drawn from the International Aid Transparency Initiative and the Humanitarian Data Exchange, both publicly accessible. The code used to construct the analysis samples and produce the results is available from the author on request.

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Footnotes

1. Farming income satisfies the parallel-trends requirement ($F(2,30) = 2.01$, $p = 0.152$)
2. Wild cluster bootstrap p-values for the three specifications are 0.073, 0.068 and 0.019.

Figures

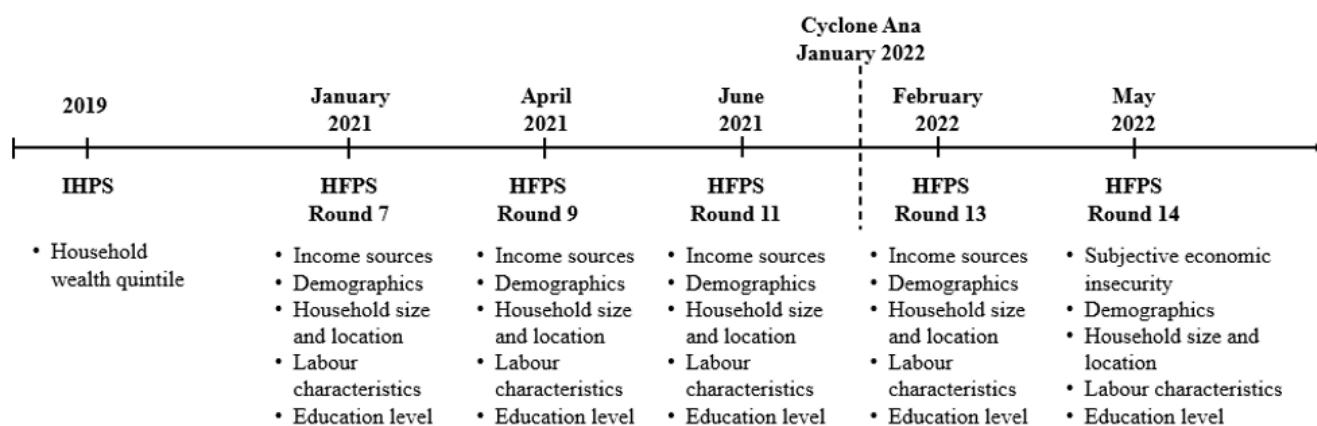


Figure 1

HFPS and IHPS variable availability by survey round.

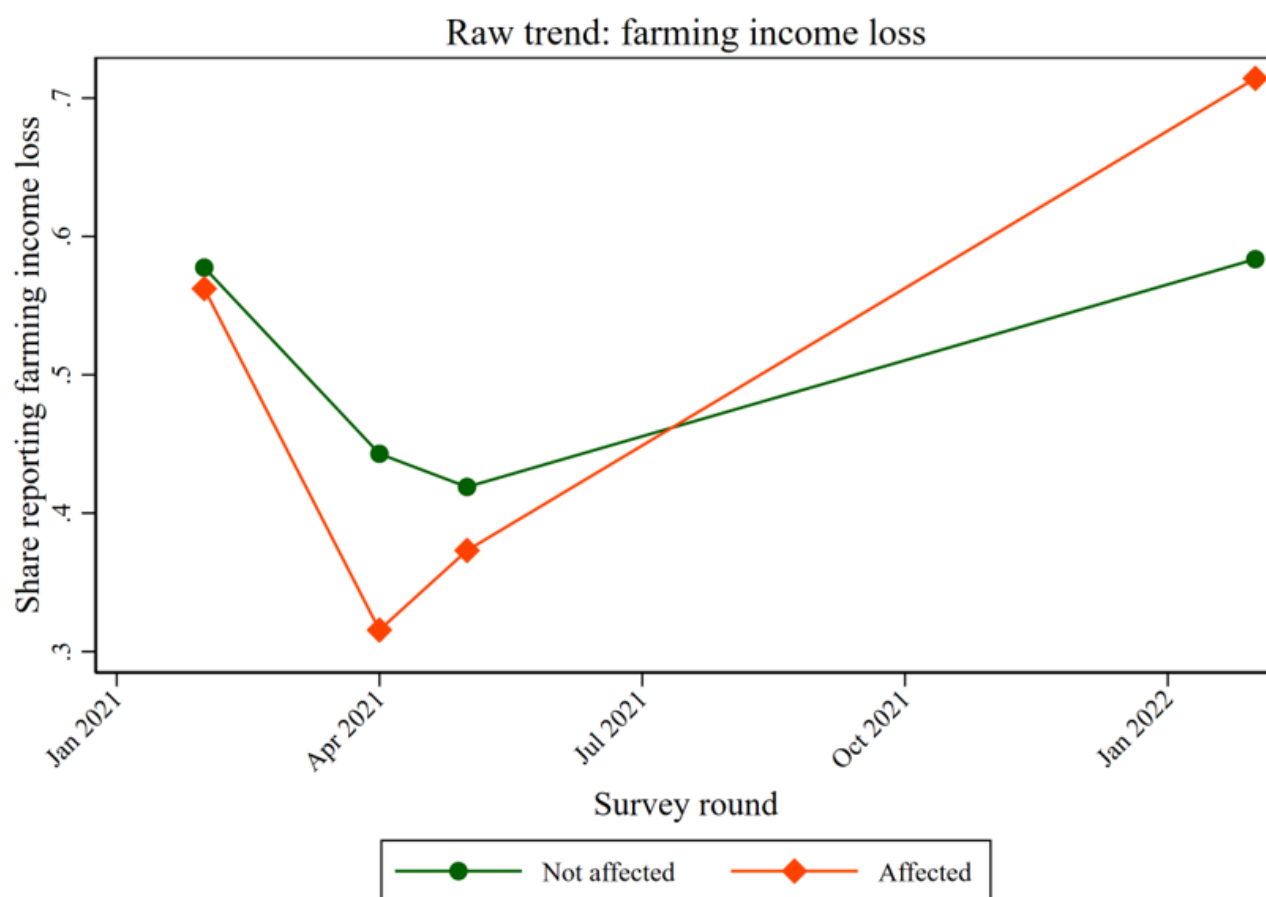


Figure 2

Farming income loss by treatment status and survey round. Y-axis: share of household heads reporting a loss (0–1).

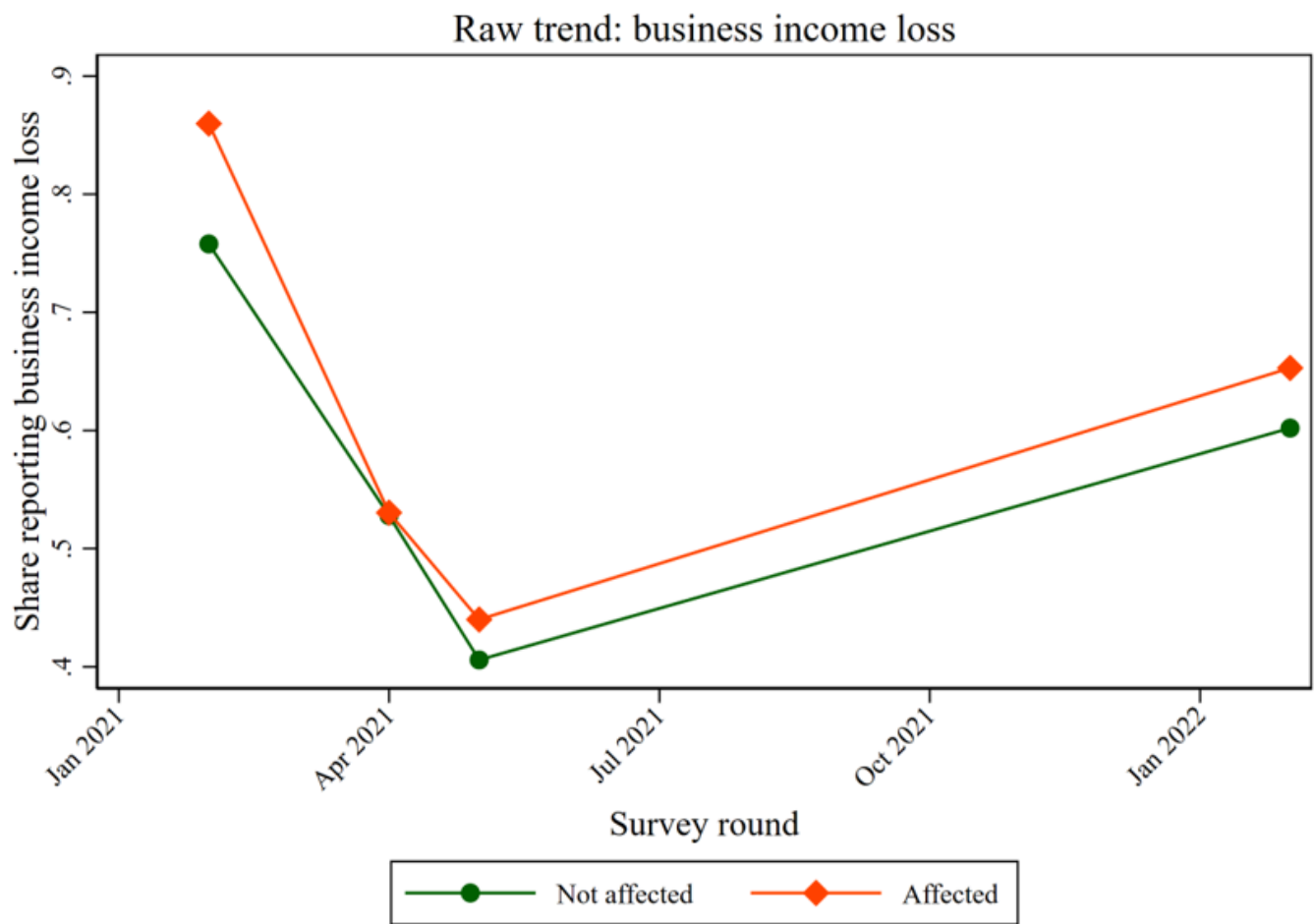


Figure 3

Business income loss by treatment status and survey round. Y-axis: share of household heads reporting a loss (0–1).

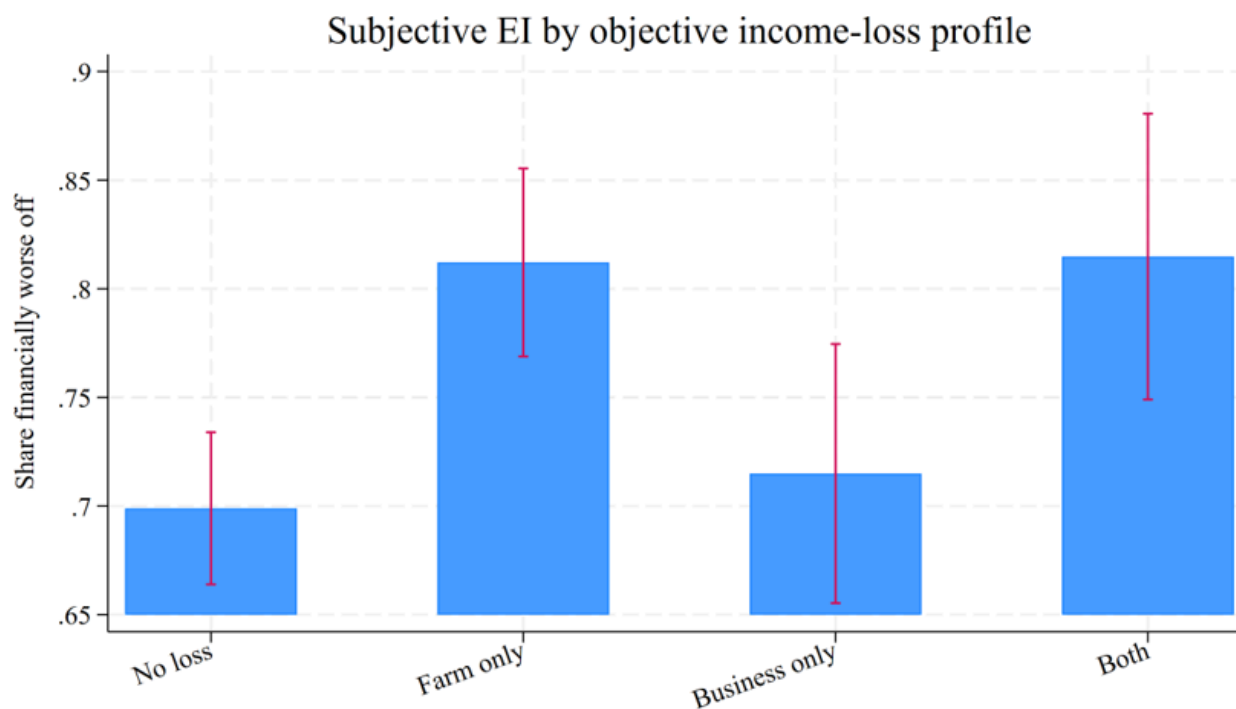


Figure 4

Round-14 subjective measures by objective loss profile. Bars show the share of household heads for whom each recoded binary indicator equals one (y-axis: share of respondents, 0–1), with 95% confidence intervals. Profiles are defined on farm and business income losses reported in round 13.

Supplementary Files

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