Financial Instrument Bundling Under Multiple Market Failures: A Household Risk Layering Approach

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Abstract

Households in disaster-prone environments face multiple market failures—credit constraints, coordination breakdowns and behavioural biases—that undermine the effectiveness of standalone financial instruments such as insurance. This paper develops a theoretical model showing that welfare-optimal household disaster risk management requires bundling financial instruments across the ex-ante and ex-post disaster risk management cycle covering prevention, mitigation, coping and recovery, layering tools by hazard probability and severity. We show that bundling dominates single-instrument approaches when it simultaneously relaxes distinct market frictions and is complemented by coordination effectiveness. Numerical simulations illustrate hazard-specific optimal portfolios for frequent floods and rare catastrophic earthquakes. We use two programs from Indonesia to illustrate how strategic bundling can be applied in practice in programme design. The framework provides testable predictions and guidance for designing integrated household financial protection systems in developing countries.

Keywords: Risk Layering, Bundling, Market Failures, Disaster Risk Management, Developing Countries, Household Finance

JEL codes: D81, G22, O16, Q54, H84, D91

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1. Introduction

Despite large subsidies, awareness programmes and marketing, insurance uptake against extreme weather or catastrophic events has been low. For example, Indonesia's National Agricultural Insurance Program *Asuransi Usaha Tani Padi* (AUTP) covering floods and droughts achieved only 45% of its enrolment target between 2015–2019 although the government subsidised 80% of the insurance premium (Yusuf et al., 2022). India's national crop insurance programme *Pradhan Mantri Fasal Bima Yojana*, launched in 2016 with premium subsidies of 70–90% to cover crop failures from droughts, floods, cyclones, and pests, achieved coverage of only 26% of cropped area by 2017–18 against a target of 50%, with voluntary enrolment declining by over 40% in several states despite being one of the world's largest government-subsidised crop insurance programmes (Ghosh et al., 2021). Even newer insurance products such as index insurance suffer from low uptake, limits to scalability, as well as failure to meet expectations as evidenced in low and middle income countries in Asia and Africa (Ahmed et al., 2020; Castaing & Gazeaud, 2025; Cole et al., 2014).

Why do standalone disaster insurance products targeted towards households have low uptake? Market failures such as information asymmetry, externalities, coordination problems, behavioural biases and barriers to entry are the root cause[1]. Insurance on its own cannot address multiple market failures, especially when they are exacerbated in disaster contexts, severely affecting both demand and supply (Cole et al., 2013; Duong et al., 2019; Gallagher, 2014; Gollier, 2005; Wu et al., 2020). A solution is to bundle insurance with other financial products such as risk-oriented credit or savings, training programs, or within social-protection programmes (Cai et al., 2020; Carter et al., 2017). Such bundling is often ad hoc and opportunistic, focusing mainly on risk mitigation (i.e., reducing potential impact) or coping (reducing impact after event materialises) rather than disaster risk management in a wider sense that includes prevention (reducing risk exposure) and recovery (rebuilding life and livelihoods). Perhaps because of this, insurance bundled with products such as credit has had mixed success in improving uptake and effectiveness (Belissa et al., 2019; Karlan et al., 2014; Mishra et al., 2021).

How can financial tools be bundled strategically to optimise household welfare? We draw inspiration from ‘risk layering’, a strategy first used by insurers to segment potential losses by disaster severity into distinct tiers (e.g., retained risk, transferred risk, backstop) and assign to each tier the most efficient risk-bearing instrument (e.g., retained reserves, insurance or capital market securities) to optimise the cost of capital and protect against solvency-threatening losses and optimise the design of

[1] Although there are other market failures such as public goods, non-competitive behaviour this paper limits the failures discussed to the four in the paper, to maintain clarity of argument. The selected failures are pertinent to disaster risk management at the household level using financial instruments.

financial protection mechanisms to cover both frequent and catastrophic losses. This conventional formulation constitutes a *vertical* logic of risk layering, slicing the loss distribution by severity, and it has increasingly been applied at the sovereign and macroeconomic levels to address disaster risk (Bangalore et al., 2016; Froot, 2001; Hochrainer-Stigler et al., 2020; Hochrainer-Stigler & Reiter, 2021; Kunreuther et al., 2013; Linnerooth-Bayer & Hochrainer-Stigler, 2015).

In the case of households, not all financial tools commonly used such as savings and asset sales, are risk-bearing—that is, not all involve a third party with a contractual obligation to provide a payout or service following an adverse event. Nonetheless, this paper argues that the concept of risk layering can be extended to the household level as a framework to enhance welfare. This extension, however, requires taking into account the temporal sequence of the disaster risk management cycle, from pre-disaster prevention and mitigation to post-disaster coping and recovery, bundling instruments across the cycle if needed. Thus, household risk layering by hazard severity and probability would match products against distinct tiers, with the products being instrument bundles addressing different market failures across the risk management cycle.

A simplified example is illustrative. Take the situation where demand for flood insurance is low because households find the premiums too expensive. But insurers cannot reduce premiums as it is not profitable, excluding many households from accessing the product. Even if the government heavily subsidises premiums, households know that post-disaster coordination failures and information asymmetries severely delay insurance payments. In this case, a standalone product such as flood insurance, even if heavily subsidised, will not improve uptake or be effective in enhancing households' capacity to cope in the aftermath of the event. However, a broader risk management cycle approach together with the market failure lens can enable strategic bundling to improve uptake and household welfare. For instance, lower premiums can be driven by household-level flood-risk prevention efforts ex-ante, funded by social impact bonds (SIBs), a form of financing where results are linked to independently verified outcomes. The outcomes in this case can be property-level prevention measures such as stilt housing or retrofitting with water-resistant materials. Certification of undertaking such adaptation measures can be a prerequisite for obtaining lower insurance premiums. Bundled with mandatory savings to smooth consumption in the immediate aftermath of a flood, insurance payments can facilitate rebuilding in the recovery phase. In this example, the instruments to manage flood risk more effectively were SIBs, insurance and savings, and instruments used as a bundle are likely to be more effective in managing disaster risk than any of the instruments on their own. If the flood impact is low, households retain risk using savings, but if impact is high, some of the risk is transferred using insurance with the SIB mediating overall impact severity.

This paper presents a model to formalize this intuition. We demonstrate that when households maximize utility under constraints shaped by market failures, standalone instruments prove inadequate. A welfare-superior equilibrium is only achieved through the deliberate co-design of financial tools. The model's propositions are demonstrated by a simulation using plausible values for hazards of varying probability and severity: low impact and high probability seasonal flooding, and high impact low probability earthquakes. We then discuss two contrasting programmes from Indonesia, with standalone versus bundled instruments: AUTP offering standalone indemnity insurance for rice farming and the Indonesia Liquidity Facility After Disaster (ILFAD) bundling four tools. Using Indonesian cases to illustrate program design is particularly instructive as it is a country with high exposure to hazards of varying frequency and severity (e.g., rare, high severity earthquakes as well as more frequent low severity seasonal floods), coexisting formal and informal financial systems, and extensive experience with disaster risk financing. This allows us to illustrate how our theoretical model about strategic bundling can be applied in practice to programme design.

The paper defines four phases in the disaster risk management cycle –prevention, risk mitigation, coping and recovery– organised across the disaster timeline, synthesising and extending established approaches in development economics and disaster risk management. From development economics come insights from the Social Risk Management framework (Holzmann & Jørgensen, 2001), which distinguished between prevention (reducing exposure), mitigation (reducing potential impact), and coping (relieving impact after risk materialises). We extend this by incorporating recovery as a fourth phase following the disaster risk management literature (UNDRR, 2015), recognising that rebuilding life and livelihoods involves qualitatively different time horizons and market failures than immediate coping responses.[2] Recent evaluations highlight that recovery remains poorly understood and typically a lower-priority aspect of risk management policy (UNDRR, 2023), making our explicit treatment of it as a distinct phase particularly salient for both theory and practice. Market failures can occur at any point in the disaster risk management cycle, though their salience and manifestations vary by phase, hazard type, and context. Disasters tend to exacerbate markets failures and their impacts when institutions are damaged, infrastructure destroyed, and supply chains disrupted (Alok et al., 2020; Gao et al., 2020; Neumayer et al., 2014).

A key contribution of this paper is to provide a theoretical framework demonstrating why and when bundling dominates standalone approaches, with testable predictions about hazard-specific instrument

[2] This four-phase approach also maps onto the Sendai Framework for Disaster Risk Reduction 2015-2030: risk reduction aligns with Sendai Priority 1 (Understanding disaster risk) and Priority 3 (Investing in disaster reduction for resilience); risk mitigation corresponds to Priority 3 and Priority 4 (Enhancing disaster preparedness); coping relates to Priority 4's effective response mechanisms; and recovery directly reflects Priority 4's "Build Back Better" emphasis UNDRR. (2015). *Sendai Framework for Disaster Risk Reduction 2015–2030*. U. Nations. https://www.undrr.org/publication/sendai-framework-disaster-risk-reduction-2015-2030.

choice. Our model uses traditional tools such as savings and informal insurance arrangements. It also uses three innovative tools: parametric insurance, forecast-based financing (FbF) and social impact bonds (SIBs). Parametric insurance, which provides households with a pre-agreed payout upon the occurrence of a specific, measurable event regardless of actual losses incurred. FbF disburses resources in advance based on hazard forecasts, allowing households to take anticipatory risk-reducing actions. SIBs are outcome-based contracts in which private investors provide upfront financing for projects or services and are repaid only if predefined outcomes, set by a commissioning authority, are achieved.

The introduction of SIBs as a novel instrument for household disaster risk reduction is a second contribution. SIBs have been used in humanitarian and international development contexts but not in the context of disasters (Bregazzi et al., 2022; Farber, 2023; Hulse et al., 2021). Developing such instruments can take time (three months to over a year), and the implementation phase usually runs for a period of 3–10 years (GoLab, 2023). This means that the instrument is best suited for the ex-ante prevention and ex-post recovery phases, for events that are relatively infrequent. Using a broader risk management cycle approach allows the use of a wider range of financial tools so that market failures are addressed earlier on in the cycle with the most appropriate instrument, preventing them from compounding and cascading into more severe losses ex-post.

A third contribution is to provide some practical insights for designing bundled products based on qualitative case studies and practitioner expertise of real-world cases.

2. Modelling household risk layering in the presence of market failures

We develop a two-period model to demonstrate why a layered portfolio of financial instruments–targeting different phases of the risk management cycle–is essential for household resilience when market frictions are present. Standalone financial instruments—whether traditional (savings, informal transfers), or innovative (parametric insurance, forecast-based finance or social impact bonds)—are shown to be insufficient.

Timeline and preferences

A representative household lives for two periods.

Period 0 (Ex-Ante): Makes financial decisions before the resolution of uncertainty i.e., before a covariate shock (disaster) occurs. Risk management in this period focuses on risk reduction (i.e., preventing or reducing exposure to hazard) or mitigation (i.e., taking actions to limit severity of consequences).

Period 1 (Ex-Post): A disaster occurs with probability $\pi \in (0,1)$. Risk management in this period focuses on coping (i.e., managing immediate direct impacts) and recovery (i.e., rebuilding life, livelihoods, assets).

The household has constant relative risk aversion (CRRA) preferences over consumption (Phelps, 2024):

$$U = \frac{c_0^{1-\gamma}}{1-\gamma} + \beta\left[\pi\frac{(c_1^d)^{1-\gamma}}{1-\gamma} + (1-\pi)\frac{(c_1^n)^{1-\gamma}}{1-\gamma}\right], \qquad \gamma > 0, \qquad \gamma \neq 1$$

where c_0 is period-0 consumption, c_1^d is consumption if a disaster occurs, and c_1^n is consumption otherwise. γ is the coefficient of relative risk aversion, with $\gamma > 0$ representing risk aversion and $\beta \in (0,1]$ is the subjective discount factor representing time preference (Frederick et al., 2002).

Disaster severity (i.e., the financial impact of disaster to household)

We introduce a parameter $\delta \in [0,1]$ to capture disaster severity, the fraction of income lost, so post-disaster income is $(1-\delta)y_1$. When $\delta = 1$ there is a total loss of period-1 income.

The financial toolbox

The household has access to a portfolio of instruments that can all reduce disaster severity, δ, but through different channels:

$b \geq 0$: Social Impact Bond conditional cash transfer in Period 0 tied to mandatory retrofitting investment reducing baseline severity from $\delta(0)$ to $\delta(b) = \delta(0)e^{-\kappa b}$, with diminishing returns (risk reduction/prevention).

$f \geq 0$: Forecast-based finance transfer realised in Period 0 upon a disaster forecast perfectly correlated with the disaster. The transfer is deployed towards anticipatory actions with effective mitigation value ϕf accruing in Period 1, where $\phi \in [0,1]$ denotes the conversion effectiveness (risk mitigation).

$s \geq 0$: Precautionary savings with no net return. We assume diminishing marginal effectiveness s^ρ where $\rho \in (0,1]$, reflecting that while initial savings provide liquidity, large cash holdings face increasing opportunity cost and management challenges (Deaton, 1991). Its severity reduction (by providing a buffer) is direct and unconditional with residual loss $\delta \cdot y_1 - s^\rho$ (coping).

$R \geq 0$: Household chooses R (participation level) in an informal risk-sharing network and pays actuarially fair premium (Rothschild & Stiglitz, 1976) πR in Period 0; receives R(1-α) in Period 1 if disaster occurs, where α ∈ [0,1] is the market failure index (coping/recovery).

$I \geq 0$: A state-contingent payout from a parametric insurance contract directly offsetting losses (innovative coping). Households pay actuarially loaded premium (Rothschild & Stiglitz, 1976) $p(I) = \pi(1+\lambda)I$, where $\lambda = 0$ is actuarially fair and $\lambda > 0$ is actuarially loaded but perceive the effective loading as $\hat{\lambda} = \lambda + \alpha$ when evaluating expected utility (recovery).

Institutional capacity and coordination efficiency

The effectiveness of all the instruments depends on an institutional quality parameter, $\theta \in [0,1]$, where a higher θ indicates stronger institutional capacity (e.g., better learning readiness, adaptive capability, trust, communication, lower transactions costs, less corruption).

Coordination effectiveness is defined as $\omega \in [-1,1]$, capturing the net effect of the interaction between the instruments at both household and system level.

$\omega = 1$: Perfect coordination. Instruments are true complements, and household mental models align with institutional offerings allowing for network effects and optimal deployment of all instruments.
$\omega = 0$: Neutral coordination. Instruments act independently.
$\omega = -1$: Destructive coordination. Instruments conflict, leading to crowding out, perverse incentives, and suboptimal deployment.

The Layering Efficiency Multiplier $\Psi(\theta, \omega) = (1+\theta)(1+\omega)$. A single instrument has $\omega = 0$ by definition (no coordination possible), yielding $\Psi(\theta, 0) = (1+\theta)$. For bundles of 2+ instruments, the multiplier amplifies financial mitigation.

The Effective Severity Δ is the net loss as a fraction of income after all instruments have done their work:

$$\begin{aligned}\Delta(s, I, b, f, R) &= \frac{\delta(b)y_1 - [s^\rho + I + R(1-\alpha) + \phi f]\Psi(\theta, \omega)}{y_1} \\ &= \delta(b) - \frac{[s^\rho + I + R(1-\alpha) + \phi f]\Psi(\theta, \omega)}{y_1}\end{aligned}$$

This formulation shows that all instruments (s, I, R, f, b) contribute to reducing the final, effective severity of the disaster Δ. The physical mitigation from retrofitting is $\big(\delta(0) - \delta(b)\big)y_1$. The total *financial mitigation* of that loss is the sum of all payouts and buffers: $s^\rho + I + R(1-\alpha) + \phi f$. Institutional quality θ and coordination effectiveness ω enhance financial mitigation through the multiplier $\Psi(\theta, \omega)$. Effective severity Δ can be negative when total financial mitigation exceeds disaster losses (over-insurance).

Market failures as frictions

The Market Failure Index $\alpha \in [0,1]$ constrains instrument effectiveness through three frictions:

Friction 1 (Credit Constraints & Missing Markets): Households face an exogenous limit $\bar{L}$ on pre-disaster investments:

$$s + \pi(1+\lambda)I + \pi R \leq \bar{L}(1-\alpha) + f + b$$

This friction explains low investment in savings and insurance. Instruments f and b directly relax this constraint by increasing effective investable resources. We assume $\bar{L} < y_0$, so the credit constraint binds before the budget constraint.

Friction 2 (Coordination Failures & Covariate Risk): Informal insurance is unreliable. The household commits to participation level R, but due to covariate risk, the effective transfer received is:

$$\text{R\_eff} = R(1-\alpha)$$

where R is the nominal commitment and $\alpha \in [0,1]$ captures the degradation from covariate shocks. As α increases, the informal safety net deteriorates.

Friction 3 (Behavioural Biases): Households perceive instrument effectiveness and costs pessimistically:

$$\hat{\delta}(b) = (1-\alpha)\delta(b) + \alpha\delta(0), \hat{\lambda} = \lambda + \alpha, \hat{\phi} = \phi(1-\alpha)$$

Households with behavioural bias ($\alpha > 0$) underestimate how much retrofitting reduces severity. They perceive it as less effective than it actually is.

Household optimization

Budget constraints:

Period 0: $c_0 + s + \pi(1+\lambda)I + \pi R = y_0 + f + b$
Period 1 (No Disaster): $c_1^n = s^\rho + y_1$
Period 1 (Disaster): $c_1^d = \big(1-\delta(b)\big)y_1 + [s^\rho + I + R(1-\alpha) + \phi f]\Psi(\theta, \omega)$

The household chooses (s, I, R) to maximize its perceived expected utility $\widehat{U}$, subject to the constraints and using perceived parameters $\hat{\delta}(b), \hat{\lambda}, \hat{\phi}$.

$$\max_{s,I,R\geq 0} \widehat{U}(s, I, R; f, b)$$

Subject to

(i) $c_0 + s + \pi(1+\lambda)I + \pi R = y_0 + f + b$

(ii) $s + \pi(1 + \lambda)I + \pi R \leq \bar{L}(1 - \alpha) + f + b$

(iii) $s, I, R \geq 0$

$\hat{\delta}(b) = (1 - \alpha)\delta(b) + \alpha\delta(0)$,

$\hat{\lambda} = \lambda + \alpha$, and $\hat{\phi} = \phi(1 - \alpha)$.

Proposition 1

A bundled portfolio of instruments dominates a single instrument if at least one of the following conditions holds:

(a) $\omega > 0$ positive coordination creates financial tool complementarities when $\Psi(\theta, \omega) > \Psi(\theta, 0)$

(b) $\omega \leq 0$ but the bundle provides compensating benefits through relaxing binding credit constraints (Friction 1) through instruments f and b, and/or addressing simultaneously multiple different market failures captured in α.

Proposition 2

The welfare gain from bundling depends on coordination, ω, given institutional quality θ.

i) With perfect coordination ($\omega = 1$) and no market failures ($\alpha = 0$), the bundle achieves first-best efficiency. For $\alpha > 0$, perfect coordination achieves constrained-efficient allocation given binding market failures.

ii) With neutral coordination ($\omega = 0$), the bundle's multiplier equals that of a single instrument: $\Psi(\theta, 0) = (1 + \theta)$. However, the bundle may still be welfare-superior by relaxing credit constraints through f and b and addressing different market failures simultaneously (e.g., I addresses covariate risk while s addresses liquidity constraints).

iii) With destructive coordination ($\omega = -1$), the multiplier $\Psi(\theta, -1) = 0$, nullifying all financial mitigation instruments. In this worst-case scenario, consumption in the disaster state relies solely on physical mitigation (b), yet the bundle may still be valuable if it relaxes Friction 1 (e.g., through f and b).

Proposition 3

Market failures create necessity for risk layering; coordination creates sufficiency for bundling to dominate.

(a) Multiple market failures ($\alpha > 0$ across Frictions 1-3) create the necessity for diverse instruments, as no single instrument can address all frictions (credit constraints, covariate risk, and behavioural biases) simultaneously.

(b) Positive coordination ($\omega > 0$) creates the sufficiency for bundling to dominate through synergistic amplification of financial mitigation when $\Psi(\theta,\omega) > \Psi(\theta,0)$.

(c) Optimal portfolio balances instrument breadth (addressing more frictions) against coordination costs ($\partial\omega/\partial n < 0$ for large n).

Policy implication: Investments in instrument coordination mechanisms—through design, sequencing, and communication—are essential complements to expanding instrument portfolios.

First order conditions and analytical proofs for propositions are provided in Appendix A.

3. Numerical Solution

We solve the household problem via constrained grid search over (s, I, R), choosing plausible though not empirically calibrated base parameter values to suit two contrasting hazards: earthquakes that are high impact but low probability events with limited forecast lead-time ($\delta = 0.8, \pi = 0.05, \phi = 0.1$), and seasonal flooding which has lower impact but high probability and forecast lead-time ($\delta = 0.25, \pi = 0.4, \phi = 0.75$). Across these two event types, we vary market failure (α), bundle coordination effectiveness (ω) and institutional quality (θ) parameters to examine three scenarios: best-case (no market failures or perfect coordination and perfect institutional quality), moderate case (realistic developing-country conditions with some friction, some coordination ineffectiveness and less than perfect institutional quality), and worst-case (highest possible market failure and coordination ineffectiveness, non-performing institutions)[3]. We introduce exogenous transfers f and b in each scenario to test how easing credit constraints affects total investment in financial instruments used to manage risk. The Appendix B provides full technical details of how the simulations were conducted.

[3] Institutional quality θ is assumed exogenous to individual program design. But we vary θ across scenarios to illustrate how institutional context moderates the gains from bundling. Holding θ constant at 0.5 across all scenarios yields qualitatively identical results.

Table 1 presents key results from the simulation. Under the best-case scenario ($\alpha = 0, \omega = 1, \theta = 1$), the household's optimal choice would be to finance disaster risk mitigation through informal insurance (R^*) for both earthquakes and floods as it offers actuarially fair protection. The worst-case scenario ($\alpha = 1, \omega = -1, \theta = 0$) results in a complete collapse of all risk management. In the moderate case, introducing some market failures, neutral coordination, and moderately weak institutions ($\alpha = 0.5, \omega = 0, \theta = 0.5$), bundling provides optimal welfare. For floods, households turn to precautionary savings bundled with parametric insurance (s^*, I^*). For earthquakes, households switch to parametric insurance (I*) but under-invest (2.79–2.9 compared to 4–4.16 under the best-case scenario), leading to a sharp rise in effective severity. Bundling with f and b across the disaster risk management cycle enables higher insurance purchase (2.79 to 2.9) and higher utility (-1.34 to -1.29).[4]

Thus, a first key insight is that bundling (as diversification or as coordination) is superior to a standalone instrument, in the moderate case. This moderate case reflects the reality of developing countries.

A second insight is that optimal portfolios exhibit hazard-specific layering: Frequent, medium-impact floods induce diversification across savings and insurance while low-frequency, high-severity earthquakes favour parametric insurance (Proposition 3a).

Third, exogenous transfers f and b relax credit constraints, crowd in private investment, increasing it 3–4% and utility 7–9% even under neutral coordination (Proposition 1b).

Fourth, coordination quality is decisive: moving from destructive (ω = -1) to perfect coordination (ω = 1) increases expected utility 2–17-fold, with households investing zero in financial instruments when ω = -1 (Proposition 2).

The results also illustrate the robustness of the model, with qualitative patterns such as welfare monotonicity in ω, zero investment at ω = -1, and transfer multiplier effects all holding across both hazard types despite 8-fold differences in disaster probability and 3-fold differences in severity. Full simulation details are provided in Appendix C Table 1.

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[4] Negative utility values arise from the CRRA utility function specification when $\gamma > 1$. This is a standard property of CRRA preferences and does not affect the model's validity, as utility is ordinal—only relative rankings matter for decision-making, not absolute levels Kimball, M. S. (1990). Precautionary Saving in the Small and in the Large. *Econometrica*, *58*(1), 53-73. https://doi.org/10.2307/2938334 .

Table 1: Optimal Instrument Portfolios Across Market Failure Scenarios

Scenario	Optimal Portfolio (s*, I*, R*)	Total Investment	Expected Utility	Effective Severity Δ
Panel A: Seasonal Floods (δ=0.25, π=0.4, ϕ=0.75)				
Best case (α=0, ω=1, θ=1)	(0, 8, 20)	28.00	-1.27	-0.55
+ Transfers (f=2, b=2)	(0, 8.32, 20.8)	28.32	-1.21	-0.70
Moderate frictions (α=0.5, ω=0, θ=0.5)	(2, 4.73, 6.17)	12.67	-1.41	0.13
+ Transfers (f=2, b=2)	(2.08, 4.92, 6.17)	13.17	-1.33	0.05
Coordination collapse (α=1, ω=-1, θ=0)	(0, 0, 0)	0	-1.44	0.25
+ Transfers (f=2, b=2)	(0, 0, 0)	0	-1.37	0.20
Panel B: Earthquakes (δ=0.8, π=0.05, ϕ=0.1)				
Best case (α=0, ω=1, θ=1)	(0, 0, 4)	4.00	-1.32	-2.40
+ Transfers (f=2, b=2)	(0, 0, 4.16)	4.16	-1.28	-2.70
Moderate frictions (α=0.5, ω=0, θ=0.5)	(0, 2.79, 0)	2.79	-1.34	0.07
+ Transfers (f=2, b=2)	(0, 2.90, 0)	2.90	-1.29	-0.13
Coordination collapse (α=1, ω=-1, θ=0)	(0, 0, 0)	0	-1.63	0.80
+ Transfers (f=2, b=2)	(0, 0, 0)	0	-1.38	0.63

Notes: α is the market failure index, ω is coordination effectiveness, and θ is institutional quality. Best case assumes no market failures (α=0), perfect coordination (ω=1), and high institutional quality (θ=1). Moderate frictions represent realistic developing country contexts with α=0.5, neutral coordination ω=0, and moderate institutional quality θ=0.5. Coordination collapse refers to destructive coordination (ω=-1) where instruments conflict and crowd each other out, nullifying financial mitigation. Transfers f and b are exogenous payments (e.g., forecast-based financing or social impact bonds) that relax credit constraints. $Total\ investment = s^* + \pi(1+\lambda)I^* + \pi R^*$.

4. Illustrative programme designs from Indonesia

The contrasting cases of AUTP–a standalone insurance product against drought, flood and pest risk in rice farming, and ILFAD–a bundle of 4 financial tools addressing all four stages of the risk management cycle to build resilience against large-scale natural hazards such as earthquake and volcanic eruption risks–allows us to illustrate how programmes can be designed to address (or not address) the core drivers of effective risk layering—coordination effectiveness (ω) and the underlying market frictions (α)— across diverse hazard types. Table 2 summarises how the examples relate to our model, while the rest of this section elaborates on the table, discussing both cases in more detail.

Our choice of examples is constrained by limited published case studies of suitable examples. There are no rigorous empirical evaluations of programme impacts or data that we can use to test the predictions of our model. The case studies, therefore, are illustrative and by no means representative, based on qualitative studies and reports showing how the programmes were designed.

Table 2: Model parameters addressed and propositions illustrated by the AUTP and ILFAD cases

	Financial instruments	Risk management Phase			
		Prevention	Risk Mitigation	Coping	Recovery
AUTP (flood, drought and pest risks)	Indemnity insurance			α (Friction 2 covariate risk).	
ILFAD (earthquake, volcanic eruptions)	savings (s)+ indemnity insurance + credit + social assistance $\equiv \{b, f\}$	ω, α (Friction 1 credit constraints)	ω, α (Friction 3 behavioural biases)	ω, α (Friction 1 credit constraint, Friction 2 covariate risk)	ω, α (Friction 1 credit constraint)

Note: θ refers to institutional quality, ω refers to coordination effectiveness, α refers to frictions manifested from market failures. Refer to Section 3 for more details of the theoretical model.

4.1. The Limits of Single Instruments (The Case of AUTP)

Indonesia's national rice-farming insurance program AUTP has been implemented since 2015. It offers a standalone product: an indemnity-based voluntary insurance scheme requiring on-the-ground verification of crop damage from flood, drought and pest risks for farmers cultivating less than 2 hectares of land. Farmers pay 20% of the actuarially fair premium per planting season, with the government subsidizing the remaining 80%. Compensation is triggered only when crop damage exceeds 70% of total yield. Administrative processes are standardized nationally through Ministry of Agriculture guidelines, and enrolment occurs via an online platform (Puspandari et al., 2025).

Between 2015–2019 the program achieved only 45% of its enrolment target (Yusuf et al., 2022), and a qualitative case study of one subdistrict, Pauh Duo in Sumatra (Kamillia & Jumiati, 2025), where farmer participation declined between 2022-2024, illustrates why standalone instruments can be inadequate when they fail to address multiple market failures.[5]

[5] This study employed a qualitative descriptive research design to examine the implementation of AUTP in subdistrict Pauh Duo in district Solok Selatan, West Sumatra. Data were collected through observation, in-depth interviews, and documentation using purposive sampling. Informants included agricultural officials, extension officers, plant and pest disease control officers, representatives from the insurance company, and farmers who both participated and did not participate in AUTP. Data validity was ensured through triangulation and audit trails. The study does not indicate how many people were interviewed or the when the interviews were conducted. We assume it was in 2024 or 2025, given the other information in the paper.

Although the large subsidy is meant to address barriers to entry and ease liquidity constraints in the risk mitigation phase, in Pauh Duo it did not. This is because cash-poor smallholder farmers lacked the liquidity ex-ante to pay even the remaining 20% subsidized premium contribution. This effectively rationed the instrument to those who are already better-off or less exposed to credit market failure (Friction 1). As a result, the subsidy was insufficient to induce broad participation.

Another issue was that the design of the indemnity mechanism introduced a severe behavioural barrier, aligning with Friction 3 (behavioural bias). The program required 70% crop damage for compensation eligibility. This high threshold created acute basis risk (the risk that a household suffers a significant but below-threshold loss). Since moderate losses of 40–60% were common, the high threshold caused farmers to perceive the instrument as having a lower utility than its actuarial cost. This low perceived value undermined the incentive effects of the price subsidy. Added to this was information asymmetry regarding the program itself with respondents reporting gaps in farmer understanding of the program. But information provision alone was insufficient to overcome behavioural biases with both farmers and extension agents identifying the need for "continuous socialization". Such biases were confirmed in other qualitative studies. For example, field work on farmer perceptions in Lampung Selatan, Sumatra, showed that 68.75% of respondents had low perception of AUTP despite awareness and marketing campaigns (Gitosaputro et al., 2023).

Concerns raised with product effectiveness in the coping phase were that claim processing was lengthy and complicated, with damage assessment processes slow. This weakened perceived usefulness of the scheme, increasing behavioural biases (Friction 3).

By design, the AUTP did not address failures in the prevention and recovery phases. But the credit constraints and information asymmetries that affected the mitigation phase are likely to have affected the prevention phase for households facing binding limits on ex-ante investment and ex-post recovery.

The example of Pauh Duo shows that while insurance addressed covariate risk, it was not sufficient to provide overall household resilience in the presence of liquidity constraints and basis risk. This meant low uptake, which in turn affected the presence of other providers in the market. The standalone instrument could not signal credible household commitment when other market failures remained unaddressed.

4.2 Coordinated Bundling: The Indonesia Liquidity Facility After Disaster (ILFAD)

ILFAD, implemented by Mercy Corps from 2011 to 2016 targeted households at risk of large natural hazards such as earthquakes and volcanic eruptions in Yogyakarta and West Sumatra. It was a proof-of-concept project, recognising that the disasters were not one-off occurrences and it was imperative to build resilience. It was used by over 2,200 clients in Yogyakarta (Java) and West Sumatra, reached via 162 Micro Finance Institutions (MFIs) such as rural banks and cooperatives (Toth & Hoy, 2017).

The program had two elements. One trained the MFIs to prepare for emergencies and then provided them with stabilizing liquidity post-disaster via parametric insurance. In terms of our model, this can strengthen coordination ω through facilitating efforts to speed recovery and stabilsing the financial sector across the risk management phases. The other element supported households with a bundle of financial products: mandatory savings, indemnity insurance, credit access, and social assistance for the poorest households, were provided via the MFIs (Mercy Corps, 2017). These financial tools were sequenced and coordinated through a single community institution that served as central coordinator, strengthening ω. The program required households to establish savings history (minimum 20% savings threshold) before accessing credit. The credit came with pre-arranged trigger points and repayment terms known in advance to both households and the MFIs. The claims process of indemnity insurance was predictable for households and insurers and independent of external forecast. The budget rules surrounding social assistance was known upfront. The predictability offered by ILFAD allowed households to plan.

By design, therefore, ILFAD addressed the prevention, mitigation, coping and recovery phases. In the prevention and mitigation phases, the mandatory savings requirement builds household buffers and eases credit constraints (Friction 1) while financial service providers build experience and trust. During the coping phase, households could access funds with speed. Credit was mobilised fast as it was prearranged with providers with no application process. Funds saved up under the mandatory savings requirement were also immediately accessible to households. Thus, households had access to emergency funding, solving a problem highlighted in field survey of 2,550 participants (Mercy Corps, 2017). Indemnity insurance for larger shocks was slower (requiring verification) but supported recovery. Social assistance further supported the poorest ex-ante. To ensure strong coordination and institutional support across the disaster risk management phase, the MFIs remained accessible throughout extended recovery.

The different instruments in the bundle were designed to address different market failures to reduce α: externalities through savings and insurance, information asymmetry through savings, insurance, and credit; coordination failure through insurance and credit; barriers to entry through savings, credit, and social assistance and behavioural biases through savings, credit, and social assistance. More details on how the market failures affect households and providers of financial services in this context, and how ILFAD addresses them, are provided in Appendix C.

ILFAD's design involved a layered approach to risk management, with insurance handling large losses (transferred to dedicated risk-bearer), credit handling medium losses (transferred to specialised lender, with lender bearing short-term risk while household repays), and savings handling small losses (borne by household through self-insurance). Thus, the ILFAD design layered risk in a vertical sense by loss severity while bundling across the disaster risk management cycle.

5. Discussion

The theoretical model predicted that when market failures bind across the disaster risk management phases, standalone instruments fail to achieve welfare-optimal outcomes. The simulation showed numerically how bundling increased household investment in risk management products and increased utility. The case of AUTP illustrated that a standalone product did not fully address market failures (e.g., 80% subsidy still made the premium unaffordable for poorer farmers, creating barriers to entry), and that design flaws together with payout delays that didn't meet emergency needs exacerbated other market failures (e.g., perception bias). Redesigning the insurance product itself could not have addressed all these failures–for example, delays in payout are almost inevitable with indemnity insurance that requires loss verification. Put differently, a single instrument cannot address all the frictions. And these frictions are not unique to a single phase. They compound over the risk management cycle. For example, credit constraint in the prevention stage means mitigation instruments can be more expensive (e.g., insurance premiums higher). This leads to exclusion due to unaffordability and as a consequence of the lack of pre-funded mechanisms ex-post. The example of ILFAD showed how programme design can incorporate the features of effective household-level risk layering (e.g., sequencing and matching complementary instruments) to improve ω in practice.

Indonesia provides further examples from other household-level standalone financial disaster risk reduction programmes on how coordination effectiveness ω can be strengthened. One way is through digitising cash transfer programs, cash and voucher assistance, and using digital platforms for identification, payment rails, and registries. Such efforts have been shown to increase speed of enrolment and assistance delivery, with coordination improved through process improvements that streamline data collection, reduce administrative burdens, and enhance transparency (Maghsoudi et al., 2023). However, behavioural biases and information asymmetries are likely to worsen in such efforts if low digital literacy, data security, and limited banking infrastructure are unaddressed.

The theoretical model incorporated institutions as exogenous rules of the game. These could be formal as well as informal, and program design needs to explicitly account for how they complement and interact. In Indonesia, informal institutions such as indigenous governance structures are known to improve coordination effectiveness, with some disaster interventions noting more success when operating through informal institutions (Andreastuti et al., 2019; Fahmy et al., 2024). For example, *Minangkabau Nagari* communities in West Sumatra rely on indigenous governance structures, explicitly involving *tungku tigo sajarangan* figures (i.e., the three pillars of leadership comprising traditional leaders, religious leaders, and intellectuals or educated people), to interpret disaster signals, coordinate collective action, and guide response behaviour during earthquakes (Nopriyasman et al., 2024). The trust, shared norms, and customary authority enable rapid coordination in disaster response. How exactly ω can be strengthened during program design with formal and informal institutions has to be further investigated.

Another important consideration is the extent to which formal financial instruments such as b, f, I can complement or displace informal ones. Remittances, informal aid, and kinship-based transfers are pivotal in post-disaster recovery of both community and household coping and recovery. Community-driven, kinship-based transfers managed outside formal aid channels are known to enable recovery, with rebuilding outcomes of both public projects and private housing closely tied to the economic success of migrant family networks (Berkel et al., 2025; Su, 2022). There is little empirical research done on how formal and informal financial tools interact to affect household welfare and bundling design needs to carefully consider this to avoid destructive coordination, $\omega < 0$.

6. Conclusion

This paper demonstrates that when multiple market failures bind simultaneously—credit constraints, coordination breakdowns, behavioural biases—no standalone financial instrument can achieve welfare-optimal household risk management. We develop a theoretical framework showing that bundled portfolios dominate through two distinct channels: positive coordination that creates instrument complementarities, and compensating benefits from simultaneously addressing different market failures across the temporal risk management cycle.

Our model makes three core contributions to the household disaster finance literature. First, we formalize the conditions under which bundling is necessary versus sufficient for welfare improvement. Second, we introduce the coordination effectiveness parameter ω as a key policy lever, that can be strengthened through program design, sequencing rules, communication and selecting complementary instrument portfolios. Third, we demonstrate that optimal portfolios must be shock-specific, layering instruments vertically by loss severity while bundling horizontally across ex-ante and ex-post phases. Our simulations show this pattern holds robustly across shocks differing eight-fold in probability and three-fold in severity: frequent medium-impact shocks induce diversification across multiple instruments, while rare catastrophic shocks concentrate investment in specialized risk-transfer mechanisms. Some financial instruments are better suited for one phase over another, and an approach incorporating all phases allows for more effective bundling that brings in new and innovative instruments into household disaster risk management.

The framework generates testable empirical predictions. First, bundled programs should achieve higher household investment in risk management instruments than standalone programs offering equivalent actuarial value. Second, coordination quality should exhibit threshold effects: welfare collapses under destructive coordination ($\omega<0$) but increases substantially under positive coordination ($\omega>0$), creating sharp welfare gains when programs shift from conflicting to complementary instrument design. Third, optimal portfolios should be shock-specific, with frequent medium-severity hazards inducing diversification across multiple instruments while rare catastrophic events induce specialization in risk-transfer mechanisms. These predictions invite rigorous empirical testing using quasi-experimental variation in program design, household heterogeneity in wealth or credit access, and natural variation in hazard probability-severity profiles.

Finally, the framework extends naturally beyond our risk management application. The same bundling logic applies wherever households face multiple market failures across temporal phases: health financing (prevention, treatment, recovery), agricultural development (input credit, weather insurance, output marketing), migration decisions (moving costs, destination income risk, remittance networks), and human capital investment (education loans, skill insurance, job search support). In each domain, instruments targeting different phases and market failures must be coordinated to achieve welfare gains.

Appendix A: Household optimisation problem and derivations

A representative household lives for two periods $t \in \{0,1\}$and faces a disaster in period 1 with probability $\pi \in (0,1)$. Preferences are CRRA:

$$U(c_0, c_1^d, c_1^n) = \frac{c_0^{1-\gamma}}{1-\gamma} + \beta \left[\pi \frac{(c_1^d)^{1-\gamma}}{1-\gamma} + (1-\pi) \frac{(c_1^n)^{1-\gamma}}{1-\gamma}\right], \gamma > 0, \gamma \neq 1.$$

The household takes y_0, y_1, f, b as given.

Disaster Severity and Mitigation

Baseline disaster severity is $\delta(0)$.

Financial instruments reduce the effective severity through:

- Social Impact bond transfer $b \geq 0$ tied to retrofitting that physically mitigates baseline severity from $\delta(0)$ to m $\delta(b) = \delta(0)e^{-\kappa b}$
- Forecast-based finance transfer $f \geq 0$ yielding mitigation ϕf
- Savings $s \geq 0$ yielding liquidity s^ρ, $\rho \in (0,1]$
- Parametric insurance $I \geq 0$ with premium $\pi(1+\lambda)I$
- Informal insurance $R \geq 0$ with premium πR and payout $R(1-\alpha)$

Coordination and institutional quality amplify financial mitigation via

$$\Psi(\theta, \omega) = (1+\theta)(1+\omega), \theta \in [0,1], \omega \in [-1,1].$$

Effective financial mitigation in the disaster state is:

$$[s^\rho + I + R(1-\alpha) + \phi f]\Psi(\theta, \omega).$$

Disaster-state consumption

$$c_1^d = (1-\delta(b))y_1 + [s^\rho + I + R(1-\alpha) + \phi f]\,\Psi(\theta, \omega).$$

Non-disaster consumption

$$c_1^n = y_1 + s^\rho.$$

Non-disaster consumption is:

$$c_1^n = y_1 + s^\rho.$$

Market Failures

Households optimize using perceived parameters distorted by friction $\alpha \in [0,1]$:

$$\hat{\delta}(b) = (1-\alpha)\delta(b) + \alpha\delta(0), \hat{\lambda} = \lambda + \alpha, \hat{\phi} = \phi(1-\alpha).$$

Perceived disaster-state consumption

$$\hat{c}_1^d = (1-\hat{\delta}(b))y_1 + [s^\rho + I + R(1-\alpha) + \hat{\phi}f]\,\Psi(\theta,\omega).$$

Budget and Credit Constraints

Period 0 budget constraint

$$c_0 + s + \pi(1+\lambda)I + \pi R = y_0 + f + b.$$

Credit constraint (Friction 1)

$$s + \pi(1+\lambda)I + \pi R \le \bar{L}(1-\alpha) + f + b,$$

with $\bar{L} < y_0$, so this constraint binds before the budget constraint in relevant regions.

Non-negativity constraints

$$s \ge 0, I \ge 0, R \ge 0.$$

Household's Optimization Problem

The household chooses (s, I, R) to maximize perceived expected utility:

$$\max_{s,I,R\ge 0} \hat{U}(c_0, \hat{c}_1^d, c_1^n)$$

subject to:

1. (Budget)

$$c_0 + s + \pi(1+\lambda)I + \pi R = y_0 + f + b.$$

2. (Credit constraint)

$$s + \pi(1+\lambda)I + \pi R \leq \bar{L}(1-\alpha) + f + b.$$

3. (Consumption definitions)

$$\begin{aligned}
c_0 &= y_0 + f + b - s - \pi(1+\lambda)I - \pi R,\\
c_1^n &= y_1 + s^\rho,\\
\hat{c}_1^d &= (1-\hat{\delta}(b))y_1 + [s^\rho + I + R(1-\alpha) + \hat{\phi}f]\Psi(\theta,\omega).
\end{aligned}$$

The household evaluates outcomes using perceived parameters $(\hat{\delta}, \hat{\lambda}, \hat{\phi})$, while true payoffs use (δ, λ, ϕ).

The Lagrangian

The household's perceived optimization problem is characterized by:

$$\mathcal{L} = \hat{U}(c_0, c_1^d, c_1^n) + \mu_1[y_0 + f + b - c_0 - s - \pi(1+\hat{\lambda})I - \pi R] + \mu_2[\bar{L}(1-\alpha) + f + b - s - \pi(1 + \hat{\lambda})I - \pi R] + \eta_s(s) + \eta_i(I) + \eta_r(R)$$

where

$$\begin{aligned}
c_0 &= y_0 + f + b - s - \pi(1+\hat{\lambda})I - \pi R,\\
c_1^n &= s^\rho + y_1,\\
c_1^d &= [1-\hat{\delta}(b)]y_1 + [s^\rho + I + R(1-\alpha) + \hat{\phi}f]\Psi(\theta,\omega),
\end{aligned}$$

and the perceived parameters are defined as:

$$\begin{aligned}
\hat{\delta}(b) &= (1-\alpha)\delta(b) + \alpha\delta(0),\\
\hat{\lambda} &= \lambda + \alpha,\\
\hat{\phi} &= \phi(1-\alpha),\\
\Psi(\theta,\omega) &= (1+\theta)(1+\omega).
\end{aligned}$$

First-Order Conditions (FOCs)

(a) Savings s

$$\frac{\partial \mathcal{L}}{\partial s} = 0 \Rightarrow -c_0^{-\gamma} + \beta[(1-\pi)c_1^{n\,-\gamma}\rho s^{\rho-1} + \pi c_1^{d\,-\gamma}\rho s^{\rho-1}\Psi(\theta,\omega)] - \mu_1 - \mu_2 + \eta_s = 0$$

Simplifying:

$$-c_0^{-\gamma} + \beta\rho s^{\rho-1}[(1-\pi)c_1^{n\,-\gamma} + \pi c_1^{d\,-\gamma}\Psi(\theta,\omega)] - \mu_1 - \mu_2 + \eta_s = 0$$

Kuhn–Tucker conditions:

$$\eta_s \geq 0, s \geq 0, \eta_s \cdot s = 0$$

(b) Parametric Insurance I

$$\frac{\partial \mathcal{L}}{\partial I} = 0 \Rightarrow -\pi(1+\hat{\lambda})c_0^{-\gamma} + \beta\pi c_1^{d\,-\gamma}\Psi(\theta,\omega) - \mu_1\pi(1+\hat{\lambda}) - \mu_2\pi(1+\hat{\lambda}) + \eta_i = 0$$

Kuhn–Tucker conditions:

$$\eta_i \geq 0, I \geq 0, \eta_i \cdot I = 0$$

(c) Informal Insurance R

$$\frac{\partial \mathcal{L}}{\partial R} = 0 \Rightarrow -\pi c_0^{-\gamma} + \beta\pi c_1^{d\,-\gamma}(1-\alpha)\Psi(\theta,\omega) - \mu_1\pi - \mu_2\pi + \eta_r = 0$$

Kuhn–Tucker conditions:

$$\eta_r \geq 0, R \geq 0, \eta_r \cdot R = 0$$

Constraints

Budget constraint:

$$\mu_1[y_0 + f + b - c_0 - s - \pi(1+\hat{\lambda})I - \pi R] = 0$$

Credit constraint:

$$\mu_2[\bar{L}(1-\alpha)+f+b-s-\pi(1+\hat{\lambda})I-\pi R]=0$$

Interior Solution

Assume $s>0, I>0, R>0$, and the credit constraint binds.
Setting $\eta_s=\eta_i=\eta_r=0$:

Savings condition:

$$c_0^{-\gamma}+\mu_1+\mu_2=\beta\rho s^{\rho-1}[(1-\pi)c_1^{n\ -\gamma}+\pi c_1^{d\ -\gamma}\Psi(\theta,\omega)]$$

Parametric insurance condition:

$$\pi(1+\hat{\lambda})(c_0^{-\gamma}+\mu_1+\mu_2)=\beta\pi c_1^{d\ -\gamma}\Psi(\theta,\omega)$$

Dividing by $\pi(1+\hat{\lambda})$:

$$\left(1+\hat{\lambda}\right)[c_0^{-\gamma}+\mu_1+\mu_2]=\beta c_1^{d\ -\gamma}\Psi(\theta,\omega)$$

Informal insurance condition:

$$c_0^{-\gamma}+\mu_1+\mu_2=\beta c_1^{d\ -\gamma}(1-\alpha)\Psi(\theta,\omega)$$

Combining yields:

1. $\beta\rho s^{\rho-1}[(1-\pi)c_1^{n\ -\gamma}+\pi c_1^{d\ -\gamma}\Psi(\theta,\omega)]=c_0^{-\gamma}+\mu_1+\mu_2$
2. $\beta c_1^{d\ -\gamma}\Psi(\theta,\omega)=(1+\hat{\lambda})[c_0^{-\gamma}+\mu_1+\mu_2]$
3. $\beta c_1^{d\ -\gamma}(1-\alpha)\Psi(\theta,\omega)=c_0^{-\gamma}+\mu_1+\mu_2$

Marginal Rates of Substitution

Between I and R, from (2) and (3):

$$(1+\hat{\lambda}) = \frac{1}{1-\alpha}$$

This defines the optimal mix between formal and informal insurance, given loading factors and covariate risk.

Between s and R**,** from (1) and (3):

$$\rho s^{\rho-1}[(1-\pi)c_1^{n\,-\gamma} + \pi c_1^{d\,-\gamma}\Psi(\theta,\omega)] = \beta c_1^{d\,-\gamma}(1-\alpha)\Psi(\theta,\omega)$$

For $\rho < 1$, as s increases, the left-hand side declines due to $\rho s^{\rho-1}$, yielding an interior optimum that shifts investment toward insurance.

Analytical Proofs of propositions 1-3

Proposition 1 (Bundling Dominates Single Instruments)

$$\Delta(s,I,R) = \delta(b) - \frac{[s^{\rho} + I + R(1-\alpha) + \phi f]\Psi(\theta,\omega)}{y_1}$$

with $\Psi(\theta,\omega) = (1+\theta)(1+\omega)$.
For $\omega > 0$: $\Psi(\theta,\omega) > \Psi(\theta,0)$, so bundles dominate single instruments.

When $\omega \leq 0$, bundling can still dominate by:

- Relaxing credit constraints (via f, b)
- Addressing multiple frictions ($\alpha > 0$)
- Diversifying away from inefficient s^{ρ}

Proof: When $\rho < 1$, $\rho s^{\rho-1} \to 0$ as $s \to \infty$; insurance instruments with linear returns remain optimal.

Proposition 2 (Welfare Gain Rises with Coordination)

$$U(s,I,R) = \frac{c_0^{1-\gamma}}{1-\gamma} + \beta\left[\pi\frac{(c_1^d)^{1-\gamma}}{1-\gamma} + (1-\pi)\frac{(c_1^n)^{1-\gamma}}{1-\gamma}\right]$$

Since c_1^d increases with $\Psi(\theta, \omega)$:

$$\frac{\partial U}{\partial \omega} = \beta\pi(c_1^d)^{-\gamma} \frac{[s^\rho + I + R(1-\alpha) + \phi f]}{y_1} > 0$$

Thus, welfare gain rises with coordination.

When $\rho < 1$, coordination partially offsets storage inefficiency; however, first-best remains unattainable due to inherent losses.

<u>Proposition 3 (Market Failures and Storage Inefficiency Create Necessity; Coordination Creates Sufficiency)</u>

Necessity: With $\alpha > 0$ or $\rho < 1$, no single instrument can fully mitigate Δ.
Linear-return instruments I, R are necessary complements when $\rho s^{\rho-1} \to 0$.

Sufficiency: Positive $\omega > 0$ increases $\Psi(\theta, \omega)$ and expected utility; bundling becomes sufficient for welfare dominance.

Optimal portfolios balance breadth of instruments, coordination costs and storage efficiency (ρ) versus loading factors (λ). Propositions 1–3 follow from aggregation using s^ρ, monotonicity of $\Psi(\theta, \omega)$, increasing CRRA utility, diminishing returns $\rho s^{\rho-1} \to 0$ as $s \to \infty$.

Appendix B

Computational method for risk layering model simulation

We solve the household's optimization problem numerically using a constrained grid search algorithm implemented in Stata 14. A global grid search optimization rather than gradient-based method is used for three reasons: (1) the non-convexity introduced by the exponential risk-reduction function δ(b) = δ_0e^(-kb); (2) the multiplier Ψ(θ,ω) creates complex interaction effects; and (3) discrete coordination regimes $\omega \in$ {-1, 0, 1} preclude smooth optimization.

The method proceeds in three steps:

Step 1: We discretize the choice space (s, I, R) by expressing each instrument as a percentage allocation of available resources. Savings s ranges over [0, 50%] of total budget in 2% increments; insurance I and informal transfers R each range over [0, 80%] of remaining budget (after prior allocations) in 4% increments. This generates approximately 10,000 candidate portfolios per scenario.

Step 2**:** For each candidate portfolio (s, I, R), we verify:

- Budget constraint: $s + \pi(1+\lambda)I + \pi R \leq y_0 + f + b$
- Credit constraint: $s + \pi(1+\lambda)I + \pi R \leq \bar{L}(1-\alpha) + f + b$
- Non-negativity: $c_0, c_1^d, c_1^n > 0.1$ (numerical stability threshold)

Invalid portfolios are discarded.

Step 3: For each feasible portfolio, we compute perceived expected utility $\widehat{U}$ using perceived parameters $\widehat{\delta}, \widehat{\lambda}, \widehat{\varphi}$) but report actual expected utility U^* using true parameters $(\delta, \lambda, \varphi)$. The optimal portfolio (s^*, I^*, R^*) maximizes U^* subject to constraints. CRRA utility with $\gamma = 2.5$ is evaluated using exact formulas; we avoid numerical instability near $\gamma = 1$ by using logarithmic utility when $\gamma \in [0.99, 1.01]$.

Calibration Strategy

Parameters are not empirically validated but chosen to plausibly reflect empirical regularities in the Indonesian/developing country context:

- Disaster probabilities**:** π = 0.05 (rare earthquakes), π = 0.40 (seasonal floods)
- Severity: δ = 0.80 (catastrophic earthquakes), δ = 0.25 (moderate floods)

- FbF effectiveness**:** $\varphi = 0.10$ (earthquakes, limited lead time), $\varphi = 0.75$ (floods, seasonal predictability)
- Credit constraint: $\bar{L} = 40 < y_0 = 100$ ensures binding constraint in high-friction scenarios
- Insurance loading: $\lambda = 0.15$ reflects insurance markets
- Risk aversion**:** $\gamma = 2.5$ (standard in development literature)

Retrofitting effectiveness follows $\delta(b) = \delta(0)e^{-\kappa b}$ with $\kappa = 0.12$, capturing diminishing returns to physical mitigation.

Validation Checks

We verify computational accuracy through:

1. Boundary conditions: $\omega = -1$ produces zero investment in (s, I, R), as predicted theoretically
2. Monotonicity: Expected utility increases in $\omega \in [0,1]$ for all scenarios.
3. Credit constraints binding: Optimal portfolios exhaust the credit limit $\bar{L}(1 - \alpha) + f + b$ in high market failure $\alpha > 0$ scenarios, confirming friction 1 binds.
4. Comparative statics: Insurance share increases with disaster severity; savings share increases with storage efficiency ρ.

Grid resolution was increased until optimal portfolios stabilized (changes < 0.1% in total investment). All results are reproducible using the replication code provided in the supplementary materials.

Appendix C

Appendix C Table 1: Optimal instrument bundles for disaster risk management

Scenarios	Market failures, bundle coordination and institutional quality			Financial tools					Total investment	Expected Utility	Effective Severity Δ	C_0	c_1^d	c_1^n
	α	ω	θ	f	b	s*	I*	R*						
Earthquake														
Best case (no transfers)	0	1	1	0	0	0	0	80	4	-1.32	-2.40	96	340	100
Best case (with transfers)	0	1	1	2	2	0	0	83.2 0	4.16	-1.28	-2.7	99.84	370.67	100
Worst case (no transfers)	1	-1	0	0	0	0	0	0	0	-1.63	0.80	100	20	100
Worst case (with transfers)	1	-1	0	2	2	0	0	0	0	-1.38	0.63	104	37.07	100
Moderate (no transfers)	0.5	0	0.5	0	0	0	48.48	0	2.79	-1.34	0.07	97.21	92.73	100
Moderate (with transfers)	0.5	0	0.5	2	2	0	50.42	0	2.90	-1.29	-0.13	101.1	113.01	100
Seasonal Floods														
Best case (no transfers)	0	1	1	0	0	0	0	20	8	-1.27	-0.55	92	155	100
Best case (with transfers)	0	1	1	2	2	0	0	20.8 0	8.32	-1.21	-0.70	95.68	169.53	100
Worst case (no transfers)	1	-1	0	0	0	0	0	0	0	-1.44	0.25	100	75	100

Worst case (with transfers)	1	-1	0	2	2	0	0	0	0	-1.37	0.2	104	80.33	100
Moderate (no transfers)	0.5	0	0.5	0	0	2	5.94	0	4.73	-1.41	0.13	95.26	86.9	102
Moderate (with transfers)	0.5	0	0.5	2	2	2.08	6.17	0	4.92	-1.33	0.05	99.08	94.9	102.1

Notes: For earthquakes $\delta = 0.8,\ \pi = 0.05, \phi = 0.1$. For floods $\delta = 0.25,\ \pi = 0.4, \phi = 0.75$). All other parameters for both scenarios are: $\gamma = 2.5,\ \beta = 0.96,\ \rho = 0.8,\ \lambda = 0.75,\ \kappa = 0.12,\ \bar{L} = 40, y_0 = y_1 = 100$. Optimal quantities (s^*, I^*, R^*) for bundles are household choices while f, b are exogenous transfers decided by the policy maker. Total investment in risk management instruments in period 0 equals $s^* + \pi^*(1+\lambda)^* I^* + \pi^* R^*$. Best case refers to scenarios with no market failure, perfect coordination and highest institutional quality. Worst case refers to scenarios with highest market failure, destructive coordination and lowest institutional quality.

How ILFAD instruments address market failures

Externalities: Refer to costs or benefits of household or provider's actions affect others but are not reflected in market prices. This can manifest in underinvestment in prevention measures, increased collective risk, higher mitigation costs, higher prices, etc. Among providers, externalities manifest as financial providers not seeing the ripple effects of their decision with the withdrawal of one provider destabilising the entire market. ILFAD addresses this through mandatory savings that makes visible household buffers reducing community contagion and attracting providers who observe stability. Indemnity insurance can reduce emergency asset sale, stabilising community prices that provider depend on. These positive externalities are visible to both households and providers, making households more resilient, attract more financial providers in the long-term and reduce learning costs for new providers entering the market[6].

Information asymmetry: Refers to market participants have unequal information causing adverse selection, moral hazard, high signalling costs missing markets, trust gaps, preventing efficient allocation. Households can be uncertain about which financial tool to use, in what order, or if providers are trustworthy while providers uncertain about household reliability and what other providers offer to offer complementary products. ILFAD addresses this through having a single community institution bunding savings, insurance and credit creates a verification chain that can ease the issues.

Coordination failure: Refers to inefficient outcomes because actors fail to align strategies, duplicate efforts, or leave gaps. For example, households face decision paralysis—"Insurance first or savings?" and timing mismatches (wants credit when provider isn't ready). Providers face the issue of each one aciting independently creating gaps in service or duplicating. In the ILFAD design, the community institution acts as central coordinator of pre-arranged credit, pre-arranged trigger points with insurance provider and indemnity insurance, coordinating with credit provider on claims. This eliminates timing mismatch between household needs and provider availability and aligns provider incentives.

Barriers to entry: Refers to structural or institutional barriers that exclude certain groups from accessing markets or support systems. For households this means that they cannot access

[6] In a different context, similar positive externalities are argued to reap 'multiple resilience dividends' Mechler, R., Żebrowski, P., Clercq-Roques, R., Patil, P., & Hochrainer-Stigler, S. (2025). Positive Externalities in the Polycrisis: Effectively Addressing Disaster and Climate Risks for Generating Multiple Resilience Dividends. *International Journal of Disaster Risk Science*, *16*(4), 575-593. https://doi.org/10.1007/s13753-025-00661-2

credit/insurance because they lack payment history and collateral, and providers see them as too risky. Providers on the other hand see barriers to serving low-income rural areas due to high transaction costs, high perceived risk and/or regulatory requirements. ILFAD instruments address it through mandatory savings that creates entry for households (proof of reliability) and for providers (lower cost per transaction, reduced risk); credit that is only available with savings history (screens for reliability, lowers provider risk; social assistance where the poorest get subsidy to meet savings requirement (removes household barrier) and subsidizes provider's cost of serving them.

Behavioural biases: Refers to deviations from rational decision-making due to cognitive biases, short-term thinking, or lack of salience. For households this may manifest in over-discount future risks, choice overload, lack commitment devices or influence by social pressure against uptake. For providers this may mean overconfidence in their risk models, loss-averse (scared of new markets), underestimate demand, herd behaviour (follow other providers out of market). ILFAD instruments address this through savings that act as a commitment device for households that demonstrates sustained demand to providers (reduces provider loss aversion); credit that reduces choice overload for households and for proof of household demand reduces overconfidence bias and herd behaviour providers; social assistance with community ins institution provides peer pressure in favour of uptake to both households and provider networks. The result is that the mandatory structure creates visibility that corrects provider biases (proves demand exists) while community support overcomes household hesitation.

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