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# Who Pays When Disaster Strikes? A Household-Centered Framework for Disaster Resilience in American Communities

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# Who Pays When Disaster Strikes? A Household-Centered Framework for Disaster Resilience in American Communities


## Abstract

Disaster finance in the United States is built around governments, insurers and federal aid. The household, where losses are absorbed first, is its least theorized layer. In 2025 the country recorded 23 disasters costing at least US$1 billion each, while 37% of adults could not cover a US$400 emergency with cash or its equivalent. This article argues that the binding constraint for many families is not the total amount of post-disaster resources but their timing. Drawing on a published National Science Foundation–funded survey of 374 households in post-earthquake rural Haiti and on published comparative evidence from Hurricane Katrina, it shows that in Haiti external aid rarely reached household livelihoods while community trust remained high. It then proposes *Resilience by Design*, a household-centered framework that links two foundational principles (economic justice and *affectio societatis*) to behavioral, financial and recovery mechanisms. Retroactive economics, the recovery mechanism, holds that reconstruction should repair the economic incapacities that predated the disaster rather than restore the status quo ante. A liquidity-gap model, a sensitivity analysis, a Monte Carlo simulation of risk pooling under correlated shocks and a stochastic fund-growth model show that a modest community savings layer can sharply reduce the size and duration of household cash shortfalls, with gains that shrink, but persist, when shocks are highly correlated. Extended models with realistic frictions, including front-loaded needs, loan repayment and clustered defaults, confirm the direction of

these results while lowering their size. The article ends with policy implications and a pilot evaluation design.

**Keywords:** household finance; disaster resilience; emergency savings; risk pooling; community finance; Monte Carlo simulation

## 1. Introduction

When disaster strikes an American community, the first balance sheet to break is usually not the federal budget or an insurer's reserves. It is the household's. Families pay for evacuation, temporary housing, lost wages and urgent repairs long before claims settle or public assistance arrives, and whether they can do so depends on something national policy rarely measures: the liquid savings they hold on the day of the shock.

The exposure is growing. In 2025 the United States recorded 23 weather and climate disasters with at least US$1 billion in damages each, about US$115 billion in total, the third-highest annual count on record (Climate Central, 2026). Between 1980 and 2019 the country averaged roughly eight such events a year (Figure 1).

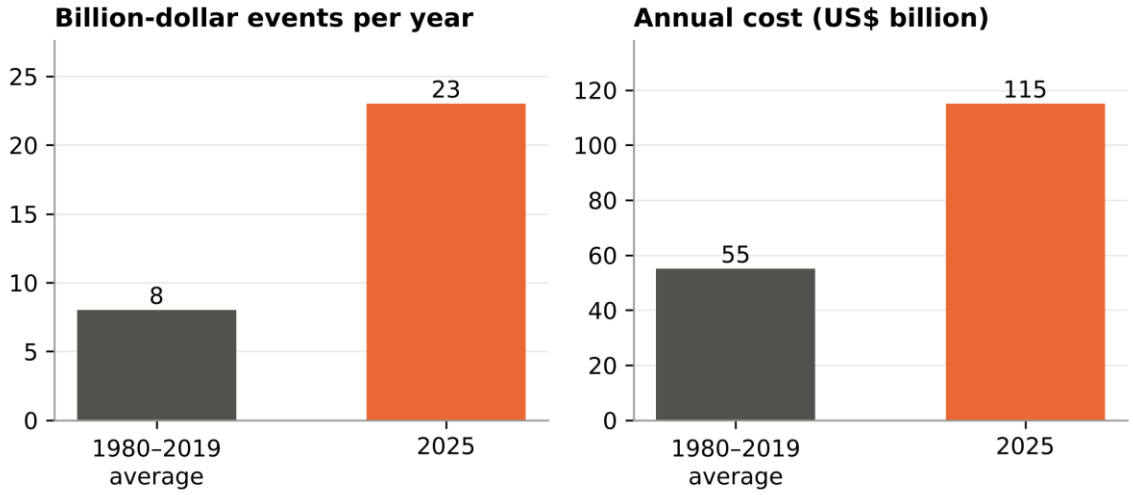


**Fig. 1** U.S. billion-dollar weather and climate disasters: 1980–2019 annual average versus 2025. Left: number of events. Right: annual cost in US$ billion. Source: Climate Central (2026)

Household buffers have not kept pace. In the Federal Reserve's most recent Survey of Household Economics and Decisionmaking (SHED), 63% of adults said they would cover a hypothetical US$400 emergency entirely with cash or its equivalent, unchanged since 2022 and below the 2021 peak of 68% (Board of Governors of the Federal Reserve System, 2026; Figure 2). A disaster costs far more than US$400. For a large share of families, the first weeks after one are therefore financed with credit cards, payday loans, missed bills and help from relatives.

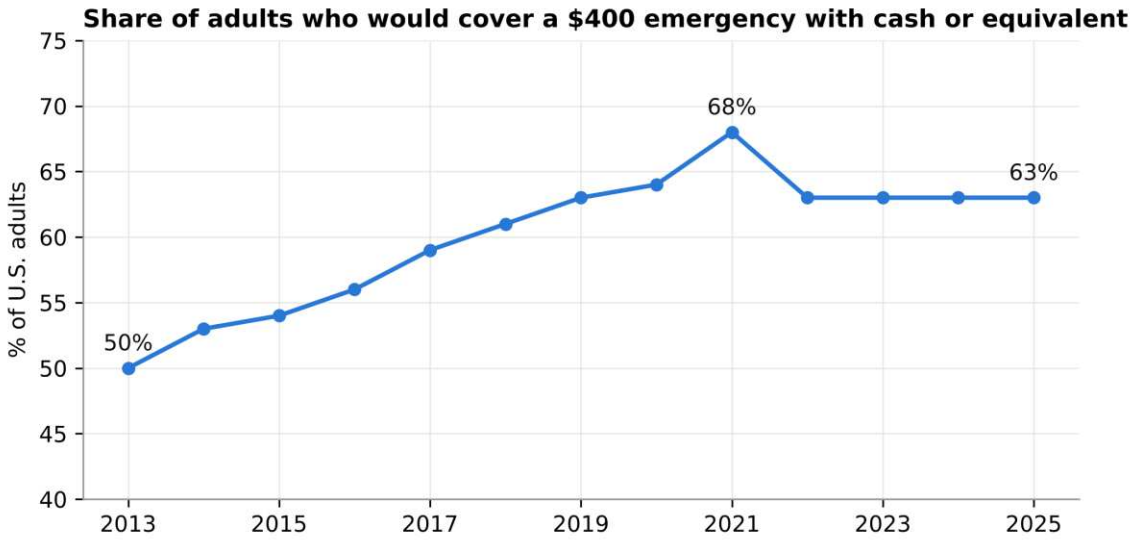



**Fig. 2** Share of U.S. adults who would cover a hypothetical US$400 emergency expense with cash or its equivalent, 2013–2025. Source: Board of Governors of the Federal Reserve System, SHED annual reports

The damage lasts. Matching credit bureau records to FEMA disaster declarations, Ratcliffe et al. (2019) found that disasters lowered credit scores and raised collections, bankruptcies and mortgage delinquencies, with effects that persisted or grew over time and were often worst after

medium-sized events that attract little long-term recovery funding. Howell and Elliott (2019) showed that disaster damage and the aid that follows widen wealth inequality.

The starting point of this article is a contrast documented in post-earthquake research in rural Haiti (Pyles et al., 2015). About two years after the 2010 earthquake, many surveyed households had lost their income almost overnight and were still waiting for programs that rarely reached their livelihoods, yet the same communities described neighbors pooling food, labor and cash within days. That contrast, between slow external money and fast but unorganized community capacity, frames the questions that follow.

The article asks who pays when disaster strikes, and how American communities could help households pay less, recover sooner and depend less on aid. It makes three contributions. First, it treats household liquidity, and especially its *timing*, as a missing layer of U.S. disaster finance. Second, it draws transferable mechanisms, not general lessons, from comparative research on rural Haiti and the U.S. Gulf Coast. Third, it proposes *Resilience by Design*, a framework that connects two foundational principles to three mechanisms across the disaster cycle, and it formalizes the framework's central claims in a set of simple, reproducible models. The article is conceptual: it builds and illustrates a framework, and it specifies how that framework can be tested.

## 2. The household gap in U.S. disaster finance

U.S. disaster finance rests on three layers: private insurance, public assistance and the borrowing capacity of governments and firms. Each is organized around assets, jurisdictions or institutions. None is designed around a family's cash flow in the first ninety days after a shock.

### 2.1 Insurance protects property, not liquidity

Households underinsure against low-probability, high-loss events because they misjudge risk, discount the future and see premiums as a cost with no visible return (Kunreuther & Pauly, 2004). Affordability matters too: in the Federal Reserve's 2024 survey, 7% of homeowners had no homeowners insurance, frequently because they could not afford it (Board of Governors of the Federal Reserve System, 2025). Even insured households face deductibles, exclusions and settlement delays. Insurance may eventually rebuild a house; it rarely pays rent or groceries on time.

### 2.2 Public aid arrives late and partially

Federal individual assistance is capped, conditioned on documentation and released after declarations and inspections. Ratcliffe et al. (2019) conclude that relief programs, together with private insurance and informal support, do not fully protect residents from the financial consequences of disasters. Households already struggling before the event are the least able to bridge the wait (Fothergill & Peek, 2004).

### 2.3 Moral hazard, charity hazard and their limits

The *Samaritan's dilemma* holds that expected help can weaken the incentive to prepare (Buchanan, 1975); in insurance, the same mechanism is called *charity hazard* (Raschky & Weck-Hannemann, 2007). U.S. evidence suggests the effect is real but modest: Kousky et al. (2018) found that federal grants reduce later flood insurance coverage, while federal loans do not. Two qualifications follow. First, for households with no savings, aid and self-protection are not substitutes at all, because there is nothing to crowd out. Second, community savings and public aid can be complements: a local buffer that pays in days makes a late public payment

more useful rather than less. The framework below is built on this complementarity, not on replacing aid.

### 2.4 Unequal exposure

The household gap is not evenly distributed. Disaster losses concentrate among households with low income, thin savings and weak institutional ties (Cutter et al., 2003), and women often carry a disproportionate share of post-disaster care and recovery work (Enarson, 2012). Access to the financial system itself is unequal. In 2023, 4.2% of U.S. households, about 5.6 million, had no bank or credit union account, but the rate reached 10.6% among Black, 9.5% among Hispanic and 12.2% among American Indian or Alaska Native households, against 1.9% among White households, and 11.2% among working-age households with a disabled member (Federal Deposit Insurance Corporation [FDIC], 2024; Figure 3). Unbanked households cannot receive electronic aid quickly, have no deposit buffer and rely on the costliest forms of credit.

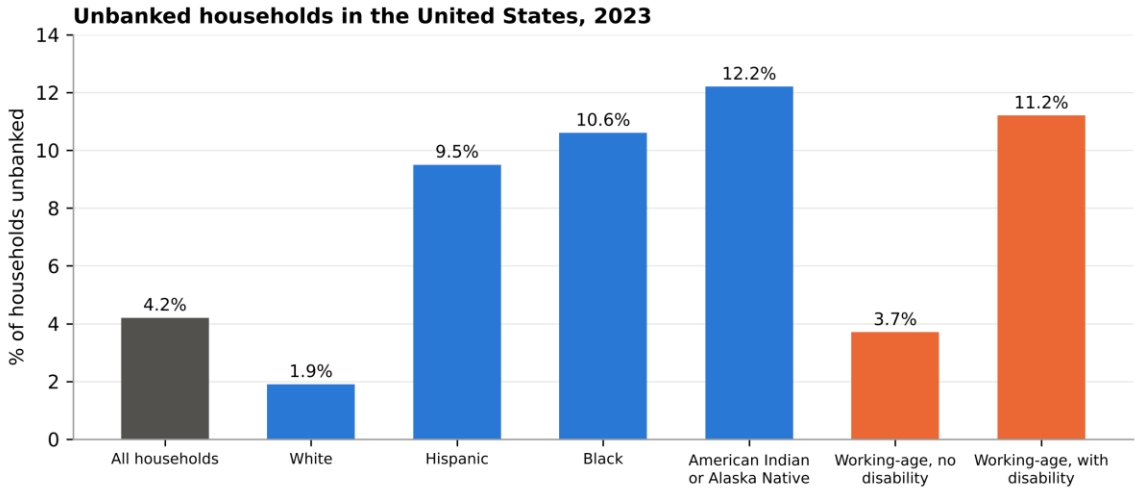



**Fig. 3** Unbanked U.S. households by race and ethnicity and by disability status, 2023, percent. Source: FDIC (2024)

### 2.5 Related frameworks and the contribution of this article

Household disaster finance has recently attracted formal attention. Himaz et al. (2026) model household risk layering in developing countries and show that bundling instruments across prevention, coping and recovery dominates single instruments such as insurance when households face several market failures at once. Low-income households also manage risk through savings clubs, rotating credit associations and family transfers (Besley et al., 1993; Collins et al., 2009).

This article differs in three ways. It focuses on the *timing* of household liquidity rather than the mix of financial products. It treats community trust and voluntary association, not instrument design, as the organizing resource. And it adds a recovery principle, retroactive economics, that asks what recovery should restore. Its setting is the United States, informed by comparative evidence from Haiti.

## 3. Lessons from rural Haiti and the U.S. Gulf Coast

The framework grows out of a three-year comparative program funded by the National Science Foundation's Disaster Resilience in Rural Communities Program (Grant #1133264), which examined how external actors and rural communities interacted during recovery from the 2010 Haiti earthquake and from Hurricane Katrina, using a capabilities approach (Gardoni & Murphy, 2008; Sen, 1999).

### 3.1 Haiti: livelihoods collapse, aid misses the household

In 2012, trained community leaders conducted random door-to-door surveys of 374 respondents in three rural communities with low (L), medium (P) and high (F) levels of earthquake impact, in the Artibonite, South-East and West departments (Pyles et al., 2015). Three findings matter here.

1. **Income collapsed and stayed down.** Eighty-five percent said the disaster cost them their ability to earn money; about two years later, only 5% had regained a source of income.
2. **Outside help rarely reached livelihoods.** Fewer than 1% had taken part in any livelihood or organizational capacity-building activity with outside actors, and 8.9% in an agricultural project. Rural households also took in relatives displaced from Port-au-Prince.
3. **Social capital stayed high.** More than 90% trusted people in their own community, and about 80% described themselves as active community members in ordinary times. Focus group participants called this *tèt ansanm*, putting heads together.

Losses were broad: 37.6% of respondents saw their homes become uninhabitable and 45.5% lost other property, and 57% expected their community to be worse in five years. Yet only 17% had joined any project with external actors, and fewer than 10% had held an active role in one (Figure 4).

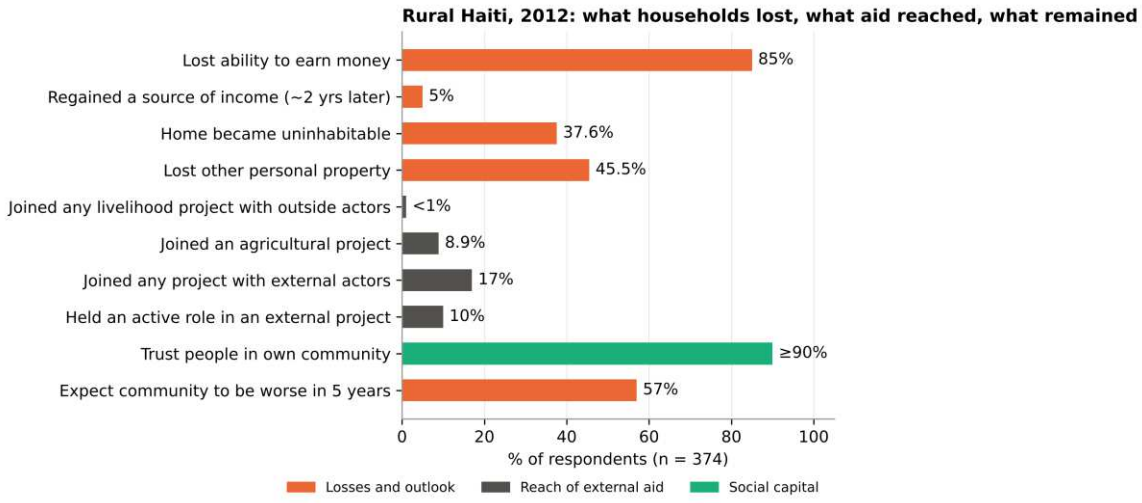



**Fig. 4** Losses, reach of external aid and social capital among 374 respondents in three rural Haitian communities, 2012. Source: author's elaboration from Pyles et al. (2015)

The averages hide large differences (Figure 5). Participation in relief or recovery projects ranged from 5% in community L to 58% in community F, which was hit hardest, lay closest to Port-au-Prince and received more outside projects. Active participation in ordinary community life, by contrast, was high everywhere, reaching 95% in community P. Emotional recovery lagged in all three: 72% to 86% said they had not recovered emotionally about 30 months after the earthquake.

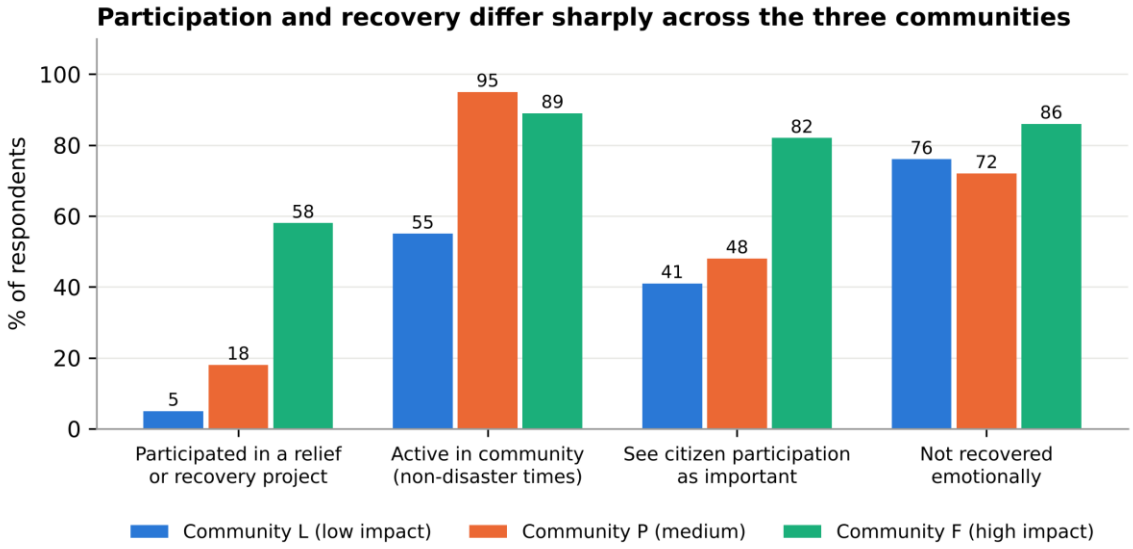



**Fig. 5** Participation and recovery indicators by community (L = low, P = medium, F = high earthquake impact), percent of respondents. Source: author's elaboration from Pyles et al. (2015)

A caution is needed. High trust is an *enabling condition* for collective finance, not evidence that collective finance works. The Haiti data show that the social precondition existed and that external programs did not build on it; they do not show what a savings layer would have achieved. That question is addressed separately, by existing studies of community savings groups and by the models in Section 5.

### 3.2 The Gulf Coast: social capital shapes American recovery too

The comparative arm surveyed rural Gulf Coast communities after Katrina. Using both datasets, Pyles et al. (2018) tested whether disaster impacts and social capital, measured as trust and civic engagement, predicted local participation in recovery, and compared the predictors across the two countries. The wider Katrina literature points the same way. Aldrich (2012) found that the strength of social networks, more than aid volume or damage, was a key driver of how fast neighborhoods recovered. Chamlee-Wright and Storr (2009) showed how a Vietnamese American Catholic parish in New Orleans East organized its community's early return, and Cain and Barthelemy (2008) documented congregations delivering material and spiritual relief.

### 3.3 What transfers, and what does not

Rural Haiti and American communities differ in income, infrastructure, state capacity and legal systems. The comparison is therefore not an argument that the two settings are equivalent. It is a search for mechanisms that operate in both, and for the conditions they need to work in the United States.

| Element | Comparable across settings | Specific to rural Haiti | Transferable mechanism | Adaptation needed in the U.S. |
|---|---|---|---|---|
| Timing of resources | Aid and insurance arrive weeks or months after the shock | Weak state, few formal payouts at all | A local buffer that pays in days | Coordinate with FEMA and insurer timelines |
| Social capital | Trust and networks predict participation | Very high neighbor | Organize finance through | Trust is uneven and often lower in mobile |

| Element | Comparable across settings | Specific to rural Haiti | Transferable mechanism | Adaptation needed in the U.S. |
|---|---|---|---|---|
| | and recovery | trust (over 90%) | existing trust networks | urban areas |
| Faith institutions | Congregations act as recovery infrastructure | Religion central to coping | Use congregations as delivery points | Add secular hubs; guarantee non-religious access |
| Collective savings practice | Informal pooling exists in both | Pooling is customary | Formalize pooling with clear rules | Comply with consumer finance and fiduciary rules |
| Recovery goal | Pre-disaster vulnerability shapes recovery | Deep historical deficits | Repair pre-existing incapacities | Link to credit-building and asset policies |

The central transferable lesson is about mechanism, not culture: where trust exists, a pre-organized local buffer can release cash faster than any external program. Where trust is weaker, the institution hosting the group must work harder to build it.

## 4. The Resilience by Design framework

*Resilience by Design* starts from one proposition: a household is resilient to disaster when it can mobilize enough liquidity, fast enough, to protect its income and capabilities through the shock, and when recovery leaves it better able to face the next one. The framework explains how that outcome is produced. It is organized in three levels rather than five parallel pillars (Figure 6). Two foundational principles define what recovery is for and what makes collective action

possible. Three mechanisms then act at different moments of the disaster cycle: a behavioral mechanism before the shock, a financial mechanism during it, and a recovery mechanism after it.

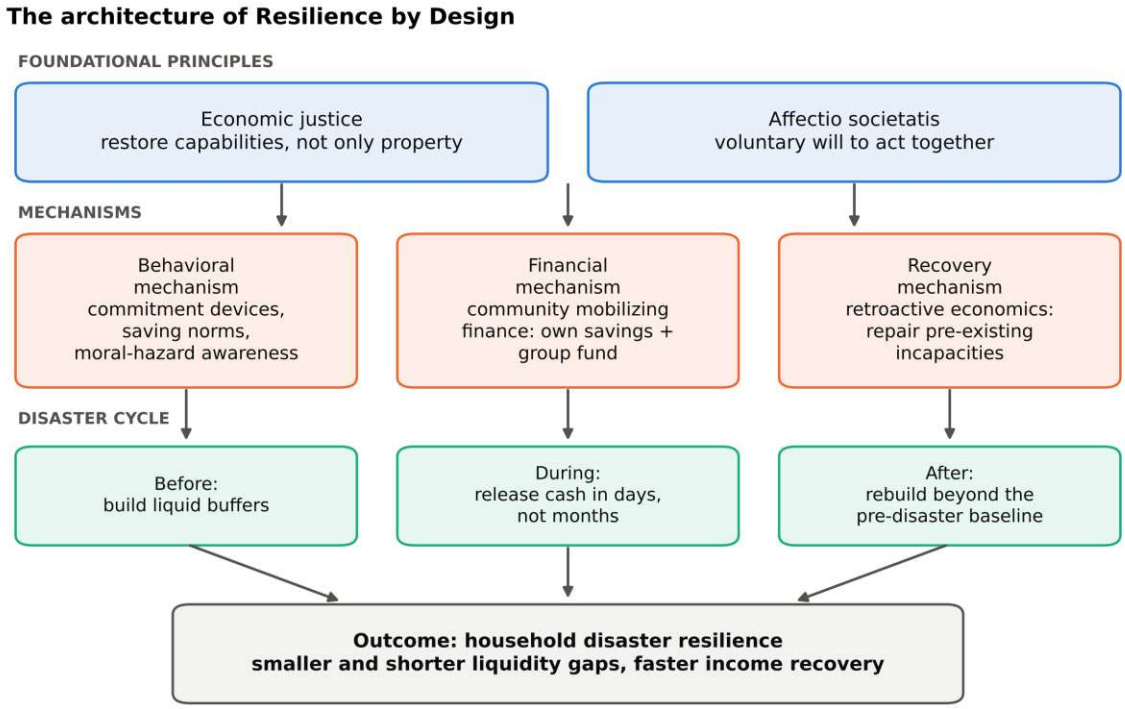



**Fig. 6** The architecture of *Resilience by Design*: two foundational principles, three mechanisms and their place in the disaster cycle. Source: author

### 4.1 Foundational principles

**Economic justice.** Recovery is judged by whether people regain the real freedom to live and work as they value, not only by the value of rebuilt property (Sen, 1999; Nussbaum, 2011). Gardoni and Murphy (2008) apply this to disasters: a disaster destroys capabilities, and recovery should restore and, where possible, enhance them. Because disasters fall hardest on households with the least savings and the least access to finance (Section 2.4), a framework that builds buffers among those households is redistributive by design.

***Affectio societatis*.** The term comes from civil-law company law, where it names the shared, voluntary intention of partners to act together in a common interest. It is the ingredient that makes savings groups and cooperatives hold: members who choose one another and accept mutual obligations. *Tèt ansanm* in rural Haiti and the congregational solidarity seen after Katrina are expressions of it (Pyles et al., 2015; Chamlee-Wright & Storr, 2009). The framework does not create trust; it gives existing trust a financial structure.

### 4.2 Behavioral mechanism: making saving the default

Present bias and inertia keep emergency saving perpetually postponed. Commitment devices reverse this: programs that commit people in advance to save more later sharply raise saving rates (Thaler & Benartzi, 2004; Thaler & Sunstein, 2008). In a group, the commitment is social as well as personal; regular meetings and visible contributions turn preparedness into a norm. The mechanism also addresses moral hazard directly, by teaching households to treat aid as a complement to their own preparedness (Section 2.3).

### 4.3 Financial mechanism: community mobilizing finance

The financial mechanism converts trust into liquidity. Members pool small, regular contributions in a group fund that can lend or advance cash to affected members within days (Besley et al., 1993; Collins et al., 2009). Evidence from community-managed savings and credit groups in Haiti links membership to higher trust and better access to health care and sanitation (Abdul-Malak & Baptiste, 2026). The money is already in the community when the disaster strikes, and decisions about its use are made by people who know one another. Section 5 models how much this layer can do and where its limits lie.

### 4.4 Recovery mechanism: retroactive economics

Retroactive economics is a historical view of recovery. A disaster disrupts the household, but the household's vulnerability was built long before the event, through low income, missing savings, exclusion from credit and insecure assets. Recovery that only restores the status quo ante restores that vulnerability too. Retroactive economics therefore holds that reconstruction must pass through the repair of pre-existing economic incapacities.

The idea has roots in two literatures. Vulnerability research shows that disasters are produced by root causes and pressures that precede the hazard (Wisner et al., 2004), and the Sendai Framework calls for recovery to "build back better" (United Nations Office for Disaster Risk Reduction [UNDRR], 2015). What retroactive economics adds is a household-level target. If $K_0$ is a household's economic capability before the disaster and $D_h$ its historical deficit, the gap between $K_0$ and what it would have reached without long-standing exclusion, the recovery target is

$$K^* = K_0 + \lambda D_h, \qquad 0 \leq \lambda \leq 1 \qquad (1)$$

where $\lambda$ is the share of the historical deficit that recovery commits to repair. Conventional recovery sets $\lambda = 0$; retroactive recovery sets $\lambda > 0$ (Figure 7). In practice, $\lambda > 0$ means using the recovery period to open accounts for unbanked members, report group repayments to build credit histories, and reinvest group funds in members' livelihoods.

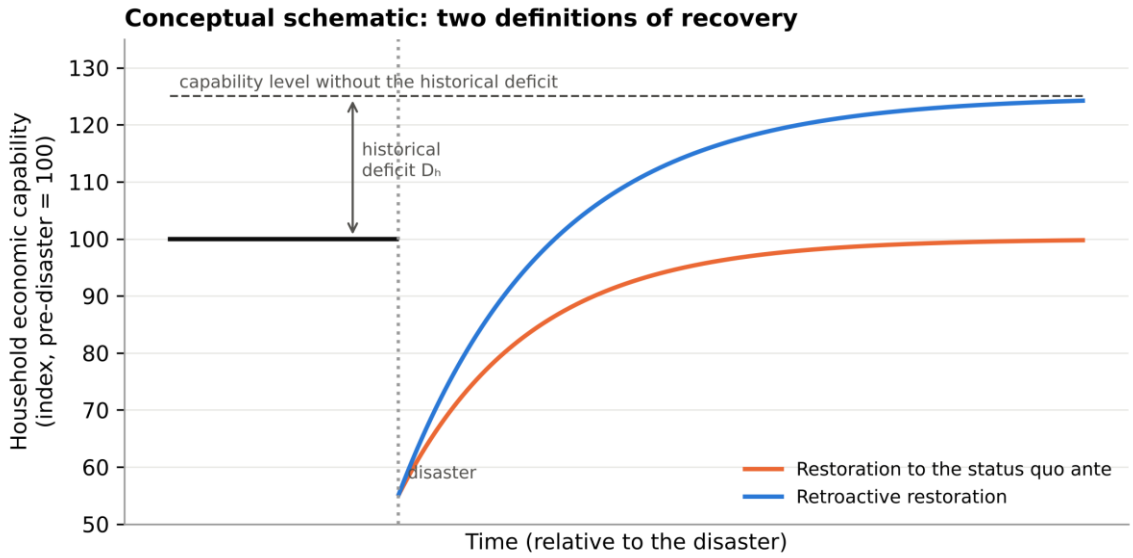



**Fig. 7** Conceptual schematic of two definitions of recovery: restoration to the pre-disaster level ($\lambda = 0$) and retroactive restoration that also repairs the historical deficit $D_h$ ($\lambda = 1$). Illustrative, not estimated. Source: author

Retroactive economics is distinct from local procurement or community wealth building (Kelly & McKinley, 2015), which concern where recovery money is spent. It concerns what recovery is for: the target is the household's capability path without its historical deficit, not its position on the day before the disaster.

### 4.5 The framework and its curriculum

A training curriculum that operationalizes the framework has been developed (details withheld for anonymous review). The argument of this article does not depend on that curriculum: each mechanism can be implemented, tested or rejected with other tools.

## 5. Modeling the framework's central claims

This section formalizes three claims: that the timing of liquidity drives household hardship after a disaster, that pooling helps even when shocks are correlated, and that a community fund can

reach a useful size in a realistic period. Sections 5.1 to 5.4 present deliberately simple baseline models; Section 5.5 relaxes their most favorable assumptions and reports what survives. All parameters are illustrative and stated in full; the complete specification, random seed and code logic are in Appendix A.

### 5.1 The household liquidity gap

Let N(t) be a household's cumulative cash needs t days after a disaster and R(t) the cash resources available by day t. The uncovered liquidity gap is

$$G(t) = \max\{0,\ N(t) - R(t)\}, \qquad R(t) = S_0 + F\mathbf{1}[t \geq t_F] + A\,\mathbf{1}[t \geq t_A] + I\,\mathbf{1}[t \geq t_I] \qquad (2)$$

where $S_0$ is own emergency savings, F a group-fund draw available at day t_F, A public aid paid at day t_A and I an insurance payment at day t_I. An uncovered gap is not the same as borrowing. It is closed in three ways: new borrowing B(t), unpaid obligations U(t) such as rent or utility arrears, and forgone consumption X(t):

$$G(t) = B(t) + U(t) + X(t) \qquad (3)$$

Only borrowing carries an explicit interest cost. With an annual rate i and a share θ_B of the gap financed by borrowing, the financing cost over a horizon T is

$$C = \frac{i}{365}\sum_{t=0}^{T} B(t) \;=\; \theta_B \frac{i}{365}\sum_{t=0}^{T} G(t) \qquad (4)$$

Arrears and forgone consumption carry their own costs, in late fees, credit damage, food insecurity and health, which Equation 4 does not price. It is therefore a lower bound on the cost of the gap.

The model is simulated over 90 days for one household facing an initial outlay of US$1,500 and US$40 a day of extra costs. Both scenarios receive the same aid (US$1,500 at day 30) and insurance (US$2,000 at day 60); they differ only in the household layer.

| Parameter or result | Scenario A: aid and insurance only | Scenario B: Resilience by Design |
|---|---|---|
| Own emergency savings $S_0$ | US$400 | US$1,000 |
| Group-fund draw F (day 3) | none | US$800 |
| Public aid A (day 30) | US$1,500 | US$1,500 |
| Insurance I (day 60) | US$2,000 | US$2,000 |
| Peak uncovered gap | US$2,260 | US$860 |
| Days with a positive gap (of 91) | 90 | 39 |
| Cumulative gap (dollar-days) | 110,400 | 15,500 |
| Cost if fully borrowed at 25% APR ($\theta_B = 1$) | US$76 | US$11 |
| Cost if fully borrowed at 390% APR ($\theta_B = 1$) | US$1,180 | US$166 |
| Gap remaining at day 90 | US$1,200 | US$0 |

The household layer does not change the size of the disaster; it changes when money arrives. In Scenario B the peak gap falls by 62% and the cumulative gap by 86%, and the household ends the 90-day window with no unpaid needs (Figure 8).

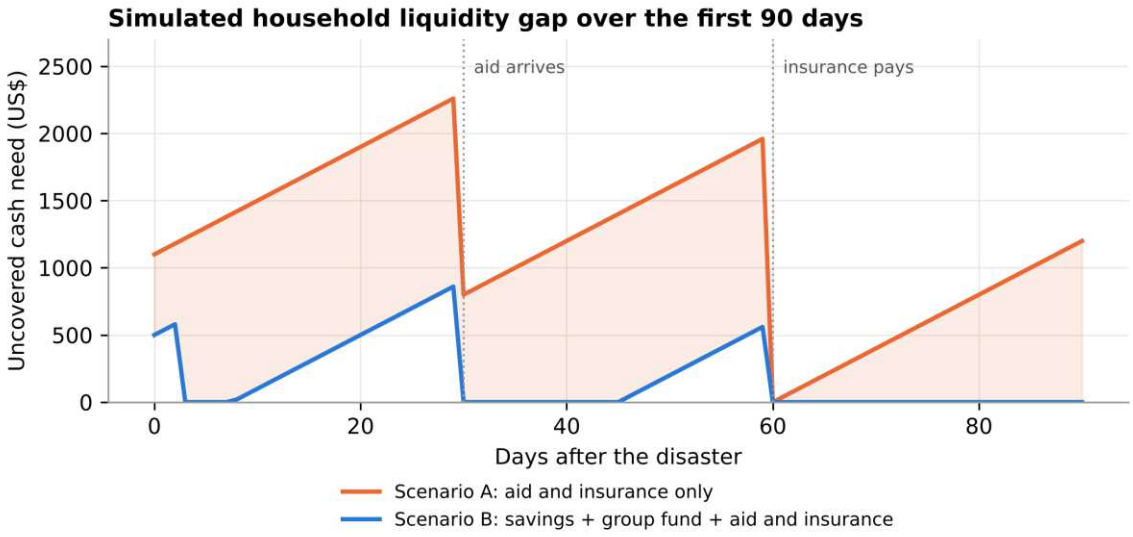



**Fig. 8** Simulated uncovered cash need of one household over the first 90 days after a disaster, Scenarios A and B. Source: author's simulation

### 5.2 Sensitivity analysis

Because the parameters are illustrative, the result must not depend on one chosen combination. Figure 9 recomputes the cumulative gap across own savings from US$0 to US$2,000 and aid arrival from day 10 to day 60. Without a group fund, the gap ranges from about 2,000 dollar-days (US$2,000 saved, aid at day 10) to 192,000 (no savings, aid at day 60); with no savings, each ten-day delay in aid adds about 15,000 dollar-days. Adding a US$800 group-fund draw at day 3 lowers the gap in every cell of the grid, by a median of 67% and by at least 36%. The direction of the result is therefore robust; its size depends, as it should, on savings and aid delays.

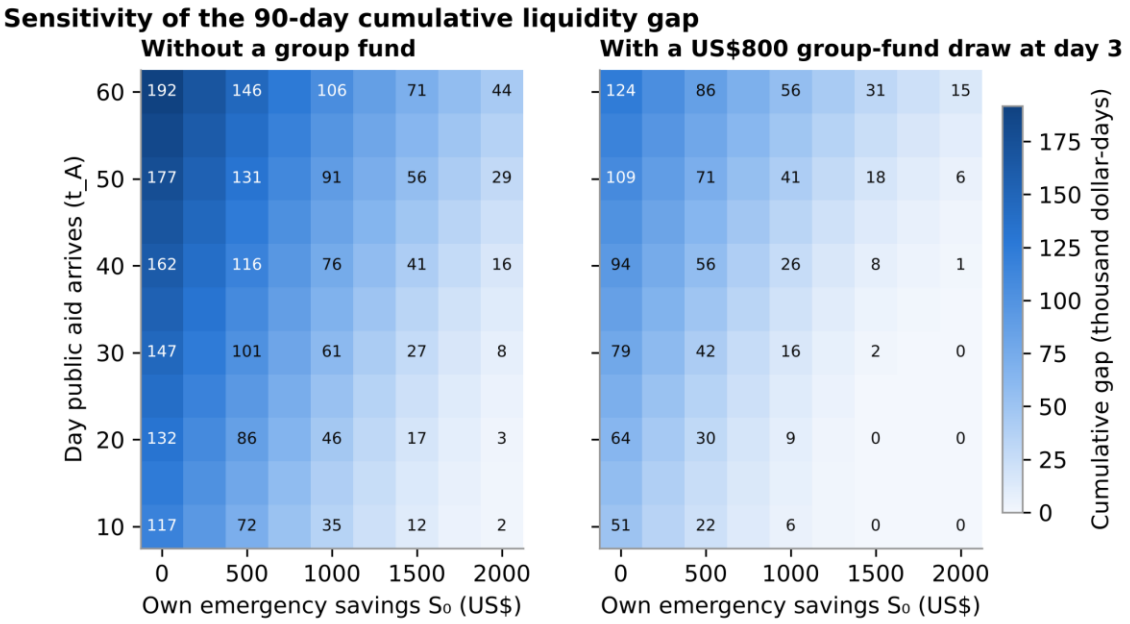



**Fig. 9** Cumulative 90-day liquidity gap (thousand dollar-days) by own emergency savings and day of aid arrival, without and with a US$800 group-fund draw at day 3. Source: author's simulation

### 5.3 Risk pooling under correlated shocks

A common objection to community savings is that disasters hit everyone at once. The objection is partly right, and it can be measured. A Monte Carlo simulation (20,000 draws per scenario) models a group of 25 households, each hit with probability 0.30, with shocks linked through a one-factor Gaussian copula of correlation ρ from 0 to 0.9. Losses among affected members are lognormal with a mean of US$1,500. Three arrangements hold the same US$1,000 of savings per member: (1) individual savings only; (2) US$600 of own savings plus US$400 paid into a group fund shared equally among affected members; (3) the same fund backed by a credit-union line of equal size. A member is "fully covered" when own savings plus its share of the fund (and line) at least equal its loss.

| Correlation of shocks (ρ) | Individual savings only | Group fund | Group fund + credit-union line |
|---|---|---|---|
| 0.0 | 46% | 75% | 90% |
| 0.3 | 46% | 68% | 84% |
| 0.6 | 46% | 62% | 78% |
| 0.9 | 46% | 53% | 70% |

Pooling raises the share of affected members fully covered from 46% to between 53% and 75%, with no extra saving by anyone (Figure 10). The gain shrinks as shocks become more correlated, because more members draw on the same fund at once. An external backstop restores much of it, keeping coverage at 70% or more even when nearly all shocks move together. The design implication is direct: group funds are the first and fastest layer, and they should be linked to regulated institutions able to lend into the group when the whole community is hit.

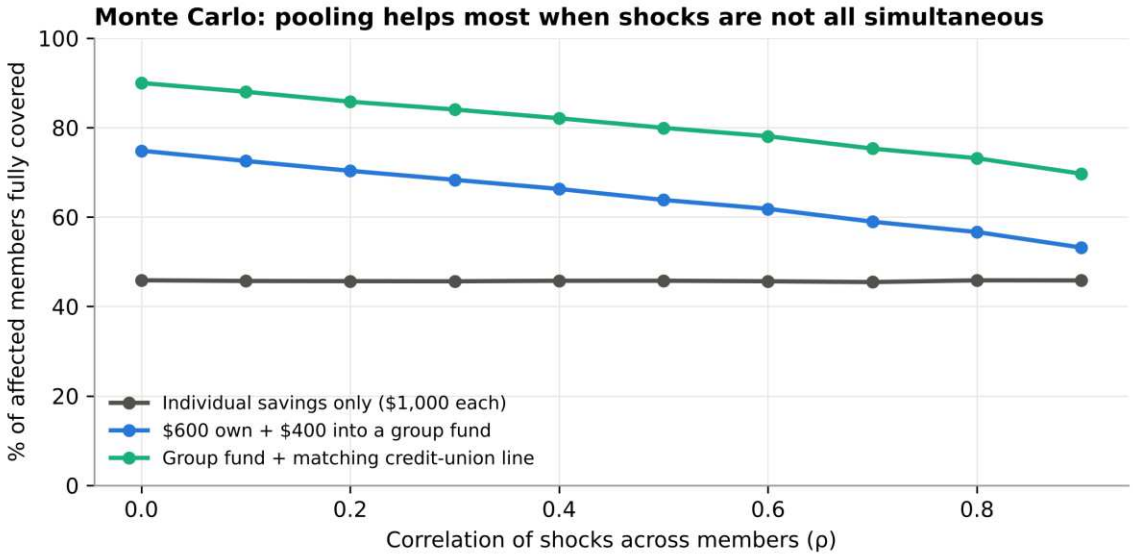



**Fig. 10** Monte Carlo estimate of the share of affected members fully covered, by correlation of shocks and savings arrangement (25 members, 20,000 draws per point). Source: author's simulation

### 5.4 How fast a group fund grows

Let a group of n members contribute c each month, with a share P_m of contributions actually paid in month m. A share λ_L of the fund is lent to members at a monthly rate r_L; a share δ_m of outstanding loans is lost to default; and administration costs a per month. The fund evolves as

$$F_{m+1} = F_m[1 + \lambda_L\,(r_L - \delta_m) - a] + c\,P_m \qquad (5)$$

With full participation and a constant default rate, this reduces to the familiar annuity formula with a net monthly return r:

$$F_T = n\,c\,\frac{(1+r)^T - 1}{r}, \qquad r = \lambda_L\,(r_L - \bar{\delta}) - a \qquad (6)$$

For 25 members contributing US$30 a month, with 70% of the fund on loan at 1% a month, an average default loss of 0.25% a month and administration costs of 0.05% a month, the net return is 0.475% a month and the full-participation fund reaches about US$19,000 after 24 months. Allowing contributions to be missed 10% of the time and default losses to vary randomly, 10,000 simulated groups reach a median of about US$8,300 after 12 months, US$17,100 after 24 months and US$26,400 after 36 months (Figure 11).

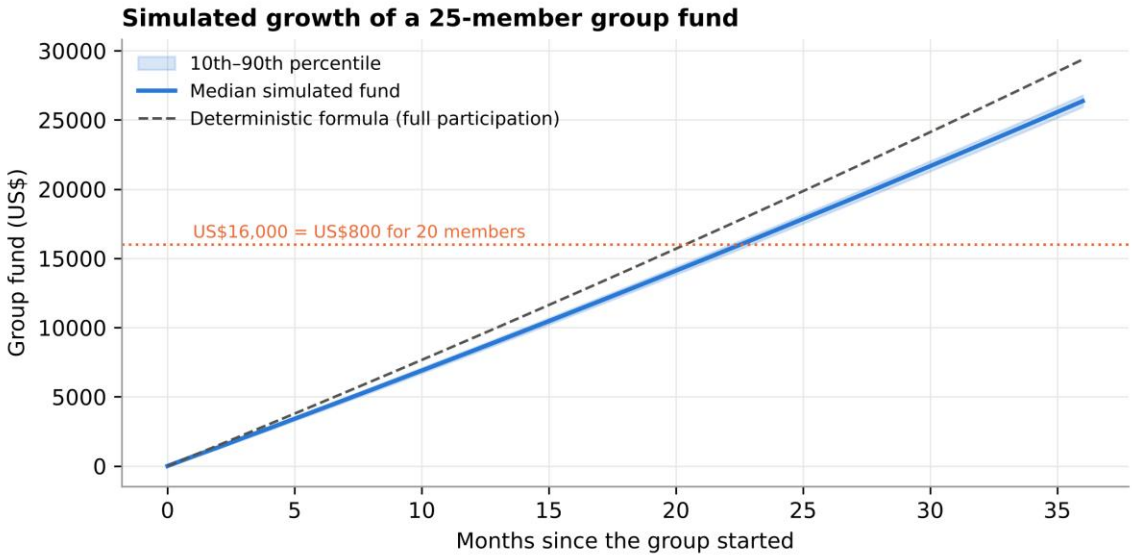


**Fig. 11** Simulated growth of a 25-member group fund: median, 10th–90th percentile band and the deterministic full-participation path. Source: author's simulation

Under these assumptions, the group could advance US$800 to each of 20 affected members (US$16,000) after about two years. That capacity is conditional, not guaranteed: at 80% participation the 24-month median falls to roughly US$15,200, below that threshold, and a disaster in the group's first year would find a much smaller fund. Section 5.5.3 revises this estimate once emergency funds are separated from loaned funds.

## 5.5 Extended models: relaxing the baseline assumptions

The baseline models in Sections 5.1 to 5.4 are deliberately simple. Several of their assumptions favor the framework: needs accrue at a flat daily rate, the group-fund draw is treated as free cash, arrears cost nothing beyond interest, pooled funds are shared equally whatever the need, loss severity does not rise with the breadth of the disaster, a local credit-union line is always available, defaults are independent from month to month, and the fund is both lent out and instantly available. This subsection relaxes each of these assumptions. The extended models keep the baseline as a reference point and show how much of the result survives.

### 5.5.1 Front-loaded needs, repayment and penalties

Post-disaster outlays are concentrated in the first days, for emergency lodging, repairs and replacement goods, and then taper off (Figure 12). Cumulative needs are modeled as

$$N(t) = N_{\infty}(1 - e^{-t/\tau}) + \beta t \qquad (7)$$

with $N\infty$ = US$3,800, $\tau$ = 12 days and $\beta$ = US$14 a day. About US$1,780 is needed in the first week alone, and the 90-day total (about US$5,060) is close to the baseline's. The horizon is extended to 180 days, and from day 45 the household recovers part of its income, which frees US$12 a day toward the gap or loan repayments.

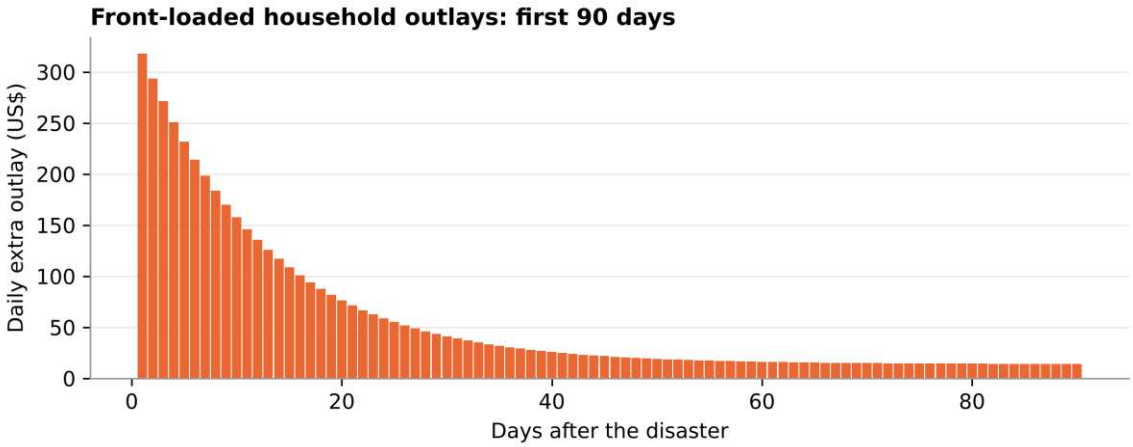



**Fig. 12** Daily extra household outlays under the front-loaded needs profile of Equation 7, first 90 days. Source: author's simulation

The group package now follows the structure of community savings groups with separate funds: a non-repayable solidarity grant g from a dedicated solidarity fund (the "red box") and an emergency loan ℓ from the savings-and-credit fund (the "green box"). The gap and its financing become

$$G(t) = \max\{0,\ N(t) + P(t) + C(t-1) - R(t)\}, \qquad R(t) = S_0 + (g+\ell)\,\mathbf{1}[t \geq t_F] + A\,\mathbf{1}[t \geq t_A] + I\,\mathbf{1}[t \geq t_I] + Y(t) \tag{8}$$

$$G(t) = B(t) + U(t) + X(t), \qquad B = \theta_B\, G, \quad U = \theta_U\, G \tag{9}$$

$$C(t) = C(t-1) + \frac{i_B}{365}\, B(t) + \frac{f_U}{30}\, U(t) + \psi\,\mathbf{1}[U > \bar{U} \text{ for 30 days}] \tag{10}$$

where P(t) is cumulative loan repayment, Y(t) cumulative income surplus and C(t) cumulative financing cost, which feeds back into the gap so that charges compound. Forty percent of the gap is financed by credit card (25% APR, daily accrual), 40% by arrears that carry a 5% monthly late fee and a US$50 reconnection charge (ψ) when arrears exceed US$300 (Ū) for 30 days, and 20% by forgone consumption. The emergency loan of US$500 is repaid in K = 6 monthly instalments at r_L = 2% a month, the MUSO credit rate, starting at day 90:

$$\pi = \frac{\ell\, r_L}{1 - (1 + r_L)^{-K}} \qquad (11)$$

which gives π ≈ US$89. A third scenario isolates the effect of own savings.

| Result over 180 days | A: aid and insurance only | B: own savings only (US$1,000) | C: savings + US$300 grant + US$500 loan |
|---|---|---|---|
| Peak uncovered gap | US$3,525 | US$2,910 | US$2,093 |
| Days with a positive gap (of 181) | 179 | 177 | 52 |
| Cumulative gap (dollar-days) | 254,609 | 133,867 | 59,465 |
| Monetary cost of the gap (interest, fees, reconnection) | US$339 | US$176 | US$56 |
| Gap remaining at day 180 | US$1,138 | US$376 | US$0 |
| Loan instalments paid by day 180 | — | — | US$357 (4 of 6) |

The extended model changes the size of the result but not its direction (Figure 13). Front-loading makes the first month harder for everyone, so the peak gap falls by 41% in Scenario C rather than 62% in the baseline. The persistence result is stronger, however. Without a household layer, the gap never closes: penalties keep it growing after insurance pays, and US$1,138 is still uncovered at day 180. Own savings alone cut the cumulative gap by 47%; the group package cuts it by a further 56%. The emergency loan is affordable because repayment starts after aid and insurance have arrived, and the household services it without reopening a gap.

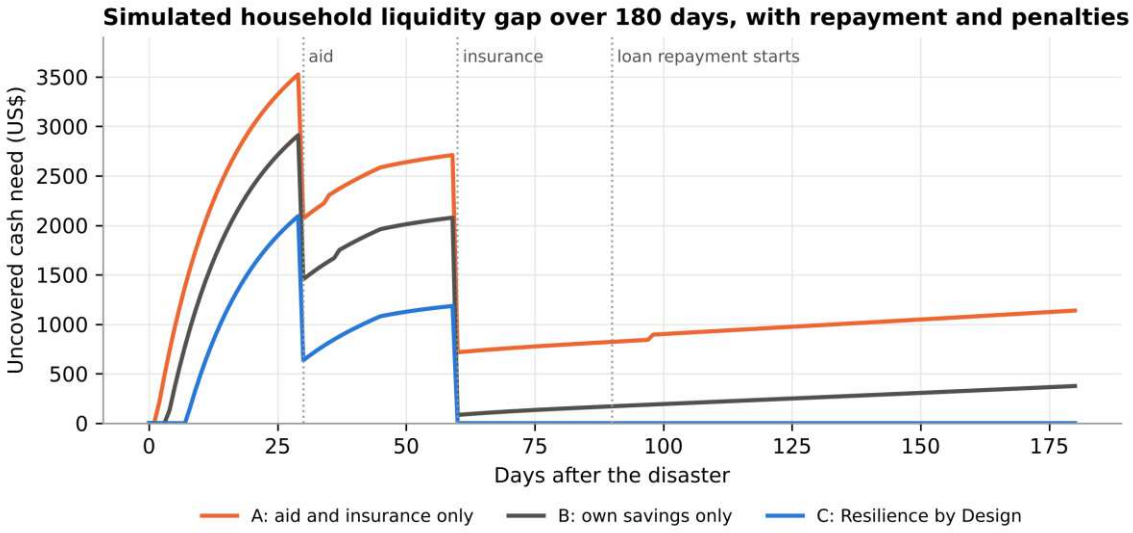



**Fig. 13** Simulated uncovered cash need over 180 days with front-loaded outlays, compounding penalties, partial income recovery and loan repayment, Scenarios A to C. Source: author's simulation

**5.5.2 Need-based allocation, rising severity and backstop risk**

The extended Monte Carlo makes three changes. Loss severity now rises with the breadth of the event: the expected loss of an affected member increases with the share k/n of members hit, doubling when all are hit (κ = 1):

$$X_j = \sqrt{\rho}\, Z + \sqrt{1-\rho}\, \varepsilon_j, \qquad \text{hit}_j = \mathbf{1}[X_j < \Phi^{-1}(p)], \qquad E[L_j \mid k] = \bar{L}\left(1 + \kappa \frac{k}{n}\right) \tag{12}$$

Second, the group fund can be allocated in proportion to verified unmet need rather than equally. Third, a local credit-union line is no longer guaranteed: when more than half of the members are hit, it is unavailable 70% of the time, because the local institution is itself under stress. An external backstop, such as a national community lender or a reinsurance arrangement, remains available. Because need-based allocation spreads the fund across all affected members, the share of total losses covered becomes the more informative measure.

| Share of total losses covered | ρ = 0 | ρ = 0.3 | ρ = 0.6 | ρ = 0.9 |
|---|---|---|---|---|

| Share of total losses covered | ρ = 0 | ρ = 0.3 | ρ = 0.6 | ρ = 0.9 |
|---|---|---|---|---|
| Individual savings only | 44% | 41% | 38% | 35% |
| Group fund, equal shares | 66% | 57% | 48% | 39% |
| Group fund, need-based | 81% | 66% | 55% | 42% |
| Need-based + local credit-union line | 96% | 78% | 63% | 48% |
| Need-based + external backstop | 97% | 85% | 73% | 58% |

Three findings stand out (Figure 14). First, allocation is a governance choice with measurable consequences: equal shares maximize the number of members fully covered, while need-based allocation covers 15 percentage points more of total losses when shocks are independent. Second, once severity rises with correlation, every arrangement loses ground in regional disasters; at ρ = 0.9 pooling still covers 42% to 58% of losses, against 35% for individual savings. Third, the difference between a local and an external backstop is negligible for local shocks (1 point at ρ = 0) but grows to 10 points at ρ = 0.9. Backstop credit should therefore come from institutions outside the affected region.

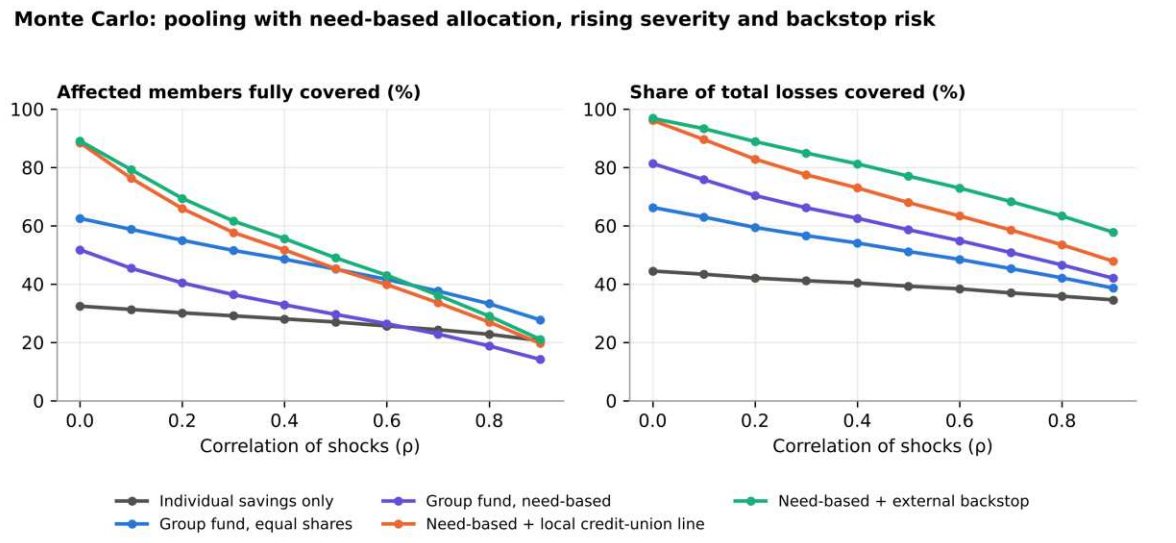


**Fig. 14** Extended Monte Carlo: share of affected members fully covered (left) and share of total losses covered (right), by correlation of shocks and arrangement, with loss severity rising with the share of members hit (25 members, 20,000 draws per point). Source: author's simulation

**5.5.3 A two-box fund with clustered defaults**

The baseline fund model assumed that 70% of the fund was on loan and yet available within days. The extended model resolves this by separating two funds and by calibrating them, wherever possible, on the operating rules and records of the community savings groups (*mutuelles de solidarité*, MUSO) supported by a community development organization in Haiti.

| Parameter | Value used | Source |
|---|---|---|
| Internal credit rate r_L | 2% a month | MUSO network rules (Organization, 2026) |
| Portfolio ratio λ_L (loans ÷ funds) | 62% | HTG 78.5 million of credit for HTG 125.9 million of funds across 92 groups, May 2025 (CECOMUSO, 2025); network target ≥ 70% |
| Credit risk | PAR30 < 5%; 98% of groups with full repayment; modeled mean loss 0.1% a month | Survey of 20 groups and 600 members (Author, 2023) |
| Cycle | 12 months, deposits in the first months, share-out of earnings at the end | MUSO network rules (Organization, 2026) |
| Solidarity fund | Separate red box, funded by | MUSO network rules |

| Parameter | Value used | Source |
|---|---|---|
| | contributions and fines, never lent, not shared out, aid voted by members | (Organization, 2026) |
| Participation in the solidarity fund | 96% of members contribute; 41.5% have received support | Kutztown University survey of MUSO members (Svistova et al., 2019) |
| Contribution amounts | US$50 a month for six months (green); US$5 a month (red) | Assumption for a U.S. setting |
| Package per affected member | US$300 grant + US$500 loan | Assumption |

The savings-and-credit fund V (green box) receives deposits during a six-month window W at the start of each 12-month cycle, lends up to 62% of its balance at 2% a month, and pays out the cycle's earnings E_m at month 12, the members' capital being redeposited. The solidarity fund Q (red box) receives US$5 per paying member each month plus fines w_m, is never lent and earns 3% a year in an insured account. Defaults follow a persistent process with a seasonal component, so that bad months cluster:

$$V_{m+1} = V_m[1 + \lambda_L\,(r_L - \delta_m) - a] + c_g\,P_m\,\mathbf{1}[m \in W] - E_m\,\mathbf{1}[m = 12k] \qquad (13)$$

$$\delta_m = \mu + \phi\,(\delta_{m-1} - \mu) + s\,\mathbf{1}[m \in \text{lean}] + \eta_m \qquad (14)$$

$$Q_{m+1} = Q_m\,(1 + r_s) + c_r\,P_m + w_m \qquad (15)$$

The group's immediate emergency capacity, the number of members who can receive the full package at once, is

$$H_m = \min\{\lfloor Q_m/g \rfloor,\ \lfloor (1-\lambda_L)\,V_m/\ell \rfloor\} \qquad (16)$$

With μ = 0.1% a month, φ = 0.6, three lean months a year and 3% annual inflation, 10,000 simulated groups of 25 members reach a median of about US$12,700 in the green box and US$2,900 in the red box after 24 months, in real terms (Figure 15). Immediate capacity is 5 members at 12 months, 10 at 24 months and 15 at 36 months. In this calibration the solidarity fund, not the credit fund, is the binding constraint: the size of the red-box contribution matters more for disaster readiness than the size of savings.

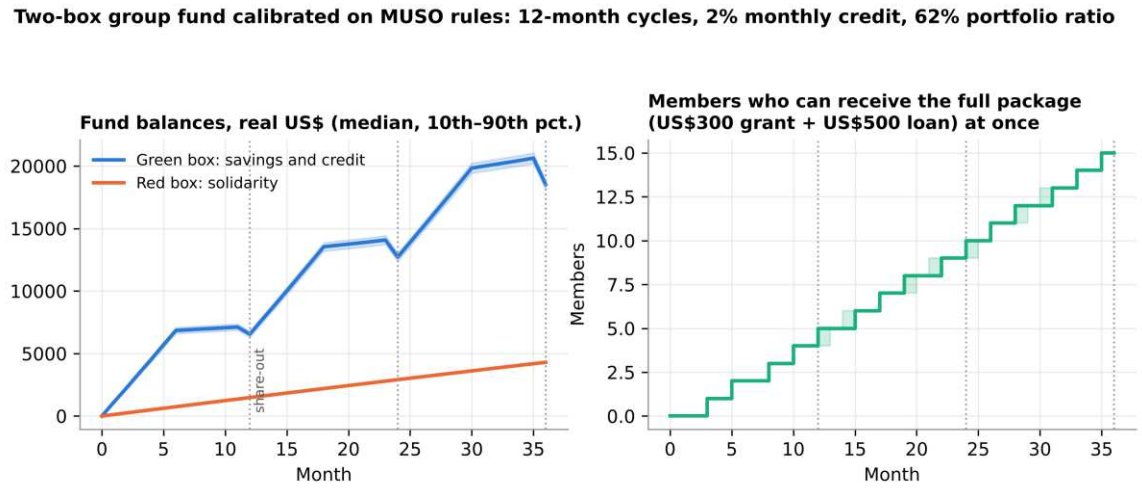



**Fig. 15** Two-box group fund calibrated on MUSO rules (12-month cycles, 2% monthly credit, 62% portfolio ratio): real balances of the savings-and-credit and solidarity funds (left) and members who can receive the full emergency package at once (right), median and 10th–90th percentile, 10,000 simulated groups. Dotted lines mark cycle share-outs. Source: author's simulation

This is a more modest estimate than the baseline's 20 members, and a more defensible one. With a 30% probability of being hit, a group of 25 expects about 7.5 affected members in a local event; by month 24 the two-box fund can serve that many from its own resources. Larger, regional events exceed any group's capacity, which is why the external backstop of Section 5.5.2 is part of the design rather than an option.

**5.5.4 What survives**

| Claim | Baseline result | Extended result | Status |
|---|---|---|---|
| A local buffer reduces the household cash gap | Cumulative gap −86% (90 days) | Cumulative gap −77% vs. Scenario A (180 days) | Confirmed, smaller |
| The buffer shortens hardship | 39 vs. 90 days with a gap | 52 vs. 179 days | Confirmed, stronger |
| Pooling helps under correlated shocks | Full coverage 53–75% vs. 46% | Losses covered 42–81% vs. 35–44% (group fund alone) | Confirmed, smaller at high $\rho$ |
| A backstop is needed for regional events | Coverage ≥70% with a local line | Local line loses 10 points to an external one at $\rho = 0.9$ | Refined: backstop must be external |
| A 25-member group can serve 20 members after 2 years | Yes, at 90% participation | 10 members with grant + loan, calibrated on MUSO rules | Revised downward |

The central claims survive realistic frictions. What changes is their size and the design lessons drawn from them: separate solidarity and credit funds, choose the allocation rule deliberately, and secure backstop credit from outside the region.

## 6. Delivery through community institutions

A household framework needs institutions that reach households regularly, are trusted and already practice mutual support. In the United States, congregations meet all three conditions. They gather the same people weekly, often across generations; many already run benevolence funds; and after Katrina they acted as first responders and coordinators of return (Chamlee-

Wright & Storr, 2009; Cain & Barthelemy, 2008). Local faith communities more generally strengthen resilience through social support and practical help (Ager et al., 2015).

Congregations are an entry point, not a boundary. Religious affiliation is declining in the United States, and many of the most exposed households belong to no congregation. The same model can be hosted by schools, unions, tenant associations, immigrant associations and community centers. Whatever the host, participation must be voluntary, open to non-members and free of religious conditions.

The framework operates at three levels:

- **Community level:** the host organization runs savings groups, trains facilitators and connects groups to local emergency planning.
- **Household level:** families set an emergency savings target, a disaster budget and a plan for the first weeks after a shock.
- **Intergenerational level:** young people learn saving and mutual responsibility alongside their parents.

### 6.1 Equity in design

The households with the largest gaps are also the hardest to reach (Section 2.4). Groups should therefore be offered in Spanish and other community languages, meet in accessible places and at times compatible with shift work and caregiving, and include women in leadership, since women often manage household budgets and carry post-disaster care (Enarson, 2012). For unbanked members, the group can be a first step toward an insured account.

### 6.2 Governance and regulation

Money held in common creates obligations. Groups need written rules on contributions, lending, defaults and withdrawals; at least two signatories; regular reporting to members; and separation between group funds and the host organization's own accounts. Above modest amounts, funds should be deposited with a regulated partner, such as a credit union or community development financial institution, rather than held in cash. Hosts should seek legal advice on consumer finance, lending and money-transmission rules in their state, which vary. These constraints are not obstacles to the model; they are part of what makes it trustworthy.

## 7. Policy implications and a pilot evaluation design

### 7.1 Implications for policy

1. **Count household liquidity as preparedness.** Preparedness and mitigation programs mostly fund infrastructure, plans and supplies. Emergency savings are preparedness too, and they reduce demand for aid after the event.
2. **Fund trusted local intermediaries before disasters.** Partnerships with faith-based and neighborhood organizations already exist for response; they can also support preparedness finance.
3. **Link community savings to regulated finance.** Credit unions and community development financial institutions can safeguard group funds, reward emergency saving and provide the backstop credit lines that Sections 5.3 and 5.5.2 show are needed when shocks are correlated. That backstop should come from institutions outside the affected region, because local lenders are hit by the same disaster.

4. **Target medium-sized disasters and excluded households.** Financial harm is often greatest where long-term recovery money is least likely to arrive (Ratcliffe et al., 2019) and among households outside the banking system (FDIC, 2024).
5. **Define recovery retroactively.** Recovery programs can include account opening, credit-building and livelihood reinvestment, so that households leave recovery stronger than they entered the disaster.

### 7.2 Pilot evaluation design

A pilot in communities exposed to recurrent hazards could enroll host organizations in staggered waves, so that sites joining later serve as comparisons for those joining earlier. Indicators would be measured at baseline and at regular intervals.

| Outcome | Indicator | Data source |
|---|---|---|
| Emergency liquidity | Share who would cover a US$400 expense with cash or its equivalent | Survey item comparable to SHED |
| Household savings | Emergency savings balance; months of expenses covered | Participant records and survey |
| Group capacity | Fund size, contribution regularity, internal loan repayment | Group ledgers |
| Financial behavior | Financial self-efficacy; youth saving reported by parents | Validated scales and parent reports |
| Post-shock recovery | High-cost credit use, arrears and time to income recovery after a hazard | Survey and, with consent, credit data |
| Retroactive recovery | Accounts opened; credit files created or | Partner institution |

| Outcome | Indicator | Data source |
|---|---|---|
| | improved | records |
| Social capital | Trust in neighbors; participation in community action | Survey items comparable to Pyles et al. (2015) |

The pilot would also estimate the parameters that Section 5 had to assume, turning illustrative simulations into calibrated ones.

## 8. Limitations and conclusion

### 8.1 Limitations

Five limitations should be kept in view. First, the article is conceptual: the framework has not yet been tested as a whole in the United States. Second, the simulations use illustrative parameters; they demonstrate mechanisms and their sensitivity, not predicted effect sizes. The extended models in Section 5.5 add realistic frictions, but parameters such as default persistence, penalty rates and backstop availability still need field calibration. Third, the Haiti survey covered three rural communities and is not generalizable to rural Haiti as a whole (Pyles et al., 2015), and the Gulf Coast data came from non-random samples. Fourth, the transfer from Haiti to the United States rests on shared mechanisms, not shared conditions, and Section 3.3 identifies adaptations that remain untested. Fifth, community savings cannot cover catastrophic losses such as the destruction of a home; the framework is a complement to insurance and public aid.

### 8.2 Conclusion

Who pays when disaster strikes? In the United States, as in rural Haiti, households pay first, and those with the least savings pay the most. Insurance and public aid remain indispensable, but

they were not built to finance a family's first ninety days. The models in this article make the point in numbers: the same aid and insurance produce very different hardship depending on whether a small local buffer can pay in the first days, and that buffer still helps, though less, when a whole community is hit at once.

*Resilience by Design* proposes to build this missing layer on what communities already have, trust and the will to act together, and to define recovery as the repair of long-standing incapacities rather than a return to the day before. The next step is a careful pilot that can confirm, calibrate or refute these claims.

## Use of AI tools

The author used a large language model to assist with drafting, language editing and implementing the simulation code. The author designed the framework and the models, directed the creation of the code, interpreted all results, and reviewed, revised and takes full responsibility for all content.

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## Appendix A. Simulation specification

All simulations were written in Python 3 with NumPy and SciPy. Random draws use NumPy's default generator with seed 2026.

**A.1 Liquidity-gap model (Sections 5.1–5.2).** Daily time step, t = 0, …, 90. Cumulative needs N(t) = 1,500 + 40t (US$). Resources follow Equation 2 with $t_F = 3$, $t_A = 30$ and $t_I = 60$ in the baseline. Scenario A: $S_0 = 400$, F = 0. Scenario B: $S_0 = 1{,}000$, F = 800. A = 1,500 and I = 2,000 in both. The cumulative gap is the sum of G(t) over all 91 days, in dollar-days. Financing costs use Equation 4 with $\theta_B = 1$ and i = 0.25 or 3.90. The sensitivity grid varies $S_0$ from 0 to 2,000 in steps of 250 and $t_A$ from 10 to 60 in steps of 5, with F = 0 or 800.

**A.2 Risk-pooling Monte Carlo (Section 5.3).** Group size n = 25; 20,000 draws for each ρ in {0, 0.1, …, 0.9}. For member j, $X_j = \sqrt{\rho}\, Z + \sqrt{(1-\rho)}\, \varepsilon_j$, with Z and $\varepsilon_j$ independent standard normal; member j is affected if $X_j < \Phi^{-1}(0.30)$. Losses of affected members are lognormal with log-scale standard deviation 0.8 and log-mean $\ln(1{,}500) - 0.8^2/2$, giving a mean loss of US$1,500. With k affected members, each receives an equal share 400n/k of the group fund, regardless of need; any unused share is not reallocated, which makes the estimates conservative. Arrangement 1: covered if loss ≤ 1,000. Arrangement 2: covered if loss ≤ 600 + 400n/k. Arrangement 3: covered if loss ≤ 600 + 2 × 400n/k. Reported values are the share of affected members covered, pooled across draws.

**A.3 Fund-growth model (Section 5.4).** Monthly time step over 36 months; 10,000 simulated groups; n = 25 and c = 30. Paid contributions each month are binomial (25, 0.9) × 30. Lending share $\lambda_L = 0.7$; loan rate $r_L = 0.01$ a month; monthly default loss $\delta_m$ drawn from a normal distribution with mean 0.0025 and standard deviation 0.0025, truncated at 0; administration cost a = 0.0005 a month. The fund follows Equation 5. Reported values are the 10th, 50th and 90th

percentiles across simulated groups. The deterministic path uses Equation 6 with r = 0.00475 and full participation.

**A.4 Extended liquidity-gap model (Section 5.5.1).** Daily time step, t = 0, …, 180. Needs follow Equation 7 with $N_\infty$ = 3,800, $\tau$ = 12 and $\beta$ = 14. Income surplus Y(t) = 12 × max(0, t − 45). Resources follow Equation 8 with $t_F$ = 3, A = 1,500 at $t_A$ = 30 and I = 2,000 at $t_I$ = 60. Scenario A: $S_0$ = 400, g = $\ell$ = 0. Scenario B: $S_0$ = 1,000, g = $\ell$ = 0. Scenario C: $S_0$ = 1,000, g = 300, $\ell$ = 500. Financing shares $\theta_B$ = 0.4, $\theta_U$ = 0.4 ($\theta_X$ = 0.2); $i_B$ = 0.25; $f_U$ = 0.05; $\psi$ = 50, triggered once when U(t) has exceeded $\bar{U}$ = 300 for 30 consecutive days. Costs accumulate in C(t) and enter the next day's gap. Loan repayment follows Equation 11 with $r_L$ = 0.02 and K = 6, instalments due at days 90, 120, …, 240.

**A.5 Extended Monte Carlo (Section 5.5.2).** As in A.2, with three changes. (i) Conditional on k affected members, losses are lognormal with log-scale standard deviation 0.8 and mean 1,500 × (1 + k/n) ($\kappa$ = 1). (ii) Need-based allocation: with own savings of 600 per member, the pooled fund of 400n is distributed in proportion to each affected member's unmet need, capped at that need. (iii) A second pool of equal size is added in two variants: a local credit-union line, available with certainty when k/n < 0.5 and with probability 0.3 otherwise, and an external backstop, always available; both are allocated in proportion to remaining unmet need. Two measures are reported: the share of affected members whose loss is fully covered, and covered losses as a share of total losses.

**A.6 Two-box fund model (Section 5.5.3).** Monthly time step over 36 months; 10,000 simulated groups; n = 25. Twelve-month cycles. Green box (Equation 13): deposits of $c_g$ = 50 per paying member in months 1–6 of each cycle (W), with paying members ~ Binomial(25, 0.9); $\lambda_L$ = 0.62; $r_L$ = 0.02; a = 0.0005; at month 12 of each cycle the cycle's earnings $E_m$ are paid out and

capital is redeposited. Defaults (Equation 14): $\mu = 0.001$, $\varphi = 0.6$, $s = 0.001$ in months 7–9 of each cycle, $\eta_m \sim N(0, 0.001^2)$, truncated at zero. Red box (Equation 15): $c_r = 5$ per paying member, paying members ~ Binomial(25, 0.96); $r_s = 0.03/12$; fines $w_m = 0.5 \times$ Poisson(10). Real values deflate by 3% annual inflation. Capacity follows Equation 16 with $g = 300$ and $\ell = 500$.