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Dynamics of informal risk sharing in collective index insurance

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Extreme weather events often prevent low-income farmers from accessing high-return technologies that would enhance their productivity. As a result, they often fall into poverty traps, a problem likely to worsen as the frequency of weather disasters increases due to climate change. Insurance offers, in principle, a solution for this conundrum and a means to guarantee households' wellbeing. Group collective index insurance constitutes an alternative to indemnity or individual index insurance, and has the potential to alleviate basis risk through within-group informal transfers. Here we show that collective index insurance introduces a coordination dilemma of insurance adoption: socially optimal outcomes are obtained when everyone adopts insurance; however, a minimum fraction of contributors is necessary before the effects of basis risk can be averaged out and individuals start taking up insurance. We further show that additional mechanisms—such as local peer monitoring and defector exclusion—are necessary to stabilize informal transfers and collective index insurance adoption. Together, collective index insurance and informal transfers may thus constitute a practical instrument to improve sustainability in developing countries.

In rural areas of many developing countries, the income of individuals—and importantly, access to credit—is seriously compromised by extreme weather events. The prevalence of weather disasters has increased in recent years due to climate change, and this increasing tendency is expected to become worse in the future[1]. Recent reports find that 22% of all damages and losses due to climate-related disasters, such as floods, droughts and tropical storms, occur in the agriculture sector[2]. In the context of droughts, agriculture is the most affected sector, absorbing about 84% of all the economic impacts. While the effect of such weather shocks is amplified in the poorest regions of the planet, the fact that these are also the areas where the formal insurance mechanisms are largely absent makes the consequences of these shocks more severe[3]. Between 1980 and 2015, only 2% of losses caused by weather-related natural catastrophes in low-income countries were covered by formal insurance products[4]. A more recent study, reporting data from 16 developing countries, found a very low level of formal insurance coverage: the overall uptake of any formal insurance was 16%, yet the uptake of crop insurance was only 1.82%[5]. This contributes to food production shocks[6] and poverty traps, as the inability to secure credit to invest in efficient technologies leads to the perpetuation of the poor condition[7,8]. Introducing insurance mechanisms has been indicated as a means of escaping such poverty traps[8–11] and guaranteeing food security[12], thus fundamentally contributing to the United Nations Sustainable Development Goals[13].

Typical indemnity-based insurance plans are difficult to implement in developing countries. First, given the lack or unreliability of data, they demand additional effort (and cost) to calculate the risk associated with a given region, in order to match insurance premiums and payouts. Second, evaluating actual losses requires the deployment of experts in field, which is often a difficult endeavour in developing regions. Third, these disadvantages are augmented by information asymmetries, adverse selection and moral hazard (for example, negligence in reducing risk exposure or malicious claims) associated with traditional insurance products. Overall, indemnity-based insurance plans acquire prohibitive implementation costs that prevent both their offer and adoption.

An alternative type of product has been proposed: index-based insurance plans[7,14]. With index-based insurance plans, payouts are made on the basis of an objective weather index (a public index number), dispensing any subjective damage evaluation. This alleviates the monitoring burden of companies, avoids the cost of experts in the field, mitigates possible moral hazardous behaviours and diminishes the information asymmetry regarding the actual exposure to a damage source. Altogether, index insurance plans constitute, in theory, cheaper and more attractive products.

In reality, however, index insurance plans face discouragingly low uptake rates[14,15]. The lack of trust in the insurance product due to basis risk is only one among many possible causes[16–18]. Basis risk is the risk of a mismatch between the actual loss and the realization of the contracted weather index. Individuals have trouble understanding the structure of these index insurance plans and often fear incurring damages but not receiving insurance payouts, despite the fact that they may also receive insurance payouts without incurring any loss.

Collective index insurance (CII) plans constitute a promising institutional deviation from individual index insurance plans. CII plans are offered to groups rather than to single individuals[18–22]. Whereas typical individual index insurance plans allow averaging out the risk of a single individual over time, CII plans allow averaging risk, in a given moment, both among a collective of individuals and over space (or over cultural networks). This alternative could allow averaging out idiosyncratic shocks (that is, events only affecting a few particular individuals at a particular time) when the same contracted index applies to a group of individuals with potentially different loss probabilities, thereby reducing basis risk. This is likely to occur, for

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example, when indexes are collected through sparse weather stations that associate the same metric to a potentially heterogeneous area[7]. CII plans can become cheaper than individual insurance, since individual allocation of insurance premiums and payouts becomes the responsibility of the group of individuals forming the collective; this potentially lowers the costs of the insurance policy and places the liability of controlling adverse selection and moral hazard—for example, assuring that loss reports are accurate and that each one devotes the needed effort to prevent catastrophe damages—on the group, which can resort to local peer monitoring. Furthermore, in under-developed rural areas, groups often abide by common norms and cultural habits of risk mitigation via exchange, which may provide additionally favourable conditions for deployment of CII. Through peer influence, CII plans can also potentiate an increased trust in the product[19]. CII can, in this way, ease the supply (moral hazard, adverse selection, and high operational and distribution costs) and demand (basis risk, lack of trust in the product, unaffordability and lack of transparency on how product is supervised) problems of formal insurance, while taking advantage of local social networks that can manage payouts according to local needs and requirements. The encouraging prospects of CII are emphasized by the evidence of diverse informal risk-sharing mechanisms, often grounded in direct or indirect transfers from other community members, which groups develop to deal with shocks. The Ethiopian *iddir*—risk-sharing arrangements rooted in altruism and reciprocity—are a paradigmatic example of informal insurance institutions that provide funeral insurance and relief in case of illness and property destruction[21,23]. The interplay between formal and informal instruments, particularly knowing whether one crowds out the other, remains an open question, and is a subject of extensive research[19,21,24–27].

In this Article, we study the dynamics of informal transfers and CII uptake using evolutionary game theory. Instead of modelling rational, utility-maximizing individuals, we assume that they adapt their strategies on the basis of the perceived expected utilities of others. As noted in previous work, social influence is an important enabler of insurance adoption[19,28–31]. By applying evolutionary game theory, we investigate the insurance characteristics that may lead a population of adaptive individuals (who are apt to imitate more successful options among their group peers[31]) to evolve towards high and stable insurance uptake rates.

First, we show that collective insurance plans combined with informal transfers—whereby individuals contribute their excessive payouts to a risk-sharing pool—provide an incentive for insurance uptake. At the population level, the dynamics of insurance adoption, when informal transfers exist, leads to a coordination dilemma: the stable social optimum is achieved when everyone takes up insurance, although the alternative situation in which all individuals refuse insurance is also stable. This means that for a population to evolve to a state where individuals adopt insurance at scale, a minimum fraction of individuals adopting insurance is required. Second, we show that if individuals have the opportunity to defect on contributions to the informal risk-sharing pool, taking up insurance is no longer stable. Individuals will first refrain from contributing to the informal risk-sharing pool, which opens space for the invasion and fixation of the strategy that refuses insurance. To circumvent this drawback, we show that the existence of efficient local peer monitoring provides stability to informal transfers and, consequently, index insurance adoption in general. As a result, we show that CII—when combined with informal transfers and monitoring—constitutes an attractive product that is likely to be adopted over time, thereby forming a practical instrument to improve sustainability in developing countries.

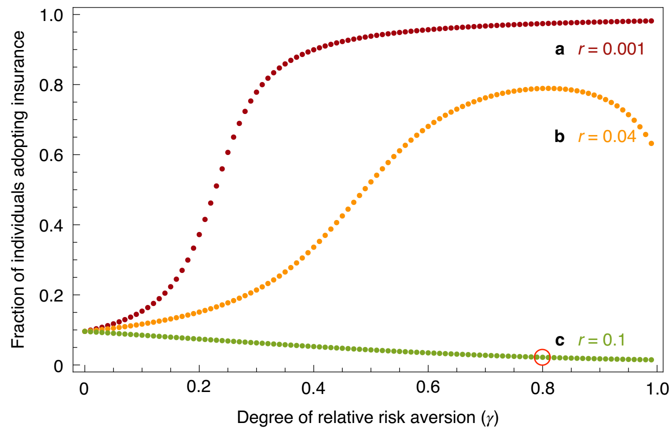

Fig. 1 | Average fraction of individuals adopting index insurance in the absence of risk-sharing pools. a–c, This quantity depends non-linearly on risk aversion (γ) and basis risk (r). We consider an actuarially unfair insurance regime from the consumer point of view ($c > wq\alpha$); in this condition, only risk-averse individuals adopt index insurance. Nevertheless, we observe three types of dependence on risk aversion, contingent on basis risk: for low basis risk (red), index insurance adoption increases with risk aversion (**a**); for intermediate basis risk (orange), there is an optimal value of risk aversion maximizing insurance adoption—in line with ref. [16] (**b**); for high basis risk (green), index insurance adoption decreases with risk aversion[32] (**c**) (additional details are provided in Supplementary Fig. 1). The red circle indicates the scenario explored in Fig. 2, for $N > 1$. Other parameters: $w = 1$, $c = 0.18$, $p = q = 0.2$, $\alpha = 0.8$, $\delta = 0$, $\beta = 10$, $Z = 100$ and $\mu = 0.01$.

Results

We assume that there is a population of Z individuals (for instance, farmers). Each individual has a total wealth w and is subject to a probability p of suffering a catastrophe. If the catastrophe occurs, individuals lose a fraction α of their total wealth. This loss can be recovered if individuals pay a premium c to buy index insurance. If this is the case, individuals will receive a compensation (recovering the full loss ($w\alpha$); that is, complete insurance) if the index contracted is attained—this occurs with a probability q. While in principle p can be close to q, there is a chance that losses occur but individuals do not receive a payout if the contracted index was not achieved (or conversely, there is a chance that they receive a payout without incurring any loss). This is the basis risk. We assume that the joint probability of having a loss without the index being attained[16] (basis risk) is r. We further assume that individuals are risk-averse and their utility is given by a power utility function, $U(w) = \frac{w^{1-\gamma}}{1-\gamma}$, defined for $w \geq 0$ and $0 \leq \gamma < 1$ (further details are provided in Methods).

Let us assume that individuals choose one of three strategies: (1) adopt CII and contribute to an informal risk-sharing pool (CII-C), (2) adopt CII yet defect on risk-sharing pool contributions (CII-D), or (3) refuse to take part in formal and informal insurance (No-CII). First, we focus on the dynamics of individual index insurance adoption; that is, in the absence of collectives with informal risk-sharing pools ($\delta = 0$, where δ is the fraction of excessive payout contributed to the informal risk-sharing pool by each CII-C; Methods). In this scenario, CII-C and CII-D become equivalent strategies associated with contracting individual index insurance that, for simplicity, we hereafter designate CII. Consequently, there are no collective (group-dependent) costs or benefits. The expected utility of an individual adopting CII (CII-C or CII-D) is given by $\mathrm{EU_{CII}} = (1-q+p-2r)U(w-c) + (q-p+r)U(w-c+\alpha w) + rU((1-\alpha)w-c)$ and $\mathrm{EU_{No\text{-}CII}} = (1-p)U(w) + pU((1-\alpha)w)$. If individuals are risk-neutral ($\gamma = 0$), we have $\mathrm{EU_{CII}} = w - c + (q-p)w\alpha$ and $\mathrm{EU_{No\text{-}CII}} = w(1-p\alpha)$. We therefore expect risk-neutral individuals to adopt insurance ($\mathrm{EU_{CII}} > \mathrm{EU_{No\text{-}CII}}$)

if $c < wq\alpha$ (that is, if the expected payout is higher than the insurance premium). Of note, in this case adoption is not contingent on the (symmetric) basis risk r, as risk neutrality ($\gamma = 0$) implies a cancellation between the excess payout that individuals may receive without incurring an actual loss and the loss they may suffer without receiving any benefit. As we consider insurance where $c > wq\alpha$ to be actuarially unfair (from the consumer point of view), whenever $\delta = 0$, adoption occurs only if individuals are risk-averse ($\gamma > 0$).

The effect of risk aversion ($\gamma > 0$) depends non-linearly on the level of basis risk. As depicted in Fig. 1 (and further detailed in Supplementary Fig. 1 with selection gradients), when basis risk is low, risk aversion always has a positive impact on insurance adoption (scenario a). At intermediate values of the basis risk, there is an optimal value of risk aversion maximizing index insurance uptake (scenario b). This same scenario was observed in previous work[16] adopting a static game framework in which rational individuals decide or not to adopt insurance coverage with the goal of maximizing their utility. If basis risk is high (a situation that is likely to occur and often indicated to be detrimental for index insurance adoption[16,24]), even risk-averse individuals refuse index insurance (scenario c). Indeed, insurance adoption seems to be negatively correlated with risk aversion (as also suggested by data from field experiments[32]).

A possible way to circumvent basis risk is by making use of informal risk transfers. These transfers can occur between those individuals (strategy CII-C, see Methods) that receive an excessive payout (that is, the index is activated without loss being suffered) and those that have an uncovered loss (that is, the index is not activated yet loss occurs). As Fig. 2 shows, transferring half of the excessive payout to a risk-sharing pool ($\delta = 0.5$) significantly increases index insurance adoption. For this to occur, groups are required to have a minimum size, provided that there are a sufficient number of individuals for risk to be effectively pooled and basis risk to be averaged out in the collective. The effect of group sizes on selection gradients is discussed in Supplementary Fig. 2. These results, however, do not account for the existence of individuals (strategy CII-D) who may adopt formal insurance while defecting on their contributions to the informal pool. In fact, one would expect that while formal insurance is enforceable, informal coverage originating from the informal pool requires that individuals honestly declare their effective losses. To some extent, informal insurance reintroduces (albeit at a smaller scale and in conditions that make it easier to monitor) the moral hazard and asymmetry of information issues characteristic of indemnity-based insurance.

Figure 3 presents the evolutionary dynamics for the full model, including all three behaviours introduced above: players that do not take part in a CII plan (No-CII), those that adopt a CII plan and donate a fraction δ of their excessive payout to an informal risk-sharing pool (CII-C), and defectors (CII-D), who despite adopting a CII plan, do not transfer any amount to an informal pool. In Fig. 3a, we observe that whenever (1) basis risk is high ($r = 0.1$), (2) individuals are risk-averse ($\gamma = 0.8$), and (3) groups are large enough to pool risk through informal contributions ($N = 40$), the optimum social outcome is obtained when everyone adopts insurance and contributes to the informal pool (that is, a large fraction of CII-C exists). However, if individuals are free to defect on their informal contributions (no peer monitoring), they will most probably do so. As more individuals give up adopting CII-C and start adopting CII-D, the benefits of informal risk sharing are hampered, which reintroduces the problems associated with basis risk. When a large fraction of the population adopts CII-D, the strategy No-CII is able to accrue (Fig. 3b). Peer monitoring, which implies exclusion of defectors from the pool benefits, can solve this dilemma (Fig. 3c). In this case, we assume that individuals not contributing to the informal risk-sharing pool can be detected with a probability m, and are excluded from pool benefits. If peer monitoring exists, individuals adopting CII-C gain an advantage over those adopting CII-D and, as shown in Fig. 3c, restoring the relation between CII-C and No-CII. In Supplementary Fig. 3 we explore dynamics for alternative values of insurance premium (c) and average fraction of resource lost to catastrophes (α).

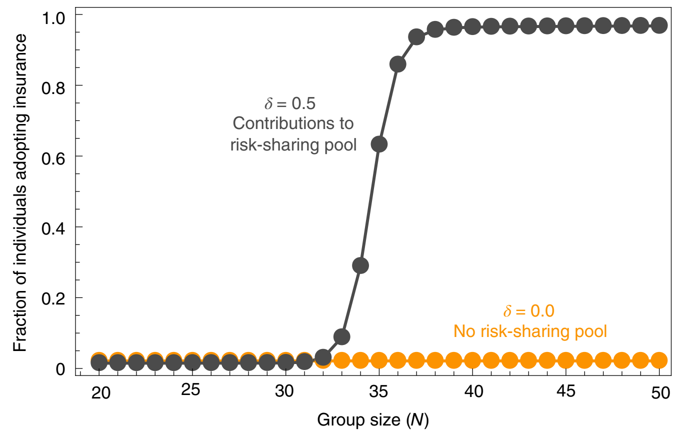

Fig. 2 | Adoption of CII with informal risk sharing. In the absence of risk sharing, nobody adopts CII, on the basis that the basis risk is high (red circle in Fig. 1). Conversely, we observe that even when basis risk is high, informal risk sharing incentivizes insurance adoption, with the take-up rate of CII increasing with the size of the collective. We assume that individuals receiving a payout without suffering a loss contribute δ of the payout to a common pool. That pool is subsequently used to compensate individuals who later suffer a catastrophe without receiving index insurance. In reality, collectives informally sharing their payouts to alleviate basis risk incur a coordination dilemma (Fig. 3 and Supplementary Fig. 2). A minimum fraction of individuals adopting CII is required before the population evolves to a state where index insurance adoption is taken up at large. Here we consider the prevalence of CII-C when only CII-C and No-CII can exist in a population. Other parameters: $r = 0.1$, $w = 1$, $c = 0.18$, $p = q = 0.2$, $\alpha = 0.8$, $\beta = 10$, $Z = 100$, $\mu = 0.01$ and $\gamma = 0.8$.

Figure 4 shows the conditions under which CII-C (and thus overall CII adoption) can be sustained in the presence of peer monitoring: (1) groups must be large enough to pool risk and (2) peer monitoring (and exclusion) must be efficient. These two conditions are not independent, as illustrated in Fig. 4; smaller group sizes require more efficient peer monitoring in order to sustain CII adoption.

Discussion

The possibility of offering index insurance plans to collectives opens new possibilities for the design of insurance products that are both attractive and easy to implement in developing countries[18–22], thus contributing to resilience, food security and human wellbeing. One of the advantages of CII plans is the possibility that individuals average out basis risk (in space and time) through informal risk-sharing mechanisms, which may use profitably existing norms of risk sharing that are already in place in these less-developed regions. Here we have analysed the evolutionary dynamics associated with the decision to adopt CII and donate excess payouts to a risk-sharing pool. We find that CII, which is associated with informal transfers, introduces a coordination dilemma of insurance adoption, whereby a minimal fraction of insurance adopters is necessary before the effects of basis risk can be averaged out and individuals start taking up insurance in large numbers. Informal contributions are, however, subject to a cooperation dilemma of their own. To solve this dilemma, we propose an additional mechanism—peer monitoring, implying the exclusion from the benefits of the risk-sharing pool of detected non-contributors. Given the possibility of local

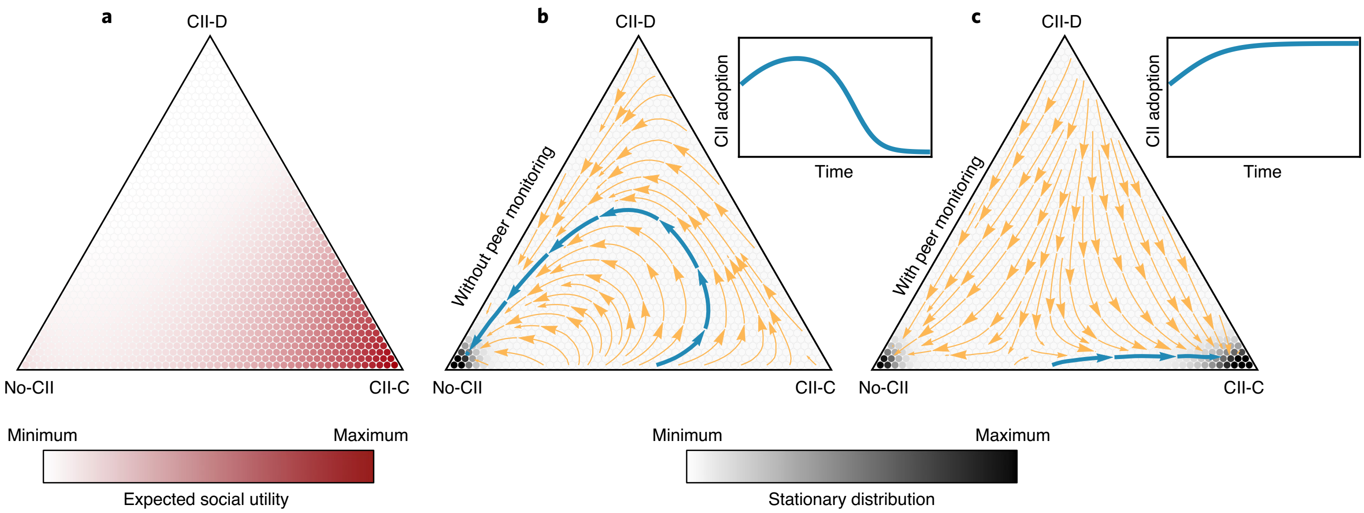

Fig. 3 | Risk-sharing pool induces a coordination dilemma of cooperation. a–c, For risk-averse farmers, the utility loss associated with the small contribution of a group member who received payout without suffering a loss converts into a correspondingly larger utility gain for the group member who suffered a catastrophe and did not receive a payout. Social utility thus increases with informal contributions. Nevertheless, individuals become better off by keeping the payout to themselves and refusing to contribute to the pool, configuring a standard social dilemma. This dilemma can be solved by introducing peer monitoring and exclusion from the pool benefits. **a**, The maximum social utility (that is, the sum of expected utilities for all individuals in the population) is obtained when everyone adopts CII-C. **b**, However, simply contributing to a risk-mitigating pool without monitoring is unstable; individuals start by refraining from contributing to the informal risk-sharing pool and, whenever individuals adopt CII-D at scale, No-CII invades and prevails. A representative trajectory illustrating this dynamic behaviour is shown in blue, starting from a configuration where about half of the population adopts CII-C and nobody adopts CII-D. Insets: the corresponding time-series, where the overall fraction of individuals adopting CII (either CII-C or CII-D) is plotted. **c**, The existence of efficient peer monitoring provides stability to CII-C, such that CII-C—and index insurance adoption—prevails, as illustrated by the blue curve starting from the same configuration as in **b**. To colour each state *i* in **a**, we interpolate between white (0) and red (1) with a factor $0 \leq ((u_i - u_{min})/(u_{max} - u_{min}))^6 \leq 1$, where u_i is the expected social utility in state *i*, and u_{min} is the minimum and u_{max} is the maximum utility over all states. Additional scenarios are explored in Supplementary Fig. 3. Other parameters: $r = 0.1$, $w = 1$, $c = 0.18$, $p = q = 0.2$, $\alpha = 0.8$, $\delta = 0.5$, $m = \{0, 0.9\}$, $\beta = 10$, $Z = 50$, $N = 40$, $\mu = 0.02$ and $\gamma = 0.8$.

monitoring, the implementation of such mechanisms are expected to be able to rely on existing social norms and networks, which is more straightforward than management by an external insurance company. We did not delve here into the nature of the peer-monitoring mechanisms, which may rely on reciprocity, as individuals may refrain from sharing the pool (or cooperating) with peers that defected in the past[33–35]. Clearly, the model we propose can be easily adapted to test how different monitoring schemes may depend explicitly on group sizes and even on specific norms and installed networks. If larger groups can impede efficient monitoring, the trade-off between efficient risk-pooling and peer monitoring leads us to expect that there will be an optional group size that optimizes the emergence of insurance adoption. Conversely, many cultures have developed informal but highly resilient norms and strategies that help farmers (and cattle breeders) to secure their survival (or the survival of their cattle stock) under adverse climate conditions. Social norms have evolved in this context and have contributed to establishing trust and confidence among groups of farmers. These informal structures may act both as important catalysts of future CII adoption, and as a means to ensure that peer monitoring within collectives is efficient and reliable. Such conditions increase the prospects of CII adoption, mostly in early stages of implementation, where basis risk may suffer inherently from the difficulty in matching p and q. The fact that these norms are culturally dependent strongly suggests that the mechanisms supporting efficient peer monitoring should adapt and profit from these cultural specificities.

In this sense, the model we developed can be interpreted as a baseline model that may be extended in the future to accommodate different environments and risk-mitigation domains. First, we assumed basis risk to be uncorrelated among the collective insurance members; this may not be the case in real scenarios[22]. Yet, it is expected that an increase in covariate risk has the same effect as reducing δ, that is, diminishing the benefits of informal transfers. This further highlights the one advantage of CII: if a weather shock affects everyone in the collective, such an event is probably severe enough to reach the index and activate insurance payouts. This compensation would not be received if individuals relied only on informal transfers[19]. Second, our analysis was based on agricultural insurance. The model, however, has the potential to be generalized to other domains in which groups and risk-mitigating strategies are essential, such as fisheries and revenue sharing[36], cattle breeding[37] or health-related insurance plans[38], where recent experience also reveals possible advantages of considering groups[39]. Indeed, as in large catastrophic shocks due to extreme weather events, the sustainability of health insurance plans amid public health crises (for example, in a pandemic) may depend on informal safety nets. Third, while we focused on peer monitoring and exclusion (which can be viewed as a form of negative incentive) to stabilize cooperation, community enforcing mechanisms may include rewards[40], punishment[35], reputation-based social norms[41] or pro-sociality among members of the collective insurance schemes[42,43].

With this work, we expect to highlight the importance of considering not only a static analysis of insurance adoption, but also the dynamics associated with such processes, in the context of communities where peer imitation and social influence have a role. Our dynamic analysis showed that CII effectively reintroduces the dilemma of information asymmetry and moral hazard that characterizes indemnity-based insurance plans. Local collectives, however, may be in prime position to establish peer monitoring and reap the benefits of both formal index insurance and informal basis risk mitigation. CII can work as an effective way of

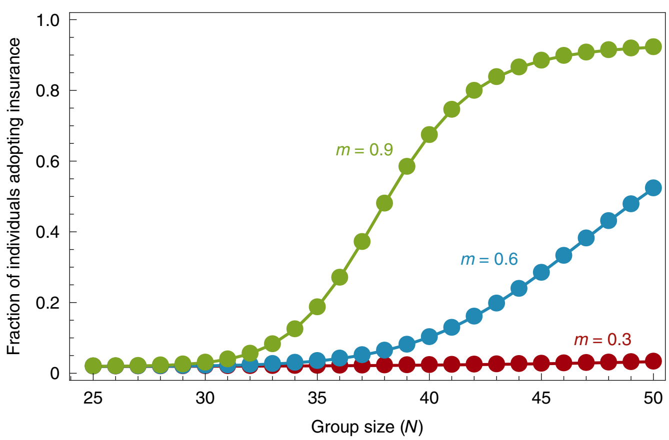

Fig. 4 | Peer-monitoring efficacy and success of CII adoption. Here we consider the prevalence of CII-C (that is, individuals who adopt index insurance and contribute to the informal risk-sharing pool) as a function of the size N of the collective, for three values of the detection probability $m=\{0.3, 0.6, 0.9\}$. The minimum group size needed to effectively pool basis risk and incentivize the adoption of index insurance decreases with increasing m, the probability of detecting CII-D and excludes individuals from the informal risk-sharing scheme. Here we use the full model (as in Fig. 3). Other parameters: $r=0.1$, $w=1$, $c=0.18$, $p=q=0.2$, $\alpha=0.8$, $\delta=0.5$, $\beta=10$, $Z=50$ and $\mu=0.02$.

alleviating basis risk—indicated as a fundamental drawback of individual index insurance—a feature that relies on within-collective informal transfers. By identifying coordination dynamics associated with index insurance and informal transfers, we make it easier to diagnose why some communities may have low rates of uptake of index insurance, even when offered seemingly attractive products. Incentivizing insurance adoption may require convincing a critical fraction of initial adopters in order to trigger evolution towards general adoption, which of course may be incentivized. Local agreements may ease this process. For example, individuals may commit to adopt insurance and contribute to informal risk-sharing pools conditionally on adoption by and contributions from others—as has been recently proposed in the context of climate agreements[44]. As in other non-linear public goods games, we also expect that communication[45] and social norm interventions[46,47] can facilitate surpassing the threshold of initial adopters. At the same time, mechanisms to guarantee efficient observation and peer monitoring—that is, to reduce information asymmetries and moral hazard between policyholders or to verify that commitments are fulfilled—should be facilitated, so that suspicion is absent and informal transfers prevail.

Methods

Here we assume a population of Z individuals. Given the risk of extreme weather events, each individual has a probability p of suffering a catastrophe. If that event occurs, individuals lose a fraction α of their total wealth w ($w>0$). This loss can be recovered if individuals have index insurance, which is associated with a premium c. When covered by index insurance, individuals receive a payout if the index contracted is attained, which occurs with a probability q. In what follows, we will assume that $w\alpha q<c$, that is, insurance plans are actuarially unfair from the consumer point of view (as insurance companies need to add transaction costs and profit margins). Individuals potentially subscribe to insurance not only due to risk aversion, but also because stable income will ensure credit access (often coupled to index insurance contracts), which enables improved yields, thus providing an escape from poverty traps.

While in principle p can be close to q, there is a chance that losses occur yet individuals do not receive any payout, if the contracted index was not achieved (or, conversely, of receiving a payout without incurring any loss). This is the basis risk. We assume that the joint probability that a loss is incurred and the index is not attained (basis risk) is r[16]. As in previous work[16,20,24], we consider four possible scenarios of interest, with their associated probabilities: (1) loss occurs and index insurance is activated ($p-r$); (2) loss occurs and index insurance is not activated (r); (3) loss does not occur and index insurance is activated ($q+r-p$); and (4) loss does not occur and index insurance is not activated ($1-q-r$). In order to guarantee that probabilities are non-negative and indexes are still associated with losses (that is, the probability that an index is achieved given that a loss is incurred is higher than the probability that index is achieved given that a loss is not incurred), we will assume that $r<p(1-q)$ and $q+r>p$.

Assuming that $r>0$, individuals can alleviate the effects of basis risk by contributing a fraction δ ($0\leq\delta\leq1$) of their excessive payout (received when the index was achieved yet no loss was incurred) to a common pool, to be divided by individuals that suffer a loss without receiving any payout (as the index was not attained). We assume that collective insurance plans are offered to groups of N ($0<N\leq Z$) individuals. Let us assume that individuals in the group have three options: (1) adopt CII and contribute to an informal risk-sharing pool (strategy CII-C), (2) adopt CII yet defect on risk-sharing pool contributions (strategy CII-D) and finally (3) refuse to take part in formal and informal insurance (strategy No-CII). At a given moment in time, there will be i individuals in the population adopting CII-C, j individuals adopting CII-D and $Z-i-j$ individuals adopting No-CII ($0\leq i, j\leq Z$ and $i+j\leq Z$). We will focus on the dynamical process of adopting these strategies.

We assume that individuals are risk-averse and their utility is given by a power utility function, $U(w)=\frac{w^{1-\gamma}}{1-\gamma}$, defined for $w\geq0$ and $0\leq\gamma<1$. This class of utility functions, commonly used in the economics and finance literature, is also denoted constant relative risk aversion or isoelastic utility function. The parameter γ defines the (Arrow–Pratt) degree of relative risk aversion; that is, the rate at which marginal utility decreases when wealth w is increased by one unit[48,49]. Higher γ represents individuals who are more risk-averse.

In these conditions, the expected utility of an individual adopting No-CII will be given by

$$\mathrm{EU}_{\text{No-CII}}=(1-p)U(w)+pU((1-\alpha)w),$$

that is, individuals refusing insurance will maintain their full wealth w with probability $(1-p)$ and will receive $(1-\alpha)\,w$ if a catastrophe occurs, which happens with a probability p.

CII plans are offered to groups composed of N individuals. Thus, groups of size N will be sampled, and each group will have k and l individuals adopting CII-C and CII-D, respectively. The expected utility of an individual adopting CII-C is given by

$$\begin{aligned}\mathrm{EU}_{\text{CII-C}}(k,l)=&(1-q+p-2r)U(w-c)+(q-p+r)U(w-c+(1-\delta)\alpha w)\\&+r\sum_{h,g,s=0}^{k,k-h,l}P(h,g,s;k,l)U\left((1-\alpha)w-c+\frac{h\alpha w\delta}{g+s+1}\right)\end{aligned}$$

If the index is activated and a catastrophe occurs or a catastrophe does not occur and the index is not activated—which occurs with a probability $1-q+p-2r$—individuals receive $U(w-c)$, as losses are fully covered. If individuals adopting CII-C receive insurance payment without suffering a loss—which happens with probability $q-p+r$—they will receive an (excessive) payout αw and contribute a fraction δ of that, having utility $U(w-c+(1-\delta)\alpha w)$. Conversely, if individuals suffer a loss without receiving insurance—which happens with probability r—they receive a share of the pool resulting from excessive payout contributions, which depends on the number of individuals that contribute to that pool (h) and the number of CII-C and CII-D individuals that suffer a catastrophe and thus divide the pool (g and s, respectively). Summing over all possible combinations of h, g and s, the total expected utility in this case yields $\sum_{h,g,s=0}^{k,k-h,l}P(h,g,s;k,l)U\left((1-\alpha)w-c+\frac{h\alpha w\delta}{g+s+1}\right)$, where $P(h,g,s;k,l)$ is the probability that h individuals adopting CII-C receive insurance without suffering loss, and g individuals adopting CII-C and s individuals adopting CII-D suffer a loss without receiving insurance.

$$\begin{aligned}P(h,g,s;k,l)=&\binom{k}{h}\binom{k-h}{g}\binom{l}{s}\\&\times(q-p+r)^{h}r^{g+s}(1-q+p-2r)^{k-h-g}(1-r)^{l-s}\end{aligned}$$

Here we avoid focusing on pool growth over time and discounting. We assume that individuals decide on the basis of the expected utility in a single time step and, for $\delta>0$, individuals may contribute to the risk-sharing pool even if nobody suffers a catastrophe. We furthermore assume that $(1-\alpha)\,w>c$, thus considering that individuals always have liquidity to pay premiums and utilities are always non-negative.

Finally, the expected utility of an individual adopting CII-D is given by

$$\begin{aligned}\mathrm{EU}_{\text{CII-D}}(k,l)=&(1-q+p-2r)U(w-c)+(q-p+r)U(w-c+\alpha w)\\&+r\sum_{h,g,s=0}^{k,k-h,l}P(h,g,s;k,l)U\left((1-\alpha)w-c+\frac{h\alpha w\delta}{g+s+1}\right)\end{aligned}$$

Note that here CII-D adopters do not contribute a fraction δ of their excessive payouts. As will be clear below, this feature may hinder their own adoption of index insurance. As stated, peer monitoring and exclusion constitute the possible mechanism that we propose to alleviate the effects of waiving contributions. To introduce peer monitoring and exclusion, we introduce a slight modification of the previous equations

$$\begin{aligned}\mathrm{EU}^{m}_{\text{CII-C}}(k,l) = &\ (1-q+p-2r)U(w-c)+(q-p+r)U(w-c+(1-\delta)\alpha w)\\ &+r\sum_{h,g,s=0}^{k,k-h,l}P(h,g,s;k,l)U\left((1-\alpha)w-c+\tfrac{h\alpha w\delta}{g+(1-m)s+1}\right)\\ \mathrm{EU}^{m}_{\text{CII-D}}(k,l) = &\ (1-q+p-2r)U(w-c)+(q-p+r)U(w-c+\alpha w)\\ &+r\sum_{h,g,s=0}^{k,k-h,l}P(h,g,s;k,l)U\left((1-\alpha)w-c+(1-m)\tfrac{h\alpha w\delta}{g+(1-m)s+1}\right)\end{aligned}$$

where $0\leq m\leq 1$ conveys the effectiveness of peer monitoring: $m=0$ means that no defector is identified and excluded, whereas $m=1$ implies that defectors never receive the benefits of the risk-sharing pool.

Previous expected utilities result from groups with a specific composition of CII-C, CII-D and No-CII. Assuming a well-mixed population of Z individuals (i of which adopt CII-C, j adopt CII-D and $Z-i-j$ adopt No-CII), we can write down the fitness of individuals, taken over all possible group compositions, as

$$\begin{aligned}f_{\text{CII-C}}(i,j) &= \sum_{k=0}^{N-1}\sum_{l=0}^{N-1-k}\mathrm{EU}_{\text{CII-C}}(k,l)H(k,l;i-1,j,Z-1,N-1)\\ f_{\text{CII-D}}(i,j) &= \sum_{k=0}^{N-1}\sum_{l=0}^{N-1-k}\mathrm{EU}_{\text{CII-D}}(k,l)H(k,l;i,j-1,Z-1,N-1)\\ f_{\text{No-CII}}(i,j) &= \mathrm{EU}_{\text{No-CII}}\end{aligned}$$

Where $H(k, l; i, j, Z, N)$ is the (hypergeometric) probability of sampling a group with k CII-C individuals, l CII-D individuals and $N-k-l$ No-CII individuals from a population with i adopting CII-C, j adopting CII-D and $Z-i-j$ adopting No-CII,

$$H(k,l;i,j,Z,N)=\binom{i}{k}\binom{j}{l}\binom{Z-i-j}{N-k-l}\Big/\binom{Z}{N}$$

Finally, we assume that individuals will adopt each strategy following a process of social learning, whereby individuals with higher average expected utility induce others to follow that strategy. $T_{\mathrm{A}}^{+(-)}(i_{\mathrm{A}}, i_{\mathrm{B}})$ is the generic probability of having one more (or less) individual adopting strategy A, in a configuration where i_{A} individuals adopt strategy A, i_{B} adopt B and $Z-i_{\mathrm{A}}-i_{\mathrm{B}}$ adopt C. We use the Fermi function $\left[1+\mathrm{e}^{-\beta(f_Y-f_X)}\right]^{-1}$ to calculate the probability that an individual with strategy X imitates one other with strategy Y; the pairwise comparison rule[50]. The parameter $\beta\geq 0$ controls the intensity of selection; in this case, the extent to which the imitation process depends on fitness (average expected utilities) difference.

Social learning happens with probability $(1-\mu)$ since, with probability μ, there will be a mutation into a randomly chosen strategy (among σ possible ones), regardless of any fitness criteria. In general, the one-step transition probabilities associated with the discrete birth–death dynamics can be written as:

$$\begin{aligned}T_{\mathrm{A}}^{+}(i_{\mathrm{A}},i_{\mathrm{B}}) &= \tfrac{(1-\mu)i_{\mathrm{A}}}{Z}\left(\tfrac{i_{\mathrm{B}}}{Z-1}\tfrac{1}{1+\mathrm{e}^{-\beta(f_{\mathrm{A}}-f_{\mathrm{B}})}}+\tfrac{Z-i_{\mathrm{A}}-i_{\mathrm{B}}}{Z-1}\tfrac{1}{1+\mathrm{e}^{-\beta(f_{\mathrm{A}}-f_{\mathrm{C}})}}\right)+\tfrac{\mu(Z-i_{\mathrm{A}})}{(\sigma-1)Z}\\ T_{\mathrm{A}}^{-}(i_{\mathrm{A}},i_{\mathrm{B}}) &= \tfrac{(1-\mu)i_{\mathrm{A}}}{Z}\left(\tfrac{i_{\mathrm{B}}}{Z-1}\tfrac{1}{1+\mathrm{e}^{-\beta(f_{\mathrm{B}}-f_{\mathrm{A}})}}+\tfrac{Z-i_{\mathrm{A}}-i_{\mathrm{B}}}{Z-1}\tfrac{1}{1+\mathrm{e}^{-\beta(f_{\mathrm{C}}-f_{\mathrm{A}})}}\right)+\tfrac{\mu i_{\mathrm{A}}}{Z}\end{aligned}$$

The previous transition probabilities allow us to define a Markov chain where states correspond to each possible combination of strategies (CII-C, CII-D and No-CII) in the population. Resorting to the stationary distribution of this process—computed through an eigenvector search—we can obtain a picture of the long-term prevalence of each possible configuration in the population. This distribution is used in Figs. 3 and 4 to calculate the average prevalence of CII-C; that is, the fraction of individuals that take up collective insurance and contribute to the informal pool. In Figs. 1 and 2 (see also Supplementary Figs 1 and 2), we use the same approach, but with two strategies (CII-C and No-CII; $\sigma=2$). The difference between birth (T^{+}) and death (T^{-}) probabilities also allows us to describe the most likely path of evolution using the gradient of selection. For each configuration, we calculate the vector $(T^{+}_{\text{CII-C}}-T^{-}_{\text{CII-C}}, T^{+}_{\text{CII-D}}-T^{-}_{\text{CII-D}})$, which corresponds to the stream plots depicted in Fig. 3 (and Supplementary Fig. 3). When only strategies CII-C and No-CII are allowed in the population, $(T^{+}_{\text{CII-C}}-T^{-}_{\text{CII-C}})$ provides the one-dimensional gradient represented in Supplementary Figs. 1 and 2. Finally, in Supplementary Table 1, we detail all the parameters of the model, their meaning, and the intervals of the values tested. Further details about implementing these equations are provided in Supplementary Notes.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

Source data are provided with this paper.

Code availability

This paper relies on theoretical results following direct implementation of the equations provided in the Methods. Further details are provided in the Supplementary Information.

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Author contributions
F.P.S., J.M.P., F.C.S. and S.A.L. conceived and designed the project. F.P.S. performed the numerical calculations and analysed the results. F.P.S., J.M.P., F.C.S. and S.A.L. discussed the results. F.P.S., J.M.P., F.C.S. and S.A.L. wrote and edited the manuscript.

Competing interests
The authors declare no competing interests.

Additional information

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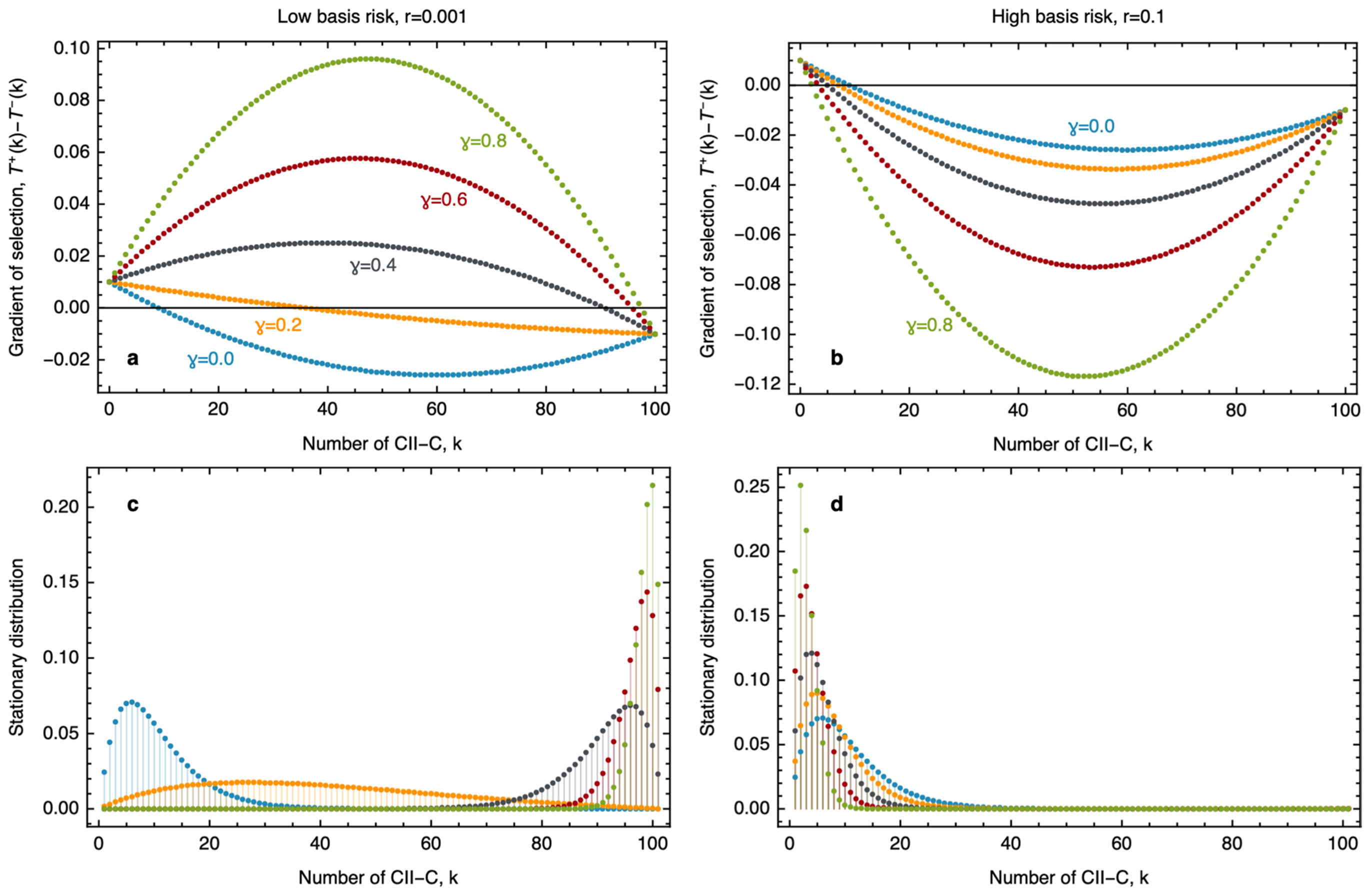
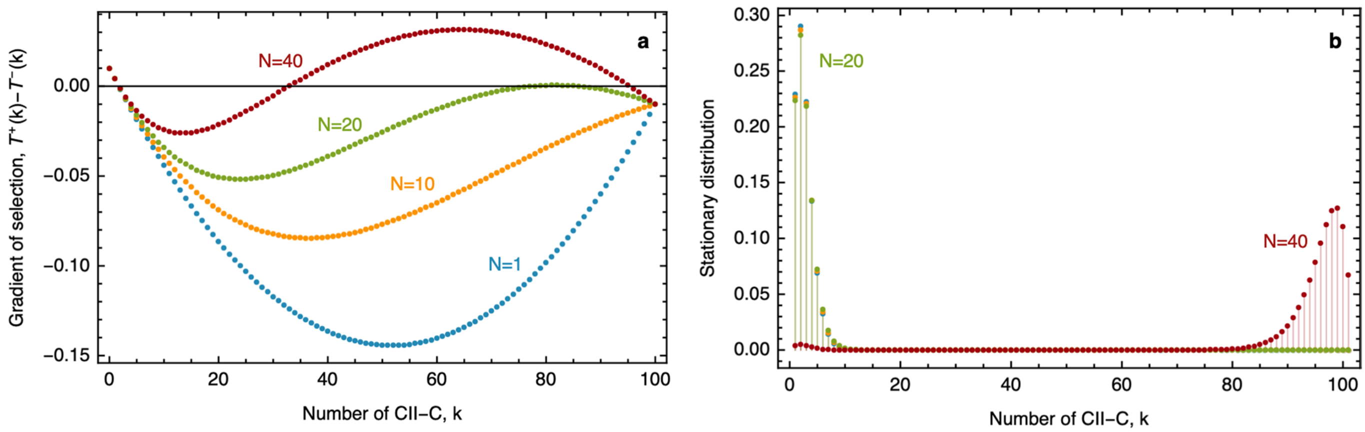
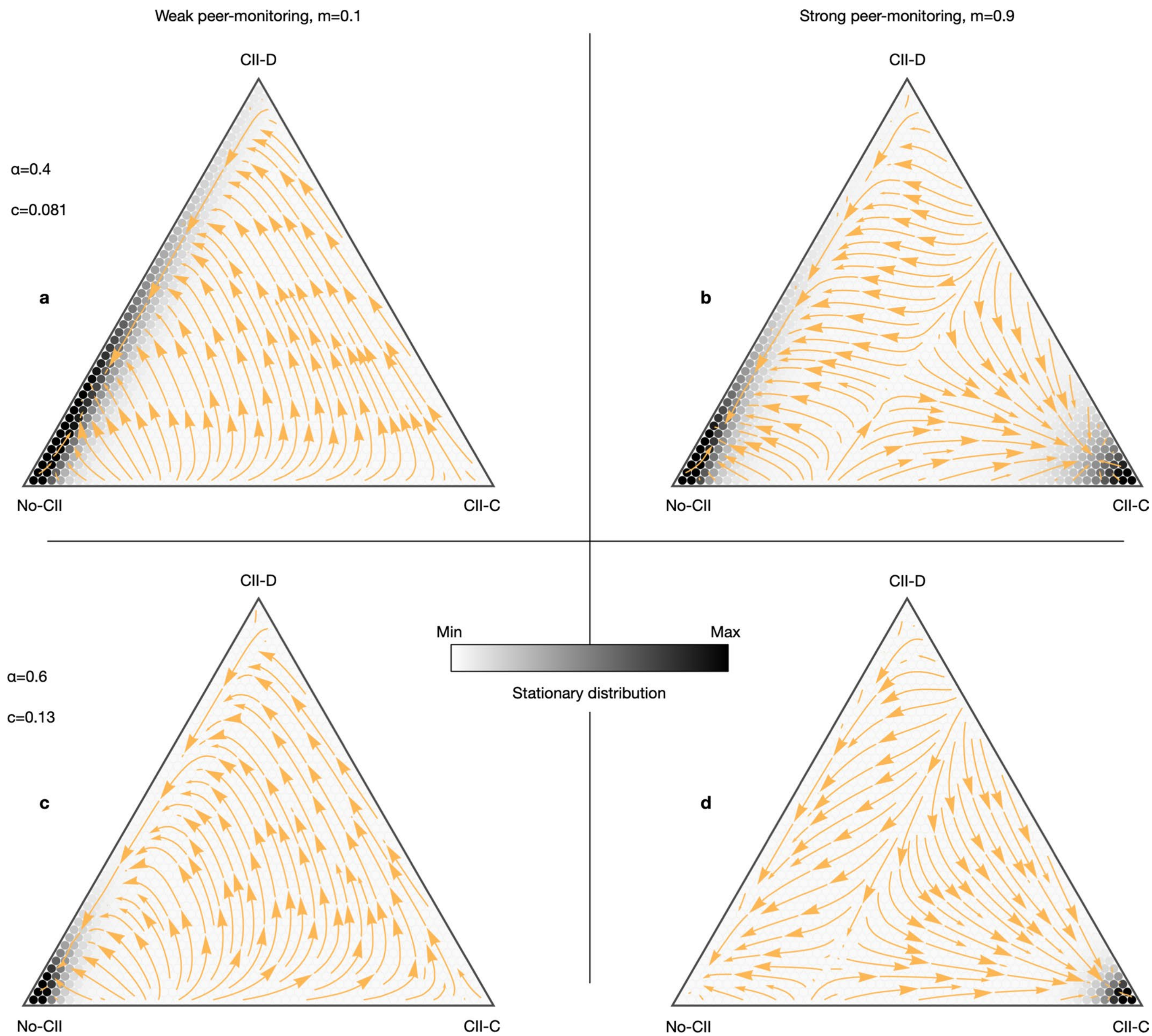


Extended Data Fig. 1 | Effect of basis risk and risk-aversion in CII dynamics. In the absence of risk-sharing pools ($\delta = 0$) adoption of index insurance depends on the risk-aversion (γ) of individuals. **a**, As we consider an actuarially unfair insurance (from the consumer point of view, *that is*, $q\alpha w < c$) only risk-averse individuals (high γ) adopt index insurance, which is evident by the positive gradients of selection for high γ. **b**, If basis risk is high, however, individuals do not adopt index insurance, which is evident by the negative gradients, implying a relative high probability of adopting **No-CII** compared with **CII-C**. **c**, The high rates of adoption of index insurance when the population is composed of risk-averse individuals is here evident by the peak in the stationary distribution over states with a high prevalence of **CII-C** individuals, when γ is high. **d**, Conversely, for high basis risk there is a peak in the stationary distribution over states with a high prevalence of **No-CII**, regardless of γ. Please note that, since $\delta = 0$, strategies **CII-C** and **CII-D** are equivalent in this context. Other parameters: $N = 1, w = 1, c = 0.18, p = q = 0.2, \alpha = 0.8, \beta = 10, Z = 100, \mu = 0.01$.



Extended Data Fig. 2 | Effect of group size in CII dynamics. The existence of sizeable groups in which individuals take part in informal risk-sharing (contributing to a common pool when they receive a payout without suffering a loss) promotes the adoption of index insurance. **a**, Sufficiently large groups introduce a coordination: if the number of individuals in the population goes above a critical fraction, the population will most likely evolve to a state where everyone adopts **CII**. **b**, If the basin of attraction towards **CII** is sufficiently large, we observe a high prevalence of individuals adopting **CII**, resulting in high index insurance take-up rates. Here we consider the prevalence of **CII-C** when only **CII-C** and **No-CII** can exist in a population. Other parameters: $r = 0.1, w = 1, c = 0.18, p = q = 0.2, \alpha = 0.8, \delta = 0.5, \beta = 10, Z = 100, \mu = 0.01$.



Extended Data Fig. 3 | The dilemma of CII adoption (and the need of peer-monitoring to solve it) in the context of less destructive events (lower values of α). As in **Figure 3** (main text) in all scenarios explored above the socially optimum outcome is achieved when all individuals adopt **CII-C**. In the absence of peer-monitoring (panels **a** and **c**) the most prevalent configurations are, however, those where individuals refuse insurance. The existence of peer-monitoring and defector exclusion from the informal pool (panels **b** and **d**) confers **CII-C** the relative advantage to be evolutionary robust. Other parameters: $r = 0.1, w = 1, p = q = 0.2, \delta = 0.5, \beta = 50, Z = 50, N = 40, \mu = 0.02$.

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