Nonlinear effects of group size on collective action and resource outcomes

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For decades, scholars have been trying to determine whether small or large groups are more likely to cooperate for collective action and successfully manage common-pool resources. Using data gathered from the Wolong Nature Reserve since 1995, we examined the effects of group size (i.e., number of households monitoring a single forest parcel) on both collective action (forest monitoring) and resource outcomes (changes in forest cover) while controlling for potential confounding factors. Our results demonstrate that group size has nonlinear effects on both collective action and resource outcomes, with intermediate group size contributing the most monitoring effort and leading to the biggest forest cover gain. We also show how opposing effects of group size directly and indirectly affect collective action and resource outcomes, leading to the overall nonlinear relationship. Our findings suggest why previous studies have observed differing and even contradictory group-size effects, and thus help guide further research and governance of the commons. The findings also suggest that it should be possible to improve collective action and resource outcomes by altering factors that lead to the nonlinear group-size effect, including punishing free riding, enhancing overall and within-group enforcement, improving social capital across groups and among group members, and allowing self-selection during the group formation process so members with good social relationships can form groups autonomously.

casual inference | commons governance | ecosystem services | biodiversity conservation | sustainability

Groups are basic units for collective action and may achieve outcomes that individual efforts cannot (1). However, the threat of free riding implies that the optimal amount of collective action does not always occur, and has led to a substantial literature trying to understand what factors facilitate or block the emergence of collective action. Because collective action is needed to manage many common-pool resources, understanding the mechanisms that shape collective action and resource outcomes is a critical challenge for sustainability (2, 3).

From Pareto in 1906 (4) and especially since the influential work by Olson in 1965 (5), group size has been hypothesized as a crucial factor affecting collective action and resource outcomes. (We note that Olson used an unusual definition of "group size": the potential number of group members. Here we follow conventional practice and consider the actual number of participants.) However, the debate on group-size effect continues with some researchers arguing that it is linear and negative (5–7), others arguing for linear and positive (8–11), and still others insisting it is curvilinear (12–14), ambiguous (1, 15–17), or nonsignificant (18–20). Even in the most recent work (8, 15, 19, 21–24), a consensus on the nature of the effect or even its existence still remains elusive.

Previous literature indicates that there are two hypothetical opposing forces through which group size affects collective action and resource outcomes (Fig. 1). Group members play different roles in collective action, ranging from free riders (i.e., members who enjoy group benefits without paying for the costs) and conditional cooperators (i.e., members who will contribute more when others contribute more) to altruists (i.e., members who contribute regardless of others' behaviors), as well as various roles mixing these strategies (25). Group size can have diverse effects. On the one hand, members tend to free ride as the group becomes larger (5, 26). As group size increases, transaction costs (e.g., communication costs, costs of monitoring to maintain a necessary level of excludability) may rise sharply (1, 7, 13–15); thus, the larger the group, the more difficult to detect and reduce free riding. If the common good has any degree of rivalry, average individual payoff will shrink as group size increases, which further aggravates free riding (15–17). On the other hand, small groups often lack the resources (e.g., labor, time, funds) that large groups can deploy (7, 13, 14, 27). When available resources are limited, it is difficult to devote additional resources to collective action (1, 15). Taking advantage of more resources, large groups may enhance enforcement through monitoring and punishment to reduce free riders and thus improve collective action and resource outcomes (13, 14, 20, 21, 24, 28). Ostrom scrutinized previous evidence and pointed out the problem of focusing on group size itself without considering factors that influence or are influenced by group size (7). Ostrom then suggested further research to focus on the hypothesized curvilinear effects of group size (7).

A few previous studies qualitatively described the curvilinear or nonlinear effects of group size (12, 26, 29), and some claimed a nonlinear relationship by simply plotting collective action against group size without controlling other factors (13, 14). However, none has provided a quantitative analysis of field evidence while controlling potential confounding factors, as suggested by Ostrom (7). Furthermore, there is little empirical examination of the mechanisms of nonlinear group-size effects, which is essential to guide commons governance.

To fill these knowledge gaps, we used empirical data from our long-term studies (30–44) in Wolong Nature Reserve, Sichuan Province, China (N 30°45′ – 31°25′, E 102°52′ – 103°24′) (Fig. 2). Wolong Nature Reserve is home to ∼10% of the total wild giant panda (*Ailuropoda melanoleuca*) population, and home to ∼4,900 local human residents distributed in ∼1,200 households. In response to degradation of forest and panda habitat because of human activities since the 1970s (31), the Reserve implemented the Natural Forest Conservation Program (NFCP) in 2001. NFCP is a nationwide conservation program that aims to conserve and restore natural forests through logging bans, afforestation, and monitoring, using a payments-for-ecosystem-services scheme to motivate conservation behavior (45). Of the total ∼120,500 ha in the NFCP monitoring area in Wolong, ∼40,100 ha were assigned to ∼1,100 rural households and the remaining areas were monitored by the staff of the reserve's administrative bureau. Meanwhile, the bureau

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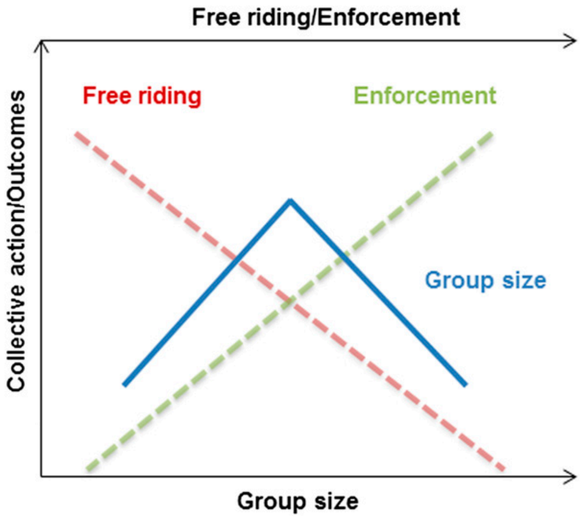

Fig. 1. Hypothetical effects of free riding, within-group enforcement, and group size on collective action and resource outcomes. Both free riding and within-group enforcement are hypothesized to be positively related to group size. However, free riding is hypothesized to be negatively related to within-group enforcement. The combined effects of free riding and within-group enforcement on collective action and resource outcomes are not expected to be additive because of interactions between within-group enforcement and free riding. The net effect of group size is determined by the dynamics (e.g., strength and variation with group size) of free riding and within-group enforcement, which may form a nonlinear pattern.

set two timber checkpoints at the two ends of the only main road crossing the reserve (Fig. 2). The common-pool resource in question in the Reserve is the forest (an essential component of the panda habitat) assigned to households. Because logging is largely the action of local residents (*SI Appendix*, Section 2.4.1), collective action (i.e., forest monitoring) has the potential to reduce illegal logging and improve resource outcomes (i.e., changes in forest cover).

The bureau administering the NFCP has assigned the forest parcels to household groups of various sizes ranging from 1 to 16 (*SI Appendix*, Table S2). Parcels distant from households were assigned to large groups with slightly higher payments (*SI Appendix*, Table S2). Households could not choose which parcel to monitor or in which household groups to participate. Our analyses indicate that the distance from a household to its monitored parcel and NFCP payment do not affect the group-size effects (*SI Appendix*, Section 2.4.3). Thus, the current distribution of group size is suitable for examining the group-size effects and mechanisms. Each assigned household group decides autonomously on its monitoring strategies (e.g., monitoring frequency, duration, and whether to subdivide to monitor in turns). The bureau evaluates the monitoring performance based on field assessments of illegal activities (e.g., logging) and rewards people who report illegal activities (in cash). All households within a group share the same monitoring responsibility and suffer the same payment deduction when any illegal activities are detected by the bureau in their comonitored parcel. However, the households are exempt from penalties if they report lawbreakers, in which case the corresponding lawbreakers are punished instead.

To understand the group-size effects and the underpinning mechanisms, we combined data on characteristics of households, household groups, and monitored parcels (*SI Appendix*, Section 1). We acknowledge that conflicts with regard to monitoring might occur within a household, but because the policy is designed to treat households—not individuals—as monitoring units, the common practice of treating households as the unit of analysis is appropriate here. We measured household monitoring efforts by the total amount of labor input (one unit of labor input is defined as one laborer working for 1 d) (*SI Appendix*, Section 2.1) through surveys. We measured resource outcomes as changes in forest cover derived from previously published forest-cover maps (*SI Appendix*, Section 1.1.1). We also measured factors that might explain the mechanisms, including free riders (i.e., households that did not participate in monitoring), the level of within-group enforcement (i.e., strong enforcement if there are punishment measures for free-riding members within the group; otherwise, weak enforcement), and within-group division (i.e., whether groups divide into subgroups to conduct monitoring in turns) (*SI Appendix*, Section 2). Some other contextual factors shown in previous studies to affect group size, collective action, or resource outcomes were used as control variables (*SI Appendix*, Section 2.3).

Results

Our results show that group size has a nonlinear effect on the monitoring efforts per household, with an intermediate group size contributing the most (Fig. 3*A* and Table 1). These results are consistent whether or not we include the households who monitored parcels individually (i.e., group size of one) and when using different combinations of control variables (*SI Appendix*, Table S13). The effect peaks at a size of eight or nine households, where a household spends 9.2 labor units per year monitoring its forest parcel. Our results also indicate that some other factors besides group size matter substantially. The level of social ties to local leaders has a significantly negative effect on per household monitoring efforts (Table 1). When all other variables are at their mean values, households with strong social ties to local leaders on average input 54% less labor units than households with weak social ties to local leaders. Our experience in the Reserve helps explain this effect. The staff members in the administrative bureau who are in charge of combatting illegal logging activities are hired from outside the Reserve, and anyone can report illegal logging and receive a cash reward from the administrative bureau. We are also not aware of a single case in which staff members turned a “blind eye” to illegal logging so households with strong ties could avoid monitoring or sanctions. Rather, additional analyses (*SI Appendix*, Section 2.4.2) reveal that, compared with households with weak social ties to local leaders, households with strong social ties often have more social relationships, power, knowledge, and experience. Our extensive fieldwork experience at the site indicates that these social ties provide social capital and reputation that discourages others from conducting illegal activities in their monitoring parcels, and thus reduce the need for them to spend efforts on formal monitoring. The distance between each household and the main road has a positive effect on a household’s monitoring efforts, with

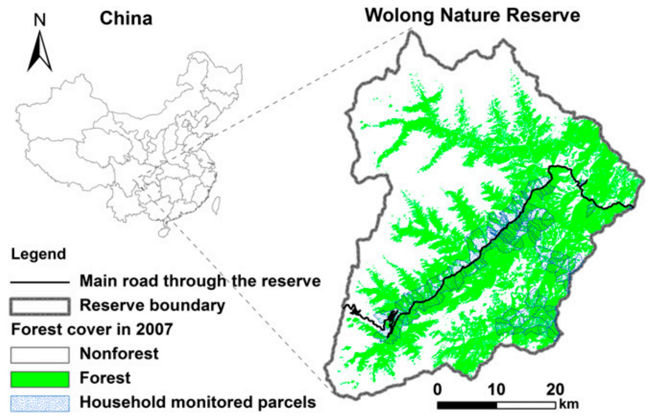

Fig. 2. Map of the location, main road, forest cover in 2007, and household monitoring parcels of Wolong Nature Reserve in Sichuan Province, China.

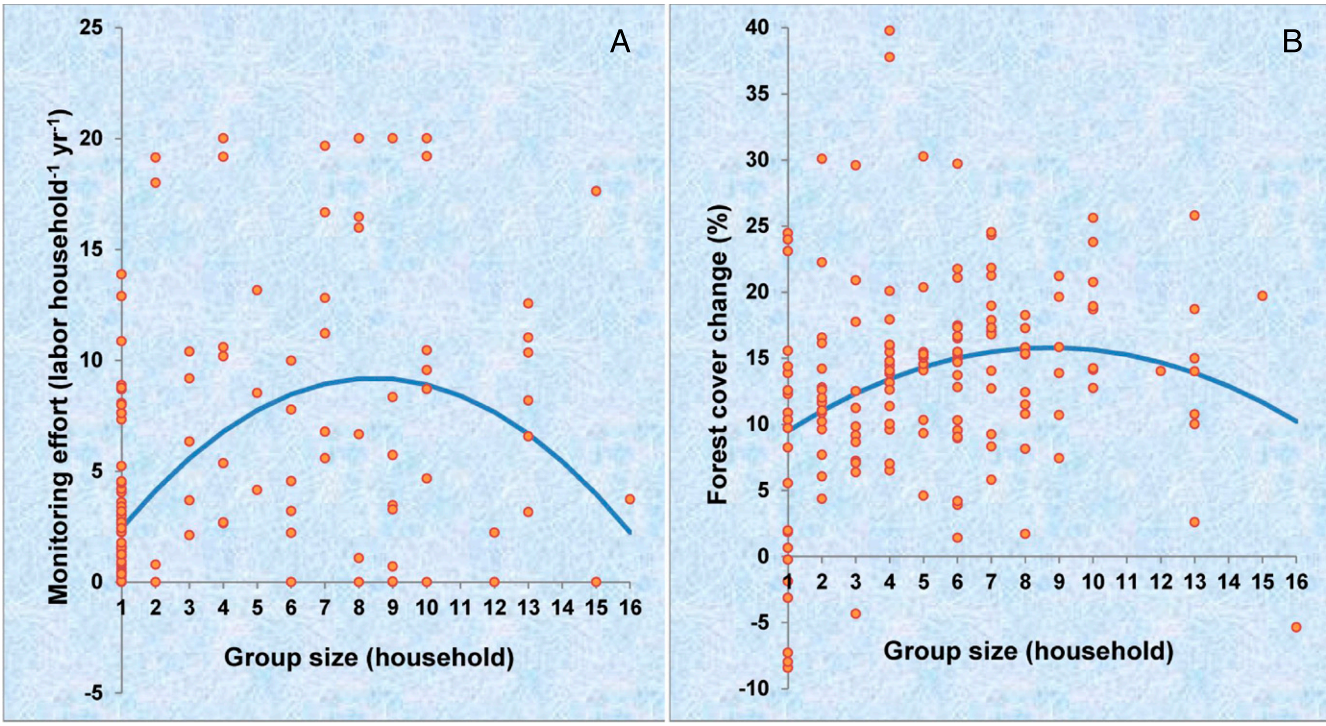

Fig. 3. The nonlinear group-size effects on collective action and forest outcomes. This figure shows the predicted monitoring effort (*A*) and forest-cover change (*B*) from 2001 to 2007 under different group sizes (i.e., number of households monitoring a single forest parcel). The graphs show the net effects of group size on per household monitoring effort and on change in forest cover, while controlling the other variables in Tables 1 and 2. The blue line is the predicted fit based on group size, and the orange dots are the actual observations. One dot may represent several overlapping observations. Except for linear and quadratic terms of group size, all other independent variables were controlled as their mean values (*SI Appendix*, Tables S1 and S3). In *B* our conclusion still holds as the nonlinear effect is still significant even when excluding the parcels with group size of one, or the two parcels with group sizes of 15 and 16 (see details in *SI Appendix*, Section 2.5.2). However, for *A* and *B*, the observations do not visually fit the predicted lines in the same way as the observations in ordinary least-squares regressions (54) because these models are not ordinary least-squares regressions (see details in *SI Appendix*, Section 2.5).

distant households doing more monitoring (Table 1). The average household that lives 1 km further from the main road on average spends 33% more labor units in forest monitoring. Additional analyses (*SI Appendix*, Section 2.3) suggest that households far from the main road are closer to the parcels they monitor (Spearman's $\rho = -0.201$, $P < 0.05$).

Our results demonstrate that group size also has a nonlinear effect on changes in forest cover, with an intermediate group size leading to the biggest gain (Fig. 3*B* and Table 2). These results are consistent whether we include the parcels monitored by single households (i.e., group size of one) or not (*SI Appendix*, Section 2.5.2). The effect peaks at a size of nine households where the forest cover increases 15.8% in comparison with the reference level in 2001. The effects of slope, wetness, initial forest cover in 2001, and spatial error correlation are also significant (Table 2).

We accounted for as many as possible alternative explanations of the observed nonlinear group-size effects based on systematic quantitative and qualitative analyses. No factor other than group size seems to account for the observed nonlinear effects. First, correlation tests (*SI Appendix*, Table S2) show that except for the two criteria used for household group assignment (see details in *SI Appendix*, Section 1.2) by the administrative bureau (i.e., distance between each household and its assigned parcel and received NFCP payment), no other factors were significantly associated with group size and thus are implausible as possible alternative explanations for the group-size effects. We used two additional approaches to ensure that the observed nonlinear effects were not caused by the two criteria used for household group assignments (*SI Appendix*, Section 2.4.3). We examined the associations between the two criteria used for household group assignment and household monitoring efforts, and we

Table 1. Coefficients of the Tobit model for the nonlinear effect of group size on collective action

Variable	Coefficients (robust SE)	Marginal effects
Intercept	8.921*** (2.360)	—
Quadratic term of group size	−0.128** (0.041)	—
Group size	1.331** (0.408)	0.767
Social ties to local leaders (binary: 0 for weak social ties; 1 for strong social ties)	−5.377** (1.920)	−3.012
Distance between each household and the main road	2.787* (1.216)	1.749
Additional controls	Not significant (*SI Appendix, Table S9*)	—

Unit of analysis is the household. Dependent variable is total labor input for monitoring per year. Additional controls include household size, number of household laborers, education of adults, household income, and percentage of agricultural income (*SI Appendix*, Table S9). Log pseudolikelihood is −390.962. Total number of observations is 156. Independent variables were mean centered before entering the model. **P* < 0.05, ***P* < 0.01, ****P* < 0.001.

Table 2. Coefficients of the spatial autoregressive error model for the nonlinear effect of group size on resource outcomes

Variable	Coefficients (SE)
Intercept	0.146*** (0.015)
Quadratic term of group size	−1.056E-03* (4.800E-04)
Group size	7.205E-03* (3.643E-03)
Slope	0.339** (0.121)
Wetness	0.048*** (0.012)
Initial forest cover in 2001	−0.269*** (0.030)
Additional controls	Not significant (*SI Appendix*, Table S16)
λ (Coefficient of spatial error correlation)	0.561***
Moran's I	0.021

Unit of analysis is the forest parcel. Dependent variable is the percent of forest-cover change from 2001 to 2007. Additional controls include parcel size, parcel size per household, elevation, distance between each parcel and the nearest household, and distance between each parcel and the main road (*SI Appendix*, Table S16). Total number of observations is 151. Log likelihood is 170.281. Independent variables were mean centered before entering the model. Detailed discussion of the spatial autoregressive models are in *SI Appendix*, Section 2.5.2. $^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$.

estimated two-step Tobit models of monitoring effort. Using either approach, all hypothesized alternatives to group size were linearly associated with household monitoring efforts, and thus could not lead to the observed nonlinear effects.

Our path analysis (Table 3) confirms that group size has effects through the two opposing forces (Fig. 1). If the balance between positive and negative effects shifts with group size, it can yield the observed nonlinear pattern. On the one hand, group size has a significantly positive effect on the probability of a household free riding ($P < 0.01$) (Table 3). With all other relevant factors controlled at their mean values, an increase of group size by one household increases the free-riding probability by 15%. On the other hand, group size has a significantly positive effect on within-group enforcement ($P < 0.01$), which significantly reduces free riding ($P < 0.01$) (Table 3). Again, controlling all other relevant variables at their mean values, an increase in group size by one household strengthens within-group enforcement by 10%, whereas a shift from weak to strong within-group enforcement reduces free riding by 52%. Additional analyses (*SI Appendix*, Section 2.4.4) suggest that as groups become larger, a group member would face higher pressure of deteriorating social relationships with the other members in each group, which enhances within-group enforcement and thus reduces free riding. This result is consistent with the significant effect of social ties on household monitoring efforts (Table 1), indicating that social capital plays an important role in affecting conservation behaviors of households. It follows that collective action might be easier to maintain when social relationships among group members are improved or members with good social relationships can form their groups autonomously.

Discussion

The coexistence of two opposing forces may also explain why previous studies found different group-size effects. If, as we argue, the net effect of group size is determined by the dynamics (e.g., strength and variation with group size) of the two opposing forces, the optimum point of the net effect (or the necessary range of group size to observe a nonlinear effect) would be dependent on the context (14). The range of group size in our study area may appear to be small. However, the nonlinear pattern we observed means that such a range is large enough to exhibit the nonlinear effect in our context. One of the reasons we find such effects with only moderate variation in group size may be because our study area is a flagship nature reserve for giant pandas. As a result, the local administrative bureau has relatively abundant resources to allocate payments for household groups to monitor parcels and evaluate their performance biannually

Table 3. Path analysis of the two opposing forces through which group size affects collective action

Path analysis	Unstandardized coefficient (SE)
Dependent variable: Free rider (binary: 0 for a household that does not free ride; 1 for a household that free rides)	
Group size	0.146** (0.051)
Within-group enforcement (binary: 0 for weak enforcement; 1 for strong enforcement)	−0.522** (0.184)
Dependent variable: Within-group enforcement	
Group size	0.103** (0.038)
Within-group division (binary: 0 for no within-group division; 1 for within-group division)	0.376 (0.266)
Group size × Within-group division	−0.050 (0.061)
Dependent variable: Group size	
Social ties to local leaders (binary: 0 for weak social ties; 1 for strong social ties)	0.052 (0.651)
Distance to main road (log)	−0.067 (0.136)
Number of laborers	−0.051 (0.350)
Household size	0.027 (0.243)
Education of adults	0.016 (0.117)
Household income (log)	−0.093 (0.311)
Percentage of agricultural income	1.839 (0.946)

Unit of analysis is the household, but both characteristics of households and their assigned groups are considered. Continuous independent variables are mean centered. All goodness-of-fit indices show that the model fit is respectably high (*SI Appendix*, Table S5). Total number of observations is 113 households. $^{**}P < 0.01$.

(*SI Appendix*, Section 1.2). Furthermore, many household activities are substantially affected by kinship and leadership, so it is not surprising that social capital matters substantially in household monitoring efforts and resource outcomes. Neither of these conditions might hold in other contexts where official engagement is less pronounced and social capital is of less importance. In our context, the optimum point can be detected even though no group is larger than 16. In other contexts, a larger range of group size might be necessary to detect nonlinear effects, which raises an important issue for future investigation: What elements of context influence the optimum point in the relationships between group size and either provision of collective action or resource outcomes?

Our study uses intensive analyses based on quantitative and qualitative data, buttressed by years of fieldwork at the site, to examine the effect of group size on per household effort and resource outcome. We acknowledge that the optimal group size may vary across contexts. In some commons management regimes, the variation in group size may not be great enough to demonstrate the nonlinear effect. The approach we have used could readily be applied to other contexts. When a literature based on analyses like ours at other sites emerges, comparison across studies would allow the identification of what aspects of context influence optimal group size, something that cannot be done in a single study.

Randomized experiments are sometimes seen as the "gold standard" for research on causal mechanisms. However, there have been no randomized experiments at our site, nor are there likely to be because of its status as a showcase for conservation efforts. In addition, in the real world, there is no randomized or even quasirandomized field experiment in this field of study. The best that can be done in many real-world resource management situations is to be careful with regard to inference. Our analyses show that significant advances in understanding can be made through careful analyses of nonexperimental data by drawing on historical data. Such efforts of ongoing programs provide a useful complement to field experiments in building a cumulative literature and forwarding the important work on collective action and resource management.

Our findings also suggest that by regulating factors interacting with group size, it should be possible to improve collective action and resource outcomes. For example, all groups of various sizes can stimulate group members to contribute and protect common-pool resources by punishing free riding and enhancing overall and within-group enforcement. Overall enforcement can be enhanced not only through intensifying costly monitoring efforts but also via improving social capital across groups. The within-group enforcement and outcomes may also be enhanced by improving social capital among group members or allowing self-selection during the group formation process so members with good social relationships can form groups autonomously.

Unprecedented deterioration of global commons requires better understandings of the mechanisms shaping collective action and resource outcomes. Because of the complexity of coupled human and natural systems (46), improving such understandings is challenging and requires efforts to integrate data and methods from multiple disciplines. The struggle to understand the group-size effects is one example showing the importance of such efforts. Our findings help disentangle the puzzle of group-size effects and guide solutions to pressing problems of coupled human and natural systems (47), as well as the design of commons governance policies.

Materials and Methods

We acquired the map of household monitoring parcels and associated documentation (e.g., the number of households that monitor each forest parcel) from the administrative bureau of Wolong Nature Reserve. To estimate forest-cover change, we used previously published forest-cover maps derived from Landsat imagery in 2001 and 2007 (48, 49). These maps included two main land-cover classes (i.e., forest and nonforest) with overall accuracies between 80% and 88% using independent ground-truth data. Topographic data, such as elevation, slope, and the Compound Topographic Index, a relative measure of wetness (50), were obtained from a digital elevation model at a spatial resolution of 90 m/pixel (51). We measured all household locations (~2,200 households) inside and surrounding the Reserve using Global Positioning System receivers. We calculated geographic metrics of forest parcels and households using the software of ArcGIS 10.1 (ESRI). These metrics include parcel size, parcel size per household, average elevation, average slope, average wetness, distance between each parcel and the nearest household, distance between each parcel and the main road, distance between each household and its monitored parcel, distance between each household and the main road, initial forest cover in 2001, and the percent of forest-cover change from 2001 to 2007.

To understand the NFCP planning, implementation, evaluation, and decision-making processes, and to prepare for the household interview, we invited eight Reserve administrative staff for focus group interviews and five officials who were or are in charge of the NFCP for personal interviews. We used best available household survey data containing NFCP implementation information in 2007 and 2009 from our long-term study in the Reserve, which has been tracking ~220 randomly sampled households across the years since 1998 (52). The panel survey elicited basic information, such as demographic status, socioeconomic conditions, and energy use (53). In the 2007 and 2009 surveys, besides basic information from panel surveys, we also asked questions regarding NFCP implementation [e.g., NFCP payments, monitoring frequency, time spent for each monitoring, monitoring strategy (e.g., within-group division), and within-group enforcement]. A total of 156 randomly sampled NFCP participating households in 2007, covering the full range of group size (i.e., 1 to 16), were used to examine how group size affects collective action (i.e., household forest monitoring). The 113 households who monitored NFCP parcels with group size larger than one (i.e., 2 to 16) in 2009 were used to examine the mechanisms of nonlinear group-size effects.

We first used a Tobit model to examine the effect of group size on monitoring efforts at the household level. We then used a spatial autoregressive model to examine the effect of group size on forest-cover change at the parcel level. Finally, we conducted the path analysis to test the two hypothetical, opposing forces on the mechanisms of nonlinear group-size effects. Detailed descriptions of data collection, processing, and model specification and construction are provided in *SI Appendix*.

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Supporting Information for

Nonlinear effects of group size on collective action and resource outcomes

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This document includes

1. Supporting methods

1.1. Data

1.1.1. Remotely sensed and geographic information system data

We acquired a map and associated documentation (e.g., the number of households assigned to monitor each forest parcel) of the Natural Forest Conservation Program (NFCP) monitored parcels from the administrative bureau of Wolong Nature Reserve (WNR). Of ~40,100 ha in household monitoring areas, ~24,300 ha in 152 parcels involving 812 households had explicit household monitoring boundaries delineated on the map. Of these 152 parcels, 23 were monitored by single households. The remaining ~15,800 ha have boundaries described in the documentation but not on the map. These non-mapped areas were all monitored by single households. We verified that even excluding the 23 parcels, the nonlinear group-size effect on forest outcomes (Table 2) still holds (see details in Section 2.5.2). In addition, one parcel co-monitored by nine households and located on the boundary between WNR and the adjacent Sanjiang Township is known to experience intensive land conversion due to tourism development. A Bonferonni test for most extreme observations (1) also indicates this parcel is the only outlier in our dataset (for this parcel, studentized residuals = – 3.786, Bonferonni p-value < 0.05; all other parcels had Bonferonni p-value > 0.05). Therefore, we excluded this parcel and used the remaining 151 spatially explicit parcels (Fig. 2) for our study.

We used previously published forest-cover maps derived from Landsat imagery in 2001 and 2007 to estimate forest-cover change (2, 3). We generated forest-cover maps via an unsupervised classification algorithm using the ISODATA technique, an iterative process for non-hierarchical pixel classification (4). We performed accuracy assessments using ground-truth points obtained in the summers of 1998 (209 points), 2000 (83 points), 2001 (83 points), and 2007 (593 points). We measured these points using GPS receivers with high accuracy (error less than 1 m). Overall accuracies of these maps were between 80% and 88%. Major disagreements occurred primarily in high-elevation areas and with complex topography (i.e., northwestern part of WNR, Fig. 2) rather than in the areas monitored by households that are the focus of our study. Thus, classification accuracies of the selected household monitoring areas should be higher than those of the overall maps. In addition, changes in land cover between field and remotely sensed data collection dates partially accounted for the disagreement between the image classification and ground-truth data. For a detailed description of classification procedures and assessments of map accuracy, please refer to the citied studies (2, 3).

We obtained data on topographic characteristics such as elevation, slope, and the Compound Topographic Index, a relative measure of wetness (5), from a digital elevation model at a spatial resolution of 90 m/pixel, acquired by the Shuttle Radar Topography Mission (6). We measured all household locations inside and surrounding WNR using GPS receivers. Based on the digitized NFCP parcel map and forest-cover maps, we calculated the size of each parcel, parcel size per household, average elevation, average slope, average wetness, distance between each parcel and the nearest household, distance between each parcel and the main road, distance between each household and its monitored parcel, distance between each household and the main road, initial forest cover in 2001, and the percent of forest cover change from 2001 to 2007.

1.1.2. Focus group, personal, and household interviews

Our research team has been investigating our study area since 1995, starting six years before the NFCP implementation. We drew upon both our experience in the area and the best available data collected by our research team in studying the underlying mechanisms of nonlinear group-size effects, supplementing quantitative analyses with information obtained from qualitative interviews.

We conducted focus group and personal interviews on NFCP in 2007. For retrospective information, we used the standard practice of life-history calendars to enhance respondents' recall accuracy (7, 8). These interviews were collected to understand the NFCP planning, implementation, evaluation, and decision-making processes and to prepare for the household interview. For focus group interviews, we interviewed eight members of the WNR administrative staff. For personal interviews, we held discussions with five officials who were and/or are in charge of the NFCP planning, implementation, evaluation, and decision making. Our understanding of how the monitoring groups were formed was based on focus groups and personal interviews, and we further examined the criteria of group assignment with household survey data (see Section 1.2).

From household interviews, we used data acquired from all households that participated in the NFCP in 2007 (surveyed at the end of 2007) and 2009 (surveyed in the summer of 2010). Usually the household heads or their spouses were chosen as interviewees because they are the decision makers and are familiar with household affairs. We tracked the same randomly sampled households across the years, but some households were missing in one year or another. For instance, some households were merged, some naturally died out, and some were away for migrant work during our entire field investigation period in a given year. A total of 156 NFCP households covering the full range of group size (i.e., from 1 to 16) were interviewed in 2007 to examine how group size affects collective action (i.e., household forest monitoring), and 113 households for group size larger than one were interviewed in 2009 to examine the mechanisms of nonlinear group-size effects. For each analysis, to avoid errors due to using data from different survey years, we only used factors that were measured for all households in the same year. The information elicited included demographic factors, household socioeconomic activities, social ties to local leaders, NFCP payment received, NFCP monitoring effort, and within-group monitoring enforcement. The instrument for household socioeconomic data was based on the standard practices of the National Bureau of Statistics of China (9). Please see a detailed description of variables used for analyses in Section 2.

1.2. Study area and group formation

Wolong Nature Reserve (N 30˚45' – 31˚25', E 102˚52' – 103˚24') is located in Wenchuan County, Sichuan Province, China (Fig. 2). It is situated in the transition of Sichuan Basin from the east to the Qinghai-Tibet Plateau on the west, with elevations ranging from 1,200 m to 6,250 m. WNR's size was ~20,000 ha in 1963 and expanded to its current size of ~200,000 ha in 1975 (10). The Reserve was established to protect regional forest ecosystems and rare plant and animal species, primarily the iconic giant panda (*Ailuropoda melanoleuca*) (10). The majority of local residents are farmers involved in activities such as cultivating maize and vegetables, raising livestock (e.g., pigs, cattle, yaks, horses), collecting traditional Chinese medicinal plants, beekeeping, and collecting fuelwood for heating and cooking. Basic demographic and socioeconomic descriptions are summarized with our household survey data in Table S1.

NFCP is a nationwide conservation program that aims to conserve and restore natural forests with logging bans, afforestation, and monitoring using a payments-for-ecosystem-services scheme to motivate conservation behavior (11). To respond to the national call, and to restrain the degradation of forest and panda habitat over the past three decades (12), WNR started to implement the NFCP in 2001. The central government allocated an annual fund of two million yuan for NFCP implementation in the Reserve. To improve enforcement of the NFCP and livelihoods of local residents, the Wolong Administrative Bureau decided to use about half of the NFCP funds to engage local households in the forest monitoring program (10).

The initial idea of the Wolong Administrative Bureau was to assign each household a forest parcel to monitor, but it turned out to be too difficult to clarify the boundaries of many small parcels and would be too costly for management. Finally, the Bureau followed natural boundaries (e.g., rivers, ridges, valleys) of forest parcels and divided and assigned them to household groups ranging from 1 to 16. Of the total ~120,500 ha NFCP monitoring area, ~40,100 ha were assigned to ~1,100 rural households; the remaining areas were monitored directly by the Bureau's staff (Fig. 2).

According to our interviews with government officials who were in charge of the NFCP implementation, large parcels were assigned to large household groups to keep parcel size per household similar across monitoring areas. Parcels distant from household locations were assigned to large household groups with slightly higher payments. We compared these arrangements with our independently collected household survey data and found the reports from household interviewees were consistent with those from the program officials (Table S2). We also conducted statistical analyses and found that the distance from each parcel to its monitoring household(s) and NFCP payment were statistically exogenous to the group-size effects (see Section 2.4.3). Thus, distribution of households to groups, although not completely random as in a classical experiment, is suitable to examine the group-size effects and the underlying mechanisms.

1.3. Tobit model

1.3.1. Model specification

The dependent variable is the total labor input per year by a household for monitoring. The distribution of this variable suggests a Tobit model, in which a large fraction of the observations cluster at the minimum value (zero in this case) or maximum value (20 in this case). Conceptually, this is a censored value model in that it treats the minimum and maximum values as if the true values of monitoring were not observed. The minimum monitoring effort is zero by default, which means a household does not spend any time in monitoring. According to our field investigation, the maximum annual payment for monitoring is ~1,000 yuan, and the local labor price in 2007 was ~50 yuan per laborer per day. This suggests the maximum monitoring effort of a household is 20 laborer days if they are purely economically rational actors. This theoretical estimate was consistent with empirical data collected from reports of local natural resource managers and monitoring households. In other words, households spent an amount of labor less or equal to the economic value they received in NFCP payments. Thus, besides zero as the minimum monitoring effort, we also set 20 as the maximum value in the Tobit model.

When analyzing censored data, traditional regression methods (e.g., ordinary least squares, OLS) may yield inconsistent estimates and provide inappropriate predictions. However censored regression (i.e., Tobit model) can produce consistent and efficient estimates of model parameters and partial effects, as well as appropriate predictions (13). A Tobit model is given by (13):

$$y_{1i} = \begin{cases} y_{1i}^{*} & a < y_{1i}^{*} < b \\ a & y_{1i}^{*} \le a \\ b & y_{1i}^{*} \ge b \end{cases} \tag{1}$$

$$y_{1i}^{*} = X_{1i}\beta_1 + u_i \ , \tag{2}$$

where y_{1i} is the observed monitoring effort, y_{1i}^{*} is a latent variable satisfying the classic linear model assumption, *a* is the minimum limit, *b* is the maximum limit, X_{1i} is a vector of exogenous explanatory variables, β_1 is a parameter vector to be estimated, *i* is the *i*th observation, and u_i is an error term that has a normal distribution with mean of zero.

When the Tobit model contains endogenous variables, Eq. (2) is specified as follows (13):

$$y_{1i}^{*} = y_{2i}\beta_2 + X_{1i}\beta_1 + u_i \tag{3}$$

$$y_{2i} = X_{1i}\varphi_1 + X_{2i}\varphi_2 + v_i \ , \tag{4}$$

where y_{2i} is a vector of potentially endogenous explanatory variables and the equation for y_{2i} is written in reduced form, X_{1i} is a vector of exogenous explanatory variables, X_{2i} is a vector of additional instruments, β_2 is a vector of structural parameter, φ_1 and φ_2 are matrices of reduced-form parameters, and v_i is an error term that has a normal distribution with mean of zero.

1.3.2. Model construction

Descriptive statistics of variables used in model construction are shown in Table S1. To improve the interpretability of coefficients and reduce the collinearity between the linear and quadratic terms of group size, all continuous independent variables and instruments were mean centered prior to their input into the regression models (14). We first constructed our models with OLS without considering the censoring effects, then constructed the Tobit models considering the censoring effects. Whether or not we took the censoring effects into account, the nonlinear group-size effects were consistent. Thus, we reported the final results from the Tobit models. Parameter and marginal effect estimations were conducted using Stata 12 (StataCorp LP, USA).

1.4. Spatial autoregressive model

1.4.1. Model specification

Previous studies on group-size effects have not considered the spatial autocorrelation of measurements across resource units (e.g., forest parcels) of key variables (e.g., percent of forest-cover change). Ignoring spatial autocorrelation may violate the assumption of independently distributed errors of classical statistical tests and may lead to incorrect conclusions (15). In brief, the ecological reason for considering spatial autocorrelation here is that a parcel is more likely to regenerate or recover faster when its surrounding parcels are forested (see detailed discussion in Ref. (15)). We constructed spatial autoregressive models to take spatial autocorrelation into consideration.

The general mixed form of the spatial autoregressive model in our study is given by (16, 17):

$$y = \rho W y + X\beta + \mu \tag{5}$$

$$\mu = \lambda W \mu + \varepsilon, \tag{6}$$

where y is the n (number of observations) × 1 vector of the dependent variable (i.e., percent of forest-cover change from 2001 to 2007), ρ is the coefficient of the spatially lagged dependent variable, W is a given n × n spatial weighting matrix, X is the n × k (number of independent variables plus intercept) matrix of the independent variables plus intercept, β is the k × 1 vector of coefficients, λ is the spatial error correlation coefficient, and ε is the n × 1 error term assumed to be independent and identically distributed. The mixed model is reduced to a spatial lag model when $\lambda = 0$, to a spatial error model when $\rho = 0$, and to a traditional regression model when both are zero.

1.4.2. Model construction

Descriptive statistics of variables used in the model construction are shown in Table S3. A spatial weighting matrix of forest parcels was created using the GeoDa software (version 0.9.9.1), defining a neighbor based on the Queen contiguity approach (i.e., common borders and corners) (18). We compared different spatial weighting matrices (i.e., Queen contiguity of order 1, Queen contiguity of order 2, Rook contiguity of order 1, and Rook contiguity of order 2), and the results are similar. Thus, we reported the results using Queen contiguity of order 1. Model construction and all statistical analyses were performed using the R software (version 2.12.2) (19). Spatial simultaneous autoregressive models were constructed with the package “spdep” in R.

1.5. Structural equation model

1.5.1. Model specification

A structural equation model (SEM) is a statistical technique for testing and estimating causal relationships (20-22). It allows analysis of multiple simultaneous causal relations among endogenous variables, and between endogenous and exogenous variables. A typical SEM contains two main components: the structural model representing potential causal dependencies between endogenous and exogenous variables, and the measurement model representing the relations between latent variables and their indicators.

The general form of SEM is given by (23):

Structural model:

$$\eta_j = \alpha_\eta + B\eta_j + \Gamma\xi_j + \varsigma_j \tag{7}$$

Measurement model:

$$y_j = \alpha_y + \Lambda_y \eta_j + \tau_j \tag{8}$$

$$X_j = \alpha_x + \Lambda_x \xi_j + \delta_j \quad , \tag{9}$$

where η_j is the vector of latent endogenous variables for unit *j*; α_η, α_y, and α_x are intercept vectors; ξ_j is the vector of latent exogenous variables; y_j and X_j are vectors of the observed indicators of η_j and ξ_j, respectively; *B* is the matrix of coefficients giving the expected effects of the latent endogenous variable (η) on each other; **Γ** is the coefficient matrix giving the expected effects of the latent exogenous variables (ξ) on the latent endogenous variables (η); Λ_y and Λ_x are the matrices of coefficients giving the effects of the latent η_j and ξ_j on y_j and X_j, respectively; ς_j, τ_j, and δ_j are the vectors of error terms; and *j* is the *j*th observation.

The commonly used factor analysis, regression analysis, and path analysis methods are all special cases of SEM. Specifically, path analysis is SEM with a structural model but no measurement model. In this study, all variables can be reasonably treated as observable. So we used SEM for path analysis of the nonlinear group-size effects. Guided by the two hypothetical, opposing forces through which group size affects collective action and then resource outcomes, based on previous literature, we hypothesized that some factors may affect group size, group size may directly affect free riding, and group size may also indirectly affect free riding through within-group enforcement (Fig. 1).

1.5.2. Model construction

Descriptive statistics of variables used in the model are shown in Table S4. Three structural models of increasing complexity were constructed. First, whether or not a household would be a free rider was estimated as a function of the size of its group and within-group enforcement. Second, within-group enforcement was estimated as a function of monitoring group size, whether or not there was within-group division (see description in Section 2.3), and interaction term of group size and within-group division. Third, other factors that may affect group size were controlled as exogenous variables acting on group size. Because some dependent variables are binary (i.e., free rider and within-group enforcement), we conducted the path analysis using Mplus (24), which handles path analysis with categorical outcomes. We used the default robust weighted least squares (WLSMV) estimator, which uses a diagonal weight matrix with standard errors adjusted, and mean- and variance-adjusted chi-square test statistics (24). The final path model retained some variables that were not significant because the goodness of fit of the path model was high (Table S5), and because those variables were theoretically interesting as controls (see Section 2.3).

2. Supporting text and analysis

2.1. Forest monitoring and within-group enforcement

2.1.1. Monitoring efforts: household labor input

The forest monitoring efforts of each household were measured by the total amount of labor input. One unit of labor input was defined as one work day (i.e., eight work hours) of a laborer spent on monitoring activities, including the time travelling to and from the monitored parcel. In our data, each household either does not send any laborer or sends only one laborer for each monitoring activity to join with other laborers from the assigned monitoring group. Therefore, for each household, the total annual amount of labor input equals the total work days that one laborer spent on monitoring (Eq. 10).

$$\text{Household labor input (laborer days)} = \text{Monitoring frequency (times)} \times \text{Time per monitoring (hours)} / 8\ (\text{hours day}^{-1}\ \text{laborer}^{-1}) \qquad (10)$$

Illegal logging activities can be detected in several ways. First, because many households live near the forest and conduct agricultural activities in and around the forest, they can hear the sounds of cutting and falling trees. Local households can also see illegal loggers when they transport the timber to their homes or along the main road to outside areas (because it is a mountainous area with complex topography, it is very difficult to transport wood except via the main road). Second, for forests far from local households, illegal activities may be detected by households who are monitoring the forests or other people who happen to pass by as they collect fulewood or conduct other legal activities. Local households are motivated to report illegal activities because the local government rewards reporters in cash. Finally, even if these ways fail, the timber checkpoints at the two ends of the main road across the reserve also can detect illegally logged timber.

2.1.2. Free riders

Free riders are defined as people who receive the NFCP payment but do not spend time and labor on forest monitoring. Here, we classified those households who self-reported that they did not conduct monitoring activities as free riders. Our team has been conducting research in this study area since 1995 and has established good social relationships with local households. Social desirability would incline respondents toward overreporting their monitoring efforts. Thus, we could be reasonably certain that those households reporting zero monitoring effort did in fact free ride.

2.2. Forest monitoring outcomes: changes in forest cover

The main aim of assigning forest parcels to households for monitoring is to prevent logging. Thus, to assess the outcomes of household monitoring efforts, the most important indicator is the number of trees in each parcel. However, it is difficult and costly, if not impossible, to count all trees. An alternative approach is to assess the forest cover. We adopted the forest definition of the Food and Agriculture Organization of the United Nations as "Land spanning more than 0.5 hectares with trees higher than five meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds *in situ*" (25). Detailed descriptions of the forest-cover data are summarized in Section 1.1 and our previous publications (2, 3). The forest monitoring outcome was therefore measured on a per-parcel basis by percent forest-cover change (i.e., percent forest cover in 2007 minus percent forest cover in 2001).

2.3. Structural factors

Two main barriers for examining group-size effects are the heterogeneities of groups and resource units (26-28). In this section, we provide a review of structural factors used in our analyses. We include factors commonly found to be relevant to collective action and commons management (27, 29-31): characteristics of household groups, households, and forest parcels.

2.3.1. Characteristics of household groups

Group size. Group size refers to the number of households assigned to monitor a single forest parcel.

Within-group enforcement. We regarded a group as having strong monitoring enforcement if punishment measures (e.g., payment deduction, verbal condemnation) existed within the group for members who did not participate in monitoring (i.e., free riding). Otherwise, we regarded a group as having weak monitoring enforcement.

Within-group division. Groups with two or more households could divide laborers to improve monitoring efficiency. In our case, if groups were divided into small subgroups to conduct monitoring in turns, we coded them as groups having within-group division of labor; otherwise, groups did not have within-group division of labor.

2.3.2. Characteristics of households

Household size. Household size refers to the number of household members.

Education of adults. Education affects an individual's attitude and behavior (31). Since adult household members are the main decision makers of household activities and actually participate in forest monitoring, we used the average education level of all adult household members.

Number of laborers. The number of laborers in a household is a measure of available household labor resources for the forest monitoring activity. A laborer is defined as an individual between the ages of 15 and 59.

Social ties to local leaders. Social organization in rural areas in China (such as our study area) is largely based on kinship and leadership. Local leaders are well documented to be influential on the behavior of group members (31). Therefore, we expected connections to local leaders to affect a household's contribution to collective action. In our study area, individuals who work as leaders in villages, administrative groups, or local government-owned enterprises are widely regarded as local leaders. We defined a household with strong social ties to local leaders as a household that had at least one household member or one immediate relative (e.g., parent, child, brother) who was a local leader; otherwise, a household had weak social ties to local leaders.

Age of adults. As individuals get older, their household structures and social ties also change because their relatives and friends die, and/or their children leave home. Thus, the age structure of a household may be an important factor affecting social ties to local leaders. Since adult household members are the actors for social ties connecting to local leaders, we used the average age of all adult members of a household as the age structure measurement for each household.

Percentage of adult females. Gender plays an important role in developing different social ties (32). Thus, differences in the proportion of women among adult household members may contribute to the differences in households' social ties to local leaders. The percentage of adult females among adults refers to the ratio of the number of female adults to total adults in a household.

Household income. We acquired gross household income data from face-to-face interviews following the standard protocol of the National Bureau of Statistics of China (9). In our study area, household income covers a wide range of categories such as agricultural income (e.g., from animal husbandry, sales of crops and/or nontimber forest products), wage income, small businesses income (e.g., operating restaurants, hotels, and other tourism-based businesses), property income (e.g., land and housing rents), gift income from relatives and friends, government payments for ecosystem services, and social security benefits (e.g., low-income subsidy, pension).

Per capita household income. Per capita household income is the total household income divided by household size.

Agricultural income. Agricultural income refers to income related to agricultural practices such as cultivating cropland, raising livestock, and collecting nontimber forest products.

Percentage of agricultural income. The percentage of agricultural income is the ratio of household agricultural income to its total household income.

Area of cropland. The area of cropland refers to the total area of cropland owned by a household.

NFCP payment. NFCP payment refers to the amount of cash subsidy a household received for participating in the NFCP forest monitoring program.

Distance between each household and the main road. In our study area, households farther from the main road are likely to cultivate more cropland (Spearman's $\rho = 0.436$, $p < 0.001$), rely more on agricultural income (Spearman's $\rho = 0.249$, $p < 0.01$), and are closer to their monitored parcels (Spearman's $\rho = -0.201$, $p < 0.05$). Such reflected heterogeneity of households may also affect their participation and contribution to forest monitoring.

Distance between each household and its monitored parcel. The further a household is away from its monitored parcel, the longer distance the household must travel and the more time it takes for a single monitoring activity. Therefore, the distance from each household to its monitored parcel is a surrogate measure of monitoring cost. Because this factor was correlated with group size and might cause an endogeneity problem (Table S2), we did not directly include it in the models (Table 1 and 2). Instead, we treated it as a hypothesized instrumental variable and examined whether the nonlinear group-size effects were caused by this factor or indeed by the group size (see Section 2.4.3).

2.3.3. Characteristics of forest parcels

Elevation. Because elevation is correlated to climatic factors such as temperature, it is an important factor influencing forest growth. Furthermore, elevation is also a natural barrier that reduces human access. However, since household-monitored parcels are mainly located along the main road and at relatively lower elevations, the variation of average elevation for each parcel is not large (Table S3).

Slope. Similar to elevation, steeper slope reduces human access and thus reduces logging and forest degradation.

Wetness. Wetness, as measured by the Compound Topographic Index, is a measurement of relative soil moisture (5). Soil moisture is an important factor affecting forest growth (3). We expected forests to recover faster in relatively wetter regions.

Parcel size. Larger parcels are more exposed to logging and require more monitoring efforts to prevent illegal access (29). Therefore, the parcel size is an important factor that may affect forest-cover changes.

Parcel size per household. Parcel size per household is the total size of a parcel divided by the number of households assigned to monitor the parcel.

Initial forest cover in 2001. Initial forest cover is a key factor to determine the potential of forest growth. A region with high initial forest cover does not have much room to grow and thus forest regeneration is more likely to occur in places with relatively lower initial forest cover.

Distance between each parcel and the main road. Since most households and household-monitored parcels are located along the main road (Fig. 2), illegal harvests closer to the main road should be easier to catch. Therefore, the distance between each parcel and the main road is a measurement of the difficulty of detecting illegal harvest. We used the distance from the centroid of each parcel to the main road as an average estimate of distance for each parcel. The same approximation of using the centroid of each parcel was adopted for measuring distances between each parcel and other locations (e.g., the nearest household, each parcel's corresponding monitoring households).

Distance between each parcel and the nearest household. Distance between each parcel and the nearest household is a factor measuring resource vulnerability to illegal harvest. Since households tend to collect forest products (e.g., fuelwood) closer to their households, forests closer to households may be more likely to suffer from illegal harvest.

2.4. Causality

Experiments with randomization are usually considered the best method for establishing causal relationships. But such experiments are hard to conduct in the field and around policy implementation, and laboratory experiments often suffer from a lack of external validity.

However, our 17-year investigation in our study area both before and after NFCP implementation and evidence from the literature and supplemental analyses of our data suggest that we have established plausible evidence for causal effects of group size on both collective action (i.e., forest monitoring by household groups in our case) and resource outcomes (i.e., changes in forest cover in our case).

2.4.1. Why does collective action contribute to resource outcomes?

Evidence from literature. The "externality" characteristic of common-pool resources explains why collective action could lead to their destruction (i.e., the tragedy of the commons) (33). This conventional wisdom was challenged by the landmark work of Elinor Ostrom and her colleagues, suggesting that collective action can guard the provision of common-pool resources by reducing free riders through means such as clarification of resource boundaries, designing adaptive access rules, and monitoring (27, 34-37). Laboratory experiments (38-40) and field observations (31, 41-43) also provided evidence that monitoring and sanctions could reduce free riders and enhance cooperation and thus improve resource outcomes.

Evidence from our analyses. Ideally, we should use forest outcome as a dependent variable and include group monitoring efforts as one independent variable with other control variables in a regression model at the parcel level (i.e., at the group level) to test the association between group monitoring efforts and group outcome. Unfortunately, we do not have household survey data for all households participating in forest monitoring activities. For instance, we may have information for two of the ten households that monitor a parcel. Thus, we could not measure group monitoring efforts at the parcel level. The alternative approach is to conduct analyses for collective action at the household level and for outcomes at the parcel level (Tables 1 and 2). Here, we provided additional analyses to explain why the monitoring efforts contributed to the forest outcomes.

First, illegal logging by people from outside WNR has not been a problem since the NFCP implementation. The complex topography provides a natural barrier to prevent illegal logging from outsiders. There is only one main road through the Reserve (Fig. 2), with a timber checkpoint located at each end. Based on our field investigation, before the NFCP implementation, some employees at the two timber checkpoints were involved in illegal log transportation with outsiders, but after the NFCP implementation, this problem was solved and the forest laws and regulations have been strenuously enforced. In addition, all our interviewed households and government officials shared a consensus view that illegal logging from outsiders had almost disappeared in WNR. Therefore, logging would be largely the action of local residents, and household monitoring efforts could effectively enhance NFCP enforcement, reduce illegal logging, and contribute to forest recovery.

Second, our results show similar nonlinear effects of group size on both collective action and resource outcomes (Tables 1 and 2). This is also indirect evidence to support the inference that collective action contributed substantially to the outcomes. Since there are no forest parcels without NFCP monitoring in our study area and surrounding regions, we could not compare the outcomes between parcels with and without monitoring. However, our study (44) compared panda habitat recovery rates between household-monitored parcels and government-monitored parcels. We found that panda habitat recovered faster in household-monitored parcels than in government-monitored parcels. Because forest is the essential part of panda habitat, the results supported that household monitoring directly improved forest and panda habitat recovery. Meanwhile, all our evidence indirectly indicates that, along with intangible social norms and networks, household monitoring prevents illegal logging and contributes to forest recovery. In the following sections, we further elucidate how tangible actions and intangible social norms and networks affected collective action and resource outcomes.

2.4.2. How do social ties to local leaders affect collective action?

Evidence from literature. Social learning theories suggest that individuals do not imitate behaviors from others randomly, but rather that leaders will be disproportionally imitated, and thus have more influence on others' behaviors (31, 45, 46). Compared to others, leaders often are elder and/or wealthier, more educated, prestigious, reputable, powerful (31, 45). Therefore, behaviors of leaders would more likely influence other members and thus affect collective action.

Although the detailed mechanisms of how social capital, including social norms, ties, and networks, affect collective action have not yet been theorized, it is widely recognized that social capital plays an important role in affecting collective action and resource outcomes (47, 48). On one hand, social capital may encourage trust and communication, ensure rule compliance, reduce monitoring and transaction costs, and thus enhance collective action (49). On the other hand, social capital may encourage political coercion and act as an obstacle to shape inappropriate social arrangements (50, 51).

Evidence from our analyses. To understand why and how social ties to local leaders affect household monitoring efforts in our case, we first examined what characteristics determine whether a household has strong or weak social ties to local leaders. Our results suggest that households with strong social ties to local leaders tend to have a higher average age and education level of adults (Tables S6 and S7). Because our measurement of social ties occurred during the NFCP implementation period, and the birth years and education levels of adult household members were determined far before the establishment of their social ties to local leaders, the causal inference can only be that higher average age and education of adult members help a household to accumulate strong social ties to local leaders rather than vice versa.

Our results (Table 1) also suggest that households with strong social ties to local leaders tended to spend less on monitoring efforts. The reasons are implied by the words of some household interviewees, for example,

> "Almost every household has been assigned to a forest parcel. If you go to cut trees in others' parcels and happen to be known by them, it will harm social relationships with them. … For households with strong social ties to local leaders, we dare not and do not want to offend them because they know more than us, have more social relationships and power, and we often need to turn to them for help."

The staff members in the Wolong Administrative Bureau who are in charge of combatting illegal logging activities are hired from outside WNR (usually college graduates) and are not related to local residents. In addition, anyone can report illegal logging and receive a cash reward from the Bureau. We are also not aware of a single case in which staff members have turned a "blind eye" to illegal logging so households with strong ties to them could avoid monitoring or sanctions. Thus, these reasons cannot explain why households with strong social ties to local leaders have less need to monitor. Rather, combining interviewees' statements and the analyses above, the reasonable explanation is that households with strong social ties to local leaders often have more social relationships, power, knowledge, and experience than households with weak social ties to local leaders, and such social ties provide social capital and repuation that prevent others from illegal activities in their monitoring parcels. Thus, these households have less need to monitor.

2.4.3. Is the nonlinear effect on collective action really caused by group size?

To answer this question, we used two approaches to support our argument that the nonlinear effect is indeed caused by group size and that instrumental variables affect collective action through group size. Since only the distance from each household to its monitored parcel and the NFCP payment were linearly associated with group size as criteria in group formation (Section 1.2, Table S2), we used them as hypothesized instrumental variables.

For the first approach, we examined the association type between each hypothesized instrumental variable and collective action. Our results (Table S8) suggest that either the distance from each household to its monitored parcel or the NFCP payment is linearly associated with collective action. Since all the additional controls are the same as the ones used in the model of nonlinear group-size effect on collective action (Table 1 or Table S9), these results suggest that the two hypothesized instrumental variables cannot explain the nonlinear effect of group size on collective action. Rather they affect collective action through group size. These results also support that the group-size distribution in our dataset, although not completely random, is still suitable to analyze the group-size effects.

For the second approach, we used a two-step Tobit model with endogenous variables. Using either the instrument of distance from each household to its monitored parcel or the NFCP payment, our results (Table S10) suggest that our instruments are powerful (F-statistic > 47, $p < 0.001$) and exogenous (Wald test of exogeneity of $p > 0.1$). The second-stage regression (Table S11) also suggests that group size has a nonlinear effect on household monitoring efforts, regardless of using any of the two hypothesized instruments. These results also suggest that the distance from each household to its monitored parcel and the NFCP payment affect collective action through group size. Again, this supports that the group formation in our study, which may not be completely random, does not constitute an impediment to examine group-size effects.

2.4.4. How does group size cause nonlinear effects on collective action and resource outcomes?

Based on the results of path analysis (Fig. 1, Table S5), we explained the mechanisms of how group size affects collective action and resource outcomes through two opposing forces in the main text. Here we provided additional qualitative evidence from our interviews to support this conclusion.

The causal inference of the mechanisms of nonlinear group-size effects were also confirmed by our interviewees. One of our household interviewees provided us a vivid example, expressing a point also made by many other interviewees, of how the cost of social relationship deterioration for free riders would increase with group size:

"If I do not go to monitor the parcel assigned to our group, only one group member would complain to me if the parcel is co-monitored by the two of us, but nine other households may do so if I am in a group of 10 households."

2.5. Supporting regression models

In this section, we present a more detailed set of the control variables for the results shown in Tables 1 and 2 in the main text. We also present regression diagnostics and results of other supporting regression models to support our results that the nonlinear group-size effects are robust even when we (i) used different combinations of control variables, (ii) did not consider spatial autocorrelation, and (iii) discarded some edge points (i.e., observations with group sizes of 1, 15, or 16) from the total set of observations.

To display the distribution of group size and how collective action or resource outcomes change with group size, we also visualized the nonlinear relationship between group size and collective action or forest outcomes (Fig. 3). However, given the nature of data and methods we used (i.e., Tobit model for censored data and spatial autoregressive model for data with spatial autocorrelation), our models are not simple, classic regression models (e.g., OLS regression). Visually, the actual observations do not fit the predicted lines in the same way as those in OLS regressions (52).

2.5.1. Supporting results and regression diagnostics of Tobit models

For supporting results and diagnostics of all combinations of Tobit models, please see Tables S9, S12, and S13.

2.5.2. Supporting results and regression diagnostics of spatial autoregressive models

For the construction of the spatial autoregressive model, we compared spatial mixed, spatial lag, and spatial error models. The coefficient of the spatially lagged dependent variable (i.e., ρ) was not significant (z-value: -0.504, $p > 0.1$) in the mixed model. The coefficient of the spatial error correlation (i.e., λ) was significant ($p < 0.001$) in both the mixed model (z-value: 5.691, $p < 0.001$) and the error model (z-value: 8.553, $p < 0.001$). Meanwhile, the error model had the minimum Akaike Information Criteria (AIC) value. The AIC values for the mixed, lag, error, and OLS models were -312.89, -298.14, -314.56, and -279.89, respectively. These results suggest that the error model was most appropriate.

We examined both the linear and nonlinear relationships between group size and the percent of forest-cover change from 2001 to 2007. The coefficient of group size in the linear model was nonsignificant ($p > 0.1$, Table S14), which is not surprising given the presence of an optimum point within the range of the data. Whether we included spatial autocorrelation or not, the coefficients of both the quadratic and linear terms of group size were significant (Tables S15 and S16). But Moran's I test suggests that spatial autocorrelation should be included (Table S15). Thus we report the results from the spatial autoregressive model in the main text. We added the cubic term of group size into the model in Table 1 (or Table S16). It was nonsignificant (z-value: 0.221, $p > 0.1$).

As mentioned in Section 1.1.1, even excluding parcels with a group size of one, the quadratic term of group size was still significant (z-value = -2.460, $p < 0.05$). Given there was only one parcel with group size of 15 and one of 16 in our dataset, we also tested the group-size effects by excluding these two parcels. The nonlinear group-size effect is still significantly present among the remaining 149 parcels (z-value = – 2.552, $p < 0.05$ and z-value = – 2.872, $p < 0.01$ for the quadratic and linear terms of group size, respectively.)

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Table S1.
Descriptive statistics of variables for 156 randomly sampled monitoring households.

Variable	Mean (S.D.)
Total labor input for monitoring (dependent variable, laborer day)	5.23 (6.15)
Group size (number of households)	3.95 (4.15)
Social ties to local leaders (binary: 0 for weak social ties; 1 for strong social ties)	0.15 (0.36)
Distance between each household and its monitored parcel (km)	4.40 (4.82)
Distance between each household and the main road (km)	0.40 (0.60)
Number of household laborers (individual)	1.98 (1.05)
Household size (number of individuals)	3.48 (1.33)
Education of adults (year)	4.80 (2.60)
NFCP payment (yuan)	862.60 (87.27)
Household income (yuan)	27,965.42 (28,637.83)
Percentage of agricultural income	41.69% (28.86%)

Table S2.

Correlation between group size and other biophysical, demographic, and socioeconomic variables. Tested with 156 randomly sampled households.

Group size	Spearman's ρ
Distance between each household and its monitored parcel (km)	0.214^{**}
NFCP payment (yuan)	0.522^{***}
Distance between each household and the main road (km)	– 0.142
Social ties to local leaders (binary: 0 for weak social ties; 1 for strong social ties)	0.051
Household size (number of individuals)	– 0.117
Average age of adults (year)	– 0.061
Education of adults (year)	0.114
Number of household laborers (individual)	0.008
Household income (yuan)	– 0.021
Per capita household income (yuan)	0.050
Agricultural income (yuan)	– 0.162
Percentage of agricultural income	– 0.161
Area of cropland (mu, 1 ha = 15 mu)	– 0.061

$^{**}p < 0.01$; $^{***}p < 0.001$

Table S3.
Descriptive statistics of variables for 151 household-monitored parcels.

Variable	**Mean (S.D.)**
Percent of forest-cover change from 2001 to 2007 (dependent variable)	13.66% (12.50%)
Group size (number of households)	5.32 (3.45)
Parcel size (100 ha)	1.59 (1.37)
Parcel size per household (100 ha per household)	0.33 (0.27)
Elevation (1,000 m, above sea level)	2.42 (0.37)
Slope (radian)	0.53 (0.07)
Wetness (unitless)	10.89 (0.52)
Distance between each parcel and the nearest household (km)	3.79 (4.64)
Distance between each parcel and the main road (km)	2.60 (3.39)
Initial forest cover in 2001	64.21% (31.75%)

Table S4.
Descriptive statistics of characteristics of 113 randomly sampled monitoring households and their assigned groups.

	Variable	**Mean (S.D.)**
Group characteristics	Within-group enforcement (binary: 0: weak enforcement; 1: strong enforcement)	0.38 (0.49)
	Group size (number of households)	7.04 (3.31)
	Within-group division (binary: 0: no within-group division; 1: has within-group division)	0.45 (0.50)
Household characteristics	Free rider (binary: 0 for a household that does not free ride; 1 for a household that free rides)	0.24 (0.43)
	Social ties to local leaders (binary: 0 for weak social ties; 1 for strong social ties)	0.27 (0.45)
	Distance to the main road (km)	0.37 (0.62)
	Number of household laborers (number of individuals)	2.53 (1.23)
	Household size (number of individuals)	3.68 (1.57)
	Education of adults (year)	5.51 (2.76)
	Household income (yuan)	34,257.02 (36,296.61)
	Percentage of agricultural income	13.74% (21.88%)

Notes: Because collective action within each group requires a group having at least two members, here only those groups with at least two members were included for analysis.

Table S5.

Path analysis of the two opposing forces through which group size affects collective action.

Path analysis	**Unstandardized coefficient (S.E.)**	**Standardized coefficient**
Dependent variable: Free rider		
Group size	0.146** (0.051)	0.314**
Within-group enforcement	– 0.522** (0.184)	– 0.476**
Dependent variable: Within-group enforcement		
Group size	0.103** (0.038)	0.243**
Within-group division	0.376 (0.266)	0.178
Group size × Within-group division	– 0.050 (0.061)	– 0.104
Dependent variable: Group size		
Social ties to local leaders	0.052 (0.651)	0.009
Distance between each household and the main road (log)	– 0.067 (0.136)	– 0.052
Number of laborers	– 0.051 (0.350)	– 0.025
Household size	0.027 (0.243)	0.017
Education of adults	0.016 (0.117)	0.018
Household income (log)	– 0.093 (0.311)	– 0.031
Percentage of agricultural income	1.839 (0.946)	0.162
Tests of model fit		
Chi-Square/degrees of freedom		10.854/18
Comparative Fit Index (CFI)		1.000
Tucker-Lewis Index (TLI)		2.898
Root Mean Square Error of Approximation (RMSEA)		0.000
90% Confidence Intervals of RMSEA		(0.000, 0.036)

Notes: Unit of analysis is the household, but characteristics of both households and their assigned groups are considered. Continuous independent variables are mean centered. Total number of observations is 113 households. $^{**}p < 0.01$.

Table S6.

Characteristics of households with strong and weak social ties to local leaders.

Variable	**Households with weak social ties**	**Households with strong social ties**	**Test statistic (t value)**
Distance between each household and the main road (km)	390.39 (51.89)	424.40 (134.00)	– 0.237
Household size (number of individuals)	3.53 (0.12)	3.33 (0.29)	0.638
Percentage of females in adults	0.48 (0.02)	0.47 (0.03)	– 0.292
Education of adults (year)	4.55 (0.22)	6.21 (0.58)	$– 2.904^{**}$
Average age of adults (year)	46.31 (0.92)	46.90 (2.07)	– 0.263
Household income (yuan)	27,132.16 (2471.90)	32,209.08 (6182.76)	– 0.763
Per capita household income (yuan)	8,309.03 (963.20)	10,858.72 (2188.14)	– 1.067
Agricultural income (yuan)	11,337.70 (1,455.17)	13,173.63 (3,113.16)	– 0.534
Percentage of agricultural income	0.42 (0.02)	0.44 (0.07)	– 0.209
Area of cropland (Mu, 1 Mu = 1/15 ha)	4.03 (0.21)	4.02 (0.44)	– 0.030

Notes: Numbers within parentheses are standard error of mean. The test used was unequal variance t-test. $^{**}p < 0.01$.

Table S7.
Logit estimation of factors associated with social ties to local leaders.

Variable	**Coefficients (Robust S.E.)**	**Marginal effects**
Intercept	$– 8.711^{*}$ (3.842)	–
Township (dummy)	0.071 (0.488)	0.008
Distance between each household and the main road	0.435(0.503)	0.052
Household size	– 0.073 (0.215)	– 0.009
Percentage of females in adults	– 0.690 (1.219)	– 0.082
Education of adults	0.321^{**} (0.109)	0.038
Average age of adults	0.048^{*} (0.024)	0.006
Household income (log)	0.352 (0.354)	0.042
Percentage of agricultural income	0.255 (0.981)	0.030
Area of cropland	– 0.053 (0.121)	– 0.006

Notes: Dependent variable is the social ties to local leaders (binary: 0 for weak social ties; 1 for strong social ties). Total number of observations is 156. Log pseudolikelihood is – 60.337. Pseudo R-squared is 0.099. Variance Inflation Factors were tested to be < 5. $^{*}p < 0.05$; $^{**}p < 0.01$.

Table S8.

Tobit models for hypothesized instrumental variables.

Variable	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
Intercept	3.533^{*} (1.568)	2.783 (1.621)	3.328^{*} (1.388)	3.341^{*} (1.379)
Distance between each household and its monitored parcel	0.351^{*} (0.160)	0.130 (0.293)	–	–
Quadratic term of distance to monitoring parcel	–	0.020 (0.021)	–	–
NFCP payment	–	–	0.019^{*} (0.008)	0.019^{*} (0.008)
Quadratic term of NFCP payments	–	–	–	– 8.250 E-06 (1.330 E-05)
Social ties to local leaders (binary)	– 4.365^{*} (1.857)	– 4.206^{*} (1.890)	– 4.898^{*} (1.875)	– 4.936^{**} (1.875)
Distance between each household and the main road	4.143^{**} (1.439)	4.089^{**} (1.430)	3.300^{*} (1.350)	3.292^{*} (1.347)
Number of laborers	0.602 (0.830)	0.557 (0.814)	0.386 (0.794)	0.370 (0.797)
Household size	– 1.003 (0.678)	– 1.034 (0.689)	– 0.999 (0.682)	– 0.992 (0.681)
Education of adults	0.313 (0.388)	0.273 (0.388)	0.253 (0.398)	0.249 (0.398)
Household income (log)	– 0.064 (1.101)	– 0.210 (1.111)	– 0.022 (1.060)	– 0.059 (1.062)
Percentage of agricultural income	– 4.398 (3.031)	– 4.768 (3.031)	– 4.904 (3.045)	– 4.875 (3.034)
Sampling weight	0.638 (1.113)	0.823 (1.067)	0.851 (0.914)	0.896 (0.933)
Log pseudolikelihood	– 395.934	– 395.530	– 395.465	– 395.381
Pseudo R-Squared	0.023	0.024	0.024	0.024

Notes: Unit of analysis is the household. Dependent variable is total labor input for monitoring. Total number of observations is 156. The numbers of left-censored and right-censored observations are 47 and 14, respectively. Independent variables were mean centered. Numbers within parentheses are robust standard errors. For clusters of households from the same monitoring groups, the sampling weight matrix is applied and standard errors are adjusted. Variance Inflation Factors were tested to be < 5. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table S9.

Coefficients of the Tobit model for the nonlinear effect of group size on collective action.

Variable	**Description**	**Coefficients (Robust S.E.)**	**Marginal effects**
Intercept		8.921^{***} (2.360)	–
Quadratic term of group size	The quadratic term of group size	-0.128^{**} (0.041)	–
Group size	The number of households for monitoring a single forest parcel	1.331^{**} (0.408)	0.767
Social ties to local leaders	Binary: 0 for weak social ties; 1 for strong social ties	-5.377^{**} (1.920)	– 3.012
Distance between each household and the main road	Euclidean distance between each household and the main road	2.787^{*} (1.216)	1.749
Laborers	Number of household laborers	0.296 (0.792)	0.186
Household size	Number of household members	– 0.741 (0.630)	– 0.465
Education	Average education of adult household members	0.309 (0.369)	0.194
Household income (log)	Total household income in 2007	– 0.011 (1.042)	– 0.007
Percentage of agricultural income	Percentage of agricultural income to total household income	– 2.452 (2.760)	– 1.539
Sampling weight	Sampling weight adjusting households sampled from the same monitoring groups	– 1.432 (1.126)	– 0.899

Notes: Unit of analysis is the household. Dependent variable is total labor input for monitoring. Log pseudolikelihood is – 390.962. Pseudo R-Squared is 0.035.Total number of observations is 156. The numbers of left-censored and right-censored observations are 47 and 14, respectively. Standard errors are adjusted for clusters of households from the same monitoring groups. Independent variables were mean centered before entering the model. Variance Inflation Factors were tested to be < 5 (Table S12). $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table S10.
First-stage regression results of the two-step Tobit model.

Dependent variable: Group size	**Model (1)**	**Model (2)**
Intercept	– 4.178*** (0.329)	– 4.213*** (0.329)
Distance between each household and its monitored parcel	0.104** (0.037)	–
NFCP payment	–	0.007** (0.002)
Quadratic term of group size	0.098*** (0.008)	0.929*** (0.008)
Social ties to local leaders (binary)	0.755 (0.479)	0.578 (0.465)
Distance between each household and the main road	0.672 (0.319)	0.444 (0.299)
Number of laborers	0.200 (0.213)	0.116 (0.206)
Household size	– 0.161* (0.164)	– 0.169* (0.159)
Education of adults	– 0.012 (0.071)	0.035 (0.069)
Household income (log)	– 0.027 (0.248)	– 0.027 (0.241)
Percentage of agricultural income	– 1.285 (0.651)	– 1.585† (0.640)
Sampling weight	1.691*** (0.228)	1.800*** (0.220)
F-statistic	47.69***	51.34***
Wald test of exogeneity $\chi^2(1)$	1.94	1.74
R-squared	0.767	0.780
Adj. R-Squared	0.751	0.765

Notes: Unit of analysis is the household. Dependent variable is group size. Log pseudolikelihood is – 399.544. Total number of observations is 156. The numbers of left-censored and right-censored observations are 46 and 14, respectively. Independent variables were mean centered before entering the model. Numbers in parentheses are standard errors. For clusters of households from the same monitoring groups, the sampling weight matrix is applied and standard errors are adjusted. Variance Inflation Factors were tested to be < 5. $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table S11.
Second-stage regression results of the two-step Tobit model.

Dependent variable: Monitoring efforts	**Model (1)**	**Model (2)**
Intercept	17.267^{*} (7.075)	14.650^{**} (5.061)
Quadratic term of group size	$-0.324^{\dagger}$ (0.166)	-0.263^{*} (0.119)
Group size	3.265^{*} (1.602)	2.667^{*} (1.132)
Social ties to local leaders (binary)	-6.648^{**} (2.491)	-6.235^{**} (2.263)
Distance between each household and the main road	1.958 (1.570)	2.195 (1.431)
Number of laborers	0.003 (1.008)	0.108 (1.052)
Household size	– 0.484 (0.783)	– 0.556 (0.732)
Education of adults	0.367 (0.336)	0.355 (0.319)
Household income (log)	– 0.027 (1.141)	– 0.010 (1.082)
Percentage of agricultural income	– 9.372 (3.461)	– 1.001 (3.107)
Sampling weight	– 4.850 (3.017)	$-3.779^{\dagger}$ (2.221)

Notes: Models (1) and (2) used distance to monitored parcel and NFCP payment as an instrument, respectively. Unit of analysis is the household. Dependent variable is total labor input for monitoring. Total number of observations is 156. The numbers of left-censored and right-censored observations are 46 and 14, respectively. Independent variables were mean centered before entering the model. Numbers within parentheses are standard errors. For clusters of households from the same monitoring groups, the sampling weight matrix is applied and standard errors are adjusted. Variance Inflation Factors were tested to be < 5. $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table S12.
Variance inflation factors for variables used in the Tobit model examining the nonlinear group-size effect (Table 1 or Table S9). VIFs should be < 5. Independent variables were mean centered before entering the model.

Variable	Variance Inflation Factor
Group size	2.86
Quadratic term of group size	2.90
Social ties to local leaders	1.07
Distance between each household and the main road	1.24
Laborers	1.98
Household size	1.70
Education	1.21
Household income (log)	1.39
Percentage of agricultural income	1.25

Table S13.
Different combinations of Tobit models for the nonlinear effect of group size on collective action.

Variable	**Model (1)**	**Model (2)**	**Model (3)**
Intercept	8.452*** (2.318)	8.918*** (2.361)	9.074*** (2.353)
Quadratic term of group size	– 0.122** (0.041)	– 0.128** (0.041)	– 0.128** (0.042)
Group size	1.283** (0.401)	1.332** (0.408)	1.369** (0.414)
Social ties to local leaders (binary)	– 5.349** (1.864)	– 5.372** (1.925)	– 5.450** (1.907)
Distance between each household and the main road	2.986* (1.208)	2.785* (1.218)	2.311* (1.145)
Laborers	0.227 (0.804)	0.304 (0.792)	0.282 (0.795)
Household size	– 0.729 (0.637)	– 0.744 (0.652)	– 0.706 (0.643)
Education	0.293 (0.358)	0.310 (0.368)	0.326 (0.366)
Percentage of agricultural income	– 4.660 (3.993)	– 2.449 (2.759)	–
Agricultural income (log)	–0.283 (0.403)	–	– 0.006 (0.278)
Income per capita (log)	–	– 0.015 (1.041)	– 0.051 (1.067)
Sampling weight	–	– 1.429 (1.123)	– 1.542 (1.064)
Log pseudolikelihood	– 390.62	– 390.962	– 391.364
Pseudo R-squared	0.036	0.035	0.034

Notes: Unit of analysis is the household. Dependent variable is total labor input for monitoring. Total number of observations is 156. The numbers of left-censored and right-censored observations are 47 and 14, respectively. For clusters of households from the same monitoring groups, the sampling weight matrix is applied and standard errors are adjusted. Independent variables were mean centered before entering the model. Numbers in parentheses are robust standard errors. Variance Inflation Factors were tested to be < 5. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table S14.
Coefficients of the spatial autoregressive error model for the linear effect of group size.

Variable	Coefficients (S.E.)
Intercept	0.132^{***} (0.014)
Group size	0.002 (0.003)
Parcel size	– 0.010 (0.009)
Parcel size per household	– 0.001 (0.038)
Elevation	0.050 (0.037)
Slope	0.340^{**} (0.123)
Wetness	0.0491^{***} (0.012)
Distance between each parcel and the nearest household	2.828E-04 (0.004)
Distance between each parcel and the main road	– 0.002 (0.005)
Initial forest cover in 2001	-0.263^{***} (0.030)
Moran's I	0.023

Notes: Unit of analysis is the parcel. Dependent variable is the percent of forest-cover change from 2001 to 2007. Total number of observations is 151. Log likelihood is 167.942. Variance Inflation Factors were tested to be < 5. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table S15.
Coefficients of the multiple linear regression for the nonlinear effect of group size.

Variable	Coefficients (Robust S.E.)
Intercept	0.161^{**} (0.011)
Group size	0.010^{*} (0.005)
Quadratic term of group size	-0.002^{**} (0.001)
Parcel size	– 0.014 (0.010)
Parcel size per household	0.038 (0.042)
Elevation	0.023 (0.040)
Slope	0.185 (0.110)
Wetness	0.035^{*} (0.021)
Distance between each parcel and the nearest household	0.002 (0.002)
Distance between each parcel and the main road	-0.009^{*} (0.004)
Initial forest cover in 2001	-0.226^{**} (0.032)
Moran's I	0.355^{**}

Notes: Unit of analysis is the parcel. Dependent variable is the percent of forest-cover change from 2001 to 2007. Total number of observations is 151. R-squared is 0.496. Adjusted R-squared is 0.460. Numbers in parentheses are robust standard errors. Variance Inflation Factors were tested to be < 5. The Moran's I for residuals is significant, indicating the multiple linear regression is inappropriate and the spatial autocorrelation should be considered. $^{*}p < 0.05$; $^{**}p < 0.001$.

Table S16.
Coefficients of the spatial autoregressive error model for the nonlinear effect of group size on resource outcomes.

Variable	**Description**	**Coefficients (S.E.)**
Intercept		0.146^{***} (0.015)
Quadratic term of group size	The quadratic term of group size (household squared)	–1.056E-03* (4.800E-04)
Group size	The number of households for monitoring a single forest parcel (household)	7.205E-03* (3.643E-03)
Parcel size	Area of each parcel (100 ha)	– 0.013 (0.009)
Parcel size per household	Ratio of parcel size to group size (100 ha per household)	0.026 (0.040)
Elevation	Average elevation of each parcel (1,000 m, above sea level)	0.034 (0.037)
Slope	Average slope of each parcel (radian)	0.339^{**} (0.121)
Wetness	Compound Topographic Index as a measurement of wetness of each parcel (unitless) (Ref.(5))	0.048^{***} (0.012)
Distance between each parcel and the nearest household	Euclidean distance from each parcel to the nearest household location (km)	4.402E-04 (0.003)
Distance between each parcel and the main road	Euclidean distance from each parcel to the main road (km)	– 0.004 (0.005)
Initial forest cover in 2001	Average forest cover of each parcel in 2001	– 0.269^{***} (0.030)
λ	Spatial error correlation coefficient	0.561^{***}
Moran's I	Moran's I test of spatial autocorrelation for model residuals	0.021

Notes: Unit of analysis is the parcel. Dependent variable is the percent of forest-cover change from 2001 to 2007. Log likelihood is 170.281. Total number of observations is 151. Independent variables were mean centered before entering the model. Variance Inflation Factors were tested to be < 5 (Table S17). $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table S17.
Variance inflation factors (VIFs) for variables used in the spatial simultaneous autoregressive error model (Table 1 or Table S16). VIFs were tested to be < 5. Independent variables were mean centered before entering the model.

Variable	**Variance Inflation Factor**
Group size	4.01
Quadratic term of group size	1.89
Parcel size	4.07
Parcel size per household	3.09
Elevation	3.54
Slope	1.44
Wetness	1.18
Distance between each parcel and the nearest household	2.09
Distance between each parcel and the main road	3.51
Initial forest cover in 2001	1.42