Coordination via Assurance:

A Lab-in-the-Field Threshold Public Goods Experiment

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Abstract

We investigate two crowdfunding mechanisms, the refund bonus mechanism (RBM, Zubrickas, 2014) and the assurance payment mechanism (APM, Li et al., 2014), for the voluntary provision of threshold public goods in rural China. Both mechanisms offer assurance to would-be contributors if the provision fails: RBM offers bonuses proportional to contributions, while APM pays a fixed assurance payment once a minimum contribution level is reached. We design an experiment varying bonus levels to compare the two mechanisms among farmers, college and high school students in large groups of size 50. We find that APM induces more individual contributions than RBM in most cases, where the assurance payment (*AP*) acts as a coordination focal point. Farmers are the most responsive heuristically to *AP*, followed by college and then high school students. RBM is more effective in terms of distributive efficiency by facilitating contributions proportional to induced values. Our results highlight the importance of salient coordination properties in crowdfunding mechanisms to provide public goods, and suggest that optimal mechanism design should depend on specific policy objectives.

Keywords: Threshold public goods, Coordination, Lab-in-the-field experiment, Different subject pools, Large groups

JEL: C72, C93, H41

1. Introduction

The provision of public goods such as education, health, water, power and transport facilities in developing regions is critical for rural development and poverty reduction (Squire, 1993; Fan et al., 2004; Bournaris et al., 2014; He et al., 2016; Aggarwal, 2018). However, in China, for example, a widening urban-rural disparity in public goods provision remains one of the most critical issues (Zhang et al., 2004; Hiroshi, 2008). One reason is that rural villages rarely receive financial redistribution or transfers from higher levels of government (Bernstein and Lü, 2000). This makes private provision of public goods through local crowdfunding more important in rural areas than in urban areas (Schwartz, 2013; Filimonova et al., 2019).

Many crowdfunding projects are marketed as threshold public goods under the point provision mechanism (PPM): the project is undertaken when the group contribution reaches a predetermined cost threshold; otherwise, the public good is not provided and contributions are refunded (Palfrey and Rosenthal, 1984; Bagnoli and Lipman, 1989). PPM has gained popularity in practice due to its simple implementation. However, the threshold in itself does not eliminate the free-riding zero-contribution inefficient equilibrium; moreover, there exist multiple provision equilibria, resulting in coordination difficulties.

Among all efforts to improve the efficiency of PPM, one novel approach is to provide an assurance to significant contributors by ensuring a minimum amount they can receive when the group provision fails. Contributions are thus incentivized to prevent non-provision. The idea was first introduced by Tabarrok (1998), and variants were proposed by Zubrickas (2014, known as the refund bonus mechanism (RBM)) and Li et al. (2014, 2021, 2023 known as the assurance payment mechanism (APM)). In short, in case of provision failure, RBM rewards contributors proportional to their contributions, while APM pays an assurance payment to contributors whose contribution reached a certain level. Experimental results show that RBM improves performance levels compared with PPM with a large group size and heterogenous population; the problem of equilibrium coordination is still present in a static setting, but RBM substantially increases the rate of funding success in a dynamic setting (Cason and Zubrickas, 2017; Cason and Zubrickas, 2019; Cason et al., 2021). APM has been found to lead to more frequent successful provision, higher group contributions, and an overall welfare improvement upon the baseline PPM (Li et al., 2021; Li et al., 2023). Li et al. (2023) specifically point out that coordination failure is the main reason for the non-provision of threshold public goods. They conjecture that although RBM and APM have similar equilibrium properties, APM may better facilitate coordination than RBM by providing an explicit focal point at the assurance payment level. All findings above are from laboratory experiments using undergraduate student samples in relatively small groups of size 5 or 10.

In this paper, we conduct a direct comparison of the two assurance mechanisms RBM and APM, paying special attention to the role the assurance payment plays in directing and coordinating contributions. We collect data from threshold public goods games with large groups of size 50 on three different samples including farmers, college students and high school students in rural China. Our study aims to inform the theory of assurance mechanism design, while at the same time provide guidelines for crowdfunding practices on targeted populations to promote rural development.

We consider three bonus levels for each of the two mechanisms. We form hypotheses based on Nash equilibrium predictions and coordination implications of RBM and APM. Specifically, aside from the equilibrium properties, APM provides participants with a clear focal point that may better coordinate contributions than RBM resulting from heuristic decision making. Results show that APM induces no less, most times more individual contributions than RBM. The reason is that compared with RBM, APM increases the frequency at which the individual contribution is not less than the assurance payment level in all three samples, supporting the coordination hypothesis. This effect is more prevalent among farmers than students, with high school students affected the least. On the other hand, higher distribution efficiency (i.e., those who have higher induced values contribute more) is achieved under RBM than APM. Our findings suggest that selection among the two mechanisms in threshold crowdfunding projects depends on the specific policy goal.

We contribute to the literature on coordination mechanisms for threshold public goods provision. With a threshold, a public goods game becomes a coordination game (Ledyard, 1995). Researchers have explored rebate mechanisms eliminating concerns for over-contribution (Marks and Croson, 1998; Spencer et al., 2009; Li et al., 2016; Liu et al., 2016; Liu and Swallow, 2019), sanctioning mechanisms (Andreoni and Gee, 2015), recommendations with or without full agreement (Croson and Marks, 2001; Alberti and Cartwright, 2016). Our paper focuses on the assurance mechanisms alleviating incentives for under-contribution (Tabarrok, 1998; Zubrickas, 2014; Li et al., 2023). A closely-related paper in this strand is Li et al. (2022, WP), who theoretically and experimentally compare performance of three assurance payment schemes, DAC (dominant assurance contract, introduced by Tabarrok, 1998), APM and RBM in both homogeneous and heterogeneous induced value environments using a laboratory experiment. They also find that with a fixed and explicit assurance payment, APM and DAC perform better in improving provision rates.

Our study contributes to the discussion of behavior across subject pools in experimental studies (Fréchette, 2015; Cason and Wu, 2019; Snowberg and Yariv, 2021). A typical concern is whether results observed among student samples still hold for field professionals at the task with which the experiment is involved, who are targeted groups of relevant policy interventions. Among the few studies that directly compare students and farmers (Maart-Noelck and Musshoff, 2014; Suter and Vossler, 2014; Gáfaro and Mantilla, 2020; Grüner et al., 2022), Suter and Vossler (2014) share many similarities with ours. They explore the performance of ambient tax mechanisms among students and dairy farmers, and find that efficacy of the chosen mechanism is robust to different subject pools, but there are individual-level deviations. We find that APM outperforms RBM in stimulating contributions through better coordination, while RBM outperforms APM in terms of distributive efficiency; this is generally true to all three samples. However, the extent to which one mechanism dominates the other differs among the subject pools. Our results resonate with the observation that in general the conclusions reached by using the standard experimental subject pool generalize to professionals; nonetheless, studying professionals can bring additional insights (Fréchette, 2015). In particular, farmers rely more on heuristics, and students (in our case, especially high school students) are more towards standard strategic thinking (for similar differences between students and non-students, see Falk et al., 2013; Belot et al., 2015; Gáfaro and Mantilla, 2020; Snowberg and Yariv, 2021).

Our work also relates to the literature of public goods provision in large groups. There is a growing literature comparing contribution incentives of large (typically with 40 group members or more) and small groups to public goods using laboratory methods (Isaac et al., 1994; Diederich et al., 2016; Li et al., 2021, Pereda et al., 2019; Weimann et al, 2019; Weimann et al., 2022), or naturally occurring data (Zhang and

Zhu, 2011). These studies consider public goods provision based on the Voluntary Contribution Mechanism (VCM) introduced by Isaac et al. (1984). To our best knowledge, we are the first to employ large groups (with 50 participants each) in threshold public goods games, complementing the afore-mentioned research to better proxy real-world socially relevant cooperation and coordination problems with many participants.

2. Theoretical Framework

Consider a group of N agents indexed by $i \in I = \{1,2,\ldots,N\}$ participating in a threshold public good game. Endowment for each agent is a constant E. The threshold of the public good C is public information. Agent i knows her individual value v_i and the distribution of other agents' value $v_k (k \neq i)$ of the public good. Agent i can contribute $g_i \in [0, E]$ to the public good. If the total contribution of all agents in the group $G = \sum g_i \geq C$, the public good is provided and agent i receives v_i and pays g_i. If $G < C$, the public good is not provided, agent i makes no payment but will receive a bonus. In this study, we employ two mechanisms for bonuses, RBM and APM, and focus on the case where the individual preferences v_i are heterogeneous. We next describe the equilibrium features of the two mechanisms (**Appendix B** provides the formal propositions that characterize the equilibrium sets of the two mechanisms).

2.1 Refund Bonus Mechanism (RBM)

Under RBM, first introduced by Zubrickas (2014), the bonus is equal to rg_i for agent i, where r is the bonus rate. That is, the bonus is proportional to the subject's contribution. Let R denote the maximal amount of bonuses payable in the limit, i.e., $R = rC$. The payoff function of agent i under RBM is given by

$$\pi_i(g_i, G) = \begin{cases} v_i - g_i, & if\ G \geq C \\ rg_i, & if\ G < C \end{cases} \quad (1)$$

Zubrickas (2014) shows that when R does not exceed the net utility from the public good ($R \leq V - C$), rewarding bonuses induce group contributions sufficient for provision. In particular, a contribution profile in which the net utility from the public good is not less than the highest possible refund bonus for each individual ($v_i - g_i \geq rg_i$) and the group contribution meets the threshold of provision ($G = C$) is a pure-strategy Nash equilibrium.

2.2 Assurance Payment Mechanism (APM)

Under APM, proposed by Li et al. (2023), the bonus is equal to AP for agents with $g_i \geq AP$ and is equal to 0 for agents with $g_i < AP$, where AP is the assurance payment in case of non-provision. The payoff function of agent *i* under APM is given by

$$\pi_i(g_i, G) = \begin{cases} v_i - g_i, & if\ G \geq C \\ I(g_i \geq AP) \times AP, & if\ G < C \end{cases} \tag{2}$$

where $I(.)$ is an indicator function.

According to Li et al. (2023), subjects are divided into two types in equilibrium analysis, type 1 with induced values strictly greater than AP ($v_i > AP$) and type 2 with induced value less than AP ($v_i \leq AP$). Let n^* denote the number of subjects with $v_i > AP$.

The mechanism eliminates non-provision equilibria when total contributions from type 1 alone can cover the cost ($n^*AP \geq C$). In this case, a group contribution that meets the threshold of provision ($G = C$) is a pure strategy Nash equilibrium outcome if the contribution of each type 1 subject does not exceed AP or the difference between the induced value and AP ($g_i \leq max\{v_i - AP, AP\}$) and the contribution of each type 2 subject does not exceed induced value ($g_i \leq v_i$). The condition for provision equilibria sets an upper bound of individual contributions: subjects will contribute at most AP if their values are not high enough ($v_i - AP \leq AP$).

If the number of type 1 subjects multiplied by AP is less than the threshold ($n^*AP < C$), both provision equilibria and non-provision equilibria exist under APM. To be specific, the case of provision equilibria is the same as when the number of type 1 subjects multiplied by AP is greater than or equal to the threshold. For non-provision equilibria, if a subject is eligible for the bonus ($g_i \geq AP$), the equilibrium condition requires that the net gain from increasing her contribution to provide the public good be not greater than the bonus AP when the public good is not provided ($v_i - (C - \sum g_{-i}) \leq AP$); if a subject is not eligible for the bonus ($g_i < AP$), the equilibrium condition requires a non-positive net gain from increasing her contribution to provide the public good ($v_i \leq C - \sum g_{-i}$). The key implication of the non-provision equilibrium condition is that assurance payments increase the lower bound of group contributions in non-provision equilibria from 0 to at least $C - AP$ which is quite close to the threshold and difficult for subjects to coordinate, implying a lower probability of non-provision.

3. Experimental design and hypotheses

3.1 Design and equilibrium properties

Table 1 provides the experimental design (**Appendix B** provides more details of the calculation of equilibria). We implement a heterogeneous induced-value setup with large groups to mimic public goods provision in reality. Five induced values {12, 14, 16, 18, 20} for the public good are evenly assigned among 50 group members with a total value of $V = 800$. The provision cost C is 500 and hence the total value-cost ratio ($\frac{V}{C}$) is 1.6. The initial endowment for each subject at the beginning of each period is 25. We consider three levels of bonuses for each of the two mechanisms: r = 0.6, 0.3 and 0.1 for RBM (denoted as RB0.6, RB0.3 and RB0.1, respectively), AP = 10, 12.5 and 16.7 for APM (denoted as AP10, AP12.5 and AP16.7, respectively), generating a total of six treatments. We group the six treatments into three pairs RB0.6/AP10, RB0.3/AP12.5 and RB0.1/AP16.7 for comparisons.

For the first pair RB0.6/AP10, we set the bonus levels (r = 0.6/AP = 10) such that both treatments eliminate non-provision equilibria, and induce a unique provision equilibrium. In equilibrium, for RB0.6, subject i's individual contribution is $\frac{1}{1+0.6}$ of her induced value (i.e., $g_i = \frac{v_i}{1.6}$; specifically, $g_i = \frac{12}{1.6} = 7.5$ if $v_i = 12$; $g_i = \frac{14}{1.6} = 8.75$ if $v_i = 14$; $g_i = \frac{16}{1.6} = 10$ if $v_i = 16$; $g_i = \frac{18}{1.6} = 11.25$ if $v_i = 18$; $g_i = \frac{20}{1.6} = 12.5$ if $v_i = 20$); for AP10, i's individual contribution is equal to the assurance payment regardless of her induced value (i.e., $g_i = 10$ for all $i \in I$). To sum,

Provision equilibrium under RB0.6: The strategy profile $\{g_i\}_{i \in I}$ s.t. $G = 500$ with $g_i = \frac{1}{1.6} v_i$ for all $i \in I$ is a pure-strategy Nash equilibrium under which the good is provided.

Provision equilibrium under AP10: The strategy profile $\{g_i\}_{i \in I}$ s.t. $G = 500$ with $g_i = 10$ for all $i \in I$ is a pure-strategy Nash equilibrium under which the good is provided.

For the second pair RB0.3/AP12.5, we set the bonus levels (r = 0.3/AP = 12.5, following Li et al. (2022)) to increase equilibrium upper bounds of individual contributions compared with the first pair. Both treatments eliminate non-provision equilibria, and now allow multiple provision equilibria with group contributions being equal to the provision cost 500. In equilibrium, for RB0.3, the upper bound of i's individual contribution is $\frac{1}{1+0.3}$ of her induced value (i.e., $g_i \leq \frac{v_i}{1.3}$; specifically, $g_i \leq \frac{12}{1.3} \approx 9.2$ if $v_i = 12$, $g_i \leq \frac{14}{1.3} \approx 10.8$ if $v_i = 14$, $g_i \leq \frac{16}{1.3} \approx 12.3$ if $v_i = 16$, $g_i \leq \frac{18}{1.3} \approx 13.8$ if $v_i = 18$, $g_i \leq \frac{20}{1.3} \approx 15.4$ if $v_i = 20$); for AP12.5, the upper bound of i's individual contribution is equal to the assurance payment (her induced value) if her induced value is greater than or equal to (less than) AP (i.e., $g_i \leq 12.5$ if $v_i \geq 12.5$ and $g_i \leq v_i$ if $v_i < 12.5$; specifically, $g_i \leq 12.5$ if $v_i \in \{14, 16, 18, 20\}$ and $g_i \leq 12$ if $v_i = 12$).

Provision equilibria under RB0.3: Any strategy profile $\{g_i\}_{i \in I}$ s.t. $G = 500$ with $g_i \leq \frac{1}{1.3} v_i$ for all $i \in I$ is a pure-strategy Nash equilibrium under which the good is provided.

Provision equilibria under AP12.5: Any strategy profile $\{g_i\}_{i \in I}$ s.t. $G = 500$ with $g_i \leq 12.5$ for $v_i \geq 12.5$ and $g_i \leq v_i$ for $v_i < 12.5$, for all $i \in I$ is a pure-strategy Nash equilibrium under which the good is provided.

For the third pair RB0.1/AP16.7, we set the bonus levels ($r = 0.1/AP = 16.7$, following Li et al. (2022)) to further increase equilibrium upper bounds of individual contributions compared with the second pair. RB0.1 eliminates non-provision equilibria, and allow multiple provision equilibria with group contributions being equal to the provision cost 500. AP16.7 generates both provision and non-provision equilibria. In equilibrium, for RB0.1, the upper bound of i's individual contribution is $\frac{1}{1+0.1}$ of her induced value (i.e., $g_i \leq \frac{v_i}{1.1}$; specifically, $g_i \leq \frac{12}{1.1} \approx 10.9$ if $v_i = 12$, $g_i \leq \frac{14}{1.1} \approx 12.7$ if $v_i = 14$, $g_i \leq \frac{16}{1.1} \approx 14.5$ if $v_i = 16$, $g_i \leq \frac{18}{1.1} \approx 16.4$ if $v_i = 18$, $g_i \leq \frac{20}{1.1} \approx 18.2$ if $v_i = 20$). In the provision equilibria of AP16.7, the upper bound of i's individual contribution is equal to the assurance payment (her induced value) if her induced value is greater than or equal to (less than) AP (i.e., $g_i \leq 16.7$ if $v_i \geq 16.7$ and $g_i \leq v_i$ if $v_i < 16.7$; specifically, $g_i \leq 16.7$ if $v_i \in \{18, 20\}$ and $g_i \leq v_i$ if $v_i \in \{12, 14, 16\}$); in the non-provision equilibria of AP16.7, if the induced value minus the difference between the threshold and the sum of others' contribution is not greater than the assurance payment, the individual contribution is not less than the AP (i.e., $g_i \geq 16.7$ if $v_i - (500 - \sum g_{-i}) \leq 16.7$); if the induced value is less than the difference between the threshold and the sum of others' contribution that is not greater than AP, the individual contribution is less than AP (i.e., $g_i < 16.7$ if $v_i < 500 - \sum g_{-i} \leq 16.7$).

Provision equilibria under RB0.1: Any strategy profile $\{g_i\}_{i \in I}$ s.t. $G = 500$ with $g_i \leq \frac{1}{1.1} v_i$ for all $i \in I$ is a pure-strategy Nash equilibrium under which the good is provided.

Provision equilibria under AP16.7: Any strategy profile $\{g_i\}_{i \in I}$ s.t. $G = 500$ with $g_i \leq 16.7$ for $v_i \geq 16.7$ and $g_i \leq v_i$ for $v_i < 16.7$, for all $i \in I$ is a pure-strategy Nash equilibrium under which the good is provided.

Non-provision equilibria under AP16.7: Any strategy profile $\{g_i\}_{i \in I}$ s.t. $G < 500$ with $g_i \geq 16.7$ only when $v_i - (500 - \sum g_{-i}) \leq 16.7$ and $g_i < 16.7$ only when $v_i < (500 - \sum g_{-i}) \leq 16.7$, for all $i \in I$ is a pure-strategy Nash equilibrium under which the good is not provided.

The equilibrium analysis above provides two implications. First, RBM may induce group contributions not less than APM, since non-provision equilibria are eliminated under RBM but not under APM with AP16.7). Second, under RBM contributions (RB0.6) or upper bound of contributions (RB0.3 and RB0.1) increase with induced values, resulting in distributive efficiency (Cason and Zubrikas, 2017), which is an important welfare criterion for public goods provision (Clark, 1998). For example, under the unique provision equilibria of RB0.6, subjects' contributions are proportional to the induced values. Under APM such as AP10, subjects' contributions are 10 in the unique provision equilibrium, which is independent of the induced value.

3.2 Coordination device: *AP* as a focal point

People usually employ cognitive heuristics to streamline their decision-making rather than conduct comprehensive and thorough information processing, especially in an environment with more complex information (Fiske and Taylor, 1991; Messick, 1993). Under APM, subjects receive bonuses when public goods are not provided if they contribute at least AP. The assurance payment may serve as a focal point for individual contributions. Indeed, Li et al. (2021) and Li et al. (2022) find strong evidence that assurance payments act as a coordination device and induce more contributions concentrated on AP, especially for agents with values above AP. In our design, the focal point of AP may be particularly effective in coordinating contributions in AP10 and AP12.5 since once all subjects with induced values greater than *AP* contribute *AP*, the threshold will be met. In AP16.7, the effect could be weakened considering that group contributions are insufficient for provision if only subjects with induced value greater than *AP* contribute *AP*. RBM, on the other hand, lacks a clear focal point. Subjects are only told the percentage of their contributions as a refund bonus in case of non-provision, which is used for equilibrium strategies in a more subtle way. Cason and Zubrickas (2017) find experimental results of contributions under RBM that systematically deviate from Nash equilibrium predictions but are consistent with a model with bounded rationality.

In sum, with a focal point, APM may better coordinate contributions than RBM, leading to higher individual contributions and higher provision rates. Moreover, some features of our setting may amplify the coordination advantage of APM over RBM, including heterogeneous induced values, large groups of 50, and subjects of farmers whose attention and computational capacities may not be comparable with college students (Gáfaro and Mantilla, 2020).

3.3 Hypotheses

We construct the following hypotheses based on equilibrium predictions and coordination implications of the two mechanisms detailed above.

Hypothesis 1a (Average individual contribution: equilibrium). The average individual contribution is the same under RBM and APM for the first two treatment pairs: RB0.6/AP10, and RB0.3/AP12.5. The average individual contribution is greater under RBM than under APM for the third treatment pair: RB0.1/AP16.7.

Hypothesis 1b (Average individual contribution: equilibrium + coordination). The average individual contribution is greater under APM than RBM for the first two treatment pairs: RB0.6/AP10, and RB0.3/AP12.5. The average individual contribution can be greater, the same, or less under RBM than under APM for the third treatment pair: RB0.1/AP16.7.

Hypothesis 2 (Distributive efficiency). Compared with APM, RBM results in more distributive efficiency.

4. Experimental Implementation and Samples

4.1 Implementation

The experiment was conducted in November 2016, in Dongying, Shandong Province, China. We recruited 100 farmers in the rural area of Dongying, 100 college students from Dongying Vocational Institute and 100 high school students from Dongying No. 1 High School. Dongying Vocational Institute is a college providing tertiary vocational education (i.e., with professional orientations) whose students typically have lower entrance exam scores than those at colleges providing general education (i.e., with academic orientations). Dongying No.1 High School is one of the best high schools in the region, with more than 90% of its graduates entering colleges with higher entrance scores than Dongying Vocational Institute. We conducted two sessions among each subject pool. Specifically, 100 farmers/college students/high school students were randomly divided into two 50-person large groups, one assigned to the RBM session, and the other to the APM session. Each session has three levels (treatments) of r or AP, with each treatment lasting two periods. We minimize possible order effects through learning in two ways. First, subjects receive no period-feedback on outcomes until the end of a session. Second, we carefully match the order of bonus levels of the RBM and APM treatments. The orders are RB0.6, RB0.3, RB0.1, and AP10, AP12.5, AP16.7, respectively. In the analysis below, we focus on comparing the two mechanisms while controlling for orders (RB0.6 vs. AP10; RB0.3 vs. AP12.5; RB0.1 vs. AP16.7).

At the beginning of each session, experimental instruction slides were presented and explained to the subjects. In each period, subjects filled in their offers on contribution cards which were then collected. At the end of the experiment, subjects filled out a questionnaire, provision outcomes were announced, subjects were informed of their payoffs and received their final payments. College students were paid in cash. As suggested by local officials, farmers were paid in grocery supplies such as laundry detergent and soap bars, while high school students were paid in stationery, both at the equivalent value of cash earned in the experiment. Sessions lasted about 70 minutes. In total, 300 subjects participated in the experiment, each making decisions in 6 periods, generating 1800 individual-level observations.

Table 1. Experimental Design

Panel A: Refund Bonus Mechanism						
Session	Value	Treatment			Subject pool	N
		1 (Periods 1-2)	2 (Periods 3-4)	3 (Periods 5-6)		
1	{12, 14, 16, 18, 20}	RB0.6	RB0.3	RB0.1	College students	50
2	{12, 14, 16, 18, 20}	RB0.6	RB0.3	RB0.1	Farmers	50
3	{12, 14, 16, 18, 20}	RB0.6	RB0.3	RB0.1	High school students	50
	Pure-strategy Nash equilibria	$g_i = \frac{v_i}{1.6}$, $G = 500$	$g_i \leq \frac{v_i}{1.3}$, $G = 500$	$g_i \leq \frac{v_i}{1.1}$, $G = 500$		
Panel B: Assurance Payment Mechanism						
Session	Value	Treatment			Subject pool	N
		1 (Periods 1-2)	2 (Periods 3-4)	3 (Periods 5-6)		
4	{12, 14, 16, 18, 20}	AP10	AP12.5	AP16.7	College students	50
5	{12, 14, 16, 18, 20}	AP10	AP12.5	AP16.7	Farmers	50
6	{12, 14, 16, 18, 20}	AP10	AP12.5	AP16.7	High school students	50
	Pure-strategy Nash equilibria	$g_i = 10$, $G = 500$	$g_i \leq 12.5$ if $v_i \geq 12.5$, $g_i \leq v_i$ if $v_i < 12.5$, $G = 500$	$g_i \leq 16.7$ if $v_i \geq 16.7$, $g_i \leq v_i$ if $v_i < 16.7$, $G = 500$; $g_i \geq 16.7$ if $v_i - (500 - \sum g_{-i}) \leq 16.7$, $g_i < 16.7$ if $v_i < (500 - \sum g_{-i}) \leq 16.7$, $G < 500$		

Note: RB0.6, RB0.3 and RB0.1 denote the three bonus rates of r=0.6, 0.3, 0.1, respectively. AP10, AP12.5 and AP16.7 denote the three assurance payment levels of AP=10, 12.5, 16.7, respectively. g_i denotes the subject i's individual contribution and $G = \sum g_i$ represents group contribution. v_i denotes the subject i's induced value. $\sum g_{-i}$ represents group contribution except for subject i.

Table 2. Demographic characteristics of subjects

Variable		Famers		College students		High school students
	N	Mean (Std. Dev.)	N	Mean (Std. Dev.)	N	Mean (Std. Dev.)
Panel A: Farmers and students						
Age	97	44.670 (10.266)	100	18.970 (2.125)	99	15.273 (0.531)
Sex (=1 if male)	96	0.750 (0.435)	99	0.020 (0.141)	98	0.439 (0.499)
Selfish	86	38.837 (27.423)	100	47.620 (16.471)	100	48.200 (14.849)
Risk averse	87	3.920 (2.059)	99	4.3740 (1.639)	98	4.673 (1.552)
Unconditional contribution	94	2.947 (0.932)	100	2.810 (0.706)	100	2.410 (0.944)
Panel B: Farmers only						
Education	96					
Elementary school (or below)	7					
Middle school	60					
(Professional) High school	21					
College or university	8					
Experience	98	0.776 (0.419)				
Roads	98	0.541 (0.501)				
Aqueducts	98	0.133 (0.341)				
Recreational facilities	98	0.327 (0.471)				
Sewage facilities	98	0.153 (0.362)				
Mutual cooperatives	98	0.194 (0.397)				
Other	98	0.031 (0.173)				
Farm income (¥1000)	91	61.813 (68.099)				
Non-farm income (¥1000)	88	44.527 (46.213)				
Panel C: Students only						
Disposable income (¥1000)			99	9.630(3.739)	95	4.324 (3.378)
Household income (¥1000)			95	60.998 (39.033)	93	149.019 (222.484)

Note: Selfish is the amount a subject keeps for herself from ¥100 in a dictator game. *Risk averse* is an integer from 1 to 7, with a greater number indicating more risk aversion. *Unconditional contribution* is an integer from 0 to 4, with a greater number indicating greater willingness to contribute to the public good even without knowing others' contributions. All three variables are self-reported measures collected in the post-experiment questionnaire (see **Appendix C** for more details).

4.2 Demographic characteristics

Table 2 summarizes the characteristics of the subjects. The average age of farmers, college students and high school students are 44.670, 18.970 and 15.273 (by *t*-tests: $p < 0.001$ for all three comparisons). 75.0% of farmers, 2% of college students and 43.9% of high school students are male. Subjects are recruited voluntarily, so we are not in a position to know their information before the experiments. The fact that our college student sample is mostly female may have some implications on our results. We defer this to the **Discussion** section. Farmers are less educated than college students and high school students, as 67 out of 96 farmers have their highest education level below high school.

We next briefly summarize non-incentivized measures of selfishness, risk attitudes and unconditional propensity to contribute to public goods elicited in the post-experiment questionnaire (denoted as Selfish, Risk averse and Unconditional contribution, respectively, in Table 2; see **Appendix C** for detailed descriptions and statistics). We adopt non-incentivized measures to simplify payment procedures and keep length of each session reasonable for field implementation. Farmers are the least selfish, consistent with Falk et al. (2013); there is no significant difference in the degree of selfishness between college students and high school students. Farmers are the least risk averse, followed by college students, and high school students are the most risk averse. Farmers have the highest propensity for unconditional contribution, followed by college students; high school students have a significantly lower propensity to contribute unconditionally.

Most farmers have some experiences with crowdfunding campaigns. 77.6% of the farmers have at least one experience in obtaining public goods services through crowdfunding in their villages within three years before the experiment. Crowdfunding for constructing roads (54.1%) and recreational facilities (32.7%) are the most common, followed by mutual cooperatives (19.4%), sewage facilities (15.3%), aqueducts (13.3%), and others (3.1%)., These results also show that crowdfunding campaigns are common in rural areas in China.

We also asked about the income of different groups. The average annual disposable incomes are ¥9,630 for college students, and ¥4,324 for high school students. The average annual household gross incomes are ¥60,998 for college students, and ¥149,019 for high school students. For farmers, on average, the annual household income is ¥106,340 composed of ¥61,813 from farm income and ¥44,527 from non-farm income.

5. Results

Table 3. Group Contributions

Treatment	College students			Farmers			High school students		
	Period 1	Period 2	Average	Period 1	Period 2	Average	Period 1	Period 2	Average
RB0.6	591	567	579	801	619.5	710.25	531	509	520
RB0.3	599	559	579	583	624.1	603.55	540	560	550
RB0.1	478	476	477	553	563	558	507	462	484.5
AP10	670	641	655.5	653	703	678	542	422	482
AP12.5	664.1	676	670.05	759	756	757.5	482	466.5	474.25
AP16.7	742	666	704	868	841	854.5	539.2	506.525	522.8625

Note: The provision cost of the good is 500. The cells with a grey background indicate that the public good is not provided while all the others indicate a provision success.

Table 3 summarizes the group contributions for each treatment in each period. The cells with a grey background indicate that the public good is not provided while all the others indicate a provision success. We start by including all three types of subjects in the sample to compare RBM and APM, and then we pool RBM and APM together to compare results between different subjects. First, provision rates under APM and RBM are the same and equal to 83.3%. APM induces 644.3 of group contributions on average, higher than 562.4 under RBM (by Wilcoxon rank-sum test: $p = 0.044$). Second, provision rates are respectively 83.8%, 100%, and 66.7% among college students, farmers, and high school students. The average group contribution of farmers (693.6) is higher than that of college students (610.8); the difference is not significant (by Wilcoxon rank-sum test: $p = 0.128$). The average group contribution of high school students (505.6) is significantly lower than that of college students (by Wilcoxon rank-sum test: $p = 0.001$) and farmers (by Wilcoxon rank-sum test: $p < 0.001$).[1] In addition, no group contributions coordinate exactly at the provision threshold. This indicates that it is difficult for people to coordinate at equilibrium in one-shot games with large groups and heterogeneous induced values.

Since we only have a small number of observations at the group level, we focus on the treatment differences at the individual level. We compare RBM and APM and test the three hypotheses above, and also explore the differences in contribution between farmers, college students and high school students. The results are summarized in three observations.

[1] Comparisons of individual contributions among samples under different treatments reveal the same pattern (see **Observation A1** of **Appendix A)**. In most cases, farmers contribute the most, followed by college students and high school students.

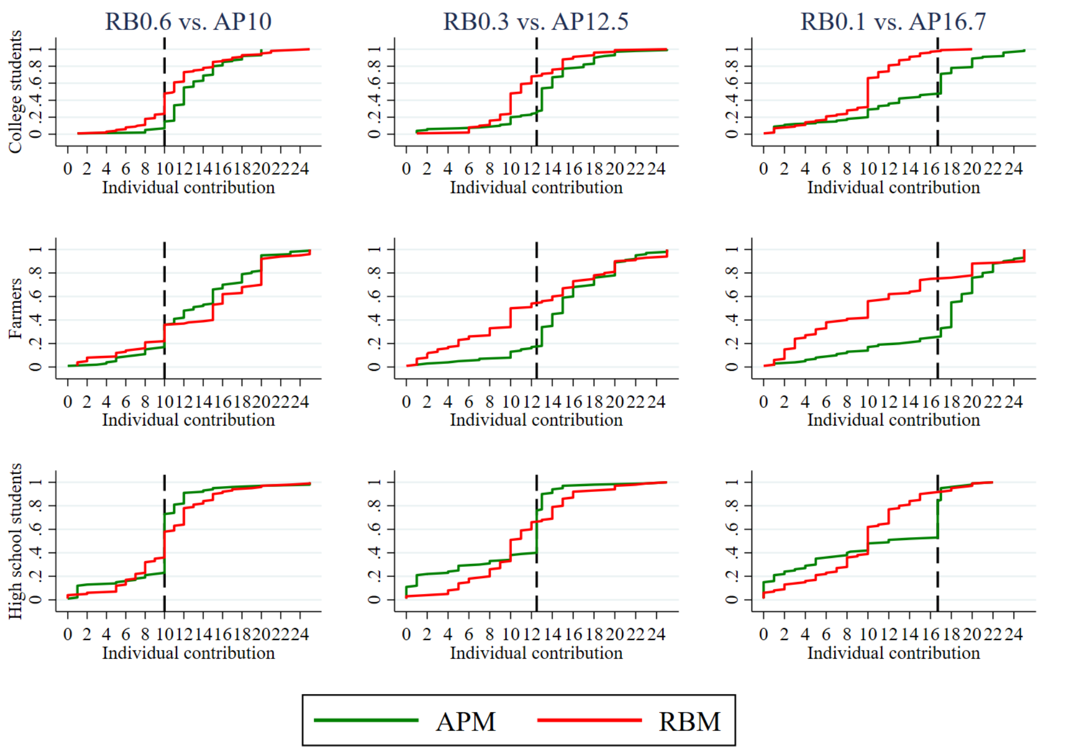

Figure 1. Cumulative Distribution of Individual Contributions

Note: The subjects in the first, second and third rows are college students, farmers and high school students, respectively. The first, second and third columns are RB0.6 vs. AP10, RB0.3 vs. AP12.5 and RB0.1 vs AP16.7, respectively. The red lines represent RBM and the green lines represent APM. The vertical dashed lines represent the value of *AP* for each treatment of APM.

5.1 Individual contributions

Observation 1. *APM induces individual contributions not less and most times significantly greater than RBM among farmers and college students. Individual contributions under the two mechanisms do not differ statistically among high school students.*

Figure 1 compares the cumulative distributions of individual contributions between APM and RBM within three subject pools. By the Kolmogorov-Smirnov test, farmers and college students contribute significantly more under APM than under RBM in all but one cases ($p < 0.001$). The only exception is that farmers show no difference in contribution between AP10 and RB0.6 ($p = 0.281$). High school students, on the other hand, do not behave consistently over the two mechanisms. They contribute less under AP10 (compared with RB0.6, $p = 0.078$) and AP12.5 (compared with RB0.3, $p = 0.001$), but they contribute significantly more under AP16.7 (compared with RB0.1, $p<0.001$).

We run two-factor random effects regressions to further compare individual contributions under RBM and APM. We present the results in **Table 4**, using college students and RBM as the base. Models 1, 3 and 5 compare individual contributions under AP10 and RB0.6, AP12.5 and RB0.3, AP16.7 and RB0.1, respectively. Models 2, 4 and 6 include key control variables.

Regression results on farmers and college students support the results based on Kolmogorov-Smirnov tests. College students contribute significantly more under APM compared with RBM for all comparisons (see the coefficients of APM). Farmers show no difference between RB0.6 and AP10, but they contribute significantly more under AP12.5 and AP16.7 (compared with RB0.3 and RB0.1, respectively) (see the coefficients of APM+APM*Farmers). The contributions of farmers and college students are consistent with **Hypothesis 1b**, indicating that *AP* may have a strong effect in stimulating contributions among these two groups.

Regression results for high school students are consistent with but weaker than those from the Kolmogorov-Smirnov tests. High school students contribute less under AP10 (compared with RB0.6) and AP12.5 (compared with RB0.3), and more under AP16.7 (compared with RB0.1), but none of the differences is significant (see coefficients of APM+APM*High school). Strategies of high school students are more consistent with **Hypothesis 1a** in the first two treatment pairs RB0.6/AP10 and RB0.3/AP12.5. While in the third treatment pair RB0.1/AP16.7, their behavior is consistent with **Hypothesis 1b**. This indicates that *AP* may also help to increase contributions to some extent.

To sum up, we find that subjects contribute not less and most times significantly greater under APM than under RBM, suggesting that the focal point *AP* may play an important role in facilitating contributions. This effect is more pronounced among college students and farmers.

Table 4. Two-Factor Random Effects Regressions of Individual Contribution

VARIABLES	(1) AP10vs.RB0.6 Contribution	(2) AP10vs.RB0.6 Contribution	(3) AP12.5vs.RB0.3 Contribution	(4) AP12.5vs.RB0.3 Contribution	(5) AP16.7vs.RB0.1 Contribution	(6) AP16.7vs.RB0.1 Contribution
Value	0.127*	0.139*	0.329***	0.334***	0.362***	0.329***
	(0.069)	(0.073)	(0.073)	(0.077)	(0.088)	(0.091)
APM	1.530**	1.617**	1.821**	1.595**	4.540***	3.985***
	(0.674)	(0.688)	(0.719)	(0.727)	(0.860)	(0.856)
Farmers	2.625***	2.773**	0.491	-0.402	1.620*	-0.790
	(0.674)	(1.322)	(0.719)	(1.397)	(0.860)	(1.644)
High school	-1.180*	-0.766	-0.580	-0.111	0.150	0.296
	(0.674)	(0.756)	(0.719)	(0.798)	(0.860)	(0.940)
APM*Farmers	-2.175**	-1.562	1.258	2.658**	1.390	2.524*
	(0.954)	(1.082)	(1.017)	(1.142)	(1.216)	(1.345)
APM*High school	-2.290**	-2.260**	-3.336***	-2.782***	-3.773***	-2.749**
	(0.954)	(0.996)	(1.017)	(1.052)	(1.216)	(1.239)
Age		0.004		0.014		0.075
		(0.038)		(0.040)		(0.047)
Sex		-0.366		-0.275		0.441
		(0.547)		(0.578)		(0.681)
Selfish		0.022*		0.001		-0.028**
		(0.011)		(0.012)		(0.014)
Risk averse		-0.121		-0.148		0.055
		(0.123)		(0.131)		(0.154)
Unconditional contribution		0.484**		1.139***		0.980***
		(0.245)		(0.257)		(0.303)
Constant	9.544***	7.343***	6.323***	3.411*	3.752**	1.411
	(1.245)	(1.842)	(1.280)	(1.938)	(1.530)	(2.367)
APM+APM*Farmers	-0.645	0.055	3.079***	4.252***	5.930***	6.509***
	(0.674)	(0.847)	(0.719)	(0.894)	(0.860)	(1.053)
APM+APM* High school	-0.760	-0.643	-1.515**	-1.187	0.767	1.236
	(0.674)	(0.731)	(0.719)	(0.773)	(0.860)	(0.910)
chi2	77.24	83.64	94.73	111.4	138.0	150.0
Observations	600	548	600	548	600	548

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. APM+APM*Farmers and APM+APM*High school are sum of coefficients of APM and interactions between APM and dummy variables for corresponding groups. The significance level is from LinCom test (linear combinations of parameters) for null hypothesis APM+APM*Farmers=0 (or APM+APM*High school=0).

5.2 *AP* as a focal point

We have shown that individual contributions under APM are not lower than those under RBM in most cases. Next, we test the effect of *AP* as a coordination device in APM.

Observation 2. *APM increases the frequency that individual contributions are not less than AP compared with RBM in all three samples.*

Figure 1 shows that the percentage of individual contributions not less than *AP* is higher under APM than under RBM in all cases. **Figure 2** further compares frequency-weighted observed individual contributions at each induced value by treatment, where the value of *AP* for each treatment of APM is indicated by a horizontal dashed line.[2] Panel A of **Table 5** reports proportions of individual contributions not less than *AP*. Panel B restricts the sample to subjects with value less than *AP.* We also provide two-sided *p*-value of proportion tests. APM increases the frequency that individual contributions are not less than *AP.* This holds even when the induced values are less than *AP*.

Table 5. Proportions of individual contributions≥*AP*

	RBM	Proportion	APM	Proportion	p-value
Panel A: full sample					
College students	RB0.6	0.77	AP10	0.94	<0.001
College students	RB0.3	0.32	AP12.5	0.76	<0.001
College students	RB0.1	0.03	AP16.7	0.53	<0.001
Farmers	RB0.6	0.79	AP10	0.84	=0.363
Farmers	RB0.3	0.46	AP12.5	0.83	<0.001
Farmers	RB0.1	0.25	AP16.7	0.75	<0.001
High school students	RB0.6	0.65	AP10	0.78	=0.042
High school students	RB0.3	0.34	AP12.5	0.61	<0.001
High school students	RB0.1	0.09	AP16.7	0.48	<0.001
Panel B: For Value<*AP*					
College students	RB0.3	0.15	AP12.5	0.70	<0.001
College students	RB0.1	0.02	AP16.7	0.50	<0.001
Farmers	RB0.3	0.50	AP12.5	0.80	=0.047
Farmers	RB0.1	0.20	AP16.7	0.70	<0.001
High school students	RB0.3	0.10	AP12.5	0.35	=0.058
High school students	RB0.1	0.03	AP16.7	0.38	<0.001

Note: P-values are from two-sided proportion tests.

Table 6 reports results from probit regressions of individual contributions not less than *AP*.[3] Models 1 to 3 compare AP10 and RB0.6, AP12.5 and RB0.3, AP16.7 and RB0.1, respectively. Results show that for each subject pool, subjects are more likely to contribute at least *AP* under APM than under RBM. This effect is significant among both student samples (see the coefficients of APM for college students, and the coefficients of APM+APM*High school for high school students). For farmers, this

[2] **Figure A1** in **Appendix A** displays mean individual contributions at each induced value by treatment pairs, along with the value of AP from the corresponding APM.
[3] Regression results are robust when we add demographic controls (See **Table A1** in **Appendix A**).

effect is significant for comparisons between AP12.5 vs. RB0.3, and AP16.7 vs. RB0.1; they are still more likely to contribute at least *AP* under AP10 than RB0.6, but the difference is not significant (see the coefficients of APM+APM*Farmers).

In Models 4 and 5, we add a dummy variable representing whether the induced value is above *AP*. We do not consider the treatments of AP10 and RB0.6 where all induced values are above $AP = 10$. Regression results show that the effect of APM on increasing the likelihood of contributing at least *AP* compared with RBM does not differ between the induced values above *AP* and those below *AP* for each subject pool (see the coefficients of APM*Value ≥ *AP* for college students, the coefficients of APM*Value ≥ *AP*+APM*Farmers*Value ≥ *AP* for farmers, and the coefficients of APM*Value ≥ *AP*+APM*High school*Value ≥ *AP* for high school students).

To summarize, our results show that APM increases the likelihood that subjects contribute at least *AP* compared with RBM. This effect exists among all three types of subjects even with values less than *AP*, supporting the coordination role played by the salient focal point in APM.

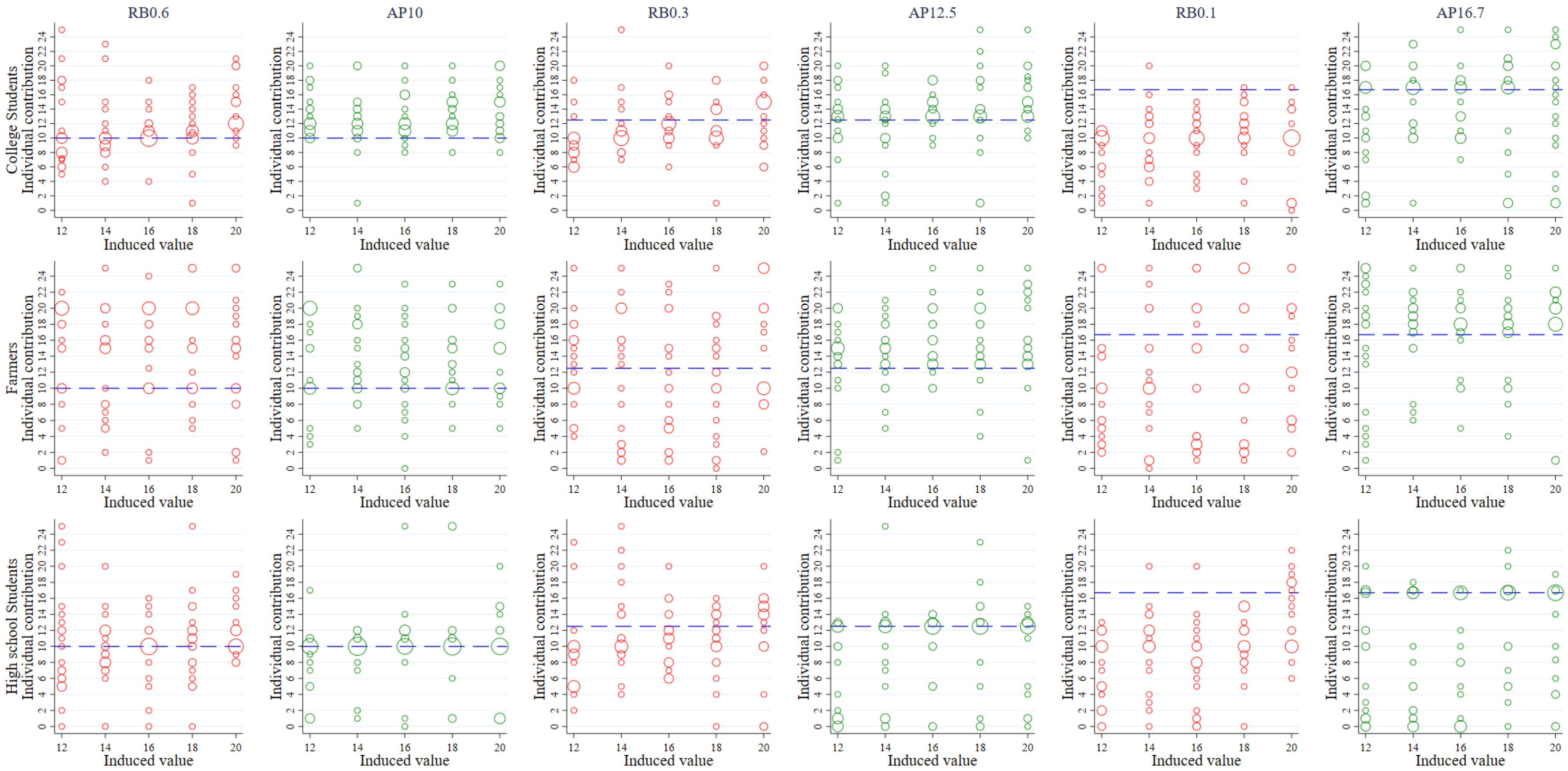

Figure 2. The Influence of Assurance on Individual Contributions

Note: The six columns are RB0.6, AP10, RB0.3, AP12.5, RB0.1, and AP16.7, respectively. The subjects in the first, second and third rows are college students, farmers and high school students, respectively. Plots in red are under RBM, and plots in green are under APM. The horizontal dashed lines represent the value of *AP* for each treatment of APM.

Table 6. Probit Regressions of Individual Contribution Not Less Than *AP*

VARIABLES	(1) AP10 vs. RB0.6 Contribution ≥ 10	(2) AP12.5 vs. RB0.3 Contribution ≥ 12.5	(3) AP16.7 vs. RB0.1 Contribution ≥ 16.7	(4) AP12.5 vs. RB0.3 Contribution ≥ 12.5	(5) AP16.7 vs. RB0.1 Contribution ≥ 16.7
APM	0.816***	1.174***	1.956***	1.561***	2.128***
	(0.243)	(0.189)	(0.280)	(0.452)	(0.430)
Farmers	0.068	0.367**	1.206***	1.036**	1.286***
	(0.198)	(0.181)	(0.285)	(0.443)	(0.439)
High school	-0.354*	0.055	0.540*	-0.245	0.294
	(0.189)	(0.184)	(0.306)	(0.513)	(0.506)
APM*Farmers	-0.628**	-0.119	-0.607*	-0.719	-0.762
	(0.319)	(0.271)	(0.340)	(0.620)	(0.498)
APM*High school	-0.429	-0.482*	-0.665*	-0.665	-0.591
	(0.308)	(0.262)	(0.354)	(0.658)	(0.556)
Value ≥ *AP*				0.685*	0.483
				(0.371)	(0.520)
APM*Value ≥ *AP*				-0.454	-0.294
				(0.499)	(0.580)
Farmers*Value ≥ *AP*				-0.810*	-0.095
				(0.486)	(0.589)
High school* Value ≥ *AP*				0.344	0.416
				(0.551)	(0.650)
APM*Farmers*Value ≥ *AP*				0.722	0.316
				(0.691)	(0.704)
APM*High school				0.265	0.010
*Value ≥ *AP*				(0.721)	(0.746)
Constant	0.739***	-0.468***	-1.881***	-1.036***	-2.128***
	(0.139)	(0.130)	(0.251)	(0.342)	(0.399)
APM+APM*Farmers	0.188	1.055***	1.349***	0.842**	1.366***
	(0.207)	(0.194)	(0.193)	(0.425)	(0.251)
APM+APM* High school	0.387**	0.692***	1.291***	0.896*	1.537***
	(0.190)	(0.181)	(0.216)	(0.479)	(0.353)
APM*Value ≥ *AP*+				0.268	0.022
APM*Farmers*Value ≥ *AP*				(0.478)	(0.400)
APM* Value ≥ *AP*+				-0.189	-0.284
APM*High school*Value ≥ *AP*				(0.520)	(0.469)
r2_p	0.049	0.119	0.245	0.142	0.267
chi2	29.86	98.22	191.5	117.2	208.5
Observations	600	600	600	600	600

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. APM+APM*Farmers and APM+APM*High school are the sum of the coefficients of APM and the interactions between APM and dummy variables for the corresponding groups. The significance level is from LinCom test for the null hypothesis APM+APM*Farmers = 0 (or APM+APM*High school = 0). APM*Value ≥ *AP*+APM*Farmers*Value ≥ *AP* and APM*Value ≥ *AP*+APM*High school*Value ≥ *AP* are the coefficients of the interactions between APM and dummy variables representing whether the induced value is not less than *AP*, plus the coefficients of the interactions of APM, dummy variables for the corresponding groups, and dummy variables representing whether the induced value is not less than *AP*. The significance level is from LinCom test for the null hypothesis APM*Value ≥ *AP*+APM*Farmers*Value ≥ *AP* = 0 (or APM*Value ≥ *AP*+APM*High school*Value ≥ *AP*).

5.3 Distributive efficiency

Observation 3. *Compared with APM, RBM results in higher distributive efficiency.*

We adopt the following definition of proportionality to compare the distributive efficiency between these two mechanisms (Hoffman and Spitzer, 1985; Clark, 1998):

$$Proportionality = \frac{\sum_i^N \left|\frac{g_i}{C} - \frac{v_i}{V}\right|}{2}$$

The closer the *Proportionality* is to zero, the greater the distributive efficiency. Note that this is an ex-ante index based on agents' individual contributions and values, with no reference to the provision outcome or realized payoff. **Table 7** shows the *Proportionality* for each sample by mechanism. For all groups, compared with APM, RBM decreases *Proportionality* (by 0.106, 0.003, 0.05, corresponding to decreases of 42%, 1%, 22%, for college students, farmers, and high school students, respectively). **Table A6** in the **Appendix A** contains detailed information of *Proportionality* in each period by treatment for each sample. RBM has a mean *Proportionality* significantly lower than APM (0.216 for RBM, 0.269 for APM, p = 0.041 by Wilcoxon rank-sum test). Therefore, RBM outperforms APM in terms of distribution efficiency.

Table 7. Contribution Proportionality

Group	RBM	APM
College students	0.146	0.252
Farmers	0.324	0.327
High school students	0.179	0.229

Note: The closer *Proportionality* is to zero, the greater the distributive efficiency.

6. Discussion

Despite of the distinct socioeconomic status of the three samples, their behavior demonstrates the prevalence of the coordination advantage of APM over RBM. However, the extent to which each sample responds to cognitive heuristics that facilitate this coordination differs. We will first report two pieces of evidence documenting this difference, and then discuss three distinctions among the subject pools that may have implications in this respect: computational and analytical abilities, gender composition, and age.

The first piece of evidence can be readily derived from Observations 1 and 2. With a clear focal point, APM facilitate coordination by increasing the likelihood that subjects contribute not less than *AP* compared with RBM among all three samples

(Observation 2). However, a closer inspection reveals that the magnitude of this effect may differ among the three subject pools. Specifically, the focal point *AP* has a stimulating effect strong enough to induce most times significantly higher individual contributions than RBM among farmers and college students; while this effect is not sufficient to induce significant difference in contributions between the two mechanisms for high school students (Observation 1). This discrepancy indicates that farmers and college students seem to rely more on cognitive heuristics than high school students in our sample.

The second piece of evidence is that a higher *r*/*AP* induces more contributions in most cases among farmers; this effect is weaker for college students; and it is rarely the case for high school students (see **Observation A2** in **Appendix A** for more details). According to equilibrium predictions, a higher *r* would not change the average individual contribution under RBM because there exist only provision equilibria. A higher *AP* level would not change the average individual contribution in AP10 and AP12.5 for the same reason; an increase of *AP* to 16.7 would even decrease the average individual contribution because it also allows non-provision equilibria. However, if people rely on heuristics, then a higher bonus rate *r*/assurance payment *AP* is likely to induce higher contribution. Under RBM, heuristics lead subjects to focus on the fact that a higher *r* implies a larger bonus of a per-unit contribution in case of non-provision, and hence they become more willing to contribute when *r* is higher. Under APM, subjects contribute at least *AP* to get the bonus in case of non-provision, so their contributions increase with *AP*. In this sense, **Observation A2** implies that farmers are the most prone to a heuristic thinking, followed by college students, and that high school students adopt a heuristic thinking the least.

One major difference among the three samples that may lead to this discrepancy is in computational and analytical abilities. Students are usually better than farmers in these aspects, and we observe farmers follow heuristics the most. Between our two student samples, high school students from a top-tier high school in the region are better than college students from a vocational college, and we see that high school students adopt heuristics the least. Hence, we conjecture that better computational abilities reduce reliance on heuristics. Similar results are reported by Gáfaro and Mantilla (2020). They find that farmers rely more on heuristics in land allocation negotiations than college students.

A second difference among the three samples is in gender composition: 75% of the farmers, 2% of the college students and 44% of the high school students are male. Research shows that women often digest incoming information more thoroughly than men do (Meyers-Levy & Maheswaran, 1991; Meyers-Levy & Sternthal, 1991; Meng and Chan, 2022). As a result, males process data more selectively and rely more heavily than females on highly salient heuristics that require less work. Our current college student sample is mostly female. If there were more males in this sample, we would expect an increase in their heuristic decision making. Nevertheless, this is still consistent with our observation that farmers and college students rely more on heuristics than high school students.

One more difference worth noting is in age: the mean age of farmers, college students and high school students are 45, 19 and 15, respectively. An investigation on cognitive aging reveals that older adults tend to look up less information and take longer to process it, and use simpler, less cognitively demanding strategies in decision making than younger people (Mata et al., 2007). The fact that farmer participants are much older than student participants may also help explain why farmers rely more on heuristics in our experiment.[4]

7. Conclusion

This study experimentally tests the potential applicability of RBM and APM in crowdfunding for threshold public goods in rural areas. Both of these two mechanisms provide bonuses to participants when public goods cannot be provided. The difference is that RBM provides bonuses proportional to contributions for all participants, while APM provides a fixed level of assurance payment (*AP*) for participants with an individual contribution at or above a predetermined minimum payment level.

APM induces most times higher individual contributions than RBM among farmers and college students; APM induces individual contributions not less than RBM among high school students. APM provides a focal point for coordination based on cognitive heuristics decision making. Compared with RBM, APM increases the frequency at which the individual contribution is not less than *AP* in all three samples.

[4] Moreover, researchers have discovered profound evidence that social-welfare preferences increase with age among population of all ages (List, 2004), and this trend develops since childhood and adolescence (Martinsson et al., 2011; Fehr et al., 2013; see Sutter et al. (2019) for a recent survey on economic behavior of children and adolescents). Our **Observation A1** (in the **Appendix A**) is in line with this age effect: farmers contribute the most, followed by college students and then high school students.

This even holds for subjects with value less than *AP*, which cannot be predicted in equilibrium. Farmers rely on heuristics more than students. We find that a higher level of *r* or *AP* induces more contributions among farmers, while this effect is much weaker among college students and high school students.

RBM outperforms APM in terms of distribution efficiency in all three samples. Specifically, subjects' contributions under RBM are more proportional to the benefits they receive from the public good than APM.

As for a practical guide for policy making, the choice between RBM and APM depends on the policy objectives. Our results suggest that in rural areas, APM should be more applicable for public goods provision than RBM if policy makers are more concerned about stimulating individual contributions. This is because APM provides a more visible basis for farmers' heuristic decisions, making it easier for farmers to coordinate. In addition, policy makers can increase the value of *AP* to an appropriate amount to further increase the contributions of heuristic decision makers under APM. On the other hand, RBM can better guide people's contributions to be positively correlated with their value of the public good than APM. RBM results in a higher distributive efficiency and is the better choice if policy makers give more weight to equity.[5]

More research is needed before we put these two mechanisms into action. First, the comparison between RBM and APM we make here is in a static environment. An important extension would be to compare the efficacy of these mechanisms in a dynamic setting where people can see real-time funding levels and adjust their own contributions in a given period (for RBM in dynamic environments, see Cason and Zubrickas, 2019; Cason et al., 2021), which resembles real-world online crowdfunding sites. Second, it is worthwhile to extend the comparison from single-unit to multi-unit public goods provision (Li et al., 2014; Cason and Zubrickas, 2019), as multiple projects may compete for funding in reality. Finally, a field study involving the provision of real public goods can be informative for practical adoption of the mechanisms.

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[5] We also present results of social surplus and allocations among agents and providers under RBM and APM (see **Table A7** in **Appendix A**). If we focus on the farmers, we find that the total realized social surplus is the same between the two mechanisms. Nevertheless, RBM distributes more surplus to the subjects and APM distributes more surplus to the producers. How policymakers weigh welfare of different sides also affect choice between the two.

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Appendix A

Table A1. Probit Regressions of Individual Contribution No Less Than *AP* (with Demographic Controls)

VARIABLES	(1) AP10 vs. RB0.6 Contribution ≥ 10	(2) AP12.5 vs. RB0.3 Contribution ≥ 12.5	(3) AP16.7 vs. RB0.1 Contribution ≥ 16.7	(4) AP12.5 vs. RB0.3 Contribution ≥ 12.5	(5) AP16.7 vs. RB0.1 Contribution ≥ 16.7
APM	0.798***	1.179***	1.929***	1.521***	2.059***
	(0.246)	(0.193)	(0.285)	(0.453)	(0.430)
Farmers	0.186	0.259	0.589	0.737	0.676
	(0.402)	(0.365)	(0.444)	(0.582)	(0.563)
High school	-0.313	0.161	0.443	-0.221	0.142
	(0.215)	(0.207)	(0.332)	(0.523)	(0.528)
APM*Farmers	-0.673*	0.057	-0.366	-0.163	-0.492
	(0.353)	(0.311)	(0.386)	(0.713)	(0.537)
APM*High school	-0.318	-0.367	-0.495	-0.379	-0.309
	(0.322)	(0.275)	(0.370)	(0.673)	(0.571)
Value ≥ *AP*				0.599	0.447
				(0.373)	(0.523)
APM*Value ≥ *AP*				-0.401	-0.186
				(0.500)	(0.586)
Farmers*Value ≥ *AP*				-0.598	-0.138
				(0.510)	(0.600)
High school*Value ≥ *AP*				0.429	0.482
				(0.558)	(0.659)
APM*Farmers*Value ≥ *AP*				0.237	0.239
				(0.769)	(0.752)
APM*High school*Value ≥ *AP*				0.030	-0.220
				(0.736)	(0.761)
Age	-0.002	0.003	0.018	0.004	0.018
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Sex	-0.051	-0.117	0.279*	-0.094	0.289*
	(0.160)	(0.150)	(0.164)	(0.153)	(0.169)
Selfish	0.006*	-0.000	-0.007**	-0.000	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Risk averse	-0.001	0.002	0.052	0.004	0.065
	(0.038)	(0.034)	(0.039)	(0.035)	(0.040)
Unconditional contribution	0.211***	0.131*	0.053	0.118*	0.043
	(0.072)	(0.068)	(0.077)	(0.069)	(0.079)
Constant	-0.081	-0.930**	-2.284***	-1.391***	-2.555***
	(0.435)	(0.402)	(0.491)	(0.517)	(0.584)
APM+APM*Farmers	0.125	1.236***	1.563***	[1.358**	1.567***
	(0.258)	(0.247)	(0.264)	(0.556)	(0.323)
APM+APM* High school	0.479**	0.812***	1.434***	1.142**	1.751***
	(0.209)	(0.199)	(0.238)	(0.500)	(0.376)]
APM*Value ≥ *AP*+				-0.164	0.052
APM*Farmers*Value ≥ *AP*				(0.585)	(0.472)
APM* Value ≥ *AP*+				-0.371	-0.406
APM*High school*Value ≥ *AP*				(0.539)	(0.487)
r2_p	0.067	0.129	0.283	0.148	0.302
chi2	38.11	97.64	201.9	111.9	215.4
Observations	548	548	548	548	548

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

APM+APM*Farmers and APM+APM*High school are the sum of the coefficients of APM and the interactions between APM and dummy variables for the corresponding groups. The significance level is from LinCom test for the null hypothesis APM+APM*Farmers = 0 (or APM+APM*High school = 0). APM*Value ≥ *AP*+APM*Farmers*Value ≥ *AP* and APM*Value ≥ *AP*+APM*High school*Value ≥ *AP* are the coefficients of the interactions between APM and dummy variables representing whether the induced value is not less than *AP*, plus the coefficients of the interactions of APM, dummy variables for the corresponding groups, and dummy variables representing whether the induced value is not less than *AP*. The significance level is from LinCom test for the null hypothesis APM*Value ≥ *AP*+APM*Farmers*Value ≥ *AP* = 0 (or APM*Value ≥ *AP*+APM*High school*Value ≥ *AP*).

Observation A1. (Difference among subjects: Contribution). *In most cases, farmers contribute the most, followed by college students and high school students.*

We also compare individual contributions among farmers, college students and high school students under each treatment. Results are shown in **Table A2** of **Appendix A**. We find that farmers contribute the most, followed by college students and high school students. To be specific, farmers contribute more than college students under all treatments, and the differences are significant except for AP10 and RB0.3. High school students contribute less than college students except for RB0.1, and the differences are significant under APM. In **Table A3**, we add control variables of demographic characteristics. In the vast majority of cases, farmers contribute more than college students, but none of the differences are significant. Under APM, college students contribute significantly more than high school students; but this difference disappears under RBM.

Table A2. Two-Factor Random Effects Regressions of Individual Contribution: Comparison among Subjects

	(1)	(2)	(3)	(4)	(5)	(6)
	AP10	AP12.5	AP16.7	RB0.6	RB0.3	RB0.1
VARIABLES	Contribution	Contribution	Contribution	Contribution	Contribution	Contribution
Value	0.112	0.384***	0.313**	0.143	0.273**	0.411***
	(0.090)	(0.099)	(0.132)	(0.104)	(0.108)	(0.116)
Farmers	0.450	1.749**	3.010***	2.625***	0.491	1.620**
	(0.626)	(0.688)	(0.913)	(0.720)	(0.748)	(0.802)
High school	-3.470***	-3.916***	-3.623***	-1.180	-0.580	0.150
	(0.626)	(0.688)	(0.913)	(0.720)	(0.748)	(0.802)
Constant	11.323***	7.250***	9.078***	9.295***	7.217***	2.967
	(1.513)	(1.661)	(2.206)	(1.796)	(1.808)	(1.937)
Observations	300	300	300	300	300	300
Farmers-High school	3.920***	5.665***	6.633***	3.805***	1.071	1.470*
	(0.626)	(0.688)	(0.913)	(0.720)	(0.748)	(0.802)
chi2	48.44	86.12	58.53	31.17	8.423	17.58

Note: This table provides the estimation results of individual contribution under different treatments using college students as the base. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Farmers-High school is the difference between the coefficients of Farmers and the coefficients of High school. The significance level is from LinCom test for null hypothesis Farmers-High school = 0.

Table A3. Two-Factor Random Effects Regressions of Individual Contribution (with Demographic Controls): Comparison among Subjects

	(1)	(2)	(3)	(4)	(5)	(6)
	AP10	AP12.5	AP16.7	RB0.6	RB0.3	RB0.1
VARIABLES	Contribution	Contribution	Contribution	Contribution	Contribution	Contribution
Value	0.132	0.417***	0.263*	0.153	0.247**	0.360***
	(0.100)	(0.107)	(0.141)	(0.106)	(0.110)	(0.116)
Farmers	0.998	0.232	-0.805	2.530	1.123	0.327
	(1.531)	(1.651)	(2.162)	(1.733)	(1.787)	(1.887)
High school	-3.101***	-2.916***	-2.483**	-1.062	0.098	0.118
	(0.777)	(0.838)	(1.097)	(0.848)	(0.874)	(0.926)
Age	0.024	0.092	0.195**	0.006	-0.036	0.028
	(0.058)	(0.062)	(0.082)	(0.054)	(0.056)	(0.059)
Sex	-0.892	0.569	0.614	-0.090	-0.661	0.459
	(0.763)	(0.823)	(1.077)	(0.788)	(0.811)	(0.858)
Selfish	0.016	0.018	-0.011	0.032*	-0.012	-0.033*
	(0.015)	(0.016)	(0.021)	(0.017)	(0.018)	(0.019)
Risk averse	-0.392**	0.066	-0.110	0.116	-0.408**	0.094
	(0.171)	(0.184)	(0.241)	(0.182)	(0.188)	(0.199)
Unconditional contribution	0.071	1.140***	0.491	0.866**	1.145***	1.395***
	(0.326)	(0.351)	(0.462)	(0.362)	(0.370)	(0.391)
Constant	11.326***	0.518	5.608	4.472*	7.571***	0.786
	(2.427)	(2.642)	(3.595)	(2.661)	(2.706)	(2.958)
Observations	266	266	266	282	282	282
Farmers-High school	4.099**	3.148*	1.677	3.592*	1.025	0.209
	(1.600)	(1.727)	(2.260)	(1.914)	(1.974)	(2.085)
chi2	50.75	93.36	64.88	41.84	25.14	39.37

Note: This table provides the estimation results of individual contribution under different treatments using college students as the base. Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Farmers-High school is the difference between the coefficients of Farmers and the coefficients of High school. The significance level is from LinCom test for null hypothesis Farmers-High school=0.

Observation A2. (Treatments within mechanisms: Contribution). *Higher r or AP induces significantly higher contribution* in most cases for farmers; this effect is weaker for college students; and it is rarely the case for high school students.

Due to potential order effects, we report this result with caution. As **Table 3** shows, farmers' contribution increases as *r* and AP increases under RBM and APM, respectively. However, there is no such consistent pattern for college students and high school students. Regression results in **Table A4** and **Table A5** confirm this observation. Models 1 to 3 and Models 4 to 6 include samples from treatments under APM and RBM, using AP10 and RB0.6 as the base, respectively. Individual contributions of farmers are significantly larger under treatments with higher *r* or *AP* except for the case between RB0.3 and RB0.1. For college students, there is no significant difference in individual contributions under different *AP* values; but the contributions for r=0.1 under RBM were significantly lower than those for r=0.6 and r=0.3. For high school students, individual contributions do not change with r or AP except for the case between RB0.3 and RB0.1.

Table A4. Two-Factor Random Effects Regressions of Individual Contribution: Effect of *AP* and *r*

VARIABLES	(1) College APM Contribution	(2) Farmers APM Contribution	(3) High school APM Contribution	(4) College RBM Contribution	(5) Farmers RBM Contribution	(6) High school RBM Contribution
Value	0.239**	0.143	0.427***	0.281***	0.175	0.370***
	(0.100)	(0.108)	(0.117)	(0.079)	(0.143)	(0.096)
AP12.5	0.291	1.590**	-0.155			
	(0.693)	(0.751)	(0.808)			
AP16.7	0.970	3.530***	0.817			
	(0.693)	(0.751)	(0.808)			
RB0.3				0.000	-2.134**	0.600
				(0.547)	(0.994)	(0.667)
RB0.1				-2.040***	-3.045***	-0.710
				(0.547)	(0.994)	(0.667)
Constant	9.286***	11.280***	2.805	7.081***	11.402***	4.480***
	(1.673)	(1.815)	(1.964)	(1.321)	(2.401)	(1.611)
AP12.5-AP16.7	-0.679	-1.940**	-0.972			
	(0.693)	(0.751)	(0.808)			
RB0.3-RB0.1				2.040***	0.911	1.310**
				(0.547)	(0.994)	(0.667)
chi2	15.65	35.53	23.12	42.63	14.11	53.72
Observations	300	300	300	300	300	300

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. AP12.5-AP16.7 is the difference between the coefficients of AP12.5 and the coefficients of AP16.7. RB0.3-RB0.1 is the difference between the coefficients of RB0.3 and the coefficients of RB0.1. The significance level is from LinCom test for null hypothesis AP12.5-AP16.7=0 (or RB0.3-RB0.1=0).

Table A5. Two-Factor Random Effects Regressions of Individual Contribution (with Demographic Controls): Effect of *AP* and *r*

VARIABLES	(1) College APM Contribution	(2) Farmers APM Contribution	(3) High school APM Contribution	(4) College RBM Contribution	(5) Farmers RBM Contribution	(6) High school RBM Contribution
Value	0.253**	0.145	0.376***	0.261***	0.081	0.329***
	(0.100)	(0.133)	(0.121)	(0.078)	(0.157)	(0.093)
AP12.5	0.220	1.774**	-0.114			
	(0.689)	(0.887)	(0.839)			
AP16.7	0.765	4.165***	1.024			
	(0.689)	(0.887)	(0.839)			
RB0.3				0.011	-2.429**	0.554
				(0.532)	(1.076)	(0.638)
RB0.1				-1.821***	-2.562**	-0.646
				(0.532)	(1.076)	(0.638)
Age	0.243	0.121***	-0.003	-0.025	-0.022	0.118
	(0.343)	(0.042)	(0.676)	(0.076)	(0.049)	(0.522)
Sex	0.155	-0.107	0.129		-0.005	-0.578
	(2.002)	(0.959)	(0.722)		(1.040)	(0.545)
Selfish	-0.043**	0.039**	0.010	-0.019	0.035	-0.040*
	(0.017)	(0.016)	(0.022)	(0.014)	(0.024)	(0.022)
Risk averse	0.037	-0.014	-0.417*	-0.243*	0.351	0.055
	(0.186)	(0.188)	(0.246)	(0.130)	(0.281)	(0.204)
Unconditional contribution	0.724	0.494	0.911**	0.619**	1.177**	1.607***
	(0.451)	(0.387)	(0.384)	(0.291)	(0.549)	(0.291)
Constant	4.233	4.233	2.812	8.165***	7.406*	1.154
	(6.866)	(3.243)	(10.579)	(2.254)	(4.380)	(8.318)
AP12.5-AP16.7	-0.545	-2.391***	-1.138			
	(0.689)	(0.886)	(0.839)			
RB0.3-RB0.1				1.832***	0.133	1.200*
				(0.532)	(1.076)	(0.638)
chi2	15.65	35.53	23.12	42.63	14.11	53.72
Observations	294	228	276	294	258	294

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. AP12.5-AP16.7 is the difference between the coefficients of AP12.5 and the coefficients of AP16.7. RB0.3-RB0.1 is the difference between the coefficients of RB0.3 and the coefficients of RB0.1. The significance level is from LinCom test for null hypothesis AP12.5-AP16.7=0 (or RB0.3-RB0.1=0).

Table A6. Contribution Proportionality

Group	Period	Treatment	*Pro*	Treatment	*Pro*
Farmers	1	RB0.6	0.369	AP10	0.255
Farmers	2	RB0.6	0.295	AP10	0.270
Farmers	1	RB0.3	0.280	AP12.5	0.298
Farmers	2	RB0.3	0.349	AP12.5	0.304
Farmers	1	RB0.1	0.339	AP16.7	0.438
Farmers	2	RB0.1	0.310	AP16.7	0.399
College students	1	RB0.6	0.122	AP10	0.191
College students	2	RB0.6	0.159	AP10	0.184
College students	1	RB0.3	0.153	AP12.5	0.240
College students	2	RB0.3	0.129	AP12.5	0.224
College students	1	RB0.1	0.190	AP16.7	0.365
College students	2	RB0.1	0.123	AP16.7	0.311
High school students	1	RB0.6	0.167	AP10	0.139
High school students	2	RB0.6	0.171	AP10	0.176
High school students	1	RB0.3	0.153	AP12.5	0.204
High school students	2	RB0.3	0.206	AP12.5	0.219
High school students	1	RB0.1	0.185	AP16.7	0.323
High school students	2	RB0.1	0.191	AP16.7	0.312
Average		RBM	0.216	APM	0.269

Table A7. Realized average social surplus and its allocation

Group	Potential maximum Social surplus		Realized Social surplus		Realized Agent surplus		Realized Provider surplus	
	RBM	APM	RBM	APM	RBM	APM	RBM	APM
College	100	100	66.667	100.000	54.411	40.883	12.260	59.120
Farmers	100	100	100.000	100.000	58.689	12.000	41.310	88.000
High school	100	100	83.333	50.000	77.733	105.821	5.600	-55.820
Average	100	100	83.333	83.333	63.611	52.901	19.723	30.433

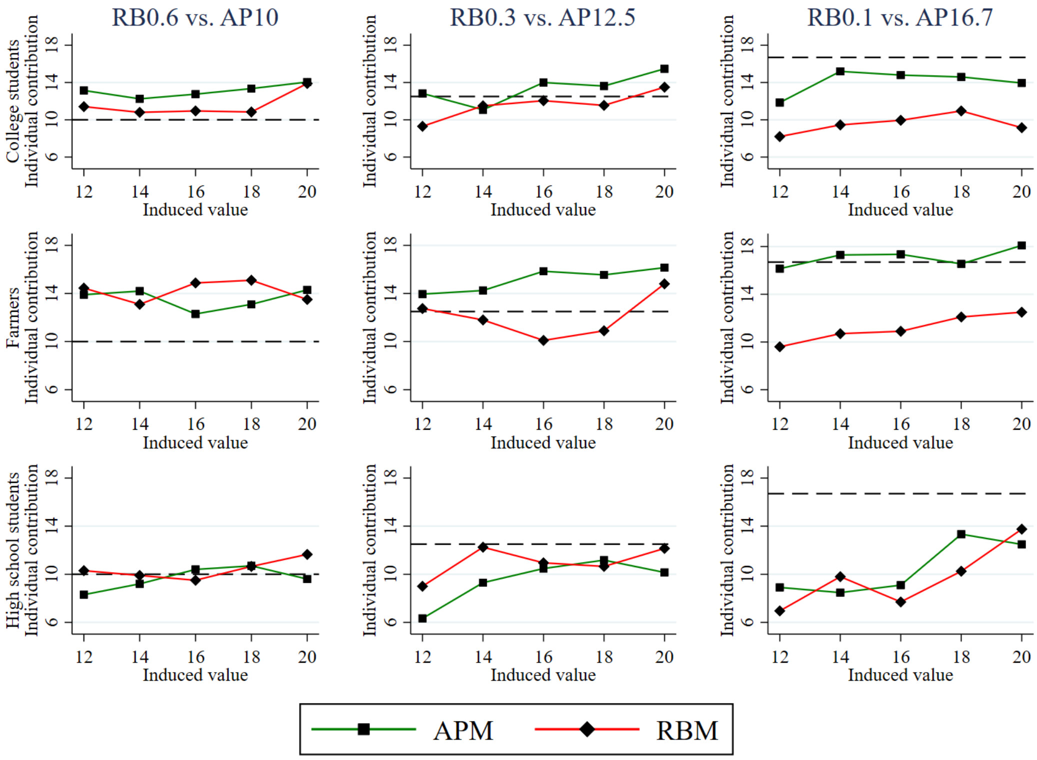

Figure A1. Mean contributions by induced value

Note: The subjects in the first, second and third rows are college students, farmers and high school students, respectively. The first, second and third columns are RB0.6 vs. AP10, RB0.3 vs. AP12.5 and RB0.1 vs AP16.7, respectively. The red line represents RBM and the green line represents APM. The horizontal dashed line represents the value of *AP* for each treatment of APM.

Appendix B

Zubrickas (2014) shows when $r \leq \frac{V}{C} - 1$, RBM only contains pure strategy Nash equilibria in which $G = C$ is, while there is no equilibrium when $r > \frac{V}{C} - 1$.

Proposition 1 (Provision equilibrium under RBM, Zubrickas, 2014). If $r \leq \frac{V}{C} - 1$, any strategy profile $\{g_i\}_{i \in I}$ s.t. $G = C$ with $g_i \leq \frac{1}{1+r} v_i$ for all $i \in I$ is a pure-strategy Nash equilibrium under which the good is provided. Otherwise, there is no equilibrium.

Li et al. (2014) show if there exists a real number v^* and an integer n^* such that $C \leq v^* n^*$ and $v_i < v^*$ for at least n^* agents, then there only exist provision equilibrium outcomes when $AP = v^*$. Otherwise there exists non-provision equilibrium.

Proposition 2 (Provision equilibrium under APM, Li et al, 2023). Any strategy profile $\{g_i\}_{i \in I}$ s.t. $G = C$ is a pure-strategy Nash equilibrium with $AP \in [\frac{C}{N}, C]$ if $g_i \leq max\{v_i - AP, AP\}$ for $v_i \geq AP$ and $g_i \leq v_i$ for $v_i < AP$, for all $i \in I$.

Proposition 3 (Non-provision equilibrium under APM, Li et al, 2023). Any strategy profile $\{g_i\}_{i \in I}$ s.t. $G < C$ is a pure-strategy Nash equilibrium with $AP \in [\frac{C}{N}, C]$ if $g_i \geq AP$ only when $v_i - (C - \sum g_{-i}) \leq AP$ and $g_i < AP$ only when $v_i \leq C - \sum g_{-i} \leq AP$, for all $i \in I$.

Appendix C Behavioral traits in the questionnaire

Selfishness

To measure selfishness, we asked a dictator-game question about how much they wanted to keep for themselves from ¥100 (defined as the variable *Selfish*).

Farmers are the most selfless, consistent with Falk et al. (2013), and there is no significant difference in the degree of selfishness between college students and high school students. On average, farmers, college students and high school students choose to take ¥38.837, ¥47.620 and ¥48.200 of ¥100 in dictator games, respectively (by t-tests: farmers vs. college students: p=0.004; farmers vs. high school students: p=0.002; college students vs. high school students: p=0.397).

Risk attitudes

To measure risk attitudes, we included a question: "Suppose that you've just won a lottery ticket worth ¥1,500. You now have another chance to buy a lottery: a 40 percent chance of winning ¥2,000, and a 60 percent chance of getting nothing. How much of the ¥1,500 would you like to pay for the lottery?" Subjects could choose from options (1) to (7) (defined as the variable *Risk averse*), with a greater number indicating more risk aversion. The seven options are "(1) more than ¥1000; (2) ¥1000; (3) ¥800; (4) ¥600; (5) ¥400; (6) ¥200; (7) ¥0".

Farmers are the least risk averse. To be specific, farmers (3.920) are less risk averse than college students (4.374), and high school students (4.673) are the most risk averse (by t-tests: farmers vs. college students: p=0.048; farmers vs. high school students: p=0.003; college students vs. high school students: p=0.095).

Unconditional contributions

In the questionnaire, we also ask about their propensity to contribute to benefit themselves and others, even without knowing whether others contribute or not. They can choose any integer from 1 to 5, with 1 representing "strongly agree" and 5 representing "strongly disagree". We subtract their answer from 5 to derive the variable *Unconditional contribution*, with a greater number indicating greater willingness to contribute even without knowing others' contributions.

Farmers have the highest propensity for unconditional contribution. The average Unconditional contribution of the farmers, college students and high school students are 2.947, 2.810 and 2.410, respectively (by t-tests: farmers vs. college students: p=0.124; college students vs. high school students: p<0.001).

Income

For college students and high school students, we ask about their disposal income each month for living expenses (excluding tuition and accommodation fees) and their parents' approximate total monthly income before taxes (from all sources). The average annual disposable incomes are ¥9,630 for college students, and ¥4,324 for high school students. The average annual household gross incomes are ¥60,998 for college students, and ¥149,019 for high school students.

For farmers, we ask about their household total income (¥) in 2015 from agriculture (both crops and land) and sources other than agriculture, respectively. On average, the annual household income is ¥106,340 composed of ¥61,813 of farm income and ¥44,527 of non-farm income.