Journal of Behavioral and Experimental Economics 122 (2026) 102579

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Economics

journal homepage: www.elsevier.com/locate/jbee

Collective agreements and social norms in impure public goods provision: Experimental evidence from farmers and foresters

Lukas Bonar Nainggolan [a,*], Alfons Oude Lansink [a], Jens Rommel [b], Julia Höhler [a]

[a] Business Economics Group, Department of Social Sciences, Wageningen University & Research (WUR), Hollandseweg 1, Building 201, Wageningen 6706 KN, the Netherlands

[b] Department of Economics, Swedish University of Agricultural Sciences, 75651 Ultuna, Uppsala, Sweden

ARTICLE INFO

JEL classification:
C93
D70
D81
Q13

Keywords:
Artefactual field experiment
Impure public goods
Focal point
Cooperative
Descriptive norm

ABSTRACT

Agricultural and forestry production are inherently connected to the provision of impure public goods, yet public good provision generally remains below socially optimal levels. One promising approach to increase provision are social norms and non-binding collective agreements facilitated through cooperatives, although existing evidence on their effectiveness is mixed. We conducted a threshold public goods experiment with 141 farmers and foresters from Greece and Italy to examine the effectiveness of collective agreements and the relationship between social norms and cooperation. Our results show that non-binding collective agreements significantly increase individual contributions. We contribute to the literature by showing that not only average social norms, but also their distribution, are correlated with individual contributions, with greater heterogeneity within groups associated with lower contributions. Overall, focal points are shaped by expectations of peers' contributions. Two key implications follow: cooperatives can effectively facilitate collective action, and managing heterogeneity among farmers and foresters is essential for sustaining cooperation.

1. Introduction

Farmers and foresters (hereafter "primary producers") often generate outputs that yield not only private returns but also non-excludable benefits for society, known as impure public goods (Cooper et al., 2009; Palm-Forster & Messer, 2021; Westhoek et al., 2013). Sustainable agricultural practices can increase crop yields and farm profits while also enhancing food security, landscapes, and biodiversity (Palm-Forster & Messer, 2021). Similarly, bioresources provision for bio-based businesses generate internal returns alongside positive spillovers for rural economies (Schmidt et al., 2012; Wesseler & Von Braun, 2017; Zilberman et al., 2018). Several experimental studies find that primary producers often exhibit pro-social preferences and demonstrate willingness to contribute to public goods (Bouma et al., 2020; Fitzsimmons et al., 2025; Rellensmann et al., 2025; Rommel et al., 2023). Yet in practice, the supply of impure public goods from the primary sector remains below socially optimal levels (Westhoek et al., 2013). Research has rarely examined how farmers cooperate in providing impure public goods (Freundt & Lange, 2021; Palm-Forster & Messer, 2021). Accordingly, there is a need to better understand primary producers' contributions to the impure public goods provision. Such research can help move provision closer to socially optimal levels, particularly in areas of growing policy interest such as sustainable agriculture and bioeconomy.

This paper's first objective is to examine whether setting non-binding collective agreements can effectively improve the provision of impure public goods. Such agreements are often established within organizations such as cooperatives, which are characterized by collective action and low levels of enforcement (Bijman & Iliopoulos, 2014; Mori, 2014). Cooperatives are well established in primary sectors and operate under democratic and voluntary principles. This collective approach is more effective than relying on individual actions taken in isolation, as cooperatives can increase bargaining power or realize economies of scale (Valentinov, 2007). The absence of formal enforcement of mutual agreements is particularly important, because enforcement attempts may crowd out cooperative behavior by shifting individuals' attention toward avoiding sanctions rather than sustaining collective outcomes (Cardenas et al., 2000; MacColl et al., 2018). Alternative mechanisms, such as peer punishment, have proven ineffective for sustaining cooperation (Almeida, 2023). Taken together, cooperatives provide a governance mechanism for primary producers to establish non-binding agreements that support the provision of impure public goods.

Earlier laboratory and artefactual field experiments in public goods

* Corresponding author.
E-mail address: lukas.nainggolan@wur.nl (L.B. Nainggolan).

https://doi.org/10.1016/j.socec.2026.102579
Received 22 September 2025; Received in revised form 16 April 2026; Accepted 24 April 2026
Available online 27 April 2026

games report mixed findings on the effectiveness of non-binding collective agreements. These agreements typically establish minimum contribution levels (Dannenberg, 2016). Several studies highlight positive effects of non-binding collective agreements on cooperation (Dal Bó et al., 2010; Dannenberg et al., 2014; Gallier et al., 2017; Isaac & Norton, 2013; Kroll et al., 2007). In contrast, more recent work suggests that such agreements may crowd out overall contributions, as higher contributors scale back their contributions (Abraham et al., 2025; Barreiro-Hurle et al., 2023; Kocher et al., 2016). Compared to agreements set by experimenters, collective agreements often fail to increase contributions (Bouma et al., 2020; Martinsson & Persson, 2019). Moreover, other studies find that collective agreements succeed only when they are binding (Alt et al., 2023; Kroll et al., 2007). These conflicting findings leave an open question on the effectiveness of non-binding collective agreements.

We argue that non-binding collective agreements can be effective in improving the provision of impure public goods. We draw on focal point theory to support this argument (Janssen, 2001; McAdams, 2000; Sugden, 1995). A focal point is a decision on which individuals coordinate because they expect others to do the same. Without an agreement, primary producers tend to perceive others as unlikely to cooperate, which leads to a focal point of low contributions (Angioloni & Cerroni, 2025; Fitzsimmons et al., 2025; Gijselinckx & Bussels, 2014; Ouvrard & Reynaud, 2026). Setting an agreement on a specific contribution level raises the focal point. Moreover, setting the agreement through voting further strengthens the focal point by signaling shared expectations and mutual commitment, thereby facilitating coordination (Feige, 2017; Gürdal et al., 2024; Katuščák & Miklánek, 2023; Szekely et al., 2021). Consistent with focal point theory, individuals often follow such agreements even in the absence of formal enforcement (McAdams, 2000). To demonstrate this, our experimental design allows participants to vote on a minimum contribution level, with the median vote selected as the minimum contribution. Selecting the median vote balances the aspirations of higher and lower contributors, setting a higher focal point and leading to higher contributions (Ching, 1997; Moulin, 1980). This approach notably differs from studies that find a crowding-out effect of agreements (e.g., Abraham et al., 2025; Bouma et al., 2020), where the focal point in the experiment with agreement becomes lower, for example when the lowest proposed contribution is selected or when the minimum contribution level is predefined in the voting options.

This paper's second objective is to examine the role of social norms on cooperation, with particular attention to descriptive norms, defined as individuals' beliefs or observations about what others do, and injunctive norms, defined as what individuals believe one should do (Cialdini et al., 1991; Dannenberg et al., 2024; Eriksson et al., 2015; Eriksson & Strimling, 2015). The role of social norms in impure public goods provision is closely linked to focal point theory, as individuals' focal points are shaped by their expectations of others' behavior. The literature generally finds that social norms strengthen pro-social preferences (Hensel et al., 2022; Ostrom, 2010; te Velde & Louis, 2022), a pattern that is also observed in the adoption of sustainable agricultural practices (Barreiro-Hurle & Rommel, 2025; Dessart et al., 2019). However, interventions that communicate others' behavior produced mixed results, suggesting that a more nuanced understanding of social norms is needed (El Benni et al., 2025; Howley & Ocean, 2022). Recent studies further indicate that not only the average of norms matters, but also how behaviors underlying the norm are distributed (Dimant et al., 2025; Schmidt, 2025). Although not directly observed in earlier studies, greater dispersion in descriptive norms reduces contributions by increasing uncertainty about appropriate behavior and eroding trust that others will contribute. This dynamic is also noted in the cooperative literature, where heterogeneity among primary producers is seen as a challenge to sustaining cooperation (Höhler & Kühl, 2018).

To address our research objectives, we conduct a public goods game experiment with primary producers, adapting the basic game to incorporate internal returns and risk in the public goods outcome (see similar adaptation in Freundt & Lange, 2021). Our main contributions to the literature are twofold. First, we identify the effectiveness of non-binding collective agreements among primary producers in the provision of impure public goods, while simultaneously reassessing recent laboratory experimental evidence suggesting that collective agreements may not be effective. Second, we examine the association between the distribution of descriptive norms and cooperation among primary producers, thereby extending the broader discussion on the effects of heterogeneity in cooperatives. Understanding how norms affect behavior has important implications, as they may help explain the effectiveness of behavioral public policy (El Benni et al., 2025; Howley & Ocean, 2022; Raineau et al., 2025). Overall, these contributions extend the application of public goods games to non-standard agricultural subjects (Bouma et al., 2020; Rellensmann et al., 2025; Rommel et al., 2023). By conducting an artefactual field experiment with non-standard subjects (Harrison & List, 2004), our study complements the laboratory evidence (Rellensmann & Thomas, 2026) and can serve as a reference for designing behaviorally relevant policies for farmers and foresters (Grüner et al., 2022; Peth & Mußhoff, 2020), particularly in coordination contexts.

2. Experimental design

We use a threshold public goods game as the overall experimental framework (Cadsby & Maynes, 1999; Isaac et al., 1989), in which the public good is provided only if total contributions reach or exceed a specific threshold. The motivation is that most public goods in the primary sector are realized only when collective investments are sufficiently large (Cooper et al., 2009).

We frame the experiment around the provision of bioresources, which captures the characteristics of impure public goods. Although the terminology may be new to some primary producers, contextualizing the experiment can enhance the relevance of recommendations for new policy initiatives (Rommel et al., 2019). The experimental design follows standard parameters from the public goods game literature (Croson & Marks, 2000). We draw insights from a study that models bioresource provision using a threshold public goods game (Luo & Miller, 2017).

Participants took part in the experiment in groups of 8–12 primary producers. The large group size was chosen to capture strategic uncertainty about others' cooperation in sizable groups (Angioloni & Cerroni, 2025; Schuch et al., 2025). Each participant i managed 50 tons of bioresources (E_{ir}), which could be distributed between sales to the municipality and to the biorefinery, with the latter representing contributions. Let M_{ir} represent the tons of bioresources sold to the municipality by participant i in round r, B_{ir} represent the tons sold to the biorefinery. The profit from selling to the municipality, denoted as π_{Mir}, for participant i in round r is given by:

$$\boldsymbol{\pi_{Mir}} = 100*\boldsymbol{M_{ir}}. \tag{1}$$

Selling to the municipality yields a fixed internal return of 100 EUR per ton. Meanwhile, selling to the biorefinery involves risk: a 50% chance of an internal return of 350 EUR or a 50% chance of losing 50 EUR per ton. The profit or loss from selling to the biorefinery, denoted as π_{Bir}, for participant i in round r, is defined as:

$$\boldsymbol{\pi_{Bir}} = \begin{cases} 350 \ \times \boldsymbol{B_{ir}} \ if \ high - price \ event \\ -50 \ \times \boldsymbol{B_{ir}} \ if \ low - price \ event. \end{cases} \tag{2}$$

The random price event applies uniformly across all participants within a group, and all participants were informed of this mechanism. Despite the risk, the expected internal return from selling to the biorefinery is higher.

The total group contribution to the biorefinery in round r, denoted as B_r, is calculated as:

$$\boldsymbol{B_r} = \boldsymbol{B_{ir}} + \sum_{j=1}^{n-1} \boldsymbol{B_{jr}}, \tag{3}$$

where $\sum_{j=1}^{n-1} B_{jr}$ represents the sums over contributions of all other participants $j = 1, \ \ldots, \ N-1$ for whom $j \neq i$ in the group in round r. The threshold T was set to 30% of the group's total bioresources. If the threshold was met, each participant received internal returns from selling to both the municipality and the biorefinery, plus an additional external return. The external return is calculated as the total group contribution to the biorefinery (B_r) multiplied by the marginal benefit, where the marginal benefit is defined as $\frac{E}{N}$, with $E = 150$ EUR and N representing the group size. The total available bioresources per group ranged from 400 to 600 tons, meaning the threshold T could range from 120 to 180 tons.

If the threshold was not achieved, participants did not earn profit from selling to the biorefinery and instead incurred a cost. The cost for participant i in round r, denoted as C_{ir}, is defined as:

$$\boldsymbol{C_{ir}} = 100 * \boldsymbol{B_{ir}}, \tag{4}$$

where each ton contributed to the biorefinery results in a loss of 100 EUR.

Therefore, the total payoff for participant i in round r (see explicit function in Appendix A.1), denoted as π_{ir}, is:

$$\boldsymbol{\pi_{ir}} = \begin{cases} \boldsymbol{\pi_{Mir}} + \boldsymbol{\pi_{Bir}} + \boldsymbol{B_r}\left(\frac{\boldsymbol{E}}{\boldsymbol{N}}\right) \ \text{if} \ \boldsymbol{B_r} \geq T \\ \boldsymbol{\pi_{Mir}} - \boldsymbol{C_{ir}} \ \text{if} \ \boldsymbol{B_r} < T \end{cases}, \tag{5}$$

where $B_r\left(\frac{E}{N}\right)$ represents the external return equally shared among participants when the threshold was achieved. In this experiment, the public goods dilemma arose from two features. First, the threshold introduces a coordination problem, as it cannot be reached through individual effort alone. Second, once the threshold is met, participants face a social dilemma akin to a linear public goods game, in which they must trade-off between contributing to maximize collective returns and minimizing contributions to increase individual payoffs. Additionally, because returns from selling to the biorefinery were risky, with a 50% chance of loss, participants had further incentives to reduce their contributions.

As maintaining identical group sizes across sessions was difficult, we allowed flexibility of 8-12 respondents to keep sizes approximately similar and preserve comparable group dynamics. Participants were informed of their group size at the beginning of the experiment. To control group size effects, we adjusted both the nominal threshold and the marginal external return (Isaac et al., 1994).

Participants did the experiments repeatedly in ten rounds. In the first five rounds, referred to as the Baseline, all participants decided on how much to contribute without an agreement. After submitting their individual decisions, they saw the contributions and payoffs of others in their group. In the following five rounds, participants were assigned to one of two treatments to assess within-subject differences.

The main treatment to address the research objective is the non-binding collective agreement, referred to as the Cooperative treatment. Participants collectively set a minimum contribution through voting. Each participant proposed a percentage of the group's total contribution. The median vote was then selected, converted into a nominal value as the total minimum contribution (${B_r}^{min}$), and divided equally to establish the individual minimum contribution (${B_{ir}}^{min}$). This minimum contribution could be lower than, equal to, or higher than the threshold. Participants were informed of the voting outcome with the message: "Half of the participants voted at least for this amount." Importantly, participants remained free to contribute less or more than the agreed amount, although they received a reminder if they initially indicated a contribution below the minimum contribution.

We also implemented a treatment where the agreement equals the threshold level, referred to as the Contract treatment. Participants were informed that the biorefinery owner suggested a minimum contribution. The minimum contribution was identical for all participants and set so that if everyone contributed the minimum, the group total would equal the threshold, that is, ${B_{ir}}^{min} = \frac{T}{N} = 15$. Participants also remained free to contribute and received a reminder.

Table 1 summarizes the differences across experimental treatments. We identify the causal effect of collective agreements by comparing the Cooperative treatment with the Baseline, and with the Contract treatment, in which the threshold level is framed as a minimum contribution. Comparing the Cooperative and Contract treatments controls for the effect of agreement framing.

We elicited descriptive norms using three variables, and injunctive norms using one variable. (see Table 2). First, we measured *Beliefs*, defined as participants' expectations about how many others in their group will contribute. Following the self-report method of Crosetto & Haan (2023), participants estimated the number of group members who would contribute at each amount of bioresources (0–50 tons), with the results presented in a distribution graph. Second, we measured *Norms*, which represents injunctive norms, by asking participants what level of contribution they considered appropriate under the given scenario. Both elicitation tasks were conducted before participants made their contributions in the first and sixth rounds, allowing for a comparison between Baseline and Treatment. For simplicity, the accuracy of beliefs was not incentivized. Third, the *Voting* outcome in the Cooperative treatment in each round was operationalized as one of the descriptive norm variables, as it reflects the group's contribution aspirations and signals whether others are likely to contribute (Oechssler et al., 2022). We also used contributions from the previous round (*Past Contribution*) as a measure of descriptive norms, since they capture actual behavior of others. Together, these four variables allowed us to examine the correlation between social norms and individual contribution.

In the Cooperative treatment, we introduced a sub-treatment: half of the participants observed the individual votes, while the other half viewed only the median vote. This enabled us to test whether the visibility of group heterogeneity influences cooperative behavior. Because some groups have an odd number of participants, the two subgroups could not always be split exactly evenly.

We implemented the experiment with cereal, wine, and horticulture farmers, as well as foresters, in Greece and Italy. These sectors are central to an EU Horizon project that aims to create value in bio-based businesses and align with policy priorities in both countries to strengthen impure public goods provision (Scheffler & Wiegmann, 2024). We targeted at least 70 participants per treatment based on power calculations from related studies (Angioloni & Cerroni, 2025; Rommel, Schulze, et al., 2023) and used convenience sampling to achieve this target (Lakens, 2022). Approximately half of the sample was recruited through the EU horizon project between February and March 2025, resulting in 73 participants from Italy and Greece. These participants were invited to in-person sessions hosted at project partners' facilities, moderated locally in the native language, while we monitored the process remotely. To complete the sample, we partnered with a market research company, which recruited an additional 80 participants

Table 1
Summary of the experimental treatments.

Rounds	Treatment group	
	Contract	Cooperative
1-5	No minimum contribution	No minimum contribution
6-10	Non-binding minimum contribution Suggested by biorefinery ${B_{ir}}^{min} = 15$	Non-binding minimum contribution Agreed upon by voting $0 \leq {B_{ir}}^{min} \leq 50$

Table 2
Summary of social norm variables.

Variables	Definition	Elicitation method
(1) Belief	Expectations about others' contributions	Number of group members for each contribution amount (self-reported)
(2) Norm	Perceived appropriate individual contribution	Numeric amount (self-reported)
(3) Voting	Aspiration for total group contribution	Decision in voting stage of Cooperative treatment (observed)
(a) Seeing the distribution	Whether participants see the distribution of voting or not	Randomly assigned
(4) Past Contributions	Observable behavioral norms	Decision in previous round (observed)

from Greece for sessions conducted in July 2025. We conducted the second wave only in Greece because the first wave yielded fewer respondents there, and running the second wave in a single country was more feasible given time and budget constraints. These sessions were held online, with individuals participating separately via Zoom and the sessions were moderated by a person speaking the local language. Participants recruited through project partners received a randomized performance-based payment (10 EUR + $\pi_{ir}/500$), with possible rewards between 0 and 120 EUR. Participants recruited through the market research company received both a show-up fee (50 EUR) and the same performance-based payment.

Participants in both the online and in-person groups completed the experiment using the oTree software platform[1] (Chen et al., 2016). The study received ethical approval from the relevant institutional review board. At the beginning of each session, participants received the experimental instructions, which included definitions of key terms used in the contextualized game (e.g., bioresources, biorefinery, bioeconomy). They were then asked to sign an informed consent form. To ensure participants understood the procedure, they were asked a series of questions. Correct answers were shown after each response to create a more participant-friendly experience and to avoid frustration or the feeling of being tested. We provided a simulation tool to help participants understand the potential payoffs from their decisions, so they did not have to compute payoffs themselves. At the end of the experiment, participants completed a brief questionnaire to collect data on their occupational status, education, gender, sector, country, age, risk attitudes, willingness to cooperate (both measured on a 11-point Likert scale), as well as their cooperative membership status. Full instructions and the questionnaire are available in Supplementary File C.

3. Theoretical predictions and hypotheses

The experiment and key hypotheses were pre-registered in the Open Science Framework (https://bit.ly/tpgg_bio). For transparency, and in line with other studies in Agricultural Economics (Schaak et al., 2024), we report in Table B.1 any analyses that follow, deviate from, or exceed the pre-registered analysis plan (Dreber, 2025).

The game features several optima, illustrating how individuals choose their contributions optimally based on best responses to their expectations[2] about other group members' contributions (Cadsby & Maynes, 1999; Schuch et al., 2025). Each participant i forms an expectation ($\widehat{F_{ir}}$) about the total contribution of other group members ($\sum_{j=1}^{n-1} B_{jr}$). This expectation is central to determine the individual best-response, which follows a three-regime function as specified in Eq. (6). First, if individuals expect total contributions by others to be too low to reach the threshold, it is optimal to contribute zero. Second, if they expect the threshold to be reached with some contribution from their endowment, it is optimal to contribute exactly the amount needed to bring total contributions to the threshold. Third, unlike non-continuous threshold games where overcontribution is inefficient, it is optimal to contribute at a level that maximizes cumulative prospect value[3] ($V(\pi_{ir})$) when others' contributions exceed the threshold. In this case, cumulative prospect value is maximized at moderate contribution levels, as the relationship between contributions and cumulative prospect value exhibits an inverted U-shape[4]. The formal definition of the optimal individual contribution is given by:

$$\boldsymbol{B_{ir}}^* = \begin{cases} 0 \text{ if } T - \widehat{\boldsymbol{F_{ir}}} > \boldsymbol{E_{ir}} \\ T - \widehat{\boldsymbol{F_{ir}}} \text{ if } 0 < T - \widehat{\boldsymbol{F_{ir}}} \leq \boldsymbol{E_{ir}} \\ \text{argmax}_{B_{ir}}\ V(\boldsymbol{\pi_{ir}}) \text{ if } T - \widehat{\boldsymbol{F_{ir}}} \leq 0 \end{cases}, \quad (6)$$

This best-response function shows that the focal point of the game depends critically on individual's expectations about others' contributions. Using backward induction under standard self-interested preferences, this threshold public goods game admits multiple Nash equilibria. First, zero contributions constitute an equilibrium. Second, any combination of contributions that exactly meets the threshold also forms an equilibrium. For aggregate contributions above the threshold, the game becomes a social dilemma and follows the equilibria of a linear voluntary contributions mechanism, in which equilibrium contributions fall short of the social optimum.

Primary producers often hold pessimistic expectations about others' willingness to cooperate (Gijselinckx & Bussels, 2014; Koutsou et al., 2014; Marshall, 2004; Stallman & James Jr, 2017). As a result, the relevant condition corresponds to the first regime in Eq. (6), implying that the best response in the Baseline is, on average, zero contribution ($B_{ir}^* = 0$). This leads to coordination failure, where the threshold is not reached and no external return is generated. Framing the threshold as an agreement ('minimum contribution') in the Contract treatment strengthens the threshold as a focal point. Individuals expect others to contribute exactly at the minimum contribution and, consequently, coordinate on symmetric contributions at T/N, corresponding to the second regime in Eq. (6). There is no incentive to contribute beyond the minimum contribution, as doing so yields a lower prospect value than that obtained by others (see Table A.1). Hence, contributions in the Contract treatment are higher than in the Baseline, but remain concentrated at the threshold level.

The Cooperative treatment resolves coordination problems. While primary producers often underestimate others' willingness to cooperate, they typically hold strong pro-social preferences (Bouma et al., 2020; Rommel, Schulze, et al., 2023). In this context, voting encourages individuals to propose contribution levels close to the social optimum (Dannenberg et al., 2014)[5]. There is little incentive to vote for a lower amount, as proposing a higher level remains individually beneficial even if others vote lower, since it increases the likelihood of raising the median vote. Even if some participants propose very low values, the final selected level reflects the choice supported by at least half of the

[1] The oTree code is available at https://github.com/lukasnainggolan/tpg_bioecon.

[2] While previous literature often uses the term beliefs (Schuch et al., 2025), we use the term expectations to distinguish this concept from our variable of *Beliefs* in descriptive norms.

[3] We evaluate payoffs using cumulative prospect theory (CPT), computing cumulative prospect values that incorporate risk and loss aversion to account for negative payoffs (Kahneman & Tversky, 1979). The explanation and derivation of the cumulative prospect values are available in Appendix A.2.

[4] See Supplementary File B for the Excel file containing the cumulative prospect values for each individual contribution, conditional on the total contributions of other group members.

[5] Proposing a higher vote also maximizes individual cumulative prospect value; because the minimum contribution anchors expectations of symmetric contributions at that level, it is rational to propose the highest possible value (see Table A.2).

participants. Consequently, we expect the collectively determined minimum contribution to exceed the threshold level. The individual best response is to contribute symmetrically at the minimum contribution level, analogous to the second regime in Eq. (6), except that T now represents the collective minimum contribution $(B_r{}^{min})$. Because the minimum contribution is determined collectively and, in cooperative settings, individuals' behavior is less driven by self-interest and increasingly influenced by factors such as social preferences and fairness (Fehr & Schmidt, 1999, 2000; MacColl et al., 2018), incentives to seek higher payoffs than others by lowering contributions are reduced. The focal point therefore shifts toward symmetric contributions at the minimum contribution level that exceeds the threshold. We therefore hypothesize that contributions in the Cooperative treatment are higher than in both the Baseline and the Contract treatments.

To summarize, our pre-registered hypotheses are as follows:

Hypothesis 1. Average individual contributions in the Contract treatment are higher than in the Baseline.

Hypothesis 2. Average individual contributions in the Cooperative treatment are higher than in both the Baseline and the Contract treatment.

We pre-registered the analysis of social norms as exploratory. Norms shape individuals' expectations about others' contributions $(\widehat{F_{ir}})$. Based on prior literature, we formulate two hypotheses. First, higher average descriptive and injunctive norms are associated with higher individual contributions, as they raise expectations about others' contributions. This relationship is consistent with evidence showing that individuals behave as conditional cooperators and tend to conform to social norms (Defrancesco et al., 2008; Dessart et al., 2019; Fischbacher et al., 2001; Kurzban & DeScioli, 2008; te Velde & Louis, 2022). Second, greater distribution in descriptive norms is expected to be negatively associated with individual contributions, as it lowers expectation about others' contribution. This expectation is based on evidence that greater distribution in norms, measured by their standard deviation, weakens the positive effect of the average norm on individual contributions (Schmidt, 2025). We test these hypotheses by directly relating our descriptive norm measures (see Table 2 for operationalization) to individual contributions. Our hypotheses are summarized as follows.

Hypothesis 3. The mean of *Belief* is positively correlated with contributions, while its standard deviation is negatively correlated.

Hypothesis 4. *Norm* is positively correlated with contributions.

Hypothesis 5a. The median of *Voting* is positively correlated with contributions, while its standard deviation is negatively correlated.

Hypothesis 5b. Seeing the distribution of *Voting* is negatively correlated with contributions.

Hypothesis 6. The mean of *Past Contributions* is positively correlated with contributions, while its standard deviation is negatively correlated.

We argue that the repeated interactions in our design allow the results to align more closely with our hypotheses. To test our main hypotheses (H1 and H2), we pre-registered non-parametric pairwise comparisons. Within-subject analyses compared mean individual contributions between the Baseline and each Treatment, while between-subject analyses compared mean contributions between the Cooperative and Contract treatments. For the exploratory analysis, we also examined the treatment effects on individual contributions using Tobit regressions, which account for the censored nature of contributions bounded by minimum and maximum limits (e.g., Billinger & Rosenbaum, 2023; Isaak et al., 2022). We applied a difference-in-differences (DID) specification in both non-parametric analysis and Tobit regression to compare the effect of Cooperative treatment relative to the Contract treatment, allowing us to control for agreement framing and other unobserved differences between treatment groups (Leyens et al., 2026). To test robustness, we estimated regressions with and without covariates, including gender, age, education, country, occupational status, risk attitude, willingness to cooperate, and membership in cooperatives. We also used Tobit regressions to analyze the correlation between contributions and our four descriptive norm variables. Both non-parametric and parametric analyses cluster standard errors at the group level to account for correlation in individual contributions within groups arising from repeated interactions and feedback in the experiment. We calculated both the mean and standard deviation of each variable of descriptive norms, except for *Norms*, which were elicited as single numeric values and therefore have no standard deviation.

4. Results

4.1. Descriptive statistics

A total of 153 farmers and foresters joined our experiment[6]. One session (12 participants) was excluded from the analysis because oTree generated only low-price events. Based on our observations, after the fifth or sixth round participants in this session came to believe that prices would remain low until the end of the experiment. These outcomes represented outliers, as the participants faced a different situation from the rest of the sample. Given the small sample size, we excluded this session to avoid bias in the main results. However, we also conducted robustness checks including this session to verify our findings. The final sample consisted of 141 participants: 70 in the Cooperative treatment and 71 in the Contract treatment.

Table 3 presents descriptive statistics of the participants by country. Compared to the broader primary producer population in Greece and Italy, our sample of producers is younger (Gittins et al., 2025; Licciardo et al., 2023). It is disproportionately male, with most participants having at least a high school education, and the majority identifying as full-time or part-time farmers or foresters. About 40% are foresters and 60% farmers, most of them in the cereal sector. Participants report higher risk-seeking attitudes than those typically found among European primary producers, who are often described as risk-averse (Iyer et al., 2020). They also show greater willingness to cooperate compared to

Table 3
Descriptive statistics of the sample (n=141) by country.

Variables	Mean	SD	Min	Max
Greece (n=96)				
Age (in years)	43.82	10.57	18	72
Male	0.7	-	0	1
At least high school education	0.78	-	0	1
Farm-forest owner-operator	0.91	-	0	1
Forester	0.20	-	0	1
Risk attitude	7.25	1.66	1	10
Willingness to cooperate	7.88	1.86	1	10
Member of cooperatives	0.38	-	0	1
Italy (n=45)				
Age (in years)	39.67	12.85	18	72
Male	1	-	0	1
At least high school education	0.74	-	0	1
Farm-forest owner-operator	0.56	-	0	1
Forester	0.89	-	0	1
Risk attitude	6.70	1.72	1	10
Willingness to cooperate	7.09	1.93	1	10
Member of cooperatives	0.27	-	0	1

[6] The data and code are available in Supplementary File A1-A3.

other primary producers in previous studies (Dourian, 2021; Koutsou et al., 2014). Cooperative membership in our sample is broadly consistent with national averages (Cooperatives Europe, 2016).

4.2. Treatment effects on contributions

Fig. 1 presents the average individual contributions per round, with rounds 1-5 representing the Baseline and rounds 6-10 the Treatment. In the Baseline of the Contract treatment, average contributions were 29.92 tons, corresponding to a 59.84% success rate, i.e. the share of contributions relative to the group's total amount of bioresources. In the Baseline of Cooperative treatment, average contributions were 29.75 tons, or a 59.50% success rate. The difference between treatment groups in the Baseline was not statistically significant ($p_{MW} = 0.946; MW = Mann - Whitney\ U\ test$), indicating the success of randomization, as participants in the two groups behaved similarly prior to the treatment.

In the Contract treatment, the average contribution in the sixth round dropped slightly, indicating a crowding-out effect, i.e. participants with higher contributions reduced their contributions. However, the repeated-round design allowed participants to recalibrate. On average, contributions in the Contract treatment rose slightly above the Baseline, reaching 30.61 tons (61.21% success rate), but the difference was not statistically significant ($p_{WSR} = 0.361; WSR : Wilcoxon\ signed - rank\ test$). Contribution variance was somewhat lower, suggesting greater convergence within groups.

In contrast, average contributions in the Cooperative treatment increased from the sixth round onward and remained higher through round ten. The average contribution reached 33.16 tons (66.31% success rate), with reduced variance, indicating convergence. This represented a 10% increase relative to the Baseline and was statistically significant ($p_{WSR} = 0.049$). The non-parametric DID shows no significant difference in average contribution changes between the treatment rounds and the baseline across the Cooperative and Contract treatments ($p_{WSR} = 0.409$), likely due to missing data, as one participant has only a single observation. However, we show later that the regression with the DID specification indicates higher contributions in the Cooperative treatment.Fig. 2.

We analyzed changes in the distribution of contributions across different cutoff values to identify the presence of a crowding-out effect (see Fig. 3 and Fig. 4). In both Cooperative and Contract treatments, the

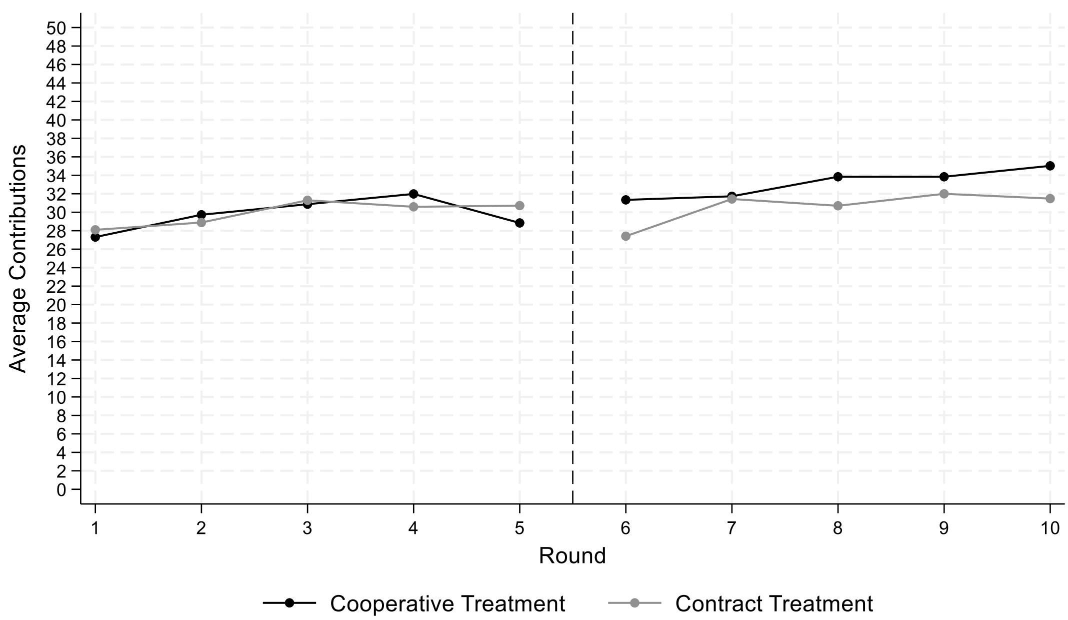

Fig. 1. Average contributions of treatment groups.

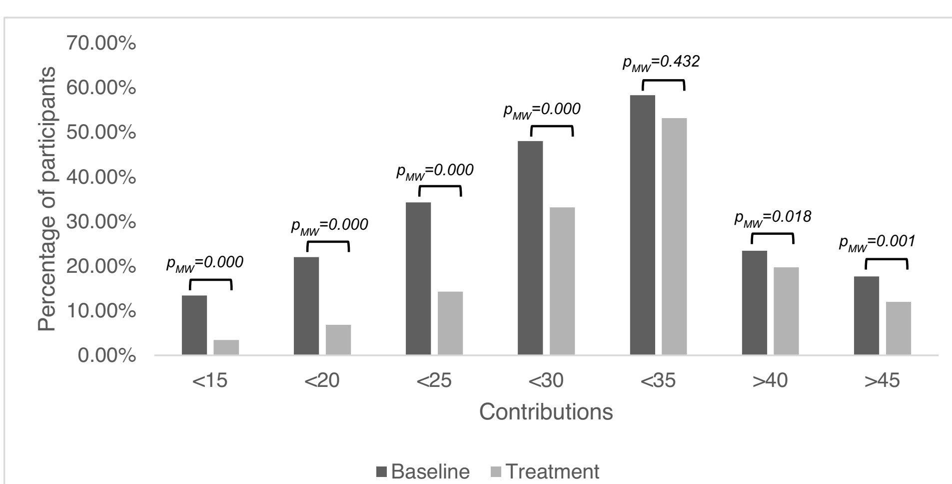

Fig. 2. Distribution of contributions for different cutoff values in Cooperative treatment.

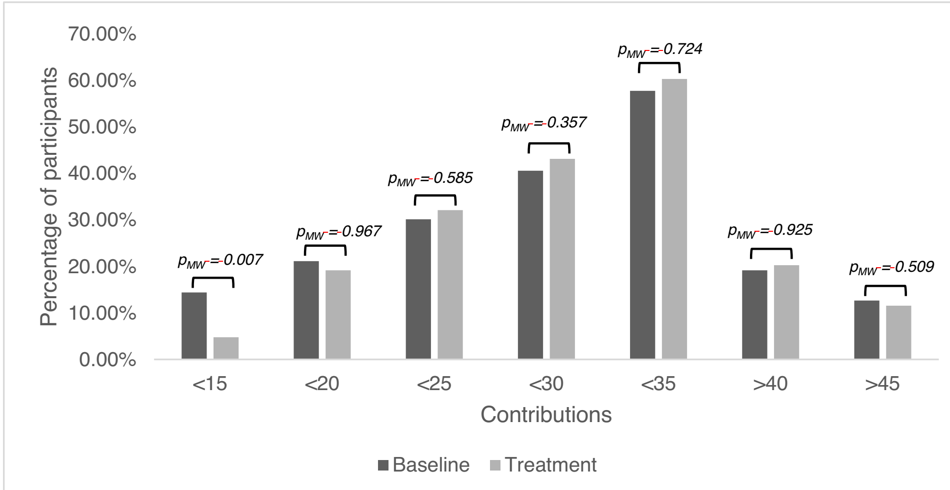

Fig. 3. Distribution of contributions for different cutoff values in Contract treatment.

share of participants contributing below 15 tons fell significantly after treatment, indicating that both agreements reduced free-riding. In the Cooperative treatment, this upward shift continued up to the 30-ton cutoff, suggesting that even moderate contributors were encouraged. By contrast, in the Contract treatment, the effect disappeared beyond the 20-ton cutoff. Contributors above 40 or 45 tons declined slightly in the Cooperative treatment, suggesting convergence toward the minimum contribution level. Overall, both treatments reduced free-riding, particularly in the Cooperative treatment, which also raised contributions among moderate contributors, while neither treatment substantially discouraged higher contributors, showing limited evidence of crowding-out.

Table 4 presents the results of the Tobit regression with standard errors clustered at the participant-group level. Regression (1) shows that the Cooperative treatment has a statistically significant positive effect on contributions relative to the Baseline. This effect remains robust when control variables were added in Regression (2). By contrast, Regression (3) shows that the Contract treatment has no statistically significant effect on contributions, with similar results after including control variables in Regression (4). Table 5 shows that, under a DID specification using a Tobit regression, the Cooperative treatment generated significantly larger contributions than the Contract treatment. We controlled the regressions for the effect of price events, group size, and recruitment wave.

We found no statistically significant association of gender, age, education, occupational status, risk attitude, or willingness to cooperate with contributions in the experiment. This suggests that farmers and foresters in our sample do not differ in their contributions based on these background characteristics. However, we observed some distinct patterns, which were explored in the heterogeneity analysis. Tables D.1-D.2 indicate that Greek primary producers contribute less on average than Italian producers, but the Cooperative treatment has a stronger effect among Greeks. This difference appears largely sector-driven: as shown in Tables D.3-D.4, the effect is smaller for foresters, who make up most of the Italian sample, suggesting the gap reflects sectoral composition rather than country origin. Another pattern emerges in Tables D.5-D.6, which show that cooperative members contribute less on average, consistent with the null effect of the Cooperative treatment among them.

Based on the findings, we draw the following conclusions regarding the proposed hypotheses:

Result 1

We reject the hypothesis that average individual contributions in the Contract treatment are higher than in the Baseline. However, we observed that the agreement encourages free-riders to contribute, with limited evidence of a crowding-out effect.

Result 2

We fail to reject the hypothesis that average individual contributions in the Cooperative treatment are higher than in both the Baseline and the Contract treatment. There is no crowding-out effect; instead, the collective agreement motivated free-riders to contribute and encouraged moderate contributors to increase their contributions further, resulting in higher total contributions.

Framing the agreement at the threshold level does not appear to change the focal point, except that some free riders in the Contract treatment increased their contributions to the minimum contribution. In contrast, in the Cooperative treatment, the collectively set agreement raised the minimum contribution above the threshold, creating a higher focal point relative to the Baseline. As a result, free riders and moderate contributors increased their contributions without discouraging higher contributors.

4.3. Social norms

Figs. 4a-4c show the distribution of participants' *Belief* about others' contributions. In the Baseline, participants across both treatment groups expected an average contribution of 17.58 tons. In the Contract treatment, this belief increased significantly to 22.44 tons ($p_{WSR} = 0.007$), while in the Cooperative treatment it increased to 21.46 tons ($p_{WSR} = 0.005$). Overall, participants consistently underestimated actual contributions, but *Beliefs* increased under both treatments. However, it should be noted that this increase could be attributed not only to the new scenario presented but also to the experience gained in the first five rounds. In addition, participants in the Cooperative treatment perceived contributions as less heterogenous, with a standard deviation of 6.80 compared to 8.00 in the Baseline and 8.30 in the Contract treatment. Notably, no participants in the Cooperative treatment believed that others would contribute zero.

On average, participants estimated the appropriate contribution (*Norm*) at 27.79 tons in the Baseline. In the Contract treatment, the *Norm* increased to 29.41 tons relative to the Baseline ($p_{MW} = 0.242$). In the Cooperative treatment, the *Norm* increased to 28.61 tons ($p_{MW} = 0.562$). Generally, participants perceived the *Norm* as higher than what they believed others would contribute (*Belief*).

Fig. 5 shows the average *Voting* outcomes per round in the Cooperative treatment. On average, participants voted for 230.24 tons as the group total, indicating a general willingness to exceed the threshold. *Voting* outcomes ranged from 139 to 311.5 tons, with one to three rounds falling below the threshold. The median vote, however, always stayed above the threshold, ranging from 15 to 34 tons, with an average of 25.73 tons. The relatively high standard deviation of voting outcomes

Table 4
Tobit regression analysis with clustered standard errors of treatment effects on contributions.

	(1)	(2)	(3)	(4)
Cooperative *(0: baseline)*	3.409***	3.007**		
	(1.34)	(1.338)		
Contract *(0: baseline)*			0.687	-0.553
			(1.144)	(1.565)
Male		2.52		1.39
		(1.998)		(2.383)
Age		0.103		0.024
		(0.13)		(0.109)
Greek producers		-3.769		-3.742
		(3.962)		(3.911)
Education		-2.748		-0.914
		(5.155)		(0.828)
Farm-forest owner-operator		-0.875		-1.906
		(2.403)		(2.376)
Forester		-2.756		-5.691
		(2.546)		(3.866)
Risk attitude		0.842		0.685
		(0.52)		(1.04)
Willingness to cooperate		0.689		-0.01
		(0.67)		(1.49)
Member of cooperatives		-2.011		-1.64
		(2.22)		(3.267)
Price event (r-1)		2.236**		2.881***
		(1.057)		(0.773)
Group size		3.283**		0.697
		(0.947)		(1.051)
Recruitment wave		-5.456		-1.88
		(4.914)		(6.657)
Constant	29.749***	-4.942	29.918***	26.045**
	(2.277)	(10.519)	(2.228)	(11.885)
Variance in error term	152.78***	125.472***	166.264***	144.825***
	(17.03)	(17.249)	(17.638)	(15.271)
Observations	700	522	710	495
Pseudo R^2	0.002	0.023	0	0.013

Clustered standard errors are in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 5
Tobit regression analysis with DID specification and clustered standards errors of treatment effects on contributions.

	(1)	(2)
Treatment group	-0.17	-1.216
(0: Contract; 1: Cooperative)	(3.078)	(3.051)
Round group	-3.119**	-2.592
(0:Baseline; 1: Treatment)	(1.376)	(1.685)
DID	2.721	3.537*
	(1.702)	(1.998)
Round	0.761***	0.457*
	(0.219)	(0.263)
Male		1.755
		(1.66)
Age		0.037
		(0.072)
Greek producers		-5.5**
		(2.359)
Education		-1.179
		(2.214)
Farm-forest owner-operator		-1.747
		(1.412)
Forester		-4.148**
		(1.665)
Risk attitude		0.884*
		(0.522)
Willingness to cooperate		0.19
		(0.694)
Member of cooperatives		-1.766
		(1.733)
Price event (r-1)		2.563***
		(0.79)
Group size		1.023
		(0.896)
Recruitment wave		-1.254
		(2.765)
Constant	27.634***	18.44**
	(2.054)	(9.112)
Variance in error term	158.411***	137.86***
	(12.33)	(11.734)
Observations	1410	1017
Pseudo R^2	0.002	0.015

Clustered standard errors are in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

indicates considerable heterogeneity in individual preferences within groups.

Almost half (47.14%) of the participants in the Cooperative treatment were shown the full distribution of votes. The correlation between seeing the distribution and individual contributions is negative, consistent with the hypothesis, but not statistically significant ($p_{pwc} = 0.948$).Similarly, the mean difference in contributions between those who saw the distribution and those who did not is not significant ($p_{MW} = 0.622$). This outcome may reflect the limited sample size, since the Cooperative treatment was split evenly and included only five rounds, leaving about 35 observations per subgroup.

Table 6 reports the Tobit regression results on the relationship between social norms and individual contributions. Regressions (1)-(3) use only observations from the Cooperative treatment in rounds six to ten. The median *Vote* was positively and significantly correlated with individual contributions, while its standard deviation was significantly negatively correlated. Seeing the full distribution of votes showed a limited negative correlation with contributions. Regressions (4)-(6) used the full sample across all rounds. *Norm* consistently exhibited a positive and significant correlation with contributions across all models. Average *Past Contributions* from previous round were also positively correlated with following contributions, while their standard deviation was negatively correlated. In contrast, *Belief* showed no significant correlation with contributions, either for the average or the standard deviation.

We examined whether specific dimensions of heterogeneity in participant characteristics help explain fragmented descriptive norms and thereby undermine cooperation. Sobel–Goodman mediation tests[7] show that heterogeneity in gender, cooperative membership, and sector is significantly and negatively associated with individual contributions, mediated by heterogeneity in descriptive norms (group contributions).

Based on these findings, we draw the following conclusions regarding the proposed hypotheses:

Result 3

We reject the hypothesis that the mean of *Belief* is positively correlated with contributions, while its standard deviation is a negatively correlated. This may be explained by the fact that individuals contribute more than they believe others will, instead of aligning their behavior with what they perceive as appropriate (*Norm*).

Result 4

We fail to reject the hypothesis that *Norm* is positively correlated with contributions.

Result 5a

We fail to reject the hypothesis that the median of *Voting* is positively correlated with contributions, while its standard deviation is negatively correlated.

Result 5b

We reject the hypothesis that seeing the distribution of *Voting* is negatively correlated with contributions.

Result 6

We fail to reject the hypothesis that the mean of *Past Contribution* is

[7] Details of the report are provided in Supplementary File E.

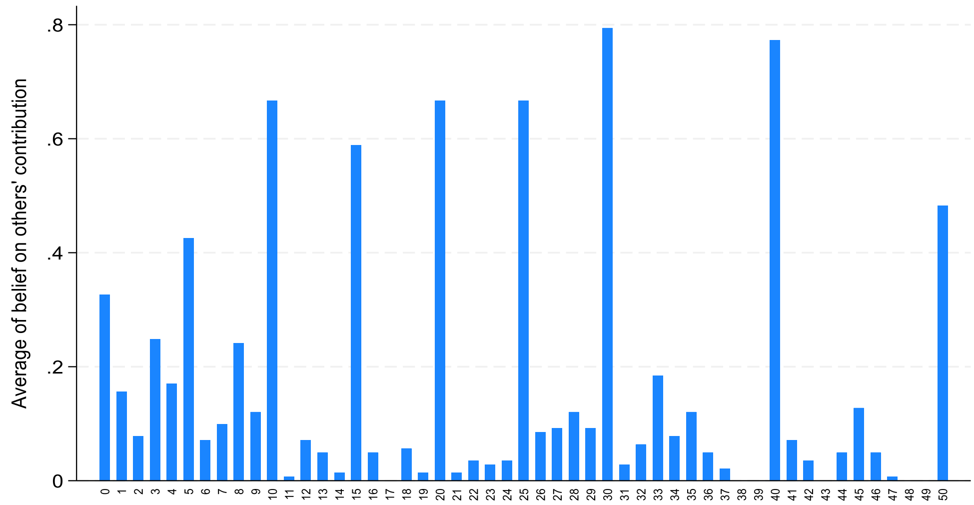

Fig. 4a. Average beliefs about others' contributions at each contribution level in the Baseline, N = 141.

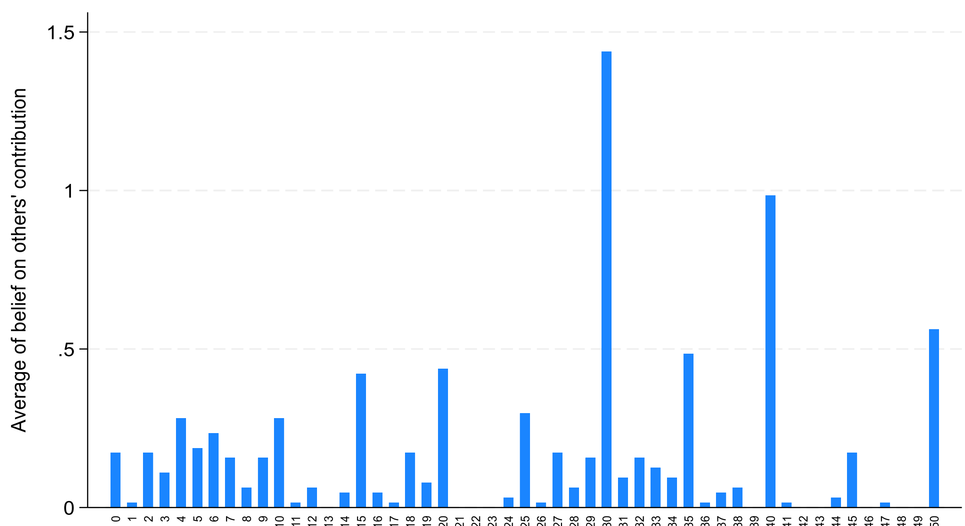

Fig. 4b. Average beliefs about others' contributions at each contribution level in the Contract treatment, N = 71.

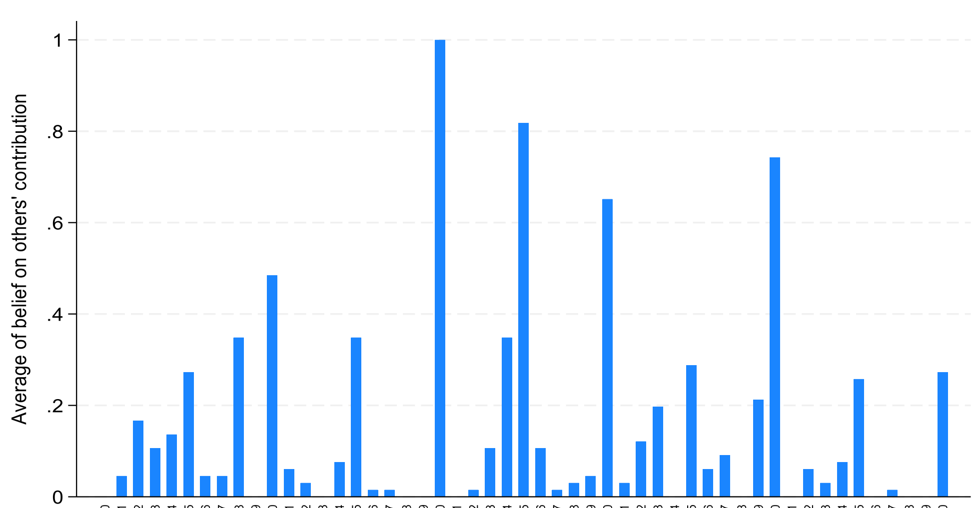

Fig. 4c. Average beliefs about others' contributions at each contribution level in the Cooperative treatment, N = 70.

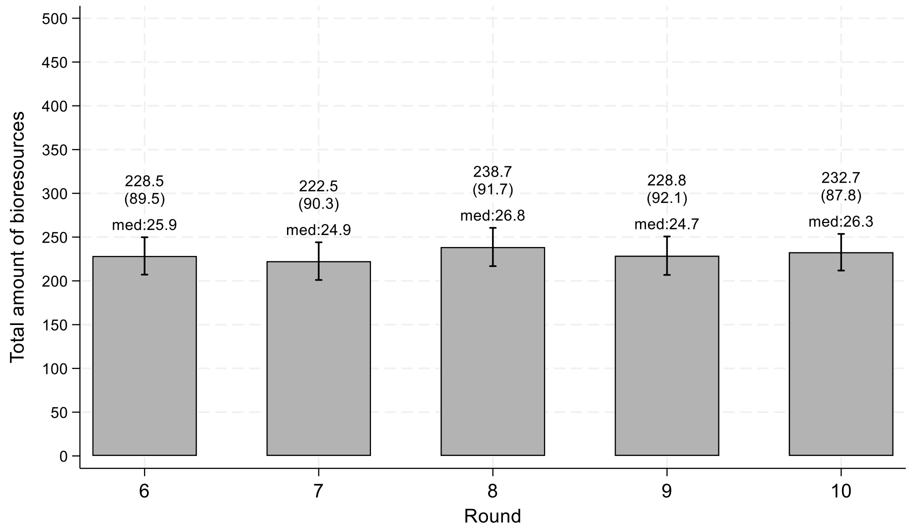

Fig. 5. Mean vote (standard deviation in parentheses) and median vote (minimum contribution).

Table 6
Tobit regression analysis with clustered standard errors of social norms.

	(1)	(2)	(3)	(4)	(5)	(6)
Median Vote	0.809***	0.384**	0.321			
	(0.19)	(0.168)	(0.202)			
Standard deviation Vote	-0.613**	-0.257**	-0.262			
	(0.302)	(0.114)	(0.184)			
Sees distribution	-0.076	2.313	2.309			
	(1.944)	(1.633)	(1.591)			
Mean Belief		-0.016	0.004	-0.006	0.023	0.029
		(0.147)	(0.157)	(0.055)	(0.051)	(0.054)
Standard deviation Belief		-0.215*	-0.208	0.089	-0.018	-0.043
		(0.119)	(0.126)	(0.129)	(0.129)	(0.131)
Norm		0.369***	0.38***	0.367***	0.337***	0.334***
		(0.079)	(0.092)	(0.076)	(0.07)	(0.07)
Mean Past Contribution (r-1)		0.051	0.026	0.643***	0.495***	0.513***
		(0.087)	(0.12)	(0.045)	(0.075)	(0.09)
Standard deviation Past Contribution (r-1)		-0.376***	-0.171	-0.219*	-0.177	-0.134
		(0.113)	(0.158)	(0.112)	(0.124)	(0.11)
Individual characteristics*	No	Yes	Yes	No	Yes	Yes
Price (r-1)	No	No	Yes	No	No	Yes
Group size	No	No	Yes	No	No	Yes
Recruitment wave	No	No	Yes	No	No	Yes
Constant	23.039***	14.81	2.817	3.051	3.597	-1.449
	(3.825)	(11.425)	(10.716)	(2.719)	(5.567)	(7.528)
Variance in error term	90.34***	63.864***	61.66***	116.641***	112.639***	110.252***
	(14.44)	(12.177)	(12.322)	(10.794)	(13.282)	(13.732)
Observations	280	216	216	1161	927	927
Pseudo R^2	0.023	0.063	0.067	0.043	0.041	0.044

**Individual characteristics include gender, age, country, education, employment status, sector, risk attitude, willingness to cooperate, membership of cooperatives*
Clustered standard errors are in parentheses
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

positively correlated with contributions, while its standard deviation is negatively correlated.

Overall, our findings support the hypotheses that the mean of descriptive and injunctive norms positively correlates with individual contributions, while greater variability in descriptive norms has a negative correlation. However, participants did not base their decisions on their *Belief*.

4.4. Robustness tests

We conducted several robustness checks to confirm our main results. We re-estimated the models using panel OLS (Tables C.1-C.3) and panel random-effects Tobit specifications (Tables C.4-C.6), and obtained similar results. The estimates remain robust when controlling for session (group) and round fixed effects; Table C.7 shows that the treatment effect is not driven by any single session or round. Results are also robust to Tobit regression with standard errors clustered at the recruitment-wave levels as displayed in Tables C.8-C.10. This clustering accounts for potential correlation within recruitment waves, where specific recruiters and minor procedural variations may introduce correlation. Separate analyses by recruitment wave show a Cooperative treatment effect in both waves, with a slightly larger effect in the second wave relative to the Baseline (see Tables C.11-C.12 for these results). Compared to the Contract treatment, the effect of the Cooperative treatment was stronger in the first wave, as the Contract treatment showed a negative effect in that wave. Overall, the main regression results for the Cooperative treatment remain robust.

We also re-estimated the non-parametric and regression analyses to include the session excluded from the main analysis (see Tables C.13-C.15 for details). The results for both types of analysis remain robust, although the coefficient for the Cooperative treatment is slightly lower. Given that approximately 20% of responses to each comprehension question were incorrect, as summarized in Table C.17, we performed a robustness test by controlling for comprehension and by running the regression on participants who answered all questions correctly. The results show that the estimated treatment effect and social norms remain robust as reported in Tables C.18-C.23. Furthermore, the Cooperative treatment effect is stronger among participants with full comprehension, indicating that our primary findings are driven by those with a better understanding of the task. One possible explanation is that better-understanding participants engage in more strategic reasoning. They expect others to choose the focal option and best respond accordingly (Camerer et al., 2004). In contrast, less-understanding participants may behave more inconsistently. However, this explanation should be interpreted with caution, as our comprehension test only captures a basic understanding of the game and participants may learn across rounds. A more focused study would be needed to test this mechanism directly.

Our further examination shows that the price effect disappears completely once the Cooperative treatment begins, as shown in Table C.16, while it appears stronger in the Contract treatment. This suggests that participants are less responsive to price events when a collective agreement is introduced.

Finally, given the limited sample size, we conducted regressions using HC3 heteroskedasticity-robust standard errors (Long & Ervin, 2000; MacKinnon & White, 1985); Tables C.24-C.26 display these results, and the main findings remain robust.

5. Discussion

The results show that primary producers from Italy and Greece in our sample contributed above the threshold in our experiment, even without an agreement. They appear to expect others to contribute at a moderate level above the threshold and therefore maximize[8] their individual contributions by contributing, on average, about 60% of the endowment. The observed success rate fell within the typical range of 40–60% (Alberti & Cartwright, 2016), though it was slightly lower than the 70% reported for primary producers in Germany and the Netherlands (Bouma et al., 2020; Rommel, Schulze, et al., 2023). This may be explained by the risk embedded in the experimental design, which amplifies the social dilemma and thereby lowers contributions. However, despite the presence of risk, contributions were not zero or very low, and we found no significant relationship between risk attitudes and individual contributions. This is consistent with earlier literature suggesting that cooperation can be sustained even under adverse conditions (Bilancini et al., 2024; Stoddard, 2017).

The first objective of the paper is to assess effectiveness of non-binding collective agreements in increasing contributions to impure public goods. We find evidence that such agreements have a positive effect on individual contributions, increasing contributions to an average of 66% of participants' endowment, with lower variation, indicating convergence toward a symmetric focal point. Primary producers collectively set minimum contributions above the threshold, which establishes a higher focal point for contribution. This conclusion is robust when controlling for agreement framing through comparison with the Contract treatment, indicating that the effect is not driven solely by framing the minimum contribution. Our results are consistent with earlier laboratory experiments (Dal Bó et al., 2010; Dannenberg et al., 2014; Gallier et al., 2017; Isaac & Norton, 2013; Kroll et al., 2007), but contrast with more recent studies reporting null or negative effects of collective agreements (Abraham et al., 2025; Barreiro-Hurle et al., 2023; Bouma et al., 2020; Kocher et al., 2016; Martinsson & Persson, 2019). Rather than observing a crowding-out effect, we find that such agreements encouraged free-riders and moderate contributors to increase their contributions, with limited evidence that higher contributors reduced theirs. These insights suggest that moving public goods provision closer to the social optimum may not require formal enforcement mechanisms (Fehr et al., 2008; McAdams, 2000; Ostrom, 2010).

Our experimental design helps explain why some studies report null or negative effects of collective agreements. By selecting the median vote as the minimum contribution, our design generates agreements at or above the threshold, creating a higher focal point. This contrasts with designs that use the lowest proposal (e.g., Bouma et al., 2020) or restrict voting options (e.g., Abraham et al., 2025), where the minimum contribution often falls below the baseline average and thus lower the focal point. Consistent with this interpretation, we observed no treatment effect in the Contract agreement, where the minimum contribution was fixed at the threshold. If the Contract treatment were interpreted as a one-shot game, the results might suggest crowding out (e.g., Abraham et al., 2025), as contributions in the sixth round are lower than in the fifth ($p_{WSR} = 0.074$). However, in our repeated setting, contributors could adjust their behavior after observing others contributed above the agreed level.

The second objective of this study is to link the social norms with contributions to impure public goods. We show that the average of descriptive and injunctive norms is positively correlated with individual contributions. This finding is consistent with evidence from broader impure public goods context, such as the adoption of sustainable agricultural practices, where primary producers are more likely to adopt when others do so or when strong normative expectations are present (Barreiro-Hurle & Rommel, 2025; Dessart et al., 2019; El Benni et al., 2025). In contrast, greater variation in descriptive norms within a group is negatively associated with contributions. This reinforces the view that heterogeneity among cooperative members can hinder cooperation (Höhler & Kühl, 2018). We contribute to the literature by directly linking the distribution of descriptive norms, measured by standard deviation of the variables, to individual contributions. This result supports the argument that uncertainty in descriptive norms weakens the effect of average norms and, in turn, undermines cooperation (Dimant et al., 2025; Schmidt, 2025). These patterns are evident in the *Norm, Voting*, and *Past Contribution* variables, indicating that producers' behavior is shaped both by what they perceive as appropriate and by their observations of others' aspirations and actual contributions. By contrast, we find no such relationship for the *Belief* variable, either in terms of its average or distribution, suggesting that participants' stated expectations about others' contributions are not correlated with their own decisions. While this may partly reflect the limits of our experimental design, our finding aligns with Suri et al. (2025) who also report no effect of beliefs on pro-social behavior, even when beliefs were updated with information or experience.

We show that the effect of the Cooperative treatment varies by sector. While the effect remains positive for foresters, it is stronger among farmers, reflecting foresters' tendency to be more passive and delegate decision-making to associations or buyers (Matilainen & Lähdesmäki, 2023; Olschewski et al., 2019). The treatment effect is nearly null for participants who are members of cooperatives. A plausible explanation is that prior negative experiences may undermine trust and make future cooperation more difficult. Although we did not directly assess participants' past experiences with cooperatives, this finding is consistent with previous studies showing that individuals with cooperative experience may exhibit a lower willingness to cooperate (Raimondo et al., 2021). We also observed that heterogeneity in gender, cooperative membership, and sector can contribute to the fragmentation of norms, which in turn undermines cooperation. This highlights the challenges of managing heterogeneity in contexts where the primary sector requires cooperation among diverse stakeholders (Imami et al.,

[8] Follows the third regime in Eq. (6).

2025; Riley et al., 2018).

6. Conclusion

In this paper, we conduct an experiment to examine farmers' and foresters' contribution to the provision of impure public goods under collective agreements and social norms. We provide evidence that collective agreements are effective because they establish a focal point at a higher level of contribution. This higher focal point emerges through voting, which allows primary producers to signal their pro-social preferences and, in turn, increases expectations that the group will achieve a higher level of provision. We also find that primary producers contribute more when their peers do so, and that individuals who perceive contributing as appropriate exhibit higher contribution levels. Conversely, individuals in groups with highly heterogeneous contribution levels tend to contribute less, likely due to norm uncertainty that weakens expectations about others' cooperative behavior. Together, these findings on collective agreements and social norms contribute to the agricultural behavioral economics literature and offer policy-relevant insights for enhancing impure public goods provision. This study extends external validity by examining these mechanisms in an artefactual agricultural context, which has previously been explored primarily in laboratory settings or through theoretical modelling.

We acknowledge several limitations in our study and outline directions for future research. First, our evidence would be stronger if we could demonstrate that collective agreements outperform exogenously set agreements. Future research could set the agreement exogenously, for instance by mirroring the minimum contribution observed in collective agreements, to test whether the same minimum contribution has different effects depending on whether it originates inside or outside the group. Second, the relationship between *Beliefs* and cooperative decisions remains a question. Our elicitation method may have lacked accuracy, as it was not fully straightforward and some participants left responses blank. Comparing alternative elicitation methods and incentivizing accuracy would help clarify whether beliefs correlate with contributions. Third, our study explored which dimensions affect the fragmentation of descriptive norms in this experimental context, though the analysis remains limited. Identifying these dimensions is important for providing clear guidance on managing heterogeneity. Future research could design experiments that manipulate specific characteristics to determine which dimensions significantly drive this fragmentation. Fourth, the randomization of price events through oTree produced an outlier in one session, which led us to exclude it from the analysis. Given the sample size, such randomization also raises concerns about comparability across groups. Future studies could address this by implementing researcher-controlled randomization, which would enhance comparability while still preserving unpredictability and uncertainty for participants. Lastly, we acknowledge that our experiment is relatively complex, relies on a small and diverse convenience sample, and involves heterogeneous group sizes. These features call for cautious interpretation of the results, which should be viewed as a reference point rather than generalized to other groups or populations. We also highlight the challenges of conducting economic experiments with farmers and foresters, particularly those that require interactive and repeated group-based designs (Englberger et al., 2025; Rosch et al., 2021). Designing complex tasks such as ours requires ensuring that participants have a clear understanding of the experimental setup before the task begins. In addition, recruitment proved costly, as our own efforts to recruit participants through freely available channels (e.g., the internet and social media) yielded few, if any, responses. Future research would benefit from collective discussions on how to build effective networks with primary producers and better communicate the benefits of participating in surveys or experiments (Slijper et al., 2026).

Finally, we reflect on the implications of our findings for impure public goods provision by primary producers. While our experimental study necessarily simplifies real-world coordination problems, which often involve higher stakes and longer-term repeated interactions compared to our lower-stakes and shorter-term repeated design, these insights remain informative for understanding how coordination can be achieved. First, forming agreements through cooperative organizations may not have adverse effects for some groups of farmers and foresters. This reinforces earlier evidence on the effectiveness of cooperatives in related contexts, such as establishing agri-environmental scheme contracts (van Dijk et al., 2015) and coordinating value chain actors to ensure sustainable bioresource supply for bio-based production (Mertens et al., 2018). However, engaging more 'passive' stakeholders, such as foresters, may require additional support to guide their decision-making (Matilainen & Lähdesmäki, 2023). Second, for certain groups of farmers and foresters, providing information about peers' behavior can promote cooperation. The mixed evidence in the literature (e.g., Chabé-Ferret et al., 2019; Howley & Ocean, 2022; Ouvrard & Reynaud, 2026) may partly stem from the heterogeneity of peer behavior conveyed in such information. For some groups, interventions may be more effective when they reinforce social norms by highlighting average or majority behavior, rather than the full distribution. Additionally, explicating injunctive norms can be more effective in nudging cooperation (El Benni et al., 2025). Targeting high-aspiration or influential producers may help amplify cooperative behavior within producer networks (Elgaaied-Gambier et al., 2018). Finally, careful governance of cooperatives is essential to manage member heterogeneity and to maintain the trust of primary producers, which is critical for sustaining long-term cooperation.

CRediT authorship contribution statement

Lukas Bonar Nainggolan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alfons Oude Lansink:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Jens Rommel:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Methodology, Formal analysis, Conceptualization. **Julia Höhler:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Acknowledgments

We are grateful for the helpful comments provided by three anonymous reviewers and Andreas Drichoutis. We also thank participants at REECAP 2024 in Córdoba and EAAE 2025 in Bonn for their valuable feedback, which helped improve the experimental design and the writing of this paper. This project has received funding from the European Union, under Grant Agreement N° 101135323 (C4B - Circular Bio-Based Business models to create high-value Bio-based products in integrated value chains).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.socec.2026.102579.

Appendix A

A.1. Explicit payoff function

We define $B_{ir} + M_{ir} = 50$ or equivalently, $M_{ir} = 50 - B_{ir}$. Thus, Eq. (1) can be expressed as:

$$\pi_{Mir} = 100 * (50 - B_{ir}). \tag{7}$$

Subsequently, the payoff function can be written as:

$$\pi_{ir} = \begin{cases} \begin{cases} 5,000 - 100(B_{ir}) + 350(B_{ir}) + 15(B_r), \textit{if } B_r \geq T \textit{ and high} - \textit{price event} \\ 5,000 - 100(B_{ir}) - 50(B_{ir}) + 15(B_r), \textit{if } B_r \geq T \textit{ and low} - \textit{price event} \end{cases}, \\ 5,000 - 100(B_{ir}) - 100(B_{ir}),\ \textit{if } B_r < T \end{cases} \tag{8}$$

We can further simplify and express the function as:

$$\pi_{ir} = \begin{cases} \begin{cases} 5,000 + 250B_{ir} + 15(B_r), \textit{if } B_r \geq 15N \textit{ and high} - \textit{price event} \\ 5,000 - 150B_{ir} + 15(B_r),\ \textit{if } B_r \geq 15N \textit{ and low} - \textit{price event} \end{cases}. \\ 5000 - 200\ B_{ir},\ \textit{if } B_r < 15N \end{cases} \tag{9}$$

A.2. Cumulative prospect value function

The CPT utility function is specified as follows (Bocquého et al., 2014):

$$V(\pi_{ir}) = \begin{cases} {\pi_{ir}}^{\sigma} \textit{ if } \pi_{ir} > 0 \\ 0 \textit{ if } \pi_{ir} = 0 \\ -\lambda(-\pi_{ir})^{\sigma} \textit{ if } \pi_{ir} < 0 \end{cases}. \tag{10}$$

The parameters of risk preferences are σ, reflecting the curvature of the utility function (risk aversion), and λ, capturing the degree of loss aversion. The reference point is set at 0, and with λ assumed to be greater than one, individuals are more sensitive to losses than to gains.

Inputting the Eq. (9) to Eq. (10), we can define the cumulative prospect value function as follows:

$$V(\pi_{ir}) = \begin{cases} \begin{cases} 0.5 * (5,000 + 250B_{ir} + 15(B_r))^{\sigma} + 0.5 * (5,000 - 150B_{ir} + 15(B_r))^{\sigma},\ \textit{if } B_r \geq 10B_{ir} - \dfrac{1,000}{3} \\ 0.5 * (5,000 + 250B_{ir} + 15(B_r))^{\sigma} + 0.5 * -\lambda(5,000 - 150B_{ir} + 15(B_r))^{\sigma},\ \textit{if } B_r < 10B_{ir} - \dfrac{1,000}{3} \end{cases} \textit{and } B_r \geq T \\ \begin{cases} (5000 - 200\ B_{ir})^{\sigma},\ \textit{if } B_{ir} \leq 25 \\ -\lambda(5000 - 200\ B_{ir})^{\sigma},\ B_{ir} > 25 \end{cases} \textit{and } B_r < T \end{cases} \tag{11}$$

In the case where the threshold is met ($B_r \geq T$), there are two sub-conditions. The first regime represents the prospect value across high and low-price events when the low-price event yields a positive payoff. The second regime captures the case where the low-price event yields a negative payoff. These outcomes depend critically on the total amount of bioresources in the group. If the group's total bioresources are sufficiently high ($B_r \geq 10B_{ir} - \frac{1,000}{3}$), which depends on others' contributions, then the low-price event results in a positive value. However, if the total bioresources are not high enough ($B_r < 10B_{ir} - \frac{1,000}{3}$), the low-price event results in a negative value. Meanwhile, when the threshold is not met ($B_r < T$), the prospect value diminishes as contributions increase and becomes negative when contributions exceed 25.

Eq. (11) serves as the basis for calculations in Supplementary File B. We simulate the variables σ and λ using average values obtained from an experiment involving European farmers (Rommel et al., 2023).

A.3. Comparison of cumulative prospect value in the Contract Treatment

a. Comparison to cumulative prospect value of contributing nothing

Assume $N = 10$, the individual minimum contribution ${B_{ir}}^{min}$ is $\frac{150}{10} = 15$. The individual has the prior expectation that other participants in the group also contribute at 15. Then, the individual compares these two expected cumulative prospect value. First, the case when the participant contributes at $B_{ir} = 15$, so the threshold is achieved at $B_r = 150$, the cumulative prospect value is (assume $\sigma = 0.314$):

$$V(\pi_{ir} |\ B_{ir} = 15;\ \ B_r = 150)) =\ 0.5 * (5,000 + 250\ (15) + 15(150))^{0.314} + 0.5 * (5,000 - 150(15) + 15(150))^{0.314} = 16.6904.$$

The second case is when the participant contributes nothing $B_{ir} = 0$, so the threshold is not achieved, $B_r = 135$, the cumulative prospect value is:

$$V(\pi_{ir} |\ B_{ir} = 0;\ \ B_r = 100)) = ((5000 - 200(0))^{0.314} = 14.5036.$$

Then, we can conclude that $V(\pi_{ir} |\ B_{ir} = 15;\ \ B_r = 150) > V(\pi_{ir} |\ B_{ir} = 0;\ \ B_r = 135)$.

b. Comparison to cumulative prospect value of others

Table A.1
Simulated individual and peers' cumulative prospect values in the CONTRACT Contract treatment.

	B_{jr}	$\sum_{j=1}^{n-1} B_{jr}$	$V(\pi_{ir})$ *(assume* $\sigma = 0.314$*)*	$V(\pi_{jr})$ *(assume* $\sigma = 0.314$*)*
15	15	135	16.5408	16.5408
16	15	136	16.5593	16.5516
17	15	137	16.5756	16.5624
…	…	…	…	…
24	15	159	16.6289[a]	16.7952
25	15	160	16.6276	16.8056
26	15	161	16.6240	16.8160

[a] the peak value

Simulation of cumulative prospect value in the Cooperative Treatment

Table A.2
Simulated individual cumulative prospect values for proposed minimum contributions.

$= B_{ir}$	$\sum_{j=1}^{n-1} B_{jr}$	$V(\pi_{ir})$ *(assume* $\sigma = 0.314$*)*
50	450	19.2723
49	441	19.2116
48	432	19.1502
…	…	…
30	270	17.9014
…	…	…
15	135	16.5408

Appendix B

Comparison of preregistration and analyses in the paper

Table B.1
Comparison between the preregistration and analyses in the paper.

Analysis aspect	Preregistration	Paper
Examination of main treatment effect: cooperative vs contract vs baseline	Compare the differences of contributions through non-parametric test. Hypothesis: T2 (Cooperative) > T1 (Baseline), T3 (Contract) > T1 (Baseline), and T2 (Cooperative) > T3 (Contract) Regression analysis with controlling covariates: farmer status, country, gender, age, education, risk attitude, cooperative membership, and willingness to cooperate (in Other).	Compare the differences of contributions through non-parametric test. Hypothesis: T2 (Cooperative) > T1 (Baseline), T3 (Contract) > T1 (Baseline), and T2 (Cooperative) > T3 (Contract) *Tobit* regression analysis with clustering standard errors on group level and controlling covariates: farmer status, country, gender, age, education, risk attitude, cooperative membership, and willingness to cooperate. Robustness test: cluster standard error based on recruitment wave.
Examination of relationship between social norms and contribution	Analyze relationship of beliefs and norms as well as seeing vote distribution on contributions (in Other). Hypothesis: none preregistered	Analyze relationship of Beliefs, *Norms, Voting,* and*Past Contributions* as well as seeing vote distribution on contributions using *Tobit regression*. Robustness test: cluster standard error based on recruitment wave. Hypothesis: averages of beliefs, norms, voting, and past contributions are positively associated with individual contributions, while greater standard deviations of these variables and seeing the distribution of votes are negatively associated with contributions.
How outliers will be defined and handled	None preregistered	Exclude sessions with consistently low prices in every round, which altered behavior due to expectations about risk-price events no longer feeling random.

Appendix C

Robustness tests
Panel OLS regression analysis with clustered standard errors

Table C.1
OLS regression analysis of treatment effects on contribution.

	(1)	(2)	(3)	(4)
Cooperative	3.409**	3.02**		
(0: baseline)				
	(1.341)	(1.367)		
Contract			0.687	-0.531
(0: baseline)				
			(1.145)	(1.577)
Male		2.543		1.382
		(2.024)		(2.415)
Age		0.104		0.024
		(0.131)		(0.111)
Greek producers		-3.569		-3.793
		(4.023)		(3.988)
Education		-2.785		-0.913
		(5.231)		(0.84)
Farm-forest owner-operator		-0.88		-1.91
		(2.436)		(2.409)
Forester		-2.761		-5.688
		(2.587)		(3.916)
Risk attitude		0.835		0.689
		(0.527)		(1.057)
Willingness to cooperate		0.696		-0.012
		(0.682)		(1.513)
Member of cooperatives		-1.996		-1.641
		(2.256)		(3.314)
Price event (r-1)		1.502**		2.469***
		(0.761)		(0.756)
Group size		3.386***		0.705
		(0.912)		(1.064)
Recruitment wave		-5.625		-1.809
		(5.006)		(6.775)
Constant	29.749***	-5.444	29.918***	26.165*
	(2.279)	(10.585)	(2.229)	(12.119)
Observations	700	522	710	495
Clustered standard errors are in parentheses				
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*				

Table C.2
OLS regression analysis with DID specification of treatment effects on contribution.

	(1)	(2)
Treatment group	-0.17	-1.216
(0: Contract; 1: Cooperative)		
	(3.082)	(3.076)
Round group	-3.119**	-2.592
(0:Baseline; 1: Treatment)		
	(1.378)	(1.699)
DID	2.721	3.537*
	(1.705)	(2.014)
Round	0.761***	0.457
	(.219)	(0.265)
Male		1.755
		(1.673)
Age		0.037
		(0.072)
Greek producers		-5.5**
		(2.378)
Education		-1.179
		(2.232)
Farm-forest owner-operator		-1.747
		(1.424)
Forester		-4.148**
		(1.678)
Risk attitude		0.884

(*continued on next page*)

Table C.2 (*continued*)

	(1)	(2)
		(0.527)
Willingness to cooperate		0.19
		(0.699)
Member of cooperatives		-1.766
		(1.747)
Price event (r-1)		2.563***
		(0.796)
Group size		1.023
		(0.903)
Recruitment wave		-1.254
		(2.787)
Constant	27.634***	18.44*
	(2.056)	(9.185)
Observations	1410	1017
Pseudo R^2	0.019	0.114
Clustered standard errors are in parentheses		
*** $p<0.01$, ** $p<0.05$, * $p<0.1$		

Table C.3
OLS regression analysis of social norms.

	(1)	(2)	(3)	(4)	(5)	(6)
Median Vote	0.675***	0.481**	0.388			
	(0.14)	(0.201)	(0.25)			
Standard deviation Vote	-0.305**	-0.189	-0.289			
	(0.128)	(0.131)	(0.218)			
Sees distribution	-0.056	2.238	2.322			
	(1.774)	(1.731)	(1.675)			
Mean Belief		-0.014	0	0.005	0.015	0.018
		(0.155)	(0.168)	(0.043)	(0.048)	(0.051)
Standard deviation Belief		-0.235**	-0.21*	0.073	-0.004	-0.022
		(0.118)	(0.127)	(0.135)	(0.147)	(0.153)
Norm		0.363***	0.374***	0.252***	0.243***	0.237***
		(0.085)	(0.095)	(0.076)	(0.075)	(0.076)
Mean Past Contribution (r-1)		-0.006	0.013	0.541***	0.439***	0.484***
		(0.101)	(0.125)	(0.052)	(0.077)	(0.101)
Standard deviation Past Contribution (r-1)		-0.234*	-0.185	-0.226**	-0.208*	-0.168
		(0.123)	(0.133)	(0.113)	(0.125)	(0.114)
Individual characteristics	No	Yes	Yes	No	Yes	Yes
Price (r-1)	No	No	Yes	No	No	Yes
Group size	No	No	Yes	No	No	Yes
Recruitment wave	No	No	Yes	No	No	Yes
Constant	21.367***	12.205	3.912	9.419***	8.593	2.697
	(3.945)	(13.461)	(11.357)	(3.263)	(6.176)	(8.421)
Observations	280	216	216	1161	927	927
Clustered standard errors are in parentheses						
*** $p<0.01$, ** $p<0.05$, * $p<0.1$						

Panel Tobit regression analyses

Table C.4
Panel Tobit regression analysis of treatment effects on contributions.

	(1)	(2)	(3)	(4)
Cooperative	3.409***	3.02***		
(0: baseline)				
	(0.685)	(0.795)		
Contract			0.687	-0.531
(0: baseline)				
			(0.751)	(0.93)
Male		2.543		1.382
		(2.958)		(2.989)
Age		0.104		0.024
		(0.098)		(0.103)
Greek producers		-3.571		-3.793
		(5.198)		(4.118)
Education		-2.785		-0.913
		(2.831)		(2.216)
Farm-forest owner-operator		-0.88		-1.91

(continued on next page)

Table C.4 (*continued*)

	(1)	(2)	(3)	(4)
		(2.794)		(3.434)
Forester		-2.761		-5.688
		(3.575)		(3.514)
Risk attitude		0.835		0.689
		(0.837)		(0.898)
Willingness to cooperate		0.696		-0.012
		(0.783)		(0.889)
Member of cooperatives		-1.997		-1.641
		(2.274)		(2.373)
Price event (r-1)		1.509*		2.47***
		(0.82)		(0.936)
Group size		3.385**		0.705
		(1.719)		(1.162)
Recruitment wave		-5.624		-1.809
		(4.173)		(4.846)
Constant	29.749***	-5.439	29.918***	26.165*
	(1.115)	(17.009)	(1.102)	(13.395)
sigma_u	8.407***	6.641***	8.135***	6.282***
	(0.794)	(0.745)	(0.787)	(0.78)
sigma_e	9.061***	9.027***	10.004***	10.267***
	(0.255)	(0.296)	(0.28)	(0.346)
Observations	700	522	710	495

Standard errors are in parentheses
**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Table C.5
Panel Tobit regression analysis with DID specification of treatment effects on contributions.

	(1)	(2)
Treatment group	-0.17	-1.216
(0: Contract; 1: Cooperative)	(0.948)	(1.151)
Round group	-3.119**	-2.592
(0:Baseline; 1: Treatment)	(1.516)	(1.676)
DID	2.721**	3.537**
	(1.341)	(1.483)
Round	0.761***	0.457
	(0.237)	(0.289)
Male		1.755
		(1.106)
Age		0.037
		(0.035)
Greek producers		-5.5***
		(1.543)
Education		-1.179
		(0.855)
Farm-forest owner-operator		-1.747
		(1.105)
Forester		-4.148***
		(1.13)
Risk attitude		0.884***
		(0.323)
Willingness to cooperate		0.19
		(0.302)
Member of cooperatives		-1.766**
		(0.841)
Price event (r-1)		2.563***
		(0.757)
Group size		1.023**
		(0.482)
Recruitment wave		-1.254
		(1.425)
Constant	27.634***	18.44***
	(0.976)	(5.363)
/var(e.contributio~)	158.411***	137.86***
	(5.966)	(6.114)
Observations	1410	1017
Pseudo R^2	0.002	0.015

Standard errors are in parentheses
**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Table C.6
Panel Tobit regression analysis of social norms.

	(1)	(2)	(3)	(4)	(5)	(6)
Median Vote	0.67***	0.464**	0.37*			
	(0.141)	(0.192)	(0.198)			
Standard deviation Vote	-0.297**	-0.201	-0.285*			
	(0.128)	(0.141)	(0.166)			
Sees distribution	-0.056	2.255	2.318			
	(1.816)	(1.655)	(1.642)			
Mean Belief		-0.015	0.002	0.006	0.015	0.018
		(0.104)	(0.104)	(0.045)	(0.051)	(0.05)
Standard deviation Belief		-0.231	-0.211	0.068	-0.004	-0.022
		(0.22)	(0.214)	(0.1)	(0.112)	(0.111)
Norm		0.364***	0.376***	0.228***	0.243***	0.24***
		(0.087)	(0.088)	(0.044)	(0.048)	(0.048)
Mean Past Contribution (r-1)		0.004	0.012	0.521***	0.439***	0.485***
		(0.157)	(0.164)	(0.065)	(0.074)	(0.074)
Standard deviation Past Contribution (r-1)		-0.267	-0.0179	-0.226**	-0.208*	-0.168
		(0.252)	(0.281)	(0.096)	(0.109)	(0.108)
Individual characteristics*	No	Yes	Yes	No	Yes	Yes
Price (r-1)	No	No	Yes	No	No	Yes
Group size	No	No	Yes	No	No	Yes
Recruitment wave	No	No	Yes	No	No	Yes
Constant	21.36***	12.766	3.667	10.709***	8.589	2.551
	(3.979)	(9.381)	(14.886)	(2.73)	(5.427)	(7.681)
sigma_u	6.79***	4.303***	4.119***	5.253***	4.126***	4.025***
	(0.729)	(0.692)	(0.676)	(0.522)	(0.528)	(0.519)
sigma_e	6.757***	6.748***	6.687***	9.631***	9.843***	9.757***
	(0.331)	(0.376)	(0.372)	(0.216)	(0.246)	(0.244)
Observations	280	216	216	1161	927	927

**Individual characteristics include gender, age, country, education, employment status, sector, risk attitude, willingness to cooperate, membership of cooperatives*
Standard errors are in parentheses
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Panel regression analysis with fixed effects and clustered standard errors

Table C.7
Panel regression analysis with fixed effects of treatment effects on contribution.

	(1)	(2)
Cooperative (0: Baseline)	3.409**	
	(1.341)	
Contract (0: Baseline)		0.687
		(1.145)
Constant	29.749***	29.918***
	(0.671)	(0.573)
Observations	700	710

Clustered standard errors are in parentheses
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Regression analyses with clustered standard errors at group and wave level

Table C.8
Tobit regression analysis with clustered standard errors at wave level of treatment effects on contribution.

	(1)	(2)
Cooperative (0: Baseline)	3.409***	0.687
	(1.214)	(1.706)
Contract (0: Baseline)		
Constant	29.749***	29.918***
	(3.376)	(1.938)
Variance in error term	152.78***	166.264
	(5.273)	(2.565)
Observations	700	710
Pseudo R^2	0.002	0

Clustered standard errors are in parantheses
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Table C.9
Tobit regression analysis with DID specification with clustered standard errors at wave level of treatment effects on contribution.

	(1)
Group	-0.17
	(1.437)
Round group	-3.119
	(2.795)
DID	2.721***
	(0.491)
Round	0.761***
	(0.218)
Constant	27.634***
	(1.286)
Variance in error term	158.411***
	(2.924)
Observations	1410
Pseudo R^2	0.002
Clustered standard errors are parantheses	
*** $p<0.01$, ** $p<0.05$, * $p<0.1$	

Table C.10
Tobit regression analysis with clustered standard errors at wave level of social norms.

	(1)	(2)
Median Vote	0.809***	
	(0.185)	
Standard deviation Vote	-0.613***	
	(0.098)	
Sees distribution	-0.076	
	(4.227)	
Mean Belief		-0.006
		(0.12)
Standard deviation Belief		0.089
		(0.261)
Norm		0.367***
		(0.097)
Mean Past Contribution (r-1)		0.643***
		(0.003)
Standard deviation Past Contribution (r-1)		-0.219
		(0.208)
Constant	23.039***	3.051***
	(6.338)	(0.134)
Variance in error term	90.34***	116.641***
	(15.588)	(16.372)
Observations	280	1161
Pseudo R^2	0.023	0.43
Clustered standard errors are in parantheses		
*** $p<0.01$, ** $p<0.05$, * $p<0.1$		

Regression for first and second wave of recruitment with clustered standard errors

Table C.11
Tobit regression of treatments effects on contribution for first and second wave of recruitment.

	(1) Second wave	(2) First wave	(3) Second wave	(4) First wave
Cooperative	4.589**	2.159		
	(2.09)	(1.771)		
Contract			2.064	-1.556
			(1.29)	(1.397)
Constant	26.467***	33.224***	28.355***	32.467***
	(3.632)	(1.558)	(2.86)	(3.383)
Variance in error term	150.751***	138.375***	162.954***	166.343***
	(21.431)	(24.107)	(24.904)	(12.174)
Observations	360	340	440	270
Pseudo R^2	0.004	0.001	0.001	0
Clustered standard errors are in parentheses				
*** $p<0.01$, ** $p<0.05$, * $p<0.1$				

Table C.12
Tobit regression with DID specification of treatments effects on contribution for first and second wave of recruitment.

	(1) Second wave	(2) First wave
Group	-1.888	.757
	(4.3)	(3.321)
Round group	-.783	-6.621***
	(.874)	(2.063)
DID	2.525	3.714*
	(2.277)	(2.064)
Round	.569**	1.013***
	(.254)	(.373)
Constant	26.646***	29.427***
	(2.756)	(2.671)
Variance in error term	156.814***	148.702***
	(16.255)	(15.749)
Observations	800	610
Pseudo R^2	0.003	0.004
Clustered standard errors are in parentheses		
**** p<0.01, ** p<0.05, * p<0.1*		

Analyses with the full sample (N=153)

Table C.13
Tobit regression analysis of treatment effects on contribution with full sample (N=153).

	(1)	(2)
Cooperative	2.022	
	(1.762)	
Contract		0.687
		(1.144)
Constant	29.305***	29.918***
	(1.975)	(2.228)
Variance in error term	166.038***	166.264***
	(15.93)	(17.638)
Observations	820	710
Pseudo R^2	0.001	0
Clustered standard errors are in parentheses		
**** p<0.01, ** p<0.05, * p<0.1*		

Table C.14
Tobit regression with DID specification of treatment effects on contribution with full sample (N=153).

	(1)
Group	-0.613
	(2.881)
Round group	-2.488*
	(1.466)
DID	1.335
	(2.037)
Round	0.635***
	(0.238)
Constant	28.013***
	(2.082)
Variance in error term	165.336***
	(11.779)
Observations	1530
Pseudo R^2	0.001
Clustered standard errors are in parentheses	
**** p<0.01, ** p<0.05, * p<0.1*	

Table C.15
Tobit regression of social norms with full sample (N=153).

	(1)	(2)
Median Vote	0.751***	
	(0.099)	
Standard deviation Vote	-0.303	
	(0.259)	
Sees distribution	0.953	
	(1.922)	
Mean Belief		0.01
		(0.053)
Standard deviation Belief		0.06
		(0.119)
Norm		0.365***
		(0.071)
Mean Past Contribution (r-1)		0.637***
		(0.042)
Standard deviation Past Contribution (r-1)		-0.265**
		(0.113)
Constant	18.466***	3.558
	(4.523)	(2.382)
Variance in error term	114.437***	122.576***
	(24.554)	(11.4)
Observations	328	1269
Pseudo R^2	0.03	0.042
Clustered standard errors are in parentheses		
*** $p<0.01$, ** $p<0.05$, * $p<0.1$		

Analysis of lagged price events

Table C.16
Tobit regression analysis of lagged price events.

	(1)	(2)	(3)	(4)	(5)	(6)
Price (r-1)	3.346***	5.722***	0.94	2.877***	2.159**	3.548***
	(1.01)	(1.879)	(1.183)	(0.829)	(0.899)	(1.261)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Group treatment	Cooperatives			Contract		
Round	1-10	1-5	6-10	1-10	1-5	6-10
Variance in error term	129.565***	163.718***	93.7***	145.224***	178.624***	110.969***
	(15.564)	(24.388)	(12.017)	(14.731)	(21.8)	(11.564)
Observations	567	252	315	495	220	275
Pseudo R^2	0.021	0.026	0.022	0.012	0.011	0.022
Clustered standard errors are in parentheses						
*** $p<0.01$, ** $p<0.05$, * $p<0.1$						

Comprehension tests

Table C.17
Descriptive statistics of answers on comprehension questions.

Question	Mean	SD	Min	Max
Q1	0,91	0,28	0	1
Q2	0,84	0,37	0	1
Q3	0,78	0,41	0	1
Q4	0,68	0,47	0	1
Q5	0,80	0,40	0	1

Table C.18
Tobit regression of treatment effects on contribution with controlling answers on comprehension questions.

	(1)	(2)
Cooperative (0: Baseline)	3.409***	
	(1.34)	
Contract (0: Baseline)		0.687
		(1.144)
Q1	1.507	1.801
	(2.92)	(2.938)
Q2	-0.292	-5.77***
	(1.777)	(1.795)
Q3	-2.862	3.875**
	(2.926)	(1.765)
Q4	-3.294	-0.353
	(2.242)	(2.418)
Q5	-3.636*	1.463
	(2.043)	(1.743)
Constant	35.766***	29.402***
	(3.383)	(3.879)
Variance in error term	143.841***	161.184***
	(13.628)	(16.488)
Observations	700	710
Pseudo R^2	0.01	0.004
Clustered standard errors are in parentheses		
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*		

Table C.19
Tobit regression with DID specification with controlling answers on comprehension questions.

	(1)
Group	-0.818
	(2.905)
Round group	-3.119*
	(1.376)
DID	2.721
	(1.702)
Round	0.761***
	(0.219)
Q1	2.323
	(2.307)
Q2	-2.802
	(1.707)
Q3	1.063
	(1.883)
Q4	-2.206
	(1.689)
Q5	-1.762
	(2.147)
Constant	30.26***
	(1.648)
Variance in error term	155.937***
	(5.873)
Observations	1410
Pseudo R^2	0.004
Clustered standard errors are in parentheses	
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*	

Table C.20
Tobit regression of social norms with controlling answers on comprehension questions.

	(1)	(2)
Median Vote	0.809***	
	(0.19)	
Standard deviation Vote	-0.613**	
	(0.302)	
Sees distribution	-0.076	
	(1.944)	
Mean Belief		0.007

(*continued on next page*)

Table C.20 (*continued*)

	(1)	(2)
		(0.06)
Standard deviation Belief		0.094
		(0.126)
Norm		0.356***
		(0.077)
Mean Past Contribution (r-1)		0.645***
		(0.047)
Standard deviation Past Contribution (r-1)		-0.195
		(0.12)
Q1		0.371
		(1.649)
Q2		-0.288
		(0.757)
Q3		0.779
		(0.946)
Q4		-0.225
		(1.019)
Q5		-1.931*
		(1.163)
Constant	23.039***	3.679
	(3.825)	(3.295)
Variance in error term	90.34***	116.151***
	(14.44)	(10.68)
Observations	280	1161
Pseudo R^2	0.023	0.043
Clustered standard errors are in parentheses		
**** p<0.01, ** p<0.05, * p<0.1*		

Table C.21
Tobit regression analysis of treatment effects on contribution by comprehension (passed vs not passed).

	(1) Passed	(2) Not passed	(3) Passed	(4) Not passed
Cooperative (0: Baseline)	5.552***	1.893		
	(0.94)	(1.657)		
Contract (0: Baseline)			1.612	-0.162
			(1.491)	(1.092)
Constant	25.876***	32.488***	29.041***	30.724***
	(3.189)	(1.755)	(2.467)	(2.472)
Variance in error term	146.708***	146.214***	168.774***	163.277***
	(22.406)	(14.519)	(24.618)	(19.06)
Observations	290	410	340	370
Pseudo R^2	0.006	0.001	0	0
Clustered standard errors are in parentheses				
**** p<0.01, ** p<0.05, * p<0.1*				

Table C.22
Tobit regression with DID specification by comprehension (passed vs not passed).

	(1)	(2)
	Passed	Not passed
Group	-3.165	1.763
	(3.879)	(2.916)
Round group	-2.662	-3.592**
	(1.8)	(1.502)
DID	3.94**	2.055
	(1.701)	(1.915)
Round	0.855***	0.686**
	(0.271)	(0.273)
Constant	26.477***	28.667***
	(2.261)	(2.365)
Variance in error term	157.155***	153.367***
	(16.458)	(11.808)
Observations	630	780
Pseudo R^2	0.005	0.003
Clustered standard errors are in parentheses		
**** p<0.01, ** p<0.05, * p<0.1*		

Table C.23
Panel Tobit regression analysis of social norms by comprehension (passed vs not passed).

	(1) Passed	(2) Not passed	(3) Passed	(4) Not passed
Median Vote	0.995***	0.696***		
	(0.207)	(0.156)		
Standard deviation Vote	-0.55	-0.581**		
	(0.388)	(0.257)		
Sees distribution	-4.027	2.148		
	(2.94)	(1.984)		
Mean Belief			0.009	0.005
			(0.063)	(0.076)
Standard deviation Belief			0.269	-0.029
			(0.225)	(0.132)
Norm			0.3***	0.389***
			(0.095)	(0.085)
Mean Past Contribution (r-1)			0.733***	0.554***
			(0.065)	(0.07)
Standard deviation Past Contribution (r-1)			-0.379**	-0.121
			(0.181)	(0.179)
Constant	17.215**	25.337***	2.014	4.923
	(6.687)	(1.578)	(2.527)	(4.057)
Variance in error term	73.083***	94.582***	100.664***	127.427***
	(18.798)	(15.799)	(6.614)	(16.447)
Observations	116	164	513	648
Pseudo R^2	0.044	0.019	0.058	0.032
Clustered standard errors are in parentheses				
*** $p<0.01$, ** $p<0.05$, * $p<0.1$				

HC3 heterogeneity robust standard errors

Table C.24
Panel Tobit regression of treatment effects on contribution with HC3 standard error.

	(1)	(2)
Cooperative	3.409***	
	(0.937)	
Contract		0.687
		(0.971)
Constant	29.749***	29.918***
	(0.761)	(0.732)
Observations	700	710
Pseudo R^2	0.019	0.001
Standard errors are in parentheses		
*** $p<0.01$, ** $p<0.05$, * $p<0.1$		

Table C.25
Panel Tobit regression with DID specification and HC3 standard error.

	(1)
Group	-0.17
	(1.055)
Round group	-3.119**
	(1.523)
DID	2.721**
	(1.345)
Round	0.761***
	(0.233)
Constant	27.634***
	(0.999)
Observations	1410
R-squared	0.019
Standard errors are in parentheses	
*** $p<0.01$, ** $p<0.05$, * $p<0.1$	

Table C.26
Panel Tobit regression of social norms.

	(1)	(2)
Median Vote	0.809***	
	(0.113)	
Standard deviation Vote	-0.613***	
	(0.179)	
Sees distribution	-0.076	
	(1.167)	
Mean Belief		-0.006
		(0.039)
Standard deviation Belief		0.089
		(0.076)
Norm		0.367***
		(0.037)
Mean Past Contribution (r-1)		0.643***
		(0.053)
Standard deviation Past Contribution (r-1)		-0.219**
		(0.101)
Constant	23.039***	3.051
	(3.382)	(2.078)
Observations	280	1161
Pseudo R^2	0.159	0.287
Standard errors are in parentheses		
*** $p<0.01$, ** $p<0.05$, * $p<0.1$		

Appendix D

Heterogeneity analysis a. Country

Table D1
Tobit regression of treatment effect on contributions.

	(1) Greece	(2) Italy	(3) Greece	(4) Italy
Cooperative	4.45***	1.646		
	(1.662)	(2.384)		
Contract			1.173	-0.642
			(1.417)	(1.804)
Constant	27.141***	34.162***	28.315***	34.305***
	(2.958)	(1.675)	(2.371)	(4.257)
Variance in error term	151.559***	133.768***	158.025***	169.291***
	(18.359)	(35.331)	(20.275)	(2.267)
Observations	440	260	520	190
Pseudo R^2	0.004	0.001	0	0
Clustered standard errors are in parentheses				
*** $p<0.01$, ** $p<0.05$, * $p<0.1$				

Table D2
Tobit regression of treatment effects with DID specification.

	(1) Greece	(2) Italy
Group	-1.174	-0.144
	(3.585)	(3.697)
Round group	-1.486	-6.898**
	(1.005)	(2.958)
DID	3.277	2.288
	(2.067)	(2.602)
Round	0.532**	1.251***
	(0.213)	(0.457)
Constant	26.72***	30.552***
	(2.306)	(3.331)
Variance in error term	154.496***	145.636***
	(13.469)	(22.53)
Observations	960	450
Pseudo R^2	0.002	0.003
Clustered standard errors are in parentheses		
*** $p<0.01$, ** $p<0.05$, * $p<0.1$		

b. Farmer or forester

Table D3
Tobit regression of treatment effect on contributions.

	(1) Forester	(2) Farmer	(3) Forester	(4) Farmer
Cooperative	2.164**	4.238***		
	(1.977)	(1.323)		
Contract			-1.716	2.55***
			(0.958)	(0.976)
Constant	32.121***	28.167***	31.335***	28.82***
	(2.121)	(2.996)	(3.006)	(2.268)
Variance in error term	152.927***	148.847***	171.313***	160.3***
	(31.649)	(17.99)	(20.602)	(30.612)
Observations	280	420	310	400
Pseudo R^2	0.001	0.004	0.001	0.001
Clustered standard errors are in parentheses				
**** p<0.01, ** p<0.05, * p<0.1*				

Table D4
Tobit regression of treatment effects with DID specification.

	(1) Forester	(2) Farmer
Group	0.786	-0.653
	(3.543)	(3.602)
Round group	-5.958**	-0.944
	(2.217)	(1.002)
DID	3.88*	1.688
	(2.091)	(1.577)
Round	0.848*	0.699***
	(0.439)	(0.247)
Constant	28.791***	26.724***
	(2.671)	(2.177)
Variance in error term	161.148***	153.457***
	(18.798)	(17.084)
Observations	590	820
Pseudo R^2	0.003	0.003
Clustered standard errors are in parentheses		
**** p<0.01, ** p<0.05, * p<0.1*		

c. Member of cooperatives

Table D5
Tobit regression of treatment effects on contributions.

	(1) A member	(2) Not a member	(3) A member	(4) Not a member
Cooperative	0.22	4.684***		
	(2.845)	(1.105)		
Contract			-0.364	1.372
			(1.796)	(1.383)
Constant	29.6***	29.808***	28.057***	31.13***
	(3.182)	(2.38)	(2.537)	(2.807)
Variance in error term	148.564***	151.343***	165.512***	160.33***
	(16.596)	(19.871)	(22.101)	(25.833)
Observations	200	500	280	430
Pseudo R^2	0	0.005	0	0
Clustered standard errors are in parentheses				
**** p<0.01, ** p<0.05, * p<0.1*				

Table D6
Tobit regression of treatment effects with DID specification.

	(1) A member	(2) Not a member
Group	1.543	-1.322
	(3.925)	(3.542)
Round group	-1.89	-3.612*

(*continued on next page*)

Table D6 (*continued*)

	(1) A member	(2) Not a member
	(1.512)	(1.869)
DID	0.584	3.312**
	(3.248)	(1.704)
Round	0.305	0.997***
	(0.206)	(0.27)
Constant	27.142***	28.14***
	(2.76)	(2.367)
/var(e.contributio~)	158.264***	153.511***
	(13.902)	(16.053)
Observations	480	930
Pseudo R^2	0.001	0.004

Clustered standard errors are in parentheses
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

References

Abraham, D., Glejtková, K., & Krčál, O. (2025). The hidden costs of imposing minimum contributions to a global public good. *Ecological Economics, 227*, Article 108346. https://doi.org/10.1016/j.ecolecon.2024.108346

Alberti, F., & Cartwright, E. J. (2016). Full agreement and the provision of threshold public goods. *Public Choice, 166*(1), 205–233. https://doi.org/10.1007/s11127-016-0321-z

Almeida, S. (2023). Punishment credibility and cooperation in public good games. *Journal of Behavioral and Experimental Economics, 106*, Article 102063. https://doi.org/10.1016/j.socec.2023.102063

Alt, M., Gallier, C., Kesternich, M., & Sturm, B. (2023). Collective minimum contributions to counteract the ratchet effect in the voluntary provision of public goods. *Journal of Environmental Economics and Management, 122*, Article 102895. https://doi.org/10.1016/j.jeem.2023.102895

Angioloni, S., & Cerroni, S. (2025). Farmers' cooperation to improve water quality under scientific uncertainty: A lab-in-the-field experiment. *Journal of Agricultural Economics, 76*(1), 45–73. https://doi.org/10.1111/1477-9552.12614

Barreiro-Hurle, J., Dessart, F. J., Rommel, J., Czajkowski, M., Espinosa-Goded, M., Rodriguez-Entrena, M., Thomas, F., & Zagorska, K. (2023). Willing or complying? The delicate interplay between voluntary and mandatory interventions to promote farmers' environmental behavior. *Food Policy, Applying Behavioral Science to Agriculture, Food, and Agri-Environmental Policy, 120*, Article 102481. https://doi.org/10.1016/j.foodpol.2023.102481

Barreiro-Hurle, J., & Rommel, J. (2025). Behaviourally informed interventions to maximize environmental delivery under the new CAP green architecture. *European Review of Agricultural Economics*, jbaf029. https://doi.org/10.1093/erae/jbaf029

Bijman, J., & Iliopoulos, C. (2014). Farmers' cooperatives in the Eu: Policies, strategies, and organization. *Annals of Public and Cooperative Economics, 85*(4), 497–508. https://doi.org/10.1111/apce.12048

Bilancini, E., Boncinelli, L., Nardi, C., & Pizziol, V. (2024). Cooperation is unaffected by the threat of severe adverse events in public goods games. *Journal of Behavioral and Experimental Economics, 108*, Article 102145. https://doi.org/10.1016/j.socec.2023.102145

Billinger, S., & Rosenbaum, S. M. (2023). On the limits of hierarchy in public goods games: A survey and meta-analysis on the effects of design variables on cooperation. *Journal of Behavioral and Experimental Economics, 107*, Article 102081. https://doi.org/10.1016/j.socec.2023.102081

Bocquého, G., Jacquet, F., & Reynaud, A. (2014). Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field-experiment data. *European Review of Agricultural Economics, 41*(1), 135–172. https://doi.org/10.1093/erae/jbt006

Bouma, J. A., Nguyen, T. T. B., van der Heijden, E., & Dijk, J. J. (2020). Analysing group contract design using a threshold public goods experiment. *European Review of Agricultural Economics, 47*(3), 1250–1275. https://doi.org/10.1093/erae/jbz045

Cadsby, C. B., & Maynes, E. (1999). Voluntary provision of threshold public goods with continuous contributions: Experimental evidence. *Journal of Public Economics, 71*(1), 53–73. https://doi.org/10.1016/S0047-2727(98)00049-8

Camerer, C. F., Ho, T.-H., & Chong, J.-K. (2004). A cognitive hierarchy model of games*. *The Quarterly Journal of Economics, 119*(3), 861–898. https://doi.org/10.1162/0033553041502225

Cardenas, J. C., Stranlund, J., & Willis, C. (2000). Local environmental control and institutional crowding-out. *World Development, 28*(10), 1719–1733. https://doi.org/10.1016/S0305-750X(00)00055-3

Chabé-Ferret, S., Le Coent, P., Reynaud, A., Subervie, J., & Lepercq, D. (2019). Can we nudge farmers into saving water? Evidence from a randomised experiment. *European Review of Agricultural Economics, 46*(3), 393–416. https://doi.org/10.1093/erae/jbz022

Chen, D. L., Schonger, M., & Wickens, C. (2016). oTree—An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance, 9*, 88–97. https://doi.org/10.1016/j.jbef.2015.12.001

Ching, S. (1997). Strategy-proofness and "median voters. *International Journal of Game Theory, 26*(4), 473–490. https://doi.org/10.1007/BF01813886

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A Focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. In M. P. Zanna (Ed.), *Advances in experimental social psychology: 24. Advances in experimental social psychology* (pp. 201–234). Academic Press. https://doi.org/10.1016/S0065-2601(08)60330-5.

Cooper, T., Hart, K., & Baldock, D. (2009). *The provision of public goods through agriculture in the European Union (Report for DG Agriculture and Rural Development, contract no 30-CE-0233091/00-28)*. Institute for European Environmental Policy.

Cooperatives Europe. (2016). *The power of cooperation –Cooperatives Europe key figures 2015*. Cooperatives Europe. https://coopseurope.coop/wp-content/uploads/2016/04/The-power-of-Cooperation-Cooperatives-Europe-key-statistics-2015.pdf.

Crosetto, P., & Haan, T.de (2023). Comparing input interfaces to elicit belief distributions. *Judgment and Decision Making, 18*, e27. https://doi.org/10.1017/jdm.2023.21

Croson, R. T. A., & Marks, M. B. (2000). Step Returns in threshold public goods: A meta- and experimental analysis. *Experimental Economics, 2*(3), 239–259. https://doi.org/10.1023/A:1009918829192

Dal Bó, P., Foster, A., & Putterman, L. (2010). Institutions and behavior: Experimental evidence on the effects of democracy. *American Economic Review, 100*(5), 2205–2229. https://doi.org/10.1257/aer.100.5.2205

Dannenberg, A. (2016). Non-binding agreements in public goods experiments. *Oxford Economic Papers, 68*(1), 279–300. https://doi.org/10.1093/oep/gpv048

Dannenberg, A., Gutsche, G., Batzke, M. C. L., Christens, S., Engler, D., Mankat, F., Möller, S., Weingärtner, E., Ernst, A., Lumkowsky, M., von Wangenheim, G., Hornung, G., & Ziegler, A. (2024). The effects of norms on environmental behavior. *Review of Environmental Economics and Policy, 18*(1), 165–187. https://doi.org/10.1086/727588

Dannenberg, A., Lange, A., & Sturm, B. (2014). Participation and commitment in voluntary coalitions to provide public goods. *Economica, 81*(322), 257–275. https://doi.org/10.1111/ecca.12073

Defrancesco, E., Gatto, P., Runge, F., & Trestini, S. (2008). Factors affecting farmers' participation in agri-environmental measures: A Northern Italian perspective. *Journal of Agricultural Economics, 59*(1), 114–131. https://doi.org/10.1111/j.1477-9552.2007.00134.x

Dessart, F. J., Barreiro-Hurlé, J., & van Bavel, R. (2019). Behavioural factors affecting the adoption of sustainable farming practices: A policy-oriented review. *European Review of Agricultural Economics, 46*(3), 417–471. https://doi.org/10.1093/erae/jbz019

Dimant, E., Gelfand, M., Hochleitner, A., & Sonderegger, S. (2025). Strategic behavior with tight, loose, and polarized norms. *Management Science, 71*(3), 2245–2263. https://doi.org/10.1287/mnsc.2023.01022

Dourian, T. (2021). New farmers in the south of Italy: Capturing the complexity of contemporary strategies and networks. *Journal of Rural Studies, 84*, 63–75. https://doi.org/10.1016/j.jrurstud.2021.03.003

Dreber, A. (2025). Predicting replication outcomes and generalizability of results. *European Review of Agricultural Economics, 52*(4), 644–661. https://doi.org/10.1093/erae/jbaf035

El Benni, N., Wang, Y., Ammann, J., Mack, G., & Finger, R. (2025). A scoping review of nudges for enhancing agricultural policy. *Applied Economic Perspectives and Policy*, 1–23. https://doi.org/10.1002/aepp.70015

Elgaaied-Gambier, L., Monnot, E., & Reniou, F. (2018). Using descriptive norm appeals effectively to promote green behavior. *Journal of Business Research, 82*, 179–191. https://doi.org/10.1016/j.jbusres.2017.09.032

Englberger, L., Colen, L., & Rommel, J. (2025). Farmers' attitudes toward economic experimentation. *Q Open, 5*(1), qoaf005. https://doi.org/10.1093/qopen/qoaf005

Eriksson, K., & Strimling, P. (2015). Injunctive versus functional inferences from descriptive norms: Comment on Gelfand and Harrington. *Journal of Cross-Cultural Psychology, 46*(10), 1330–1332. https://doi.org/10.1177/0022022115605387

Eriksson, K., Strimling, P., & Coultas, J. C. (2015). Bidirectional associations between descriptive and injunctive norms. *Organizational Behavior and Human Decision Processes, SI: Social Norms and Cultural Dynamics, 129*, 59–69. https://doi.org/10.1016/j.obhdp.2014.09.011

Fehr, E., Kremhelmer, S., & Schmidt, K. M. (2008). Fairness and the optimal allocation of ownership rights. *The Economic Journal, 118*(531), 1262–1284. https://doi.org/10.1111/j.1468-0297.2008.02169.x

Fehr, E., & Schmidt, K. M. (1999). A theory of fairness, competition, and cooperation*. *The Quarterly Journal of Economics, 114*(3), 817–868. https://doi.org/10.1162/003355399556151

Fehr, E., & Schmidt, K. M. (2000). *Theories of fairness and reciprocity—Evidence and economic applications (SSRN scholarly paper no. 255223)*. Social Science Research Network. https://doi.org/10.2139/ssrn.255223

Feige, C. (2017). *Determinants of the successful provision of threshold public goods with refund and threshold uncertainty (SSRN scholarly paper no. 3061773)*. Social Science Research Network. https://doi.org/10.2139/ssrn.3061773

Fischbacher, U., Gächter, S., & Fehr, E. (2001). Are people conditionally cooperative? Evidence from a public goods experiment. *Economics Letters, 71*(3), 397–404. https://doi.org/10.1016/S0165-1765(01)00394-9

Fitzsimmons, J., Peterson, H. H., & Lavoie, N. (2025). Farmers' pro-social motivations and willingness-to-accept in markets with public goods. *American Journal of Agricultural Economics*. https://doi.org/10.1111/ajae.70004. *n/a*(n/a).

Freundt, J., & Lange, A. (2021). On the voluntary provision of public goods under risk. *Journal of Behavioral and Experimental Economics, 93*, Article 101727. https://doi.org/10.1016/j.socec.2021.101727

Gallier, C., Kesternich, M., & Sturm, B. (2017). Voting for burden sharing rules in public goods games. *Environmental and Resource Economics, 67*(3), 535–557. https://doi.org/10.1007/s10640-016-0022-6

Gijselinckx, C., & Bussels, M. (2014). Farmers' cooperatives in Europe: Social and historical determinants of cooperative membership in agriculture. *Annals of Public and Cooperative Economics, 85*(4), 509–530. https://doi.org/10.1111/apce.12049

Gittins, P., Apostolopoulos, S., Anastasopoulou, E. E., & Apostolopoulos, N. (2025). Responding to Greece's constrained agricultural context: Farm diversification strategies used by family farmers. *Journal of Rural Studies, 113*, Article 103522. https://doi.org/10.1016/j.jrurstud.2024.103522

Grüner, S., Lehberger, M., Hirschauer, N., & Mußhoff, O. (2022). How (un)informative are experiments with students for other social groups? A study of agricultural students and farmers. *Australian Journal of Agricultural and Resource Economics, 66*(3), 471–504. https://doi.org/10.1111/1467-8489.12485

Gürdal, M. Y., Gürerk, Ö., Kaçamak, Y., & Kart, E. (2024). How to increase and sustain cooperation in public goods games: Conditional commitments via a mediator. *Journal of Economic Behavior & Organization, 228*, Article 106789. https://doi.org/10.1016/j.jebo.2024.106789

Harrison, G. W., & List, J. A. (2004). Field experiments. *Journal of Economic Literature, 42*(4), 1009–1055. https://doi.org/10.1257/0022051043004577

Hensel, L., Witte, M., Caria, A. S., Fetzer, T., Fiorin, S., Götz, F. M., Gomez, M., Haushofer, J., Ivchenko, A., Kraft-Todd, G., Reutskaja, E., Roth, C., Yoeli, E., & Jachimowicz, J. M. (2022). Global behaviors, perceptions, and the emergence of social norms at the onset of the COVID-19 pandemic. *Journal of Economic Behavior & Organization, 193*, 473–496. https://doi.org/10.1016/j.jebo.2021.11.015

Höhler, J., & Kühl, R. (2018). Dimensions of member heterogeneity in cooperatives and their impact on organization – A literature review. *Annals of Public and Cooperative Economics, 89*(4), 697–712. https://doi.org/10.1111/apce.12177

Howley, P., & Ocean, N. (2022). Can nudging only get you so far? Testing for nudge combination effects. *European Review of Agricultural Economics, 49*(5), 1086–1112. https://doi.org/10.1093/erae/jbab041

Imami, D., Xhoxhi, O., Babayan, D., Herzfeld, T., & Rakhmetov, R. (2025). Treatment effect heterogeneity of farmers participating in cooperatives. *Journal of Agricultural Economics, 0*, 1–13. https://doi.org/10.1111/1477-9552.70009

Isaac, R. M., & Norton, D. A. (2013). Endogenous institutions and the possibility of reverse crowding out. *Public Choice, 156*(1), 253–284. https://doi.org/10.1007/s11127-011-9897-5

Isaac, R. M., Schmidtz, D., & Walker, J. M. (1989). The assurance problem in a laboratory market. *Public Choice, 62*(3), 217–236. https://doi.org/10.1007/BF02337743

Isaac, R. M., Walker, J. M., & Williams, A. W. (1994). Group size and the voluntary provision of public goods: Experimental evidence utilizing large groups. *Journal of Public Economics, 54*(1), 1–36. https://doi.org/10.1016/0047-2727(94)90068-X

Isaak, A., Schwieren, C., & Iida, Y. (2022). Reaching agreement on contribution behavior in different cultures-a public goods game with representatives in Japan and Germany. *Journal of Behavioral and Experimental Economics, 99*, Article 101894. https://doi.org/10.1016/j.socec.2022.101894

Iyer, P., Bozzola, M., Hirsch, S., Meraner, M., & Finger, R. (2020). Measuring farmer risk preferences in Europe: A systematic review. *Journal of Agricultural Economics, 71*(1), 3–26. https://doi.org/10.1111/1477-9552.12325

Janssen, M. C. W. (2001). Rationalizing focal points. *Theory and Decision, 50*(2), 119–148. https://doi.org/10.1023/A:1010349014718

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263. https://doi.org/10.2307/1914185

Katuščák, P., & Miklánek, T. (2023). What drives conditional cooperation in public good games? *Experimental Economics, 26*(2), 435–467. https://doi.org/10.1007/s10683-022-09756-9

Kocher, M. G., Martinsson, P., Persson, E., & Wang, X. (2016). Is there a hidden cost of imposing a minimum contribution level for public good contributions? *Journal of Economic Psychology, 56*, 74–84. https://doi.org/10.1016/j.joep.2016.05.007

Koutsou, S., Partalidou, M., & Ragkos, A. (2014). Young farmers' social capital in Greece: Trust levels and collective actions. *Journal of Rural Studies, 34*, 204–211. https://doi.org/10.1016/j.jrurstud.2014.02.002

Kroll, S., Cherry, T. L., & Shogren, J. F. (2007). Voting, punishment, and public goods. *Economic Inquiry, 45*(3), 557–570. https://doi.org/10.1111/j.1465-7295.2007.00028.x

Kurzban, R., & DeScioli, P. (2008). Reciprocity in groups: Information-seeking in a public goods game. *European Journal of Social Psychology, 38*(1), 139–158. https://doi.org/10.1002/ejsp.443

Lakens, D. (2022). Sample size justification. *Collabra: Psychology, 8*(1). https://doi.org/10.1525/collabra.33267

Leyens, A., Feisthauer, P., Börner, J., Hartmann, M., & Storm, H. (2026). Round effects in economic experiments—A novel probabilistic programming approach to round-dependent response behaviour. *European Review of Agricultural Economics, 53*(1), 1–29. https://doi.org/10.1093/erae/jbaf061

Licciardo, F., Tarangioli, S., Gargano, G., Tomassini, S., & Zanetti, B. (2023). The 7th Census of Italian agriculture: Characteristics, structures and dynamics of generational renewal. *Rivista Di Economia Agraria, 78*(2), 109–118. https://doi.org/10.36253/rea-14578

Long, J. S., & Ervin, L. H. (2000). Using heteroscedasticity consistent standard errors in the linear regression model. *The American Statistician, 54*(3), 217–224. https://doi.org/10.1080/00031305.2000.10474549

Luo, Y., & Miller, S. A. (2017). Using game theory to resolve the "chicken and egg" situation in promoting cellulosic bioenergy development. *Ecological Economics, 135*, 29–41. https://doi.org/10.1016/j.ecolecon.2016.12.013

MacColl, S., Onyango, P., Reimer, M. N., & Stopnitzky, Y. (2018). Unintended consequences of enforcement in a cooperative institution: Experimental evidence from Tanzanian fishers. *Ocean & Coastal Management, Coastal Systems in Transition, 162*, 158–169. https://doi.org/10.1016/j.ocecoaman.2017.10.021

MacKinnon, J. G., & White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of Econometrics, 29*(3), 305–325. https://doi.org/10.1016/0304-4076(85)90158-7

Marshall, G. R. (2004). Farmers cooperating in the commons? A study of collective action in salinity management. *Ecological Economics, 51*(3), 271–286. https://doi.org/10.1016/j.ecolecon.2004.06.016

Martinsson, P., & Persson, E. (2019). Public goods and minimum provision levels: Does the institutional formation affect cooperation? *The Scandinavian Journal of Economics, 121*(4), 1473–1499. https://doi.org/10.1111/sjoe.12321

Matilainen, A., & Lähdesmäki, M. (2023). Passive or not? – Examining the diversity within passive forest owners. *Forest Policy and Economics, 151*, Article 102967. https://doi.org/10.1016/j.forpol.2023.102967

McAdams, R. H. (2000). A focal point theory of expressive law. *Virginia Law Review, 86*(8), 1649–1729. https://doi.org/10.2307/1073827

Mertens, A., Van Meensel, J., Willem, L., Lauwers, L., & Buysse, J. (2018). Ensuring continuous feedstock supply in agricultural residue value chains: A complex interplay of five influencing factors. *Biomass and Bioenergy, 109*, 209–220. https://doi.org/10.1016/j.biombioe.2017.12.024

Mori, P. A. (2014). Community and cooperation: The evolution of cooperatives towards new models of citizens' democratic participation in public services provision. *Annals of Public and Cooperative Economics, 85*(3), 327–352. https://doi.org/10.1111/apce.12045

Moulin, H. (1980). On strategy-proofness and single peakedness. *Public Choice, 35*(4), 437–455. https://doi.org/10.1007/BF00128122

Oechssler, J., Reischmann, A., & Sofianos, A. (2022). The conditional contribution mechanism for repeated public goods – The general case. *Journal of Economic Theory, 203*, Article 105488. https://doi.org/10.1016/j.jet.2022.105488

Olschewski, R., Tzanova, P., Thees, O., & Polosek, P. (2019). How does wood mobilization depend on marketing decisions? A country comparison based on choice experiments. *Annals of Forest Science, 76*(4), 103. https://doi.org/10.1007/s13595-019-0894-z

Ostrom, E. (2010). Analyzing collective action. *Agricultural Economics, 41*(s1), 155–166. https://doi.org/10.1111/j.1574-0862.2010.00497.x

Ouvrard, B., & Reynaud, A. (2026). Misperception of descriptive norms and adoption of eco-schemes by French farmers. *Journal of Behavioral and Experimental Economics, 120*, Article 102496. https://doi.org/10.1016/j.socec.2025.102496

Palm-Forster, L. H., & Messer, K. D. (2021). Chapter 80—Experimental and behavioral economics to inform agri-environmental programs and policies. In C. B. Barrett, & D. R. Just (Eds.), *Handbook of Agricultural Economics: 5. Handbook of Agricultural Economics* (pp. 4331–4406). Elsevier. https://doi.org/10.1016/bs.hesagr.2021.10.006.

Peth, D., & Mußhoff, O. (2020). Comparing compliance behaviour of students and farmers. An extra-laboratory experiment in the context of agri-environmental nudges in Germany. *Journal of Agricultural Economics, 71*(2), 601–615. https://doi.org/10.1111/1477-9552.12352

Raimondo, M., Caracciolo, F., Cembalo, L., Chinnici, G., Pappalardo, G., & D'Amico, M. (2021). Moving towards circular bioeconomy: Managing olive cake supply chain through contracts. *Sustainable Production and Consumption, 28*, 180–191. https://doi.org/10.1016/j.spc.2021.03.039

Raineau, Y., Giraud-Héraud, É., & Lecocq, S. (2025). Social comparison nudges: What actually happens when we are told what *others* do? *Ecological Economics, 228*, Article 108436. https://doi.org/10.1016/j.ecolecon.2024.108436

Rellensmann, T., Engel, S., Rommel, J., & Thomas, F. (2025). *Risk-sharing under result-based payments with collective contracts: Experimental evidence (SSRN Scholarly Paper No. 5178362)*. Social Science Research Network. https://doi.org/10.2139/ssrn.5178362

Rellensmann, T., & Thomas, F. (2026). Trade-offs between internal and external validity in economic experiments to inform agricultural policy. *Q Open, 6*(1), qoag008. https://doi.org/10.1093/qopen/qoag008

Riley, M., Sangster, H., Smith, H., Chiverrell, R., & Boyle, J. (2018). Will farmers work together for conservation? The potential limits of farmers' cooperation in agri-environment measures. *Land Use Policy, 70*, 635–646. https://doi.org/10.1016/j.landusepol.2017.10.049

Rommel, J., Hermann, D., Müller, M., & Mußhoff, O. (2019). Contextual framing and monetary incentives in field experiments on risk preferences: Evidence from German farmers. *Journal of Agricultural Economics, 70*(2), 408–425. https://doi.org/10.1111/1477-9552.12298

Rommel, J., Sagebiel, J., Baaken, M. C., Barreiro-Hurlé, J., Bougherara, D., Cembalo, L., Cerjak, M., Čop, T., Czajkowski, M., Espinosa-Goded, M., Höhler, J., Kuhfuss, L., Lagerkvist, C.-J., Lapierre, M., Lefebvre, M., Matzdorf, B., Ott, E., Paparella, A., Quendler, E., … Zagórska, K. (2023). Farmers' risk preferences in 11 European farming systems: A multi-country replication of Bocquého et al. (2014). *Applied Economic Perspectives and Policy, 45*(3), 1374–1399. https://doi.org/10.1002/aepp.13330

Rommel, J., Schulze, C., Matzdorf, B., Sagebiel, J., & Wechner, V. (2023). Learning about German farmers' willingness to cooperate from public goods games and expert predictions. *Q Open, 3*(3), qoac023. https://doi.org/10.1093/qopen/qoac023

Rosch, S., Raszap Skorbiansky, S., Weigel, C., Messer, K. D., & Hellerstein, D. (2021). Barriers to using economic experiments in evidence-based agricultural policymaking. *Applied Economic Perspectives and Policy, 43*(2), 531–555. https://doi.org/10.1002/aepp.13091

Schaak, H., Rommel, J., Sagebiel, J., Barreiro-Hurlé, J., Bougherara, D., Cembalo, L., Cerjak, M., Čop, T., Czajkowski, M., Espinosa-Goded, M., Höhler, J., Lagerkvist, C.-J., Rodriguez-Entrena, M., Tensi, A., Thoyer, S., Tomić Maksan, M., Vecchio, R., & Zagórska, K. (2024). Who can predict farmers' choices in risky gambles? *Q Open, 4*(2), qoae021. https://doi.org/10.1093/qopen/qoae021

Scheffler, M., & Wiegmann, K. (2024). *EU 2040 climate target: The role of agriculture.*

Schmidt, O., Padel, S., & Levidow, L. (2012). The bio-economy concept and knowledge base in a public goods and farmer perspective. *Bio-Based and Applied Economics*, 47–63. https://doi.org/10.13128/BAE-10770

Schmidt, R. (2025). Social norm uncertainty: Measurement using coordination games and behavioral relevance. *Journal of Economic Behavior & Organization, 232*, Article 106937. https://doi.org/10.1016/j.jebo.2025.106937

Schuch, E., Nhim, T., & Richter, A. (2025). Coordinating on good and bad outcomes in threshold games – Evidence from an artefactual field experiment in Cambodia. *Ecological Economics, 232*, Article 108547. https://doi.org/10.1016/j.ecolecon.2025.108547

Slijper, T., Höhler, J., Šumrada, T., Rommel, J., Alif, Ž., Barreiro-Hurle, J., Dietrich, A. S., Gottlieb, U., Ha, T. M., Hakelius, K., Hansson, H., Huang, V. W., Knez, K., Leduc, G., Lind, N., de Mey, Y., Novak, A., Opdenbosch, H., Owusu-Sekyere, E., … Yanore, L. (2026). Surveying the farmer survey: A synthesis of research practices in the Netherlands, Slovenia and Sweden. *Journal of Agricultural Economics*, 1–17. https://doi.org/10.1111/1477-9552.70024

Stallman, H. R., & James, H. S., Jr (2017). Farmers' willingness to cooperate in ecosystem service provision: Does trust matter? *Annals of Public and Cooperative Economics, 88*(1), 5–31. https://doi.org/10.1111/apce.12147

Stoddard, B. (2017). Risk in payoff-equivalent appropriation and provision games. *Journal of Behavioral and Experimental Economics, 69*, 78–82. https://doi.org/10.1016/j.socec.2017.06.002

Sugden, R. (1995). A theory of focal points. *The Economic Journal, 105*(430), 533–550. https://doi.org/10.2307/2235016

Suri, D., Bongers, N., & Kube, S. (2025). Is pro-environmental effort affected by information about others' behavior? *Ecological Economics, 228*, Article 108437. https://doi.org/10.1016/j.ecolecon.2024.108437

Szekely, A., Lipari, F., Antonioni, A., Paolucci, M., Sánchez, A., Tummolini, L., & Andrighetto, G. (2021). Evidence from a long-term experiment that collective risks change social norms and promote cooperation. *Nature Communications, 12*(1), 5452. https://doi.org/10.1038/s41467-021-25734-w

te Velde, V. L., & Louis, W. (2022). Conformity to descriptive norms. *Journal of Economic Behavior & Organization, 200*, 204–222. https://doi.org/10.1016/j.jebo.2022.05.017

Valentinov, V. (2007). Why are cooperatives important in agriculture? An organizational economics perspective. *Journal of Institutional Economics, 3*(1), 55–69. https://doi.org/10.1017/S1744137406000555

van Dijk, W. F. A., Lokhorst, A. M., Berendse, F., & de Snoo, G. R. (2015). Collective agri-environment schemes: How can regional environmental cooperatives enhance farmers' intentions for agri-environment schemes? *Land Use Policy, 42*, 759–766. https://doi.org/10.1016/j.landusepol.2014.10.005

Wesseler, J., & Von Braun, J. (2017). Measuring the bioeconomy: Economics and Policies. *Annual Review of Resource Economics, 9*(1), 275–298. https://doi.org/10.1146/annurev-resource-100516-053701

Westhoek, H. J., Overmars, K. P., & van Zeijts, H. (2013). The provision of public goods by agriculture: Critical questions for effective and efficient policy making. *Environmental Science & Policy, Special Issue on Ecosystem Services and Rural Land Management, 32*, 5–13. https://doi.org/10.1016/j.envsci.2012.06.015

Zilberman, D., Gordon, B., Hochman, G., & Wesseler, J. (2018). Economics of sustainable development and the bioeconomy. *Applied Economic Perspectives and Policy, 40*(1), 22–37. https://doi.org/10.1093/aepp/ppx051