Unpacking Side-Selling: Experimental Evidence from Rural Mexico *

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Abstract

Marketing cooperatives offer their members a guaranteed minimum price and other services. Their existence is threatened when members side-sell a part of their harvest to outside buyers. We conduct a lab-in-the-field experiment with indigenous coffee producers in southern Mexico to examine the effect of four factors in the marketing decision: extra income, the presence of microcredit and/or technical assistance, average outside buyer price, and harvest quantity. Our results show that participants allocate on average 83% of their harvest to the certain-price buyer. Changes in harvest quantity and outside-buyer price have minimal effects. The offer of complementary services has a null effect. Moreover, 25% of the participants always allocate their entire harvest to the certain-price buyer. Extra income increases this probability by 9.6%. Subgroup analysis reveals that this effect is limited to existing cooperative members.

JEL Codes: C91, C93, D81, O13, Q13.
Keywords: Lab-in-the-field experiment, Side-Selling, Price Risk, Cooperatives, Coffee, Mexico.

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1 Introduction

Smallholder agricultural producers face many challenges that hinder their ability to participate in markets and thus reduce their welfare. Chief among these challenges are output price volatility, unexpected income shocks, and poor crop quality. In response, marketing cooperatives offer their members a bundle of products that address these issues: a guaranteed minimum price to cope with price volatility, microcredit to deal with unexpected income shocks, and technical assistance to improve crop quality. To finance these products, these cooperatives often use contracts with downstream processors that provide a consistent source of revenue. Fulfilling these contracts in turn depends on a consistent volume of sales from their members. Ensuring this consistency poses an important challenge because the members of a cooperative often do not sell their entire harvest to the cooperative and instead sell a portion to other intermediaries, a phenomenon called side-selling. This side-selling can occur for one of two reasons. Either the rules of the cooperative allow it or they prohibit it but the cooperative cannot enforce this prohibition, possibly because it cannot detect it. In either case, cooperatives must compete with other intermediaries in a competitive market to attract members' sales like any other firm. Competing effectively requires that they gauge the demand for their products, that is, that they understand the marketing decisions of their producer members.

Modeling marketing decisions of cooperative members poses a challenge to agricultural economists (Tack & Yu, 2021). Under expected utility theory (EUT), risk-neutral producers would sell their entire harvest to the intermediary that offered them the highest price (Wuepper et al., 2023). In contrast, choosing between a certain-price and an uncertain-price intermediary, risk-averse producers would tolerate a lower certain price up to the certainty equivalent. Indeed, most literature has found that agricultural producers are risk-averse (Chavas & Holt, 1990; Friend & Blume, 1975; Hansen & Singleton, 1983; Saha et al., 1994). A key question, however, is whether EUT with a risk-averse utility function is enough to model marketing decisions or whether an alternative framework is needed. One such alternative framework is prospect theory (PT) (Tversky & Kahneman, 1992). Modeling marketing decisions with PT instead of EUT would use a value function instead of a utility function; moreover, this value function would include additional factors such as a reference point (Kőszegi & Rabin, 2006).

This paper examines the impact of four possible additional factors on producer marketing decisions: price certainty, harvest size, the presence of complementary services, and additional income. These factors have been examined separately but not together in previous literature. First, as we noted above, a long tradition beginning with experimental work by Binswanger (1980) has revealed that producers are risk-averse. Next, Fafchamps (2004) and Wollni and Fischer (2015) both found that harvest size plays a role in the decision of whether to sell at the farmgate or market. Third, a review by Liverpool-Tasie et al. (2020) indicates the prevalence of the provision of complementary services by small and medium-sized intermediaries in addition to large ones. Finally, additional income from crop diversification, migrant remittances, or off-farm work can also affect marketing decisions (Woldeyohanes et al., 2017) as distinct from the production decision (Pfeiffer et al., 2009). Indeed, according to Newbery and Stiglitz (1981), rural households seek not price stabilization but income stabilization and consumption stabilization.

To examine the impacts of these factors, we conduct an incentivized lab-in-the-field experiment with 275 indigenous coffee producers in Chiapas, Mexico. In the experiment, each round corresponds to a marketing year. At the beginning of each round, participants learn their harvest for that marketing year from the roll of a die. Next, they allocate this harvest between a certain-price buyer and an uncertain-price buyer. The certain-price buyer always offers the same price. The uncertain-price buyer offers a price whose mean varies by round: either above, below, or the same as the certain-price buyer. Participants only learn the realized price of the uncertain-price buyer after they allocate their harvest. This basic setup allows us to test the impact of risk aversion and harvest size on the marketing decision.

We use two additional elements of the experiment to test the impact of complementary services and additional income on the marketing decision. First, in blocks of 20 rounds, we vary the framing of the certain-price buyer: providing only a certain price (game 1); certain-price and microcredit (game 2); or certain price, microcredit, and technical assistance (game 3). The order of the games is randomized for each participant. This variation in framing allows us to test the effect of the availability of these services on the marketing decision. Second, at the start of the experiment, we randomly assign half of the participants to receive extra income each round that increases their score. This treatment allows us to test the effect of additional income on their marketing decision. Based on their total score at the end of the experiment, participants receive vouchers redeemable for dry goods on site at the end of the experiment.

Our results contribute to three distinct strands of the literature. First, we contribute to the literature on marketing decisions of agricultural producers. Previous literature has examined determinants of participation in cooperatives (Bernard & Spielman, 2009; Mojo et al., 2017) and intensity of participation (Bhuyan, 2007; Fischer & Qaim, 2014; Klein et al., 1997; Mujawamariya et al., 2013) using reduced-form models on cross-sectional data sources. Fafchamps and Hill (2005), Woldie (2010), and Wollni and Fischer (2015) propose structural models and test their predictions, once again on cross-sectional data. Instead of the extensive or intensive margin of cooperative participation, here we examine the demand for the services that cooperatives typically provide. Our results provide insight into the mechanisms behind cooperative patronage.

Second, we contribute to the literature on the use of experiments to understand producer decision-making. Palm-Forster and Messer (2021) provides a recent review of the use of experiments to study the behavior of agricultural producers. Lab-in-the-field experiments are not new, as the pioneering work of Binswanger (1980) demonstrates. Nevertheless, they remain as relevant now as ever. They improve on the internal validity of the cross-sectional research above at a fraction of the cost of a RCT. Moreover, they provide an empirical way to test the predictions of competing models like the ones we describe above in a context that allows for direct policy application. Our experiment is most similar to three recent experiments. Bellemare et al. (2020) tests the prediction of Sandmo (1971) that producers reduce production in situations of price risk and finds that this prediction does not hold. Boyd and Bellemare (2022) both corroborate this finding and also finds that the provision of insurance causes producers to increase production in situations of price risk. Mattos and Zinn (2016) finds evidence for the existence of producer reference prices in marketing decisions. These experiments survey a mix of 119 college students and producers, 101 producers, and 75 producers respectively. Our sample size of 275 producers improves on their external validity.

Third, we contribute to the small literature on price risk (Boyd & Bellemare, 2020). In situations of output price risk, Newbery and Stiglitz (1981) propose methods for evaluating the welfare effects of commodity price stabilization programs. Their work and much of the following work focuses on the differential effects of such programs depending on whether agricultural households are net buyers or sellers of the good in question (Barrett, 1996; Bellemare et al., 2013; Finkelshtain & Chalfant, 1991). In contrast, we examine the short-term marketing decisions of producers, which we consider like an asset-allocation decision following Finkelshtain and Chalfant (1993) and Wollni and Fischer (2015). Two additional features of this particular situation support the usefulness of this model. First, coffee is a cash crop, not a staple, so we need not consider the producers' own welfare as a consumer. Second, coffee is not usually stored from year to year. Thus the marketing decision reduces to a two-time period asset allocation decision. In the first period, producers 'invest' their coffee harvest with either a certain-price buyer or an uncertain-price buyer and in the second period they realize the potential gains or losses from their investment.

Our results are as follows. First, price certainty matters at both the intensive and extensive margins. At the overall margin, producers allocate on average 82% of their harvest to the certain-price buyer. At the extensive margin, 21% of producers (58 out of 273) allocate their entire harvest to the certain-price buyer in every round.

Second, harvest size and mean price of the uncertain-price buyer only affect the marketing decision slightly: at most 3% in either direction. While the sign of these point estimates may suggest producers behave according to the asset allocation model in Wollni and Fischer (2015), their magnitude suggests that the effect of extra income dominates them. The presence of complementary services does not affect the marketing decision.

Third, extra income matters at the extensive margin but not the intensive margin. At the extensive margin, it increases by 9.6% the probability of selling the entire harvest to the certain-price buyer. At the intensive margin, it does not affect round-level performance. When we estimate the extensive margin of the effect of the extra income separately for the cooperative members and non-members, we find significant heterogeneity in the point estimates: 13.6% for members and 1.8% for non-members. Neither effect is significant at the 10% level.

These results suggest the continued relevance of the claim of Newbery and Stiglitz (1981): agricultural producers seek not price certainty but income stabilization. The price certainty for cash crops offered by marketing cooperatives stabilizes income to some extent. Still, other methods to diversify the income source of agricultural producers remain necessary to provide a stronger foundation for their household economics.

Our paper proceeds as follows. Section 2 describes the design of the experiment and relates it to previous work. Section 3 describes our data and descriptive statistics. Section 4 presents the empirical strategy we use to test the effect of the four additional factors on the marketing decision. Section 5 presents and discusses the results. Section 6 concludes.

2 Experimental Design

In this section, we describe our experimental protocol that examines the marketing decision of coffee producers. Within the taxonomy of field experiments, our experiment is an artefactual field experiment (Harrison & List, 2004) or a lab-in-the-field experiment (Eckel & Londono, 2021) because we invite members of the target population to replicate a concrete task that they perform in their daily lives.

Figure 1 summarizes the marketing decision of a coffee producer in the region: sell to an intermediary (dotted line) or a cooperative (the solid line). The cooperative offers a guaranteed minimum price to its members throughout the growing season, provided they meet minimum quality standards. The intermediary's price varies throughout the growing season and is based on the world price of coffee plus an additional markup. Until early 2021, it was always below the cooperative price. Since then, it has risen above the cooperative price for certain periods of the year. During these periods, cooperative members can potentially earn more revenue by marketing their coffee through an intermediary than through the cooperative. If too many members market their coffee through an intermediary, however, the cooperative will not earn sufficient revenue to finance the services it provides: a guaranteed minimum price, microcredit, and technical assistance. Thus the continued viability of the cooperative depends on understanding the marketing decision of producers and adapting its product in response.

In the experiment, we present participants with a simplified version of the real world marketing decision above. Their task is to allocate their harvest between a certain-price buyer and an uncertain-price buyer. Unlike the situation above, where only members can sell coffee that meets a minimum quality threshold to the cooperative, here any participant can sell any amount of their harvest to the certain-price buyer. Moreover, we eliminate transaction costs associated with the sale to either buyer.

In the experiment, participants market their coffee sixty times over three games of twenty rounds apiece. Through these sixty rounds, we vary four factors to determine their effect on the marketing decision.

1. Half of the participants receive **extra income** at the start of the experiment that increases their earnings in every round of the three games they play.

2. By game, we vary the presence of **complementary services**: a certain price (game 1); a certain price and microcredit (game 2); a certain price, microcredit, and technical assistance (game 3). All participants play all three games in a random order.

3. By round, we vary the **harvest size of the participants** and the **mean price of the uncertain-price buyer**. All participants play 20 rounds of each game.

The experiment has six steps. We describe each step in detail below: both the antecedents in the literature and the practical details in our experiment.

1. Extra Income Treatment

2. Preliminary Activities

3. Eckler-Grossman Lottery

4. Order of Games

5. Each Game

6. Final Activities

2.1 Extra Income Treatment

At the beginning of the experiment, half of the participants receive 3000 MXN in fake money that serves as extra income in each round of the three games and contributes to their overall earnings. The treated participants are selected based on their identification number within the sample: participants with odd numbers receive the money and participants with even numbers do not receive the money.

The extra income in the game is meant to proxy for the real-world effect of income from another source, e.g. the sale of another cash crop, income from off-farm labor, or support from a Mexican government program. We choose a comparable amount (3000 MXN) to what producers could conceivably earn from these sources in a month.

1. **Another cash crop**. The principal alternative cash crop in the region is honey. According to records from a honey cooperative in the region, producer members earned on average 20000 MXN from honey sales over the three and a half months of the honey season the year before the experiment, or just under 6000 MXN per month.

2. **Income from off-farm labor**. Similarly, weekly pay is 1500 MXN in manufacturing plants on the US/Mexico border, where many producers report migrating seasonally. With one to two months of work, minus expenses, a producer could earn about 6000 MXN.

3. **Support from a Mexican government program**. Finally, participants in this region are eligible for a Mexican government agricultural support program (Sembrando Vida), in which smallholder farmers can earn up to 6000 MXN per month by planting trees on their land parcels (*Reglas de Operación del Programa Sembrando Vida*, 2022).

Randomly assigning this treatment allows us to determine the effect of extra income on the marketing decisions of participants who receive it. To our knowledge, we are the first to test experimentally the effect of extra income on the marketing decision of a cash crop. Pfeiffer et al. (2009) examined the effect of extra income on the production decision of cash crops and found that extra income causes producers to increase production in the presence of a credit market failure because they use it to finance the purchase of production inputs. Woldeyohanes et al. (2017) find that farmers market less of staple goods in the presence of off-farm income in order to keep a food reserve and insure consumption. Here there is no benefit to keeping a reserve of coffee to sell in a subsequent year since there is no storage in the game. Any effect of the extra income will indicate deviation from purely profit maximizing behavior. Wollni and Fischer (2015) hypothesize that non-agricultural income will increase member deliveries to cooperatives. In their model, however, cooperatives deliver patronage refunds at the end of the marketing year, so the non-agricultural income merely allows for consumption smoothing across time periods.

2.2 Preliminary Activities

After receiving their treatment assignment, participants answer three preliminary arithmetic and probability questions.

1. What is 40% of 100 MXN?

2. If you produce 17 bags of coffee and sell 9, how many remain?

3. Imagine that there are 3 blue balls and 7 red balls. You pick a ball at random. Is it more probable that it is red or blue?

Originally, we intended to exclude participants who missed more than one of the questions. Based on guidance from our implementing partner, however, we did not exclude any participants because of local social norms. The three variables are reported in Table 3 and show that almost all of the participants would have qualified to participate.

Next, the order in which the three games and the lottery will be played is randomized by a roll of a 12-sided die. Table 4 shows the results of this randomization. Half of the participants complete the lottery before the three games and the other half complete it after the three games.

2.3 Eckel-Grossman Lottery

Participants complete an Eckel-Grossman lottery to measure their risk preferences. Eckel and Grossman (2008) propose a simple task for measuring risk preferences similar to that of Binswanger (1980, 1981). Subjects choose one of five gambles, each with a low payoff and a high payoff that occur with 50% probability. The gambles are increasing in both expected payoff and risk, as measured by the standard deviation between the two payoffs. After subjects choose their preferred gamble, they roll a die and receive the corresponding payoff.

One advantage of the Eckel-Grossman lottery compared to other lotteries such as that of Holt and Laury (2002) is its simplicity (Charness et al., 2013). This simplicity allows its use in other settings in Latin America with a similar population to our indigenous coffee growers (Cárdenas et al., 2009; Moya, 2018). Moreover, despite its simplicity, the subject's choice of gamble can be used to estimate his or her risk preferences in the form of a CRRA parameter of the power utility function $U(x) = x^{(1-r)}/(1-r)$.

Table 6 shows the Eckel-Grossman lottery that we present to our participants. The authors provide two sets of gambles: one with negative payoffs (to test for loss aversion) and one without. For simplicity, we use the no-loss lottery and scale the payoffs (\$16 = 10000 MXN) so that the first gamble has a guaranteed payoff of 10000 MXN. We choose 10000 MXN because it is the average payoff in a round of the game (4 quintals $\cdot$ 60 kilos per quintal $\cdot$ 50 MXN per kilo = 10000 MXN).

2.4 The Presence of Complementary Services

After the preliminary activities, participants complete 10 rounds of game 1 for practice. The results of this practice game are not recorded. Next they complete games 1-3 in a random order. The games vary the framing of the certain price buyer by describing two complementary services that the participant could have received last year from the buyer. In addition, in the third game the certain price buyer is described as a cooperative.

Game 1 Certain price buyer offers a fixed price of 50 MXN per kilo.

Game 2 Certain price buyer offers a fixed price of 50 MXN per kilo **and gave the participant**

microcredit in the past year.

Game 3 A cooperative offers a fixed price of 50 MXN per kilo **and gave the participant microcredit and technical assistance last year**.

Microcredit and technical assistance are provided by the cooperative that operates in this region. Their welfare-enhancing effects are confirmed by a recent systematic review (Liverpool-Tasie et al., 2020). Providing these services, however, imposes additional costs on the cooperative that lower the guaranteed minimum price they can offer members for their coffee. Here we are interested in whether the producers value these services enough to market at least a fraction of their coffee through a buyer that offers these services even if they could earn more by marketing it through a buyer that does not.

2.5 Harvest Quantity

Each round corresponds to a marketing year. At the beginning of the round, the producer's harvest quantity for that year is determined randomly by the roll of a 12-sided die. Each of the four possibilities for harvest quantity – 2, 4, 6, or 8 quintals – appear with equal probability (25%). A quintal is a local unit that corresponds to 60 kilos of green coffee. Once the harvest quantity is realized, participants receive a corresponding number of miniature burlap bags.

Under a profit-maximizing framework, harvest quantity should not impact the marketing decision. Profit-maximizing producers should sell their entire harvest to the buyer that gives them the best price. Nevertheless, previous studies indicate that quantity affects the marketing decision; moreover, it affects it differently for poor producers and rich producers. Fafchamps and Hill (2005) examine the binary decision to sell coffee at the farmgate or market by Ugandan coffee producers. They find a U-shaped relationship: the very poor and very rich are more likely to sell at the farmgate, because of lack of transportation for the former and a higher opportunity cost of time for the latter. Wollni and Fischer (2015) also allow producers to allocate their coffee harvest across two buyers. They too find a U-shaped relationship between farm size and coffee deliveries. Initially, the relative profitability of marketing to outside buyers increases with farm size and so farmers with medium-size farms sell more to outside buyers. As farm size continues to increase, however, the discount rate for patronage refunds decreases as well because larger farmers have more access to other sources of income to insure, consumption, however. Thus large farmers sell a smaller share of their harvest to outside buyers than medium-sized farms.

2.6 Certain vs Uncertain Price Buyer

In each round, producers allocate their harvest between the certain price and the uncertain price buyer. Before the allocation decision, the mean price of the uncertain price buyer is randomized: below (45 MXN), the same (50 MXN), or above (55 MXN) the price of the certain price buyer. All three situations share the same approximately normal distribution, as illustrated in figure 6. The twelve support points of each distribution approximate a normal distribution with a 12-sided die.

Once the mean price of the uncertain price buyer is revealed, producers allocate their coffee harvest between the two buyers in increments of one quintal. They must sell the entire harvest and cannot store coffee for subsequent rounds. They are shown a payoff table such as the table in figure 6 specific to the coffee harvest and distribution of uncertain price buyer of their particular round.

Under an expected utility framework, a risk-neutral producer would sell the entire harvest to the certain price buyer (50 MXN) in the first situation (45 MXN), be indifferent in the second situation (50 MXN), and sell the entire harvest to the uncertain price buyer in the third situation (55 MXN). Notably, in all three situations, depending on the realization of the price of the uncertain price buyer, a producer could potentially make more revenue selling to the uncertain price buyer.

Here the producer's decision resembles an asset allocation decision as in Finkelshtain and Chalfant (1993). Producers "invest" their coffee harvest across a safe asset (the certain price buyer) and a risky asset (the uncertain price buyer). Producer's allocation decisions reveal their risk preferences. Examining allocation decisions in the second situation allows us to determine producers' preferences for price certainty. Adding the other two situations tests the effect of small changes in the market environment on these preferences. For example, these changes could reflect transaction costs.

Participants allocate their coffee harvest between the two buyers. Next, they learn the price that the uncertain price buyer gave them. It is revealed by the roll of a die. Finally, they learn their earnings for the round, including the extra income if applicable.

Final Activities Those participants that did not complete the Eckler-Grossman lottery before the three games complete it now. All participants complete an exit survey with socio-demographic information.

Compensation We compensate participants based on their performance in the experiment. At the advice of our implementing partner, we do not give cash payments, in order to distinguish ourselves from the representatives of the Mexican government who distribute various support programs. Rather, we provide vouchers redeemable on-site for dry goods: a bottle of cooking oil, laundry detergent, a bag of sugar, a bag of salt, or a bag of rice. Each voucher corresponds to earnings of 250000 MXN in the game. Participants can earn between three and six vouchers. The possible compensation is nearly the same for treated and non-treated participants. Recall that treated participants receive 180000 MXN of extra income across sixty rounds. At most, they receive one voucher more compared to a counterfactual scenario with identical performance in the game but without the treatment.

This compensation fulfills the three criteria proposed by Eckel and Londono (2021). It is *monotonic* because participants who do better in the game receive more compensation. It is *salient* because participants understood how their actions in the experiment translated to their level of compensation. It is *dominant* because the market value of these products corresponded to the opportunity cost of a day's wages that participants gave up to participate in the game.

2.7 Power Calculations

The design of field experiments includes power calculations to determine the MDE (minimum detectable effect). In our experiment, power calculations are particularly important because of the null effect of several of the round-level treatments, so we describe here the power calculations we performed during the experiment's design and compare them to our subsequent results.

Duflo et al. (2007) give guidelines for computing MDEs in field experiments based on Bloom (1995). These guidelines informed our preliminary analysis as we examined a variety of scenarios as part of the IRB submission process. Here we present the scenario that corresponds most accurately to our final sample, which contains 275 individuals who play 60 rounds apiece. In this scenario, we use a small effect size of 0.25 standard deviations, a power of 80%, and a two-sided t-test at the 10% level. The minimum sample size is approximately 200 rounds per group (treatment or comparison).

We can interpret this in terms of our treatments above as follows. For the harvest quantity treatment, we can consider the three quantities (2, 6, and 8 quintals) and the reference case of 4 quintals as four treatment arms. Thus we need a minimum sample size of 800 rounds. For the uncertain-price buyer treatment, we can consider the two possible average prices (45 and 55 MXN per kilo) and the reference case of 50 MXN as three treatment arms. Thus we need a minimum sample size of 600 rounds. We can consider the complementary services treatment in the same way in terms of three arms (microcredit or microcredit and technical assistance).

Of course our rounds are not independent since the same subjects play many round. Therefore we cluster the rounds by subject. As Duflo et al. (2007) point out, in the case of clusters, the intracluster correlation ρ determines the effective sample size. They advise using previous experiments to estimate ρ. In the absence of such data, we present here a scenario with a high degree of intraclass correlation: $\rho = 0.75$. Intuitively, a high ρ means that individual preferences are "sticky" over time and do not change much in response to treatment. In this scenario, the design effect is

$$D = \sqrt{1 + (n-1)\rho} = \sqrt{1 + 799 \cdot 0.75} \approx 25 \tag{1}$$

That means we must adjust the above estimates to 20000 and 15000 rounds respectively, to detect an effect of a 0.25 standard deviation change in the share allocated in a given round in response to the treatments.

As part of our analysis, we revisited the power calculations above in light of our actual data and results. Our actual sample size is $275 \cdot 60 = 16500$ rounds. Tables 3 and 5 indicate that the true standard deviations of our outcomes of interest is 0.276 for the average share per subject-round, respectively. Moreover, the ICC in our data is 0.73, which indicates that our guess above of 0.75 is a good approximation. In our sample, a change of 0.25 standard deviations would be 6.9% for the subject-round treatment.

We do not find effects of this size for any of the three subject-round treatments. Moreover, effect sizes of smaller than 6.9% at the round level would not make sense for the following reason. Recall that subjects can only vary their allocation levels in one quintal units. In a round with eight quintales, the smallest possible variation is 12.5%. An average treatment effect of less than 6.9% would indicate significant treatment heterogeneity, in which half or less of the subjects responded to the treatment.

Calculating minimum detectable effects in an experiment with clusters is as much as an art as a science. We argue that our experiment is correctly powered and that our null results are not due to insufficient sample size.

3 Data and Descriptive Statistics

3.1 Sample Selection

Data come from individual lab-in-the-field experiments that we conducted with 275 indigenous coffee farmers in northeast Chiapas in summer 2022. During this period, we scheduled eleven field visits to eight of the ten regional centers in the area served by the Batsil Maya coffee cooperative. For logistical reasons, we could not visit two of the regions. The field visit dates were announced and arranged through local churches and community centers, so cooperative members and non-members were equally aware of the opportunity to participate. At three regional centers, more participants volunteered than we could accommodate in a single day, so we returned for a second day to those sites in order to accommodate all participants. After all field visits were completed, we used the Batsil Maya cooperative membership roster to determine which participants came from families that marketed their coffee through the cooperative and classified them accordingly. Table 1 gives an overview of the field visits and a breakdown of the number of cooperative members and non-members who participated in the experiment at each regional center.

We discuss briefly the external validity of the study. The external validity of our study refers to the extent to which results are representative of those of the population under study, indigenous coffee farmers. Frijters et al. (2015) found selection bias into an artefactual field experiments in rural China. We try to minimize any possible selection bias here for the following reasons:

1. Any coffee grower can participate in the experiment. We do not allow more than one individual from the same family to participate because of the limited amount of dry goods we bring on the field visit for compensation.

2. Participation is not associated with on-farm economic opportunities. We conduct the experiments in the summer between the planting season and the harvest season. Their coffee harvest would not be affected if they neglect it for one day to participate in the experiment. Similarly, it is unlikely that their neighbors would request their help with their coffee fields at this time. Thus there is no social or financial opportunity cost to participating in the experiment.

3. Participation is not associated with off-farm economic opportunities. Though some indigenous in this region internally migrate to work off-farm in the summer months, whole families do not. Thus if one member of a family is away pursuing off-farm work, then a family can send another member to participate. In fact, some did.

4. Our sample of 275 farmers is larger than the sample for similar experiments. It is slightly larger than Binswanger (1980), who surveyed 240 Indian farmers, and it is considerably larger than Mattos and Zinn (2016), who surveyed 75 grain producers in Manitoba; Bellemare et al. (2020), who surveyed a combination of 119 US undergraduates and Peruvian potato farmers; and Boyd and Bellemare (2022), who surveyed 101 Peruvian potato farmers.

The external validity of our study also includes the extent to which our results generalize to other populations. Our study is the first of which we are aware to survey indigenous farmers from Latin America, so we cannot comment on whether these results are representative of the preferences of other indigenous farmers from Mexico or other Latin American counties.

3.2 Descriptive Statistics at the Subject Level

Table 3 presents summary statistics at the subject level. The first group of characteristics comes from the exit survey that participants complete after the experiment. All participants grow coffee and 74% report being able to read and write. The sample is evenly balanced between men and women. The mean age of participants is 43 years old with a standard deviation of 16 years old. In addition to gender, we also report the education level of participants. Mexico requires nine years of compulsory education: six of primary school and three of secondary school. Most participants (75%) report only a primary school education. 14% report only a middle school (secondary school) education. 10% have completed high school (preparatory school) as well. As we mention above, after completing all of the field visits, we matched participant names to the Batsil Maya cooperative member roster to label 128 participants as cooperative members.

The second group of characteristics come from the preliminary activities: filter questions, treatment assignment, and lottery. Participants answer three preliminary questions before participating in the experiment to assess their understanding of basic mathematical concepts. Section 2.2 gives more information. All 275 answer the arithmetic question correctly, 273 answer the percentage question correctly, and 201 answer the probability question correctly. After the preliminary questions, they are randomly assigned 3000 MXN extra non-farm income. We see an nearly equal number of treatment (n=138) and control (n=137) participants.

After the preliminary activities, participants complete three games of 20 rounds apiece. The games differ in how they frame the certain-price buyer. Section 2.4 gives more information. We randomize game order and lottery placement using a 12-sided die. Table 4 shows the results of this randomization.

Participants complete an Eckel-Grossman risk preference elicitation lottery either before or after the games. Section 2.3 gives more information. Eckel and Grossman (2008) find gender differences in lottery preferences. Men's preferences are right-skewed with the highest preference for gamble 5. Women's preferences follow a normal distribution with the highest preference for gamble 3. In contrast, we do not find gender differences in lottery preferences. Figure 4 shows participant gamble choices broken down by gender. In our results, men and women display the same preferences with the highest preference for gamble 5.

3.3 Descriptive Statistics at the Subject-Round Level

Table 5 presents summary statistics at the subject-round level. Because of surveyor error, two participants are missing one game apiece, so we drop all of their results from all three games. In each round, the size of the participant's harvest and the mean of the price offered by uncertain price buyer both vary randomly according to a role of a 12-sided die. We code both of these experimental variables as dummy variables with four and three possibilities, respectively. Perfectly randomized experimental variables would exhibit means of 0.25 for the harvest and 0.33 for the mean of uncertain price buyer. Our sample slightly favors a harvest of 6 or 8 quintales and a Mean of Uncertain Price Buyer of 50 MXN.

3.4 Outcomes of Interest

The outcome of interest is the share of the harvest that participants allocate to the certain price buyer in each round of the experiment. We compute it as follows. Let i denote the participant, $g \in \{1, 2, 3\}$ denote the game, and $1 \leq t \leq 20$ denote the round. In each round, participants learn the size of their harvest, $q^g_{i,t} \in \{2, 4, 6, 8\}$, and the mean price of the outside buyer $p^{pg}_{i,t} \in \{45, 50, 55\}$. They choose how many quintals $z^g_{i,t} \in \{0, 1, 2, 3, 4, 5, 6, 7, 8\}$ to allocate to the certain price buyer. We compute the share as $\delta^g_{i,t} = z^g_{i,t}/q^g_{i,t}$.

When we pool all three games across the same participant, the notation above changes slightly. Here we denote the round as $1 \leq t \leq 60$ and drop the g superscript from the harvest and outside buyer price, so they are $q_{i,t}$ and $p^p_{i,t}$ respectively. The participant's choice is $z_{i,t}$. We compute the share as $d_{i,t} = z_{i,t}/q_{i,t}$ For the round-level regressions, our outcome of interest is precisely either the game-level allocation $\delta^g_{i,t}$ or the pooled allocation $d_{i,t}$. They are analytically equivalent. Table 5 gives descriptive statistics for this outcome.

For the subject-level regressions, we aggregate the pooled subject-round allocation $d_{i,t}$ across rounds as follows. Because one quarter of the sample (n=58) allocate their entire harvest to the certain price buyer in every round, we break down the total margin into the extensive and intensive margin so that we can analyze them separately. Table 3 gives descriptive statistics for these outcomes.

1. The **overall margin** is the average allocation for a participant over 60 rounds, or $d_i = \frac{1}{60}\sum_{t=1}^{60} d_{i,t}$.
2. The **extensive margin** is an indicator variable for whether the participant allocates their entire harvest to the certain price buyer in all rounds, or $\bar{d_i} = I[d_i = 1]$.
3. The **intensive margin** is the average allocation for those participants that do not allocate their entire harvest to the certain price buyer in all rounds.

Figure 5 presents a density plot of the overall margin broken down into the participants that received the 3000 MXN extra income treatment and the participants that did not. The left shift in the allocation of the treated group suggests that the treatment is associated with a decrease in the overall margin.

Figure 6 presents a density plot of the overall margin broken down by cooperative membership status. The left shift in the allocation of the non-members suggests that cooperative membership status is associated with a decrease in the overall margin.

4 Empirical framework

We now describe our empirical framework. First, we discuss our estimation strategy at the subject-game-round level, the subject-round level, and the subject level. Next, we discuss our identification strategy. Finally, we discuss subgroup analysis among cooperative members and non-members.

4.1 Estimation Strategy

We estimate the effect of the presence of extra income, the framing of the certain price buyer, the harvest quantity, and mean price of the uncertain price buyer on the marketing decisions of participants. Since these four factors vary at three levels, we estimate at each of these levels. First, we estimate the effect of harvest quantity and uncertain buyer price at the round level for each game. Next, we pool all three games and estimate the effect of harvest quantity, uncertain buyer price, and game framing, once again at the round level. Finally, we aggregate subject performance across all 60 rounds and estimate the effect of the extra income treatment at the subject level.

4.1.1 Subject-Round Estimation

Recall from section 3.4 that we denote round-level outcomes in two ways to distinguish between the estimation in this section, which separate allocations by game, and the estimation in the next section, which pools allocations across all three games. Table 5 gives descriptive statistics for both outcomes of interest.

1. The expression $\delta^g_{i,t}$ denotes the share that individual i allocates to certain price buyer in round t of game g. Here $g \in \{1, 2, 3\}$ and $1 \leq t \leq 20$.

2. The expression $d_{i,t}$ denotes the share that individual i allocates to certain price buyer in round t. Here $1 \leq t \leq 60$.

We estimate the following equation for each game:

$$\delta^g_{i,t} = \alpha^g_i + \sum_{s \in \{45,55\}} \beta^{pg}_s I[p^{pg}_{i,t} = s] + \sum_{h \in \{2,6,8\}} \beta^{qg}_h I[q^g_{i,t} = h] + \lambda^g t + \epsilon^g_{i,t} \tag{2}$$

To allow for non-linear effects, we code the uncertain buyer price and the harvest quantity using dummy variables. For the uncertain buyer price, we use two dummy variables for the situations in which the mean price is below (45 MXN) and above (55 MXN) the price offered by the certain price buyer (50 MXN). The reference case is the situation in which the mean price of the uncertain price buyer is the same as the price offered by the certain price buyer.

Similarly, we code the harvest quantity with three dummy variables for a harvest of 2 quintals, 6 quintals, and 8 quintals, respectively. Recall that 1 quintal is 60 kilograms. We use 4 quintals (240 kilograms) as a reference case because it is the closest to the typical harvest size of participants.

The exit survey indicates that their mean coffee harvest is 371 kilograms and the median coffee harvest is 270 kilograms.

We include a linear time trend λ^g to control for the effect of later rounds, either positive (learning) or negative (fatigue). As we discuss in the identification section below, we include subject fixed effects α_i^g to control for unobserved subject-level heterogeneity that does not vary by round. We cluster standard errors at the subject level to allow for correlation among unobservables within rounds played by the same subject.

4.1.2 Round-Level Estimation Pooled Across All Games

Next, we pool results across all three games and estimate Equation 3, a modified version of Equation 2 that includes the framing of the game (the complementary services provided by the certain price buyer). Here Latin letters correspond to the same parameters as the Greek letters in equation 2. The coefficients on the dummies for the mean price of the uncertain price buyer are denoted by b_{1s}^p. The coefficients for the harvest quantity are denoted by b_h^{1q}. As before, we include subject fixed effects a_{1i} and the linear time trend l_1. We include game dummies for games 2 and 3 and denote their coefficients with c_{1g} These coefficients capture the effect of the framing of game 2 and game 3 compared to game 1.

$$\begin{aligned} d_{i,t} = a_{1i} &+ \sum_{s\in\{45,55\}} b_{1s}^p I[p_{i,t}^p = s] + \sum_{h\in\{2,6,8\}} b_{1h}^q I[q_{i,t} = h] \\ &+ \sum_{g\in\{2,3\}} c_{1g} I[g_{i,t} = c] + l_1 t + e_{1i,t} \end{aligned} \tag{3}$$

4.1.3 Subject-Level Estimation

Finally, we aggregate the sixty rounds per subject to construct a measure of overall participation in the game: the average allocation to the certain-price buyer across all 60 rounds, which we denote by d_i below. Wollni and Fischer (2015) use a similar outcome of interest: the fraction of coffee harvest sold to one buyer They note that this dependent variable is a fractional variable bounded between 0 and 1. For this reason, they use the quasi-likelihood estimator proposed by Papke and Wooldridge

(1996). We do not follow their approach. Instead, we estimate equation 4 separately for the total margin, the extensive margin, and intensive margin. Section 3.4 describes the construction of these outcome variables in more detail.

$$d_i = \theta \text{extra}_i + \beta X_i + \epsilon_i \tag{4}$$

The coefficient of interest is θ, the effect of the extra income on these three outcomes. In addition, as controls we include the same subject-level covariates as in equation **??**: age, gender, education level, CRRA calculated based on the Eckel-Grossman lottery, practice game completion, correct answer on the probability filter question, game order, and lottery position. Since the unit of analysis is the subject and the treatment is at the subject level, we do not cluster the standard errors. We simply compute heteroskedasity-robust standard errors.

4.2 Identification Strategy

Identification of the effect of the four parameters of interest is straightforward because we randomize them within the experiment. At the round level, we randomize harvest size and the mean of uncertain price buyer, so the corresponding parameters in equations 2 and 3 are causally identified. imilarly, game order is randomized and all subjects play all three games, so we argue that the corresponding parameters in equation 3 is also causally identified.

Two concerns remain for causal identification. First, we consider potential correlation between the allocated share in each round and subject-level unobservables such as risk preferences or skill at playing the game. We use subject-level fixed effects to control for these unobservables. Second, earlier rounds and later rounds might differ in unobservable ways, because of participant learning or fatigue. For this reason, all participants play ten rounds of a practice game that are not counted, either in their score or our regression results. The practice game controls for participants who learn the game faster than others. Moreover, we include a linear time trend to control for boredom or fatigue.

Finally, we turn to the subject-level equation 4. Here the extra income treatment is randomized at the subject level, so this parameter is causally identified.

4.3 Subgroup Analysis

Half of our participants are cooperative members, and we would like to compare the effect of the four factors above for cooperative members and non-members. Cooperative membership is a time-invariant participant characteristic, so we cannot include a membership dummy in equation 2 or 3 because it would be absorbed in the fixed effects. Moreover, it is a choice variable based on observed and unobserved characteristics, so we cannot add it to the vector of controls X in Equations **??** and 4.

For this reason, we use subgroup analysis. We estimate equations 3 and 4 separately for cooperative members and non-members and present the results side-by-side to allow for a comparison of the estimated parameters. We argue that the parameters in these estimated results are causally identified for the reasons we discussed in the previous section. The only drawback to this approach is the reduced sample size, which limits the statistical power of the associated hypothesis tests.

5 Results and discussion

5.1 Subject-Round Results

Table 6 presents results from estimating equation 2. Recall from table 5 that the baseline allocations for games 1, 2, and 3 are 0.818, 0.824, and 0.815 respectively. The strong preference for price certainty across all participants stands out at the most important result at the subject-round level. Moreover, these figures give context to the point estimates below. Varying the details of the allocation decision only affects this preference slightly.

We examine the effect of varying harvest size and the mean price of the uncertain price buyer. Regarding harvest size, we see that participants allocate less of their harvest to the certain price buyer in rounds with a a smaller (2 quintal) or larger (8 quintal) harvest: 3% and 2% less respectively. This result does not match EUT. Under EUT, harvest size would not affect the allocation decision. Rather, it suggests an asset-allocation model of Finkelshtain and Chalfant (1993). In a year with half of the normal harvest (2 quintals), participants invest more in the uncertain price buyer because of the possibility of a higher return. In a year with double the normal harvest (8 quintals), participants also invest more in the uncertain price buyer as a way to gamble for extra income.

Regarding the mean price of the uncertain price buyer, a 5 MXN reduction is associated with allocating approximately 2% more of the harvest to it. This result also does not match EUT. One possible interpretation is that participants are investing a slightly larger share of their coffee with the uncertain price buyer to keep the total value of their portfolio the same. Curiously, a 5 MXN increase in the mean price of the uncertain price buyer does not affect allocation decisions.

The baseline allocations for the three games are very close. Moreover, neither the harvest size parameters nor the parameters for the changing mean of the uncertain price buyer vary much across the three games. These two results suggest that the game framing does not make much of a difference.

Table 7 presents results from estimating equation 3, a specification that pools results across all three games with individual fixed effects. The parameter estimates here do not differ meaningfully from the those in the previous specification. This specification includes dummies for game 2 and game 3. The framing of the certain price buyer in game 2 (microcredit) appears not to affect the allocation decision. The framing in game 3 (cooperative with microcredit and technical assistance) causes participants to allocate 1% less coffee to the certain price buyer. This result lacks statistical significance.

5.2 Subject Results

Table 8 presents results from estimating equation 4 on the aggregate outcomes at the subject-level. The inclusion of the covariates substantially reduces the baseline share that is allocated to the certain-price buyer from over 80% above to 61% here. This difference indicates substantial heterogeneity of the preferences of individual participants. At the upper bound, recall from Table 3 that 58 of 273 participants do not vary their allocation decision. They allocate the entire harvest to the certain price buyer in every round. Thus we break down the total margin into the extensive and intensive margin.

One result stand outs in particular from the extensive margin estimation. The presence of extra income increases the likelihood by 9.6% that a participant will not vary their allocation decision. This result contradicts EUT and suggests income-targeting behavior. One possible explanation is that the extra income allows treated participants to earn a desired income level more quickly and once they have earned this level of income, they prefer the certainty of the certain price buyer.

Three covariates are associated with allocation decisions at the subject-level: only middle school education, understanding probability, and completing the practice game. We present these as associations that warrant further study. Otherwise, the other covariates (gender, age, and CRRA as measured by the Eckel-Grossman risk preference lottery) do not appear to be associated with the average allocation.

5.3 Breakdown by Cooperative Membership Status

Finally, we estimate the round-level outcomes and the subject-level outcomes separately for cooperative members and non-members. Recall that figure 6 shows a density plot of the subject-level outcomes separately by group. Table 9 presents results from estimating the round-level outcomes with individual fixed-effects. The already-small parameter values for the harvest size and price of uncertain price buyer are even smaller for the cooperative members. This fact indicates that these factors do not influence cooperative members' preference for the certain-price buyer.

Tables 10 and 11 present results for the subject-level outcomes on the cooperative members and non-members respectively. The smaller sample size (127 members and 143 non-members) limits the statistical power of hypothesis tests. Nevertheless, we see that the parameter value of the extra income treatment at the extensive margin is 13.6% for the cooperative members and 1.8% for the non-members. This result suggests that the extra income may relieve a budget constraint that allows cooperative members who already prefer price certainty to pursue it even more.

6 Conclusion

Side-selling matters a lot to cooperatives that serve smallholder agricultural producers. In many settings, these cooperatives offer a guaranteed price to their members throughout the marketing year. This price insurance protects them against the volatility of international commodity markets. At the same time, other intermediaries compete for the patronage of cooperative members by offering a price that varies by the week or the day. This price can exceeds the cooperative price for at least part of the year. In order to finance their price insurance, cooperatives may depend on a certain minimum volume of sales. Moreover, they may offer additional services such as microcredit or technical assistance that they finance through their patronage. In periods when the market price exceeds their guaranteed price, side-selling by their members puts their viability at risk. A better understanding of side-selling will strengthen cooperatives and improve their ability to increase the welfare of their members in a challenging market environment.

We have presented the results of an experiment to examine four possible determinants of side-selling behavior for indigenous coffee farmers in Mexico: extra income, harvest size, average price of an outside buyer, and framing of the certain price buyer. In the experiment, the participants perform a very similar task to one that they do every marketing year. In three blocks of 20 rounds, they first learn their harvest and the average price of an outside buyer and then allocate their coffee harvest accordingly. The framing of the certain price buyer varies by the game (20 round block). Half of participants receive extra income which factors into their score in every round. Participants receive vouchers for dry goods based on their performance.

Our results show that producers overwhelmingly prefer price certainty and that approximately a quarter of them allocate their entire harvest to the certain price buyer in every round. Beyond that, neither harvest size, nor the framing of the certain price buyer, nor small changes (5 MXN) in the average price of the outside buyer change producer behavior. Extra income causes nearly 10% more to allocate their harvest to the certain price buyer. Cooperative members respond in particular to the presence of extra income.

Our study suffers from two limitations. First, we designed the state space of the experiment to correspond to the number of rounds (60), so that all participants would face all possible marketing decisions. New technology in adaptive experiments would allow us to expand the state space: for example to test more than three possibilities for outside price, four possibilities for harvest quantity, or different amounts of extra income. A larger state space would allow us to measure the effects of this variation by adapting subsequent rounds to participant preferences in the initial rounds.

Second, the framing of the certain price buyer was done verbally, while the other randomization was done physically: small coffee bags for the coffee harvest, dice for the price of the uncertain price buyer monopoly money for the extra income. This indigenous population may understand tactile variation better than verbal variation. Moreover, the services offered by the framed buyers (microcredit and technical assistance) did not affect outcomes in the game. In real life, microcredit would smooth consumption and technical assistance would affect harvest quantity. Subsequent experiments could improve on both of these areas.

Forty years after Newbery and Stiglitz (1981), commodity markets are more integrated as a result of free trade, and many agricultural producers have not experienced the promised welfare gains. Our results suggest that producers desire first and foremost income stability. Even a small amount of income support (3000 MXN or $150 USD per year) can change behavior. With the short-term relief that this income support provides, producers will be more likely to invest in long-term institutions like coffee cooperatives that provide price support, microcredit, and technical assistance. Thus we provide insight into the design of more effective policies and programs to help the population of smallholder agricultural producers.

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Appendix

List of Figures

List of Tables

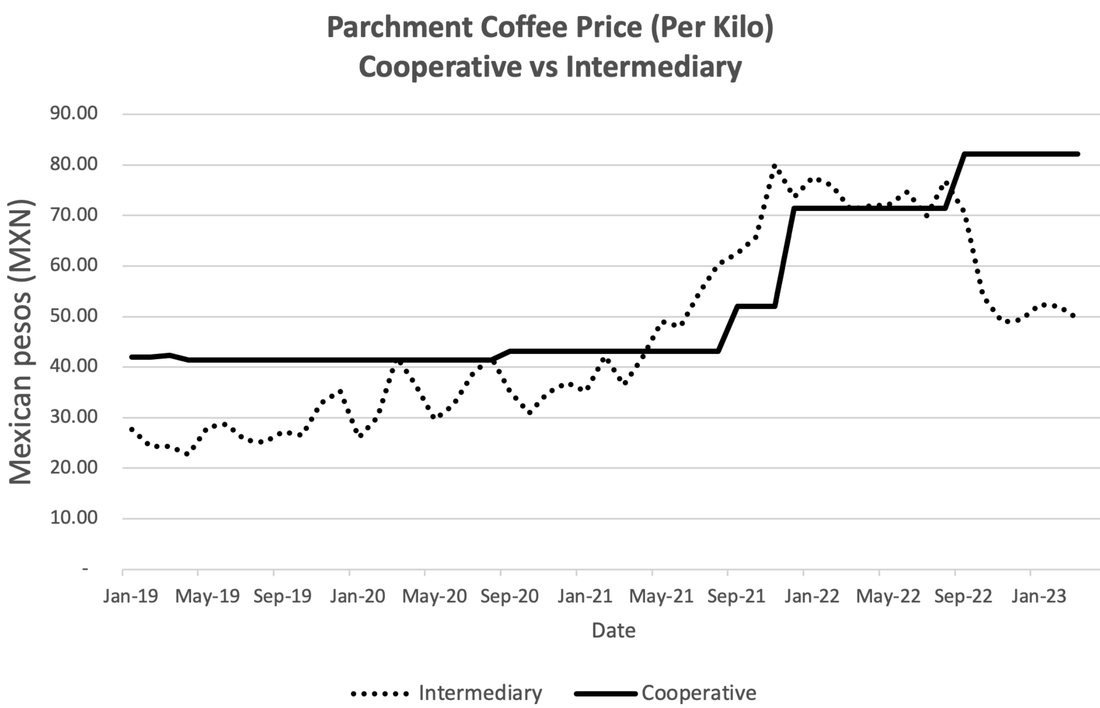


Figure 1: Local Coffee Market

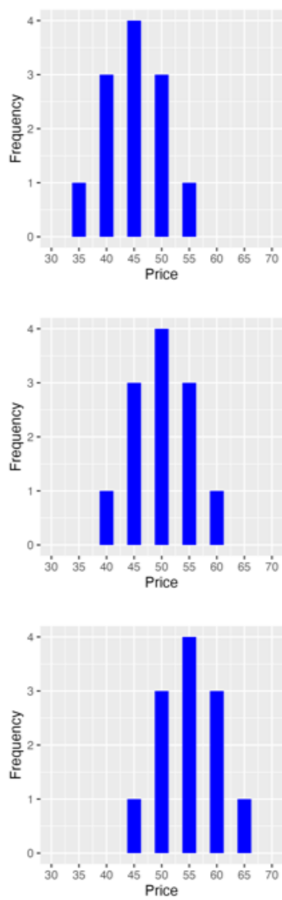
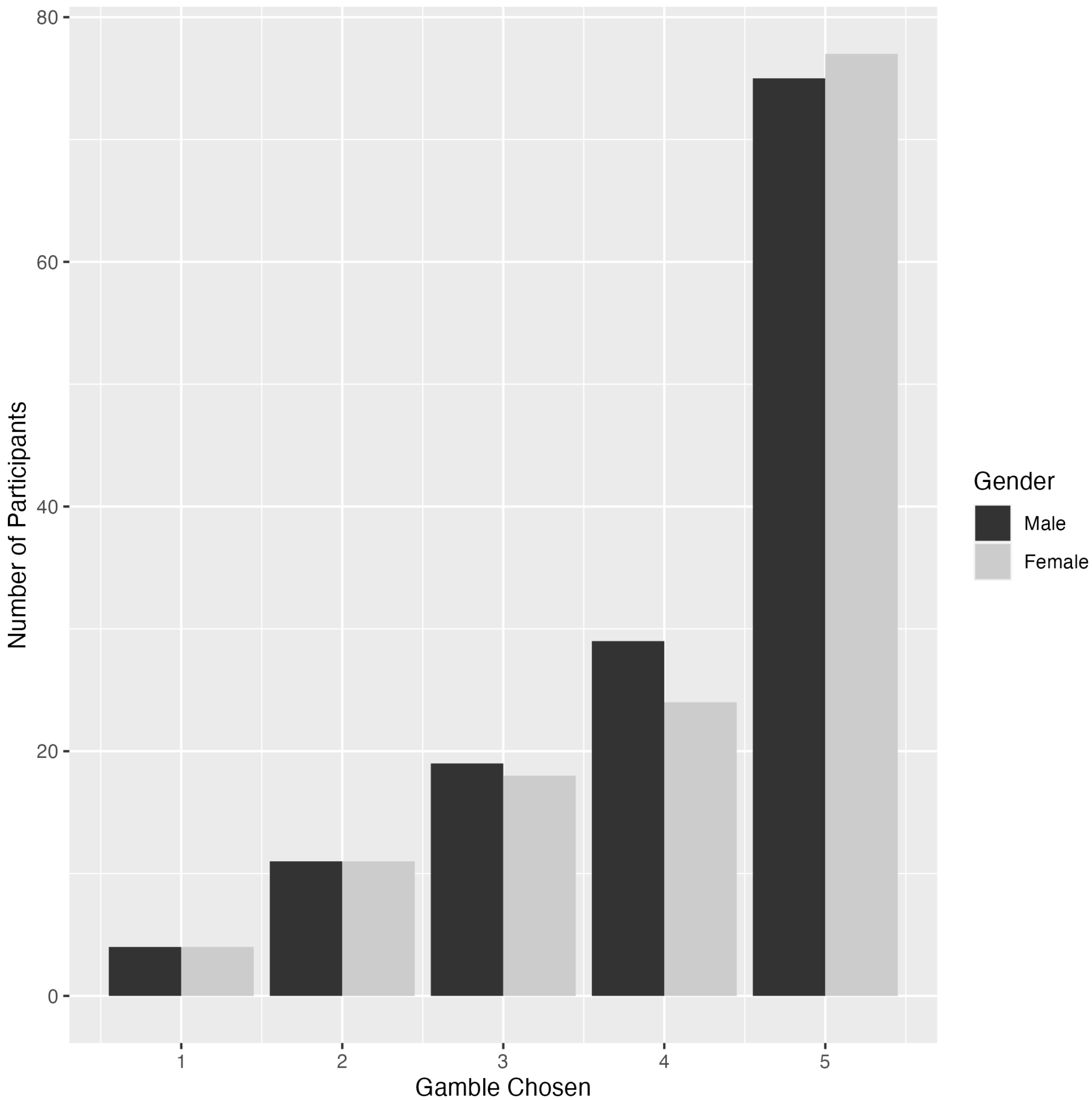


Figure 2: Outside Buyer Price Distributions
The three distributions are centered on 45 MXN, 50 MXN, and 55 MXN.

	Quintals sold to Buyer 1								
	0	1	2	3	4	5	6	7	8
	Quintals sold to Buyer 2								
	8	7	6	5	4	3	2	1	0
	Revenue from Sales								
	Revenue from Buyer 2 (50 MXN per Kg.)								
	0	3,000	6,000	9,000	12,000	15,000	18,000	21,000	24,000
Price per Kg. of Buyer 2	Revenue from Buyer 1 (Price per Kg. depends on die result)								
45	21,600	18,900	16,200	13,500	10,800	8,100	5,400	2,700	0
50	24,000	21,000	18,000	15,000	12,000	9,000	6,000	3,000	0
55	26,400	23,100	19,800	16,500	13,200	9,900	6,600	3,300	0
60	28,800	25,200	21,600	18,000	14,400	10,800	7,200	3,600	0
65	31,200	27,300	23,400	19,500	15,600	11,700	7,800	3,900	0

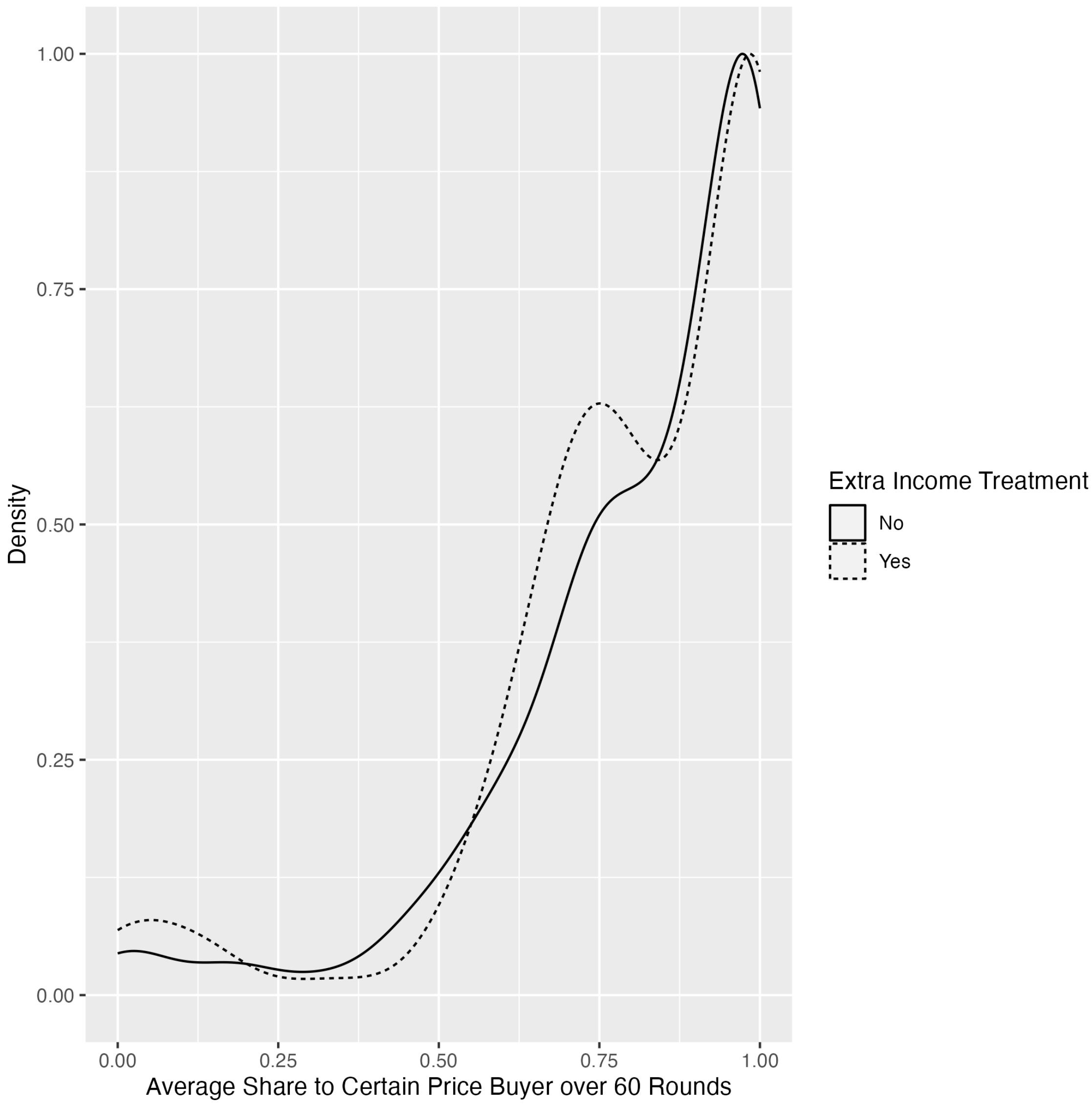
Figure 3: Representative Payoff Table
Participants are shown a version of this table each round that differs according to harvest size and uncertain price buyer distribution.

Figure 4: Lottery Gamble Choices by Gender



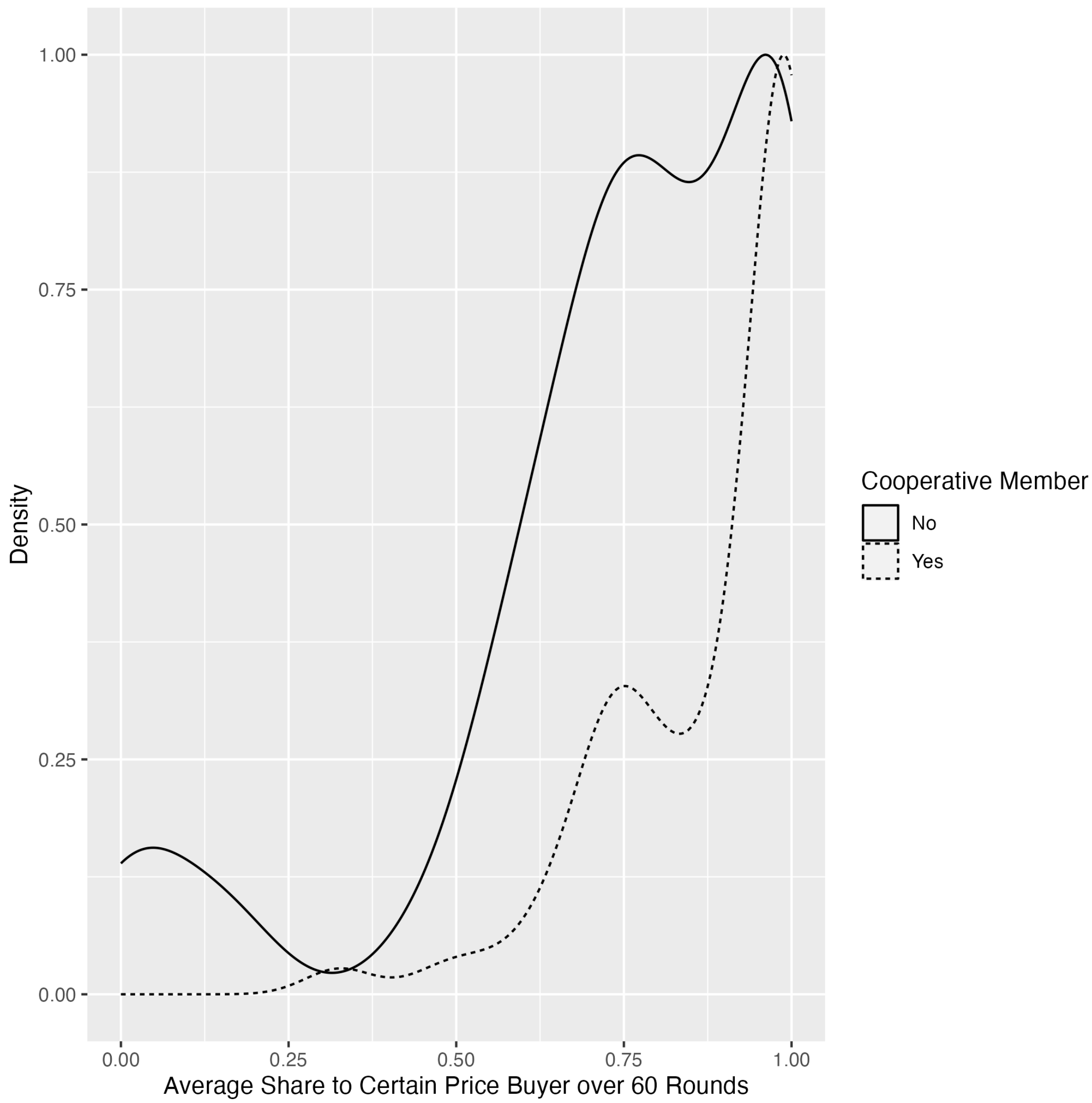
This figure displays a histogram of gamble choices from a no-loss lottery based on Eckel and Grossman (2008). It is comparable to Figure 1 in that paper. Here we do not see differences between the gamble choices of men and women.

Figure 5: Total Margin by Treatment Status



This figure displays a density plot of average share of harvest allocated over all 60 rounds by participants, broken down by treatment status. Treated participants receive 3000 MXN of extra income in every round.

Figure 6: Total Margin by Cooperative Membership Status



This figure displays a density plot of average share of harvest allocated over all 60 rounds by participants, broken down by cooperative membership status.

Table 1: Field visits to regional centers served by Batsil Maya.

	Dates	Participants: Non-Members	Participants: Members	Participants: Total
Agua Dulce Tehuacan	15 July	9	12	21
Chilón	N/A	—	—	—
Coquilte'el	20 July	13	12	25
Nuevo Progreso	3 Aug; 22 Aug	48	10	58
Paraiso Chic'otanil	14 July	4	22	26
San Jose Veracruz	29 June; 2 Aug	18	30	48
Tzubute'el	19 July	6	20	26
Yaxwinic	30 June; 1 July	47	16	63
Ye'tal Ts'ahc	N/A	—	—	—
Yochibha	28 June	2	6	8
Total	—	147	128	275

[1] Field visits were conducted in summer 2022.

[2] For logistical reasons, we could not visit two of the ten regional centers.

[3] After all of the field visits were completed, we used the Batsil Maya cooperative membership roster to determine whether experiment participants were in cooperative member families.

Table 2: Gamble choices, expected payoff, and risk[1]

Choice	Event	Probability (%)	Payment (MXN)	Expected Payoff	Risk[2]	CRRA[3]
1	A	50%	10000	10000	0	$r > 2$
	B	50%	10000			
2	A	50%	15000	11250	3750	$0.67 < r < 2$
	B	50%	7500			
3	A	50%	20000	12500	7500	$0.38 < r < 0.67$
	B	50%	5000			
4	A	50%	25000	13750	11250	$0.20 < r < 0.38$
	B	50%	2500			
5	A	50%	30000	15000	15000	$r < 0.20$
	B	50%	0			

[1] Adapted from Table 1 in Eckel and Grossman (2008)
[2] Measured as standard deviation of expected payoff.
[3] Calculated as the range of r in the function $U(x) = x^{1-r}/(1-r)$ for which the subject chooses each gamble assuming constant relative risk aversion utility.

Table 3: Subject-level variables.

	N	Yes	No	Mean	SD
Exit Survey					
Grows coffee (1 = Yes)	275	275	0	1.000	0.000
Can read/write (1 = Yes)	275	204	71	0.742	0.438
Gender (1 = Female)	275	137	138	0.498	0.501
Age	275	—	—	43.425	15.656
Completed Only Middle School (1 = Yes)	275	39	236	0.142	0.349
Completed High School (1 = Yes)	275	29	246	0.105	0.308
Cooperative Member (1 = Yes)	275	128	147	0.465	0.500
Preliminary Activities					
Understands arithmetic (1 = Yes)	275	275	0	1.000	0.000
Understands percentages (1 = Yes)	275	273	2	0.993	0.085
Understands probability (1 = Yes)	275	204	71	0.742	0.438
Extra income treatment (1 = Yes)	275	138	137	0.502	0.501
CRRA (from Eckel-Grossman Lottery)	272	—	—	0.527	0.651
Practice game (1 = Yes)	275	234	41	0.851	0.357
Outcome of Interest					
Overall Margin	273	—	—	0.819	0.221
Extensive Margin	273	58	215	0.212	0.410
Intensive Margin	215	—	—	0.770	0.225

[1] Three participants did not complete lottery because of surveyor error.
[2] 41 participants did not complete the practice game because of surveyor error.
[3] Two participants did not complete all three games because of surveyor error.
[4] Overall Margin is average allocation to certain price buyer across 60 rounds.
[5] Extensive Margin is 1 if a participant always allocates entire harvest to certain price buyer across 60 rounds, 0 otherwise.
[6] Intensive Margin is the average allocation for the subset of participants for whom Extensive Margin is not 1.

Table 4: Game Order

	Order	Count
Lottery Before		
	Lottery, Game 1, Game 2, Game 3	27
	Lottery, Game 1, Game 3, Game 2	26
	Lottery, Game 2, Game 1, Game 3	23
	Lottery, Game 2, Game 3, Game 1	25
	Lottery, Game 3, Game 1, Game 2	24
	Lottery, Game 3, Game 2, Game 1	20
Subtotal	—	145
Lottery After		
	Game 1, Game 2, Game 3, Lottery	19
	Game 1, Game 3, Game 2, Lottery	25
	Game 2, Game 1, Game 3, Lottery	16
	Game 2, Game 3, Game 1, Lottery	23
	Game 3, Game 1, Game 2, Lottery	23
	Game 3, Game 2, Game 1, Lottery	22
Subtotal	—	128
N/A		
	Not entered (surveyor error)	2
Total	—	275

[1] All participants completed three games and an Eckel-Grossman risk preference lottery before or after the three games.
[2] The order of the lottery and the games was determined with a roll of a 12-sided die.
[3] The game order for two participants was not entered because of surveyor error.

Table 5: Descriptive statistics at the subject-round level

	Game 1		Game 2		Game 3		Pooled	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Experimental Variables								
Harvest 2 quintales (1 = Yes)	0.157	(0.364)	0.155	(0.362)	0.151	(0.359)	0.154	(0.361)
Harvest 4 quintales (1 = Yes)	0.197	(0.398)	0.207	(0.405)	0.192	(0.394)	0.199	(0.399)
Harvest 6 quintales (1 = Yes)	0.304	(0.460)	0.316	(0.465)	0.326	(0.469)	0.315	(0.465)
Harvest 8 quintales (1 = Yes)	0.342	(0.474)	0.322	(0.467)	0.330	(0.470)	0.331	(0.471)
Mean of Uncertain Price Buyer 45 MXN (1 = Yes)	0.204	(0.403)	0.212	(0.409)	0.202	(0.402)	0.206	(0.405)
Mean of Uncertain Price Buyer 50 MXN (1 = Yes)	0.429	(0.495)	0.426	(0.495)	0.419	(0.493)	0.425	(0.494)
Mean of Uncertain Price Buyer 55 MXN (1 = Yes)	0.367	(0.482)	0.361	(0.480)	0.379	(0.485)	0.369	(0.483)
Outcome of Interest								
Allocation to Certain Price Buyer	0.818	(0.277)	0.824	(0.271)	0.815	(0.280)	0.819	(0.276)
Observations								
Subjects	273	—	273	—	273	—	273	—
Rounds	5460	—	5460	—	5460	—	16380	—

Results from two participants missing because of surveyor error.

Table 6: Impact on Share to Certain Price Buyer by Game (Fixed Effects)

	Dependent variable:		
	Share Sold to Certain-Price Buyer		
	Game 1	Game 2	Game 3
	(1)	(2)	(3)
Harvest 2 quintales (1 = Yes)	−0.031***	−0.029***	−0.014
	(0.009)	(0.010)	(0.010)
Harvest 6 quintales (1 = Yes)	0.003	0.004	0.017***
	(0.006)	(0.006)	(0.006)
Harvest 8 quintales (1 = Yes)	−0.022***	−0.019***	−0.014*
	(0.008)	(0.007)	(0.007)
Mean of Uncertain Price Buyer 45 MXN (1 = Yes)	−0.026***	−0.027***	−0.018**
	(0.008)	(0.007)	(0.007)
Mean of Uncertain Price Buyer 55 MXN (1 = Yes)	−0.004	0.003	−0.001
	(0.006)	(0.005)	(0.006)
Linear Time Trend	0.0001	−0.0001	0.001
	(0.001)	(0.0004)	(0.0004)
Subject Fixed Effects	Y	Y	Y
Subjects	273	273	273
Rounds	60	60	60
Observations	5,460	5,460	5,460
R^2	0.010	0.012	0.010
Adjusted R^2	−0.043	−0.041	−0.044
F Statistic (df = 6; 5181)	8.576***	10.861***	8.373***

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at the subject level.
Reference harvest is 4 quintales.
Reference mean of uncertain price buyer is 50 MXN.
In Games 1, 2, and 3, certain price buyer offers 50 MXN.
In Game 2, certain price buyer also offered microcredit to subject last year.
In Game 3, certain price buyer is a cooperative that offered
microcredit and technical assistance last year.

Table 7: Impact on Share to Certain Price Buyer (Fixed Effects)

	Dependent variable:
	Share Sold to Certain-Price Buyer
Harvest 2 quintales (1 = Yes)	-0.026^{***}
	(0.007)
Harvest 6 quintales (1 = Yes)	0.008^{**}
	(0.004)
Harvest 8 quintales (1 = Yes)	-0.017^{***}
	(0.006)
Mean of Uncertain Price Buyer 45 MXN (1 = Yes)	-0.024^{***}
	(0.005)
Mean of Uncertain Price Buyer 55 MXN (1 = Yes)	−0.002
	(0.004)
Game 2 (Microcredit)	0.002
	(0.007)
Game 3 (Coop with Microcredit and Technical Assistance)	−0.009
	(0.011)
Linear Time Trend	0.0002
	(0.0003)
Subject Fixed Effects	Y
Subjects	273
Rounds	60
Observations	16,380
R^2	0.010
F Statistic	19.664^{***} (df = 8; 16099)

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at the subject level.
Reference harvest is 4 quintales.
Reference mean of uncertain price buyer is 50 MXN.
In Games 1, 2, and 3, certain price buyer offers 50 MXN.
In Game 2, certain price buyer also offered microcredit to subject last year.
In Game 3, certain price buyer is a cooperative that offered
microcredit and technical assistance last year.

Table 8: Subject-level Outcomes

	Average Allocation to Certain-Price Buyer Over 60 Rounds		
	Overall Margin	Extensive Margin	Intensive Margin
	(1)	(2)	(3)
3000 MXN Extra Income	0.001 (0.026)	0.095* (0.051)	−0.020 (0.030)
Female (1=Yes)	0.005 (0.028)	0.032 (0.056)	−0.008 (0.034)
Age	−0.0001 (0.001)	−0.0003 (0.002)	−0.0001 (0.001)
CRRA	0.015 (0.013)	0.016 (0.039)	0.017 (0.016)
Completed Only Middle School (1=Yes)	−0.088* (0.053)	−0.146** (0.067)	−0.069 (0.059)
Completed High School (1=Yes)	−0.045 (0.053)	0.023 (0.094)	−0.053 (0.070)
Played Practice Game (1=Yes)	−0.135*** (0.033)	−0.259*** (0.085)	−0.116** (0.048)
Understands Probability (1=Yes)	−0.088*** (0.031)	−0.161** (0.066)	−0.050 (0.037)
Can Read/Write (1=Yes)	0.027 (0.037)	0.039 (0.064)	0.016 (0.044)
Constant	0.712** (0.321)	0.264 (0.275)	0.682** (0.303)
Game Order and Lottery Position Dummies	Y	Y	Y
Observations	270	270	212
R^2	0.133	0.108	0.116

*p<0.1; **p<0.05; ***p<0.01
In column (2), the dependent variable is a dummy which equals 1 if the subject allocates the entire harvest to the certain price buyer in all rounds; 0 otherwise. Column (3) presents the same regression as column (1) on the subset of subjects for whom the dummy variable is 0.
By surveyor error, 41 participants did not complete 10 round practice game
71 participants answered basic probability question incorrectly before game
All three columns present heteroskedasticity-robust standard errors.

Table 9: Impact on Share by Cooperative Membership Status (Fixed Effects)

	Dependent variable:	
	Share Sold to Certain-Price Buyer	
	Members	Non-Members
	(1)	(2)
Harvest 2 quintales (1 = Yes)	−0.019**	−0.033***
	(0.010)	(0.011)
Harvest 6 quintales (1 = Yes)	0.008**	0.006
	(0.003)	(0.006)
Harvest 8 quintales (1 = Yes)	−0.001	−0.032***
	(0.006)	(0.009)
Mean of Uncertain Price Buyer 45 MXN (1 = Yes)	−0.008*	−0.040***
	(0.004)	(0.009)
Mean of Uncertain Price Buyer 55 MXN (1 = Yes)	−0.0004	−0.002
	(0.004)	(0.006)
Game 2 (Microcredit)	0.011	−0.005
	(0.008)	(0.011)
Game 3 (Coop with Microcredit and Technical Assistance)	0.010	−0.027
	(0.011)	(0.019)
Linear Time Trend	−0.00002	0.0003
	(0.0002)	(0.0004)
Subject Fixed Effects	Y	Y
Subjects	128	145
Rounds	60	60
Observations	7,680	8,700
R^2	0.006	0.016

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at the subject level.
Reference harvest is 4 quintales.
Reference mean of uncertain price buyer is 50 MXN.
In Games 1, 2, and 3, certain price buyer offers 50 MXN.
In Game 2, certain price buyer also offered microcredit to subject last year.
In Game 3, certain price buyer is a cooperative that offered
microcredit and technical assistance last year.

Table 10: Subject-level Outcomes (Cooperative Members)

	Average Allocation to Certain-Price Buyer Over 60 Rounds		
	Overall Margin	Extensive Margin	Intensive Margin
	(1)	(2)	(3)
3000 MXN Extra Income	0.015 (0.026)	0.158* (0.083)	−0.012 (0.035)
Female (1=Yes)	0.022 (0.034)	0.016 (0.110)	0.009 (0.047)
Age	−0.001 (0.001)	−0.001 (0.003)	−0.0004 (0.001)
CRRA	−0.0004 (0.019)	0.061 (0.063)	−0.015 (0.027)
Completed Only Middle School (1=Yes)	−0.038 (0.048)	−0.240 (0.153)	−0.001 (0.058)
Completed High School (1=Yes)	0.067 (0.060)	0.184 (0.192)	0.073 (0.095)
Played Practice Game (1=Yes)	−0.083** (0.036)	−0.264** (0.115)	−0.062 (0.052)
Understands Probability (1=Yes)	−0.084*** (0.030)	−0.218** (0.098)	−0.059 (0.044)
Can Read/Write (1=Yes)	−0.051 (0.032)	−0.073 (0.104)	−0.057 (0.046)
Constant	0.391** (0.150)	0.028 (0.483)	0.412** (0.174)
Game Order and Lottery Position Dummies	Y	Y	Y
Observations	127	127	90
R^2	0.291	0.212	0.259

*p<0.1; **p<0.05; ***p<0.01

In column (2), the dependent variable is a dummy which equals 1 if the subject allocates the entire harvest to the certain price buyer in all rounds; 0 otherwise. Column (3) presents the same regression as column (1) on the subset of subjects for whom the dummy variable is 0.

By surveyor error, 41 participants did not complete 10 round practice game

71 participants answered basic probability question incorrectly before game

All three columns present heteroskedasticity-robust standard errors.

Table 11: Subject-level Outcomes (Cooperative Non-Members)

	Average Allocation to Certain-Price Buyer Over 60 Rounds		
	Overall Margin	Extensive Margin	Intensive Margin
	(1)	(2)	(3)
3000 MXN Extra Income	−0.025 (0.045)	0.001 (0.064)	−0.023 (0.049)
Female (1=Yes)	0.067 (0.049)	0.129* (0.070)	0.042 (0.053)
Age	−0.001 (0.002)	−0.0005 (0.003)	−0.0001 (0.002)
CRRA	0.026 (0.036)	−0.088* (0.050)	0.046 (0.038)
Completed Only Middle School (1=Yes)	−0.096 (0.065)	−0.116 (0.092)	−0.091 (0.071)
Completed High School (1=Yes)	−0.055 (0.071)	0.025 (0.101)	−0.060 (0.080)
Played Practice Game (1=Yes)	−0.215*** (0.076)	−0.168 (0.107)	−0.245*** (0.090)
Understands Probability (1=Yes)	−0.103** (0.052)	−0.144* (0.073)	−0.044 (0.058)
Can Read/Write (1=Yes)	0.110* (0.058)	0.199** (0.082)	0.071 (0.062)
Constant	0.989*** (0.297)	0.132 (0.419)	0.999*** (0.306)
Game Order and Lottery Position Dummies	Y	Y	Y
Observations	143	143	122
R^2	0.205	0.175	0.211

*p<0.1; **p<0.05; ***p<0.01
In column (2), the dependent variable is a dummy which equals 1 if the subject allocates the entire harvest to the certain price buyer in all rounds; 0 otherwise. Column (3) presents the same regression as column (1) on the subset of subjects for whom the dummy variable is 0.
By surveyor error, 41 participants did not complete 10 round practice game
71 participants answered basic probability question incorrectly before game
All three columns present heteroskedasticity-robust standard errors.