Three Essays in Development Economics: Evidence from the Philippines

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Declaration

I certify that the thesis I have presented for the doctoral degree in Economics at the University of Mannheim is solely my own work other than where I have clearly indicated that it is the work of others.

The first chapter draws on work that was carried out jointly with equal share by Stefan Penczynski and me. The second chapter is my own work. The third chapter was carried out jointly with equal share by Andreas Landmann, Christian Biener, and me.

María Isabel Santana-Penczynski, 10. Mai 2017

Para mis padres, Felipe e Idalia Santana y mi esposo Stefan Penczynski.

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Preface

Incorporating psychological insights regarding human behavior to explain how individuals make economic decisions is providing new perspectives to research questions in development economics. Understanding the way that people make the decisions is key for the design of programs that aim at improving the livelihood of people in poverty throughout the developing world. In this dissertation I incorporate behavioral economic tools to examine how people in the Philippines make decisions in three areas: institutions, savings and insurance.

In chapter 1, Stefan Penczynski and I propose a novel way of experimentally measuring trust in institutions, drawing on the experimental method used to elicit time preferences. Our method enables the elicitation of levels of trust towards institutions in an incentivized way and is not identified by the participants as a measure of trust. In contrast to other measures of trust, it provides a meaningful metric of subjective probability of trustworthiness of the trustee. We measure trust in two institutions, a formal Philippine microfinance institution and informal local money lenders. The trust in the formal institution is robustly measured to be significantly higher than in the informal institution. We find that unincentivized survey measures indicate a much stronger difference in the same direction, suggesting that survey measures are driven by further factors such as preferences. Additionally, we exploit the random variation generated by our experiment to examine whether a higher level of trust in the formal institution leads to a change in financial behavior. Savings in the formal institution increase significantly when the promise of future payment is fulfilled.

In chapter 2, together with a microfinance institution in the Philippines, I implement a financial education program that focuses on savings and evaluate the effect on participants' savings balance. I also investigate whether the effects of the program propagate to members of the participants' social networks.

In chapter 3, together with coauthors Andreas Landmann and Christian Biener, we examine the effects of contract non-performance on insurance demand. We extend models of probabilistic insurance to allow for ambiguity in contract nonperformance risk, and derive formally that mean-preserving ambiguity reduces demand. The results of a field lab experiment are consistent with this logic. In particular, we find that a 10 percent contract nonperformance risk reduces insurance demand by 17.1 percentage points even when premia are adjusted accordingly. Ambiguity about this contract nonperformance probability further decreases demand by 14.5 percentage points. While the demand-reducing effect of ambiguity is more pronounced for high-numeracy and ambiguity-averse individuals, it appears to be little affected by experience. The reason for an insurance contract failure to perform does not significantly influence the strength of these effects, but independently affects demand of low-numeracy and ambiguity-averse individuals.

1 Measuring Trust in Institutions: A Lab-in-the-Field Study Using Time Preference Elicitation

1.1 Introduction

Economic transactions are based on bilateral exchange of goods, services or money. These transactions often involve private or governmental institutions. The more the transacting parties trust each other, the easier the organisation of important sequential exchanges. Trust has a causal impact on economic development via channels on the financial, product and labor markets (Algan and Cahuc, 2014) and has positive consequences for financial behavior in the microfinance sector (Karlan, 2005). It is relevant for the demand for financial products when household financial literacy and legal protection are low (Cole, Gine, Tobacman, Topalova, Townsend, and Vickery, 2013).[1] While trust is an important economic factor, little is known about trust directed towards institutions because it is difficult to measure.

In this study, we propose a behavioral measure of trust in institutions that is – like all experimental measures – based on the behavioral definition of trust put forward by Coleman (1990) and Fehr (2009). "An individual trusts if she voluntarily places resources at the disposal of another party without any legal commitment from the latter. In addition, the act of trust is associated with an expectation that the act will pay off in terms of [this individual]'s goals." (Fehr, 2009, p. 238)

The most commonly used measures of trust are hypothetical questions in surveys. However, behavioral measures of trust capture trust more accurately than reported measures (Fehr, 2009; Algan and Cahuc, 2014). After all, it is not clear whether individuals that declare trusting an institution would actually behave in a more cooperative way or be willing to transact with the institution. Therefore, measures that rely on the actions and choices of the individual is a better way of capturing the individual's trust levels. The most commonly used behavioral measures of trust is the trust game by Berg, Dickhaut, and McCabe (1995).[2] Since the trust game is commonly played between anonymous participants, it captures the notion of general trust rather than trust directed towards any specific person or institution.[3] Additionally, other-regarding preferences, such as altruism, as well as the trustor's belief about the

[1] Generally, trust has been shown to be positively related to GDP (Porta, Lopez-De-Silane, Shleifer, and Vishny, 1997; Knack and Keefer, 1997; Zak and Knack, 2001), trade (Guiso, Sapienza, and Zingales, 2009), and to stock purchases (Guiso, Sapienza, and Zingales, 2004, 2008).

[2] Another behavioral measure of trust is the gift-exchange game by Fehr, Kirchsteiger, and Riedl (1993).

[3] The trust game has been used extensively in laboratory and field experiments as a way to measure general trust both in developed and in developing countries (Karlan, 2005; Glaeser, Laibson, Scheinkman, and Soutter, 2000; Barr, 2003; Tu and Bulte, 2010; Buck and Alwang, 2011).

trustee's reciprocity should not contribute strongly towards trust in institutions, although they have been shown to matter for trusting behavior in the trust game (Cox, 2004; Ashraf, Bohnet, and Piankov, 2006).

We propose a behavioral trust measure inspired by the time preference elicitation method, in which an institution is responsible for the future payment.[4] We identify trust by providing a payment securement in form of a post-dated check and examining the difference to the unsecured setting. To test our measure and for comparison, we implement the measure for a formal and an informal institution. Note that the uncertainty of future payment delivery in time preference elicitation is analogue to the situation described in the definition of trust. Indeed, the time preference literature documents the challenge to make subjects trust completely in the experimenter and in the completion of the future payment (e.g. Coller and Williams, 1999). Our idea is then to look for differences in behavior between treatments in which different institutional settings govern the future payment. If such differences occur between two random samples of the same population, they can be attributed to different levels of trust in the institutional setting.

There are various ways to elicit time preferences. Traditionally, multiple price lists (MPL) have been used that confront subjects with a set of binary choices between a smaller, sooner and a larger, later payment. Preferences are inferred from the indifference point (Coller and Williams, 1999). Andersen, Harrison, Lau, and Rutström (2008) use one MPL for time and one for risk preferences (DMPL). Recently, the implementation of a Convex Time Budget (CTB) has been introduced by Andreoni and Sprenger (2012a), allowing for an inference from the optimality of the consumption allocation between two points in time. In order to capture differences between treatments as finely as possible, we implement convex choice sets. For robustness, we add features of the DMPL method such as separate risk preference elicitation and binary choice sets.

Our trust elicitation is equipped to measure trust in an institution because there is a clearly defined, known trustee: the institution that is responsible for the future payment. In addition, an advantage of the experimental nature of the games and our method is that they lead to the observation of incentivized, not hypothetical behavior. Furthermore, coming in the guise of a measure of time preferences, trust is elicited without the subjects suspecting a trust measurement or hearing the word "trust". In contrast to both survey and common experimental measures, our data allows us to quantify the trust in an institution in terms of the subjective probability of following through on a promise.

In this study, we implement our trust elicitation method alongside a trust game and survey questions on trust in the context of a lab-in-the-field study in the Philippines. The two institutions that are responsible for the future payment are on the one side a formal regional microfinance institution called Negros Women for Tomorrow

[4]See Frederick, Loewenstein, and O'Donoghue (2002) for a survey and references.

Foundation (NWTF) and on the other side local money lenders (ML), an informal lending institution.

We observe significant differences in trust in the expected direction and quantify the subjective probability of payment completion to be 0.60 and 0.54 relative to payments with securement by check in our preferred specification. The trust in the formal institution NWTF is throughout measured to be higher than in the informal institution ML. The survey measures of trust are differing between the two institutions to a much stronger degree. Although they cannot be translated into an objective metric, the results suggest that the hypothetical question for trust invokes additional elements beyond trust, such as social preferences, that are distinct from the definition of trust as presented above.

We further look at the determinants of trust, namely risk and social preferences, as their effects on trust have been shown in the literature.[5] While we find no effect of estimated risk preferences on our behavioral measure of institutional trust, we do find that reported risk preferences affects reported measures of institutional trust. Looking at betrayal aversion, for both institutions, we find surprisingly that the more our subjects report to avoid being betrayed, the higher their level of behavioral trust. Effects of betrayal aversion go in the opposite direction for reported measures of institutional trust. Overall, the analysis supports the view that behavioral measures of trust are less related to preferences than reported measures of trust.

Finally, our experiment has the potential to provide exogenous, random variation on the level of trust in an institution. In particular, the fulfillment of the promise of the future payment delivery could affect trust positively and change financial behavior. To investigate this, we exploit the random selection of the round to be paid which determines whether subjects were to receive a future payment or not. Using administrative data from the formal institution, we find that the fulfillment of the promise increases savings by approximately 25% above baseline levels. To our knowledge this is the first instance of randomly impacting trust in the field and using this random variation to show the effects of trust on economic outcomes.

We also contribute to the experimental literature of time preference elicitation by investigating the relevance of payment securement for time preference measurement. In particular, the results confirm that a post-dated check helps raise the trust in the reception of the later payment and thus has an influence on the measured time discount factor. We are not aware of another study that deliberately manipulates the institutional context in order to investigate aspects of subjective uncertainty.

The paper is structured as follows. Section 1.2 shows how our study relates and contributes to different strands of the literature. Sections 1.3 presents our experimental design and 1.4 presents the theoretical background and the statistical model. Sections 1.5 and 1.6 present the data and the main results. Section 1.7 relates reported

[5]See Eckel and Wilson (2004), Cox (2004), Bohnet and Zeckhauser (2004), Ashraf, Bohnet, and Piankov (2006), Schechter (2007), Fehr (2009), and Houser, Schunk, and Winter (2010).

and elicited measures of trust and preferences. Section 1.8 investigates the effect of the possible exogenous variation of trust on savings. Finally, sections 1.9 and 1.10 discusses our findings and conclude the paper.

1.2 Related Literature

In economics, the facilitating effects of trust have been recognized since John Stuart Mill acknowledged that the "advantage to mankind of being able to trust one another penetrates into every crevice and cranny of human life" (Mill, 1865, p. 68). Currently, one of the most immediately quantifiable impacts of trust in institutions is discussed in the literature that investigates trust in the financial sector. Guiso, Sapienza, and Zingales (2008) study the potential effects of a lack of trust on stock market participation and find that less trusting individuals are less likely to purchase stock. Trust in financial institutions has also been linked to the 2008 financial crisis. Sapienza and Zingales (2012) attribute the recession to a sharp loss in trust in the financial sector, finding a correlation between low levels of trust after the crisis and people's willingness to invest in the stock market and their tendency to withdraw deposits (see also Corsetti, Devereux, Guiso, Hassler, Saint-Paul, Sinn, Sturm, and Vives, 2010). In a broader context, Stevenson and Wolfers (2011) explore the link between the recession that followed the financial crisis and mistrust in public institutions in the US. All these studies use survey measures of trust to assess trust levels towards financial and public institutions.[6] We contribute to this literature by providing a measure of trust in institutions that relies on incentivized choices and behavior rather than on reported levels of trust.

We also contribute to the literature on the determinants of trust. The effects of risk preferences on trust are mixed as some studies find no statistical relationship (Eckel and Wilson, 2004; Houser, Schunk, and Winter, 2010) while others find a relation between trust and risk attitudes (Schechter, 2007; Sapienza, Toldra-Simats, and Zingales, 2013). Other-regarding preferences such as altruism have been shown to have an effect in the amount sent in the trust game (Cox, 2004; Ashraf, Bohnet, and Piankov, 2006). Betrayal aversion has been identified to play a role in trusting behavior (Bohnet and Zeckhauser, 2004). From the perspective of survey measures of trust, risk aversion, betrayal aversion and altruism have been also shown to correlate with trust (Fehr, 2009). We contribute to the literature by contrasting our behavioral and survey measures of institutional trust and showing that reported measures are more driven by social preferences than our behavioral measures.

Our study further relates to the strand of the literature that investigates causal links between trust and economic outcomes in both developed and developing countries (Porta, Lopez-De-Silane, Shleifer, and Vishny, 1997; Knack and Keefer, 1997; Zak and Knack, 2001; Guiso, Sapienza, and Zingales, 2004, 2008; Karlan, 2005; Tu and Bulte,

[6] They use survey data from the World Value Survey (WVS), the General Social Survey (GSS) and the Financial Trust Index Survey (FTIS).

2010). In developing countries, the effects of trust on financial behavior have been documented (Cole, Gine, Tobacman, Topalova, Townsend, and Vickery, 2013; Bachas, Gertler, Higgins, and Seira, 2016; Mehrotra, Somville, et al., 2016). Karlan, Ratan, and Zinman (2014) identify lack of trust as a barrier to savings by poor people (see also Dupas, Green, Keats, and Robinson, 2014). We add to these insights by exploiting the random variation generated by our experimental design and documenting the effects of an exogenous variation on trust towards an institution on financial behavior.

Since we employ methods of time preference elicitation, our study is related to the wide area of experimental work that measures intertemporal discounting. In particular, the survey by Frederick, Loewenstein, and O'Donoghue (2002) emphasizes that delayed rewards are subject to uncertainty, which could be a confounding factor in the measurement. The importance of perceived risk in intertemporal choice has been highlighted by Halevy (2008) and explicitly investigated with the implementation of objective uncertainty by Andreoni and Sprenger (2012b). Their work points to a disproportionate preference for certainty over uncertainty.

Since the delay of a payment comes with inherent uncertainty about its future enjoyment, the literature has always aimed to establish subjects' trust in the experimenter's full commitment to realize the payment. For that purpose, it is common practice to use notarized certificates, post-dated checks or equivalent financial instruments to assure the future payment (e.g. Coller and Williams, 1999; Benjamin, Choi, and Strickland, 2010; Andersen, Harrison, Lau, and Rutström, 2008). At times, studies appeal to the reputation of the investigator, use personal checks and distribute business cards for possible complaints (e.g. Andreoni and Sprenger, 2012a,b).

The literature on experimental time preference elicitation features two alternative elicitation methods. In order to account appropriately for utility function curvature, Andersen, Harrison, Lau, and Rutström (2008) use two multiple price lists (DMPL) of binary choices for the simultaneous elicitation of time and risk preferences. Andreoni and Sprenger (2012a,b) put forward a single elicitation that features a convex time budget (CTB) to identify curvature and discounting at the same time. This method has been subject of controversial debates (Harrison, Lau, and Rutström, 2013; Cheung, 2015; Andreoni and Sprenger, 2015; Andreoni, Kuhn, and Sprenger, 2015) as the profession is converging on the preferable method.

For our implementation we use the CTB-method for the high informational content in each choice. However, we enabled a DMPL-type estimation by further eliciting binary choices and risk preferences. We see that binary choices are highly predictive of the choices from CTBs. Our results are robust across both approaches. However, advances and convergence in the literature of time preference elicitation would improve and facilitate trust measurements of the kind we propose.

1.3 Experimental design

In our experiment, we measure trust in institutions with a method that is similar to time preference elicitation. For this purpose, we vary between-subject the institution that carries responsibility for the correct implementation of the later payment. Furthermore, we vary within-subject whether the payment is secured by a post-dated check. In the following, the chronology of a session guides us through the details of the design.

A session begins with the first part of a questionnaire (from now on pre-questionnaire) administered individually by a research assistant. Subsequently, subjects go through the trust elicitation task (TE), the risk preference elicitation task (RPE) as well as the trust game (TG), each starting with its respective instructions in the plenary. One decision from TE and RPE is chosen for payment by a random draw of the subject. Participants then answer the second part of the questionnaire (from now on post-questionnaire) and finally collect their immediate payments from the one decision and the TG.

1.3.1 Trust elicitation task

The main idea behind the trust elicitation task is that a subject places more resources in the hands of an institution the higher is her belief of receiving these resources, bare any legal commitment, from the institution in the future. By varying the institution or providing benchmarks in the form of a check, changes in behavior allow us to estimate the subjects' beliefs P of compliance by the institution. We call P the level of trust in institution I. The intertemporal utility of the allocation of money to two points in time depends on the probability of obtaining the future payment as follows,

$$DU(c_t, c_{t+d}) = u(c_t) + \delta^d \left[P \cdot u(c_{t+d}) + (1 - P) \cdot u(0)\right]. \tag{1.1}$$

Decision Subjects are presented 36 decisions which feature two delay lengths until the later payments, $d = (7, 28)$ days, and two payment securements $S = (NC, C)$, depending on a securement in form of a check being offered (C) or not (NC). For each combination of S and d, subjects are presented with nine different interest rates $(1 + r)$ ranging from 1 to 40.

Drawing on the Convex Time Budget (CTB) approach of Andreoni and Sprenger (2012a), in each of the decisions subjects choose an amount $c_t \in [a, 150]$ in Philippine Pesos (PHP) for immediate payment. The interest rate $1 + r$ determines the future amount to be $c_{t+d} = (150 - c_t) \cdot (1 + r)$. For interest rates ranging from 1 to 2.67, the budget set begins at $a = 0$. For $1 + r = (4, 8, 40)$, we set $a = (50, 100, 140)$, respectively, and thus cap the earnable amount c_{t+d} at a maximum of 400. Table 1.1 presents the parameters of the 36 decisions.

Table 1.1 Choice parameters in TE.

Delay d	Securement S	Minimum amount a	Interest rate $1+r$	Daily rate $1+r_{\text{daily}}$
7	NC	0	1	1
7	NC	0	1.33	5.20
7	NC	0	1.67	8.57
7	NC	0	2	11.41
7	NC	0	2.33	13.87
7	NC	0	2.67	16.04
7	NC	50	4	22.90
7	NC	100	8	35.59
7	NC	140	40	70.38
28	NC	0	1	1
28	NC	0	1.33	2.03
28	NC	0	1.67	2.84
28	NC	0	2	3.51
28	NC	0	2.33	4.07
28	NC	0	2.67	4.57
28	NC	50	4	6.08
28	NC	100	8	8.71
28	NC	140	40	15.08
7	C	0	1	1
7	C	0	1.33	5.20
7	C	0	1.67	8.57
7	C	0	2	11.41
7	C	0	2.33	13.87
7	C	0	2.67	16.04
7	C	50	4	22.90
7	C	100	8	35.59
7	C	140	40	70.38
28	C	0	1	1
28	C	0	1.33	2.03
28	C	0	1.67	2.84
28	C	0	2	3.51
28	C	0	2.33	4.07
28	C	0	2.67	4.57
28	C	50	4	6.08
28	C	100	8	8.71
28	C	140	40	15.08

Decision protocol The 36 TE decisions are divided in four blocks of nine questions with different interest rates. In the first and third blocks, subjects make their choices for $d = 7$ and in the second and fourth blocks for $d = 28$. Once a block is finished, subjects have to wait for the research assistant to enter a code and remind them of the features of the new block. Depending on the order of NC and C, a payment securement is offered in the two first or two last blocks. Between the first and last two blocks, the instructor reminds subjects of the upcoming decisions and the change in provision of the payment securement.

From the start of the instructions, posters with screenshots illustrate in detail the decisions and help the understanding of the subjects. In each block, before they take the payoff-relevant decisions, participants do a trial round and go over all upcoming decisions. For simple and intuitive use, decisions are taken on tablet computers.[7]

[7]We used Android™ supported tablets and Open Data Kit (ODK), an open source survey pro-

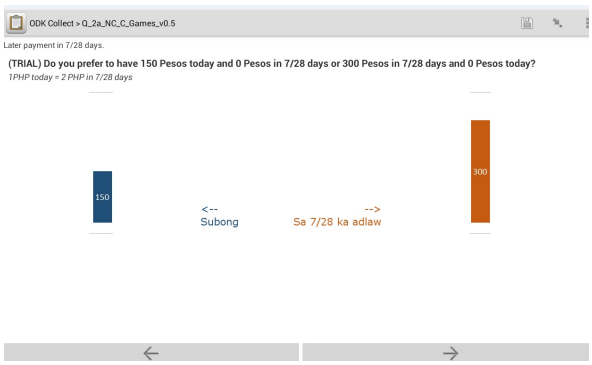
Throughout, subjects are accompanied by a research assistant ready to explain the decision again. Appendix A.3 presents the instructions.

Each decision involves three steps. First, subjects make a binary choice between extreme options $c_t = 150$ and $c_t = a$, similar to a multiple price list choice. After thus getting familiar with the key parameters of the decision, subjects can choose any amount $c_t \in [a, 150]$ in steps of 10. Both c_t and the remaining amount $c_{t+d} = (150 - c_t) \cdot (1 + r)$ are visualized. Finally, subjects can refine their choice to the unit level in a dropdown menu.[8] The screenshots of these steps are presented below in figure 1.1.[9]

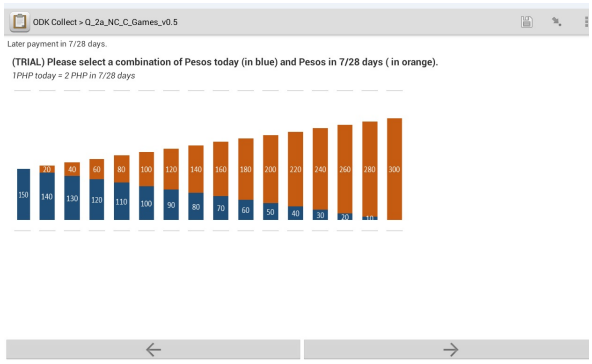
gram.

[8] Only steps 2 and 3 are payoff relevant.

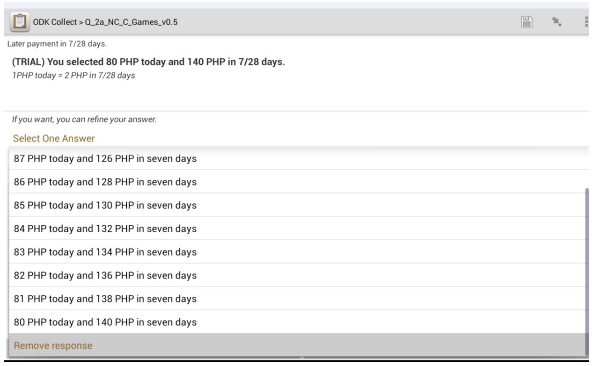
[9] The screenshots correspond to the trial session that the subjects did before the real ones. The screenshots read "Later payment in 7/28 days". The expression "7/28" is only for illustrative purposes. Participants were always shown choices to be delivered in either 7 or 28 days.



(a) Step 1.



(b) Step 2.



(c) Step 3.

Figure 1.1: Screenshots of the trust elicitation task in trial round.

Payment procedures Given our study's goal of measuring trust in institutions, the specific arrangements for the later payment – and the subject's understanding thereof – are important. While the current payments, c_t, are made at the end of the session, the future payments are delivered in cash to the subjects' homes. The subjects are informed that the local institution, NWTF or ML, is responsible for storage and delivery of the money. The money itself is handed over to the institution by the experimenters after the session.[10] Later payments are delivered by research assistants representing the two different institutions.[11]

We vary the confidence in the payment exogenously by the provision of a post-dated check for the future payment in half of the decisions (C). Many experiments measuring time preferences use similar procedures to increase the subjects' confidence in the realization of the later payment (Coller and Williams, 1999; Benjamin, Choi, and Strickland, 2010; Andersen, Harrison, Lau, and Rutström, 2008; Andreoni and Sprenger, 2012b). Since the check provides the same payment securement for subjects irrespective of the treatment institution, it provides a benchmark setting to which we can relate the non-secured setting (NC) in each treatment.

The checks are presented as our, the experimenters' means of choice for payment securement, which we do not provide for all decisions. During instruction, participants are shown a sample check, signed and post-dated with the name of one of the participants as an example (see appendix A.3). We place a stamp of the University of Mannheim on the check. Overall, we intend to associate ourselves, researchers from the University of Mannheim, with the check payment, not the unsecured payments. In contrast, subjects know that the non-secured default procedure relies on the treatment institution which safeguards the money in the meantime, a procedure outside of the experimenter's control after the handing over of the money envelopes.

The checks were issued from Banco de Oro (BDO), the largest bank in the Philippines. While BDO branches are common in cities, they are less common in rural areas. To avoid that subjects face large transportation costs when cashing the check subjects are informed that we offer a second possibility to cash the checks within the community. No details are provided before the payment at the end of the session. For this option, NWTF kindly assisted with their local offices to cash the check out of our funds. This procedure is implemented in all sessions, but subjects are only disclosed the details of the local option after the decisions had been made. Subjects are familiar with this form of payment.[12]

[10] The solvency of the institution is thus not problematic. The risk of the future payment depends only on the reliability of the institution.

[11] 667 subjects were to be paid in the future and only four did not receive their payment due to absence and non-traceability. Subjects were contacted several times, one was not interested in receiving the amount (20 PHP) and the others could not be reached. From the remaining three subjects that could not be reached, two had a check as payment securement. Additionally, 6 people cashed their checks mostly at the local option shortly before the due date. This was known at the time of the delivery, and the envelopes with their later payments was not given to them, since they had cashed their checks.

[12] The majority of our subjects are clients of NWTF, and have loans with them. Their loans are

To account for order effects, we randomize the order of the (NC, C) decisions. Thus, approximately half of the subjects first make 18 NC decisions without payment securement and then 18 C decisions with payment securement (NC/C treatment) and vice versa (C/NC treatment).

Although our study's goals differ from standard time preferences elicitation studies, our payment procedures are not only symmetric between treatments, the delivery to the homes is implemented in order to equalize the transaction costs between the possible payment dates. This ensures an unbiased measure of time discounting and avoids any possible interaction of transaction costs with our treatments.

Other studies such as Coller and Williams (1999); Andersen, Harrison, Lau, and Rutström (2008); Andreoni and Sprenger (2012a) minimize the procedural difference between the current and the future payment by implementing a front end delay. Our focus on the uncertain nature of the future payment suggests to not have the front end payment subject to such uncertainty, but to make sure that front end payment arrangements do not differ between treatments.[13]

Institutions In order to see whether the trust measure can pick up differences between institutions, we chose two financial institutions $I \in \{\text{NWTF}, \text{ML}\}$ in which subjects are expected to trust in to a different extent. Both institutions are well-known and provide lending and savings products.[14]

Negros Women For Tomorrow Foundation (NWTF) The Negros Women for Tomorrow Foundation is a nonprofit microfinance institution (MFI) that operates in the Visayas Region of the Philippines. NWTF provides loans at modest rates to poor women from rural communities to start or expand their own small businesses following the Grameen Bank credit methodology of group lending (Besley and Coate, 1995). The loan program has a minimum loan of 1,000 PHP and a maximum of 30,000 PHP (between 21 and 638 EUR, approximately).

Local Money Lenders (ML) Local Money Lenders are an informal financial institution in the Philippines also referred to as "5-6" lenders. They lend money usually to poor people that might not have access to formal lending institutions such as banks or MFIs. These types of lenders charge a nominal interest rate of 20 percent over a time period of usually one or two months. Local money lenders do not require collateral or any documents from their borrowers (Kondo, 2003). "5-6" lenders are

disbursed through checks. 10% of our sample report never cashing a check before (123 subjects). Out of which 56 correspond to members of four villages in which we randomly selected participants of the village's household list, and not of NWTF's client pool. From the remaining 67, 66 were clients of NWTF at the time of the baseline. It could be that someone cashed the check with their loan disbursement for them, but they would know how a check works.

[13] As a consequence, we cannot estimate a potential present-bias.

[14] Although the experiment features future payments with interest and thus makes saving institutions fit in naturally, the trust measure can universally be applied to any institution.

widely known by the population and usually seen as a last resort for borrowing money. In general, this type of credit institution has a negative reputation among the population since it is perceived as charging very high interest rates to the detriment of the borrower.[15] The identity of the individual money lender is not revealed to subjects, but the institution is well-known in the whole population.

Our sample is in its majority current or previous clients of NWTF (95%).[16] To try our measure we want to use an institution that is equally known for everyone. One way of guaranteeing that was to use the client pool of NWTF. As another benchmark institution, it would be ideal to use an institution that the majority of subjects know. We selected ML since it is a well-known institution throughout the country, partially solving that problem. However, due to security reasons, the exact identity of the ML could not be disclosed. We could work with the ML institution on the condition of anonymity. This implies that people assigned to the ML treatment would draw on their own previous experiences and private information about local money lenders when making their choices.[17]

1.3.2 Risk preference elicitation task

In the experiment's second task, subjects allocate money between a safe and a risky lottery in 18 decisions. The parameters of the task are chosen analogously to the TE task, the risky lottery mimics the later payment that possibly does not take place. Winning the risky lottery multiplies the money allocated by $1 + r \in \{2, 4\}$, losing it reduces the payment to 0. The 9 probabilities of winning the lottery are $p_w \in \{0.1, 0.2, \ldots, 0.9\}$. The safe lottery pays out the amount allocated to it for sure. Like before, subjects allocate an amount $l \in [a, 150]$ to the safe lottery and thus obtain a prize of $(1 + r) \cdot (150 - l)$ when winning the lottery. The amount of a is 0 and 50 for the two values of r, respectively, analogue to TE. Table 1.2 presents the choice parameters and appendix A.3 presents the screenshots of the task.

1.3.3 Trust game

In order to have a behavioral measure of general trust we implement the trust game. This game is played in a way similar to the original one by Berg, Dickhaut, and McCabe (1995) and does not differ across treatments. Participants are randomly assigned to the role of investor or investee. Investors are given an initial endowment of PHP 50. They then choose an amount ranging from 0 to PHP 50 to send to the investee. This amount is tripled and the investee chooses how much to send back from

[15] The lucrative and risky business attracts many Indian nationals and has a long history in the Philippines (Times of India, 2013).

[16] 77 subjects were randomly selected from four villages' household list (outside of NWTF pool of clients). Out of which 2 are clients of NWTF and 5 had been clients in the past.

[17] Only 18% of subjects in the ML treatment report knowing who is the institution responsible for the future payment.

Table 1.2 Choice parameters in RPE.

Interest rate $1+r$	Minimum Amount a	Probability p_w	EV of Δl PHP
2	0	0.1	0.2
2	0	0.2	0.4
2	0	0.3	0.6
2	0	0.4	0.8
2	0	0.5	1
2	0	0.6	1.2
2	0	0.7	1.4
2	0	0.8	1.6
2	0	0.9	1.8
4	50	0.1	0.4
4	50	0.2	0.8
4	50	0.3	1.2
4	50	0.4	1.6
4	50	0.5	2
4	50	0.6	2.4
4	50	0.7	2.8
4	50	0.8	3.2
4	50	0.9	3.6

the tripled amount. Participants do not know which participant has been matched with them in the opposite role.

1.4 Theoretical background and statistical model

We assume the expected utility framework with exponential discounting

$$DU(c_t, c_{t+d}) = u(c_t + \omega) + \delta^d P u(c_{t+d} + \omega) + \delta^d (1 - P) u(0 + \omega), \tag{1.2}$$

where $u(\cdot)$ is a separable and stationary over time utility function, c_t is the payment at time t, c_{t+d} is the payment d periods into the future of t, ω is background consumption, and δ is the discount factor. Importantly, P is our parameter of interest, namely the probability that the subject attaches to receiving the future payment from institution I. With probability P the subject receives the future payment c_{t+d}, and with probability $1 - P$ the subject does not receive the future monetary outcome, in this case he gets 0.[18]

In order to properly estimate P, we estimate the discount factor δ and the curvature of the utility function. We therefore implement three statistical specifications. Specification 1 uses only the TE data, and we implement it with two different utility functions (Andreoni and Sprenger, 2012b, similar to). Specifications 2 and 3 make use of both the TE and the RPE data. While specification 2 is based on the choices from the convex budget sets, specification 3 uses the binary choices (Andersen, Harrison, Lau, and Rutström, 2008, similar to). Implementing the three specifications allows for comparisons across methods and robustness checks of the estimates.

[18] We assume that the institution is believed to deliver either the full promised amount or nothing in period $t + d$. We view the belief that the institution shows up to provide only a fraction of the promised amount as very unlikely.

1.4.1 Specification 1: theoretical and statistical model

Thanks to the CTB design, specification 1 delivers estimates of both discounting and curvature on the basis of the TE data alone. The structure follows the setup of Andreoni and Sprenger (2012a).

CRRA utility Consider a time separable CRRA utility function for current consumption c_t and future consumption c_{t+d},

$$DU(c_t, c_{t+d}) = \frac{1}{\alpha}(c_t - \omega)^\alpha + \frac{1}{\alpha}\delta^d P(c_{t+d} - \omega)^\alpha + \frac{1}{\alpha}\delta^d(1-P)(0-\omega)^\alpha. \tag{1.3}$$

Maximizing the utility subject to the future valued budget constraint,

$$m = c_t(1+r) + c_{t+d}, \tag{1.4}$$

the optimal consumption allocation for $\alpha < 1$ is characterized by

$$\frac{c_t - \omega}{c_{t+d} - \omega} = \left[(1+r)P\delta^d\right]^{\frac{1}{\alpha-1}}. \tag{1.5}$$

Taking logs of equation 1.5, we get the estimable equation

$$\ln\left(\frac{c_t - \omega}{c_{t+d} - \omega}\right) = \left(\frac{1}{\alpha - 1}\right) \cdot \ln(1+r) + \left(\frac{\ln P}{\alpha - 1}\right) \cdot \mathbf{1}_S + \left(\frac{\ln \delta}{\alpha - 1}\right) \cdot d, \tag{1.6}$$

in which $\mathbf{1}_S$ is an indicator function that takes the value of 1 when there is no payment securement (NC) and 0 when there is a payment securement (C).

The random assignment of treatments allows us to obtain unbiased estimates of our parameters by estimating

$$y = \gamma_1 \ln(1+r) + \gamma_2 \cdot \mathbf{1}_S + \gamma_3 \cdot d, \tag{1.7}$$

where $y = \ln\left(\frac{c_t - \omega}{c_{t+d} - \omega}\right)$. Rearrangements of the estimated coefficients $\hat{\gamma}$ allow us to calculate our parameters of interest, the curvature parameter $\hat{\alpha} = \frac{1}{\hat{\gamma}_1} - 1$, the discount rate $\hat{\delta} = \exp\left(\frac{\hat{\gamma}_3}{\hat{\gamma}_1}\right)$, and $\hat{P} = \exp\left(\frac{\hat{\gamma}_2}{\hat{\gamma}_1}\right)$.

Exponential utility Consider now a time separable constant absolute risk aversion (CARA) utility function:

$$DU(c_t, c_{t+d}) = -\left[\exp(-\rho(c_t - \omega)) + \delta^d P \exp(-\rho(c_{t+d} - \omega)) + \delta^d(1-P)\exp(-\rho(0-\omega))\right], \tag{1.8}$$

where ρ is the coefficient of absolute risk aversion. Under this specification, the optimal consumption allocation is defined by the equation

$$\exp\left(-\rho(c_t - c_{t+d})\right) = (1+r)(\delta^k P).$$

Taking logs yields a similar estimable equation independent of ω

$$c_t - c_{t+d} = \left(\frac{1}{-\rho}\right) \cdot \ln(1+r) + \left(\frac{\ln P}{-\rho}\right) \cdot \mathbf{1}_S + \left(\frac{\ln \delta}{-\rho}\right) \cdot d,$$

whose rearrangement allows us to estimate the parameters of interest as before.

1.4.2 Specification 2 and 3: theoretical model and statistical specification

We use a simple stochastic specification that translates the discounted utility into choice probabilities, allowing us to specify likelihoods conditional on the model. This is an extension of the probabilistic approach used by Holt and Laury (2002) and Andersen, Harrison, Lau, and Rutström (2008) that has been outlined by Harrison, Lau, and Rutström (2013) as an appropriate analogue for CTB data. This approach deals with corner choices and the constrained action space in a natural way and allows for the incorporation of the RPE data.

In the two specifications, we implement a CRRA utility function for choices from both RPE and TE. For the latter, the specification is identical to equation 1.3.

Theoretical model for RPE For RPE choices, the expected utility can be written as

$$\mathrm{EU}(l) = \frac{1}{\alpha} p_w [(1+r) \cdot (150 - l) + l - \omega]^\alpha + \frac{1}{\alpha}(1 - p_w) \cdot [0 + l - \omega]^\alpha. \tag{1.9}$$

Recall that subjects can allocate an amount $l \in [a, 150]$ to the safe lottery. The complementary amount $(150 - l)$ is allocated to the risky lottery, which turns into $(1+r) \cdot (150 - l)$ with probability p_w when the lottery is won and 0 otherwise.

Therefore, equation 1.9 represents the situation that the subject faces depending on the state of the world. If p_w realizes and the lottery is won, then the subject's outcome is the amount l assigned to the safe option plus the payment $(1+r) \cdot (150 - l)$ from the risky lottery plus the background consumption ω. However if $1 - p_w$ realizes, the subject gets l plus 0 from the risky lottery plus the background consumption ω.

Statistical specification Let us denote as $U(z)$ the utility $DU(c)$ or $EU(l)$, depending on the task being TE or RPE, respectively. We define the index ∇U ("nabla

U").[19]

$$\nabla \mathrm{U}(z) = \frac{\mathrm{U(z)}}{\sum_{\tilde{z}=a}^{150} \mathrm{U}(\tilde{z})}. \tag{1.10}$$

This index translates the discounted utility into a probability. The denominator reflects the feasible actions available to the subject, $z \in [a, 150]$.
The log-likelihood of observing the K decisions z_{ik} of individual i is then

$$\ln L_i \quad = \quad \sum_{k=1}^{K} \ln \nabla \mathrm{U}(z_{ik}).$$

The sample likelihood is the sum over all individual likelihoods

$$\mathcal{L}^U = \sum_i \ln L_i = \sum_i \sum_{k=1}^{K} \ln \nabla \mathrm{U}(z_{ik}). \tag{1.11}$$

The joint likelihood of TE and RPE can be expressed as

$$\mathcal{L} = \mathcal{L}^{DU} + \mathcal{L}^{EU}. \tag{1.12}$$

1.4.3 Specification 3

The binary data from the first decision step in the decision can similarly be analyzed with this stochastic specification. Just like the denominator previously accounted for the constrained action space, it now reflects binary data with a simple two-term sum. The index becomes

$$\nabla \mathrm{U}(z) = \frac{\mathrm{U(z)}}{\mathrm{U}(a) + \mathrm{U}(150)}. \tag{1.13}$$

The further analysis works analogously to the previous estimation procedure and is – due to the binary data – the most similar to the procedure in Andersen, Harrison, Lau, and Rutström (2008).

1.4.4 Discussion

Our way of measuring trust builds on experimental methods and estimation techniques designed to analyse time preferences. At the time of setting up the experiment, the two main methods are on the one hand joint estimations of multiple price lists for time and risk (Andersen, Harrison, Lau, and Rutström, 2008) and on the other hand the Convex Time Budget method (Andreoni and Sprenger, 2012a).

[19] We refrain from the formulation with a precision parameter ν. For convex utility ($\alpha > 1$) – a likely outcome of this specification with a high frequency of corner choices (see later results and Harrison, Lau, and Rutström, 2013) – this parameter is not separately identified from α. For us, robustness of the trust estimates for a given level of $\nu = 1$ is sufficient.

For our purposes, the latter seems particularly fitting since (a) its convex budget set nests the MPL approach, thus providing weakly more information, and (b) the action space can reflect consequences of variations in P in fine nuances.

For example, we can construct a rough trust measure by simply relating the consumption choices in the C and NC treatments. A subject's "c_t-ratio" , $\frac{c_t^C}{c_t^{NC}}$, is equal to 1 if the securement does not influence the money allocation over time. It is smaller than 1 if the current consumption c_t with securement is smaller and thus the investment in the future is higher. It is expected that the estimate $\hat{P}$ is 1 when the c_t-ratio is 1 and that in general c_t-ratio is proportional to $\hat{P}$.

The method has been subject of vivid discussions. On the basis of the Andreoni and Sprenger (2012b) data, Harrison, Lau, and Rutström (2013) expect a convex utility function that explains the frequently occurring corner allocations. They deem these implausible results to be a consequence of poor comprehension of subjects. We observe a smaller, but still substantial share of corner allocations. The distribution of choices over the interval $[0, 150]$ is shown in appendix A.1. At the same time, the method has been applied successfully to numerous studies in laboratory experiments, in developing countries and on children and teenagers (see Andreoni and Sprenger, 2015, for references).

We use the CTB implementation and deliberately added features of the MPL framework in order to obtain a more holistic perspective on the trust measure.[20] In particular, the binary decision at the beginning of each choice and the elicitation of risk preferences for each subject allow us to analyse behavior with the tools of MPL and joint estimation. The plenary and individual instructions, the tablet implementation and posters are in place to make sure subjects comprehend the tasks at hand.

1.5 Data and sample statistics

The experiments were conducted in the Philippine provinces of Guimaras, Capiz and Iloilo during the months of March, April and May 2015. Overall, 1,251 subjects took part in the experiment. The experiment took place during a morning or afternoon and lasted about 3 hours. On average, subjects were paid 290.15 PHP (ca. 6.17 EUR).[21]

Subjects participating in our study are clients of NWTF[22] and are randomly selected from the pool of clients in the three provinces. Individuals are randomly assigned to four treatment groups, following the 2×2 design with two institutions and two orders of the payment securement.[23]

[20] Recent evidence by Andreoni, Kuhn, and Sprenger (2015) suggests advantages of CTB over double MPLs in terms of out-of-sample prediction.

[21] The exchange rate at the time of the experiment was 47 PHP for 1 EUR. Thus 150 PHP amount to 3.19 EUR.

[22] Out of the 1,251 subjects, 77 are not NWTF members, but randomly chosen community members of villages with NWTF clients.

[23] Prior to randomization, we divide our sample into 60 bins, each of which contains on average 90 clients. The bins are composed of clients in different locations, and the criteria to form a bin is the minimal distance between villages within the bin and number of clients. The bins are randomly

In order to recruit the participants we first get permission from the Municipality Mayor and subsequently from the Village head, locally known as Barangay Captain. Barangay Captains would additionally authorize the use of the village facilities, usually the Barangay Hall, where we hold the experiment sessions. Subjects are invited to participate in the experiment via an invitation letter delivered to their houses.

1.5.1 Trust survey questions

In the post-questionnaire after the incentivized games, we elicit general trust attitudes and trust in institutions with standard survey questions. In particular, we use General Social Survey (GSS) questions on trust: "Generally speaking, would you say that most people can be trusted or that you cannot be too careful in dealing with people?", fairness: "Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair" and helpfulness: "Would you say that most of the time people try to be helpful or that they are mostly just looking out for themselves?". The particular trust question, however, has raised concerns since it might not only be drawing on people's belief about others' trustworthiness, but also on their own preferences towards risks. (Fehr, 2009; Miller and Mitamura, 2003). Thus, we also include a direct trust question "Do you think that most people can be trusted?" with answer categories on a 7-point Likert scale ranging from "not at all" (1) to "completely trusted" (7) as in Miller and Mitamura (2003).

We adapt the direct trust questions to the institutions we are interested in, implementing them for both ML and NWTF, for the full sample. The trust, fairness and helpfulness questions as in the GSS are adapted for NWTF. The direct trust question is also asked for other institutions, family members, lending center members, lending group members and the loan officer.

1.5.2 Sample statistics

Table 1.3 reports summary statistics for the full sample and the different treatments, as well as the equality of means t-test between the order treatments (NC/C and C/NC) and the institution treatments (NWTF and ML).

Our sample is composed in its majority of women (97%), which is to be expected since we are drawing mainly from the client pool of NWTF and their clients are women.[24] Subjects are on average 43 years old, they have 8.8 years of education and their household has around 5 members. Less than half of them are employed, and roughly half have a regular income. The people in our sample are poor, earning

assigned to one of the four treatments (NWTF, ML, C/NC, NC/C), and subsequently subjects are randomly chosen within each bin. Using an optimally designed mechanism that guarantees similarity across the four groups in terms of financial characteristics (loan size and amount of savings), village size and distance from the village to the municipality center. This procedure minimizes the Mahalanobis distance of the covariates to its cluster average weighted by the covariance matrix (see Morgan and Rubin, 2012).

[24] The 44 men in our sample are not members of NWTF.

a monthly income of approximately 1,500 PHP (33 EUR) and having an individual weekly consumption of 350 PHP (7 EUR) and of 1000 PHP (21 EUR) for the household, implying a daily consumption of 50 PHP. Half of the participants live in a dwelling with cement floors and 88% own their dwelling.

Subjects borrow on average 6,000 PHP (127 EUR) from microfinance institutions and banks and save approximately one fourth of that amount. On a scale from "1–no trust" to "7–complete trust", the trust level is on average 6 in NWTF and 3.8 in the local money lender. Subjects report to be slightly risk averse, trying to avoid betrayal and to be taken advantage of, and are willing to offend if offended and to take revenge in case they suffer a serious wrong. Subjects report that the nearest bank is approximately 32 minutes away, and 90% of the subjects have cashed a check before.

Given that the treatments are randomly assigned, we expect individuals in the NWTF treatment to be similar to individuals in the ML treatment, and individuals in the NC/C treatment to be similar to individuals in the C/NC treatment. The table shows that our expectation holds in general. The number of significant differences are within the bounds expected to occur by chance.

Some differences are worth discussing. The distance to the bank is significantly different between subjects in the NWTF treatment and those in the ML treatment. This difference, however, is driven by remote outliers. When we exclude the top 1 percentile, the difference loses statistical significance. Further, we provide a local cashing option, which makes the distance to the bank not so important. The same is true for the variable "Ever cashed a check", as clients of NWTF receive the loan disbursement through a check, however 77 subjects are not clients of NWTF and once they are excluded the difference reverses. Finally, the variable that asks whether the subject knows the institution presents a considerable difference.

Our subjects are in its vast majority clients of NWTF, therefore a large share of the sample knows the institution. However, only 18% of subjects in the ML treatment report to know the institution. As mentioned earlier, this is probably due to the fact that the exact identity of the money lender was not disclosed. On one hand due to security reasons for the money lender, and on the other hand we wanted that each subject related the institution to whatever knowledge of a local money lender they have.

	(1) Full Sample	(2) ML	(3) NWTF	(4) ML− NWTF	(5) NC/C	(6) C/NC	(7) NC/C− C/NC
Age	42.90	43.04	42.79	0.244	43.14	42.68	0.459
				(0.675)			(0.669)
Years of education	8.799	8.798	8.800	-0.00257	8.776	8.820	-0.0447
				(0.165)			(0.163)
Married	0.835	0.855	0.820	0.0357*	0.816	0.852	-0.0366*
				(0.0213)			(0.0211)
Household size	5.358	5.335	5.375	-0.0402	5.381	5.337	0.0438
				(0.120)			(0.119)
Employed	0.473	0.490	0.461	0.0287	0.470	0.476	-0.00588
				(0.0288)			(0.0285)
Regular income	0.557	0.568	0.550	0.0180	0.557	0.558	-0.00124
				(0.0285)			(0.0282)
Monthly income (PHP)	1539.7	1491.8	1576.5	-84.73	1615.3	1471.7	143.6
				(251.8)			(250.0)
Background consumption (weekly)	350.2	351.7	348.7	3.004	342.2	357.2	-15.03
				(22.05)			(22.06)
HH Background consumption (weekly)	1002.7	1025.7	981.2	44.49	1041.1	968.3	72.78*
				(42.14)			(42.14)
Official position in village	0.0794	0.0827	0.0769	0.00578	0.0711	0.0869	-0.0158
				(0.0155)			(0.0153)
Rooms in HH for sleeping	1.796	1.835	1.766	0.0682	1.773	1.816	-0.0423
				(0.0449)			(0.0445)
Cement floor at dwelling	0.496	0.506	0.488	0.0175	0.492	0.498	-0.00609
				(0.0286)			(0.0284)
Flush toilet at dwelling	0.887	0.898	0.878	0.0202	0.885	0.889	-0.00378
				(0.0181)			(0.0180)
Electricity at dwelling	0.878	0.885	0.873	0.0126	0.880	0.877	0.00334
				(0.0187)			(0.0186)
HH source of drinking water	0.365	0.370	0.361	0.00946	0.376	0.355	0.0205
				(0.0276)			(0.0273)
Own dwelling	0.888	0.883	0.892	-0.00907	0.888	0.889	-0.000225
				(0.0180)			(0.0179)
N	1249	533	716	1249	592	657	1249

Notes: Standard error in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(a) Pre-questionnaire data collected before experiment.

Table 1.3 Descriptive statistics.

	(1) Full Sample	(2) ML	(3) NWTF	(4) ML− NWTF	(5) NC/C	(6) C/NC	(7) NC/C− C/NC
Am't borrowed from MFI/Banks	5959.9	5917.6	5996.3	-78.69	5861.5	6047.8	-186.3
				(429.2)			(428.6)
Savings in MFI/rural bank	1471.3	1431	1504.5	-73.46	1134.7	1783.8	-649.2
				(397.2)			(394.7)
Trust level in NWTF[1]	6.144	6.113	6.168	-0.0550	6.090	6.193	-0.104
				(0.0784)			(0.0776)
Trust level in ML[1]	3.831	3.822	3.838	-0.0162	3.794	3.865	-0.0706
				(0.114)			(0.113)
Risk preference[2]	4.209	4.259	4.172	0.0871	4.294	4.132	0.161
				(0.147)			(0.146)
Betrayal aversion[3]	1.660	1.666	1.655	0.0110	1.688	1.635	0.0528
				(0.0854)			(0.0845)
Avoid being taken advantage of[3]	1.827	1.760	1.877	-0.117	1.904	1.758	0.146
				(0.0952)			(0.0943)
Revenge if suffer serious wrong[4]	6.476	6.503	6.455	0.0475	6.412	6.533	-0.121
				(0.0748)			(0.0740)
Reciprocity[5]	6.421	6.433	6.412	0.0214	6.395	6.444	-0.0492
				(0.0791)			(0.0784)
Sociability[6]	4.234	4.233	4.235	-0.00199	4.221	4.245	-0.0238
				(0.0704)			(0.0697)
Bank distance (minutes)	32.25	35.23	30.03	5.192***	32.39	32.12	0.272
				(1.942)			(1.929)
Ever cashed a check	0.902	0.925	0.884	0.0409**	0.909	0.895	0.0138
				(0.0170)			(0.0169)
Knows institution	0.538	0.183	0.870	-0.687***	0.515	0.559	-0.0432
				(0.0218)			(0.0301)
Trustworthiness beliefs[7]	5.805	5.819	5.793	0.0262	5.796	5.813	-0.0173
				(0.0976)			(0.0977)
N	1249	533	716	1249	592	657	1249

Notes: Standard error in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[1] 1–no trust, 7–complete trust,
[2] Avoid/prepared to take risks: 1–avoid, 7–fully prepared,
[3] Avoid being betrayed/taken advantage of: 1–completely avoid, 7–do not avoid,
[4] 1–revenge, 7–no revenge,
[5] If offended, offend back?: 1–offend,7–not offend,
[6] Meet friends, relatives, neighbor: 1–never, 2–seldom, 3–monthly, 4–weekly, 5–daily,
[7] How certain is payment in 28 days?: 1–surely not reach me, 7–absolutely certain.

(b) Post-questionnaire data collected before experiment.

Table 1.3 Descriptive statistics.

1.6 Results

In this section, we report basic patterns in simple statistics of the data and then proceed to the trust results from the structural estimations.

1.6.1 Descriptive statistics

In response to the experimental variations in terms of payment securement, institution, delay d, and interest rate $1 + r$, we expect four effects to show in the choice behavior.

First, the payment securement in form of the check is expected to influence the subjective probability of receiving the later payment in a positive way. This increase in expected future payment should result in an increased "investment" and a reduced current consumption.

Effect 1 *Ceteris paribus, choices with check provision result in lower current consumption than choices without check provision.*

Second, given the differences in the formality and reputation of the two financial institutions, we expect the subjects to exhibit more trust in the more formal institution NWTF. Compared to ML, the allocation to the future payment is then higher in expectation and should result in an increased "investment" and a reduced current consumption.

Effect 2 *Ceteris paribus, choices with the responsible institution being NWTF result in lower current consumption than with ML.*

Third, due to standard exponential time discounting, a higher delay d makes the investment with a given interest rate less attractive. Therefore, since under $d = 28$ the later payment will be discounted more heavily, the smaller present value of the later payment should result in a higher current consumption than under $d = 7$.

Effect 3 *Ceteris paribus, the stronger discounting under the longer delay results in higher current consumption choices under* $d = 28$ *than under* $d = 7$.

Finally, for similar reasons, a higher interest rate $1 + r$ makes the investment more attractive and should lead to lower current consumption as $1 + r$ increases.

Effect 4 *Ceteris paribus, a higher interest rate results in lower current consumption choices.*

For a first glance at the data, table 1.4 presents average differences over all decisions for the three first effects. The data indeed exhibits the first two effects while the effect of time discounting does not appear.

Column 1 shows that – as expected – without a payment securement, current consumption is significantly higher by 16.21 PHP than with the securement. Figure

Table 1.4 Equality of means test for c_t.

	(1)	(2)	(3)
Δ	NC−C	ML−NWTF	7−28 Days
Δc_t	16.19***	4.293**	0.245
	(0.000)	(0.023)	(0.597)
N	45036	45036	45036

Notes: p-values in parentheses, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered on the subject level.

1.2 graphically illustrates this differences with the average choices by securement and institutions for interest rates $1 + r < 3$. For both institutions, the left panel (NC) shows visibly higher current consumption levels than the right panel (C). The clear downward trend in the interest rate $1 + r$ provides support for the fourth effect.

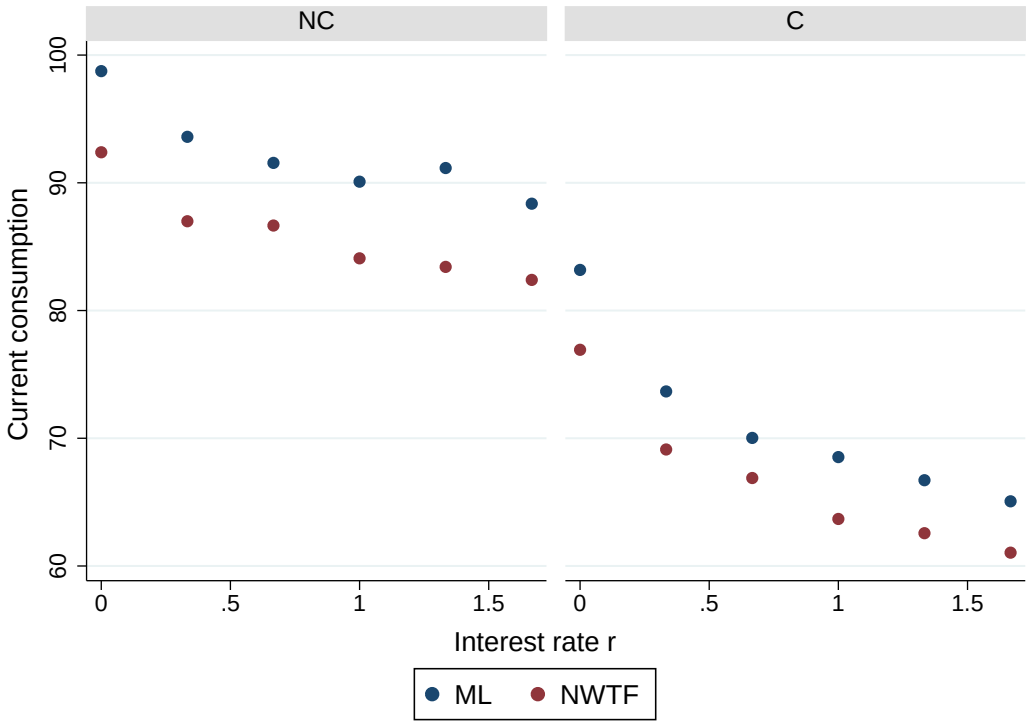


Figure 1.2: Current consumption c_t by interest rate and institution: NC vs. C.

Column 2 of table 1.4 shows that the current consumption is significantly higher by 4.29 PHP in the ML treatment than in the NWTF treatment. This regularity is also visible in figure 1.2.

The differences between institutions are quantified in table 1.5. Interestingly, without check securement, the difference in the current consumption between the two institutions is statistically significant at each interest rate level as shown in the top of table 1.5. However, when the check is provided the difference in current consumption across

the institution treatments is smaller and in most cases not significantly different from zero as shown in the bottom of table 1.5. This suggests that as expected the check securement reduces the relevance of the two institutions responsible for payment.

In order to arrive at the institutional trust measure we relate the choices in NC to the ones in C, normalizing the latter to $P = 1$. The remaining choice differences between institutions in C imply that even when the check is provided, beliefs or preferences towards the institutions still matter slightly. This might result in an overestimation of trust if the c_t choice in the ideal $P = 1$ scenario was even lower. Also, due to the remaining differences in C, the magnitude of differences in trust between institutions could be underestimated.

Table 1.5 Equality of means tests of c_t by interest rate ($\Delta c_t = c_t^{ML} - c_t^{NWTF}$).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$1+r$	1	1.33	1.67	2	2.33	2.67	4	8	40
Δc_t	6.35**	6.61**	4.90	6.00**	7.74**	5.96*	5.38**	2.37**	0.43*
NC	(0.040)	(0.032)	(0.107)	(0.048)	(0.012)	(0.050)	(0.013)	(0.036)	(0.061)
Δc_t	6.26**	4.58	3.15	4.85	4.15	4.03	3.29*	1.03	0.18
C	(0.049)	(0.137)	(0.308)	(0.108)	(0.159)	(0.172)	(0.091)	(0.252)	(0.329)
N	2502	2502	2502	2502	2502	2502	2502	2502	2502

Notes: p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered on the subject level.

Finally, column 3 of table 1.4 suggests that there is no statistically significant difference in current consumption between delay lengths $d = 7$ and $d = 28$ days. Figure 1.3 illustrates the differences by interest rate for both NC and C. Table 1.6 shows that there is no significant difference in current consumption between the two delay lengths for any level of the interest rate. The results suggest that if there is any discounting, it is very small.

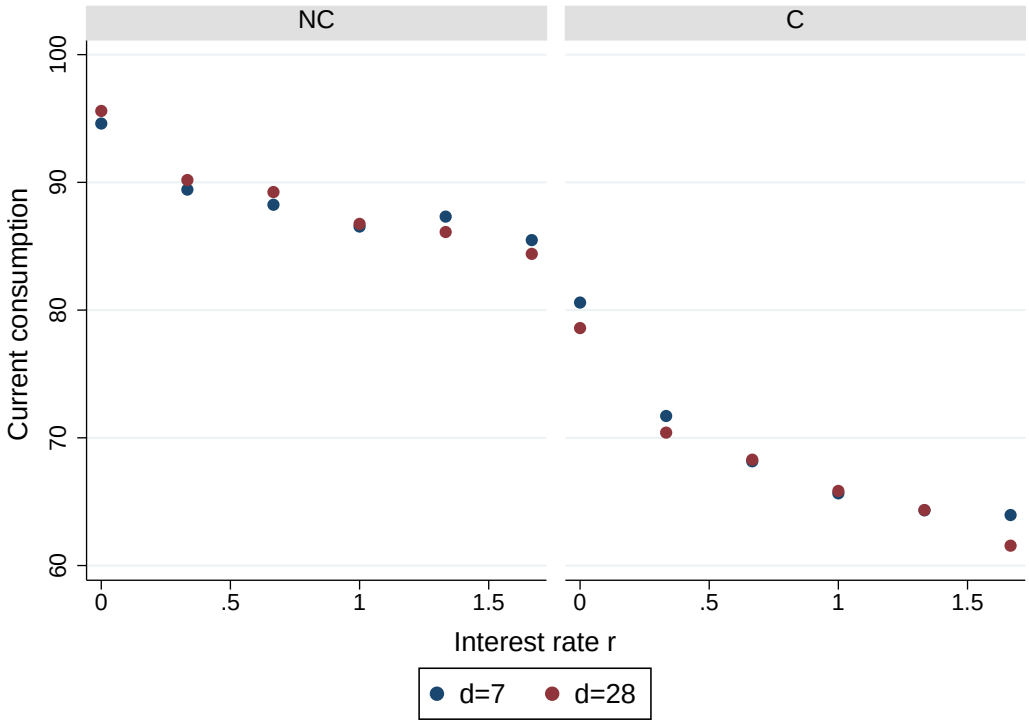


Figure 1.3: Current consumption c_t by interest rate and delay lengths: NC vs. C.

Table 1.6 Equality of means tests of c_t by interest rate ($\Delta c_t = c_t^7 - c_t^{28}$).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$1+r$	1	1.33	1.67	2	2.33	2.67	4	8	40
Δc_t	-0.98	-0.75	-0.99	-0.21	1.21	1.08	-0.96	-0.11	0.15
NC	(0.474)	(0.578)	(0.459)	(0.877)	(0.338)	(0.422)	(0.300)	(0.829)	(0.105)
Δc_t	2.01	1.31	-0.13	-0.20	-0.01	2.40**	0.36	0.19	0.05
C	(0.180)	(0.343)	(0.920)	(0.880)	(0.991)	(0.049)	(0.687)	(0.652)	(0.517)
N	2502	2502	2502	2502	2502	2502	2502	2502	2502

Notes: p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered on the subject level.

1.6.2 Estimation

Specification 1: CRRA utility Table 1.7 presents two-limit Tobit Maximum Likelihood estimates following section 1.4.1.[25] In columns 1-2, the estimated CRRA curvature $\hat{\alpha}$ is estimated around 0.77, a level in between estimates of Andreoni and Sprenger (2012a, $\hat{\alpha} \in [0.71, 0.92]$) and Andersen, Harrison, Lau, and Rutström (2008, $\hat{\alpha} = 0.26$). The daily discount rate $\hat{\delta}$ is estimated to be close to 1, with a level significantly higher than 1 in NWTF.[26]

Removing the payment securement is estimated to significantly change the perceived probability of receiving the later payment. This probability is 0.44 in the NWTF sample, higher than the 0.34 in the ML sample. Therefore, compared to a benchmark with a payment securement that is independent of the institution, the trust in a non-secured payment from NWTF is higher than for ML. The difference is statistically significant, we reject the null hypothesis that $\hat{P}_{NWTF} = \hat{P}_{ML}$ ($\chi^2_1 = 15.71$, $p < 0.001$).

When including background consumption in the utility function, we set $\omega = -50.25$ PHP, the average daily consumption in our sample. As shown in columns 3-4, this reduces the estimates of the CRRA parameter as in Andreoni and Sprenger (2012a) and in Andersen, Harrison, Lau, and Rutström (2008) due to the required curvature at the shifted wealth level. However, the reduction is stronger in our case and more in line with the results of Andersen, Harrison, Lau, and Rutström (2008). In this specification the probability $\hat{P}$ of receiving the later payment is 0.53 for the NWTF sample and 0.46 for the ML sample. The difference is again statistically significant, we reject the null hypothesis that $\hat{P}_{NWTF} = \hat{P}_{ML}$ ($\chi^2_1 = 16.04$, $p < 0.01$).

Overall, compared to an independent benchmark with payment securement, we can see that the trust in the institution as expressed in the probability of receiving the later payment is relatively low. As we expected, the level of trust in NWTF is higher than the level of trust in ML. The differences in the levels between the two institutions are, however, gradual and smaller than expected.

Specification 1: CARA utility The exponential CARA utility specification is a useful robustness check that is independent of background consumption levels. Results are presented in columns 5-6 in table 1.7. As before, we estimate our model separately for both NWTF and ML. We find that the curvature parameter ρ is estimated to be 0.005, similar to the parameter estimated by Andreoni and Sprenger (2012a). The differences in discount rates are qualitatively similar to the previous specification.[27]

[25] Due to the estimation technique, we restrict the sample to the choices with unconstrained action space for $1 + r < 3$.

[26] The curvature $\hat{\alpha}$ is not statistically different between the NWTF and ML treatments ($\chi^2_1 = 0.75$, $p = 0.386$). However, we reject the null hypothesis that $\delta_{NWTF} = 1$ ($\chi^2_1 = 8.70$, $p < 0.01$), while we do not reject $\delta_{ML} = 1$ ($\chi^2_1 = 0.00$, $p = 0.949$).

[27] Similar to our CRRA utility estimates, we find that curvature when estimated for the NWTF sample is not significantly different to curvature when estimated for the ML sample. We do not reject

Table 1.7 CRRA and CARA parameters estimates.

	(1) NWTF	(2) ML	(3) NWTF	(4) ML	(5) NWTF	(6) ML
Curvature $\hat{\alpha}$ (CRRA)	0.770	0.781	0.111	0.128		
	(0.0099)	(0.0119)	(0.0259)	(0.0327)		
Curvature $\hat{\rho}$ (CARA)					0.005	0.005
					(0.0001)	(0.0002)
Daily discount rate $\hat{\delta}$	1.004	1.000	1.002	0.9995	1.002	0.9998
	(0.0014)	(0.0017)	(0.0009)	(0.0012)	(0.0007)	(0.0010)
$\hat{P}$	0.437	0.345	0.534	0.464	0.602	0.536
	(0.0197)	(0.0232)	(0.0140)	(0.0174)	(0.0117)	(0.0147)
Back. cons. ω	-0.01	-0.01	-50.25	-50.25		
Observations	17232	12792	17232	12792	17232	12792
LL	-38084.6	-27636.4	-21608.8	-16253.4	-66977.4	-47398.4
Uncensored	9244	6354	9244	6354	9244	6354
Clusters	718	533	718	533	718	533

Notes: Two-limit Tobit Maximum Likelihood estimators. Standard errors in parenthesis calculated via the delta method.

Compared to the benchmark setting with check, the probability attached to receiving the later payment by the institution, is 0.60 for NWTF and 0.54 for ML. The difference is statistically significant, we reject the null hypothesis that $\hat{P}_{NWTF} = \hat{P}_{ML}$ ($\chi^2_1 = 19.86$, $p < 0.001$). For now, we favor this specification over others since it is independent of ω and makes use of the choices from the CTB.

Specification 2 and 3: convex choice sets and binary choice data Table 1.8 presents the results from the probabilistic specification that are based on both the TE and the RPE decisions.[28] Due to many corner allocations, the estimates for α are indeed such that the curvature is greater than 1, as hypothesized by Harrison, Lau, and Rutström (2013).[29] At the same time, the daily discount rate is now lower at values around 0.97. This difference to the earlier estimates results probably from the compensation of the now risk-loving attitude towards the risky future payment.

Finally, table 1.9 presents the results of estimating our probabilistic model with the binary data. We find that $\hat{P}$ is estimated to be 0.52 for NWTF and 0.43 for the ML. Results are lower when background consumption is included, but the difference between the institutions persists. Estimates for the curvature parameter are considerably lower than those found for the convex sets. For NWTF, $\hat{\alpha} = 0.334$ when no background consumption is included and $\hat{\alpha} = 0.669$ when background consumption is -50.25. For ML, these values are 0.266 and 0.572, respectively. These results are in

$\rho_{NWTF} = \rho_{ML}$, ($\chi^2_1 = 0.01$, $p = 0.907$). However, we reject the null hypothesis that $\delta_{NWTF} = 1$, ($\chi^2_1 = 7.94$, $p = 0.005$), while we do not reject $\delta_{ML} = 1$, ($\chi^2_1 = 0.04$, $p = 0.851$).

[28] Results based on only the TE decisions are qualitatively similar and reproduced in appendix A.2.

[29] The data is suggestive of the existence of both types of players, those with predominant corner allocations ($\alpha > 1$) and those with mostly interior allocations ($\alpha < 1$).

line with those of Andersen, Harrison, Lau, and Rutström (2008). The discount rate is estimated to be at or slightly above 1 throughout the different specifications.

Table 1.8 CRRA parameters estimates from probabilistic specification.

	(1) NWTF	(2) ML	(3) NWTF	(4) ML
CRRA Curvature $\hat{\alpha}$	1.853	1.910	2.308	2.374
	(0.045)	(0.052)	(0.065)	(0.075)
Daily discount rate $\hat{\delta}$	0.984	0.974	0.984	0.974
	(0.002)	(0.003)	(0.003)	(0.003)
$\hat{P}$	0.313	0.271	0.303	0.258
	(0.021)	(0.022)	(0.023)	(0.024)
Background consumption ω	-0.01	-0.01	-50.25	-50.25
Observations	38772	28782	38772	28782
LL	-176938.54	-131316.57	-177324.97	-131661.89

Table 1.9 CRRA parameters estimates from probabilistic specification, using the binary choices.

	(1) NWTF	(2) ML	(3) NWTF	(4) ML
CRRA Curvature $\hat{\alpha}$	0.334	0.266	0.669	0.572
	(0.018)	(0.016)	(0.026)	(0.026)
Daily discount rate $\hat{\delta}$	1.010	1.002	1.022	1.004
	(0.002)	(0.003)	(0.005)	(0.006)
$\hat{P}$	0.523	0.437	0.291	0.103
	(0.032)	(0.041)	(0.050)	(0.074)
Background consumption ω	-0.01	-0.01	-50.25	-50.25
Observations	38772	28782	38772	28782
LL	-25212.08	-18935.396	-25802.883	-19381.035

1.6.3 Individual Estimates

To conclude the results of these data we explore the possibility of estimating individual trust estimates. Tables 1.10 to 1.12 present statistics of individual estimates of trust, curvature parameter and discount factors for specifications 1, 2 and 3. For each subject, we estimate the parameters of equation 1.3 using our different econometric specifications, restricting $\omega_1 = \omega_2 = 0$. The parameters $\hat{P}$, $\hat{\alpha}$ and $\hat{\delta}$ are estimated using the two-limit Tobit maximum likelihood estimator shown in table 1.10, restricting the sample to the unconstrained choice sets for $1 + r < 3$. In tables 1.11 and 1.12, we estimate the parameters jointly using the trust elicitation and the risk elicitation tasks, with the data from the convex budget sets and the binary data, respectively.

Using the Tobit model, we are able to estimate the trust parameters for 740 subjects as shown in table 1.10. Although convergence is achieved for 925 subjects, 185

subjects have an estimated $\hat{\alpha} \geq 1$, which leads to implausible estimates of the trust and delta parameters, given that the optimality condition only holds for $\alpha < 1$. We therefore restrict our analysis to subjects with $\hat{\alpha} < 1$. The median estimated trust is 0.67, slightly larger than the estimates presented in table 1.7. The median estimated $\hat{\alpha}$ is 0.63, slightly lower than the estimates for the full sample. The median $\hat{\delta}$ is 1. The differences might be due to the non-reported subjects. Their average current consumption with and without securement is smaller than for reported subjects. This might be the reason for median individual estimates of $\hat{\alpha}$ being lower compared to the results in table 1.7.

Individual parameter estimates of specifications 2 and 3 are presented in tables 1.11 and 1.12. When we estimate the individual parameters using our probabilistic model with the convex budget sets data, the estimated median $\hat{P}$ is 0.38, similar to our estimates in table 1.8. The estimated median $\hat{\alpha}$ is 2.22 and the estimated median $\hat{\delta}$ is 0.96. The number of subjects for which we are able to estimate the parameters at the individual level is considerably low, at 385, due to the strong data requirements of this method. For each subject, we only have 54 data points in total, which might not be enough for such a demanding estimation procedure.

Estimates of individual parameters in this model with the binary data are presented in table 1.12. The estimated median $\hat{P}$ is 0.46, in line with our estimates presented in table 1.9. The estimated $\hat{\alpha}$ is 0.60 and the estimated $\hat{\delta}$ is 1.01, both in line with our results. As before, we find that the number of subjects for which we are able to individually estimate the parameters is low with 442. Compared to the probabilistic estimation using the convex budget set data, and similar to the previous estimation, we find that the median estimate of $\hat{\alpha}$ is closer to the common estimates in the literature when the parameters are estimated using the binary data.

Figure 1.4 illustrates the distribution of $\hat{P}$ for the three specifications. Notice that $\hat{P} > 1$ can be interpreted as a higher probability attached to receiving the payment without securement.

Table 1.10 Individual estimates, specification 1, $\alpha < 1, 1 + r < 3$.

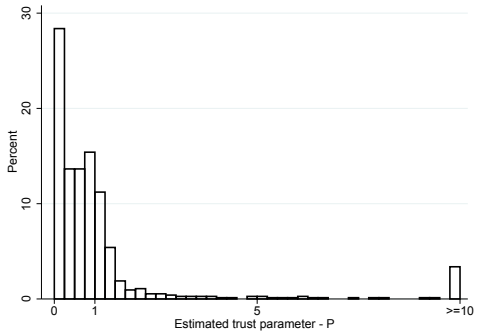
	N	Min	Max	5th Perc.	Median	95th Perc.
$\hat{P}$	740	0.00	8.25e+09	0.00	0.67	5.28
$\hat{\alpha}$	741	-1545.31	1.00	-1.82	0.63	0.98
$\hat{\delta}$	741	0.00	4.74e+19	0.89	1.00	1.11

Table 1.11 Individual estimates, specification 2.

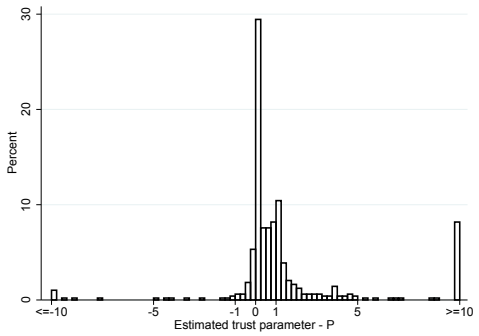
	N	Min	Max	5th Perc.	Median	95th Perc.
$\hat{P}$	385	-4.14	39.23	-0.13	0.38	4.36
$\hat{\alpha}$	385	-0.52	12.39	0.67	2.22	6.13
$\hat{\delta}$	385	-44.32	2007.04	-0.81	0.96	1.17

Table 1.12 Individual estimates, specification 3.

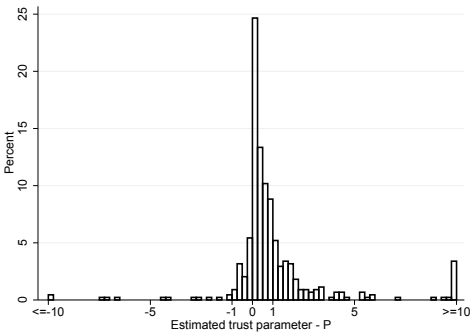
	N	Min	Max	5th Perc.	Median	95th Perc.
$\hat{P}$	442	-30.70	47.75	-0.63	0.46	5.45
$\hat{\alpha}$	442	-0.07	60.16	0.17	0.60	3.93
$\hat{\delta}$	442	-0.97	250.88	0.70	1.01	7.55



(a) Specification 1, $\alpha < 1$, $1 + r < 4$.



(b) Specification 2, convex budget set data.



(c) Specification 3, binary data.

Figure 1.4: Histograms of $\hat{P}$ using specifications 1-3.

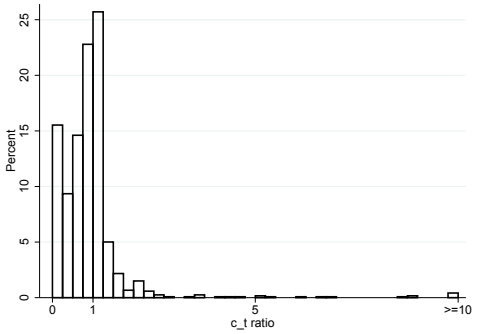
All estimation techniques considered so far infer a lot of information from few observations per person and fail frequently mostly due to lack of variation. In order to yield an approximate trust measure on each individual, we introduce an additional simple indicator, the c_t-ratio $= \frac{\bar{c}_t^C}{\bar{c}_t^{NC}}$, which relates the mean consumption choices in the C and NC treatments. It is equal to 1 if the securement does not influence the money allocation over time. It is smaller than 1 if the current consumption c_t with securement is smaller and thus the investment in the future is higher than without. It is expected that the estimate $\hat{P}$ is 1 when the c_t-ratio is 1 and that in general c_t-ratio is proportional to $\hat{P}$.

In order to incorporate the data corresponding to $r \geq 3$, we implement a linear transformation of $c_t \in [a, 150]$ into $[0, 150]$, for $r \geq 3$. We further align the mathematical value with the economic interpretation as follows. 28 subjects have $\bar{c}_t^{NC} = \bar{c}_t^C = 150$ and would have a ratio of 1. We decide, however, not to include these subjects since no trust in the institution is involved when the prospect of a future payment is avoided. Furthermore, 98 subjects have $\bar{c}_t^{NC} = \bar{c}_t^C = 0$ and thus an undefined c_t-ratio. We set their c_t-ratio to 1 since these decisions involve maximal future payments and they are uninfluenced by the payment securement. 25 subjects have a $\bar{c}_t^{NC} = 0$ and $\bar{c}_t^{NC} > 0$, which does not allow to quantify the c_t-ratio. Thus, in total 53 individuals have no c_t-ratio.

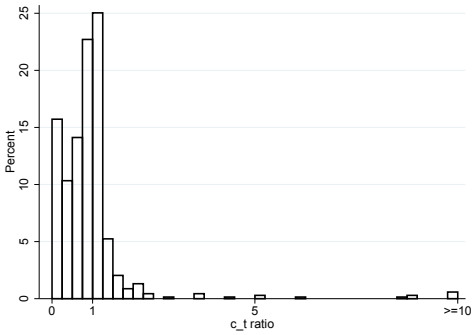
For this measure, table 1.13 compares statistics of the individual estimates for the full sample and across the treatments NWTF and ML. Similarly, figure 1.5 illustrates its distributions. Based on these data and in contrast to the findings in the previous estimations, no differences between treatments can be identified. The median c_t-ratio is well below 1, reflecting that subjects have a smaller current consumption and thus more investment into the future with payment securement.

Table 1.13 Summary of transformed individual c_t-ratio estimates.

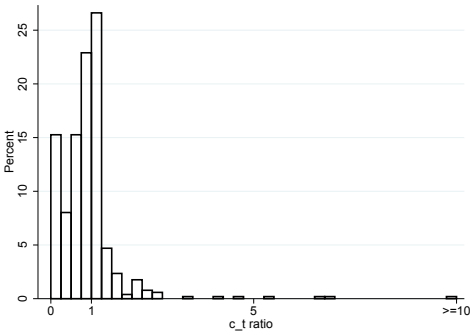
	N	Min	Max	5th Perc.	Median	95th Perc.
Full Sample	1198	0	52.50	0	0.86	1.73
NWTF	687	0	52.50	0	0.86	1.68
ML	511	0	18.86	0	0.86	1.75



(a) Full sample.



(b) NWTF sample.



(c) ML sample.

Figure 1.5: Histograms of the c_t-ratio distribution.

1.7 Reported and Elicited Trust

Our elicitation tasks, the trust game and the survey question provide us with a wide array of data to investigate differences between elicited and reported measures as well as relationships between trust, social preferences and risk preferences.

1.7.1 General and institutional trust

The amount invested in the trust game is commonly seen as a measure of general trust since players are confronted with a random, anonymous opponent from a known, general population. The reported measure of trust in our questionnaire is the question: "Do you think that most people can be trusted?" Participants can answer this question on a 7-point Likert scale ranging from "1–not at all" to "7–completely trust".[30]

To measure institutional trust, we ask participants the question: "Do you think that NWTF can be trusted?" Participants can answer this question on a 7-point Likert scale ranging from "1–not at all" to "7–completely trust". In the case of the local money lenders, the statement was formulated as "Please indicate how much trust you have in the local money lender." Participants can answer this question on a 7-point Likert scale ranging from "1–no trust" to "7–complete trust".[31]

The top part of table 1.14 presents the amounts invested and received in the trust game. Out of 50 PHP, subjects on average invest 25.7 PHP and return 30.8 PHP. The levels of trust and trustworthiness with a return on investment slightly higher than 1 are in line with other results in the literature (Berg, Dickhaut, and McCabe, 1995). Comparing the ML and NWTF samples, we see that there is a slight but insignificant difference between treatments. In ML, slightly higher amounts are invested and returned.

For the validity of our previous results on institutional trust it is comforting that the two samples do not differ in general trust neither as measured in the trust game nor as self-reported. Furthermore, as expected, we see that the responsible institution in the TE task does not have an influence on general trust.

The bottom part of table 1.14 reports stark differences in trust ratings between NWTF and ML, irrespective of the sample. While NWTF's rating are on the top end of the scale, ML only gets middle ratings. The institution being responsible in the TE task has little influence on the trust reports. In the ML sample the difference is

[30] We also implemented an alternative measure of trust, following the World Value Survey (WVS): "Generally speaking, would you say that most people can be trusted or that you cannot be too careful in dealing with people?" The answer categories are "Most people can be trusted", "Cannot be too careful", "Depends", "Do not know", "Refused". We use a more direct and fine-grained question of trust, since it has been identified that the trust question as implemented in the WVS can lead people to agree with both most people can be trusted and can not be too careful since both risk preferences and beliefs influence trust. Miller and Mitamura (2003) show that the confound in this question can be problematic when measuring trust.

[31] We are aware that the accidental difference in the wording of the question makes a comparison less clean, but we do think that the questions are sufficiently similar and do not drive the strong results.

small and insignificant. For NWTF, the ratings are slightly, but significantly higher in the NWTF treatment, probably due to the familiarity subjects have with NWTF in combination with the TE task.

Although the Likert-ratings come without a metric, the reported differences in trust differ qualitatively from the trust measured in the TE task. It is possible that the self-reported trust levels include evaluations of further aspects of these institutions, like general preference, fairness of their terms and conditions, helpfulness, and others. Factors which are not part of the trust in the institution in terms of the belief in the institution's compliance.

Table 1.14 Trust game and survey questions.

	Full Sample	NWTF treatment	ML treatment	ML-NWTF
	(1)	(2)	(3)	(4)
Invested amount in TG	25.70	26.31	25.26	1.048
	(8.62)	(9.03)	(8.28)	(0.688)
Returned amount in TG	30.82	31.67	30.19	1.480
	(14.49)	(15.34)	(13.81)	(1.185)
General trust level	4.31	4.32	4.29	0.030
	(1.35)	(1.34)	(1.37)	(0.077)
Trust level in NWTF	6.14	6.11	6.17	-0.065
	(1.37)	(1.36)	(1.38)	(0.078)
Trust level in ML	3.83	3.82	3.84	-0.013
	(1.99)	(1.98)	(2.01)	(0.114)
Observations	1249	533	716	

Notes: The trust survey questions are based on a 7-point Likert scale: 1–no trust, 7–complete trust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In parenthesis is the standard deviation (columns 1-3) and standard errors of the equality of means test (column 4).

1.7.2 Trust and Social Preferences

We can investigate some candidate preference factors by looking at the relationship of trust with risk and social preferences. Fehr (2009) reports that risk and social preferences correlate with reported trust.

We explore this question with survey measures of social preferences such as betrayal aversion, reciprocity and sociability. Betrayal aversion is measured with the question "Generally speaking, do you try to avoid that others get in a position where others can betray you?". Participants can answer this question on a 7-point Likert scale ranging from "1–completely avoid" to "7–do not avoid at all". The extent to which people are willing to reciprocate wrong-doing when experiencing an offense is reflected in the statement "If someone offends me, I will also offend him/her." Subjects answer the question on a Likert scale from "1–I will offend" to "7–I will not offend". Given that more sociable people are more likely to have access to information regarding the institutions' reputation we measure sociability by asking "Do you meet

friends, neighbors or relatives often?" with possible answers "1–never", "2–seldom", "3–monthly", "4–weekly", and"5–daily". Dohmen, Falk, Huffman, and Sunde (2012) have documented the link between sociability and the transmission of trust attitudes.

To measure risk preferences we ask participants "Are you, generally speaking, a person who is fully prepared to take risks, or do you try to avoid taking risks?" Respondents answer on a 7-point Likert scale going from "1–try avoiding any risk" to "7–fully prepared to take risk". Additionally, we use the data from the RPE task to structurally estimate individual risk preferences.[32] Our measure, α, implies risk aversion if $\alpha < 1$, risk neutrality if $\alpha = 1$ and risk loving behavior if $\alpha > 1$.[33]

We use the c_t-ratio=$\frac{\bar{c}_t^C}{\bar{c}_t^{NC}}$ as individual measure of behavioral trust.[34] We also make use of the beliefs subjects hold about the reception of the payment that are elicited with the question "How certain are you that the payment in 28 days will reach you?" The answer categories are "1–will surely not reach me", "2–I have very strong doubts", "3–I have strong doubts", "4–It might or might not happen, it is a coinflip", "5–I have slight doubts", "6–I have only very slight doubts" and "7–Absolutely certain".

Table 1.15 shows regressions of reported and behavioral general trust on risk and social preferences to which we add demographic and socio-economic controls.[35] Column (1) shows that risk aversion, betrayal avoidance and sociability significantly correlate with reported trust. A one standard deviation in risk loving behavior leads to a 0.17 standard deviation increase in trust towards people in general. Similarly, not avoiding betrayal as well as being more sociable leads to more trusting behavior. In column (2), we use the behavioral measure of risk preferences and find no significant relation between risk and reported trust.

Columns (3) and (4) report results for the behavioral trust as measured by the amount invested in the trust game. We find no effect of reported risk or social preferences (column 3), but we find that a one standard deviation increase in the subject's risk loving behavior leads to a 0.11 standard deviation increase in the amount invested in the trust game (column 4). While consistent within themselves, elicited and reported measures do not relate to each other in the expected way. This suggests that self-reported attitudes and exhibited behavior differ.

Analogue results for institutional trust are presented in table 1.16. Columns (1) and (2) show the result when survey institutional trust is the dependent variable and columns (3) and (4) when the c_t-ratio is the dependent variable. Similar as in table 1.15, we find effects of survey measures of risk and social preferences on survey measures of institutional trust. Risk aversion, betrayal aversion, reciprocity

[32]To estimate them, we follow the same procedure as for specifications 2 and 3, but only taking into account the RPE task. That implies, that only the data of the RPE task is used to feed the likelihood function, $\mathcal{L} = \mathcal{L}^{EU}$. We use $\omega = 0$ to estimate it.

[33]The median α is 0.60. In order to reduce effects due to outliers, we drop observations with α below the 5^{th} percentile and above the 95^{th} percentile.

[34]In order to reduce effects due to outliers, we drop observations with a c_t-ratio below the 1^{th} percentile and above the 99^{th} percentile.

[35]We control for age, household size and whether the household's dwelling has electricity.

and sociability significantly affect trust. We find that the more risk loving subjects are, the more they trust in both NWTF and in the local money lender. Betrayal avoidance plays no role in reported trust towards NWTF but it does in reported trust towards the local money lender. Subjects that avoid less to be betrayed exhibit more trust towards the local money lender. Reciprocity plays a role in trust towards NWTF. Subjects that are less willing to offend back if offended exhibit higher trust towards NWTF. For the local money lender, the effect is positive but insignificant. Finally, we find that sociability has a positive effect in trust towards NWTF and a negative effect on trust towards the local money lender. The more often people meet with friends, family and neighbors the more they trust NWTF and the less they trust the money lender. This might be the result of information transmission. More sociable subjects are more likely to have access to information regarding the institutions, possibly receiving positive information from NWTF and negative information from local money lenders, given their bad reputation.

Columns (3) and (4) report the effect of risk and social preferences on behavioral measures of institutional trust. For both institutions, we find a negative effect of betrayal aversion, implying that the less participants avoid being betrayed the lower the trust they exhibit towards the money lender. These results are contrary to what we would expect. Beliefs regarding the institution's trustworthiness have no effect. We find an effect of sociability on trust towards the local money lender. Risk aversion has a positive but insignificant effect, in the direction that subjects that are more willing to take risks trust more in the local money lender.

Overall, the analysis supports the view that the elicited trust measure is less related to individual preferences including social preferences than the reported trust measures.

1.8 Effect of the Promise on Savings

Lack of trust in financial institutions has been identified as one of the possible causes for low levels of savings with formal financial institutions in developing countries (Karlan, Ratan, and Zinman, 2014; Dupas, Green, Keats, and Robinson, 2014). If a realized future payment increases the trust in an institution, the higher trust might lead to an increase in that amount of savings held at the institution.

We investigate this question by exploiting the random variation generated by the choice of the round to be paid. Subjects make 54 decisions, of which 36 correspond to the TE task and 18 to the RPE task. One of the 54 choices is selected at random to be paid to the subject. All choices in the TE task might include a future payment in $t + d$, where $d = 7, 28$. This depends on subjects' choices.[36] The future payment, kept and delivered by the institution, constitutes a promise of delivery to the subject.

[36] If subjects choose $c_t = 150$, then $c_{t+d} = 0$, thus leading to no future payment although the subject is paid for a TE task. Choices in which interest rates are low have a higher likelihood of $c_t = 150$

Table 1.15 Effect of risk and social preferences on general trust

	Reported General Trust		Invested in Trust Game	
	(1)	(2)	(3)	(4)
Risk loving	0.17***		0.039	
(reported)	(0.000)		(0.318)	
Betrayal	0.088***	0.094***	-0.036	-0.043
non-avoidance	(0.005)	(0.005)	(0.374)	(0.302)
Reciprocity	0.036	0.033	0.0083	0.012
	(0.214)	(0.293)	(0.818)	(0.759)
Sociability	0.11***	0.100***	-0.047	-0.052
	(0.000)	(0.000)	(0.251)	(0.234)
Risk loving, α		-0.0020		0.11***
(estimated)		(0.951)		(0.009)
N	1247	1148	638	584
Covariates	Yes	Yes	Yes	Yes

Notes: OLS-regressions of trust on risk and social preferences measures with robust standard errors. We shows standardized coefficients with p-values in parentheses. Reported general trust, risk loving, betrayal non-avoidance are measured on a 7-point Likert scale. Sociability takes values of 1-"never", 2-"seldom", 3-"monthly", 4-"weekly", or 5-"daily". Risk loving, α estimated using data from the RPE task, excluding bottom 5^{th} and top 95^{th}. $\alpha < 1$, implies risk aversion, $\alpha = 1$ risk neutrality and $\alpha > 1$ risk loving. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Fulfillment of that promise would constitute a positive effect on the subject's trust towards the institution.[37]

In contrast, choices in the RPE task are paid fully at the end of the experiment, since RPE payoffs do not feature any time delay. Therefore, subjects paid for the RPE task do not have the opportunity to see their trust in the delivery by the institution paying off. 34% of all subjects were paid for the RPE task and 66% were paid for a choice taken in the TE task. Figure 1.9 in Appendix B shows the distribution of decisions paid in the experiment.

For this investigation, we focus on the sample in the NWTF treatment, since we have detailed financial information from NWTF clients, including weekly data on savings held at NWTF. Our aim is to test whether the possible positive effect on trust experienced by subjects has a positive effect on their savings with NWTF. Table 1.20 in appendix B.2 show descriptive statistics for the sample of interest.[38] Covariates are balanced between subjects paid for a TE task and subjects paid for a RPE task.[39]

[37] Out of the 1,251 subjects, four did not receive the future payment, because they could not be reached at their homes, after several trials. One of the subjects did not want to receive the future payment (PHP20). Three of them were in the NWTF treatment and one in the ML treatment, and two had a check as a payment securement.

[38] The sample is reduced, since not all the subjects that were in the NWTF treatment are NWTF clients.

[39] Our sample was further reduced in the weeks following the experiment, since subjects might leave the NWTF sample if there loan comes to an end. We check for the balancing of covariates for those in the 8 weeks used for the analysis, and results are the same as presented in B.2. Electricity in the

Table 1.16 Effect of risk and social preferences on institutional trust

	Reported Inst. Trust		c_t-ratio: $\frac{\bar{c}_t^C}{\bar{c}_t^{NC}}$	
	NWTF	ML	NWTF	ML
	(1)	(2)	(3)	(4)
Risk loving (reported)	0.049*	0.053*		
	(0.079)	(0.063)		
Betrayal non-avoidance	-0.019	0.074**	-0.068*	-0.084**
	(0.477)	(0.023)	(0.072)	(0.026)
Reciprocity	0.090***	0.0063	0.0030	-0.027
	(0.003)	(0.824)	(0.940)	(0.407)
Sociability	0.082***	-0.079***	-0.014	-0.12**
	(0.005)	(0.002)	(0.740)	(0.037)
Risk loving, α (estimated)			-0.019	0.080
			(0.694)	(0.372)
Trustworthiness belief			-0.054	-0.029
			(0.286)	(0.508)
N	1247	1247	495	458
Covariates	Yes	Yes	Yes	Yes

Notes: OLS-regressions of trust on risk and social preferences measures with robust standard errors. We shows standardized coefficients with p-values in parentheses. Reported general trust, risk loving, betrayal non-avoidance are measured on a 7-point Likert scale. Sociability takes values of 1–"never", 2–"seldom", 3–"monthly", 4–"weekly", or 5–"daily". c_t-ratio data excluded for the top 99^{th} percentile and the bottom 1^{st} to account for outliers. Risk loving, α estimated using data from the risk task, excluding bottom 5^{th} and top 95^{th}. $\alpha < 1$, implies risk aversion, $\alpha = 1$ risk neutrality and $\alpha > 1$ risk loving. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To examine our question we run the following regression

$$\text{Sav}_{i,t+k} = \theta + \phi_1 \cdot T_i + \phi_2 Z_i + \phi_3 \cdot X_i + \varepsilon_{i,t+k},$$

where $\text{Sav}_{i,t+k}$ corresponds to the weekly savings level of subjects in the NWTF treatment. We look at the effects in the 8 weeks after the experiment took place, $k = \{1, \ldots, 8\}$. The treatment indicator is $T_i = 1$ if the subject was paid on a TE task and thus eligible to receive the future payment from NWTF and $T_i = 0$ otherwise.[40]

Since subjects' earnings in the experiment could have an effect on their savings level after the experiment, we control for the total amount earned in the experiment, Z_i. Finally, X_i is a vector of covariates which includes risk aversion estimates, covariates used for balancing during the sampling (baseline savings, loan amount, distance to municipality and urban indicator) and household characteristics (household size, age, electricity in the household's dwelling). Standard errors are clustered at the center level.[41]

Table 1.17 shows a positive and significant effect on savings of being eligible for receiving the later payment from NWTF. Savings increase by 65 PHP, representing 25% of baseline savings. In a second step, we investigate whether the effects are driven by those that had a later payment in $d = 7$ or in $d = 28$ days. We would expect that the longer the delay in the future payment delivery, the stronger the trust shock subjects experience. We therefore split our treatment indicator T_i into a treatment indicator for those that were to receive the future payments 7 days and 28 days after the experiment, respectively. There is a positive and significant effect for those that received the payment in 7 days, while for those receiving the future payment 28 days after the experiment the effect is positive, smaller and not significant. A longer time distance to the promised payment thus does not increase the saved amounts.

1.9 Discussion

From our structural estimations, we obtain levels of trust $\hat{P}$ between 0.10 and 0.60, which result from differences clearly visible in the descriptive statistics, but which are arguably lower than expected. The variation of $\hat{P}$ across estimations shows that the measure depends considerably on estimates of utility curvature and discounting. In this respect, the trust measure would benefit from a convergence in the literature on the best way to identify time and risk preferences. For the moment we take away from the results that the provision of a payment securement reduces uncertainty about the

dwelling and banking distance is different across groups, and we control for electricity in the dwelling in our analysis. We do not control for bank distance, given that there was a local option for cashing the check.

[40] Approximately 80% of subjects that were paid for TE decision chose a positive future payment.

[41] The subjects, all of which are clients of NWTF, borrow in the context of the group lending method. Several groups meet once a week to make their loan installments, in lending centers. Several subjects of a center may take part in the experiment. Given that they might have common traits across centers, we cluster standard errors at the center level.

Table 1.17 Effect of intervention on savings

	$\text{Sav}_{i,t+k}$	
	(1)	(2)
Future payment, T_i	64.82**	
	(29.92)	
Future payment ($d = 7$), $T_{i,d=7}$		61.19*
		(36.37)
Future payment ($d = 28$), $T_{i,d=28}$		46.89
		(38.24)
Experiment earnings, Z_i	-0.127	-0.160*
	(0.0868)	(0.0860)
Constant	-119.2	-96.62
	(104.2)	(102.1)
Covariates	Yes	Yes
R^2	0.42	0.42
N	4,100	4,100

Notes: Standard errors in parentheses, clustered at the lending center level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

future payment considerably across institutions.

We normalize the behavior when a payment securement is provided to $P = 1$. Still, the choices under the payment securement are showing some dependence on the responsible institution and might favor even more investment in the full absence of such dependence. This implies that the level of $\hat{P}$ could be overestimated. At the same time, depending on the influence of this dependence, the difference between institutions might be underestimated because it would come out larger if the behavior under payment securement did not differ.

We carefully design our experiment to pick up differences in trust in institutions across the two financial institutions as well as across different modes of payment securement. With the random allocation of treatments and the constant parameters across the TE tasks we make sure that systematic differences in the valuation of later payments can be related to the different institutions. It is possible, however, that subjects have preferences over elements of the later payment, such as the delivery mode, the information necessary to find them, the storage at the institution, and the check transaction, that might limit this clean attribution.

For example, regarding the delivery, subjects might not want to have a representative of the institution come to their house, for example, possibly due to pending loans. This could make subjects avoid contact by avoiding future payments at all ($\bar{c}_t = 150$), depending on the institution. Howver, there is no difference across treatments on the extensive margin of avoiding future payments. 17 out of 716 (2.4%) do this in NWTF, 11 out of 533 (2.1%) in ML. Thus, such occurrences of extremely front-loaded

allocations probably result from particular time preferences that are equally present in both treatments.

The payment securement via a check is established on top of the organized delivery. To the extent that the payment is expected not to be delivered, the equivalence of the check payment to the immediate payment depends on beliefs with respect to the funds of the check, the time necessary to cash it, the familiarity with cashing a check, etc. We know that subjects are familiar with checks since loan payments are distributed this way by NWTF. Furthermore, while the bank distance is substantial for some subjects, we deliberately established a local option for cashing the check that made the transaction easily feasible and informed subject prior of the decisions. We thus believe that the check is not systematically viewed as unwieldy, after all, we see many more future allocations under such a payment securement.

In a first application of our trust measure, we use it on two financial institutions. The handling of money is a natural activity of the two institutions but the method is not limited to financial institutions. One can think of any public or private institution to be responsible for a payment delivery, even if, for example, the institution is normally providing other services, such as national education services. Of course, a service closer to the institution at hand might be used if the substitute for the monetary payment is an equally well quantifiable object of time preferences. The strong drawback of such an approach would be the non-comparability with measures of trust towards other institutions. We view our measure as a universal measure of trust in generic institutions.

1.10 Conclusion

We propose a novel way of experimentally measuring trust in institutions which draws on the experimental method of eliciting time preferences. In particular, we are implementing a time preference elicitation and vary the institutional setting as defined by the terms of and responsibilities for the future payment. We employ the CTB method as proposed by Andreoni and Sprenger (2012a) and add features of the DMPL method, such as a separate risk preference elicitation task and binary choice sets, in order to check the robustness of our measure (Andersen, Harrison, Lau, and Rutström, 2008).

Our method allows us to elicit levels of trust towards institutions in an incentivized way and at the same time is not identified by the participants as a measure of trust. In contrast to any other measure of trust, it is provided directly in the the meaningful metric of subjective probability of completion of a payment.

In a field study in the Philippines, we measure trust towards two institutions, a Philippine microfinance institution and local money lenders. We show that our trust measure is able to differentiate between these institutions in the expected way, namely that the subjective probabilities of payment completion is higher throughout for the more formal institution. We contrast this measure with other ways of measuring trust, the trust game and non-incentivized survey questions. The survey responses indicate a substantially larger differences in levels of trust than the incentivized measures, suggesting the relevance of other factors such as preferences. Additionally, we find that reported measures of trust might be different from the actual willingness to transact with the institution.

We also exploit the random variation in the trust level in the formal institution generated by our experiment. Subjects that were randomly selected to be paid in the future exhibit a significant increase in savings held at the formal institution. We take this as evidence of a positive effect on financial behavior due to the fulfillment of a promised future payment.

Overall, the results show that time preference elicitation can be a useful method to measure trust in institutions in a way that is incentivized, readily quantifiable, not recognized as such and not confounded with other factors such as preferences. In that sense, it is a useful measure to quantify trust in or the perceived reliability of particular institutions. Additionally, on a methodological level, our results confirm that the institutional setting is an important aspect of any time preference elicitation and can substantially change estimates of utility parameters. Furthermore, the potential of an exogenous variation of trust resulting from the measure opens new paths of investigating the influence of trust in institutions on economic behavior.

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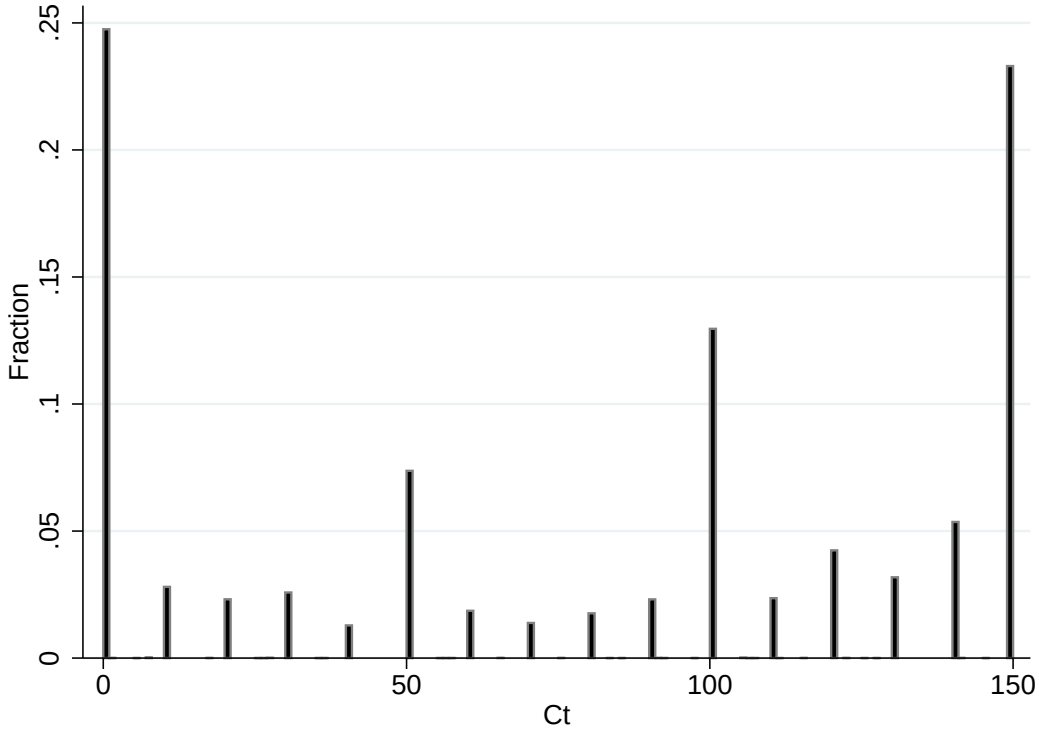
A Appendix

A.1 Choice histogram



A.2 Further probabilistic specification results

Table 1.18 CRRA parameters estimates from probabilistic specification based only on TE data.

	(1) NWTF	(2) ML	(3) NWTF	(4) ML
CRRA Curvature $\hat{\alpha}$	3.093	3.213	4.077	4.233
	0.025	0.029	0.032	0.038
Daily Discount Rate $\hat{\delta}$	0.959	0.947	0.955	0.944
	0.001	-0.001	-0.001	-0.001
$\hat{P}$	0.213	0.179	0.196	0.163
	0.006	0.006	0.006	0.006
Background consumption ω	-0.01	-0.01	-50.25	-50.25
Observations	25848	19188	25848	19188
LL	-112190.97	-83068.402	-112065.72	-83030.178

A.3 Experiment materials

Instructions

Experiment Protocol

English version

Instructions

§1. Thank you all for taking the time to join us here today. My name is XXX and this is Maria Isabel Santana/Frederik Weber. I am a research assistant and Maria Isabel/Frederik is a researcher at the University of Mannheim, in Germany. The complete session will last approximately 3 hours. In this study we want to play some games for the purpose of economic research. Some decisions will involve actual money, and whatever you earn today will be paid to you in private at the end of the session and is yours to take home.

§2. The money you can earn today is not Maria Isabel's/Frederik's own money. The funds for this project are provided by the German Ministry of Science particularly for this research study. The study is carried out with similar games throughout Iloilo, Capiz and Guimaras.

§4. It is very important that you understand the games… If there is something you do not understand, you may always ask the assistants to explain the rules.

§5. Before the games you participated in the first part of a small survey. After the games, you will be asked to participate in the second part of the survey by answering some additional questions. Once the second part of the questionnaire is completed, you will receive your payment.

§6. There will be four parts of games played in this session [refer to agenda]. The first two parts are a money valuation game, the third one is a lottery game, and the fourth one is an investment game. We will explain you the rules for each game before each of the games are to be played. The games are to be played by each player individually, therefore we kindly ask you to remain silent during the games and to take decisions individually.

§7. After you have played the games and answered the questionnaire, Maria Isabel/Frederik will give you your payment and a receipt for you to sign.

Upcoming decisions

§9. Within the three first parts, you will take 54 decisions [show bag with balls]. You will be paid for only one decision. At the end of all games, you will randomly select one of 54 balls that indicates the number of the decision paid for you. All decisions are equally likely to be selected by you; therefore you should make each decision seriously as the one that would be paid out.

Money Valuation Game

§10. In this game you are asked to make decisions about how to allocate money between two dates, one date would be today and the other date will be later in time. The later date in which you will possibly receive your payment is either in 1 week, that is in 7 days from today or in 4 weeks, that is in 28 days from today. In parts 1 and 2, you will in each part make 18 decisions of the same kind.

§11(NWTF). If the decision to be paid to you has a payment to be paid today, then you will receive this payment today together with any other additional payments from the game played in part 4. If the decision to be paid to you has a payment in a later date, then this payment will be kept for storage at Negros Women for Tomorrow foundation (NWTF), which is the organization that runs Project Dungganon and delivered to you to your house at the according date, either in 7 days or in 28 days. §11(ML). If the decision to be paid to you has a payment to be paid today, then you will receive this payment today together with any other additional payments from the game played in part 4. If the decision to be paid to you has a payment in a later date, then this payment will be kept for storage at ____, a local moneylender from the municipality of _____, and delivered to you to your house at the according date, either in 7 days or in 28 days.

Part 1 [refer to agenda]

§14(No-Check/Check; NWTF). NWTF is responsible for payment at the later date and promises that the payment will be delivered to you, but we cannot provide you with any written legal note to secure this payment for the 18 questions in this part 1. Only for the later 18 questions in part 2 we will be able to – on top of the promise – offer to secure the payment with a signed check to your name which is dated for the due date of the payment and which you can take home with you.

§14(Check/No-Check; NWTF). NWTF is responsible for payment at the later date and promises that the payment will be delivered to you. On top of that promise and only for the coming 18 questions in this part 1, we will be able to offer to secure this payment with a signed check to your name which is dated for the due date of the payment and which you can take home with

you. [Show example check and pass around so participants can see it.] This is an example check made to be paid out in 7 days under the name of one of the participants.

You do not need to cash the check. It is only a securement of payment. When the later payment is delivered to you at your house, you have to return the check and receive your later payment. Of course, if the delivery does not happen you can cash the check and this way receive the promised later payment. The check can be cashed in a BDO branch. Alternatively, we have arranged for cashing methods within your local area which will be specified at the payment.

For the 18 questions coming later in part 2, we cannot provide you with any written legal note to secure the payment.

§14(No-Check/Check; Moneylender). The Moneylender ____ is responsible for payment at the later date and promises that the payment will be delivered to you, but we cannot provide you with any written legal note to secure this payment for the 18 questions in this part 1. Only for the later 18 questions in part 2 we will be able to – on top of the promise – offer to secure the payment with a signed check to your name which is dated for the due date of the payment and which you can take home with you.

§14(Check/No-Check; Moneylender). The Moneylender ____ is responsible for payment at the later date and promises that the payment will be delivered to you. On top of that promise and only for the coming 18 questions in this part 1, we will be able to offer to secure this payment with a signed check to your name which is dated for the due date of the payment and which you can take home with you. [Show example check and pass around so participants can see it.] This is an example check made to be paid out in 7 days under the name of one of the participants.

You do not need to cash the check. It is only a securement of payment. When the later payment is delivered to you at your house, you have to return the check and receive your later payment. Of course, if the delivery does not happen you can cash the check and this way receive the promised later payment. The check can be cashed in a BDO branch. Alternatively, we have arranged for cashing methods within your local area which will be specified at the payment.

For the 18 questions coming later in part 2, we cannot provide you with any written legal note to secure the payment.

§15. In the money evaluation game, we will present you with options of receiving money today or receiving money with interest at a later date. Your decision is reached in a two- to three-stage process. In a first stage[point to the first screenshot on the poster], you will decide between an option of getting 150 PHP today and 0 Pesos later and another option of receiving a higher amount in either 7 or 28 days and 0 or little today. You can view this as either using

money today or saving it for the future and earning interest. In a second stage [point to the second screenshot on the poster], you have these two options plus further options in which you get some of the 150 Pesos today and let only the remainder earn interest for later. Finally [point to the last screenshot on the poster], you get a confirmation of your choice and the option to define your choice to the Peso unit. Throughout the screens, amounts received today are shown in blue, amounts received in the later date are shown in orange.

§16. Let us now consider one of the interest rates as an example. Here, you are first asked whether you prefer getting 150 Pesos today and 0 later [point again to the first screenshot, now on the blue bar, RA associates real money to column (150-0)] or 0 pesos today and 300 pesos in 7 days. [point again to the first screenshot, now on the orange bar, associate money to (0-300)]. Take a moment to think which one you would prefer and click the bar when you are decided. You will then see the same two options and further options in between Note that towards the left columns the today payments gets higher, and towards the right the later payments get higher [point again to the second screenshot, RA associates real money to columns (150-0, 0-300, 50-200, 20-260, 80-140)]. Again, take a moment to consider which combination of payments today and later you prefer. Click the bar of the combination that you prefer. On the last screen you get a confirmation of your choice. If you want, you can also specify your choice to the Peso level in a drop-down menu.

Overall, you can allocate any amount between 0 and 150 today. The remaining amount will be multiplied and paid out later. You will see that the interest increases from low to very high, and it is shown at the top of the screen. That means that if you for example decide to keep 80 today in the first decision you get 70 in 7 days, but in subsequent decisions you get 93, 117, 140, 187 and even higher amounts in 7 days. The same with any other amount that you choose to keep between 0 and 150 for today. Whatever you save for later will increase in value throughout the decisions.

Please note that steps 2 and 3 are the ones that count. You can at any point go back to change your decision.

Please note that in decisions 1-9 you receive the amount saved for later in 7 days and in decisions 10-18 you make the same decision but receive the amount saved for later in 28 days.

Do you have any questions? It is important that you understand the options available to you. Before you take your decisions that count for your payment, we will go through a trial of the 9 decisions. If you do not understand the options available to you or the way you can choose the option that you would like to have paid to you, you may always ask the assistants for an explanation. Once everybody is finished and all questions are answered we will start the decisions that count. We now start the trial.

[SNACKS]

Part 2 [refer to agenda]

§24. Now, comes part 2. Here, you will again like in part 1 be asked to make 18 decisions about payment options on two dates, one date being today and the other date being in 7 or in 28 days. Remember that the upcoming 18 decisions are also part of the 54 decisions of which one will be randomly chosen and paid out to you.

§25(No-Check/Check; NWTF). Like before, NWTF is responsible for payment at the later date and promises that the payment will be delivered to you. On top of that promise and only for the coming 18 questions in this part 2, we will be able to offer to secure this payment with a signed check to your name which is dated for the due date of the payment and which you can take home with you. [Show example check and pass around so participants can see it.] This is an example check made to be paid out in 7 days under the name of one of the participants.

You do not need to cash the check. It is only a securement of payment. When the later payment is delivered to you at your house, you have to return the check and receive your later payment. Of course, if the delivery does not happen you can cash the check and this way receive the promised later payment. The check can be cashed in a BDO branch. Alternatively, we have arranged for cashing methods within your local area which will be specified at the payment.

§25(Check/No-Check; NWTF). Like before, NWTF is responsible for payment at the later date and promises that the payment will be delivered to you, but we cannot provide you with any written legal note to secure this payment for the 18 questions in this part 2.

§25(No-Check/Check; Moneylender). Like before, the Moneylender ____ is responsible for payment at the later date and promises that the payment will be delivered to you. On top of that promise and only for the coming 18 questions in this part 2, we will be able to offer to secure this payment with a signed check to your name which is dated for the due date of the payment and which you can take home with you. [Show example check and pass around so participants can see it.] This is an example check made to be paid out in 7 days under the name of one of the participants.

You do not need to cash the check. It is only a securement of payment. When the later payment is delivered to you at your house, you have to return the check and receive your later payment. Of course, if the delivery does not happen you can cash the check and this way receive the promised later payment. The check can be cashed in a BDO branch. Alternatively, we have arranged for cashing methods within your local area which will be specified at the payment.

§25(Check/No-Check; Moneylender). Like before, the Moneylender ____ is responsible for payment at the later date and promises that the payment will be delivered to you, but we cannot provide you with any written legal note to secure this payment for the 18 questions in this part 2.

Do you have any questions?

Lottery Game (Part 3) [refer to agenda]

§18. In this game you are asked to allocate money between a certain payment and a risky lottery. All payments from this game will be paid out today after the session. The upcoming 18 decisions are the last part of the 54 decisions of which one will be randomly chosen and paid out to you.

§19. In the lottery game, we will present you with options of receiving a payment for sure or playing a risky lottery that might lead to a larger payment or no payment. The result of the risky lottery depends on a random draw of yours of one of ten balls in this red bag.

§19a. You will win when an orange ball is drawn and lose when a white ball is drawn. The chance of winning depends on the number of orange balls in this bag of ten balls. The number of orange balls in the coming decision will be between 1 and 9. There is no decision without an orange ball, since then it would be sure that you lose. With 1 orange ball, out of 10 people drawing a ball, on average only 1 will win the lottery. [Prepare such a bag, maybe a transparent bag] With 2 orange balls, 2 out of 10 people on average will win the lottery, and so on. [Prepare such a bag] With 9 orange balls it is very certain to win since 9 out of 10 draws on average win the lottery. [Prepare such a bag] There is no decision with 10 orange balls since it would be sure that you win.

§20. In the first stage of the lottery game [point to the first screenshot on the poster], you will decide between an option of getting 150 PHP for sure and another option of receiving a higher amount when winning the lottery and 0 or little when losing. In a second stage[point to the second screenshot on the poster], you have these two options and further options in which you get some of the 150 Pesos for sure and put some money into the risky lottery. Finally [point to the last screenshot on the poster], you get a confirmation of your choice and the option to define your choice to the Peso level. Throughout the screens, amounts received for sure are shown in blue, amounts received when winning the lottery are shown in orange. The amount received from a lost lottery is always 0.

§21. Let us now consider an example. In this example, the chance that you win is 60%, that is, there are 6 orange balls and 4 white balls in the bag. [Prepare a bag with 6 orange balls and 4 white balls in front of the participants.] The chance that you win is always indicated at the top of the screen [point to the screenshot]. You are first asked whether you prefer getting 150 Pesos for sure [point again to the first screenshot, now on the blue bar, no money handling] or 300 pesos when you win the lottery and 0 otherwise. [point again to the first screenshot, now on the orange bar]. Take a moment to think which one you would prefer and click the bar when you are decided. You will then see the same two options as well as further options in between. Again, take a moment to consider which combination of a sure payment and a risky lottery you prefer. Click the bar of the combination that you prefer. On the last screen you get a confirmation of your choice. If you want, you can also specify your choice to the peso level in a drop-down menu. Overall, you can decide to get any amount between 0 and 150 for sure. The remaining amount will be multiplied and paid out when you win the lottery. Please note that steps 2 and 3 are the ones that count. You can at any point go back to change your decision.

Note that in each question, the number of orange balls will be different, that is, the chance that you win changes going from a low chance to a higher chance. Also, there are 9 decisions in which the lottery wins you up to 300 pesos and 9 decisions in which the lottery wins you up to 400 pesos while you still get at least 50 pesos for sure.

Do you have any questions? It is important that you understand the options available to you. Before you take your decisions that count for your payment, we will therefore go through all 9 decisions that you will take for a possible lottery gain of 300 pesos. Further, we will go through 2 decisions for a lottery gain of 400. If you do not understand the options available to you or the way you can choose the option that you would like to have paid to you, you may always ask the assistants for an explanation.

Once everybody is finished and all questions are answered we will start the decisions that count. We now start the trial.

Investment Game (Part 4) [refer to agenda]

§26. This game is played by pairs of individuals. Each pair is made up of an Investor and a Recipient. Half of you will be Investors, the other half of you will be Recipients. You will be notified on the screen which role you have. You will be playing with someone from this session, but none of you will know exactly with whom you are playing.

§27. If you are an Investor you will start with 50 PHP. You have to choose how much of the 50 PHP you would like to send to the Recipient. Whatever amount you choose will be tripled and then go to the Recipient.

§28. If you are a Recipient you will be informed about the amount available to you. You then indicate how much of the tripled amount you want to send back to the Investor. You can freely choose to return a part, everything or nothing. You simply keep what you do not return. Then the game is over.

§29. Whatever you hold as an Investor or Recipient, we will pay you in cash at the end of the meeting.

In summary, first the investor indicates the amount to be sent to the Recipient. It could be 0, 10, 23, 46. Any amount between 0 and 50 Pesos. Then, the amount sent is tripled and notified to the Recipient.

Once the Recipient knows the amount available, he decides how much to send back to the Investor and indicates it in the screen. Could be 0, 10, 50, 150, that is any amount between 0 and the full amount available to the Recipient.

Finally, the investor and recipient will be informed of the total earnings. The Investor earns the amount kept and the amount returned by the Recipient. And the Recipient earns the amount that was not returned from the available tripled amount.

The amounts earned will be paid out at the end of the session, after the games are played and the second part of the questionnaire is completed.

Do you have any questions? If there are no further questions, let's start the Investment Game.

Choice of Round to be Paid

Now, we will choose the round to be paid. To do this, we will insert 54 numbered balls in this big black bag, from where you will take one ball and the number in the ball will be the round paid out to you.

[2 RAs place numbered white balls in the big black bag clearly so participants have no doubt of numbers of balls in the bag]

Many thanks for your participation. We are almost done.

We will now ask you to please answer the second part of the questionnaire. Afterwards, you will collect your payment. One final comment regarding your payment. Your payment receipt will have a secret code enclosed in the envelope with the later payment. You will be given a copy of this code. Please keep this code with you. In order to get your payment, you need to present this code otherwise you will need to present an id. If you have received a check, you will need to hand in the check when you receive your payment in the later date.

Figure 1.6: Risk preference elicitation: sample decision, step 1

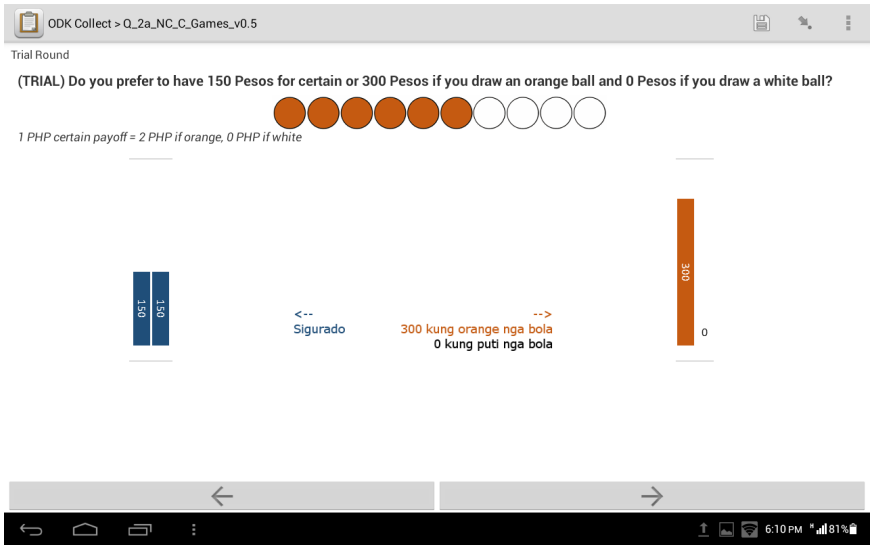
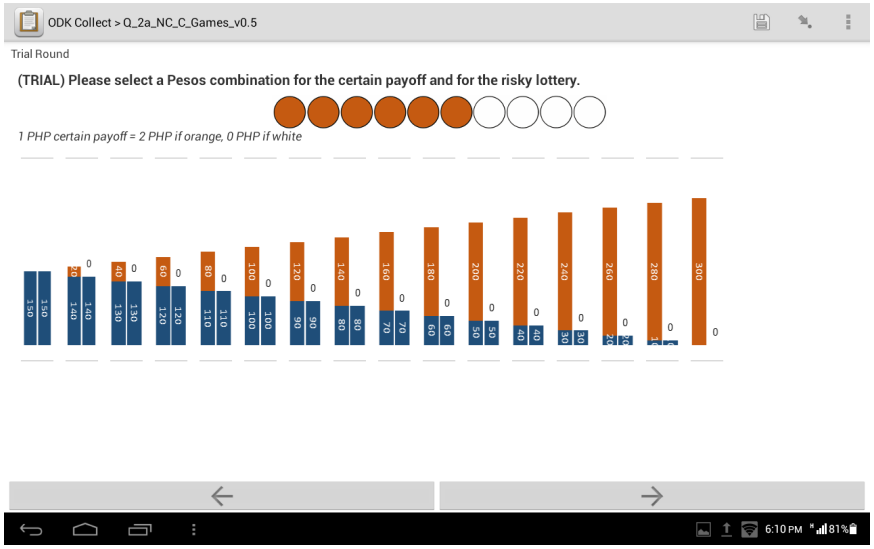


Figure 1.7: Risk preference elicitation: sample decision, step 2



Risk preference elicitation screen shots

Figure 1.8: Risk preference elicitation: sample decision, step 3

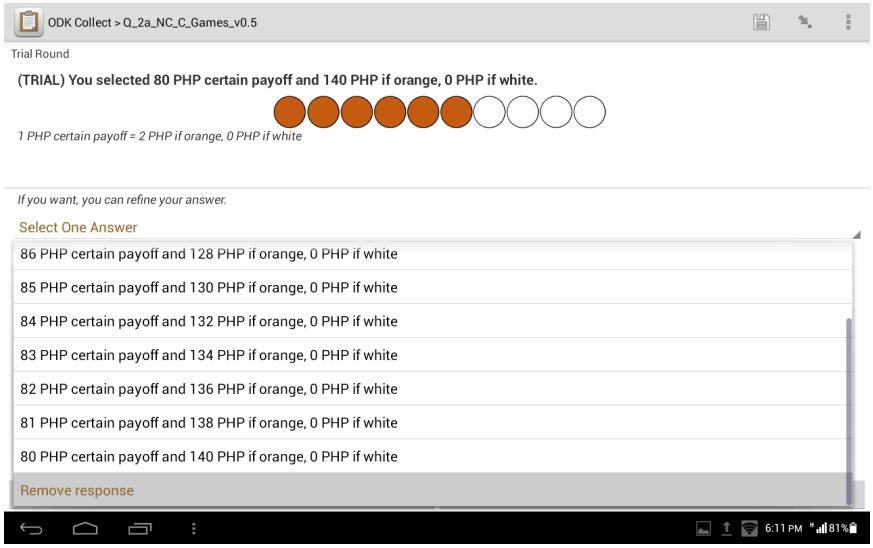
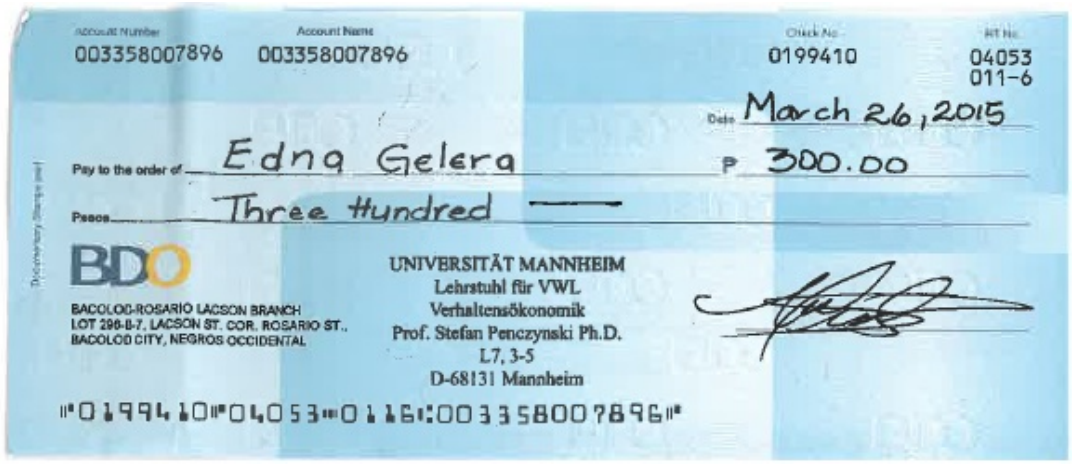


Table 1.19 Sample check.



Payment securement: check

B Effect of Promise on savings

B.1 Histogram of paid rounds

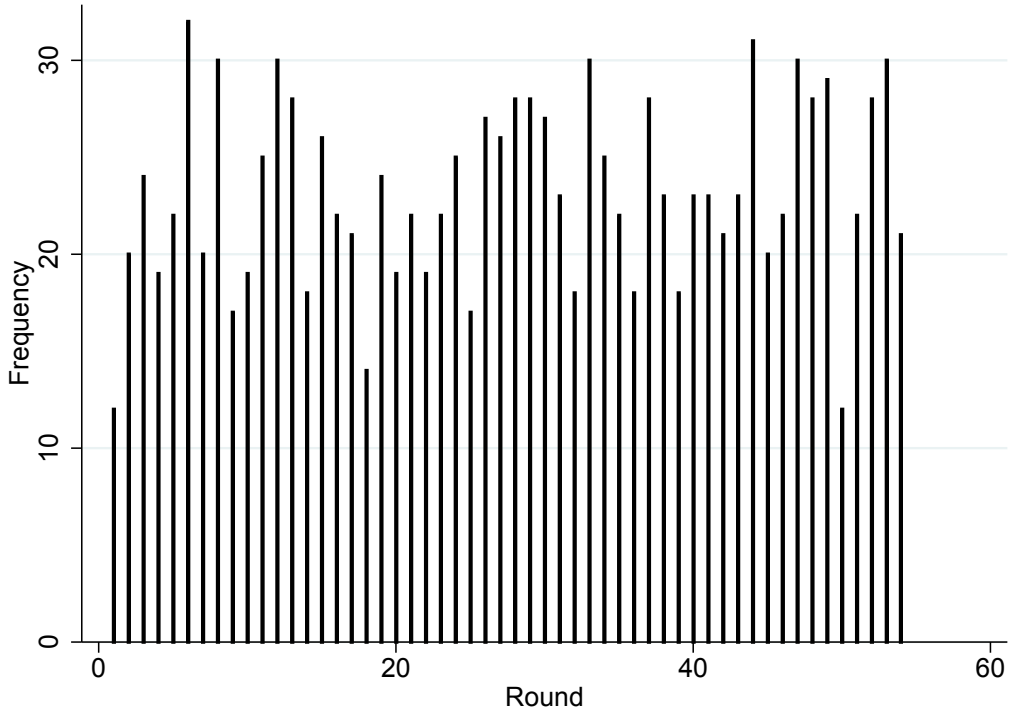


Figure 1.9: Distribution of rounds to be paid

B.2 Descriptive statistics

Table 1.20 Descriptive statistics - Savings Analysis

	No future payment		Future payment		Difference	
	mean	sd	mean	sd	b	se
Age	42.5	(11.0)	41.6	(11.3)	0.94	(0.95)
Years of education	8.7	(3.1)	9.0	(2.8)	-0.26	(0.25)
Married	0.8	(0.4)	0.8	(0.4)	0.00	(0.03)
Household size	5.6	(2.2)	5.4	(2.1)	0.15	(0.18)
Employed	0.5	(0.5)	0.5	(0.5)	0.04	(0.04)
Regular income	0.6	(0.5)	0.5	(0.5)	0.02	(0.04)
Monthly income (PHP)	1210.9	(2131.8)	1536.6	(3467.7)	-325.73	(346.58)
Background consumption	329.7	(416.3)	331.4	(306.6)	-1.70	(31.91)
Background consumption HH	1001.4	(725.0)	946.9	(643.2)	54.53	(61.17)
Official position in village	0.1	(0.2)	0.1	(0.3)	-0.02	(0.02)
Rooms in HH for sleeping	1.7	(0.7)	1.8	(0.8)	-0.04	(0.06)
Flush toilet at dwelling	0.9	(0.4)	0.9	(0.3)	-0.03	(0.03)
Electricity at dwelling	0.8	(0.4)	0.9	(0.3)	-0.06**	(0.03)
Own dwelling	0.9	(0.3)	0.9	(0.3)	-0.03	(0.03)
Am't borrowed from MFI/Banks	5457.4	(2711.5)	5597.5	(2804.5)	-140.16	(256.18)
Savings in MFI/rural bank	1201.1	(2033.5)	1464.4	(6326.9)	-263.34	(632.21)
Trust level in NWTF [1]	6.4	(1.1)	6.4	(1.0)	0.03	(0.09)
Trust in ML[1]	3.9	(2.0)	3.8	(2.1)(1-7)	0.07	(0.17)
Risk preference[2]	4.2	(2.6)	4.2	(2.5)	0.03	(0.22)
Betrayal aversion[3]	1.7	(1.6)	1.7	(1.5)	0.02	(0.13)
Avoid being taken advantage of[3]	1.9	(1.8)	1.9	(1.7)	0.02	(0.15)
Revenge if suffer serious wrong[4]	6.5	(1.4)	6.5	(1.4)	0.02	(0.12)
Reciprocity[5]	6.4	(1.4)	6.5	(1.4)	-0.07	(0.12)
Sociability[6]	4.3	(1.2)	4.1	(1.3)	0.19	(0.11)
Bank distance (minutes)	27.7	(21.3)	32.4	(31.8)	-4.71	(2.41)
Ever cashed a check	1.0	(0.2)	1.0	(0.2)	-0.02	(0.02)
NWTF information (PHP)						
Savings	261.6	(404.2)	244.1	(329.4)	17.53	(30.65)
Loan amount	5393.2	(2555.5)	5514.4	(2918.4)	-121.12	(236.79)
Loan balance	3116.2	(2767.8)	2889.2	(2381.9)	227.04	(215.20)
Repayment	247.7	(206.8)	244.3	(163.6)	3.34	(15.37)
Emergency fund balance	783.6	(872.1)	814.0	(821.5)	-30.36	(71.72)
Loan cycle	4.3	(2.2)	4.4	(2.2)	-0.06	(0.19)
Principal amortization	221.1	(166.2)	221.2	(119.2)	-0.06	(11.78)
Observations	222		369			

2 Financial Education, Social Networks and the Decision to Save: Evidence from a Field Experiment in the Philippines

2.1 Introduction

In recent years a wide variety of financial programs and interventions focused on making savings more attractive and accessible for people in developing countries. Many studies have found large impacts of access to subsidized or specialized savings products on downstream behavior (see Karlan, Ratan, and Zinman (2014) for a review). The interventions analyzed in these studies try to overcome different barriers to saving such as lack of knowledge (Drexler, Fischer, and Schoar, 2014; Cole, Gine, Tobacman, Topalova, Townsend, and Vickery, 2013), behavioral barriers (Ashraf, Karlan, and Yin, 2006; Brune, Giné, Goldberg, and Yang, 2015; Dupas and Robinson, 2013a,b; Prina, 2015), transaction costs (Dupas and Robinson, 2013b), and others.

Providing savings products has become easier with the improved access to credit thanks to the spread of microfinance institutions (MFI). It is becoming more and more common for MFIs to encourage their clients to save by providing savings accounts along with borrowing products (Karlan, Ratan, and Zinman, 2014). When a savings account – with usually no requirements on minimum balance – is a byproduct of having a loan and considerably reduces transaction costs, it is puzzling that savings levels are low.[42]

If individuals have easy access to savings products at a very low cost, could individuals have little knowledge about the savings technology? I investigate this research question by evaluating whether a financial training program that focuses on savings leads to an increase in participant's savings.

Beyond the training effect on participants, it is also likely that saving decisions affect their peers. Duflo and Saez (2003) analyze the role of information and social interactions in employees' decisions to enroll in a tax deferred account (TDA) retirement plan and find a strong effect on TDA enrollment for the treated individuals but also for the peers of the treated individuals. Thus, I also investigate the social network effects of the training on other participants and their peers.

[42]It could be argued that instead of savings, clients should rather pay their loans quicker, since their loans usually involve high interest rates. However, precautionary savings in these contexts and particular easy access to funds in case of emergencies, justify why individuals might want to borrow and save at the same time (Dupas and Robinson, 2013). Additionally, it might not be possible for clients to repay their loans earlier, making it more profitable to put any excess funds into a savings account earning interest.

In particular, I analyze whether the effect of the intervention is stronger the more treated subjects an individual is connected to. I further investigate spillover effects on peers of the treated individuals in their financial network. Together with a MFI in the Philippines, I implement a randomized evaluation that analyzes the effect of participating in a financial training program as well as the effect of the program on the participant's peers. Clients of the MFI that are part of the MFIs group lending scheme, are randomly assigned to the training program (injection points) or to a control group (control subjects).

I define two levels of peers, the first level corresponds to the lending group members of injection points and control subjects (group peers). The second level of peers includes members of the lending center to which the injection points and control subjects belong to (center peers). The two peer levels are interesting to analyze separately. While the group peers are close to participants because their financial decisions are connected via the group lending mechanism, center peers might also be connected to the participants through primary kinship bonds.

I find that the savings training increases the injection points' saving account balances with the MFI by 114 PHP, representing a 43% increase of baseline savings. Having other friends receiving the training reinforces the effect of the program: savings increase by 28 PHP when an additional friend participates in the training, this is equivalent to 24% of the main effect. There is no statistically significant differential effect between injection points that are connected to other injection points and those not connected to any other injection points.

The training effect spills over to members of the participant's networks. Group peers experience an increase of 71 PHP, representing 24% of baseline savings, while center peers' savings increase by 65 PHP, 25% of baseline savings. Group peers are less affected by the program when they are connected to an injection point, with savings increasing by 48 PHP while for group peers not connected to injection points savings increase by 185 PHP, 63% of baseline savings.

For center peers however, kinship connections matter more since primary kinship connections are not allowed within the group but within the center. I construct an alternative network measure using the information in individuals' last names and find a stronger effect of the kinship connection compared to group peers. There is no effect on group peers of kinship connections.

The design of the training is not fully equipped to distinguish across the different mechanisms through which the program affects savings. It is possible however that behavioral factors might play a role. I analyze the effects of the program for participants that report knowing what a saving plan is and compare it to the effect for those that report not knowing. If the effect of the program is exclusively due to learning how to use the savings technology, I should find a stronger effect on participants that report not knowing. This is however not the case, I find a stronger effect in participants that know what a savings plan is, suggesting that behavioral factors might be

one of the mechanisms through which the program is affecting savings. I also find that participants with higher literacy experience a stronger effect of the program.

Finally, I am interested in investigating whether the observed effects are robust through time. I find that the effects are short lived, with the main effects of the program present for the three to four months after the intervention and then fading out. This is not surprising. Changes in financial behavior have been shown to be difficult to achieve and a more persistent program might be required in order to generate long lasting effects.

The paper proceeds as follows. The next section provides the background and reviews the available literature. Section 2.3 presents the experimental design. Section 2.4 discusses the data and the empirical strategy. Section 2.5 presents the results before section 2.6 concludes.

2.2 Background and Literature Review

2.2.1 Barriers to Savings

Savings allow households to smooth consumption and finance investments in human and business capital. However, in developing countries, there are considerable barriers to savings. On the supply side individuals might face transaction costs, regulation barriers as well as low levels of trust in the financial organizations which might limit the access to saving products. On the demand side, individuals might be confronted with low levels of financial knowledge, behavioral biases as well as social restrictions.

Regardless of these obstacles, there is evidence that individuals in developing countries have a demand for savings products. Diaz, Ledesma, Ravi, Singh, and Tyler (2011) report that people in the Philippines save for emergencies (42%), children's education (34%), food and daily needs (6.6%), retirement, and the future (5.9%) among others. The study also reports that low income individuals keep their savings mainly at home (63.5%), followed by rural banks (9.7%), cooperatives (9.4%), and self-help groups (6.7%). The authors cite convenience and accessability as important criteria for storage location of savings, after all two thirds save for emergencies that might require liquidity. Moreover, intimidation and unfamiliarity are cited as reasons for the lack of formal savings. They also find a strong gap in saving levels across urban and rural populations, with a high share of rural individuals saving at home due to lower trust and unfamiliarity with formal savings products.

Many microfinance institutions are now providing to their clients financial services on top of their main microcredit products. For example, our partner MFI, provides savings accounts for all clients with microcredit loans free of charge. In spite of having a savings account, a considerable share of the client sample report saving at home, a technology that earns them no interest. This is puzzling, and leads to the question: why are microfinance clients not using their savings account to which they have access free of charge and instead decide to keep their savings at home?

Several reasons might explain this puzzle. Clients i) have low levels of financial literacy and education, or they ii) do not know how savings work or how they can get themselves to save. Thus, financial education programs could affect financial outcomes through different mechanisms: by i) providing information on how to make financial decisions and how financial products work, ii) mediating behavioral biases such as structuring financial goals, making financial plans more salient, providing reminders of financial goals, among others. In the next subsection I discuss financial education programs in more detail.

Although saving is important, it is not clear whether individuals should save while having loans. A more reasonable approach might be to pay existing debt which often comes with high interest rates. However, there are reasons why poor individuals might want to save and borrow at the same time. In the very short term, it might not be possible to repay a loan without incurring additional fees or it might not be possible to repay early at all.[43] More importantly, precautionary savings motives might lead individuals to save and borrow at the save time.

Telyukova and Wright (2008) examine the credit card puzzle in the US consisting of individuals owning significant credit card debt and at the same time, sizable amounts of low-return liquid assets. They show precautionary savings – households needing easily accessible money for possible contingencies – to be the reason for the puzzle. This is a plausible reason in the Philippines, where evidence shows that households save mainly for emergencies. In case of urgent need of liquidity the outside option for low income individuals in the Philippines are "5/6 money lenders", that charge 20% interest rate per month, a 240% annual interest rate. Thus one possible reason why women in our sample save and borrow at the same time is to avoid the possibility of relying on 5/6 money lenders in case of an emergency.

Financial Education This chapter relates to a vast literature that looks at the effects of financial literacy on financial outcomes. Lack of financial knowledge might lead to suboptimal financial choices. In developed countries, households with low levels of financial education have been shown: to i) be less likely to plan for retirement (Lusardi and Mitchell, 2011), ii) borrow at higher interest rates (Lusardi and Tufano, 2015), iii) purchase fewer assets (Lusardi and Mitchell, 2007), and i) have lower participation in the stock market (Van Rooij, Lusardi, and Alessie, 2011).

In developing countries, although it has been established that financial knowledge is low (Cole, Sampson, and Zia, 2011; Xu and Zia, 2012), a large body of evidence illustrates that financial education programs have not been successful in unequivocally leading to lasting knowledge or to a lasting change in people's financial behavior (Fernandes, Jr., and Netemeyer, 2014).

Cole, Sampson, and Zia (2011) implement a two-hour financial education program to teach households about bank accounts. They find modest effects in that only

[43] Loans taken with the partner MFI cannot be repaid until the last 2 weeks before maturity.

individuals with low levels of financial education increase demand for bank accounts.

Carpena, Cole, Shapiro, and Zia (2017) implement a randomized experiment in India to measure the impact of a financial literacy intervention on numeracy skills, financial awareness, and financial attitudes and perceptions with the aim of capturing the effects of the program on financial knowledge and subsequently on financial behavior. Their training program was a video-based training and they complemented the financial education with a pay-for-performance knowledge test, personalized financial counseling and financial goal setting. They find that financial education alone does not lead to improved financial outcome. They find no impact of the pay for performance test but they do find an effect of counseling and goal setting on financial outcomes, such as on opening bank accounts.

Field, Jayachandran, and Pande (2010) together with a local partner institution implement a 2-day training program for Indian women that covered basic financial literacy, business skills, and aspirations. The program did not lead to an increase in savings, although it increased borrowing and business income for women in the more restrictive social stratum.

Seshan and Yang (2014) measure the influence of a saving-focused 3-hour financial literacy training on financial decisions of Indian migrant workers. The workshop aimed at improving financial habits and encouraging joint decision-making with spouses back home. They find that wives of treated migrants became more likely to seek financial education and the couples became more likely to make joint financial decisions. Similar to previous studies they find a stronger effect for workers with lower initial levels of savings.

From this glimpse look into the current literature it is evident that the different programs implemented are very diverse, tackle different aspects of the financial education curriculum, and have a different focus on the outcomes intended to affect. Several lessons have been drawn from the available literature on how to design financial education programs in order to improve their impact on financial behavior.

Karlan, Ratan, and Zinman (2014) suggest that programs should allow to disentangle the effect of the program from low take-up of treatments, target the content to match the recipients, make it timely so that the financial education received coincides with financial decisions to be made, and be simple so that individuals can easily implement the acquired content.

This study contributes to the literature by implementing the suggested improvements and testing the effectiveness of such a program in the short and medium term.

Albeit the progress of the literature on identifying ways of improving the reach of financial education programs, the knowledge gained is not long lasting (Fernandes, Jr., and Netemeyer, 2014). Financial behavior is a conduct learned over a long period of time that like many other habits is difficult to change. In developing countries individuals face stronger constraints that might hinder their capacity to work on changing behaviors (Schilbach, Schofield, and Mullainathan, 2016). Moreover, designing pro-

grams that manage to modify conduct and lead people in poverty to achieve healthier financial decision making may have a strong positive impact on their livelihoods. I revisit this topic in the conclusion after discussing the results of the study.

2.2.2 Social Networks

This work is further related to a strand of the literature that analyzes the role of networks in the diffusion of information and social learning. Banerjee, Chandrasekhar, Duflo, and Jackson (2013) evaluate how information of a new microfinance program diffuses through social networks in India. They find that participation in the new microfinance program is higher when the initially informed individuals are more central in the network.

Bursztyn, Ederer, Ferman, and Yuchtman (2014) investigate whether social learning or social utility are the channels through which peers' financial decision making is affected. They find that both channels have an effect on asset investments and that social learning effects are stronger when the learning peer is financially unsophisticated.

Cai, De Janvry, and Sadoulet (2015) study how social networks affect the adoption of weather insurance in rural China. Together with a local insurance provider they introduce a new weather insurance for rice farmers and they randomize the intensity of the product information in order to create variation in the understanding of the product. The phased timing in the provision of the information allows them to identify the social network effects on insurance take-up. They find a strong effect of having an additional friend receiving the first set of product information on insurance take-up. Looking at the mechanisms, they find that the effect does not operate through passing of information about peers' purchases but rather through transfer of information regarding the functioning and benefits of the product.

My work relates to this literature and contributes by extending the social network analysis to the area of financial education and its effects on financial outcomes.

2.3 Experimental Design

2.3.1 The Institution: Negros Women For Tomorrow Foundation (NWTF)

The Negros Women for Tomorrow Foundation is a MFI that operates in the Visayas Region of the Philippines, with 101 branches serving more than 180,000 clients. NWTF provides credit and savings services to poor women from rural communities to start or expand own small businesses. In its Project Dungganon program, it follows the Grameen Bank credit methodology of group lending (Besley and Coate, 1995).[44]

The main credit service is a general loan between PHP 1,000 and 5,000 payable in a 25-weeks loan cycle.[45] Clients make weekly, equally-sized installment payments.

[44] Other financial services, such as micro-insurance, are also offered.

[45] The exchange rate at the time was 1 EUR = PHP 50 and 1 USD = PHP 44.

Conditional on good behavior, clients get subsequent loans possibly with an increased loan amount as well as a longer repayment period. Once the fourth loan cycle is reached, loans can be increased up to PHP 30,000. Clients can take a break of at most two months between loan cycles.[46] The purpose of the loan is capital build-up or initial capital for businesses.

Clients are offered the *Alkansya* Fund (AF), a voluntary savings account from which clients can withdraw or deposit cash at anytime. In addition, an individual compulsory fund (ICF) is obligatory and clients can only withdraw from it in case of emergencies. Clients make weekly deposits to the ICF and 5% of the loan amount is deducted from the loan and deposited in the ICF.[47] Both funds earn interest at the rate of 4% per annum, computed quarterly.

Individuals are encouraged to deposit excess earnings as well as excess amounts from the ICF into the AF savings account. All deposits and withdrawals are recorded in the individual's passbook, which is a paper booklet used to record transactions. Loan officers and branch staff are required to maintain confidentiality on the AF savings of a member.

Clients form groups of 5 people, and 7-8 groups form a center. According to NWTF regulations, group members must be friends, and their houses should be close to each other (within 150 meters). Group members cannot be relatives (sisters, mother/daughters or in-laws) and their age, educational attainment and economic status should be similar. They should also have knowledge of the business proposed for financing. Despite these requirements, it is possible for two group members not to be linked. Loans are covered by a social contract that obliges the rest of the group members to pay in case that a group member defaults. Loan size and disbursement can differ across group members.

All center members meet weekly to make their loan installment payments. Center meetings are held at a fixed place, time and day of the week in consultation with the center members. The meetings are presided by a NWTF loan officer, who collects installment payments, deposits, and registers attendance of the center members. During the meeting, a report of the status of members' businesses is provided.

Loan usage monitoring is done jointly by the loan officer and group members. Soon after the release of a loan, the loan officer together with a group member verify the proper use of the funds. Random checks are also performed by the loan officer and the branch manager.

As described, in the case that a group member cannot repay its weekly loan installment, the group becomes responsible. If the group cannot cover the total amount, the

[46] In case that clients take a longer break, they are able to take a subsequent loan, but they are treated as new clients. That implies that they start again from loan cycle one and have to start with a small loan.

[47] Weekly contributions are PHP x per week per loan cycle number x. For example, clients in their first loan cycle contribute PHP 1 weekly, clients in their second loan cycle contribute PHP 2 weekly, and so on.

defaulting member could ask to draw on a center fund, called the Paga-sa Fund, which every member contributes to. Even in the case of such a default, the savings held in the defaulting member's AF savings account can only be accessed with the member's permission. NWTF would only resort to these funds in case the loan has not been paid at the loan maturity date. In the same line, savings of group members in their AF savings account cannot be used for repayment of other members' installments in case of default, without that member's permission. Only the member can dispose of the funds in the AF savings accounts.

2.3.2 The Intervention

The intervention consisted of a financial education program focused on savings. The training taught participants how saving plans and budgets work, in a one time training that lasted 45 minutes. The training first motivated the topic by explaining why it is important to save. Participants were then introduced to the concept of a savings plan and the steps necessary in order to make the plan. Subsequently, participants were taught what a budget is and the steps to follow in order to create a budget. Both parts of the seminar were supported by visual material in the form of posters, in which participants could see step by step how a savings plan and a budget work as well as how the two are related. A detailed description of the training content is provided in table 2.1.

Additionally, each participant was provided with a toolkit containing all the information discussed during the training. The toolkit included a brochure with the explanations of how to make a savings plan and a budget, and the example savings and budget forms discussed in detail during the training. As a part of the toolkit, blank savings and budget forms were provided so that participants could start their own. Participants also received five additional copies of the toolkit to share with their lending group members, family, and friends.

The aim was to provide the training in a simple way and to focus on topics and behaviors related exclusively to savings. Karlan, Ratan, and Zinman (2014) suggest that less is more when it comes to financial training programs, particularly for adults. This is important as well since our sample of participants are women, and a long duration of the program may have interfered with their work or family responsibilities, making them prone to impatience and leading to a reduction of their attention towards the training. Seshan and Yang (2014) present an example of a successful short-timed savings-focused financial literacy training that focuses on particular topics.

Finally, it was also important that participants could identify with the topics covered in the training and that the message was delivered in a simple manner. Therefore, we focused on providing the information in a very simple way that participants could easily understand and implement on their own. Examples exist of successful training programs that focus on providing the training in a simplified style. Drexler, Fischer,

and Schoar (2014) find an effect on financial outcomes when a financial education program is provided in a simple way as compared to a more standard accounting training.

The financial education program was developed together with our Philippine research team in order to provide a program adapted to local conditions. The training follows international standards and is comparable to programs previously implemented elsewhere, such as the two first modules of the training program implemented by Drexler, Fischer, and Schoar (2014).

Table 2.1 Summary of training program

	Training Content
Module 1	**Savings**
	Importance of savings
	Identify saving goals
	Determine the costs
	Set target date
	Financial instruments for saving
Module 2	**Budget**
	Definition/importance of budget
	Set goals: incorporate saving goals
	Know your income
	Make your expenditure plan
	Track your expending
	Personalize your budget
Module 3	**Connecting Savings and budget**
	Tips for improving savings and budgeting
	Compare actual and planned expenditures
	Stay on target: Update savings and budget plan periodically

2.4 Data and Empirical Strategy

2.4.1 Randomization

The field experiment was conducted in the Philippine provinces of Guimaras, Capiz and Iloilo during the month of April 2015 (see figures 2.1 and 2.2).

Subjects participating in the study are clients of NWTF and were randomly selected from the pool of clients in the three provinces, belonging to three branches of NWTF. The randomization procedure had two steps. In the first step, suitable centers were divided into bins according to minimum distance between centers, and the bins where randomly allocated to the training treatment and to a control group. In a second step individuals were randomly selected from the treatment and control pools. All clients selected to be treated as well as clients selected as control, took part in a series of experimental games before the savings training. See Penczynski and Santana (2016) (chapter 1) for more details about the experimental games.

Figure 2.1: Location of experimental sessions

The clients across the three NWTF branches were distributed across 175 centers, located in 155 different villages (called barangays). It was not logistically possible to hold sessions in each barangay, therefore several centers were grouped together in a bin, based on their geographical location. In order to select the barangays (centers) that would form a bin, the minimum geographical distance across barangays was computed, and bins with the minimum distance and with approximately 90 clients were selected.

Bins had on average three barangays, and the sessions were held in one of the barangays of the bin. The selection of the barangay where the session was to be held depended on the facilities, the proximity to the municipality and the accessibility.[48]

In order to have the information required for the randomization, recruiters surveyed the barangays to collect data about the facilities and resources available. The survey, implemented with tablets, enabled the collection of geographical reference data of the barangays and municipalities as well as pictures of the facilities (see appendix A.2). Recruiters also gathered information about the barangay head and the possibility to acquire permission to hold the sessions in the barangay.

The first step of the randomization process assigned the 60 client bins to one of four treatment arms, a two-by-two design with two institutions and a treatment

[48]Four of the bins were composed of only one barangay. In these cases, the entire village was mapped to get the complete network of those four villages.

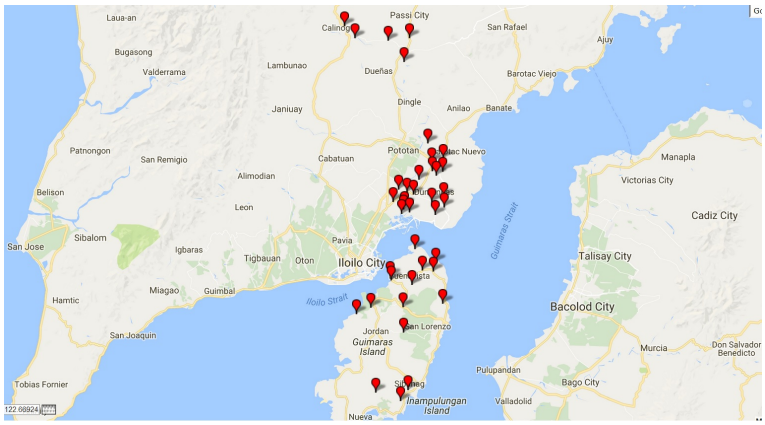


Figure 2.2: Location of experimental sessions in detail

and a control for the savings intervention. The institutions arm was related to the experimental games and implied receiving a later payment from either NWTF or Local Money Lenders (ML) (see Penczynski and Santana (2016) for more details). Given that receiving a promised later payment from the microfinance institution, NWTF, could have a positive effect on the trust level of the client towards NWTF and thus have an effect on savings, I constrain the main analysis to those allocated to the ML treatment.

In order to improve precision of our estimates, a rerandomization procedure based on a set of covariates was implemented, following Morgan and Rubin (2012). The procedure uses available data to check for covariate balance across treatment and control groups. If a lack of balance is present, then rerandomization could help to ensure balance. Figure 2.3, taken from Morgan and Rubin (2012), shows the steps of the procedure.

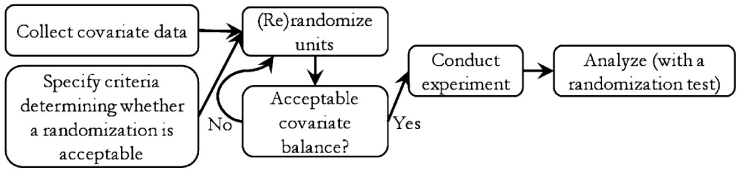


Figure 2.3: Rerandomization procedure
Source: Morgan and Rubin (2012)

To establish the rerandomization criteria, the Mahalanobis distance M was utilized:

$$M = (\bar{X}_T - \bar{X}_C)\left[cov(\bar{X}_T - \bar{X}_C)\right]^{-1}(\bar{X}_T - \bar{X}_C), \tag{2.1}$$

where $\bar{X}_T - \bar{X}_C$ is the k-dimensional vector of the difference in covariate means between the treatment and control groups and $cov(x)$ is the sample covariate matrix of x. A randomization is acceptable whenever M is below a certain threshold.

NWTF administrative data such as loan size, AF savings balance, ICF balance as

well as an urban area indicator, the population of the bin, and the average distance from the bin to the municipality were taken as covariates. In the rerandomization procedure the distance across the covariates of the four different treatments arms was compared, allowing for comparison of any two treatment arms against each other.

In order to recruit the participants permission from the municipality mayor was requested and subsequently from the village head, locally known as barangay captain. Barangay captains would additionally authorize the use of the village facilities, usually the barangay hall, where the savings seminar was held. Subjects were invited to participate in the experiment via an invitation letter delivered to their houses.

I define as "injection points" individuals that received the savings training and participated in the experimental games. I denote the treatment status of the injection points with $T_i = 1$. Individuals that also participated in the experimental games but did not receive the savings training are the injection points' control group, and I identify them as control subjects. I denote the treatment status of control subjects as $T_i = 0$.

I am also interested in the effects of the training on the peers of the injection points. I define two groups: group peers denoted by $g(i)$ and center peers denoted by $c(i)$. I denote the dummy variable $T_{g(i)}$ as the group treatment indicator. $T_{g(i)} = 1$ if and only if there is a group member that did not take part in the training but that had an injection point in his lending group. I refer to them as "treated group peers". Consequently, $T_{g(i)}$ takes a value of 0 for group members of clients that participated in the experiment, but did not receive the training, which are the group members of those that form the control group of the injection points. I refer to them as "control group peers".

Finally, $T_{c(i)}$ indicates the treatment indicator at the center level, and takes a value of 1 for members that are in centers with at least one injection point, excluding the lending group to which the injection point belongs. I refer to them as "treated center peers". $T_{c(i)}$ takes a value of 0 for members whose center has at least one member that attended the experimental games but did not participate in the training, excluding the group member of the control subjects. I refer to them as "control center peers".

I have 205 injection points and 197 control subjects, a total of 402 individuals.[49] They are distributed across 85 centers, out of which 42 have at least one injection point ($T_{c(i)} = 1$), and 43 have at least one control subject ($T_{c(i)} = 0$).

I have 352 individuals as peers in treated groups and 360 individuals as peers in control groups, a total of 712 peers at the group level. At the center level, I have 381 individuals as peers in treated centers and 394 individuals as peers in control centers,

[49] Initially, we had 256 injection points and 243 control subjects, a total of 499 individuals. I lose 97 individuals due to the fact that their loans end and that I only observe active clients. I focus the analysis on clients that were active at the time of the savings training. Since I have data only on active clients, it is possible that a client that was on a loan cycle break at the time of the training and therefore not marked in April as an active client, appears in subsequent periods in my sample, once she takes up the next loan. For now, I abstract from these clients.

a total of 775 center peers.[50]

2.4.2 Data and Descriptive Statistics

I use three data sources, administrative data from NWTF on all active clients, survey data collected before and after the intervention took place, and data from the experimental games, the latter two only on the injection points and their control subjects. The administrative data from NWTF is monthly data for the three branches with information regarding AF savings balance, loan size, loan balance, principal amortization, repayment start date, maturity date, loan cycle, and number of weeks in which payments were missing. Repayment data is available only at baseline. In the baseline survey, information was collected on household characteristics, financial practices, social preferences, risk attitudes, trust and – importantly – social networks. The experimental games data provide estimates of behavioral measures of trust as well as risk attitude parameter estimates (see Penczynski and Santana (2016) for more detail on the estimation of these parameters).

Summary statistics are reported in table 2.2. Panel A presents household and financial characteristics for the injection points and control subjects, and panels B and C NWTF financial data for group and center peers. All individuals in the sample are women. As shown in panel A, they are on average 43 years old, have a household size of 5 people and hold a loan size of PHP 5,456. Their average AF savings in NWTF is PHP 267 and their average ICF balance is PHP 812. 55% report to have some sort of savings, and the average reported amount of savings is PHP 1,351. Their reported savings is higher than the AF savings in NWTF, it may be that it includes their ICF balance since 80% of those that mentioned having savings with an MFI or bank, said that it was with NWTF. 22% of them have savings at home, averaging PHP 1,044.

Their businesses are mainly general stores (sari-sari stores), trading, and food services. Their average start-up capital is PHP 3,990. The main reason for taking up a loan is the sourcing of working capital for their business. They also take it for food and daily needs, education, emergencies, and to buy assets (e.g., livestock, tricycle). 64% of the individuals know what a savings plan is, out of which 67% report having ever made a savings plan. Out of those women that have made a savings plan, 85% report that they are able to follow it. Therefore, 64% of all women either do not know how to make a savings plan, have never made one or have not followed their savings plan. It is also striking that 64% of women know what a savings plan is but only 55% of them report having any type of savings. Savings at home are slightly higher for women that report knowing how a savings plan works (on average PHP 700), compared to those that report not knowing (PHP 500), however the difference is not statistically different from 0.

I also collected data on risk attitudes. Subjects self report to be slightly risk loving,

[50] Initially, I had 774 peers at the group level and 833 peers at the center level.

with a reported risk avoidance of 4.3 on a Likert scale of 1 to 7. However, when using risk aversion estimates from the experimental games, I find that 73% of the subjects are risk averse.[51] Subjects also report high levels of trust towards NWTF, with 6.2 out of a 1 to 7 Likert scale.

The social network questions in the survey asked participants about their social links in twelve different dimensions: relatives in the village, non-relatives with whom they socialize, from whom they would borrow money, from whom they would lend money, to whom they would ask for help in case of emergency, from whom they hear the news in the village from, whom do they think is a well connected person, whom visits them on a regular basis, whom do they visit on a regular basis, with whom do they go to church with, from whom they borrow or lend goods (i.e., sugar, eggs or rice), and to whom do they lend goods. Questions were asked openly, so that participants could mention all people in each category. Additionally, participants were asked to name their lending group members, and answer the same questions (except whom they would ask for help in emergency) as reported above.

The data collected is very rich, however, it was only collected for the participants of the experiment. From this data, I compute several network measures: i) the degree, $Degree_i$, which is the number of connections in the network of a participant, ii) an indicator measure P_i, which takes a value of 1 if another participant j in i's center mentioned participant i, and 0 otherwise; iii) an intensity measure Z, which takes a value of 0, 1 or 2 if participant i was mentioned 0, 1 or 2 or more times by other participants in her center and iv) the number of participants connected to divided by the total number of friends, $NetShare_i$.

Additionally, I compute an alternative definition of the network. I define a person being connected to another person within the center if one of their two last names is the same. Last names in the Philippines carry information about kinship. Names in the Philippines are composed of a first name, a middle name and a last name. The last name corresponds to the paternal last name and the middle name constitutes the maternal last name.[52] A member of a center is connected to another center member if at least one of their two names is the same, otherwise they are not connected. Using this information, I construct the measure family center degree, $DegreeFam_i$, which corresponds to the number of links a member has within her center, according to this alternative definition. The measure is of particular interest because it allows me to estimate the center connections on the dimension of kinship, which I believe might be of particular importance for center peers.

As presented in table 2.2 panel A4, injection points and control subjects have

[51] The risk avoidance question asked subjects "Are you, generally speaking, a person who is fully prepared to take risks, or do you try to avoid taking risks?" 1-avoid, 7-fully prepared. The risk aversion parameters were estimated from a risk task elicited in the experimental games by having subjects choose between risky and safe lotteries. For more details see Penczynski and Santana (2016).

[52] When a woman marries, the norm is that her maiden surname becomes her middle name, and her husband's surname becomes her new surname or last name.

on average 9 friends in their network, 70% of them are connected to on average 2 other injection points or control subjects and on average they have 4.5 friends in the center. According to the alternative degree measure, $DegreeFam_i$, they have 2.6 family connections within the center.

Table 2.3 reports summary statistics for injection points and control subjects from the administrative and the survey baseline data, for clients that are active in the month after the training was implemented, May 2015. Given the random assignment of treatment, I expect injection points to be similar to the control subjects. As can be seen in the table, these expectations hold across a wide range of characteristics. Only two characteristics are statistically different from each other, whether the household has electricity and whether they have a flush toilet. I control for these in the regressions. The treatment assignment variable, T_i, is not explained by the covariates presented in table 2.3. The F-test for this regression is 0.98 with a p-value of 0.50. The same holds for the originally intended sample before attrition.[53]

I expect that group peers of the injection points are similar to group peers of the control subjects. Table 2.4 presents the balance of covariates for group peers. Given that the baseline questionnaire was only implemented for the injection points and the control subjects, covariates information is only available from the administrative data. As shown in the table, group peers from the control subjects are on average similar to the group peers of the injection points, except in their AF savings account balance. They hold a loan of PHP 5,679, installment payment of PHP 253, and are on the third loan cycle, on average. Their average AF savings account balance is PHP 293 and their ICF balance is PHP 866. Compared to the injection points and control subjects, the group peers have slightly higher AF savings account balance, ICF balance and loan size.[54]

The AF savings account balance is higher for the group peers of the injection points compared to the group peers of the control subjects. The difference is significant at the 5% significance level. I control for this covariate in the analysis. The covariates presented in table 2.4 do not jointly determine the treatment assignment indicator at the peer group level, $T_{g(i)}$. The F-test is 0.97 and the p-value is 0.43.

Lastly, I also expect that center peers of the injection points are similar to center peers of the control subjects. Table 2.5 presents the balance of covariates for center peers. As with group peers, I only have administrative data available. Center peers

[53]Table 2.10 presents the balance of covariates for the baseline, for all clients originally included in the study. The results are practically the same as the ones reported in table 2.3, with the exception that injection points are slightly more likely to know what a savings plan is, and the difference is significant at the 10% level. I control for this covariate in the analysis. As in table 2.3 the treatment assignment variable T_i is not explained by the covariates, the F-test is 1.04 and the p-value is 0.41.

[54]Table 2.11 presents the balance of covariates for the group peers at baseline of all injection points and control subjects included in the study. Covariates are balanced across the group peers, including the AF savings balance. Although the AF savings balance is higher for the group peers of the injection points, the difference is not statistically significant from 0. I also look into balance of covariates for all subsequent months in the analysis, and all the shown covariates are not statistically different across group peers.

have an AF savings account balance of PHP 264, loan size of PHP 5,454, and ICF balance of PHP 882, similar to group peers. They repay weekly on average PHP 243 with a principal amortization of PHP 220. Variables are balanced, except for the installment amount which is larger for center peers of the injection points. The difference is significant at the 5% significance level. I control for this covariate in the analysis. Similar to group peers, I analyze the balance of covariates for all subsequent months and results are similar to the ones just described.

Table 2.2 Summary statistics

	mean	sd
Panel A. Injection Points and Control Subjects		
A1. Household Characteristics		
Age	43.4	(12.1)
Household size	5.2	(1.9)
Has regular income	0.6	(0.5)
Daily consumption	332.8	(319.8)
HH daily consumption	994.7	(704.0)
Years of education	12.5	(4.8)
Trust level in NWTF[1]	6.2	(1.3)
Risk aversion[2]	.73	(0.44)
Avoid taking risks[3]	4.3	(2.6)
Sociability[4]	4.3	(1.2)
A2. Reported Financial Characteristics		
Borrowed from MFI/Banks	5969.3	(3571.2)
Savings in MFI/Banks	1351.8	(3615.3)
Know what a savings plan is	0.6	(0.5)
Made a savings plan	0.7	(0.5)
Followed a savings plan	0.9	(0.4)
A3. NWTF Financial Characteristics		
AF balance	267.6	(324.8)
Loan size	5456.2	(2481.7)
Loan balance	2899.2	(2241.3)
Installment amount	237.6	(138.1)
ICF balance	812.5	(923.4)
A4. Network Characteristics		
Number of friends	9.1	(3.8)
Connected to other IP or control subjects	0.7	(0.5)
Number of IP or subjects connected to	2.1	(1.2)
Number of friends in center	4.5	(2.0)
Family center degree	2.6	(4.0)
Panel B. Group Peers		
AF balance	293.5	(589.8)
Loan amount	5678.6	(3021.9)
Connected to an IP or control subjects	0.8	(0.4)
Number of IP or subjects connected to	1.6	(0.9)
Family center degree	2.2	(3.0)
Panel C. Center Peers		
AF balance	263.6	(356.0)
Loan amount	5453.5	(2804.9)
Number of IP or subjects connected to	1.3	(0.6)
Connected to an IP or control subjects	0.2	(0.4)
Family center degree	2.0	(3.1)

[1] 1–no trust, 7–complete trust, [2] 0-risk loving, 1-risk averse, [3] Avoid/prepared to take risks: 1–avoid, 7–fully prepared, [4] Meet friends, relatives, neighbor: 1–never, 2–seldom, 3–monthly, 4–weekly, 5–daily.

Table 2.3 Summary statistics of control subjects and injection points

	Control		Injection points		Difference		N
	mean	sd	mean	sd	b	p	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Client Characteristics							
Age	44.1	(11.9)	42.6	(12.3)	1.55	(0.20)	401
HH water source	0.1	(0.3)	0.1	(0.3)	0.02	(0.44)	402
HH roof material	4.6	(1.3)	4.5	(1.3)	0.04	(0.73)	401
Electricity in HH	0.9	(0.2)	0.8	(0.4)	0.09	(0.00)***	401
Rooms used for sleeping	1.8	(0.8)	1.8	(0.8)	-0.04	(0.58)	401
HH ownership	0.9	(0.3)	0.9	(0.3)	0.02	(0.63)	400
Household size	5.2	(2.0)	5.2	(1.9)	-0.07	(0.72)	401
HH floor material	2.9	(6.9)	3.8	(11.7)	-0.93	(0.34)	401
Flush toilet in HH	1.0	(0.2)	0.8	(0.4)	0.11	(0.00)***	402
Has regular income	0.6	(0.5)	0.6	(0.5)	-0.03	(0.49)	401
Daily consumption	314.2	(283.7)	350.6	(350.6)	-36.33	(0.26)	401
HH daily consumption	983.1	(715.8)	1005.9	(694.0)	-22.76	(0.75)	402
Employment	4.1	(2.0)	4.0	(2.0)	0.11	(0.57)	396
Official position in village	0.1	(0.3)	0.1	(0.3)	0.01	(0.75)	401
Years of education	12.8	(4.8)	12.2	(4.7)	0.58	(0.23)	394
Panel B. Social Preferences							
Trust in NWTF[1]	6.2	(1.2)	6.2	(1.3)	-0.02	(0.90)	402
Trust in local money lender[1]	3.8	(1.9)	3.7	(2.1)	0.07	(0.74)	402
Avoids taking risks[2]	4.4	(2.5)	4.1	(2.6)	0.31	(0.22)	402
Avoids being betrayed[3]	1.7	(1.5)	1.7	(1.5)	0.02	(0.91)	402
Avoids being taken advantage of[3]	1.8	(1.6)	1.7	(1.5)	0.12	(0.44)	402
Revenges if suffers serious wrong[4]	6.4	(1.3)	6.6	(1.1)	-0.14	(0.23)	402
Offends back if offended[5]	6.4	(1.3)	6.5	(1.3)	-0.04	(0.75)	402
Sociability[6]	4.3	(1.2)	4.3	(1.2)	0.04	(0.73)	402
Panel C. Reported Financial Characteristics							
Borrowed from MFI/Banks	6256.1	(3821.9)	5690.3	(3295.5)	565.84	(0.13)	365
Savings in MFI/Banks	1290.7	(1593.2)	1415.7	(4921.4)	-124.97	(0.80)	217
Bank distance	35.0	(52.9)	40.1	(37.5)	-5.09	(0.27)	402
Ever cashed a check	0.9	(0.2)	0.9	(0.3)	0.01	(0.78)	402
Know what savings plan is	0.6	(0.5)	0.7	(0.5)	-0.07	(0.12)	402
Made a savings plan	0.7	(0.5)	0.7	(0.5)	0.03	(0.56)	260
Followed savings plan	0.8	(0.4)	0.9	(0.3)	-0.08	(0.12)	175
Panel D. NWTF Financial Characteristics							
AF Savings balance	251.4	(347.5)	283.2	(301.3)	-31.74	(0.33)	402
Loan size	5445.7	(2616.6)	5466.3	(2351.2)	-20.66	(0.93)	402
Loan balance	2967.6	(2570.2)	2833.5	(1875.8)	134.15	(0.55)	402
Installment amount	241.8	(145.0)	233.6	(131.4)	8.17	(0.55)	402
Tenure	482.9	(436.3)	469.7	(442.3)	13.19	(0.78)	344
ICF balance	783.1	(922.9)	840.7	(925.2)	-57.58	(0.53)	402
Observations	197		205				402

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

[1] 1-no trust, 7-complete trust,

[2] 1-avoid, 7-fully prepared,

[3] 1-completely avoid, 7-do not avoid,

[4] 1-revenge, 7-no revenge,

[5] 1-offend, 7-not offend,

[6] Meets friends, family, neighbors: 1-never, 2-seldom, 3-monthly, 4-weekly, 5-daily.

Table 2.4 Descriptive Statistics, group peers

	Control		Savings training		Difference		N
	mean	sd	mean	sd	b	p	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AF savings balance	249.1	(421.0)	336.9	(715.1)	-87.83	(0.05)**	711
Loan amount	5675.2	(3322.2)	5681.9	(2701.9)	-6.73	(0.98)	711
Installment amount	254.4	(208.4)	252.3	(149.4)	2.13	(0.88)	712
ICF balance	862.2	(1108.5)	869.4	(949.0)	-7.20	(0.93)	711
Loan cycle	3.1	(2.1)	3.1	(2.1)	-0.03	(0.84)	711
Principal amortization	230.8	(166.1)	229.3	(111.3)	1.51	(0.89)	711
Observations	352		360				712

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table 2.5 Descriptive Statistics, center peers

	Control		Savings training		Difference		N
	mean	sd	mean	sd	b	p	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AF savings balance	245.9	(357.5)	280.6	(354.2)	-34.70	(0.18)	774
Loan size	5324.1	(2925.0)	5578.7	(2681.4)	-254.53	(0.21)	775
Installment amount	231.2	(171.6)	256.2	(148.2)	-25.03	(0.03)**	775
ICF balance	847.9	(1225.0)	914.9	(1123.2)	-66.95	(0.43)	774
Loan cycle	3.0	(2.1)	3.1	(2.3)	-0.18	(0.27)	775
Principal amortization	214.5	(122.3)	226.2	(108.2)	-11.69	(0.16)	775
Observations	381		394				775

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

2.4.3 Empirical Strategy

The random assignment of the savings training allows me to get unbiased estimates of the effect of receiving the training by estimating the following equation:

$$Y_d = \alpha + \beta_1 T_d + \gamma' X_d + \varepsilon_d, \tag{2.2}$$

where $d = i, g(i), c(i)$. Y_d is the AF savings balance of individual belonging to group d for the months following the training – the outcome of interest. T_d is an indicator of the savings training and X_d is a vector of baseline characteristics.

I run this regression on the three groups of interest. I first look at $d = i$, which corresponds to the injection points and their control subjects. As mentioned above, T_i is an indicator of the savings training. A value of 1 indicates that the individuals received the savings training, and we refer to them as injection points. A value of 0 indicates that they are the control subjects, that is individuals in other centers randomly selected to be the control subjects which also participated in experimental games but did not get the savings training. X_i is a vector of baseline characteristics including age, electricity in the HH, household size, average background consumption, knowledge of a savings plan, trust in NWTF, amount earned in the experimental games, risk aversion parameter, trust level in money lenders and the number of links within the network. Additionally, we also include the covariates on which we balanced the randomization: AF savings balance, ICF balance, loan amount, population, and the average distance to the municipality.[55]

In a second step, I am interested in analyzing whether there is a differential effect across group peers and center peers. The second group of interest, is therefore group peers, for which $d = g(i)$. For this group, $T_{g(i)} = 1$ if and only if there is a group member that did not take part in the training but that had an injection point in his lending group. $T_{g(i)} = 0$ for group members of clients that participated in the experiment, but did not receive the training, which are the group members of those that form the control group of the injection points.

The third group of interest is center peers. For this group, $T_{c(i)}$ takes a value of 1 for members that are in centers with at least one injection point, excluding the lending group to which the injection point belongs to. $T_{c(i)}$ takes a value of 0 for members whose center has at least one member that attended the experimental games but did not participate in the training, excluding the group member of the control subjects.

For sets $g(i)$, and $c(i)$, the vector of baseline characteristics corresponds to the AF savings balance, ICF balance, loan amount, loan balance, loan cycle, average distance to municipality, population and number of clients in the center.

To test the effect of the social network on savings, I run the following regression on the three groups of interest:

[55]The urban indicator is not included due to multicolinearity.

$$Y_d = \alpha + \phi_1 T_d + \phi_2 P_d + \phi_3 T_d \times P_d + \psi \cdot degree_d + \gamma' X_d + \varepsilon_d, \quad (2.3)$$

where $d = i, g(i), c(i)$. P_d takes a value of 1 if an injection point (or a control subject) reported individual belonging to group d as a connection and 0 otherwise. The set of baseline covariates are as before. For set i, $degree_i$ corresponds to the total number of links.

To test whether intensity of the connection matters, I run the following regressions on the three groups of interest:

$$Y_d = \alpha + \beta_1 T_d + \beta_2 Z_{1d} + \beta_3 Z_{2d} + \beta_4 (Z_{1d} \times T_i) + \beta_5 (Z_{2d} \times T_d) + \psi \cdot \text{degree}_d + \gamma' X_d + \varepsilon_d, \quad (2.4)$$

where $d = i, g(i), c(i)$. Z_{1d} takes a value of 1 if and only if individual belonging to group d is connected to 1 injection point for treated centers, or to 1 control subject in control centers, and 0 otherwise. Z_{2i} takes a value of 1 if and only if individual in group d is connected to two or more injection points in the case of treated centers or 2 or more control subjects in the case of control centers, and 0 otherwise.[56]

The effect of the training, conditional on not being connected to an injection point, is β_1. The effect of the training conditional on being connected to another injection point is $\beta_1 + \beta_4$. The effect of the training conditional on being connected to two or more injection points, is $\beta_1 + \beta_5$.

2.5 Results

2.5.1 Injection Points

I first look at the effect of the training on the AF savings balance of the injection points by estimating equation (2.2) for the injection points ($d = i$). Y_i is the AF savings balance of injection point i for the first three months after the intervention.[57] Results in table 2.6, column 1, show that the AF savings balance of the injection points increases by PHP 114.6, a 43% increase of baseline average AF savings.

To test the effect of the social network on savings for the injection points, I estimate:

$$Y_i = \alpha + \phi_1 T_i + \phi_2 NetShare_i + \psi \cdot Degree_i + \gamma' X_i + \varepsilon_i, \quad (2.5)$$

where $NetShare_i$ is the share of participants to whom i is connected over i's total number of friends and $Degree_i$ is a set of dummy variables that indicate i's number of friends.

[56] I do not include $Degree_d$, $d = g(i), c(i)$ in specifications (2.3) and (2.4), since the data on number of friends is not available for group and center peers.

[57] I run a pooled regression for the three months after the intervention took place. The main reason for looking at the effects for this short period of time is the dynamic nature of the network. Once a client's loan cycle ends, clients can be inactive until they start their next loan or leave. That implies that members of the network could come and go depending on their cycle maturity and when their next loan starts. Therefore I look at the short term effects in order to abstract of the dynamics of the network. In the next section I analyze the medium term effects of the program.

Results for this specification are reported in column 2. I find a positive effect of the social networks on the AF savings balance, of PHP 252.9. This implies that having an additional friend receiving the training, which raises $NetShare_i$ by 11 percent, leads to an increase of the AF savings by PHP 28 (252.9×0.11). This represents 24% of the main effect presented in column 1.

Equation (2.6) is an alternative specification, to test whether there is an effect on savings of having a friend also participating in the experiment:

$$Y_i = \alpha + \phi_1 T_i + \phi_2 P_i + \psi \cdot Degree_i + \gamma' X_i + \varepsilon_i, \tag{2.6}$$

where P_i takes a value of 1 if individual i is connected to an injection point or control subject, and 0 otherwise. Results are presented in column 3. I find a positive effect of PHP 48 on savings of being connected to someone that also received the training, but the effect is not significant.

Next, I examine whether having other injection points as friends leads to a stronger effect of the training program. To this end, I estimate equation (2.3) and instead of $Degree_i$ I include a set of dummy variables indicating the number of friends in the network. Results, presented in column 4, show that injection points with other friends as injection points do not experience a stronger effect of the training, the effect size is PHP 92.5 ($\phi_1 + \phi_3$=139.9-47.4), however the effect is not significant. For injection points not connected to another injection point, the effect is much stronger and significant. They experience an increase of PHP 139.9 on savings, representing 52% of baseline savings. This implies that injection points are less influenced by their friends when they have direct information about the training.

I further investigate this by estimating equation (2.4) and as before include a set of dummy variables indicating the number of friends. Results are presented in column 5 indeed showing that the effect does not intensify when an injection point is connected to 1 or 2 or more other injection points.

2.5.2 Spillover effects: group peers

In this section, I analyze the effect of the training on the AF savings balance of group peers. I first assess the basic effect of the training by estimating equation (2.2) for the group peers ($d = g(i)$). Results are shown in table 2.7, column 1. I find a positive effect of the savings training on group peers of PHP 71, representing 24% of baseline savings of group peers.

To assess the social network effect on savings of the group peers, I estimate equation (2.3) where $P_{g(i)}$ takes a value of 1 if the group peer is connected to an injection point or a control subject, and 0 otherwise. Results are shown in columns 2 and 3, the former not including the interaction term $\phi_3 T_{g(i)} \times P_{g(i)}$.

Column 2 shows that being connected to an injection point or control subject leads to a positive but insignificant effect of PHP 40 on group peer savings. More interesting

Table 2.6 Effect of training on savings, injection points

	(1)	(2)	(3)	(4)	(5)
Savings training, T_i	114.6**	96.83*	106.0*	139.9**	143.2**
	(55.43)	(50.16)	(53.63)	(60.20)	(60.07)
Share of friends as IP, $NetShare_i$		252.9***			
		(91.60)			
Connected to IP, P_i			47.96	66.63*	
			(37.03)	(36.81)	
Savings training × Connected to IP, $T_i \times P_i$				-47.39	
				(87.29)	
Connected to 1 IP, Z_{1i}					22.86
					(41.27)
Connected to 2 or more IP, Z_{2i}					101.9**
					(48.92)
Savings training× Connected to 1 IP, $T_i \times Z_{1i}$					-103.2
					(84.10)
Savings training× Connected to 2 IP, $T_i \times Z_{2i}$					-30.24
					(101.2)
Constant	79.94	18.12	57.42	43.66	115.2
	(138.1)	(144.7)	(138.8)	(137.8)	(136.7)
Observations	1030	1030	1023	1023	1024
Village Characteristics	Yes	Yes	Yes	Yes	Yes
Financial Characteristics	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes
R^2	0.256	0.268	0.258	0.258	0.272
p-value joint significance:					
ϕ_1, ϕ_3				0.0405**	
$H_0 : \phi_1 + \phi_3 = 0$				0.1835	
$H_0 : \beta_1 + \beta_4 = 0$					0.5736
$H_0 : \beta_1 + \beta_5 = 0$					0.1879

Notes: Clustered standard errors at the center level. $NetShare_i$ is the ratio of participants i is connected to over total number of friends. Village characteristics: average distance to municipality and population. Financial characteristics: Baseline levels of savings, loan, amount, ICF balance and loan cycle. Household characteristics: Age, electricity, background, consumption, trust in NWTF, experiment earnings and estimated risk aversion parameter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

are the results in column 3. The effect of the saving training on those not connected to an injection point is PHP 185.4, representing 63% of baseline savings. Group peers are less influenced by the program when they have a direct contact to the injection points. The effect of the training for those connected to an injection point is PHP 48 ($\phi_1 + \phi_3$=185.4-137.2), which corresponds to a 16% of group peers' baseline savings.

I further investigate this by estimating equation (2.4) where $Z_{jg(i)}$ takes a value of 1 if an individual in group peer $g(i)$ is connected to 1 or 2 or more injection points or control subjects $j = 1, 2$, and 0 otherwise. This specification allows me to analyze in more detail the smaller effect of the training for group peers connected to an injection point. Results are presented in column 4. As before, we have that for subjects not connected to an injection point the effect of the training is strong, increasing savings by PHP 185. As can be seen, the negative effect for those connected to one injection point is driven by those with 2 or more connections. Treated group peers connected to one injection point experience an increase in savings of PHP 78.8 ($\beta_1 + \beta_4 = 185.1 - 106.3$), however the effect is not significant. Treated group peers with 2 or more connections to injection points experience an increase in savings of only PHP 12 ($\beta_1 + \beta_5 = 185.1 - 172.9$). The effect is considerably smaller than for those not connected to an injection point and is not statistically different from zero.

Incorporating further dummy variables for those with 3, 4, 5, and 6 connections, it can be seen in column 6 that results are mainly driven by those with more than 3 connections to the injection points, representing a very small number of group peers (corresponding to 10 percent).

Results in this section suggest that there is a stronger effect of the training on those not directly connected to the injection points. This also supports the presence of spillover effects through nonfriends.

Finally, I investigate whether kinship matters by estimating the following specification:

$$Y_{g(i)} = \alpha + \tau_1 T_{g(i)} + \tau_2 DegreeFam_{g(i)} + \tau_3 T_{g(i)} \times DegreeFam_{g(i)} + \gamma' X_{g(i)} + \varepsilon_{g(i)}. \quad (2.7)$$

By adding the kinship network measure I assess whether family connections have an effect on the savings level of group peers, and moreover whether this effect is stronger for those group peers with at least one injection point as a group member. Results are presented in column 5. As expected, there is a small and insignificant effect of the kinship network. Kinship connections should be stronger at the center peer level and not at the group peer level, since close family members cannot be part of a same lending group.

2.5.3 Spillover effects: center peers

In this section I investigate the effects of the training on the AF savings balance of the center peers. In particular, I expect a larger importance of the kinship network,

Table 2.7 Effect of training on savings, group peers

	(1)	(2)	(3)	(4)	(5)	(6)
Savings training, $T_{g(i)}$	71.06*	68.64*	185.4***	185.1***	57.36	185.1***
	(40.60)	(40.34)	(61.38)	(60.82)	(39.87)	(60.72)
Connected to IP, $P_{g(i)}$		40.63	95.55***			
		(30.96)	(26.57)			
Savings training ×			-137.2**			
Connected to IP, $T_{g(i)} \times P_{g(i)}$			(63.58)			
Connected to 1 IP, $Z_{1g(i)}$				94.69***		95.29***
				(27.45)		(27.96)
Connected to 2 or more IP, $Z_{2g(i)}$				94.98**		
				(39.90)		
Savings training ×Connected				-106.3		
to 1 IP, $T_{g(i)} \times Z_{1g(i)}$				(71.36)		
Savings training ×Connected				-172.9**		
to 2 IP, $T_{g(i)} \times Z_{2g(i)}$				(70.29)		
$DegreeFam_{g(i)}$					2.212	
					(10.70)	
Savings training ×					4.397	
$DegreeFam_{g(i)}$					(10.81)	
Connected to 2 IP						80.54**
						(36.55)
Connected to 3 IP						59.39
						(70.82)
Connected to 4 IP						495.2
						(333.6)
Connected to 5 IP						-24.81
						(43.52)
Connected to 6 IP						-82.97
						(58.26)
Training×Connected to 1 IP						-106.4
						(71.53)
Training×Connected to 2 IP						-144.5**
						(68.45)
Training×Connected to 3 IP						-160.8
						(102.4)
Training×Connected to 4 IP						-565.7
						(343.6)
Training×Connected to 5 IP						-133.7*
						(77.54)
Constant	169.6*	141.5	102.8	98.73	176.8*	95.82
	(94.33)	(91.89)	(88.40)	(86.57)	(94.31)	(85.73)
Observations	2085	2085	2085	2085	2043	2085
Village & Financial Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.239	0.240	0.243	0.246	0.241	0.254
$H_0 : \phi_1 + \phi_3 = 0$			0.2633			
$H_0 : \beta_1 + \beta_4 = 0$				0.1410		
$H_0 : \beta_1 + \beta_5 = 0$				0.8170		
$H_0 : \tau_1 + \tau_3 = 0$					0.1166	

Notes: Clustered standard errors at the center level. Connected to IP, $P_{g(i)}$, takes a value of 1 if the group peer is connected to an injection point or control subject, $DegreeFam_{g(i)}$ is the alternative network measure based on kinship. Village characteristics: average distance to municipality, population, number of clients. Financial characteristics: Baseline levels of savings, loan amount, loan balance, ICF balance and loan cycle. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

given that family members are not allowed to be in the same group, but they can be in the same center. First, I assess the overall effect of the training on the center peers by estimating equation (2.2) for the center peers ($d = c(i)$). Results are presented in table 2.8, column 1. The training has a positive effect on center peers' savings of PHP 65.6, which represents a 25% of baseline center peer savings.

To investigate the effect of social networks on the center peers, I run the same set of regressions as for the group peers. I start by estimating equation (2.3). Columns 2 and 3 show the results. In column 2, I incorporate only $P_{c(i)}$, which takes a value of 1 if an injection point or a control subject indicates a peer in $c(i)$ as a connection. I find a positive and insignificant effect of the connection indicator of PHP 18, as shown in column 2.

Results in column 3 suggest that for center peers not connected to the injection points, the effect of the training is PHP 87.4, representing 33% of baseline center peers' savings. For those that are connected to an injection point, the effect is PHP -8.1 ($\phi_1 + \phi_3$=87.4-95.5) but insignificant. These results go in the same direction as for the group peers, but at a lower intensity.

Although the effect for center peers connected to an injection point is not significant, I investigate the source of the negative effect, by estimating equation (2.4). Results are presented in columns 4 and 5, where column 4 does not include the interaction terms. Similar as for group peers, I find that the negative effect for center peers connected to an injection point is driven by those with 2 or more connections. Only 4% of center peers have 2 or more connections to an injection point or control subject.

Finally, in columns 6 and 7, I assess the effect of the kinship network measure and its interaction with the training. In a first step, I estimate equation (2.2) and control for the family connectivity, $DegreeFam_{c(i)}$. Column 6 presents an effect of 17 PHP in center peers' savings, although insignificant ($p = 0.12$).

In a second step, I estimate equation (2.7) to assess whether the effect of the training is stronger for kinship connections at the center peer level. As shown in column 7, for center peers without family connections within the center, I find a positive and significant effect of PHP 90.3 corresponding to 34% of baseline center peers' savings. On the other hand, the effect for center peers with at least one family member within the center, PHP 65 ($\tau_1 + \tau_3 = 90.35 - 25.24$), is lower but still statistically different from zero.

Comparing results for the two peer levels, I find a stronger effect of being connected to an injection point for peers at the group level compared to peers at the center level. On the other hand, kinship networks plays a stronger roll for peers at the center level and no role for peers at the group level.

Table 2.8 Effect of training on savings, center peers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Savings training, $T_{c(i)}$	65.58*	65.93*	87.40**	66.56**	87.04**	44.84	90.35**
	(33.65)	(33.58)	(34.04)	(33.21)	(34.23)	(32.38)	(38.61)
Connected to IP, $P_{c(i)}$		17.94	67.00*				
		(33.50)	(34.67)				
Savings training × Connected to IP, $T_{c(i)} \times P_{c(i)}$			-95.50				
			(62.71)				
No. of IP connected to				43.17			
				(34.74)			
Connected to 1 IP, $Z_{1c(i)}$					-21.15		
					(31.65)		
Connected to 2 IP, $Z_{2c(i)}$					340.8**		
					(132.3)		
Savings training ×Connected to 1 IP, $T_{c(i)} \times Z_{1c(i)}$					-33.44		
					(51.99)		
Savings training ×Connected to 2 IP, $T_{c(i)} \times Z_{2c(i)}$					-289.9		
					(201.6)		
$DegreeFam_{c(i)}$						17.16	34.60***
						(10.90)	(11.88)
Savings training × $DegreeFam_{c(i)}$							-25.24
							(20.63)
Constant	88.12	86.25	71.52	82.87	75.00	72.08	59.10
	(79.96)	(79.38)	(80.05)	(79.53)	(79.02)	(82.38)	(79.75)
Observations	2249	2249	2249	2249	2249	2156	2156
Village Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.347	0.347	0.349	0.350	0.362	0.368	0.373
p-value:							
$H_0 : \phi_1 + \phi_3 = 0$			0.8986				
$H_0 : \beta_1 + \beta_4 = 0$					0.2246		
$H_0 : \beta_1 + \beta_5 = 0$					0.3328		
$H_0 : \tau_1 + \tau_3 = 0$							0.0270

Notes: Clustered standard errors at the center level. Connected to IP, $P_{c(i)}$, takes a value of 1 if the group peer is connected to an injection point or control subject, $DegreeFam_{c(i)}$ is the alternative network measure based on kinship. Village characteristics: average distance to municipality, population, number of clients. Financial characteristics: Baseline levels of savings, loan amount, loan balance, ICF balance and loan cycle. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9 Heterogenous effect of training on savings, injection points

	Knows what a Savings Plan is		Financial Literacy	
	No	Yes	Low	High
	(1)	(2)	(3)	(4)
Savings training, T_i	85.02	111.2*	70.64	119.1*
	(50.97)	(55.97)	(47.72)	(60.98)
Constant	-81.26	180.4	78.16	227.8
	(168.6)	(164.3)	(126.4)	(216.4)
Observations	394	701	363	732
R^2	0.445	0.157	0.368	0.203

Notes: Clustered standard errors at the center level. Village characteristics: average distance to municipality and population. Financial characteristics: Baseline levels of savings, loan amount, ICF balance and loan cycle. Household characteristics: Age, electricity, background consumption, trust in NWTF, experiment earnings and estimated risk aversion parameter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5.4 Heterogeneity Analysis

In this section I analyze the heterogeneity of effects of the savings training on the injection points. I am particularly interested in whether subjects that report knowing what a savings plan is experience a stronger effect of the program. This might help shed some light on the possible mechanisms of how the savings training works. There are several reasons why the savings training might lead to a change in individuals' saving behavior. i) Individuals learn how to save or put differently they learn how to use the product, or ii) Individuals know how the product works and the savings training serves to mitigate behavioral reasons that hinder savings. In the case that the savings training is working through the first mechanism, I expect that individuals that report not knowing what a savings plan is experience a stronger effect of the program.

Table 2.9 reports the results of estimating equation (2.2) in columns 1 and 2. The effect of the savings training is stronger for individuals that report knowing what a savings plan is, although the difference is not statistically significant. This implies that the main mechanism through which the program is having an impact is not only through learning how the product works. Although this cannot be ruled out, there might be other mechanisms such as behavioral reasons.

In a second step I analyze whether more financial literate individuals experience a stronger effect of the program. Subjects are defined to have high financial literacy if they have three out of six financial literacy questions asked in the survey correctly. Otherwise, they are classified as low literacy subjects.[58] Results are presented in

[58]Financial literacy questions: 1) What is 5+3?, 2) What is 3*7?, 3) What is 1/10 of 300?, 4) What is 5% of 200?, 5) Imagine that we roll a fair, six-sided die 100 times. Out of 100 rolls, how many times do you think the die would come up as an even number (2,4, or 6)?, 6) In another lottery, the chance of winning a car is 1 in 1,000. What percent of lottery tickets win a car?. No participant answered all six questions correctly.

columns 3 and 4, and they show that indeed subjects with a high financial literacy level experience a stronger effect of the program.

2.5.5 Medium Term effects

The main effects of the program presented in section 2.5 are short term effects, namely the effects of the programs for the three months after the intervention took place. What about the effects of the program in the medium term, are they stable? I answer this questions by examining the effects of the savings training on savings up to 9 months after the intervention, for the different groups of interest.[59]

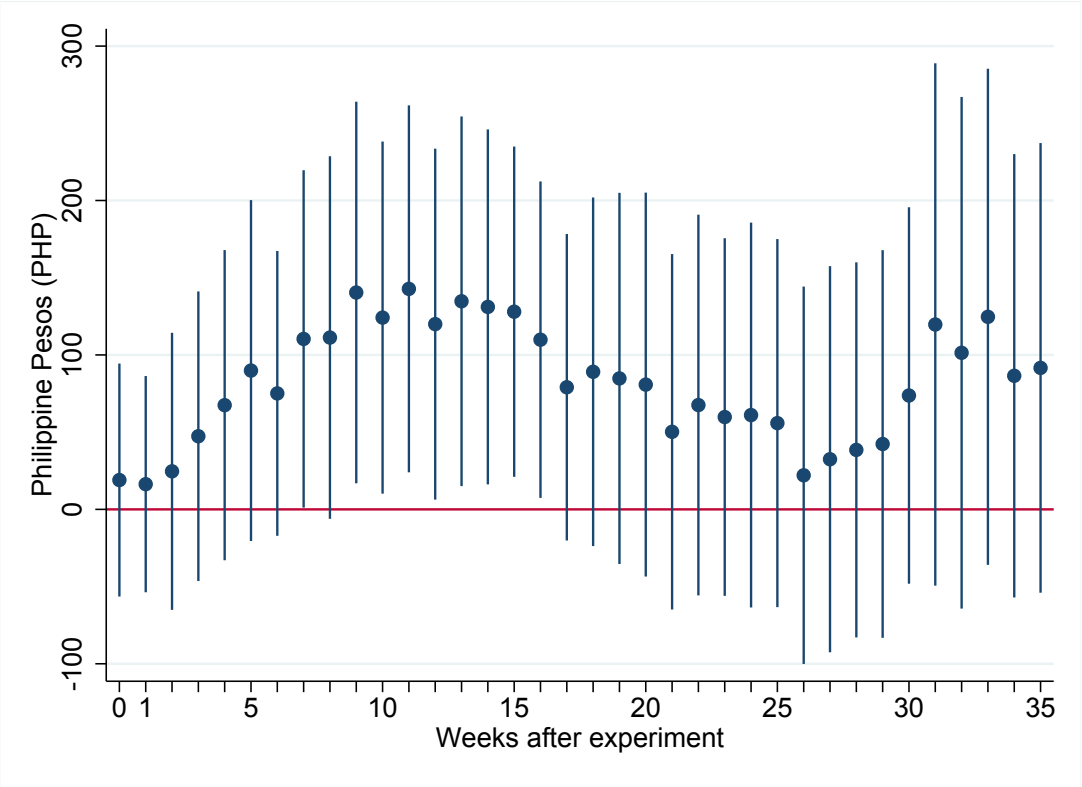


Figure 2.4: Weekly effect of the training on savings, T_i, injection points

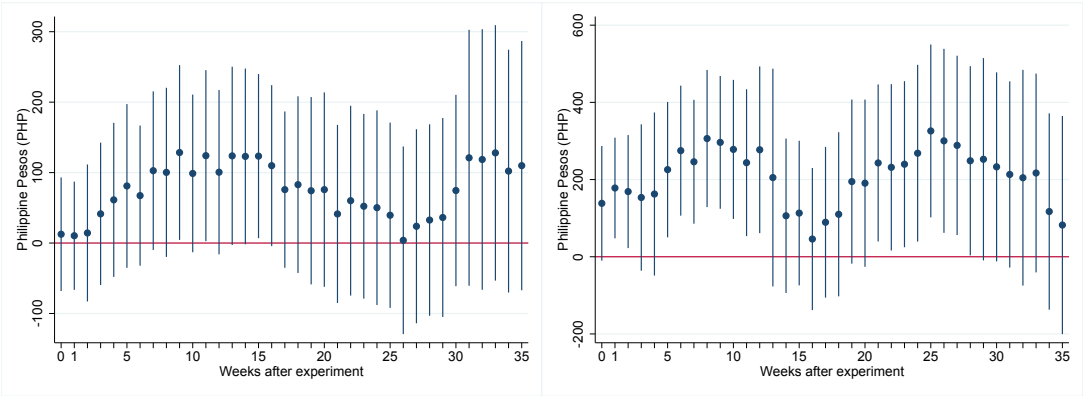
Injection Points To answer this question for the injection points, I use weekly data from NWTF to estimate equation (2.2) for the 35 weeks after the intervention took place. For the analysis I take as week 0 the week in which the experiment took place. Results presented in figure 2.4 show that the effect of the training is short lived. In week 2 the effects start to increase reaching a positive and significant effect at week 7 until week 16. Thereafter the effect of the training decreases and is not significant.

The results are not surprising. If the savings training is impacting individuals' savings through behavioral aspects rather than information about how the product

[59]Figures 2.4 to 2.9 present results of the estimations. The central dots are the monthly estimates and the lines indicate the 95% confidence intervals.

works, a more persistent training program designed to change the individuals' saving behavior might be more desirable.

Figure 2.5 presents the results of estimating equation (2.5) for the 35 weeks following the experiment. The social network effect is more persistent. It steadily increases in the first weeks after the experiment, reaching an average effect of 268.5 PHP from weeks 5 to 12, leading to an increase in savings of PHP 29 (268.5×0.11). This represents 26% of the main effect presented in table 2.6, column 1. The social network effect starts to decrease 13 weeks after the experiment reaching a level of almost 0 in week 16. It then starts an upward tendency, with a significant average effect of PHP 27.6 (251×0.11) between weeks 19 and 30.



(a) Savings training, T_i. (b) Share of friends as IP, $NetShare_i$.

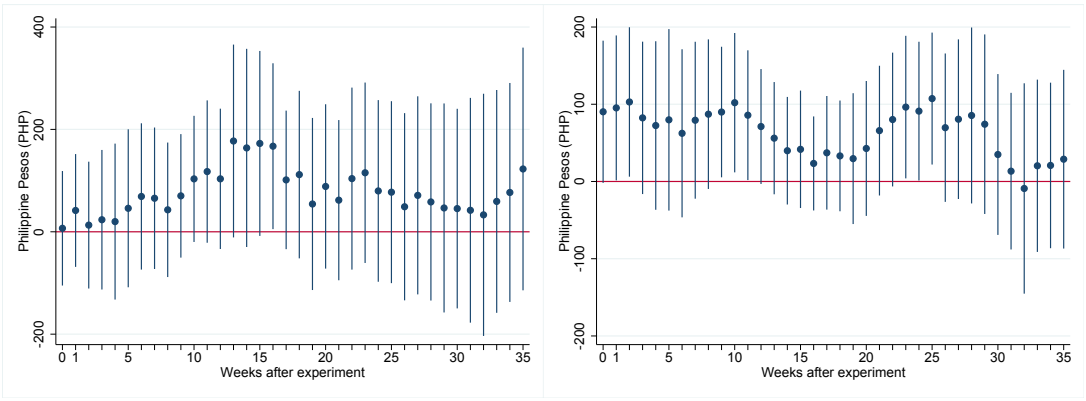
Figure 2.5: Weekly social network effects for injection points

Figure 2.6 shows the results of estimating equation (2.3) with the weekly data. As in the main effect presented in table 2.6, column 4, I find no differential effects for injection points that have other injection points as friends. The interaction effect presented in figure 2.6c is insignificant throughout the 35 weeks after the training took place.

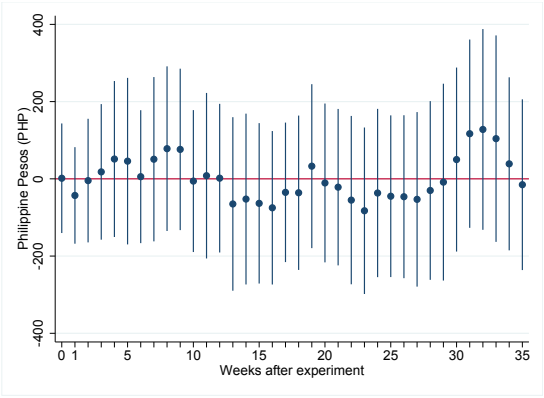
Group and center peers I examine the medium term effect for group and center peers using monthly data up to nine months after the training took place, from May 2015 until January 2016. Figure 2.7 shows the results of estimating equation (2.2) for group and center peers. As for the injection points, the effect of the training is short lived. For group peers, the effect is positive and significant until the third month after the experiment took place. Beyond the third month effects are lower and insignificant.[60]

In the case of the center peers, effects are even weaker. The effects are positive and significant for the two months after the intervention, afterwards they are close to zero (and even negative) and insignificant.

[60]Results for July 2015 are significant at the 10% significance level.



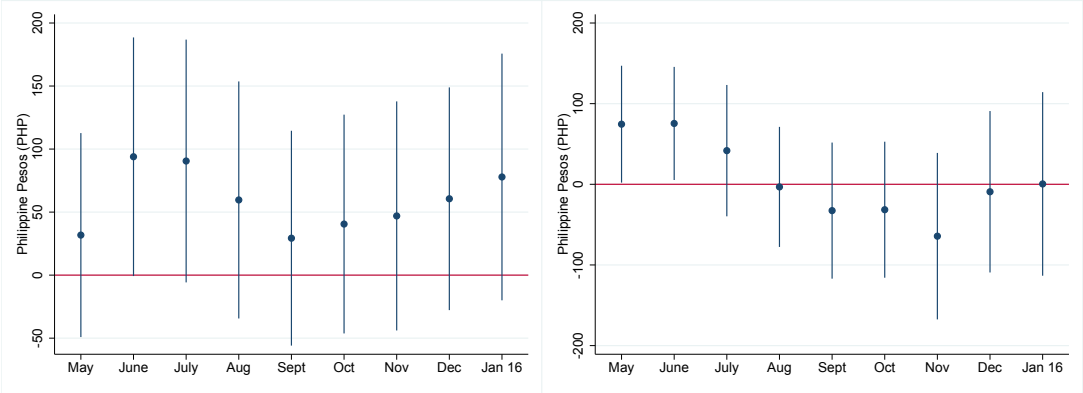
(a) Savings training, T_i. (b) Connected to IP, P_i.



(c) Savings training×Connected to IP, $T_i \times P_i$.

Figure 2.6: Weekly social network effects for injection points

The results are to be expected, given the short term effect of the program on the injection points. The weaker medium term effect on center peers compared to group peers is also to be anticipated since a larger share of group peers might have a stronger connection to the injection points than those in center peers connected by kinship to the injection points.



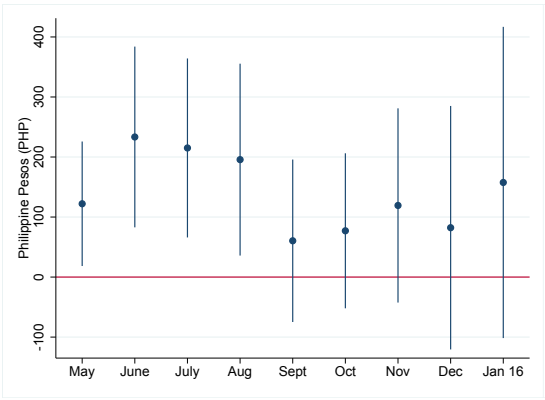
(a) Group peers, $T_{g(i)}$. (b) Center peers, $T_{c(i)}$.

Figure 2.7: Monthly basic effects of the savings training, group and center peers

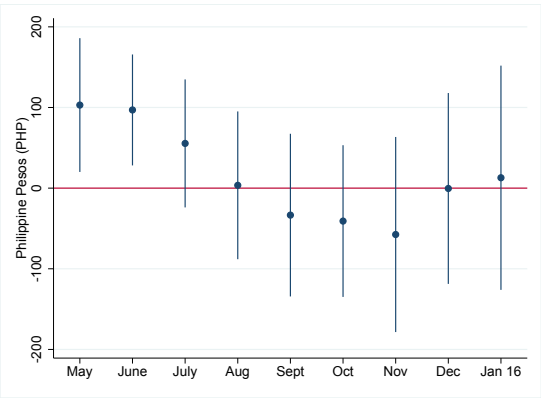
Figure 2.8 presents the medium term effects of estimating equation (2.3) for group peers, 2.8a, 2.8b, and 2.8c, and for center peers, 2.8d, 2.8e, and 2.8f. Group peers experience a lower but positive and significant effect of the training program when they are connected to other injection points, consistent with the short term effect presented in table 2.7, column 3. Group peers that are not connected to an injection point experience an average effect of 191 PHP for the four months after the training, corresponding to a 65% of baseline savings. Group peers that are connected to an injection point have a smaller effect of 44 PHP, representing 15% of baseline savings.

A similar but much weaker effect is reported for center peers for the first month after the intervention. Center peers that are not connected to injection points have a positive and significant effect of the training of 103 PHP, corresponding to a 39% of baseline savings. However, center peers that are connected to an injection point have a negative effect of the training of 25 PHP, a 9% of baseline savings. In the second month after the training the effect of the training is positive and significant and not statistically different for peers connected or not connected to an injection point (the interaction, term $T_{c(i)} \times P_{c(i)}$, is not significant). Afterwards the effects are weak and insignificant throughout.

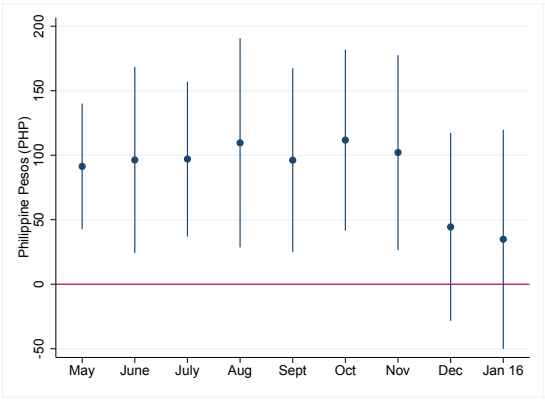
Finally, in figure 2.9, I examine the social network medium term effects of kinship connections, both at the group and at the center level. The estimation corresponds to equation (2.2) and controls for the kinship measure $DegreeFam_d$, where $d = g(i), c(i)$. Figures 2.9b and 2.9d show that the effects are stronger for center peers. For group peers, the effects are smaller and insignificant throughout. For center peers, the effects are stronger and significant for the first three months after the intervention,



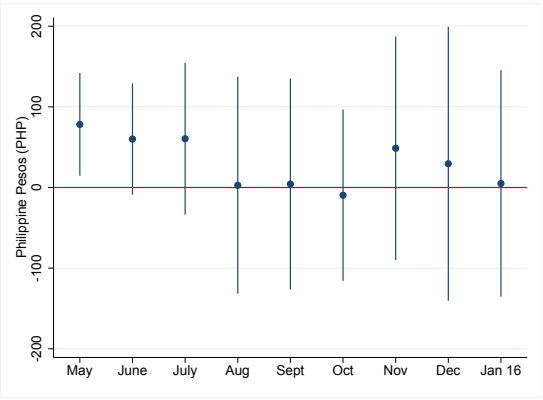
(a) Savings training, $T_{g(i)}|P_{g(i)} = 0$.



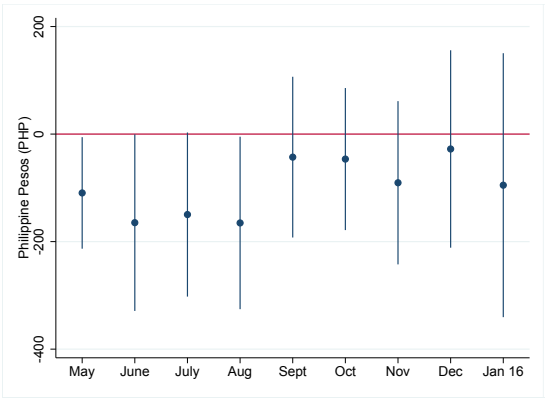
(d) Savings training, $T_{c(i)}|P_{c(i)} = 0$.



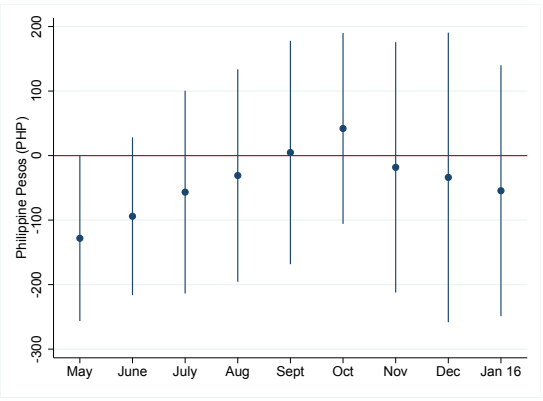
(b) Connected to IP, $P_{g(i)}$.



(e) Connected to IP, $P_{c(i)}$.



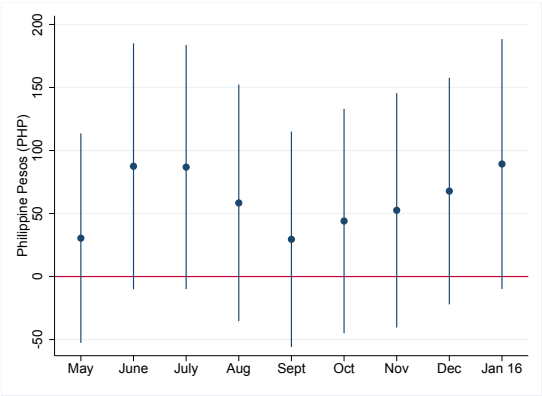
(c) Savings training ×Connected to IP, $T_{g(i)} \times P_{g(i)}$.



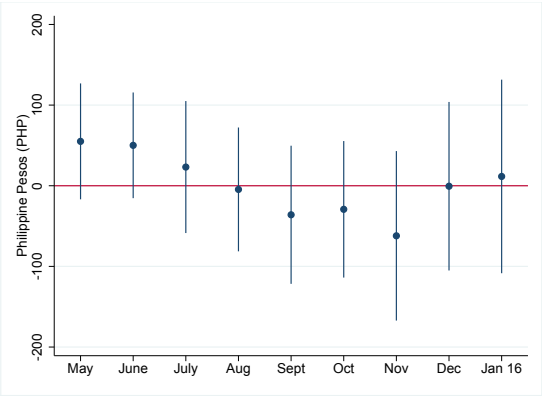
(f) Savings training ×Connected to IP, $T_{c(i)} \times P_{c(i)}$.

Figure 2.8: Monthly social network effects for group and center peers

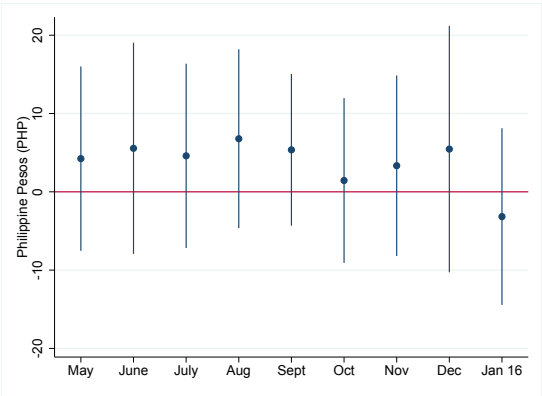
afterwards they are insignificant. Results are consistent with those presented above where we show that kinship connections matter at the center peer level but not at the group peer level. Results are however short lived.



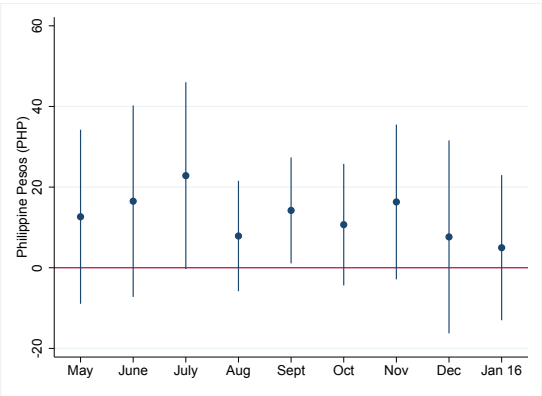
(a) Savings training, $T_{g(i)}$.



(c) Savings training, $T_{c(i)}$.



(b) $DegreeFam_{g(i)}$.



(d) $DegreeFam_{c(i)}$.

Figure 2.9: Monthly social network effects for group and center peers

2.6 Conclusion

This paper uses a randomized field experiment implemented in the Philippines to examine the impact of a training program focused on savings on participants' savings balance and the role of social networks in enhancing the effects.

I find a strong short term effect of the program on participants' savings balance and the effect is stronger for participants not connected to other subjects that participated in the training.

I also examine the effects of the program on the participants' social networks, distinguishing across two type of peers, peers belonging to the participants' lending group that did not participate in the training and peers from the same center as the participants.

I construct network measures to account for the connection between peers and participants and find that group peers experience a positive effect of the training but the effect is not enhanced when they are connected to a participant. This might suggest that effects are channeled through second order connections. Center peers further experience a positive effect of the training through kinship connections within the center.

I examine the possible mechanisms of the training and find that not only knowledge about the financial product plays a role, but possibly also behavioral factors. Finally, I find that results are short lived, lasting until about three to four months after the intervention.

The results of the study have important policy implications. First, as it has been found in other applications, social networks are a powerful mechanism to enhance the spread of information and allow for social learning, allowing to reduce the costs of introducing new tools that can improve financial literacy.

Results support the findings in the financial literacy literature that less is often better in terms of designing financial education programs, however more has to be done to ensure lasting effects. The programs' design should move in a direction that fosters a change in habits bearing in mind the particular constraints faced by people in developing countries (Schilbach, Schofield, and Mullainathan, 2016). Additionally, programs that rely on generating changes in financial behavior through intrinsic motivation rather than through the use of extrinsic intensives might be preferable to avoid crowding out intrinsic motivation in the long run (Gneezy, Meier, and Rey-Biel, 2011).

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A Appendix

A.1 Training Materials

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How to make a Savings Plan and Budget?

Gamay nga giya sa pagsupot

Ang pagsupot importante sa tanan nga butang. Kung may ara ka emerhensya: nadulaan ka sang imo nga trabaho, na aksedente ka ukon ano man nga klase sang pinansyal nga krisis, ang pagsupot maka bulig sa imo nga lampuwasan ang mga emerhensya paagi sa pinansyal nga sandigan.

Ang pagsupot importante man sa pag plano sang aton palaabuton: kung gusto mo mag pakal sang balay, tricycle, mag bayad sa edukasyon sang imo kabataan, kag pag retiro. Ang pagsupot sa palaabuton nga tinutuyo maka tugot sa pagsuporta sa imo pamilya ukon palaabuton nga mga plano kag handom.

Gani mahatag kami sa inyo sang madasig nga pag-giya para sa pagsupot kag pinansyal nga plano.

Pag himo sang plano sa pagsupot

1. **Kilalahon ang inyo tinutuyo sa pagsupot.** Mag himo sang listahan sang mga butang nga gusto mo suptan, kung ibakal sang tricycle, pagsugod sang negosyo ukon pundo sa kolehiyo.

   Kuhaa ang listahan sang tanan nga pinansyal nga tinutuyo mo nga gusto mo malab-ot sa malip-ot kag sa malawig nga termino.

   Ang mga malip-ot nga tinutuyo mahimo nga indi mag lawig sang isa ka tuig para ini malab-ot.
   Ang malawig nga mga tinutuyo mahimo nga magdugay sang tinuig para ini malab-ot typical nga halimbawa amo nga pagsupot para sa pag retiro ukon para sa edukasyon sang imo bata.

2. **Pag determinar sang presyo,** sunod isipa ang presyo sang kada tinutuyo mo. Sa mga bagay nga imo pwede bayran tanan sang tingob pareho sang tricycle, sakup ang tangan nga presyo. Sa mga butang nga gusto mo utangon, pareho sang pagsugod sang negosyo, mga butang nga dapat hulugan.

3. **Pag butang sang target.** Subong bantaa ang kalawigon sang oras mo sa pagsupot sa kada tinutuyo mo. Sa mga tinutuyo mo nga isa ukon duha ka tuig ang kadugayon, konsidirar mo nga taguon anay ang imo sinuptan sa isa ka regular nga sinuptan. Para sa malawig nga mga tinututyo, pwede mo makonsiderar ang sinuptan pareho sang time deposit.

4. **Obrahon naton ang pag-suma.** Subong aton partidahon ang kabilogan nga bili sang aton kada tinutuyo (halin sa ikaduha nga tikang) paagi sa pag kuha sa kung pila ka bulan nga gusto mo hulaton (halin sa ika tatlo nga tikang), kag idugang ang tanan para makita kung pila ang imo kinahanglan nga supton sa kada bulan.

5. **Pag adyas kung kinahanglanon.** Ikomparar ang kada bulan nga target halin sa imo listahan sa imo sinuptan sa subong ang kadakuon sang imo sinuptan. Kung wala ka sang bastante nga sinuptan pwede nga:
   a. Padakuon ang imo sinuptan paagi sa pag pagamay sang imo bulanan nga gusto. Ang naga plano sa pag budget makabulig sa imo pangita sang pamaagi para mapa hagan-hagan ang imo gusto para maka supot ka sa kada bulan.
   b. Pag adyas sang imo tinutuyo, paagi sa pagkuha sang indi gid importante nga butang ukon pag atras sang target nga petsa para sa tinutuyo mo pag pa-atrasar.

Budget

Ang kinahanglanon nga parte sang plano sa pagsupot amo ang pagplano sa pag budget. Ang pag tukod sang budget amo ang pag akto sang pag dapon sang imo kita kag galastuhan para ikaw maka desisyon kung pila ang imo gusto para sa isa ka butang, kag kung pila sa isa pagid, kag sa iban pagid antes mo actual nga gastuhon ang kwarta.

Paano kita maghimo sang budget? Ini mahapos lang. Sunda lang ang mga masunod nga simple nga tikang:

1. **Pagbutang sang imo tinutuyo**. Sa nag ligad nga tikang nag butang kita sang plano sa pagsupot, para aton mahibaloan ang aton mga pinansyal nga tinutuyo. Ang kantidad nga imo nahibaloan nga imo masupot sa kada bulan makadto ini sa imo budget bilang parte sang imo mga galastuhan.

2. **Paghibalo sang imo insakto nga kita**. Ang una nga tikang sa paghimo sang budget amo nga mahibaloan ang kwarta nga masulod, ukon ini amo ang imo kita.

3. **Paghimo sang plano**. Magsugod ka sa pag parte-parte sang imo insakto nga kita sa 2 ka masangkad nga kategoria sa pag gasto: sigurado nga gasto kag naga lain-lain nga gasto. Ang iban mo nga gasto pareho sang balayran mo sa loan ini siya matuon sa sigurado nga pag gasto kag ini sya ginabayran mo kada bulan ukon kada semana. Ang iban nga galastuhan pareho sang pagkaon, kalingawan ukon gas para sa imo tricycle matuon ini sa naga lai-lain nga gasto kay ini naga baylo-baylo sa kada bulan.

   Pwede mo man partidahon ang imo mga galastohan sa tatlo ka importante nga kategoria: kinahanglanon, pagsupot kag mga kagustuhan.

4. **Hibalu-a ang imo galastuhan**. Indi ikaw sigurado kung pila ang lain-lain nga mga gastos pareho sang groceries ukon pagkaon sa guwa kada bulan? Ang amo ni nga mga galastusan mabudlay hibaluon.

   a. Journal sa pag gastos: Mangita ka sang gamay nga notebook kag didto mo i-galista ang imo mga pinamakal sa kada adlaw sa amo na nga bulan.
   b. Ang tipunon ang tanan na resibo kag sumahon sa katapusan sang bulan.

   c. Mag separar sang iban nga kantidad para sa naka skedyul nga galastuhan. Halimbawa, 400 Pesos para sa groceries kag lantawa kung ano ka dugay sa kada bulan ikaw maka kuha sang amo na nga kantidad sang imo nga groceries.

Figure 2.10: Toolkit materials: Brochure, part 1

Kung ikaw may ara maayo nga pag banta sang imo mga galastusan kada bulan, imo igalakip sa imo nga personal nga listahan sa budget.

Sunda ang 4 nga mahapos nga tikang sa pag umpisa himo sang personal nga listahan sa budget.

1. Ilista ang imo adlaw-adlaw na gastos sa bisan ano nga imo pwede madala pareho sang ballpen kag papel ukon isa ka bagay sa imo smartphone.
2. Magplano sa sunod nga mga galastusan kag income para indi ikaw makibot sa ulihi.
3. Mag pangita sang iban nga pamaagi para sa magamay na gastos. Ang gamay nga sinuptan pwede makadugang para sa pagdamo sang kwarta.
4. Mangita sang pamaagi para mapabaskog ang imo kita.

May ara ka bulanan nga check in. Lantawa ang imo galastuhan sa kada bulan kag ikomparar ini sa imo personal nga listahan sa pag budget para imo makita kung diin pakadto ang mag bagay bagay. Kung imo makita nga masami ikaw ga sobra sa imo budget kag sa iban pa nga lugar nga guwa na sa imo kinahanglanon, Imo dapat konsiderahon ang pag pagamay sang iban na bagay para mapadayon nga imo ini kontrolado. Siguraduha nga i-update ang listahan sang plano sa pagsupot kung sa diin ang plano sa pagsupot ukon budget maga bago, kag imo regular na lantahon ini para masigurado nga ikaw ara gihapon sa imo target.

Savings Plan

Para sa kada savings target ikaw maga desisyon kung pala ini short-term ukon long term goal. Para sa short-term goals ibutang kung pila ka bulan imo plano nga magsupot para malab-ot ina. Para sa long-term goals, ibutang kung pila katuig mo ini malab-ot. Ibutang man ang kabilogan nga kantidad nga imo kinahang lan para malab-ot ang imo goals kagang kantidad nga imo na nasupot. note: Ibutang ang kada savings goal sang kaisa lang.

SHORT-TERM GOALS	(1) Total Needed	(2) Already Saved	(3) = (1) - (2) Left to Save	(4) Months to Save	(5) = (3) / (4) Monthly Savings
Emergency Fund	- PHP	- PHP			- PHP
Retirement	- PHP	- PHP			- PHP
Children's Education	- PHP	- PHP			- PHP
Debt Repayment	- PHP	- PHP			- PHP
Computer	- PHP	- PHP			- PHP
Television / Electronics	- PHP	- PHP			- PHP
Furniture	- PHP	- PHP			- PHP
Home Appliance(s)	- PHP	- PHP			- PHP
Wedding / Special Event	- PHP	- PHP			- PHP
Capital to start/expand business	5,000.00 PHP	- PHP	5,000.00 PHP	12	416.67 PHP
Buy Land	- PHP	- PHP			- PHP
House Repair	- PHP	- PHP			- PHP
House Construction	- PHP	- PHP			- PHP
Vacation	- PHP	- PHP			- PHP
Other	- PHP	- PHP			- PHP
Other	- PHP	- PHP			- PHP
I. TOTAL SHORT TERM GOALS	**5,000.00 PHP**	**- PHP**	**5,000.00 PHP**		**416.67 PHP**

LONG-TERM GOALS	(1) Total Needed	(2) Already Saved	(3) = (1) - (2) Left to save	(4) Years to Save	(5) = (3) / [(4)*12] Montly Savings
Emergency Fund	20,000.00 PHP	2,000.00 PHP	18,000.00 PHP	4	375.00 PHP
Retirement	50,000.00 PHP	- PHP	50,000.00 PHP	20	208.33 PHP
Children's Education	20,000.00 PHP	- PHP	20,000.00 PHP	5	333.33 PHP
Debt Repayment	- PHP	- PHP	- PHP		- PHP
Computer	- PHP	- PHP	- PHP		- PHP
Television / Electronics	- PHP	- PHP	- PHP		- PHP
Furniture	- PHP	- PHP	- PHP		- PHP
Home Appliance(s)		- PHP	- PHP	5	- PHP
Wedding / Special Event	20,000.00 PHP	3,000.00 PHP	17,000.00 PHP	10	141.67 PHP
Capital to start/expand business	- PHP	- PHP	- PHP		- PHP
Buy Land	- PHP	- PHP	- PHP		- PHP
House Repair	- PHP	- PHP	- PHP		- PHP
House Construction	- PHP	- PHP	- PHP		- PHP
Vacation	- PHP	- PHP	- PHP		- PHP
Other	- PHP	- PHP	- PHP		- PHP
Other	- PHP	- PHP	- PHP		- PHP
II. TOTAL LONG TERM GOALS	**110,000.00 PHP**	**5,000.00 PHP**	**105,000.00 PHP**		**1,058.33 PHP**
III. TOTALS (I + II)					**1,475.00 PHP**

I kumparar ang kantidad sang imo nasupot sa kada bulan. Kung ang kabilogan parehas lang ukon mas manaba sa imo sinuptan subong, ara kana sa target nga malab-ot mo ang imo savings goals. Kung mas damo, mangita ka sang pamaagi para mapataas ang imo sinuptan ukon bag-ohon ang imo nga goals.

Household Budget

Ibutang ang imo estimated nga kita kada bulan kag ang mag galastuhan para ma intidihan kung ano ang dapat lainun nga imo pagahimuon para mangabuhi para lang sa budget nga maayo para sa imo.

PART 1: MONTHLY INCOME	Estimated	Actual
Person 1: Monthly income (full and part time job)	3,000.00 PHP	3,000.00 PHP
Person 2: Monthly income (full and part time job)	2,000.00 PHP	2,000.00 PHP
Pantawid Pamilyang Pilipino Program	500.00 PHP	500.00 PHP
Remittances	1,000.00 PHP	1,000.00 PHP
Other	- PHP	- PHP
Other	- PHP	- PHP
Other	- PHP	- PHP
Other	- PHP	- PHP
TOTAL	***6,500.00 PHP***	***6,500.00 PHP***

PART 2: MONTHLY EXPENSE	Estimated	Actual
Mortgage / Rent	700.00 PHP	700.00 PHP
Loan Payment	300.00 PHP	300.00 PHP
Health Insurance	25.00 PHP	25.00 PHP
Education Fees	100.00 PHP	100.00 PHP
Electric Bill	75.00 PHP	75.00 PHP
Water Bill	45.00 PHP	45.00 PHP
Groceries	1,500.00 PHP	1,500.00 PHP
Phone Bill	200.00 PHP	200.00 PHP
Transportation	300.00 PHP	300.00 PHP
Gasoline	50.00 PHP	50.00 PHP
House Repairs	500.00 PHP	1,000.00 PHP
SAVINGS	**1,475.00 PHP**	**1,475.00 PHP**
Clothing/footwear	80.00 PHP	80.00 PHP
Recreation	200.00 PHP	200.00 PHP
Other		
Other		
Other		
Other		
Other		
Unplanned: Trycicle repair		500.00 PHP
Unplanned: trip to Iloilo City		500.00 PHP
Unplanned:		
Unplanned:		
TOTALS	***5,550.00 PHP***	***7,050.00 PHP***

PART 3: RESULTS	Estimated	Actual
1. TOTAL MONTHLY INCOME	***6,500.00 PHP***	***6,500.00 PHP***
2. TOTAL MONTHLY EXPENSE	***5,550.00 PHP***	***7,050.00 PHP***
3. VARIANCE *(1 - 2)* *(This is how much over, or under, your budget you are.)*	***950.00 PHP***	***-550.00 PHP***

If this number is positive, good work! Ikaw naga gasto sang mas manubo kay sa imo ginabatun. If it is a negative number, imo dapat ikonsiderar ang mag pamaagi para maka supot ukon ireprioritize ang imo nga galastuhan.

How to make a Savings Plan and Budget?

UNIVERSITY OF MANNHEIM

Figure 2.11: Toolkit materials: Brochure, part 2

Savings Plan

Para sa kada savings target ikaw maga desisyon kung pala ini short-term ukon long term goal. Para sa short-term goals ibutang kung pila ka bulan imo plano nga magsupot para malab-ot ina. Para sa long-term goals, ibutang kung pila katuig mo ini malab-ot. Ibutang man ang kabilogan nga kantidad nga imo kinahang lan para malab-ot ang imo goals kagang kantidad nga imo na nasupot. note: Ibutang ang kada savings goal sang kaisa lang.

SHORT-TERM GOALS	(1) Total Needed	(2) Already Saved	(3) = (1) - (2) Left to Save	(4) Months to Save	(5) = (3) / (4) Monthly Savings
Emergency Fund					- PHP
Retirement					- PHP
Children's Education					- PHP
Debt Repayment					- PHP
Computer					- PHP
Television / Electronics					- PHP
Furniture					- PHP
Home Appliance(s)					- PHP
Wedding / Special Event					- PHP
Capital to start/expand business					- PHP
Buy Land					- PHP
House Repair					- PHP
House Construction					- PHP
Vacation					- PHP
Other					- PHP
Other					- PHP
I. TOTAL SHORT TERM GOALS	- PHP	- PHP	- PHP		- PHP

LONG-TERM GOALS	(1) Total Needed	(2) Already Saved	(3) = (1) - (2) Left to save	(4) Years to Save	(5) = (3) / [(4)*12] Montly Savings
Emergency Fund					- PHP
Retirement					- PHP
Children's Education					- PHP
Debt Repayment					- PHP
Computer					- PHP
Television / Electronics					- PHP
Furniture					- PHP
Home Appliance(s)					- PHP
Wedding / Special Event					- PHP
Capital to start/expand business					- PHP
Buy Land					- PHP
House Repair					- PHP
House Construction					- PHP
Vacation					- PHP
Other					- PHP
Other					- PHP
II. TOTAL LONG TERM GOALS	- PHP	- PHP	- PHP		- PHP
III. TOTALS (I + II)					- PHP

I kumparar ang kantidad sang imo nasupot sa kada bulan. Kung ang kabilogan parehas lang ukon mas manaba sa imo sinuptan subong, ara kana sa target nga malab-ot mo ang imo savings goals. Kung mas damo, mangita ka sang pamaagi para mapataas ang imo sinuptan ukon bag-ohon ang imo nga goals.

Figure 2.12: Toolkit materials: Savings form

Household Budget

Ibutang ang imo estimated nga kita kada bulan kag ang mag galastuhan para ma intidihan kung ano ang dapat lainun nga imo pagahimuon para mangabuhi para lang sa budget nga maayo para sa imo.

PART 1: MONTHLY INCOME	Estimated	Actual
Person 1: Monthly income (full and part time job)		
Person 2: Monthly income (full and part time job)		
Pantawid Pamilyang Pilipino Program		
Remittances		
Other		
Other		
Other		
Other		
TOTAL	***- PHP***	***- PHP***

PART 2: MONTHLY EXPENSE	Estimated	Actual
Mortgage / Rent		
Loan Payment		
Health Insurance		
Education Fees		
Electric Bill		
Water Bill		
Groceries		
Phone Bill		
Transportation		
Gasoline		
House Repairs		
SAVINGS		
Clothing/footwear		
Recreation		
Other		
Other		
Other		
Other		
Other		
Unplanned: Trycicle repair		
Unplanned: trip to Iloilo City		
Unplanned:		
Unplanned:		
TOTALS	***- PHP***	***- PHP***

PART 3: RESULTS	Estimated	Actual
1. TOTAL MONTHLY INCOME	***- PHP***	***- PHP***
2. TOTAL MONTHLY EXPENSE	***- PHP***	***- PHP***
3. VARIANCE *(1 - 2)* *(This is how much over, or under, your budget you are.)*	***- PHP***	***0.00 PHP***

If this number is positive, good work! Ikaw naga gasto sang mas manubo kay sa imo ginabatun. If it is a negative number, imo dapat ikonsiderar ang mag pamaagi para maka supot ukon ireprioritze ang imo nga galastuhan.

Figure 2.13: Toolkit materials: Budget form

A.2 Randomization

Figure 2.14: Example barangay data collected by recruiters

Figure 2.15: Example barangay data collected by recruiters

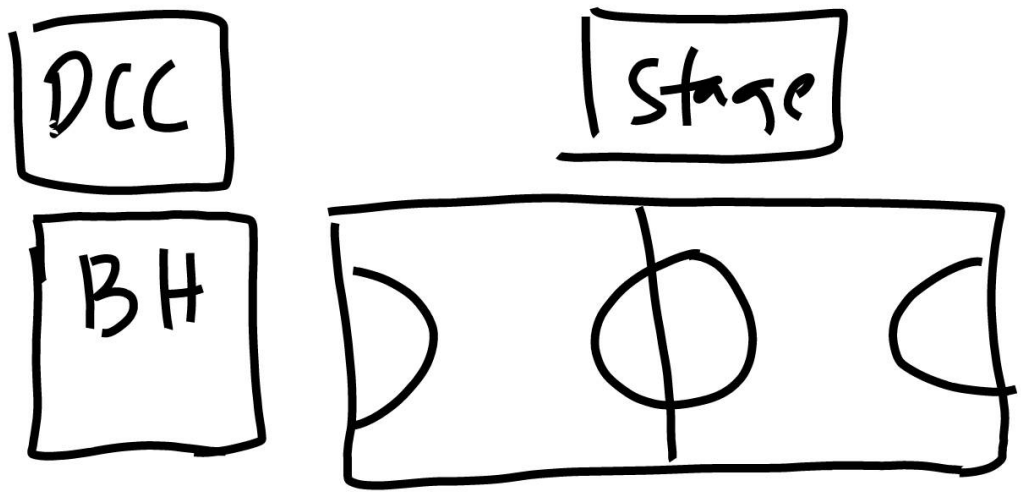


Figure 2.16: Example facilities sketch drawn using tablets by recruiters
DCC=day care center, BH=Barangay hall

A.3 Descriptive Statistics

Table 2.10 Summary statistics of control and injection points, original sample

	Control		Savings Training		Difference		N
	mean	sd	mean	sd	b	p	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Client Characteristics							
Age	43.8	(11.7)	42.2	(12.2)	1.62	(0.13)	498
HH water source	0.1	(0.3)	0.1	(0.3)	0.01	(0.62)	499
HH roof material	4.6	(1.2)	4.5	(1.3)	0.11	(0.32)	498
Electricity in HH	0.9	(0.3)	0.8	(0.4)	0.09	(0.00)***	498
Rooms used for sleeping	1.8	(0.8)	1.8	(0.8)	-0.04	(0.59)	498
HH ownership	0.9	(0.3)	0.9	(0.3)	0.01	(0.84)	497
Household size	5.2	(2.0)	5.4	(1.9)	-0.19	(0.27)	498
HH floor material	2.8	(6.3)	3.5	(10.5)	-0.70	(0.37)	498
Flush toilet in HH	1.0	(0.2)	0.8	(0.4)	0.13	(0.00)***	499
Regular income	0.6	(0.5)	0.6	(0.5)	-0.03	(0.47)	498
Daily consumption	345.6	(383.0)	336.7	(323.1)	8.92	(0.78)	498
HH daily consumption	1037.1	(769.9)	1004.2	(674.1)	32.94	(0.61)	499
Employment	4.1	(2.0)	4.0	(2.0)	0.06	(0.74)	492
Official position in village	0.1	(0.3)	0.1	(0.3)	0.01	(0.73)	498
Years of education	12.9	(4.9)	12.4	(4.7)	0.48	(0.27)	489
Group degree	2.4	(1.6)	2.4	(1.5)	-0.06	(0.67)	499
Center degree	0.33	(0.8)	0.36	(0.8)	-0.04	(0.60)	499
Panel B. Social Preferences							
Trust level in NWTF	6.1	(1.3)	6.2	(1.3)	-0.07	(0.54)	499
Trust in local money lender	3.8	(1.9)	3.8	(2.0)	0.09	(0.63)	499
Avoid taking risks	4.4	(2.6)	4.2	(2.6)	0.21	(0.37)	499
Avoid being betrayed	1.7	(1.5)	1.7	(1.5)	0.01	(0.93)	499
Avoid being taken advantage of	1.8	(1.7)	1.7	(1.5)	0.12	(0.40)	499
Revenge if suffers serious wrong	6.4	(1.3)	6.6	(1.1)	-0.13	(0.22)	499
Offends back if offended	6.4	(1.4)	6.4	(1.4)	-0.05	(0.71)	499
Sociability	4.3	(1.2)	4.2	(1.2)	0.04	(0.71)	499
Panel C. Reported Financial Characteristics							
Borrowed from MFI/Banks	6129.8	(3757.3)	5649.3	(3134.7)	480.42	(0.14)	444
Savings in MFI/Banks	1332.4	(1683.2)	1476.3	(4696.4)	-143.90	(0.75)	251
Bank distance	34.0	(49.0)	38.5	(35.6)	-4.45	(0.24)	499
Ever cashed a check	0.9	(0.3)	0.9	(0.3)	-0.00	(1.00)	499
Know what savings plan is	0.6	(0.5)	0.7	(0.5)	-0.08	(0.07)*	499
Made a savings plan	0.6	(0.5)	0.6	(0.5)	-0.00	(0.99)	326
Followed savings plan	0.8	(0.4)	0.9	(0.3)	-0.06	(0.19)	208
Panel D. NWTF Financial Characteristics							
AF savings balance	239.9	(329.0)	255.1	(290.4)	-15.17	(0.58)	499
Loan size	5301.6	(2486.1)	5443.8	(2313.2)	-142.10	(0.51)	499
Loan balance	2681.9	(2430.7)	2591.2	(1855.4)	90.69	(0.64)	499
Installment amount	237.6	(137.0)	235.1	(127.8)	2.48	(0.83)	499
Tenure	491.1	(442.9)	461.7	(434.0)	29.39	(0.52)	370
ICF balance	754.4	(917.7)	815.0	(903.4)	-60.63	(0.46)	499
Observations	243		256				499

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

[1] 1-no trust, 7-complete trust,

[2] 1-avoid, 7-fully prepared,

[3] 1-completely avoid, 7-do not avoid,

[4] 1-revenge, 7-no revenge,

[5] 1-offend, 7-not offend,

[6] Meets friends, family, neighbors: 1-never, 2-seldom, 3-monthly, 4-weekly, 5-daily.

Table 2.11 Descriptive Statistics, group peers (original sample)

	Control		Savings Training		Difference		N
	mean	sd	mean	sd	b	p	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AF savings balance	272.2	(431.2)	330.0	(698.8)	-57.72	(0.17)	774
Loan size	5678.3	(3214.4)	5674.4	(2733.6)	3.88	(0.99)	774
Installment amount	255.3	(201.8)	253.8	(149.8)	1.45	(0.91)	774
ICF balance	870.3	(1082.4)	872.3	(958.9)	-2.02	(0.98)	774
Loan cycle	3.1	(2.1)	3.1	(2.2)	-0.01	(0.95)	774
Principal amortization	230.6	(159.8)	228.8	(112.3)	1.72	(0.86)	774
Observations	387		387				774

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table 2.12 Descriptive Statistics, center peers (original sample)

	Control		Savings Training		Difference		N
	mean	sd	mean	sd	b	p	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AF savings balance	248.8	(363.3)	272.0	(345.7)	-23.19	(0.35)	833
Loan size	5385.3	(3003.0)	5546.3	(2649.1)	-161.01	(0.41)	833
Installment amount	231.6	(175.1)	257.8	(150.6)	-26.21	(0.02)**	833
ICF balance	862.6	(1212.5)	903.3	(1103.2)	-40.64	(0.61)	833
Loan cycle	3.0	(2.1)	3.1	(2.2)	-0.08	(0.60)	833
Principal amortization	217.9	(125.6)	226.7	(109.4)	-8.79	(0.28)	833
Observations	401		432				833

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

3 Contract Nonperformance Risk and Ambiguity in Insurance Markets

3.1 Introduction

The concept of probabilistic insurance was first introduced by Kahneman and Tversky (1979) as an insurance policy that, in the event of a loss, reimburses policyholders only with some probability, strictly less than one. Various circumstances, such as insolvency, discord about the losses covered, and payment delays, can cause total or partial contract nonperformance. Hence, from an insurance demand perspective, contract nonperformance risk is not restricted to situations where legally valid claims are not settled, but more generally applicable to all rejected claims that are perceived as valid by the policyholders (Doherty and Schlesinger, 1990). In this paper, we extend the probabilistic insurance model to allow for ambiguity in contract nonperformance probabilities. Furthermore, we test theoretical predictions derived from the extended model through a behavioral experiment conducted with rural villagers from the Philippines, focusing on the role of contract nonperformance risk and its ambiguity for insurance demand.

Even in the absence of ambiguity, contract nonperformance risk has significant implications for classic results of insurance demand theory. Doherty and Schlesinger (1990) show that risk-averse individuals do not fully insure at actuarially fair prices, that increasing risk aversion and decreasing loadings do not generally induce higher optimal insurance demand, and that optimal insurance demand is not necessarily a monotonic function of contract nonperformance risk. Hau (1999) reconsiders this problem for co-insurance policies in a multiple-state model, providing further explanation for the results of Doherty and Schlesinger (1990). Then, Mahul and Wright (2007, 2004) generalize their results to the case of partial indemnification under contract nonperformance. Subsequent empirical works by Zimmer, Gründl, Schade, and Glenzer (2016), Zimmer, Schade, and Gründl (2009), Herrero, Tomás, and Villar (2006), Albrecht and Maurer (2000), and Wakker, Thaler, and Tversky (1997) support the hypothesis of strong detrimental effects of contract nonperformance risk on insurance demand.

As opposed to contract nonperformance risk, where probabilities can be assigned to all possible outcomes, ambiguity relates to situations where the probabilities of outcomes are unknown (Epstein, 1999).[61] Ambiguity is of general relevance to eco-

[61] The literature uses different terms to refer to situations where probabilities are known or unknown. The word "risk," as opposed to "uncertainty," has been used in Knight (1921). The terms "unambiguous" and "ambiguous" were introduced by Ellsberg (1961). While Savage (1954) uses the terms "precise" and "vague," Gärdenfors and Sahlin (1982) differentiate between the levels of "epistemic

nomic decision making and resembles real world scenarios in that probabilities can be assigned to all possible outcomes only in very few cases. The presence of an aversion to ambiguity could be identified in the laboratory under different conditions (Einhorn and Hogarth, 1986; Sarin and Weber, 1993; Epstein, 1999; Chow and Sarin, 2001).

While some studies have examined the effect of ambiguous loss probabilities on insurance demand (Bajtelsmit, Coats, and Thistle, 2015; Gollier, 2014; Alary, Gollier, and Treich, 2013; Huang, Huang, and Tzeng, 2013; Hogarth and Kunreuther, 1989) as well as on the demand for self-insurance and self-protection (Snow, 2011), the ambiguity in contract nonperformance risk has so far been neglected in the theoretical and empirical literature. One exception is Bryan (2013), who studies the role of ambiguity aversion in the context of a new index insurance contract. While the setting differs from our paper along some important dimensions, his findings suggest that ambiguous probabilities of insurance payouts are relevant for insurance demand.[62] Our discussion of ambiguous probabilities is also distinct from approaches capturing divergent beliefs about the probability distribution of contract nonperformance risk between insurers and their customers (Cummins and Mahul, 2003). In such a setting contracting parties might hold different beliefs, but each of them perceives no ambiguity and hence ambiguity aversion plays no role.

In line with the preceding literature, our model predicts a decrease in insurance demand when introducing contract nonperformance risk, in particular for highly risk-averse individuals. Making the contract nonperformance probability ambiguous further decreases demand for ambiguity-averse individuals. This is because ambiguity aversion essentially makes people more pessimistic about contract nonperformance probabilities. We test these theoretical predictions through a behavioral experiment conducted with rural villagers from the Philippines. In this field lab experiment, we vary the presence of contract nonperformance risk, the existence of ambiguity, and the causes for nonperformance of insurance contracts and evaluate the effects on insurance demand. We find that introducing contract nonperformance risk (i.e., the insurer does not always pay a claim) and making contract nonperformance ambiguous decreases insurance demand. In the former case, we observe a significant 17.1 percentage points decrease in uptake resulting from increasing contract nonperformance risk from 0 to 10 percentage points. Then, relative to a known 10 percent chance of contract nonperformance, ambiguity about contract nonperformance risk leads to a further significant decrease in uptake of 14.5 percentage points. The effects of ambigu-

reliability" of a probability estimate to infer the amount of information available on all possible states and outcomes. We rely on the term "ambiguity" because it is common in the literature (Camerer and Weber, 1992).

[62] Bryan (2013) provides a theoretical framework and empirical evidence from Kenya and Malawi, showing that ambiguity-averse clients have a lower propensity to take up a new index insurance product. The setup relates to our case, because basis risk in index insurance (i.e., the probability that the index does not trigger a payout even when the insured faces a loss) might play a role similar to contract nonperformance risk. However, the setting differs from ours in important aspects. Besides the presence of both upside and downside risk, insurance decisions are combined with the adoption of a new production technology. Thus, theoretical predictions of insurance demand differ from ours.

ity appear little affected by experience and remain stable over time. We also consider the effect of different causes of contract nonperformance on insurance demand. This is because Kunreuther, Meyer, Zeckhauser, Slovic, Schwartz, Schade, Luce, Lippman, Krantz, Kahn, and Hogarth (2002) and Zimmer, Schade, and Gründl (2009) suggest that emotions play a role in insurance decisions and we suspect that varying the causes of contract nonperformance risk might in particular evoke different emotions. Low-numeracy and ambiguity-averse sub-samples show substantial and significant effects of framing the cause of contract nonperformance as the insurer's unwillingness as opposed to the insurer's inability to pay claims, but overall the effects are insignificant. In addition, framing does not significantly magnify the treatment effects of contract nonperformance and its ambiguity.

Aside from the experimental implementation in the Philippines, the pertinence of our setup extends to insurance markets in developed economies, where significant efforts are undertaken to disseminate information on insurers' reputations for servicing claims (Mahul and Wright, 2004), and consumer complaint statistics suggest that there is good reason to do so.[63] The negative effects of contract nonperformance risk on insurance demand are from a developed country perspective. Zimmer, Schade, and Gründl (2009), Herrero, Tomás, and Villar (2006), Albrecht and Maurer (2000), and Wakker, Thaler, and Tversky (1997) examine the effects on hypothetical willingness to pay, and Zimmer, Gründl, Schade, and Glenzer (2016) implement an incentive-compatible experiment with real monetary payoffs; these studies further testify to the strong detrimental effects of contract nonperformance risk on insurance demand. Thus, even in an environment with high levels of regulation, customer protection, and access to reliable information, perceived contract nonperformance risk is highly relevant to insurance demand.

Several factors magnify contract nonperformance risk and ambiguity in low-income insurance markets. Individuals face a broad variety of perils that are not easily quantifiable arising from geographic settings (e.g., natural disasters), lack of public infrastructure (e.g., risk of diseases due to lack of water provision), and economic (e.g., unemployment), political (e.g., lack of education), and legal (e.g., lack of contract enforcement) environments. Furthermore, perceptions of high contract nonperformance risk are fueled by limited trust in regulators and legal institutions to enforce contracts and supervise markets. This might explain why, despite significant efforts, insurance demand of low-income consumers remains low, even though the widespread use of risk transfer through insurance solutions holds potentially significant social welfare benefits. Claims considered eligible by the insured but not paid by the insurer emerge as a potential piece of the puzzle explaining the low insurance demand in developing countries. Recently, Liu and Myers (2016) provided theoretical evidence for significant

[63] Roughly 50 percent of all complaints reported to the U.S. state regulators in 2014 related to denials and delays of claims and unsatisfactory settlements, amounting to over 30,000 cases (National Association of Insurance Commissioners, 2016).

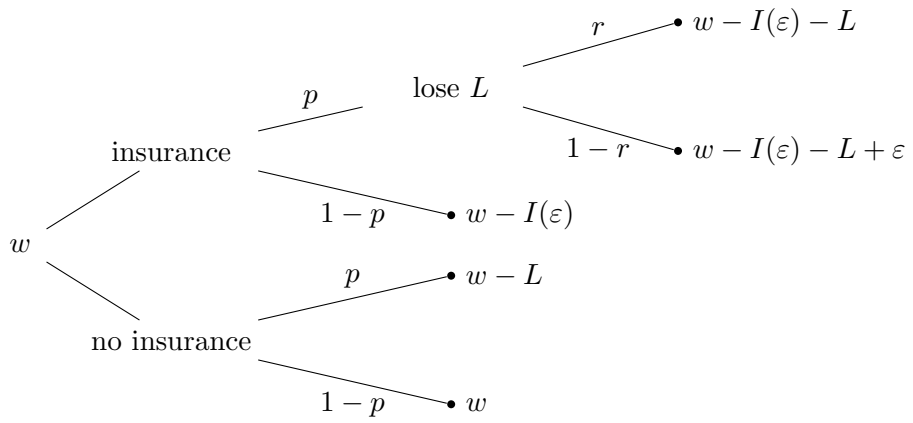


Figure 3.1: Decision Tree

reductions in insurance demand due to perceived insurer default in low-income insurance contexts, and Cole, Gine, Tobacman, Topalova, Townsend, and Vickery (2013) empirically reveal trust as an important market friction constraining demand.

The remainder of this paper proceeds as follows. In Section II, we present our theoretical framework and derive the hypotheses. The experimental design and field implementation, including sample characteristics, are explained in Section III. In Section IV, we discuss our empirical results, and Section V concludes the paper.

3.2 Model

3.2.1 Preliminaries

Below we formalize the characteristics of contract nonperformance risk and ambiguity and relate them to optimal insurance demand. To this end, we rely on the theoretical foundations of Doherty and Schlesinger (1990) for contract nonperformance risk and Alary, Gollier, and Treich (2013) and Klibanoff, Marinacci, and Mukerji (2005) for ambiguity and attitudes toward ambiguity. Figure 1 describes the process we consider here. We assume that a decision maker with initial wealth w has a positive probability p of suffering a loss $L > 0$, against which she can purchase insurance that pays ε, for some premium $I(\varepsilon)$.[64] In the case that the decision maker buys insurance and the loss does not occur (with probability $1 - p$), she is left with $w - I(\varepsilon)$.

In the case that the decision maker buys insurance and incurs a loss of L, there is a positive probability r that her claim is not reimbursed. In this case, she is left with $w - I(\varepsilon) - L$; otherwise, the insurer pays the claim and the decision maker gets $w - I(\varepsilon) - L + \varepsilon$. Thus, any decision maker evaluates the expected utility of the upper branch of the tree (i.e., insurance) against the lower branch (i.e., no insurance) shown in Figure 1.

[64] Note that we remain general in our definition of a premium and do not presume that the insurance is priced as being actuarially fair.

3.2.2 Demand for Probabilistic Insurance

Our benchmark probabilistic insurance setting is one with a known probability of contract nonperformance r. We use von Neumann–Morgenstern preferences with utility functions $u(.)$ that are continuous, monotonously increasing ($u'(.) > 0$) and three times continuously differentiable. We furthermore restrict our attention to risk-averse agents ($u''(.) < 0$) with positive prudence ($u'''(.) > 0$). The decision maker's expected utility under the insurance policy (EU_r) is defined as:

$$\begin{aligned} EU_r =& (1-p)u(w - I(\varepsilon)) \\ &+ p[(1-r)u(w - I(\varepsilon) - L + \varepsilon) \\ &+ ru(w - I(\varepsilon) - L)]. \end{aligned} \tag{3.1}$$

Our first area of interest is how insurance decisions change when we introduce a positive probability that the insurance fails to perform. Therefore, we compare the benchmark setup, with $r > 0$, to a situation with $r = 0$. Let $I_0(\varepsilon)$ be the premium for non-probabilistic insurance with $r = 0$. Note that when changing r and not adapting the premium accordingly (i.e., $I(\varepsilon) = I_0(\varepsilon)$) we change the expected payout and, hence, the loading factor $(1+\alpha) = \frac{I(\varepsilon)}{p(1-r)\varepsilon}$ of the insurance policy.[65] It is obvious that under these circumstances non-probabilistic insurance is always preferred because it features lower risk and a lower loading, ceteris paribus (the proof is presented in Appendix A).

The case becomes less trivial when the premium is discounted by the contract nonperformance probability, thus, keeping the loading factor constant. Let $I(\varepsilon)$ be the insurance premium for $r > 0$, while, again, $I_0(\varepsilon)$ denotes the premium for $r = 0$. Specifying $I(\varepsilon) = (1-r)I_0(\varepsilon)$ leads to a constant loading factor. The expected utility derived from probabilistic insurance becomes:

$$\begin{aligned} EU_r =& (1-p)u(w - I_0(1-r)) \\ &+ p[(1-r)u(w - I_0(1-r) - L + \varepsilon) \\ &+ ru(w - I_0(1-r) - L)], \end{aligned}$$

whereas the expected utility derived from non-probabilistic insurance is:

$$EU_0 = (1-p)u(w - I_0) + pu(w - I_0 - L + \varepsilon).$$

[65] The loading of the insurance policy is the difference between the premium and the expected payout; the loading factor is the ratio between the two. Thus, if the premium is higher than the expected payout, this implies a positive loading and a loading factor greater than one. When there is a positive probability of contract nonperformance, the expected payout decreases, which, ceteris paribus, influences the loading.

With a constant loading factor, introducing contract nonperformance risk decreases both, premium and expected payout. Whether the decrease in premium or the decrease in expected payout is larger, depends on the loading of the insurance. If it is actuarially unfair (i.e., a positive loading), clients might even profit from contract nonperformance risk in terms of expected wealth. On the other hand, this entails the risk of a default on insurance claims. These advantages and drawbacks are weighted differently by different types of agents and it is not possible to derive a monotonous relationship between optimal coverage and contract nonperformance risk in general (Doherty and Schlesinger, 1990). To provide more detailed results suited to our empirical setup, we focus on the case of a binary insurance decision with a given coverage level ε. We also define two measures of risk aversion for our formal discussion. One is the Arrow-Pratt measure of absolute risk aversion: $ARA(x_0) = -\frac{u''(x_0)}{u'(x_0)}$. The other is a more general measure based on normalized concavity (see Liu and Meyer, 2013): $C(x; x_0) = -\frac{u''(x)}{u'(x_0)}$. The latter is defined more broadly than absolute risk aversion. This measure is important in particular for Lemma 2, where the proof depends on risk aversion at multiple points. Lemma 1, in contrast, only depends on absolute risk aversion at a single point. For notational convenience, we furthermore define $x^\star = w - I_0 - L + \varepsilon$. The following lemmas can be shown to hold (see proof in Appendix A):

Lemma 1. For each loading factor $(1 + \alpha) \in [1, \frac{1}{p}]$ there exist agents with sufficiently high absolute risk aversion $ARA(x^\star)$ such that $EU_0 > EU_r$. In particular: $ARA(x^\star) > \frac{2\alpha\varepsilon}{(\varepsilon - rI_0)^2} \Rightarrow EU_0 > EU_r$.

Lemma 2. For each loading factor $(1+\alpha) > 1$ there exist agents with sufficiently low risk aversion $C(x, x^\star)$ such that $EU_r > EU_0$. In particular:
$pr\varepsilon\alpha > a_4 C(c_4, x^\star) + a_1 C(c_1, x^\star) + a_2 C(c_2, x^\star) + a_3' C(c_3', x^\star) \Rightarrow EU_0 < EU_r$,
where a_4, a_1, a_2, a_3' are bounded constants > 0
and $c_4, c_1, c_2, c_3' \in (w - L - (1 - r)I_0, w)$.

In binary uptake decisions, decreasing the utility derived by a product implies (weakly) lower demand and vice versa. The above lemmas hence shed light on the circumstances under which demand reductions can be expected when introducing contract nonperformance risk. For actuarially fair insurance (i.e., $\alpha = 0$), our setting simplifies to a similar case in Doherty and Schlesinger (1990). Here, Lemma 2 is rendered irrelevant, and the condition for Lemma 1 always holds, in the sense that all risk-averse agents prefer non-probabilistic insurance over probabilistic insurance. Therefore, similarly to Doherty and Schlesinger (1990), we expect lower insurance demand for probabilistic insurance. Given actuarially unfair premiums, Lemma 2 presumes a weak demand-increasing effect of contract nonperformance risk for agents with low risk aversion. However, agents with low risk aversion are more sensitive to

loadings, exhibiting a decreasing insurance-demand pattern with increasing loadings (Mossin, 1968; Smith, 1968), and are hence less likely to purchase insurance irrespective of the presence of contract nonperformance risk. Overall effects ultimately hinge on the shape of the utility function. We therefore run simulations over a range of loading and risk aversion parameters. These simulations clearly predict a decrease in demand when contract nonperformance risk is introduced.[66] Thus, we expect that the share of the population actually switching to buying probabilistic insurance is relatively small and formulate the first hypothesis accordingly:

Hypothesis 1. Contract nonperformance risk reduces insurance demand ($H1$).

3.2.3 Demand for Ambiguous Probabilistic Insurance

Next, we focus on the effect of ambiguity of contract nonperformance risk on insurance demand (i.e., r is unknown). We redefine contract nonperformance risk as the ambiguous probability $r(\gamma)$, depending on the unknown parameter γ. The ambiguity is defined as a probability distribution for γ with discrete support $\{1, \ldots, n\}$. Let $q(\gamma)$ denote the subjective probability that the true value of the parameter is γ, with $\sum_{\gamma=1}^{n} q(\gamma) = 1$. We assume that ambiguity is mean preserving (i.e., $\sum_{\gamma=1}^{n} q(\gamma) r(\gamma) = r$). In the case that γ is known to be $\gamma^\star$ (i.e., $q(\gamma^\star) = 1$), we define the expected utility derived from probabilistic insurance as follows:

$$\begin{aligned} EU_{r(\gamma^\star)} =& (1-p)u(w - I(\varepsilon)) \\ &+ p[(1 - r(\gamma^\star))u(w - I(\varepsilon) - L + \varepsilon) \\ &+ r(\gamma^\star)u(w - I(\varepsilon) - L)]. \end{aligned}$$

Following the smooth ambiguity approach of Klibanoff, Marinacci, and Mukerji (2005), we model ambiguity aversion using an increasing and concave valuation function Φ for the expected utility derived from each state of γ. Thus, the decision maker's expected utility derived from ambiguous probabilistic insurance corresponds to:

$$\Phi^{-1}\left(\mathbb{E}_\gamma \Phi(EU_{r(\gamma)})\right) = \Phi^{-1}\left(\sum_{\gamma=1}^{n} q(\gamma)\Phi(EU_{r(\gamma)})\right).$$

An ambiguity-neutral agent uses a linear valuation function, essentially using EU_r from Equation (3.1) and replacing r with $\mathbb{E}_\gamma r(\gamma)$. Concavity of Φ expresses ambiguity aversion, that is, an aversion to mean-preserving spreads in the random probability

[66] We simulate decision makers exhibiting constant relative risk aversion (CRRA)-type utility functions over a range of loading and risk aversion parameters (see Appendix B for details). The results are clear-cut in that the set of parameter combinations predicted to take up probabilistic insurance is a subset of the parameter combinations predicted to take up non-probabilistic insurance.

of contract nonperformance $r(\gamma)$. Ambiguity-averse agents assign higher weights to states of γ that are associated with low utility. In our case, this would lead to an overweighting of contract nonperformance probabilities. For ambiguity-loving agents, Φ is convex, and higher weights are assigned to favorable (i.e., high utility) probabilities, leading to an underweighting of contract nonperformance probabilities. Using the above general formula for ambiguity preferences and plugging in the expected utility definition from Equation (3.1), we can see that individuals maximize the following expression when deciding about insurance uptake:

$$\begin{aligned} \mathbb{E}_\gamma \Phi(EU_{r(\gamma)}) = & \mathbb{E}_\gamma \Phi[(1-p)u(w-I(\varepsilon)) \\ & + p[(1-r(\gamma))u(w-I(\varepsilon)-L+\varepsilon) \\ & + r(\gamma)u(w-I(\varepsilon)-L)]]. \end{aligned} \tag{3.2}$$

Under this setting, the following Lemma holds (see proof in Appendix A):

Lemma 3. For ambiguity-averse (-loving) agents, the marginal willingness to pay for additional insurance is strictly lower (higher) at every coverage point after introducing mean-preserving ambiguity over contract nonperformance risk.

This result on the marginal willingness to pay applies to both continuous and binary insurance decisions. It implies that the optimal coverage level decreases (increases) for ambiguity-averse (-loving) individuals once ambiguity with respect to contract nonperformance risk is introduced. It also implies that for binary insurance decisions, insurance with known contract nonperformance risk is always preferred by ambiguity-averse agents, as opposed to insurance with ambiguous contract nonperformance risk. This, in turn, implies that demand for non-ambiguous probabilistic insurance should be higher for ambiguity-averse agents. The result is in line with Mukerji and Tallon (2001) who show that risk sharing opportunities on financial markets that involve ambiguity can be less attractive to ambiguity-averse agents.

There are arguments as to why the effect of ambiguity-averse, as opposed to ambiguity-neutral or -loving preferences, should dominate. Based on a sample of 30 countries, Vieider, Lefebvre, Bouchouicha, Chmura, Hakimov, Krawczyk, and Martinsson (2015) show that individuals seem to be, on average, averse to ambiguity. In addition, risk aversion seems to be positively correlated with ambiguity aversion, and only risk-averse individuals are potential clients, which could be affected by ambiguous contract nonperformance risk. Thus, we state the second hypothesis as follows.

Hypothesis 2. Ambiguity about contract nonperformance probabilities reduces insurance demand ($H2$).

It is possible to conduct further comparative statics beyond the introduction of ambiguity. For example, it might be interesting to show the effect of changing the extent of ambiguity or changing ambiguity preferences. In Appendix A, we derive the central condition for the development of marginal willingness to pay when such changes happen. This condition generally holds in our setting of mean-preserving ambiguity and smooth ambiguity aversion as proposed by Klibanoff, Marinacci, and Mukerji (2005). In particular, we derive that any change in ambiguity aversion or the extend of ambiguity leading to an increase in the correlation between $r(\gamma)$ and $\Phi'(EU_{r(\gamma)})$ will decrease the marginal willingness to pay and vice versa. The effect on the marginal willingness to pay directly translates into changes of optimal coverage in both continuous and binary insurance decisions.

3.3 Experimental Design

3.3.1 Insurance Experiment

We implement a field lab experiment where subjects decide whether to purchase probabilistic insurance in a risky environment. Participants received an initial endowment W, and could opt to buy insurance at cost I. Once the insurance decision was made, participants experienced a loss with probability p_{Loss}. Participants who bought insurance could claim a payment from the insurer, contingent on having experienced a loss. Whether the insurer paid the claim was determined by another random draw, with probability p_{Def} for the contract not performing. All random draws are implemented using opaque bags, each containing 10 balls, some of which were orange and the rest white. In the first draw, orange balls represented a loss of L, while in the second draw (i.e., only in the case of an insurance claim), orange balls indicated nonperformance of the insurance contract. Hence, the mixtures of orange and white balls determine the loss probability p_{Loss} and the contract nonperformance probability p_{Def}. Participants were grouped in sessions of six participants. They were not allowed to exchange information or talk amongst themselves during the first round of the experiment. This procedure aims to avoid peer effects on a participant's initial belief about probabilities. Participants were then allowed to communicate with other members for the remaining rounds, such that they could learn from their peers' experiences.

An additional lottery choice task was played prior to the insurance experiment in order to classify each participant in terms of risk and ambiguity preferences. Here, participants were presented with pairs of monetary lotteries, with one to four outcomes, of which they had to choose one (Glöckner, 2009). The outcome values varied between -250 and 250 Philippine pesos (PHP), and participants played up to 122 lotteries, depending on their response time.[67] Here, we use lotteries following Ellsberg

[67]Lotteries were divided into four blocks, and each block had a maximum amount of time the participant could spend on it. Once the time limit was reached, the next block was presented. The lotteries were assigned randomly within each block.

Table 3.1 Experimental Treatments

	Treatments				
	C	T_{NoDef}	T_{Amb}	T_{Fr}	T_{Amb-Fr}
Panel A: Universal parameters					
Initial endowment (in PHP)	210	210	210	210	210
Loss (in PHP)	150	150	150	150	150
p_{Loss}	0.3	0.3	0.3	0.3	0.3
Panel B: Treatment characteristics					
Ambiguous contract nonperformance probability	No	No	Yes	No	Yes
p_{Def}	0.1	0	0.1	0.1	0.1
Framing	Neutral	Neutral	Neutral	Negative	Negative
Insurance premium (in PHP)	50	60	50	50	50
Panel C: Participants and sessions					
Number of subjects	144	162	168	174	168
Number of sessions	24	27	28	29	28

(1961), from which we classify individuals as ambiguity-averse, ambiguity-neutral, or ambiguity-loving (details in Section 3.4.3). Participants earned the average of four randomly drawn gambles, two from the gain domain and two from the loss domain.

3.3.2 Treatments

A complete overview of all treatments is presented in Table 3.1. Every participant was provided with an initial endowment of PHP 210. Under the benchmark control treatment C, both the 30 percent probability of losing PHP 150 and the 10 percent probability of experiencing contract nonperformance were known to participants. The variation in contract nonperformance probability introduced in treatment T_{NoDef} (i.e., the elimination of the 10 percent contract nonperformance risk) allows for an inference about hypothesis $H1$. The elimination of contract nonperformance risk is accounted for in terms of a higher premium of PHP 60 for treatment T_{NoDef}, as opposed to PHP 50 for all other treatments.[68]

Comparing treatment T_{Amb} with control treatment C allows us to identify the effect of ambiguity on insurance demand and, thus, to test hypothesis $H2$. Here, the contract nonperformance probability was ambiguous to the participants. In order

[68] Because the actual price of an insurance policy is its loading, we added a 30 percent markup to all insurance treatments. To make the resulting premium values manageable in our experimental setting using artificial PHP bills, we rounded premium values to even amounts, resulting in actual loadings of 25 percent and 33 percent for the T_{NoDef} treatment. Given that rounding necessarily leads to different loadings, we made sure that the loading for insurance without contract nonperformance risk was at least as high as that with contract nonperformance risk. This implies that our results are lower bounds of the effect of contract nonperformance risk on insurance demand. In general, insurance premiums commonly include risk and cost loadings, which are often particularly high in low-income insurance markets (Biener, 2013).

to provide the participants with an initial signal of probabilities, to form their prior beliefs, the balls in the bags of the ambiguous treatments (T_{Amb} and T_{Amb-Fr}) were selected blindly from a big bag containing 100 balls, during the instructions by one research assistant. Of the 100 balls in the big bag, 10 were orange and 90 were white. One of the participants was invited to count the balls in the bag blindly to make sure that 10 balls were placed in the ambiguous bags. Our setting with multiple rounds allows us to analyze the effects over time, which is especially interesting under ambiguity when experience about losses and contract nonperformance can be shared within the peer network. In particular, one might expect ambiguity to decrease over time, once sufficient learning has taken place.

We employ treatments T_{Fr} and T_{Amb-Fr} to make inferences about potential framing effects. The standard framing of contract nonperformance is that the insurer cannot pay the claim. This framing is neutral, and was implemented in the control treatment C, as well as in T_{NoDef} and T_{Amb}. The negative framing in treatments T_{Fr} and T_{Amb-Fr} presents the source of potential contract nonperformance as the insurer's unwillingness to pay (e.g., owing to policy exclusions). Thus, not paying claims is at the discretion of the insurer in the negative framing, whereas the insurer has no discretion under the neutral framing.

3.3.3 Procedures and Sample Characteristics

We conducted a field lab experiment in the Philippine provinces of Iloilo and Guimaras in October and November 2013. Four treatments and one control setting of this experiment were randomized across four sessions, played in each of a total of 42 villages.[69] This random assignment was implemented such that distinct treatments were played in each village in order to reduce the likelihood of correlations between village-level covariates and treatment assignment or order. Furthermore, we applied a two-stage randomization procedure. In the first stage, rural villages were selected randomly.[70] In the second stage, individuals aged between 18 and 65 years were selected randomly from complete household lists, as provided by village officials. The recruitment procedure resulted in 24 participants per village, forming four groups (or sessions) of six participants.

The structure of an experimental session was as follows. First, a pre-experimental survey was conducted to gather individual and household characteristics, followed by the lottery choice task to measure risk and ambiguity attitudes. Next, the insurance experiment began with an instructional part. Detailed explanations were provided by one instructor, with the help of visual aids. We ensured participants' understanding

[69] One additional treatment, unrelated to ambiguous contract nonperformance risk, was conducted. Thus, six variants were randomized altogether. The omitted treatment is irrelevant to the research questions analyzed in this paper, but more details are available upon request.

[70] Villages from municipalities with high income (top two income classes out of five) were excluded from the study; income classes are defined by the Department of Finance Republic of the Philippines (2008).

by conducting a test questionnaire. Only when all questions of the test questionnaire could be answered correctly was a participant allowed to continue. Each participant played six rounds of the insurance experiment, and the initial endowment was restored at the start of each round. In order to gather participants' beliefs about contract nonperformance probabilities, a brief survey was implemented at the beginning of rounds 1, 2, 4, and 6 (i.e., before the insurance decisions). Here, participants provided their beliefs about the number of orange balls in the respective bag, and stated the minimum and maximum numbers of orange balls they believed were in the bag. The first survey at the beginning of round 1 provides participants' beliefs of the contract nonperformance probabilities in the absence of any peer or network effects.

A post-experimental survey was conducted to gather data on mathematical and numerical capabilities, past real-life loss experiences, insurance ownership, and other beliefs. Finally, participants were paid one of the six rounds played in the insurance experiment, plus the proceeds from the lottery choice task and a show-up fee, in real PHP. The round of the insurance experiment that was paid out was selected randomly by the participant from another opaque bag, with six numbered balls representing the six rounds of the experiment. The average earnings from the experiment were PHP 156.5 in the insurance experiment, and PHP 13.5 in the lottery choice task. Additionally, participants received a show-up fee of PHP 100,[71] amounting to PHP 270, or approximately USD 6.2—a substantial amount for the average participant.[72]

In total, we conducted 136 sessions with 816 participants in 42 villages. Table 3.2 presents the mean values of individual characteristics and equality of means tests by treatment group. The results show that individual characteristics are balanced throughout the treatments (i.e., versus the control treatment C) and that few variables exhibit significant differences. Treatments T_{NoDef} and T_{Fr} have slightly higher proportions of female participants. The proportion of employed participants in the T_{Fr} treatment is a bit lower than in the control treatment C. The mean risk aversion score is larger under treatment T_{Amb-Fr} than it is in the control treatment C. However, overall, it is apparent that the sample is balanced across treatment groups, with only one variable not balanced in treatment T_{Amb-Fr} versus the control treatment C, and two variables not balanced in treatments T_{NoDef} and T_{Fr}. All variables were balanced in treatment T_{Amb}.

As a further balancing check, we implement a multivariate analysis of variance to test for differences between means across treatment groups on each of the variables presented in the summary statistics. The last column of Table 3.2 shows the p-values associated with the F-statistic based on Wilks' lambda. We do not reject the null

[71] The show-up fee was increased by PHP 20 if the participant was the head of the household.

[72] The official exchange rate was PHP 43.3 to USD 1 in early October 2013. Note that the stakes of PHP 210 in the experiment are close to the minimum daily wage of PHP 250 in the agricultural sector in the Iloilo province, as of October 2013 (Republic of the Philippines, 2008), which few participants are able to earn. The median daily earnings of those participants receiving a daily wage (12 percent of total sample) is only PHP 180.

Table 3.2 Descriptive Statistics

	C	T_{NoDef}	T_{Amb}	T_{Fr}	T_{Amb-Fr}	Equality of Means (p-value)[d]
Panel A: Socio-demographic characteristics						
Age	39.86	38.80	38.96	38.76	39.86	0.745
(*in years*)	(10.50)	(10.08)	(9.966)	(10.94)	(9.755)	
Gender	0.741	0.840*	0.810	0.833*	0.786	0.185
(1 = *female*)	(0.439)	(0.368)	(0.394)	(0.374)	(0.412)	
Financial responsibility[a]	0.958	0.994**	0.964	0.977	0.970	0.34
(1 = *yes*)	(0.201)	(0.0786)	(0.186)	(0.150)	(0.170)	
Married or in partnership	0.903	0.889	0.869	0.902	0.899	0.848
(1 = *yes*)	(0.297)	(0.315)	(0.338)	(0.298)	(0.302)	
Education	9.573	9.580	9.911	9.552	9.381	0.402
(*in years*)	(2.642)	(2.472)	(2.476)	(2.210)	(2.619)	
Employment status	0.465	0.358	0.387	0.351*	0.429	0.187
(1 = *employed*)	(0.501)	(0.481)	(0.488)	(0.479)	(0.496)	
Regular income	0.270	0.295	0.282	0.250	0.275	0.985
(1 = *yes*)	(0.447)	(0.460)	(0.453)	(0.436)	(0.449)	
Seasonal income	0.716	0.787	0.732	0.653	0.637	0.3
(1 = *yes*)	(0.454)	(0.413)	(0.446)	(0.479)	(0.484)	
Owns land	0.133	0.142	0.113	0.167	0.161	0.635
(1 = *yes*)	(0.341)	(0.350)	(0.318)	(0.374)	(0.368)	
Owned dwelling	0.799	0.895*	0.845	0.839	0.851	0.232
(1 = *yes*)	(0.402)	(0.307)	(0.363)	(0.369)	(0.357)	
Reduced meals in last month	0.273	0.210	0.214	0.218	0.244	0.666
(1 = *yes*)	(0.447)	(0.408)	(0.412)	(0.414)	(0.431)	
Panel B: Mental capabilities, risk and ambiguity aversion						
Mathematical ability score	6.660	6.654	6.661	6.655	6.494	0.873
(0 *min* 8 *max*)	(1.698)	(1.815)	(1.630)	(1.612)	(1.754)	
Numerical ability score	9.236	9.142	9.119	9.040	8.994	0.961
(0 *min* 16 *max*)	(3.084)	(2.988)	(2.999)	(2.930)	(2.958)	
Risk aversion[b]	5.493	5.354	5.583	5.434	5.820*	0.197
(1 *min* 7 *max*)	(1.840)	(1.935)	(1.859)	(1.989)	(1.744)	
Ambiguity aversion[c]	1.763	1.734	1.774	1.756	1.776	0.989
(1 *min* 3 *max*)	(0.711)	(0.767)	(0.786)	(0.768)	(0.799)	
Panel C: Loss and insurance experience						
Insurance ownership	0.528	0.580	0.577	0.557	0.542	0.863
(1 = *yes*)	(0.501)	(0.495)	(0.495)	(0.498)	(0.500)	
Illness or accident shocks	0.625	0.627	0.631	0.590	0.563	0.654
(1 = *yes*)	(0.486)	(0.485)	(0.484)	(0.493)	(0.498)	
Weather or livestock shocks	0.451	0.391	0.423	0.439	0.425	0.861
(1 = *yes*)	(0.499)	(0.490)	(0.495)	(0.498)	(0.496)	
Observations	144	162	168	174	168	

Notes: Mean coefficients reported; standard errors in parentheses. [a]Indicator variable in which 1 indicates responsibility for financial decision-making in the household. [b]Scores based on survey measure, "I avoid risky things," on a seven-point Likert scale: 1-strongly disagree, 7-strongly agree. [c]Ambiguity classification: 1-ambiguity averse, 2-ambiguity neutral, 3-ambiguity loving. [d]p-values for multivariate equality of means test based on Wilks' lambda test statistics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ indicate significance levels for equality of means t-tests of all treatments versus the control treatment C.

hypothesis that the means across the groups are all equal. Thus, we conclude that the participants' characteristics shown in Table 3.2 are balanced across treatments.

3.4 Experimental Results

3.4.1 Main Results

We show the average uptake across treatments in Figure 3.2. Appendix Table 3.7 mirrors the figure using estimates from linear probability and probit models, and shows that the results are robust to the inclusion of control variables.[73] In all our analyses, we account for potential correlation within our unit of randomization (i.e., the experimental session) via clustered standard errors.

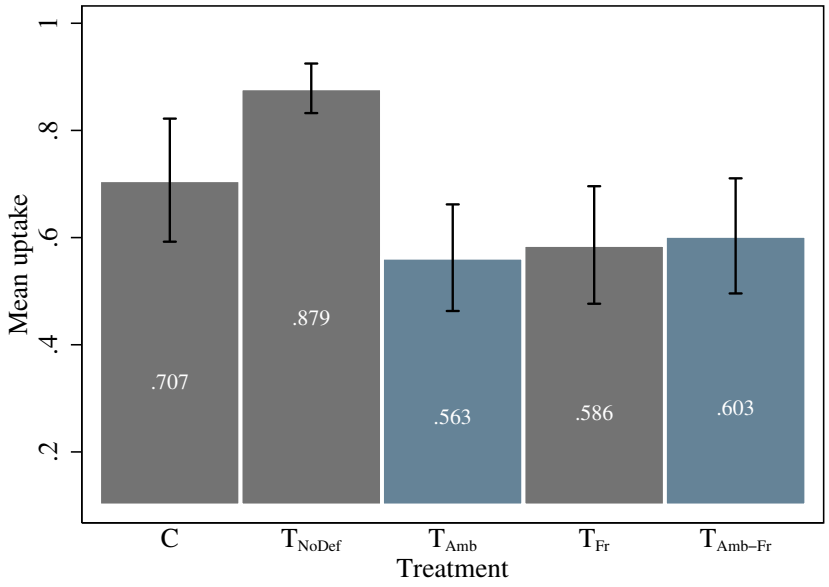


Figure 3.2: Average Insurance Uptake by Treatment

Notes: The bars represent the mean proportion of individuals taking up insurance for the different treatment groups. Error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

The discussion of results is structured along the hypotheses defined in Section 3.2. Eliminating contract nonperformance risk in treatment T_{NoDef}, that is, setting $p_{Def} = 0$ instead of $p_{Def} = 0.1$, results in a significant increase in insurance uptake of 17.1 (p=0.007) percentage points. For all specifications, the treatment dummy is significant at the 1 percent level. Hence, the risk that the insurance contract might

[73]The added covariates are age, gender, financial responsibility, marital status, education, employment, owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. We also include round controls and the additional variable *Typhoon*, which takes a value of one if the subject was exposed to typhoon Haiyan, and zero otherwise. Typhoon Haiyan passed by the Iloilo Province halfway through our experiment, in November 2013. Our main effects are consistent before and after the typhoon.

not perform is clearly unattractive to participants, on average, even if they are compensated by lower premiums. This is in line with $H1$ as well as the findings of prior studies (Zimmer, Gründl, Schade, and Glenzer, 2016; Zimmer, Schade, and Gründl, 2009; Herrero, Tomás, and Villar, 2006; Albrecht and Maurer, 2000; Wakker, Thaler, and Tversky, 1997).

Result 1. The presence of contract nonperformance risk in an insurance contract considerably decreases uptake, even when premiums are adjusted for the potential default on valid claims on an actuarially fair basis.

When introducing ambiguity in the probability of contract nonperformance in treatment T_{Amb}, insurance uptake is reduced by 14.5 percentage points (p=0.062). For all specifications, the treatment dummy is significant at least at the 10 percent level. The results suggest that the presence of ambiguity in contract nonperformance risk decreases insurance uptake compared to when the nonperformance risk is known. In particular, the magnitude of the effects indicate that the reduction of insurance uptake induced by contract nonperformance risk is almost twice as strong in the presence of ambiguity, thus providing evidence for hypothesis $H2$.

Result 2. The reduction in insurance uptake induced by the presence of contract nonperformance risk is amplified significantly if the nonperformance probability of the insurance contract is ambiguous.

Framing the insurer's contract nonperformance risk negatively rather than neutrally, as represented by treatments T_{Fr}, leads to a 12.1 percentage point reduction (p=0.134) in insurance uptake. This is almost equal to the effect of ambiguity. Thus, ambiguity about contract nonperformance risk and our negative frame seem to have similar negative effects on insurance uptake. However, the effects are not additive in that introducing ambiguity about contract nonperformance risk to the negatively framed setting in T_{Amb-Fr} does not reduce uptake further with a treatment effect of 10.4 percentage points (p=0.193). However, because the treatment effects for T_{Fr} and T_{Amb-Fr} are not statistically significant, we are careful about deriving strong implications from the observed results.

3.4.2 Numeracy

Here, we analyze treatment effects, conditional on subjects' numeracy levels, because a minimum level of numeracy skills might be useful to adequately understanding the experiment and, thus, to reacting to the treatment manipulations. In order to assess subjects' levels of numeracy, we use a survey on mathematical ability and numeracy (Weller, Dieckmann, Tusler, Mertz, Burns, and Peters, 2013). We construct a total

numeracy score by joining the results from the mathematical ability and numeracy scales. The total score ranges from 0 (i.e., no correct answer) to 16 (i.e., all answers correct). High-numeracy subjects are those with a total score of 10 or higher, and low-numeracy subjects are those with a score of 9 or less. Table 3.3 shows average treatment effects by numeracy level. Columns 1 and 2 show the high-numeracy subsample, and Columns 3 and 4 show the low-numeracy subsample. High numeracy subjects seem to exhibit stronger treatment effects. Eliminating contract nonperformance risk in treatment T_{NoDef} increases insurance demand by 20.8 percentage points (p=0.003) for the high-numeracy sample, but only 13.8 percentage points (p=0.063) in the low-numeracy sample.

Ambiguity about the probability of contract nonperformance, as implemented in T_{Amb}, leads to a reduction of 18.5 percentage points (p=0.035) in insurance uptake for the high-numeracy sample, which is 7 percentage points more than that of the low-numeracy sample (p=0.361). The significance of the average ambiguity treatment effect disappears in the low-numeracy sample (p=0.187). This could suggest that some level of sophistication is needed in order to recognize and avoid ambiguity in our setting (see discussion in Chew and Sagi (2008)).

Result 4. Participants with higher numeracy skills exhibit stronger treatment effects and react more to contract nonperformance ambiguity.

Table 3.3 Average Treatment Effects by Numeracy

	High numeracy		Low numeracy	
	(1)	(2)	(3)	(4)
T_{NoDef}	0.208***	0.227***	0.138*	0.145*
	(0.0699)	(0.0696)	(0.0734)	(0.0735)
T_{Amb}	-0.185**	-0.166*	-0.113	-0.0982
	(0.0868)	(0.0858)	(0.0851)	(0.0865)
T_{Fr}	-0.0978	-0.0889	-0.141	-0.122
	(0.0917)	(0.0872)	(0.0877)	(0.0847)
T_{Amb-Fr}	-0.180*	-0.177*	-0.0421	-0.0364
	(0.0958)	(0.0901)	(0.0788)	(0.0788)
Constant	0.691***	0.658*	0.721***	0.558**
	(0.0670)	(0.394)	(0.0627)	(0.218)
Observations	2,238	2,232	2,658	2,640
R-squared	0.096	0.128	0.044	0.070
F test	21.23	6.892	5.730	2.633
Covariates	No	Yes	No	Yes

Notes: Linear probability models are used with the dependent variable set to 1 if the subject takes up insurance. Standard errors (reported in parentheses) are corrected for clustering at the session level. Covariates are age, gender, financial responsibility, marital status, education, employment, owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance levels of 10, 5, and 1 percent, respectively.

Ambiguity towards the negatively framed probability of contract nonperformance, as implemented in T_{Amb-Fr}, reduces insurance uptake by 18 percentage points for the high-numeracy sample (p=0.062). However, in the low-numeracy sample, the reduction is statistically insignificant with an effect size of 4.2 percentage points (p=0.594). Our estimates also suggest that framing plays no role in insurance demand for individuals with high numeracy skills. As shown in Table 3.3, the effects of T_{Amb} and T_{Amb-Fr} on subjects with high numeracy are similar, leading to the conclusion that the reduction of insurance uptake for the high-numeracy subgroup is driven by the ambiguity towards the probability of contract nonperformance, and not by framing. These results make intuitive sense, because framing of the treatment provides no additional information on the probability of contract nonperformance, which is the element we expect rational subjects to use when assessing their insurance choices.

3.4.3 Ambiguity and Risk Aversion

Following our theoretical model, individual ambiguity aversion should be the major factor explaining the sign and strength of the ambiguity effect. Therefore, we exploit the fact that we can classify participants with respect to ambiguity aversion, given their behavior in the lottery choice task prior to the insurance experiment. In particular, we use two Ellsberg (1961) lottery choices to classify individuals as ambiguity-averse, ambiguity-neutral, or ambiguity-loving.[74] Table 3.4 presents average treatment effects for ambiguity-averse (Columns 1 and 2), ambiguity-neutral (Columns 3 and 4), and ambiguity-loving subjects (Columns 5 and 6).

The results for ambiguity-averse subjects are in line with our theoretical predictions. There is a strong reduction in insurance demand when the probability of contract nonperformance is ambiguous, in both the T_{Amb} and the T_{Amb-Fr} treatments. When ambiguity-averse subjects are confronted with the T_{Amb} treatment, insurance demand is reduced by 18.2 percentage points (p=0.048), and when the negative framing condition is added to the ambiguous contract nonperformance risk, insurance demand falls by 22 percentage points (p=0.02). For ambiguity-neutral and -loving subjects, all effects of contract nonperformance ambiguity are smaller and statistically insignificant. However, even for ambiguity-loving subjects, the effects of ambiguity have a negative sign, even though we would expect a positive effect on demand in this subsample. Such patterns could be explained by an imprecise classification of participants. In addition, we cannot reject the hypothesis that the effects are, in fact, positive, given the limited precision in the ambiguity-loving subsample. Overall, the pattern of stronger reductions in demand for participants who are more ambiguity-averse is in line with our theoretical predictions.

[74] Those choices are between lotteries with known and unknown content. Participants who chose the known content twice were classified as ambiguity-averse, those with one choice for known content were classified as ambiguity-neutral, and those choosing unknown content twice were classified as ambiguity-loving.

Table 3.4 Average Treatment Effects by Ambiguity Aversion

	Ambiguity averse		Ambiguity neutral		Ambiguity loving	
	(1)	(2)	(3)	(4)	(5)	(6)
T_{NoDef}	0.166**	0.135*	0.200**	0.217**	0.162	0.106
	(0.0677)	(0.0694)	(0.0921)	(0.0960)	(0.131)	(0.123)
T_{Amb}	-0.182**	-0.184**	-0.155	-0.136	-0.0861	-0.0907
	(0.0909)	(0.0872)	(0.103)	(0.100)	(0.151)	(0.132)
T_{Fr}	-0.192**	-0.191**	-0.0460	-0.0281	-0.127	-0.164
	(0.0897)	(0.0851)	(0.110)	(0.104)	(0.156)	(0.143)
T_{Amb-Fr}	-0.220**	-0.229**	-0.0296	-0.0237	-0.0762	-0.104
	(0.0934)	(0.0891)	(0.0987)	(0.0986)	(0.156)	(0.133)
Constant	0.747***	0.822***	0.658***	0.506**	0.738***	0.931**
	(0.0638)	(0.233)	(0.0791)	(0.253)	(0.127)	(0.381)
Observations	2,004	1,986	1,614	1,608	918	918
R-squared	0.101	0.158	0.058	0.078	0.051	0.158
F test	17.48	8.812	5.742	1.803	4.908	2.226
Covariates	No	Yes	No	Yes	No	Yes

Notes: Linear probability models are used with the dependent variable set to 1 if the subject takes up insurance. Standard errors (reported in parentheses) are corrected for clustering at the session level. Covariates are age, gender, financial responsibility, marital status, education, employment, owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance levels of 10, 5, and 1 percent, respectively.

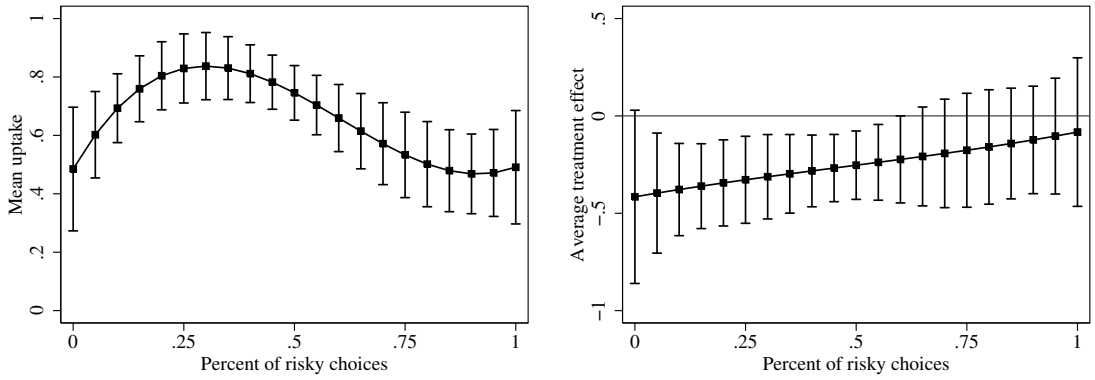
Result 5. The effect of ambiguity in contract nonperformance probabilities on demand tends to be more pronounced among ambiguity-averse individuals than it is among non-ambiguity-averse individuals.

Interestingly, negatively framing known contract nonperformance risk in T_{Fr} also reduces insurance uptake of ambiguity-averse subjects (-19.2 percentage points, p=0.034), while it has no significant effect on ambiguity-neutral and ambiguity-loving subjects (all p-values > 0.4). One potential explanation is that aversion to framing is correlated with ambiguity aversion, but that they are independent concepts. Another possibility is that mentioning negative motives of the insurer creates a feeling of uncertainty, similarly to making the contract nonperformance probability unknown, particularly for ambiguity-averse participants.

So far, we have focused on the role of ambiguity aversion, because the predictions of its influence on the treatment effect are the most straightforward. However, together with ambiguity aversion, risk aversion also determines decisions in ambiguous (i.e., inherently also risky) environments. Deriving exact predictions on the interplay of risk and ambiguity aversion without further assumptions is difficult. Therefore, we simulate insurance demand under parametric specifications of the utility function (see Appendix B for details). Specifically, we assume constant relative risk aversion (CRRA) and constant relative ambiguity aversion (CRAA); otherwise, we use all parameters as given in our experimental setup. The simulations predict that with contract nonperformance risk, (1) insurance should be taken up primarily by indi-

viduals within a range of "moderate" risk aversion parameters (see Appendix Figure 3.5(b)), and that (2) the effects for ambiguity-averse subjects should be observed primarily at the boundaries of this "moderate" range (see Appendix Figure 3.6). The first prediction is in line with Doherty and Schlesinger (1990), who show a violation of the standard monotonic relationship between risk aversion and optimal insurance demand when contract nonperformance is present. Similarly, Clarke (2016) makes the case for a hump-shaped relationship between risk aversion and optimal insurance demand for index insurance with basis risk, which is similar to the notion of contract nonperformance risk considered here, except that it has both upside and downside risk.[75]

Therefore, we start by analyzing whether insurance uptake is indeed higher in a certain "moderate" range of risk aversion. The behavior in the lottery choice task prior to the insurance experiment again serves as a basis to classify participants. In particular, we use the percentage of risk-seeking choices made in a set of Holt and Laury (2002) lotteries as a measure of risk aversion, where risk aversion increases with a decreasing share of risk-seeking choices. Figure 3.3 (a) shows the expected effect of higher insurance uptake by "moderately" risk-averse individuals.



(a) Average Insurance Uptake for C and T_{Amb} (b) Treatment Effect of T_{Amb}

Figure 3.3: Average Insurance Uptake and Treatment Effect by Risk Aversion

Notes: In this figure we focus on the subsample of participants in Treatments C and T_{Amb}. The dots in (a) represent the mean proportion of individuals taking up insurance under C and T_{Amb}, conditional on the percentage of risky choices in the Holt and Laury (2002) lotteries; (b) shows average treatment effects of T_{Amb}. All estimates are based on third-degree polynomials interacting with T_{Amb} for the subsample of ambiguity-averse participants used in Table 3.4. Error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

Testing the second simulation result (highest ambiguity effect at boundaries of "moderate" risk aversion range) is more complicated. Our measure of risk aversion is noisy and difficult to translate into the parameters used in our simulation. In addition, the "location" of effects is sensitive to the model specifications. However,

[75] However, note that the decrease in optimal index insurance demand with basis risk in risk aversion is driven by the downside risk, not by the upside potential. This is equivalent to what we observe here.

it is clear that the effects of introducing ambiguity on ambiguity-averse individuals should be driven by those who are risk-averse. The reason is that risk-loving subjects should not take up insurance, irrespective of the presence of ambiguity and ambiguity aversion. Thus, we expect that the effects of the T_{Amb} treatment should materialize primarily among the risk-averse. Figure 3.3 (b) shows average treatment effects of T_{Amb}, conditional on our measure of risk aversion. We find that average treatment effects become stronger with risk aversion (i.e., with a lower percentage of risky choices treatment effects are more pronounced). These results show that predictions from utility theory are, to some extent, supported by our empirical results. This lends further credibility to our interpretation of the effects.

3.4.4 Ambiguity over Rounds

Ambiguity is essentially due to a lack of information. In our setting, participants lack information about the exact contract nonperformance probability, which is governed by the mixture of orange and white balls in an opaque bag. An interesting question is whether individuals can accumulate information via experience and, hence, decrease the ambiguity over time. Rational individuals should update their beliefs about the unknown stochastic process based on newly available information. As the number of observations increases, the true probability can be estimated more precisely.[76] In terms of our model in Section II, the subjective probability distribution $q(.)$ over the possible probabilities should converge towards a degenerate distribution, with value one, at the true probability. Thus, decreasing ambiguity with experience should be reflected in the participants' insurance decisions. In particular, the effect of ambiguity in the contract nonperformance probability on insurance demand should converge to zero. Studying dynamic ambiguity is important, because, in reality, individuals collect and share experiences of the outcomes of ex-ante uncertain situations. Whether repeated exposure to such situations (directly or indirectly, via peers) decreases ambiguity effectively has clear implications for the relevance of the results of a static analysis. Therefore, we analyze the trend in ambiguity effects over the six rounds in the experiment.

Figure 3.4 shows pooled treatment effects for ambiguity treatments T_{Amb} and T_{Amb-Fr}, separately, by round for the total sample and for a subsample of ambiguity-averse subjects. If anything, we expect to find a convergence of treatment effects to zero in the ambiguity-averse subsample. However, contrary to the updating hypothesis, the effect of ambiguity exhibits no clear trend, and remains consistent in both the overall sample and the ambiguity-averse subsample. All treatment effects remain negative, irrespective of the experience accumulated, while the effects are more pronounced and more significant in the ambiguity-averse subsample.

[76] For example, ambiguity measured by the standard error of a simple probability estimate, based on averages, should decrease with the square root of observed realizations.

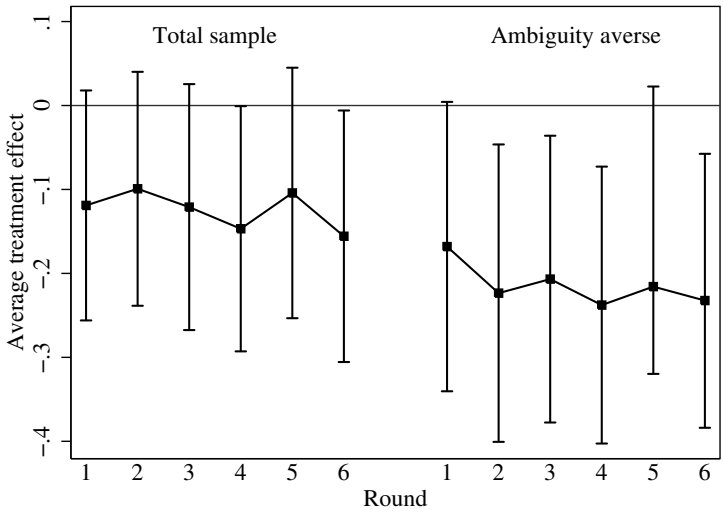


Figure 3.4: Average Treatment Effects by Round

Notes: The bars represent the average treatment effects for the pooled treatment groups T_{Amb} and T_{Amb-Fr}, by round, for the total sample and for a subsample of ambiguity-averse subjects. The error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

We compare these findings to participants' beliefs about the contract nonperformance probability. Recall that we elicited beliefs by having participants guess (1) the number of orange balls contained in the bag from which contract nonperformance was drawn, and (2) the minimum and maximum number of orange balls they deemed possible. In addition to observing the "best guess" of participants, we use the spread between the minimum and maximum number of orange balls as a proxy for subjective ambiguity. Finally, the absolute deviation between the best guess and the real number of orange balls serves as an objective measure of uncertainty.[77] Table 3.5 shows how the best guesses, spread between the minimum and maximum guesses, and error of guesses evolve over rounds for different treatments. For each of these three measures, the averages are presented separately for treatments T_{Amb} and T_{Amb-Fr}.

Participants appear to be very pessimistic in treatments T_{Amb} and T_{Amb-Fr}, because the average guess is substantially above one. If anything, these guesses show a subtle upward tendency away from the real number of orange balls contained in the bags. The spread between the maximum and minimum guesses (Columns 3 and 4) seems to decrease over rounds, suggesting a decrease in the extent of ambiguity. On the other hand, the decrease is very small, and a substantial spread remains. In addition, the difference between the number of orange balls that participants believe are in the bag and the actual number of orange balls (Columns 5 and 6) shows no such downward tendency. Overall, participants do not improve their guesses significantly over the rounds. In summary, there is no clear evidence of a reduction in ambiguity over rounds. This holds for both the T_{Amb} and T_{Amb-Fr} treatments, and is consistent

[77] Because the actual number of orange and white balls was drawn randomly, it varies between sessions for the ambiguous treatments. Thus, we recorded the actual number of orange and white balls at the end of each session.

Table 3.5 Individuals' Probability Beliefs

	Mean best guess		Mean subjective spread		Mean absolute error of guess	
	T_{Amb}	T_{Amb-Fr}	T_{Amb}	T_{Amb-Fr}	T_{Amb}	T_{Amb-Fr}
Round 1	2.589	2.613	1.81	2.071	2.027	1.687
Round 2	2.673	2.601	1.934	1.909	2.166	1.636
Round 4	2.542	2.78	1.632	1.788	2.042	1.728
Round 6	2.655	2.696	1.554	1.83	2.161	1.632
N	168	168	155	154	155	154

Notes: Guesses were elicited via a short survey in rounds 1, 2, 4, and 6 on the average, minimum, and maximum number of orange balls, from a total of 10 balls (see Section III). The mean subjective spread is computed as the difference between the minimum and maximum number of orange balls stated. The mean absolute error of guesses measures the difference between the guesses and the actual number of orange balls. We restrict the sample for the mean subjective spread and the mean absolute error of guesses to those participants with meaningful statements about the minimum and maximum numbers of orange balls (i.e., minimum $\leq$ maximum).

with their persistent negative treatment effects on insurance uptake.

Result 6. The negative impact of contract nonperformance ambiguity on insurance uptake is not eliminated over time by updating beliefs about probabilities.

There might be reasons for the absence of learning that are particular to our experiment. For example, it is possible that participants did not have all the information from other players, in which case they could not properly update on their signals. Second, participants might have needed more experience in order to reduce ambiguity; that is, updating processes might take longer than the duration of the experiment permits. In order to obtain an intuitive understanding of the potential improvement in agents' assessments of probabilities, we simulate Bayesian updating under perfect information transmission for all participants. That is, we assume that all participants in one session shared their experiences, and then followed a Bayesian updating rule.[78] The result suggests that for ambiguous contract nonperformance probabilities, agents have access to limited information, because insurance performance can only be observed if there is a loss *and* insurance had been purchased previously. Hence, ambiguity decreases slowly (see Appendix D).

Even with a longer time horizon, there are good reasons why ambiguity might persist. First, information transmission might be imperfect, thus further increasing the time needed to accumulate the necessary information. Second, consistently updating beliefs is a difficult task, particularly if information is arriving sporadically. Under such circumstances, it is possible that subjective ambiguity remains high, even if sufficient information has eventually been accumulated.

[78] Appendix D provides more detail on the updating process and the assumptions involved.

3.5 Conclusion

We show the detrimental impact of contract nonperformance risk and ambiguity on insurance demand, both theoretically and empirically. Typically, the probability of an insurance contract failing to perform is considered to be known. We extend the theory by allowing contract nonperformance risk to be ambiguous, and show that demand for probabilistic insurance decreases with increasing mean-preserving ambiguity about contract nonperformance risk if agents are ambiguity-averse.

Our results from a field lab experiment in the Philippines are consistent with this logic. In particular, we establish empirically that the effects of contract nonperformance risk (a decrease in insurance uptake by 17.1 percentage points) and its ambiguity (a further decrease in insurance uptake by 14.5 percentage points) are similar in magnitude. These results suggest that the reduction in insurance demand induced by contract nonperformance risk is reinforced by ambiguity. This pattern is strongest among participants classified as ambiguity-averse in a separate lottery choice task.

The causes for the failure of insurance contracts also seem to be important, under some circumstances. While they play a smaller role for participants with high numeracy, negatively depicting the insurer as unwilling to pay claims significantly reduces insurance demand for ambiguity-averse subjects. Interestingly, in this subsample, the negative framing seems to have a similar effect to that of introducing ambiguity.

We present additional evidence that the effects of ambiguity are not easily eliminated over time by updating beliefs about probabilities. In reality, learning might be more effective than it is in the lab. However, it seems intuitive that villagers from a low-income setting cannot update their beliefs effectively or compute confidence bounds around their probability guesses, in either the experiment or in reality.

According to our results, ambiguity about contract nonperformance risk clearly influences insurance demand, and has a similar economic relevance to that of contract nonperformance risk. Our results imply that in addition to ensuring low contract nonperformance risk, regulators should have an interest to reduce its ambiguity, for example, by making the repayment practices of insurers transparent. Similar to the case of contract nonperformance risk, such measures might not be in the best interests of individual insurance providers. Here, many potential reasons for contract nonperformance are endogenous to management decisions (e.g., more risky investments, less solvency capital, delaying payments) that benefit the owners of an insurance company. Thus, there is a particular trade-off between the costs and benefits that can be exploited by insurers, which the regulator may want to restrict. Furthermore, in the case of ambiguity, reasons not to create transparency may be endogenous to management decisions. For example, an insurance provider publishing data about claims payment practices might, at the same time, send an unintended negative signal about claims payment probabilities, or lose the possibility of denying contract nonperformance risk towards clients. These and other strategic reasons might limit the

incentives for transparency, even though the insurance market as a whole might profit from reduced ambiguity.

For emerging low-income insurance markets, with limited insurance demand, the effects of contract nonperformance risk and ambiguity are particularly relevant in terms of market development. In line with our results is a call for sound regulatory frameworks. Such frameworks should focus on ensuring low levels of contract nonperformance risk and ambiguity through solvency regulation, contract validation, and market transparency. In particular, there is room for such improvements in low-income insurance markets, because of currently low regulatory oversight, limited customer protection, and low levels of trust. For the management of an insurance company, a strategic focus on sound policies and practices may prove beneficial to gaining a competitive advantage and building trust in an emerging market.

Our conclusions are based on the empirical results presented in this paper, but their interpretation inevitably rests on certain assumptions, because randomizing all potential factors influencing insurance demand under ambiguity is impossible. For example, in our experiment, groups consist of six individuals, and it is not clear how the results would change with larger groups and, thus, more information potentially being available under the ambiguous settings. In addition, varying the contract nonperformance probability is potentially interesting, enabling us to judge the sensitivity of demand with regard to this factor in greater detail. However, prior work suggests that the largest part of the demand-reducing effect of contract nonperformance risk can be attributed to whether this risk is present, and that sensitivity of demand is highest when moving from non-probabilistic insurance to insurance with a non-zero contract nonperformance probability (Zimmer, Gründl, Schade, and Glenzer, 2016). In a similar vein, further research may investigate the role of the degree of ambiguity and the way it is introduced, which we did not vary in our experiments. Therefore, in the absence of additional experimental findings across a range of parameters, it is crucial to think about the interpretation of results theoretically in order to judge their plausibility and generalizability. Our main empirical findings are in line with the hypotheses derived from the theoretical model and the corollary findings appear to be sensible: the demand effects of ambiguity are strongest for ambiguity- and risk-averse subjects, and demand seems to follow an inverted U-shape with respect to risk aversion (Doherty and Schlesinger, 1990; Clarke, 2016). These properties suggest that the findings are meaningful, and might hold when moving beyond the restricted parameter set tested here.

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A Proofs

A.1 Probabilistic Insurance

In this appendix, we prove that introducing contract nonperformance risk, without adjusting premiums, decreases the willingness to pay. This is intuitive, because there is no reason why a contract nonperformance feature should be valued by clients. In the following, we compare the marginal willingness to pay under both scenarios. The marginal willingness to pay when $r > 0$ can be obtained from the first-order condition when optimizing Equation (3.1) with respect to coverage ε:

$$\begin{aligned}\frac{\partial EU_r}{\partial \varepsilon} =&(1-p)u'(w-I(\varepsilon))(-I'(\varepsilon)) \\ &+p[(1-r)u'(w-I(\varepsilon)-L+\varepsilon)(-I'(\varepsilon)+1) \\ &+ru'(w-I(\varepsilon)-L)(-I'(\varepsilon))]=0.\end{aligned} \tag{3.3}$$

We solve Equation (3.3) for $I'(\varepsilon)$ and get the following marginal willingness to pay for probabilistic insurance:

$$\frac{p(1-r)u'(w-I(\varepsilon)-L+\varepsilon)}{(1-p)u'(w-I(\varepsilon))+p[(1-r)u'(w-I(\varepsilon)-L+\varepsilon)+ru'(w-I(\varepsilon)-L)]},$$

which can be rewritten as:

$$\frac{pu'(w-I(\varepsilon)-L+\varepsilon)}{(1-p)u'(w-I(\varepsilon))\cdot\frac{1}{(1-r)}+p[u'(w-I(\varepsilon)-L+\varepsilon)+\frac{r}{(1-r)}u'(w-I(\varepsilon)-L)]} \tag{3.4}$$

Then, we set $r = 0$ in Equation (3.3), and solve for $I'(\varepsilon)$ to get the following marginal willingness to pay for non-probabilistic insurance:

$$\frac{pu'(w-I(\varepsilon)-L+\varepsilon)}{(1-p)u'(w-I(\varepsilon))+pu'(w-I(\varepsilon)-L+\varepsilon)} \tag{3.5}$$

When comparing Equation (3.4) and (3.5), it follows that the marginal willingness to pay for probabilistic insurance is lower than it is for the same insurance that settles claims with certainty, irrespective of the coverage point ε (i.e., the numerator is the same, but the denominator is larger). This implies a lower overall willingness to pay at all coverage points and, hence, lower demand for insurance with contract nonperformance risk, irrespective of individual risk aversion. This result holds for both binary and continuous insurance decisions.

A.2 Lemma 1 and Lemma 2: Premium-Adjusted Probabilistic Insurance

The setting is less trivial once we account for contract nonperformance risk by reducing premiums proportionally (i.e., $I(\varepsilon) \neq I_0(\varepsilon)$). In this case, agents face a trade-off between effective coverage and lower premiums. Doherty and Schlesinger (1990) already

show that optimal coverage is not necessarily monotonic in contract nonperformance risk in such a situation. Given this more general result, we focus on the case of a binary insurance decision with a given coverage level ε here. This is in line with our empirical setup and should help us to shed further light on reasons for potential non-monotonicities and the direction of the effect which is likely to dominate. We hence compare EU_r and EU_0, holding coverage ε constant. In binary insurance decisions, a lower (higher) utility for policies with contract nonperformance risk implies weakly lower (higher) insurance demand.[79] The following equation denotes the difference between EU_r and EU_0 at a given level of ε:

$$\begin{aligned} EU_r - EU_0 =&(1-p)[u(w - I_0(1-r)) - u(w - I_0)] \\ &+ p(1-r)[u(w - I_0(1-r) - L + \varepsilon) - u(w - I_0 - L + \varepsilon)] \\ &- pr[u(w - I_0 - L + \varepsilon) - u(w - I_0(1-r) - L)]. \end{aligned}$$

If the difference is positive, individuals prefer insurance with contract nonperformance risk, and vice versa. The expression can be transformed using the Taylor theorem for approximating the difference.[80] In the following, we use $x^\star = w - I_0 - L + \varepsilon$ for notational convenience:

$$\begin{aligned} EU_r - EU_0 =&(1-p)[\underbrace{u(w - I_0 + rI_0)}_{=u(w-I_0)+u'(w-I_0)rI_0+\tau_1} - u(w - I_0)] \\ &+ p(1-r)[\underbrace{u(w - I_0(1-r) - L + \varepsilon)}_{=u(x^\star)+u'(x^\star)rI_0+\tau_2} - u(x^\star)] \\ &- pr[u(x^\star) - \underbrace{u(w - I_0 - L + rI_0)}_{=u(x^\star)-(\varepsilon-rI_0)u'(x^\star)+\tau_3}] \\ =&(1-p)[\underbrace{u'(w - I_0)}_{=u'(x^\star)+\tau_4} rI_0 + \tau_1] + p(1-r)[u'(x^\star)rI_0 + \tau_2] - pr[u'(x^\star)(\varepsilon - rI_0) - \tau_3], \end{aligned} \tag{3.6}$$

[79] In non-binary insurance decisions, a lower (higher) utility for policies with contract nonperformance risk implies that less (more) utility can be derived, even if optimal coverage changes. To see this, let $\varepsilon^\star$ denote the optimal coverage of agents when $r = 0$, and $\varepsilon^{\star\star}$ when $r > 0$. Then:

$$\begin{aligned} &EU_r(\varepsilon) < EU_0(\varepsilon) \Longrightarrow EU_r(\varepsilon^{\star\star}) < EU_0(\varepsilon^\star), and \\ &EU_r(\varepsilon) > EU_0(\varepsilon) \Longrightarrow EU_r(\varepsilon^{\star\star}) > EU_0(\varepsilon^\star). \end{aligned}$$

This follows from the fact that $EU_0(\varepsilon^{\star\star}) < EU_0(\varepsilon^\star)$ and $EU_r(\varepsilon^{\star\star}) > EU_r(\varepsilon^\star)$ under the optimal coverage decision. However, the implications for demand are less straightforward, and require additional assumptions.

[80] We exploit that—under assumptions about continuity and differentiability—$f(x)$ can be approximated by a n-th order Taylor expansion from x_0 in the following way:
$f(x) = f(x_0) + f'(x_0)(x - x_0) + ... + \frac{f^n(x_0)}{n!}(x - x_0)^n + \frac{f^{n+1}(c)}{(n+1)!}(x - x_0)^{n+1}$
with c between x_0 and x.

where

$$\begin{aligned}
\tau_1 =& \frac{(rI_0)^2}{2}u''(c_1),\\
\tau_2 =& \frac{(rI_0)^2}{2}u''(c_2),\\
\tau_3 =& \frac{(\varepsilon - rI_0)^2}{2}u''(c_3), \text{ or}\\
=& \frac{(\varepsilon - rI_0)^2}{2}u''(x^\star) - \frac{(\varepsilon - rI_0)^3}{6}u'''(c_3'), \text{ and}\\
\tau_4 =& (L-\varepsilon)u''(c_4),
\end{aligned}$$

with

$$\begin{aligned}
c_1 &\in (w - I_0, w - I_0 + rI_0),\\
c_2 &\in (w - I_0 - L + \varepsilon, w - I_0 - L + \varepsilon + rI_0),\\
c_3, c_3' &\in (w - I_0 - L + rI_0, w - I_0 - L + \varepsilon),\\
c_4 &\in (w - I_0 - L + \varepsilon, w - I_0).
\end{aligned}$$

Given the concavity of the utility function all approximation errors (τ_i) are negative. Equation (3.6) can be rewritten as follows:

$$EU_r - EU_0 = u'(x^\star)pr\varepsilon\alpha - (1-p)rI_0\tau_4 + (1-p)\tau_1 + p(1-r)\tau_2 + pr\tau_3.$$

Now plugging in the definitions of τ_i and defining the the positive constants $a_4 = (1-p)rI_0(L-\varepsilon)$, $a_1 = (1-p)\frac{(rI_0)^2}{2}$, $a_2 = p(1-r)\frac{(rI_0)^2}{2}$, $a_3 = pr\frac{(\varepsilon - rI_0)^3}{6}$, and $a_3' = pr\frac{(\varepsilon - rI_0)^2}{2}$ yields:

$$\begin{aligned}
\frac{EU_r - EU_0}{u'(x^\star)} =& pr\varepsilon\alpha + a_4 \underbrace{\frac{u''(c_4)}{u'(x^\star)}}_{-C(c_4,x^\star)} + a_1 \underbrace{\frac{u''(c_1)}{u'(x^\star)}}_{-C(c_1,x^\star)} + a_2 \underbrace{\frac{u''(c_2)}{u'(x^\star)}}_{-C(c_2,x^\star)} + a_3' \underbrace{\frac{u''(c_3)}{u'(x^\star)}}_{-C(c_3,x^\star)} \qquad \text{or}\\
=& pr\varepsilon\alpha + a_4\frac{u''(c_4)}{u'(x^\star)} + a_1\frac{u''(c_1)}{u'(x^\star)} + a_2\frac{u''(c_2)}{u'(x^\star)} - a_3\underbrace{\frac{u'''(c_3')}{u'(x^\star)}}_{>0} + pr\frac{(\varepsilon - rI_0)^2}{2}\underbrace{\frac{u''(x^\star)}{u'(x^\star)}}_{-ARA(x^\star)},
\end{aligned}$$

where $C(x, x^\star)$ is the risk aversion / concavity measure (Liu and Meyer, 2013) discussed in the main text, normalized at $u'(x^\star)$, and $ARA(x)$ is the Arrow-Pratt measure of absolute risk aversion.

The above term might be positive or negative, depending on the loading factor and risk aversion. For actuarially fair insurance (i.e., $\alpha = 0$) and with risk-averse agents the expression is strictly negative, while for insurance with a positive loading (i.e., $\alpha > 0$) and risk neutral agents, the term is strictly positive.

It is easy to see from the above equation that if
$ARA(x^\star) > \frac{2\alpha\varepsilon}{(\varepsilon - rI_0)^2} \Leftrightarrow pr\frac{(\varepsilon - rI_0)^2}{2}ARA(x^\star) > pr\varepsilon\alpha \Rightarrow EU_r - EU_0 < 0$

which constitutes Lemma 1. The lower α, the lower the risk aversion level required such that insurance without contract nonperformance risk is preferred. In binary insurance decisions, this implies that for these agents, the average insurance demand must be weakly lower for insurance with contract nonperformance risk.

On the other hand, $\forall \alpha > 0$, $\exists u(x)$ s.t. $C(x, x^\star) > 0$ at $x = c_4, c_1, c_2, c_3$ and $pr\varepsilon\alpha > a_4 C(c_4, x^\star) + a_1 C(c_1, x^\star) + a_2 C(c_2, x^\star) + a_3' C(c_3, x^\star) \Rightarrow EU_r - EU_0 > 0$.
To see this, we can define a sequence of utility functions $u_\lambda(x)$ with $C_\lambda(c_1, x^\star), C_\lambda(c_2, x^\star), C_\lambda(c_3, x^\star), C_\lambda(c_4, x^\star) \overset{\lambda \to \infty}{\to} 0$.[81]
This ensures that the weighted sum of risk aversion measures will become small enouh to satify the condition, which constitutes Lemma 2. The higher α, the higher the risk aversion level allowed such that insurance with contract nonperformance is preferred. Preferring insurance with contract nonperformance risk implies weakly higher demand for such an insurance contract for these agents. However, agents with low risk aversion are also more sensitive to loadings and tend not to buy insurance that is too expensive (Mossin, 1968; Smith, 1968). So even though they prefer the contract with nonperformance risk they might not buy any insurance voluntarily.

Ultimately, the results hinge on the shape of the utility function. Therefore, we implement simulations over a range of parameters to obtain more precise predictions. The simulation results can be found in Appendix B. They strongly suggest that contract nonperformance risk decreases demand.

A.3 Lemma 3: Ambiguous Probabilistic Insurance

Lemma 3 can be shown by comparing the marginal willingness to pay when r is known to that when r is ambiguous. The marginal willingness to pay can be obtained from the first-order condition when optimizing Equation (3.2) with respect to coverage ε:

$$\begin{aligned}&\mathbb{E}_\gamma \Phi'(EU_{r(\gamma)})[(1-p)u'(w - I(\varepsilon))(-I'(\varepsilon)) + p[(1 - r(\gamma))u'(w - I(\varepsilon)\\ &- L + \varepsilon)(-I'(\varepsilon) + 1) + r(\gamma)u'(w - I(\varepsilon) - L)(-I'(\varepsilon))]] = 0.\end{aligned}$$

The marginal willingness to pay $I'(\varepsilon)$ for a reduction ε in loss is:

$$\frac{pu'(w - I(\varepsilon) - L + \varepsilon)}{(1-p)u'(w - I(\varepsilon))\hat{r} + p[u'(w - I(\varepsilon) - L + \varepsilon) + \bar{r}u'(w - I(\varepsilon) - L)]}, \tag{3.7}$$

where $\hat{r} = \frac{\mathbb{E}_\gamma \Phi'(EU_{r(\gamma)})}{\mathbb{E}_\gamma (1 - r(\gamma))\Phi'(EU_{r(\gamma)})}$ and $\bar{r} = \frac{\mathbb{E}_\gamma r(\gamma)\Phi'(EU_{r(\gamma)})}{\mathbb{E}_\gamma (1 - r(\gamma))\Phi'(EU_{r(\gamma)})}$.

We are interested in comparing the above marginal willingness to pay to the

[81] Such sequences exist. For example, let $u_0(x)$ denote a utility function satisfying all conditions set in this paper and define the sequence $u_\lambda(x) = \frac{\lambda - 1}{\lambda} u_0'(x^\star)x + \frac{u_0(x)}{\lambda}$.
This ensures that $C_\lambda(x, x^\star) = -\frac{u_0''(x)}{\lambda u_0'(x^\star)} \overset{\lambda \to \infty}{\to} 0$. In this sequence, c_4, c_1, c_2, c_3 even remain constant across λ. This can be shown via inserting the transformation in the Taylor expansion formula and showing equivalence across different values of λ.

marginal willingness to pay for probabilistic insurance with known contract nonperformance risk derived in Equation (3.4):

$$\frac{pu'(w-I(\varepsilon)-L+\varepsilon)}{(1-p)u'(w-I(\varepsilon))\cdot\frac{1}{(1-r)}+p[u'(w-I(\varepsilon)-L+\varepsilon)+\frac{r}{(1-r)}u'(w-I(\varepsilon)-L)]}.$$

In order to compare the two equations, it will suffice to compare $\frac{1}{1-r}$ to $\hat{r}$ and $\frac{r}{1-r}$ to $\bar{r}$. If $\hat{r}>\frac{1}{1-r}$ and $\bar{r}>\frac{r}{1-r}$, it follows that the marginal willingness to pay decreases, and vice versa. We begin by showing that both conditions are equivalent:

$$\begin{aligned}
&\hat{r}>\frac{1}{1-r} \\
\Leftrightarrow\ &\frac{\mathbb{E}_\gamma\Phi'(EU_{r(\gamma)})}{\mathbb{E}_\gamma(1-r(\gamma))\Phi'(EU_{r(\gamma)})}>\frac{1}{1-r} \\
\Leftrightarrow\ &\mathbb{E}_\gamma r(\gamma)\Phi'(EU_{r(\gamma)})>r\cdot\mathbb{E}_\gamma\Phi'(EU_{r(\gamma)}) \\
\Leftrightarrow\ &\frac{\mathbb{E}_\gamma r(\gamma)\Phi'(EU_{r(\gamma)})}{\mathbb{E}_\gamma(1-r(\gamma))\Phi'(EU_{r(\gamma)})}>\frac{r}{1-r} \\
\Leftrightarrow\ &\bar{r}>\frac{r}{1-r}.
\end{aligned} \tag{3.8}$$

The desired result can now be obtained from Equation (3.8) by exploiting the shape of $\Phi(.)$. For ambiguity-averse agents, $\Phi(.)$ is concave. This means that as $r(\gamma)$ increases (and $EU_{r(\gamma)}$ decreases), $\Phi'(EU_{r(\gamma)})$ increases as well. That is, $r(\gamma)$ and $\Phi'(EU_{r(\gamma)})$ are positively correlated, such that the expectation of their product is greater than the product of their expectation, and Equation (3.8) holds. The reverse is true for ambiguity-loving agents. Hence, we have established that for ambiguity-averse (-loving) agents, the willingness to pay for insurance with ambiguous contract nonperformance risk is lower (higher) than it is in the case where it is known.

A.4 Generalizing Lemma 3

Lemma 3 refers to the *introduction* of ambiguity regarding contract nonperformance risk. Other comparative statics such as increasing ambiguity aversion or increasing the extend of ambiguity are interesting as well. In the following we show that the development of the marginal willingness to pay boils down to one central property:

$$corr\left(r(\gamma),\Phi'(EU_{r(\gamma)})\right).$$

If this correlation increases, the marginal willingness to pay decreases and vice versa. To see this, consider Equation (3.7) for two alternative situations with distinct ambiguity in contract nonperformance risk ($r(\gamma_1)$ versus $r(\gamma_2)$) and distinct ambiguity preferences (Φ_1 versus Φ_2). Comparing the marginal willingness to pay between both settings leads to comparing $\hat{r}_1$ with $\hat{r}_2$ and $\bar{r}_1$ with $\bar{r}_2$. If $\hat{r}_2>\hat{r}_1$ and $\bar{r}_2>\bar{r}_1$, it follows

that the marginal willingness to pay decreases from situation 1 to 2, and vice versa. We again begin by showing that both conditions are equivalent:

$$
\begin{aligned}
& \hat{r_2} > \hat{r_1} \\
\Leftrightarrow & \frac{\mathbb{E}_{\gamma_2}\Phi_2'(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2}(1-r(\gamma_2))\Phi_2'(EU_{r(\gamma_2)})} > \frac{\mathbb{E}_{\gamma_1}\Phi_1'(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1}(1-r(\gamma_1))\Phi_1'(EU_{r(\gamma_1)})} \\
\Leftrightarrow & 1 - \frac{\mathbb{E}_{\gamma_1} r(\gamma_1)\Phi_1'(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1}\Phi_1'(EU_{r(\gamma_1)})} > 1 - \frac{\mathbb{E}_{\gamma_2} r(\gamma_2)\Phi_2'(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2}\Phi_2'(EU_{r(\gamma_2)})} \\
\Leftrightarrow & \frac{\mathbb{E}_{\gamma_2} r(\gamma_2)\Phi_2'(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2}\Phi_2'(EU_{r(\gamma_2)})} > \frac{\mathbb{E}_{\gamma_1} r(\gamma_1)\Phi_1'(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1}\Phi_1'(EU_{r(\gamma_1)})} \\
\Leftrightarrow & \mathbb{E}_{\gamma_2} r(\gamma_2)\Phi_2'(EU_{r(\gamma_2)}) \cdot \mathbb{E}_{\gamma_1}\Phi_1'(EU_{r(\gamma_1)}) > \mathbb{E}_{\gamma_1} r(\gamma_1)\Phi_1'(EU_{r(\gamma_1)}) \cdot \mathbb{E}_{\gamma_2}\Phi_2'(EU_{r(\gamma_2)}) \\
\Leftrightarrow & \frac{\mathbb{E}_{\gamma_2} r(\gamma_2)\Phi_2'(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2}(1-r(\gamma_2))\Phi_2'(EU_{r(\gamma_2)})} > \frac{\mathbb{E}_{\gamma_1} r(\gamma_1)\Phi_1'(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1}(1-r(\gamma_1))\Phi_1'(EU_{r(\gamma_1)})} \\
\Leftrightarrow & \bar{r}_2 > \bar{r}_1.
\end{aligned}
\tag{3.9}
$$

Note that the expected contract nonperformance probability is assumed to lie in the interval $(0,1)$ and that $\Phi_1'(.), \Phi_2'(.) > 0$ such that the direction of inequality holds through all divisions and multiplications. Dividing Equation (3.9) by r ($= \mathbb{E}_{\gamma_1} r(\gamma_1) = \mathbb{E}_{\gamma_2} r(\gamma_2)$) and subsequently subtracting one yields the condition:

$$
corr\left(r(\gamma_2), \Phi_2'(EU_{r(\gamma_2)})\right) > corr\left(r(\gamma_1), \Phi_1'(EU_{r(\gamma_1)})\right). \tag{3.10}
$$

The evolution of this correlation uniquely determines whether the marginal willingness to pay uniformly decreases (if the inequality holds), remains the same (if equality holds), or increases (if the reverse inequality holds). From here, different kinds of comparative statics can be derived. Note, for example, that our derivation of Lemma 3 is a special case of the above general statement. Without ambiguity in the initial situation ($r(\gamma_1)$ being a constant), the right hand side of Equation (3.10) is necessarily zero. Ambiguity aversion implies that on the left hand side $r(\gamma_2)$ and $\Phi_2'(EU_{r(\gamma_2)})$ are positively correlated (negatively for ambiguity loving subjects), which proves Lemma 3.

Beyond the result of Lemma 3, it is intuitive that the willingness to pay will decrease when increasing the extend of ambiguity or increasing ambiguity aversion. For this proposition to hold, however, these changes must lead to an increase in the correlation. The above derivation hence delivers a useful criterion which facilitates proving further comparative statics.

B Simulations

We have shown that under some circumstances (i.e., high premium loadings and low risk aversion), insurance with contract nonperformance risk might be preferred. Intuitively, some types might value the gain in the expected payoff as being greater than the risk of the contract failing to perform. To assess the extent of this phenomenon, we specify a CRRA utility function of the form $u(A) = \frac{A^{1-\rho}}{1-\rho}$, where $\rho = 0$ indicates risk neutrality, and risk aversion increases in ρ. In order to estimate the expected utilities of the different options, we fix the parameters as defined in Table 3.6 (i.e., following treatments C and T_{NoDef} in our experimental setup).

Table 3.6 Parameters

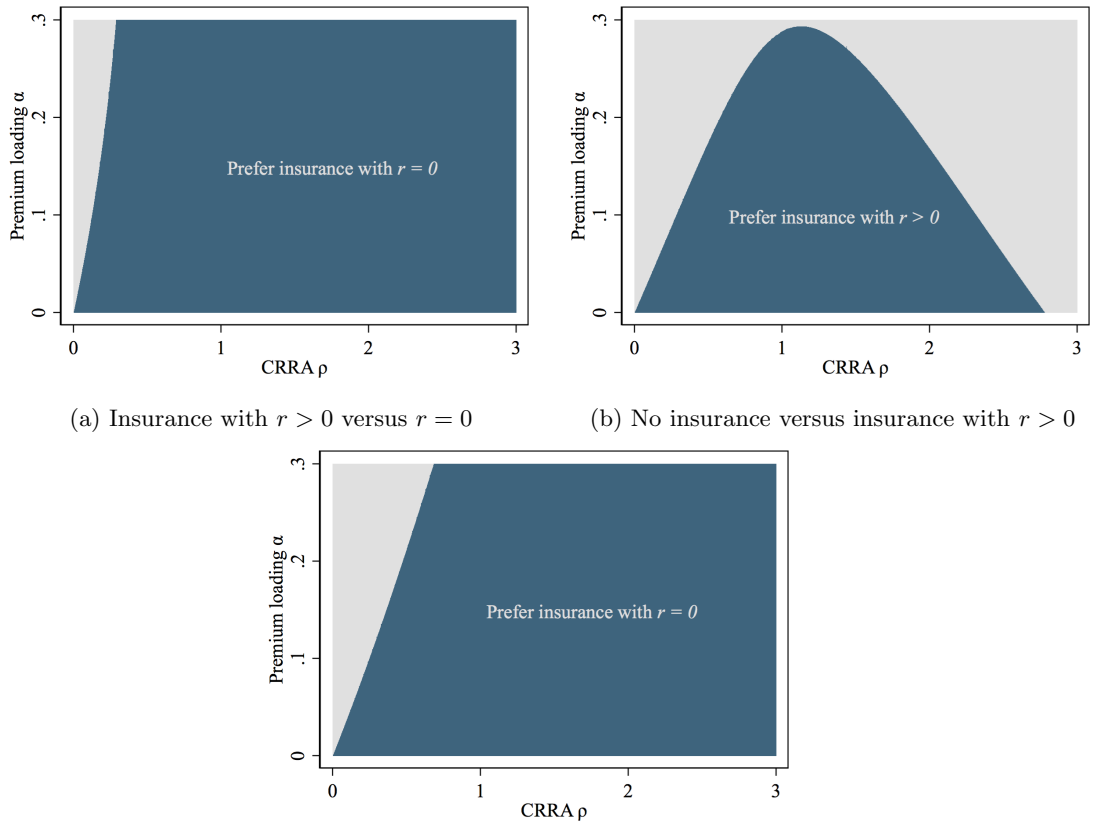
	C	T_{NoDef}	T_{Amb}
Initial endowment	210	210	210
Loss probability	0.3	0.3	0.3
Loss	150	150	150
Insurance coverage	150	150	150
Contract nonperformance probability	0.1	0	0.1
Contract nonperformance probability ambiguous	No	No	Yes
Insurance premium	$I_0(1-r)$	I_0	$I_0(1-r)$
Loading factor	α	α	α

The insurance premium depends on the loading factor because $I = (1+\alpha)\varepsilon p = (1+\alpha)45$. Using the specifications shown in Table 3.6, we can calculate the expected utility difference $EU_r - EU_0$ for any combination of α and γ. Figure 3.5 (a) shows the result of this simulation. As derived theoretically, low risk-aversion types facing insurance policies with high premium loadings might prefer the policy with inherent contract nonperformance risk. However, for high premium loadings, the types preferring insurance with inherent contract nonperformance risk might not opt for insurance anyway. To illustrate this, Figure 3.5 (b) shows the simulation results for the trade-off between insurance with inherent contract nonperformance risk and no insurance.

Indeed, only those who would not take up insurance anyway prefer insurance with contract nonperformance risk. This implies that demand for insurance not prone to contract nonperformance risk must be larger, because it is always preferred by those who are sufficiently risk-averse. Figure 3.5 (c) shows the results of our simulations for the trade-off between insurance without contract nonperformance risk and no insurance.

In summary, our previous analysis of demand is confirmed when comparing Figures 3.5 (b) and 3.5 (c); that is, the preference region for insurance with contract nonperformance risk is a subset of the preference region for insurance without contract nonperformance.

When considering the impact of ambiguity on insurance demand in our simulation, we need to make an assumption on the functional form of ambiguity aversion. Therefore, for choices involving ambiguous probabilities, we assume constant relative



(a) Insurance with $r > 0$ versus $r = 0$

(b) No insurance versus insurance with $r > 0$

(c) No insurance versus insurance with $r = 0$

Figure 3.5: Demand for Insurance with Known Contract Nonperformance Risk

ambiguity aversion (CRAA) of the form $\phi(EU) = \frac{EU^{1-\zeta}}{1-\zeta}$ for $EU \in \mathbb{R}^+$ and, thus, for $\rho < 1$. For all $\rho > 1$, we apply the adapted CRAA function for negative utilities $\phi(EU) = \frac{-(-EU)^{1-\zeta}}{1-\zeta}$ defined in Gollier (2011). For simplicity, we assume loading α to be the loading defined in our experimental setup for T_{Amb} (i.e., 25 percent).

The simulation results in Figure 3.6 clearly suggest that the preference region for insurance with ambiguous contract nonperformance risk in the binary trade-off between insurance and no insurance is a subset of the preference region for insurance with known contract nonperformance risk (i.e., the grey horizontal line at CRRA $\zeta = 0$) for ambiguity-averse individuals (i.e., $\zeta > 0$).[82] Thus, we confirm our previous analysis of demand in that the demand for ambiguous probabilistic insurance is always lower than that for non-ambiguous probabilistic insurance, for ambiguity-averse individuals.

[82] This result holds irrespective of the premium loading α.

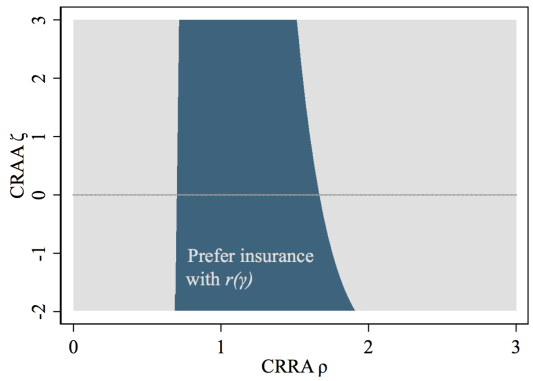


Figure 3.6: Demand for Insurance with Ambiguous Contract Nonperformance Risk

C Linear Probability and Probit Models for Average Treatment Effects

Table 3.7 Average Treatment Effects

	(1) (OLS)	(2) (OLS)	(3) (OLS)	(4) (Probit[a])
T_{NoDef}	0.171***	0.172***	0.187***	0.223***
	(0.0626)	(0.0629)	(0.0638)	(0.0718)
T_{Amb}	-0.145*	-0.143*	-0.133*	-0.124*
	(0.0768)	(0.0782)	(0.0763)	(0.0713)
T_{Fr}	-0.121	-0.119	-0.111	-0.103
	(0.0803)	(0.0796)	(0.0771)	(0.0722)
T_{Amb-Fr}	-0.104	-0.101	-0.1	-0.0943
	(0.0795)	(0.0791)	(0.0769)	(0.0725)
Typhoon		0.038	0.0319	0.0324
		(0.0442)	(0.0430)	(0.0422)
Round		0.00294	0.00267	0.00309
		(0.00371)	(0.00371)	(0.00376)
Constant	0.707***	0.678***	0.632***	
	(0.0580)	(0.0631)	(0.158)	
Observations	4,896	4,896	4,872	4,872
R-squared	0.0612	0.0629	0.0832	0.0709
F-test	15.02	11.17	4.84	
Covariates	No	No	Yes	Yes

Notes: Linear probability models are used, with the dependent variable set to 1 if the subject takes up insurance. Standard errors (reported in parentheses) are corrected for clustering at the session level. Covariates are age, gender, financial responsibility, marital status, education, employment, owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. [a] The probit model results are provided in terms of marginal effects.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance levels of 10, 5, and 1 percent, respectively.

D Bayesian Updating

In this appendix, we present the results of simulated Bayesian updating under perfect information transmission, for all participants. This serves as a benchmark for how well rational and well-informed individuals could, in principle, decrease ambiguity over time in our setting. We assume that all participants in a session share their experiences. Then, we follow a Bayesian updating rule to predict the probability that the insurer pays a claim in the case of a loss, and the uncertainty around this probability. In our setup, the number of orange balls ($\#_\gamma$) determines the contract nonperformance probability ($r(\gamma) = \#_\gamma/10$) under the different states of the world γ. Formally, each participant is assumed to calculate the probability that the state of nature $\gamma = h \in [0, ..., 10]$, given the observation of K orange balls out of N draws, as:

$$P(\gamma = h|K \text{ of } N) = \frac{P(K \text{ of } N|\gamma = h) \cdot P(\gamma = h)}{\underbrace{\sum_i (P(K \text{ of } N|\gamma = i) \cdot P(\gamma = i))}_{P(K \text{ of } N)}},$$

where $P(\gamma = i)$ is the initial prior for the probability of the respective mix in the ambiguous bag. The ambiguous bag is a random subset of a big bag with known content (see Section III.B for more detail). Hence, the initial prior can be calculated using a hypergeometric distribution. In addition, the probability of observing K nonperformance outcomes out of N draws ($P(K \text{ of } N|\gamma = i)$) is easy to compute for each of the different possible numbers of orange balls $\#_i$ in the ambiguous bag. Thus, a Bayesian updater can calculate the likelihood for each probability state ($\gamma = h$) based on the history of draws, according to the above formula. In other words, this enables us to calculate the distribution of possible contract nonperformance probabilities based on past experiences, as well as any moment of this distribution.

Table 3.8 shows two main statistics. The first column describes how the expected number of orange balls, given the experiment history, deviates from the actual number ($|E[\#_\gamma|K \text{ of } N] - \#|$). This "prediction error" decreases slightly over the rounds. The second statistic describes the "remaining uncertainty" agents face, given the experiment history. This is calculated as the standard deviation of the possible contract nonperformance probabilities ($SD[\#|K \text{ of } N]$); that is, we calculate how much a rational Bayesian updater should expect the real number of orange balls to deviate from the expected value. Consistent with the bias of best guesses, uncertainty also decreases over the rounds. However, this downward trend is very modest, and most of the bias and the uncertainty remain until the end of the experiment. The reason is that, until round six, only 5.2 insurance performances can be observed, on average, which is not sufficient to considerably compress the belief distribution around the correct value.

Table 3.8 Bayesian Updating Simulation for T_{Amb} and T_{Amb-Fr}

	Mean Deviation	Mean Remaining Uncertainty
Round 1	0.734	0.89
Round 2	0.725	0.855
Round 3	0.708	0.824
Round 4	0.669	0.795
Round 5	0.621	0.763
Round 6	0.614	0.733

Notes: "Deviation" measures the difference between the expected number of orange balls, given the experiment history, and the actual number of orange balls for the Bayesian updaters. "Remaining Uncertainty" is the standard deviation of orange balls, given the updated probability distribution for the number of orange balls.

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