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General Introduction

This dissertation consists of three self-contained chapters. The unifying theme of these chapters is their focus on understanding rural households' decision making with regards to the adoption of innovative technologies. In chapter 1, we study small-holder farmers' adoption of improved agricultural inputs in response to receiving access to such inputs. In chapters 2 and 3, we investigate important demand and supply side factors in the provision of voluntary health insurance policies. In chapter 2, I study the role of households' social network in their demand decision. In chapter 3, we investigate the presence of adverse selection in a low-income health insurance market, its potential welfare effects, and provide measures to mitigate such adverse effects. The following paragraphs provide a brief summary of these chapters.

Chapter 1

Access and Adoption of Hybrid Seeds: Evidence from Uganda

This chapter was written during my research stay and internship with IDinsight. It is joint work with Nikolaus Axmann, Kevin Keller, Kevin Leiby, Daniel Stein and Paul Wang. It has received a Revise and Resubmit at the Journal of African Economies.

In this chapter, we focus on understanding the phenomenon of low adoption of improved agricultural inputs among small-holder farmers across the African continent. Generally, the adoption of such inputs is oftentimes hindered by a combination of both economic and behavioral factors such as a lack of market access, lack of information or trust in improved seeds, liquidity constraints or present-biasedness. We conduct a field-experiment designed to overcome several potential barriers to adoption of improved inputs. In particular, we measure the effect of offering hybrid maize seeds for purchase during a time when potential customers have high liquidity. Working with a large buyer of agricultural commodities in Northern Uganda, we randomly offer smallholder farmers the opportunity to purchase certified hybrid maize seeds at the same time as they sell crops from a previous harvest in stores of this buyer. We find that 16% of those offered purchase hybrid seeds, and that average adoption of hybrid maize among those offered increases by 8 percentage points compared to a control group who does not receive the offer. Among those who accept the offer, we see an increase in hybrid maize planting of 50 percentage points. This effect is more pronounced for female farmers than for their male counterparts. Our findings suggest that providing access to certified agricultural inputs at the place and time of post-harvest sales is a promising strategy to increase input usage. At the same time, we find that adoption decisions are inhibited by many factors that are not easily overcome, even when addressed simultaneously.

Chapter 2
Social Interaction Effects in the Demand for Low-Income Health Insurance

In this chapter, I study the role of the social network in rural households' decision to adopt an innovative health insurance policy. Around the world, there is a growing interest to provide such formal insurance policies to low-income households. To mitigate vulnerability to adverse health shocks, insurance is oftentimes offered to pre-existing jointly liable credit groups. In this chapter, I argue that it is not clear how expected choices in the social network affect insurance take-up. On the one hand, social norms and conformity considerations might lead to similar behavior in the group. On the other hand, externalities arising from being insured potentially create incentives to free ride. Using data from a randomized control trial in Pakistan, I estimate a static simultaneous move game of incomplete information that allows to estimate rational equilibrium expectations. I find that a ten percentage point increase in peer expectations increases demand by 3.5 to 4.3 percentage points. Elasticity estimates suggest that this effect is comparable to a price decrease of about 4.5 to 6 percent. These findings are driven by positive social interaction effects in individual insurance policies that allow to insure any number and combination of dependents. In contrast, for household policies in which all dependents need to be insured, positive and negative social interaction effects seem to cancel out. These findings are in line with a reduced taste for conformity due to higher prices to conform with expected peer choices and larger incentives to free ride resulting from stronger externalities of other's take-up.

Chapter 3
Adverse Selection in Low-Income Health Insurance Markets: Evidence from a RCT in Pakistan

This chapter is joint work with Markus Frölich and Andreas Landmann.[1]

[1] The studied experiment has received IRB approval at the University of Mannheim and is registered in the American Economic Association (AEA) RCT Registry under the ID AEARCTR-0000604.

In this chapter, we study supply side factors of the above insurance intervention. In particular, the selection of high-risk individuals into the insurance pool is an often cited impediment for the sustainability of such schemes. We provide robust evidence on the presence of adverse selection from a large randomized control trial on health insurance in rural Pakistan. Our experimental setup allows us to separate adverse selection from moral hazard, to estimate how selection changes at different points of the demand curve and to test measures against adverse selection. The results suggest that there is substantial adverse selection if health insurance coverage can be individually assigned. In particular, adverse selection tends to become worse with higher premium prices, creating a trade-off between cost recovery and the quality of the insurance pool. In contrast, adverse selection is mitigated when bundling insurance policies at the household or higher levels. Further analyses suggest that adverse selection in individual products has non-negligible welfare consequences and that these are less pronounced in relative terms when bundling policies.

Chapter 1

Access and Adoption of Hybrid Seeds: Evidence from Uganda

1.1 Introduction

There is compelling evidence that hybrid seeds can significantly improve agricultural production and reduce its variance compared to conventional seeds, thereby increasing and smoothing farmers' profit (Kathage et al., 2012; Mathenge et al., 2014; Suri, 2011; Jones et al., 2012; Harou et al., 2017). Despite its proven merits, usage of hybrid seeds among smallholder farmers in Africa is low (Nyangena and Juma, 2014).[1] Many barriers to adoption of hybrid seed and other agricultural inputs have been studied and include factors like liquidity constraints (Simtowe et al., 2009; Carter et al., 2013; Karlan et al., 2014; Beaman et al., 2013), lack of information (Aker, 2011; Matsumoto et al., 2013), lack of access to markets (Karlan et al., 2014; Asfaw et al., 2016), uncertainty (Bold et al., 2015; Emerick et al., 2016; Suri, 2011) and behavioral factors (Allcott and Mullainathan, 2010; Brune et al., 2015; Taffesse and Tadesse, 2017; Duflo et al., 2011).

In this paper, we evaluate a randomized intervention that is designed to jointly relax several constraints to adoption of hybrid seeds. In cooperation with the Gulu Agricultural Development Company (GADC), an agribusiness operating in Northern Uganda, we randomly offer smallholder farmers the opportunity to purchase a fixed quantity of certified hybrid maize seed at the time when they sell crops from a previous harvest. This offer is made at stores run by GADC to farmers who are visiting the store to sell crops, and the operational cost to the company is negligible. Although hybrid seed is available for purchase at local markets, providing the opportunity to purchase certified hybrid seeds at the point of sale helps overcome barriers related to access, information, trust, cognitive biases and liquidity.

We find that 16% of farmers offered hybrid maize seed decide to purchase it. Farmers are more

[1] Usage in this context is understood as the "actual application of that resource in productivity-producing outputs [...]"(Peterman et al., 2014)

likely to accept this offer if the revenue they make from their post-harvest sale is larger, suggesting that liquidity constraints play a particularly important role. In the following maize season, we find that farmers offered hybrid maize seed are 8 percentage points more likely to plant a non-zero amount of hybrid maize compared to an average of 20% of farmers planting hybrid seeds in the control group (intention to treat, ITT estimator). Those farmers accepting the offer at baseline increase hybrid maize planting by 50 percentage points (treatment on the treated, TOT estimator).

We find that the treatment effect on the adoption decision is stronger for female farmers, who make up 45% of our sample.[2] Females are slightly less likely to accept the offer to purchase hybrid seeds, and the ITT treatment estimate for female farmers is higher than that for men. However, neither of these differences are statistically significant. In the TOT specification, though, we find a much higher and statistically significant effect for women: 100 percentage points versus 25 percentage points for men. This suggests among the "compliers" who choose to purchase the seed, the effect on planting maize is much larger for women. While this study is not designed to disentangle the underlying channel, the significantly larger TOT estimate for female farmers suggests that female compliers would have been much less likely to purchase hybrid seeds in the absence of the intervention, compared to their male counterparts.

The studied intervention is designed to overcome several of the barriers to higher adoption of hybrid seeds at the same time. First, in Uganda (as in many places) there is limited access to hybrid seeds. Although hybrid seeds are available at markets and agro-dealers in the area, farmers frequently live far from these sources and only visit them infrequently. At endline, around 60% of farmers who were not using hybrid seed state that they do not know where to purchase them. This intervention reduces access costs for the intervention population (those selling crops to GADC) by providing hybrid seeds for purchase at the same time and place of post-harvest sale, saving farmers additional travel and search costs.

Even if farmers are able to access hybrid seeds, uncertainty about the quality of seeds might hinder adoption. The quality of hybrid seeds is not observable, and potential buyers must trust the seller. In fact, the prevalence of counterfeits in the Ugandan setting is shown to potentially result in negative returns on adoption for farmers (Ashour et al., 2015; Bold et al., 2015).[3] This intervention mitigates such concerns by having GADC distribute the hybrid seeds. GADC is a trusted institution in the area due to its history of purchasing agricultural products and providing extension services. In our field-experiment, none of the farmers who declined to purchase hybrid seeds lists a lack of trust of GADC as a reason.

Furthermore, an interplay of behavioral biases and liquidity constraints can prevent higher adoption of improved inputs. Generally, the seasonal nature of farming results in a gap between

[2] We define female farmers as women making the purchase of hybrid seeds at the time and point of sale. This does not necessarily mean that these women are the head of the household, though.

[3] It is well established that the marginal value of hybrid seeds depends on the complementary use of inorganic fertilizer (Nyangena and Juma, 2014). While hybrid seeds have a positive effect on yield on their own, the effect is substantially larger when combined with fertilizer.

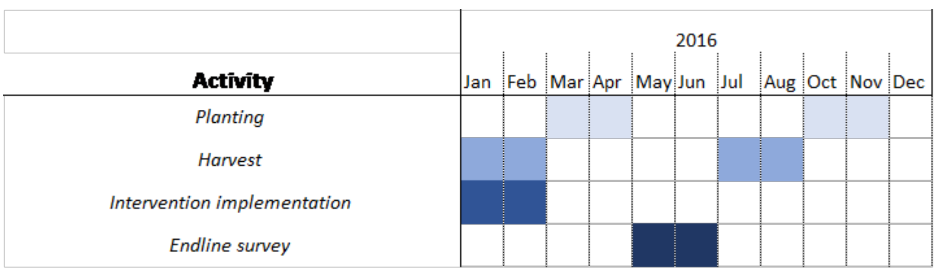
when a household receives harvest income and when it must purchase inputs for the next season. Bridging this gap requires either pre-purchasing the inputs or saving, both of which can be difficult for poor households. Brune et al. (2016) show that providing farmers access to commitment savings accounts can increase spending on inputs, though the primary mechanism may be mental accounting as opposed to the savings accounts themselves. Duflo et al. (2011) find that farmers' low input usage is in line with a model of present-biased decision making that traps present-biased farmers in a low investment low yield equilibrium. The authors offer small, time-limited reductions in the cost of purchasing fertilizer (in the form of free delivery) at the time of harvest to find fertilizer use increase by 47 to 70 percent. The intervention studied here - while not testing explicitly for present biased decision making – adopts the general idea of jointly overcoming present-biasedness and liquidity constraints in providing access to certified hybrid seeds at the time of selling crops, when cash is more likely to be readily available.

A number of recent studies have shown that input usage is frequently lower for female farmers in developing countries (Peterman et al., 2014; World Bank, 2015). This suggests that the barriers to inputs listed above may be stronger for female farmers than their male counterparts (Udry, 1996). Although our intervention is not designed to address barriers to adoption specific to women, we would expect it to be more effective for women if the barriers it addresses are stronger amongst women. We do find stronger results for women, suggesting that providing hybrid seeds at the time and place of post-harvest sales addresses barriers that are especially important for women in our context.

1.2 Setting and Intervention

The majority of farmers in Northern Uganda are smallholders who cultivate a number of different crops for household consumption and food security. The primary food crops are cassava and sorghum, while popular cash crops include sesame and cotton. Maize is popular as both a food and a cash crop. There are two primary cropping seasons in Northern Uganda (as illustrated in Figure 1.1), though changing weather patterns have resulted in many farmers cultivating at non-traditional times. The main cash crop harvest tends to be in December/January, while the July/August harvest is more oriented towards subsistence crops.

Figure 1.1 – Agricultural seasons and project timeline



Adoption of improved inputs in Northern Uganda is relatively low. According to the 2008/2009 Agricultural Census, only 21% of farmers in northern Uganda used any improved seeds (hybrid or otherwise) and 18% used any fertilizer (Uganda Bureau of Statistics, 2010). In the baseline, 47% of farmers self-reported having planted hybrid seed in the past 12 months, but self-reported adoption tends to be unreliable because farmers typically consider any seed they *purchased* (as opposed to re-used) to be a hybrid. A more rigorous measure constructed based on reported purchasing source, seed variety and price is used at endline. This more reliable measure of adoption results in adoption rates of hybrid seed of around 20% in the control group.

The Gulu Agricultural Development Company (GADC) is an agribusiness based in Gulu, Uganda, that works with a network of approximately 70,000 smallholder farmers to purchase and process cotton, sesame, sunflower, and chili. GADC provides trainings on good agronomy practices and has a network of area coordinators, field officers, and lead farmers that work directly with farmers on a year-round basis. In 2015, GADC expanded its operations to include the purchase and processing of maize. As a part of this expansion, GADC devoted resources to boosting maize yields and production through maize agronomy trainings and by offering farmers in-kind access to hybrid maize seeds. Larger farmer yields are a positive for GADC because it increases the amount of maize available for purchase on the market. Beyond GADC, there are some governmental and non-governmental extension services in the area, but penetration is insufficient to provide input access and training to most farmers.

While overall adoption of hybrid maize seeds is low, demand for such seeds appears to be present in the target population of this article. An IDinsight scoping survey of 220 smallholder farmers randomly selected from the GADC network (conducted in July 2015) found that nearly all respondents (97%) would be interested in an intervention that makes hybrid seeds more accessible. Among self-reported non-adopters, the respondents name either the high costs of such seeds and/or the lack of access to such seeds as main barriers (both 38%).

1.2.1 Description of Intervention

The target population of the intervention studied here consists of all farmers that sold crops in 16 GADC stores in the intervention period from January 15th to February 5th, 2016. These 16 stores were randomly selected from all 52 GADC stores.[4] The dates of the intervention were selected since these two weeks were in the harvest window for multiple crops and post-harvest sales were expected to peak during this period. Farmers may have been waiting longer than normal to sell their harvest because the elections in 2016 delayed the start of the school year, and thereby the due date of school fees typically paid with incomes from harvest sales.

Once farmers sold their crops, they were invited to take a short survey collected on mobile tablets (programmed with SurveyCTO) by trained interviewers. At the end of the questionnaire,

[4] These stores bought cotton, sesame, and maize at fixed prices that are consistent in all stores in this study.

the survey application granted the respondent - with 50% probability - the opportunity to purchase one two-kilogram bag of certified hybrid seeds. The randomization is thus within store at the individual level. GADC did not offer seeds (or any other input) to farmers who do not receive the randomized offer to purchase hybrid seeds.

The hybrid seeds offered by GADC were sourced from Equator Seeds, which is well-known among smallholder farmers as a producer of high quality seeds. The exact variety of seed sold was Longe 7H, which —according to GADC's agronomist and FAO— is expected to increase average yield in particular in drought affected regions without having to increase complimentary inputs.[5] The two-kilogram bag of hybrid seeds was sold for 11,000 Ugandan Shillings (approximately \$3.26[6]), which equals the price at which GADC sourced the hybrid seeds from the distributor.[7] This bag size was determined by GADC and corresponds to the recommended quantity to cover a plot size of 20 to 25 percent of an acre (Matsumoto et al., 2013). GADC structured the intervention in this way because they believed that smallholder farmers would not be willing to buy a large quantity of seed from a new input provider without testing it first. Also, keeping the per-person amount of hybrid seed low allowed GADC to more accurately control their supply chain without risk of running out of seeds. If scaled up, GADC intends to allow larger purchases, and states that there is no barrier to doing so.[8]

For GADC, the cost of the intervention was minimal since seeds were sold rather than given away for free, and seed distribution and storage was effectively integrated into existing operational processes. GADC chose to sell the seeds at cost since they viewed increasing the maize supply as a more central goal than establishing input sales as a separate revenue stream. If priced above the cost of acquisition, transport, and storage, selling seeds (and other inputs) could be profit generating for GADC.

Smallholders did not receive additional information treatments along with the offer to purchase hybrid seeds. This is because adopting the hybrid variety does not entail any changes to existing maize farming procedures. There is some risk involved in purchasing seeds early, though, as seeds could spoil during storage before they are planted. Our data shows that is a minor but not negligible risk. In our endline survey, 12% of farmers that purchased the certified hybrid seeds reported some of the seeds spoiling before planting.

Given the relatively small quantity of seed offered, the primary objective of this intervention was not to have a measurable impact on maize yield, but rather to increase the number of small-

[5] Longe 7H is reported to be particular tolerant to drought, major leaf diseases, (GLS, NLB, MSV), low nitrogen and rust. Moreover it exhibits excellent stay green quality and good lodging resistance (Source: `http://teca.fao.org/read/8920`). The maturity period is about 120 days. Average yield per acre under optimal smallholder conditions is reported between 2.5 to 3.5 tons, thus significantly higher than smallholder farmers' average maize yield of 600kg per acre for traditional maize seed varieties (Okoboi, 2010).

[6] Exchange rate of 1 UGX = 0.000296470 USD. *Source:* `Xe.com`. Accessed September 2, 2016.

[7] This equates to a cost of 5,500 UGX / KG for high-quality hybrid seed. For comparison, non-hybrids can be purchased from local markets for as cheap as 500 UGX / KG

[8] Providing bags of smaller sizes was not discussed with GADC, though as far as we know smaller bags were never requested by customers.

holder farmers adopting this improved input. Even if farmers only used a small quantity initially, they will potentially increase their use of hybrid seeds once they observe the benefits of the reliable seed sold by GADC.

1.2.2 Data and Summary Statistics

Given logistical constraints, it was not possible to survey all 16 stores at each day of the intervention period. Instead, the IDinsight survey team attempted to balance spending *some* days at each store (for representativeness) with spending *more* time at busier stores (in order to increase sample size). Therefore our sample is skewed towards busier stores. The enumeration team visited eight stores per day during a total of 21 days.

After the first week of the survey, GADC communicated the potential of purchasing hybrid seed more widely through its networks (after limited communication before that), with the hope of inducing more sales during the experiment. Therefore, our sample may also be skewed towards smallholder farmers with a higher baseline interest in purchasing hybrid maize. Overall, our results apply to a specific subset of farmers in Uganda who chose to sell crops to GADC while our evaluation was taking place. Note that since randomization was done within-store at the individual level, the selection of store and farmer communication do not compromise internal validity. This is because only smallholder farmers selected in the lottery are eligible to purchase certified hybrid maize seeds from GADC.

One worry is that farmers not receiving the offer could directly benefit from the intervention through receiving seeds from their peers.[9] To asses this concern, we conducted a telephonic follow-up survey with farmers who purchased hybrid seeds. We reached 40% (30 out of 75) of farmers who purchased hybrid seeds, none of whom reported selling or giving the seeds away to neighbors or friends. These results mitigate internal validity concerns.

In each store that is surveyed at a given day, every farmer selling any crop to GADC is part of our sample. After crops were sold, enumerators administered a short survey that covered demographic information and farming behavior.[10] A total of 996 farmers were surveyed during the baseline, of which 481 farmers received the offer to purchase hybrid maize seeds (treatment). At two stores less than five surveys were conducted, as there were few farmers selling crops to GADC in those areas.[11]

We followed up with the evaluation sample to conduct an endline survey from May-June 2016.

[9] The next section discusses that — if such contamination was present — our results would be a lower bound of the estimated treatment effect.

[10] No potential participants declined to be surveyed.

[11] The analysis below will omit store fixed effects for these two stores because there is no variation in treatment status for the farmers sampled in these stores. The four respondents from these two stores are still included in the analysis, though. Robustness checks reveal that dropping these respondents from the sample does not affect the results. Moreover, since the sample already focuses on a specific subset of farmers, we do not think including or excluding these farmers affects external validity.

The timing was chosen to be before harvest, as the survey was designed to gather data about planting decisions and agricultural practices. 98% (974 out of 996) of farmers surveyed at baseline were also surveyed at endline. Out of the 22 that were not surveyed at endline, 15 were confirmed moved or passed away, while the field team was unable to locate 7 farmers. Our final sample therefore consists of 974 farmers, of which 467 were offered the hybrid maize seeds.

Our main outcome variable to measure adoption is a binary variable that takes a value of 1 if the respondent planted hybrid maize seed. At baseline, we create this variable by simply asking respondents whether they had planted hybrid maize within the last year. As self-reported data on seed type tends to be unreliable, though, we follow a more sophisticated approach at endline. Since hybrid seeds lose their genetic advantage if replanted, we are convinced that a farmer could only have actually planted true hybrid seeds if he bought them from a reputed retailer (or received them from an NGO). Also, there is an issue of counterfeit hybrid seeds being sold for relatively low prices in the area. For these reasons, we additionally consider the price paid for the reported hybrid seed. At endline, we categorize a farmer to have planted hybrid seed if she reports having received hybrid seeds from the government or an NGO, or purchasing hybrid seeds from a reputed retailer at a price higher or equal than 2,000 UGX / kg.[12]

Table 1.1 provides summary statistics and balancing tests of the baseline characteristics. Overall, 55% of sampled farmers are male and are 37 years old on average. About 37% have completed primary education and about 53% or 42% are reachable by phone or own a phone respectively. Average landholdings amount to 1.43 acres and landholdings are unknown for about 18% of the sample.[13] 82% of sampled farmers grew maize in the last 12 months and 34% report to have grown hybrid maize. About 21% of farmers sold maize on the day of the baseline interview. The farmers' revenue from post-harvest sales at the time of the interview averages to about 49,000 UGX.[14] The subsequent columns of Table 1.1 provide subgroup means by treatment status. While baseline characteristics are largely balanced, we observe that farmers receiving the offer to purchase certified hybrid maize seeds are significantly older and appear more likely to have sold maize to the agribusiness.[15] The final column of Table 1 presents p-values from a Kolmogorov-Smirnov test for continuous variables. While the age distribution appears to be balanced, the revenue distribution seems unbalanced. This observed imbalance can be explained with a single outlier in the 99%

[12] This price was stated by local experts as the minimum price for which any sort of hybrid maize seeds could be purchased. Given that no other proxies that allow to objectively assess whether respondents have planted hybrid maize, we assess the sensitivity of our results using proxies for source and price. We conduct robustness checks of this price cut-off with thresholds at 1,800 and 2,200 UGX, respectively, and find that the results are essential unchanged in terms of effect size and level of significance. These results are available upon request. We report additional robustness checks of the definition of growing reliable hybrid maize in the Appendix.

[13] The landholdings variable has been winsorized at the 99.5 percentile to account for imbalance in outliers across the treatment and comparison group.

[14] Note that revenue information is missing for about 8% of the sample. This variables is missing because it was not included early versions of the survey due to a programming error. Missing revenue information is dealt with in the analysis with zero-imputation and inclusion of a missing variable indicator.

[15] The main empirical strategy employed below does not control for any baseline covariates. A second specification, meant to increase precision of the estimates, controls for a set of baseline characteristics including those two variables that appear unbalanced.

quantile of the treatment group. The lower panel of Table 1.1 presents results from a joint test for model significance from a regression of the treatment indicator on the set of all observable characteristics. While the results indicate that we are able to reject the null that these characteristics do not jointly explain treatment assignment, this is to be expected given the number of covariates controlled for. Overall, we interpret the results of Table 1.1 as supporting the conclusion that our randomization procedure achieved balance on observable characteristics.

Table 1.1 – Summary Statistics and Covariate Balance

	Overall	No Offer	Offer	P-Value Mean	P-Value KS
Growing Maize	0.82	0.83	0.81	0.20	
	(0.384)	(0.374)	(0.395)		
Grew Hybrid Maize	0.34	0.33	0.34	0.78	
	(0.473)	(0.470)	(0.476)		
Age	37.39	36.52	38.34	0.04	0.28
	(13.904)	(13.843)	(13.923)		
Gender: Male	0.55	0.56	0.54	0.89	
	(0.498)	(0.497)	(0.499)		
Completed Primary Education (or above)	0.37	0.38	0.36	0.66	
	(0.483)	(0.486)	(0.480)		
Reachable by Phone	0.53	0.52	0.53	0.62	
	(0.500)	(0.500)	(0.499)		
Owns Phone	0.42	0.41	0.43	0.61	
	(0.494)	(0.493)	(0.495)		
Crop Sold: Cotton	0.25	0.26	0.24	0.97	
	(0.434)	(0.440)	(0.426)		
Crop Sold: Sesame	0.51	0.51	0.50	0.16	
	(0.500)	(0.500)	(0.501)		
Crop Sold: Maize	0.21	0.20	0.23	0.07	
	(0.410)	(0.397)	(0.423)		
Revenue (UGX)	48928.04	46233.94	51867.64	0.43	0.00
	(128801.165)	(109559.408)	(147028.481)		
Revenue Missing	0.08	0.08	0.08	0.83	
	(0.273)	(0.270)	(0.277)		
Plot Size planted with Maize (Acres)	1.43	1.51	1.35	0.25	0.32
	(2.202)	(2.466)	(1.872)		
Plot Size missing	0.18	0.17	0.20	0.15	
	(0.386)	(0.374)	(0.398)		
Grow: Beans	0.68	0.68	0.67	0.90	
	(0.468)	(0.465)	(0.471)		
Grow: Cassava	0.76	0.75	0.76	0.82	
	(0.429)	(0.433)	(0.426)		
Grow: Cotton	0.37	0.38	0.36	0.97	
	(0.483)	(0.486)	(0.479)		
Grow: Groundnuts	0.50	0.51	0.50	0.88	
	(0.500)	(0.500)	(0.501)		
Grow: Pigeon Peas	0.24	0.25	0.24	0.04	
	(0.428)	(0.431)	(0.425)		
Grow: Sesame	0.79	0.79	0.79	0.70	
	(0.409)	(0.410)	(0.409)		
Grow: Sorghum	0.53	0.53	0.53	0.58	
	(0.499)	(0.500)	(0.500)		
Grow: Soya	0.19	0.18	0.20	0.28	
	(0.395)	(0.387)	(0.403)		
Grow: Sweet Potato	0.39	0.38	0.39	0.92	
	(0.487)	(0.487)	(0.487)		
Grow: Vegetables (Salad,Greens)	0.20	0.19	0.20	0.70	
	(0.399)	(0.395)	(0.403)		
N	974	507	467		
F-statistic (Joint)	3.5059				
P-value (Joint)	0.0000				

Note: This table reports (sub-)sample means and standard deviations (in parentheses). The *P-value (Mean)* column provides the p-value of the difference in mean between treatment and comparison group. This value is derived from OLS regression of the variable on a binary treatment indicator, controlling for 14 store fixed effects and using Huber-White robust standard errors. Two of the 16 store indicators are excluded because the low sample from these stores resulted in no variance in the treatment status. The final column reports p-values from a Kolmogorov-Smirnov test of equal distributions for continuous characteristics. Further, we conduct a joint test for model significance of a regression of the treatment indicator on all variables. The F-statistic and the corresponding p-value are reported in the lower panel. Exchange rate of 1 UGX = 0.000296470 USD. *Source:* `Xe.com`. Accessed September 2, 2016.

1.3 Empirical Strategy

We first explore correlates of accepting the offer to purchase certified hybrid maize seeds for the subsample of farmers who received the offer. We model farmer i's decision to accept the offer of certified hybrid seeds, $AcceptOffer_{ib}$, when selling crops at store b via a linear probability model (LPM). The model can be written as

$$AcceptOffer_{ib} = \alpha_0 + \gamma_0 X_{ib} + \omega_{0b} + \varepsilon_{ib} \tag{1.1}$$

X_{ib} is a vector of farmer specific baseline characteristics that among others includes age, gender, education, whether the respondent owns a phone, the type of crops planted that season and the type of crop sold that day, the revenue from this sale and whether the farmer grew (hybrid) maize. ω_{0b} is a vector of binary variables for each store, capturing store fixed effects[16] and ε_{ib} is a mean zero iid farmer specific error term.

Next, we estimate the impact of the intervention on farmer's decision to plant reliable hybrid maize seeds. First, we consider the overall effect of improved *access* to reliable hybrid maize seeds on adoption of such seeds in farmers' subsequent planting decisions (regardless of whether the offer has been accepted or not). Second, we are interested in the effect of accepting the offer on adoption decisions.

The first approach is the *intention-to-treat* (ITT), which compares adoption decisions of farmers who have received improved access to farmers who have not. Our estimation uses the following linear probability model to identify this difference

$$PlantHybrid_{ib} = \alpha_1 + \beta_1 OfferedHybrid_{ib} + \gamma_1 X_{ib} + \omega_{1b} + u_{ib} \tag{1.2}$$

where $PlantHybrid_{ib}$ is the outcome indicator of having planting hybrid seeds at endline and $OfferedHybrid_{ib}$ is the binary treatment indicator that equals 1 if the farmer has received access to certified hybrid seeds. u_{ib} is a mean-zero, iid error term and the remaining variables are defined as in (1.1). Due to random assignment, β_1 reflects the causal effect of being offered seeds on planting. As treatment is exogenous, our first regression specification does not include baseline covariates. The additional information is included in a second regression, though, as it may increase precision of the estimates.

The second approach is the *treatment-on-the-treated* (TOT) estimator, which compares adoption decisions of farmers that are induced to purchase hybrid seeds due to having received the offer to adoption decisions of farmers that would have purchased the hybrid seeds had they received the offer. We estimate the following system of linear equations in a two-step instrumental variables

[16] In the analyses, we will include 14 binary indicators for the 16 stores included in the study. For the remaining two stores, for which we sampled less than four clients each, there is no variation in treatment status, causing identification issues in the fixed effects estimation. Therefore we leave these stores as the omitted category.

framework (TSLS) to identify the TOT effect.

$$AcceptOffer_{ib} = \alpha_2 + \beta_2 OfferedHybrid_{ib} + \gamma_2 X_{ib} + \omega_{2b} + \varphi_{ib} \tag{1.3}$$
$$PlantHybrid_{ib} = \alpha_3 + \beta_3 AcceptOffer_{ib} + \gamma_3 X_{ib} + \omega_{3b} + v_{ib} \tag{1.4}$$

In equation (1.4), the purchasing decision of certified hybrid seeds from GADC, $AcceptOffer_{ib}$, is potentially correlated with other unobservable characteristics that also explain the adoption of hybrid seeds, i.e. the population error term v_{ib}. We therefore instrument $AcceptOffer_{ib}$ using the randomly assigned offer to purchase certified seeds, $OfferedHybrid_{ib}$. We report results from first stage relationship in (1.3) separately. While the offer is voluntary, only farmers receiving the offer are able to purchase certified hybrid seeds from the implementation partner at baseline. For this reason, the situation is characterized by one-sided non-compliance.

Given the conventional relevance and exclusion restriction, the TOT estimates described above are identified. To assess the relevance of our instrument, we show that the treatment indicator is a strong predictor for purchasing seeds from GADC. Regarding the exclusion restriction, we believe that it is unlikely for the treatment to increase planting of hybrid seeds through simply the offer of purchasing hybrid maize, as opposed to the purchase itself. The justification for this follows the same reasoning as why we think spillovers are low: there is already good knowledge of hybrid seeds but much difficulty obtaining them from sources other than GADC.

We also conduct a heterogeneity analysis, in which — for the ITT analysis — we include a binary subgroup indicator and an interaction term of this subgroup indicator with the random treatment indicator, $OfferedHybrid_{ib}$. The estimation equation is

$$\begin{aligned} PlantHybrid_{ib} = \alpha_3 4 + \beta_4 OfferedHybrid_{ib} + \gamma_4 Group_{ib} \\ + \delta_4 OfferedHybrid_{ib} * Group_{ib} + \omega_{4b} + u_{ib} \end{aligned} \tag{1.5}$$

where $Group_{ib}$ is the binary subgroup indicator and all other variables are defined as above. Note that the heterogeneity analysis accounts for store fixed effects, but excludes any additional baseline characteristics. The coefficients estimates $\hat{\delta}_4$ capture the differential treatment effect for the specific subgroups. The results tables below report estimates of the subgroup means from this specification, given by $\hat{\beta}_4$ and $\hat{\beta}_4 + \hat{\delta}_4$.

In the TOT analysis, the analogous interaction term of the subgroup indicator with the take-up indicator $AcceptOffer_{ib}$ is endogenous. Therefore, we use the interaction of the treatment indicator $OfferedHybrid_{ib}$ with the respective subgroup indicator as an additional instrument.

In general, inference relies on Huber-White-robust standard errors. While there could be a case for correlated error terms of the planting decisions on the store level, we choose to not cluster standard errors on this level because treatment is assigned on the farmer level[17]. As a robustness check, we present inference using cluster wild bootstrapped standard errors in the Appendix.

1.3.1 Threats to Identification

The main threat to our main (ITT) identification strategy is spillovers, as the experiment was randomized at the individual level. The worry is that treatment farmers could sell or give hybrid seeds to farmers in the control group. We think this is unlikely to be a major concern for two reasons. First, the small amount of seed distributed makes it unattractive for farmers to give away a portion of it. Second, the previously-mentioned phone survey revealed that no treatment farmer reported giving away or selling the seeds. Additionally, one may be concerned that simply learning about the offer of hybrid seeds could act as a marketing mechanism for farmers in the control group, spurring them to seek hybrid seeds from other sources. While we don't have evidence on whether this mechanism was in play, we find it unlikely as hybrid seed was already well-known by farmers in our sample. At endline, 58% of control farmers stated that they would not know where to purchase hybrid seeds if they wanted them. Therefore, we do not expect the information about hybrid seeds to encourage non-treated farmers to buy hybrid seeds from other sources. If these information spillovers were present, they are expected to positively affect adoption outcomes in the control group, thus leaving the impact estimates presented below as a lower bound.

If we assume that the conventional relevance and exclusion restrictions hold, the TOT estimates described above should be also be identified. To assess the relevance of our instrument, we show that the treatment indicator is a strong predictor for purchasing seeds from GADC. Showing that the exclusion restriction holds is of course far more difficult. The key assumption is that the offer of hybrid seed can only induce greater planting of hybrid seed through the channel of purchasing seed from GADC during our experiment. This assumption could fail, for instance, if the offer of hybrid seeds reminded farmers to purchase them from other sources. While plausible, in this case we think these alternative channels are unlikely. The justification for this follows the same reasoning as why we think spillovers are low: there is already good knowledge of hybrid seeds but much difficulty obtaining them from sources other than GADC. Overall, we believe that the assumptions required for the TOT estimates to be valid are likely to hold.

As for every experimental study, even if internal validity holds, the results are likely context specific. In this paper, we study a particular set of smallholder farmers who sell crops from a previous harvest during a particular time at a particular set of stores. If better informed or more market oriented farmers learn about the opportunity to purchase hybrid seeds, they might for example be more keen to make sales during that time period, limiting external validity.

[17] Note that there is an ongoing discussion in the literature about appropriate inference in such settings of individual level treatment assignment for which the analysis includes group fixed effects (Imbens and Kolesár, 2016).

1.4 Results

We are interested both in characterizing the demand for these hybrid seeds in terms of observable baseline characteristics and providing causal estimates of this offer on the adoption of hybrid seeds in subsequent planting decisions. First, we explore how uptake of the offer to purchase seeds is correlated with farmer characteristics. Second, we estimate the causal impact of the offer of reliable hybrid seeds on hybrid seed adoption in subsequent planting decisions. Finally, we test whether the treatment effects differs among specific subgroups of farmers.

1.4.1 Demand for Hybrid Seeds

Table 1.2 reports how individual characteristics affect the choice to accept the offer to purchase hybrid seeds. Column 1 restricts the sample to those offered seeds, and provides results from a linear probability model for a regression of the binary acceptance indicator on a set of baseline characteristics and store fixed effects, as indicated in equation (1.1). Column 3 includes the whole sample, and adds the treatment indicator to the regression. It represents the first stage of the TOT regressions that will be presented later.[18]

We observe that, in both specifications, the acceptance decision is correlated with the revenue from crop sales made at the time of baseline and the respondent's phone ownership. On average, an increase in revenue from crop sales by 1% increases the probability to accept by 2.4 percentage points.[19] Further, farmers who own a phone are on average about eleven percentage points more likely to purchase than does who do not. In both specifications, these correlations is statistically significant at the 10% level.

Table 1.3 provides some insights as to why treatment farmers who were offered hybrid seeds choose to not purchase. A vast majority of these farmers (70%) state that not having any money available is one of the reasons for not purchasing. Also, about a fifth of the respondents mention having to discuss the purchase with other members of the family. Only 5% of respondents mention that the price of seeds is too expensive. Other reasons, are mentioned by less than 5% of the respondents.

[18] The first stage F-statistics reported column (2) of Table 1.2 come from i) a model that controls for store fixed effects, ii) the same model that does not control for store fixed effects. We see that excluding store fixed effects in the first stage regression suggests a strong and statistically significant relationship between the random offer and the acceptance of the offer.

[19] The statistical significance of the missing revenue variable in columns 1 and 3 of Table 2 can be explained by observations from one specific store during the first week of the survey for which the data collection tool did not ask about crop revenue. This question was only added to the survey instrument during the first week of data collection. Therefore 85% of respondents from that store during the first week have missing revenue information. At the same time, a relatively large fraction of farmers selling crops at this store accepted the offer to purchase (38%). The results from including a binary indicator for respondents from that specific store in the first week of survey in columns 2 and 4 of Table 1.2 reveal that the missing revenue variable is no longer statistically significant.

Table 1.2 – Uptake of Hybrid Seed Offer

	LPM	LPM	First Stage	First Stage
Treatment			0.161***	0.161***
			(0.017)	(0.017)
Growing Maize	0.040	0.049	0.009	0.010
	(0.049)	(0.048)	(0.024)	(0.024)
Grew Hybrid Maize	0.063	0.056	0.035*	0.034
	(0.042)	(0.042)	(0.021)	(0.021)
Age	-0.000	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Gender: Male	-0.031	-0.023	-0.001	0.001
	(0.040)	(0.040)	(0.019)	(0.019)
Completed Primary Education (or above)	0.023	0.019	0.004	0.000
	(0.040)	(0.039)	(0.019)	(0.019)
Reachable by Phone	0.024	0.018	0.007	0.003
	(0.058)	(0.059)	(0.028)	(0.028)
Owns Phone	0.117*	0.113*	0.057*	0.057*
	(0.063)	(0.063)	(0.031)	(0.031)
Crop Sold: Cotton	-0.131	-0.129	-0.065	-0.053
	(0.153)	(0.153)	(0.074)	(0.075)
Crop Sold: Sesame	-0.242	-0.239	-0.118	-0.108
	(0.152)	(0.152)	(0.072)	(0.073)
Crop Sold: Maize	-0.212	-0.222	-0.122*	-0.114
	(0.152)	(0.152)	(0.073)	(0.074)
Log(Revenue, UGX)	0.022*	0.021	0.012*	0.012*
	(0.014)	(0.013)	(0.006)	(0.006)
Revenue Missing	0.330**	0.188	0.164**	0.116
	(0.163)	(0.166)	(0.077)	(0.076)
Plot Size planted with Maize (Acres)	-0.001	-0.003	0.000	0.000
	(0.008)	(0.008)	(0.003)	(0.003)
Grow: Beans	0.014	0.015	0.021	0.019
	(0.046)	(0.046)	(0.022)	(0.022)
Grow: Cassava	-0.033	-0.024	-0.009	-0.007
	(0.041)	(0.040)	(0.020)	(0.020)
Grow: Cotton	-0.064	-0.060	-0.031	-0.032
	(0.050)	(0.049)	(0.025)	(0.025)
Grow: Groundnuts	0.016	0.013	0.004	0.002
	(0.038)	(0.038)	(0.019)	(0.019)
Grow: Pigeon Peas	-0.003	-0.002	0.003	0.003
	(0.043)	(0.043)	(0.020)	(0.020)
Grow: Sesame	-0.003	-0.004	0.014	0.015
	(0.053)	(0.052)	(0.026)	(0.026)
Grow: Sorghum	-0.034	-0.029	-0.021	-0.018
	(0.044)	(0.044)	(0.021)	(0.021)
Grow: Soya	0.017	0.012	0.023	0.021
	(0.052)	(0.052)	(0.026)	(0.026)
Grow: Sweet Potato	0.041	0.038	0.021	0.021
	(0.037)	(0.036)	(0.018)	(0.017)
Grow: Vegetables (Salad,Greens)	-0.023	-0.022	-0.015	-0.015
	(0.035)	(0.037)	(0.018)	(0.018)
Specific Store (Week 1)		0.349**		0.152**
		(0.165)		(0.075)
Constant	0.187	0.196	-0.006	-0.021
	(0.242)	(0.241)	(0.112)	(0.113)
Store Fixed Effects	Yes	Yes	Yes	Yes
N	467	467	974	974
R^2	0.211	0.222	0.181	0.186
F-Statistic	3.07	3.11	2.85	2.79

Note: This table reports results from a linear probability model (LPM) of purchasing hybrid seeds. Column 1 includes the subsample of farmers that was offered such seeds. Column 2 includes the whole sample. Farmers not offered seeds are not eligible to purchase. The coefficient from missing revenue indicator is omitted. Robust standard errors are reported in parentheses.* significant at 10%, ** significant at 5%, *** significant at 1%

Table 1.3 – Reasons for Not Buying Hybrid Maize

	Mean (SD)
No Money available	0.70
	(0.457)
Need to discuss with family	0.18
	(0.383)
Unfamiliar with hybrid seeds	0.03
	(0.158)
Too expensive	0.05
	(0.225)
Other plans to use revenue	0.03
	(0.179)
Concerned about storage	0.03
	(0.172)
Intends to buy later in the year	0.02
	(0.141)
N	393

Note: This table provides the relative frequency distribution of reasons stated for not buying hybrid maize when offered (treatment group). The original question is a multiple choice, implying that the stated reasons do not need to sum to 100%. Reasons mentioned by less than 2% of respondents are not displayed. Standard deviations in parentheses.

1.4.2 Adoption of Hybrid Seeds

ITT and TOT Analysis

Columns 1 and 2 of Table 1.4 report ITT results of the effect of improved access to certified hybrid seeds at the time and place of post-harvest crop sales on the adoption of reliable hybrid seeds in the subsequent planting season. As described above, the ITT results come from a linear probability model that includes buyer fixed effects and uses Huber-White-robust standard errors. The offer to purchase hybrid seeds increases planting of hybrid seeds by 8 percentage points compared to a control group mean of 20%. This 40% relative change in adoption is statistically significant at the 1% level. Controlling for additional baseline covariates does not change the point estimate, but increases overall explanatory power of the model. Further, column 2 shows that hybrid seed adoption at endline is higher among male farmers and farmers who have planted hybrid seeds at baseline.

Columns 3 and 4 of Table 1.4 provide TOT results on the causal effect of purchasing certified hybrid seeds on adoption in the following planting season. The result in column 3 shows that farmers purchasing certified hybrid seeds at the time and place of post-harvest crop sale are 50 percentage points more likely to grow hybrid seeds in the subsequent planting season compared to farmers who have not accepted this offer. Column 4 confirms that the magnitude of this effect is unchanged when controlling for additional baseline covariates.

As mentioned earlier, our main outcome variable is a dummy of whether the farmer planted reliable hybrid seeds, and is calculated using various information received about the seed the farmer planted. In appendix Table A.1 we show that our primary results are robust to alternative definitions of "reliable" hybrid seeds. We compare three alternative definitions. First, we consider self-reported hybrid maize adoption. Second, we consider self-reported hybrid seed adoption if the seeds were sourced from an NGO, the government or bought at a shop, without imposing a minimum price threshold. Third, we consider the main outcome variable that imposes a price threshold and require in addition that the reported seed variety is of type Longe.

The ITT and TOT results give different perspectives on the intervention's effect, with both being potentially policy-relevant. The ITT results state that the probability of planting hybrid seeds for an average farmer that is offered to buy certified seeds increases by 8 percentage points compared to a farmer not given the offer. In contrast, the TOT results state that someone who accepts the offer increases their propensity to plant hybrid seeds by 50 percentage points.[20] This TOT estimate is valid for the so-called compliers, who are the participants who purchased seed when given the offer to do so. It suggests that around half of the people who purchased seeds as part of our experiment would have cultivated hybrid seeds even in the absence of our intervention.

Appendix Table A.2 reports equivalent ITT and TOT results that account for clustered standard errors at the store level using via a cluster-wild bootstrap routine.[21] The reported p-values coincide with the fraction of bootstrap test-statistics larger than the test statistic originally observed. While standard errors increase, the results show that the significance of the effects — both for ITT and TOT — persists under the more conservative approach.[22]

Heterogeneity Analysis

We examine differences in adoption patterns by gender, age, growing hybrid maize at baseline, and affordability of the certified seeds based on the revenue from crop sold at baseline.

Table 1.5 presents ITT and TOT results for these four different subgroups of farmers. Each row of Table 1.5 presents either the first stage, ITT or TOT approach described in the previous section. The first column presents point estimates and standard errors of the treatment effect for the indicated subgroup, e.g. female farmers, the second column reports the results for the

[20] The 50 percentage point TOT estimator reflects both the fact that some farmers would have planted seed in absence of the intervention, and that some farmers purchased the seed but then did not report planting them before the endline survey. We reached out to some farmers who purchased seed but did not plant them to derive anecdotal evidence of why this was the case. Some farmers reported that dry conditions induced them to save the seed for future seasons. Other farmers reported planting the seed even though they did not report this in the survey, suggesting there was some measurement error in the original survey.

[21] Inference is based on STATA's boottest routine with 1000 Bootstrap samples.

[22] To assess whether GADC announcing the opportunity to purchase hybrid seeds after the first week of the survey affects external validity, we compare impact estimates by survey week. In Appendix Table A.3, we find very similar ITT estimates of around 13.5 percentage points for survey weeks 1 and 2, suggesting that announcements do not alter the composition of our sample. At the same time, the effect is not statistically significant for week 3. The pattern of the TOT estimates suggests decreasing take-up towards later weeks of the survey. These findings could be interpreted as suggestive evidence of information about the availability of hybrid seeds spreading irrespective of additional advertising, and leading likely adopters to sell crops earlier rather than later.

Table 1.4 – ITT and TOT Estimates of Hybrid Seed Adoption

	ITT	ITT	TOT	TOT
Seeds Offered	0.082***	0.084***		
	(0.026)	(0.026)		
Accepted Offer			0.505***	0.517***
			(0.157)	(0.156)
Age		-0.000		-0.000
		(0.001)		(0.001)
Gender: Male		0.067**		0.068**
		(0.031)		(0.030)
Growing Maize		-0.031		-0.035
		(0.039)		(0.038)
Grew Hybrid Maize		0.064*		0.045
		(0.033)		(0.032)
Crop Sold: Maize		-0.238**		-0.175*
		(0.101)		(0.096)
Log(Revenue, UGX)		0.001		-0.006
		(0.011)		(0.011)
Completed Primary Education (or above)		-0.009		-0.011
		(0.032)		(0.031)
Reachable by Phone		0.082		0.077
		(0.054)		(0.052)
Owns Phone		-0.037		-0.065
		(0.054)		(0.052)
Crop Sold: Cotton		-0.217**		-0.185*
		(0.106)		(0.101)
Crop Sold: Sesame		-0.244**		-0.185*
		(0.100)		(0.095)
Plot Size planted with Maize (Acres)		0.004		0.004
		(0.007)		(0.007)
Grow: Beans		0.025		0.015
		(0.036)		(0.035)
Grow: Cassava		0.052		0.057*
		(0.034)		(0.032)
Grow: Cotton		-0.036		-0.020
		(0.045)		(0.043)
Grow: Groundnuts		-0.013		-0.015
		(0.030)		(0.029)
Grow: Pigeon Peas		0.056		0.055
		(0.039)		(0.037)
Grow: Sesame		0.004		-0.003
		(0.040)		(0.038)
Grow: Sorghum		0.013		0.023
		(0.031)		(0.031)
Grow: Soya		0.030		0.018
		(0.042)		(0.040)
Grow: Sweet Potato		0.007		-0.004
		(0.029)		(0.028)
Grow: Vegetables (Salad,Greens)		-0.037		-0.029
		(0.042)		(0.042)
Store Fixed Effects	Yes	Yes	Yes	Yes
N	974	974	974	974
R^2	0.074	0.120	0.118	0.151
Control Mean	0.20	0.20		

Note: This table reports Intention-to-treat and treatment-on-the-treated outcome estimates based on linear linear probability / TSLS models, using robust standard errors. The outcome is an indicator for whether the farmer reliably planted hybrid maize at endline. The coefficient from missing revenue indicator is omitted.* significant at 10%, ** significant at 5%, *** significant at 1%

complement of this subgroup, i.e. male farmers. As discussed in the Empirical Strategy section the latter are obtained as the sum of the coefficient estimates of the treatment indicator and the interaction term of the treatment indicator with the binary subgroup indicator. The third column provides the difference in these treatment effects, i.e. the coefficient estimate on the interaction term. Thus, we find evidence for differential treatment effects by subgroup if the latter estimate is statistically significant from zero.

Panel A presents heterogeneity results by gender. On average, improved access to certified hybrid seeds increases adoption among female farmers by 12 percentage points. This ITT effect for female farmers is statistically significant at the 5% level. The corresponding ITT for male farmers is 5 percentage points, but not statistically significantly different from 0. Column 3 shows that we cannot reject the null of these two ITT estimates being equal. Regarding the TOT results, we observe that the probability of adopting hybrid seeds among female farmers who have purchased certified hybrid seeds on average increases by 100 percentage points. This TOT effect is statistically significant at the 1% level. The corresponding TOT for male farmers is 25 percentage points, but not statistically significant from 0. Column 3 provides evidence for differing TOT effects by gender.

The large coefficient for the TOT for females and its difference in the coefficient in the male sample warrants additional discussion. Note that (as shown in the first stage), there is 5 percentage point difference in acceptance of the offer between male and female customers, and that there is an 8 percentage point difference in the ITT estimates across gender. None of these differences is statistically significant at conventional levels. Taken together, however, these result in large differences for TOT, suggesting that the intervention had much larger effects on female purchasers than male purchasers. The fact that the TOT estimate for females is near 1 seems very high, and should be interpreted with caution. There were only 26 females who accepted the offer, which meaning that this estimate is potentially skewed due to the small effective sample.

Panel B present heterogeneity results across baseline planting decisions. While not statistically significant, the effects of access to hybrid maize seeds are 4 percentage points higher for farmers that grew hybrid maize in the 12 months preceding the baseline survey than farmers who did not. Panels C and D shows that there is no evidence for heterogeneous effects with respect to the revenue received from crop sale and farmer age.

Table 1.5 – Heterogeneity of Adoption Decision

Panel A	(1)	(2)	(3)
	Female	Male	Difference
First Stage	0.1346***	0.1854***	0.0508
	(0.0229)	(0.0237)	(0.0326)
ITT	0.1267***	0.0457	-0.0811
	(0.0353)	(0.0380)	(0.0518)
TOT	1.0066***	0.2523	-0.7543**
	(0.3039)	(0.1958)	(0.3715)
N	440	534	
Panel B			
	No Hybrid	Hybrid	Difference
First Stage	0.1505***	0.1864***	0.0359
	(0.0201)	(0.0295)	(0.0355)
ITT	0.0686**	0.1100**	0.0414
	(0.0326)	(0.0446)	(0.0553)
TOT	0.4516**	0.5892**	0.1377
	(0.2156)	(0.2294)	(0.3190)
N	646	328	
Panel C			
	Rev.>Price	Rev. <=Price	Difference
First Stage	0.2076***	0.0774***	-0.1302***
	(0.0231)	(0.0203)	(0.0308)
ITT	0.0847**	0.0738*	-0.0108
	(0.0346)	(0.0399)	(0.0529)
TOT	0.4111***	0.9766*	0.5655
	(0.1585)	(0.5510)	(0.5729)
N	626	348	
Panel D			
	Age>=35	Age<35	Difference
First Stage	0.1469***	0.1775***	0.0306
	(0.0229)	(0.0245)	(0.0335)
ITT	0.1155***	0.0530	-0.0626
	(0.0382)	(0.0365)	(0.0529)
TOT	0.7796***	0.2857	-0.4939
	(0.2498)	(0.2037)	(0.3251)
N	458	516	

Note: This table reports heterogeneous treatment effets by gender, type of sale, revenue and age. Each row presents results from one regression. First stage results are derived from OLS of the uptake decision on the subgroup indicator, the exogenous treatment indicator and an interaction term of these. ITT estimates are derived in the same manner and TOT estimates come from TSLS. Instead of the treatment indicator, the TOT models include the take-up decision and an interaction of the take-up indicator with the subgroup indicator. The take-up decision and the interaction term are instrumented with the the treatment indicator and the interaction of the treatment with the subgroup indicator. In addition, both ITT and TOT approaches control for store fixed effects, but exclude baseline covariates. Columns (1) and (2) present the treatment effects for the respective subgroups along with robust standard errors. Column (3) provides results for whether these effects differ by subgroup. Technically, column (1) provides the coefficient of the treatment/take-up indicator. Column (2) provides the coefficient of the interaction term, and column (2) is the sum of (1) and (3).* significant at 10%, ** significant at 5%, *** significant at 1%

1.5 Conclusion

In this paper, we study the effects of simultaneously addressing barriers to adoption related to market access, quality of seeds, liquidity constraints and behavioral biases on the decision to plant hybrid seeds. In particular, we provide smallholder farmers with access to certified hybrid seeds at the time and place of post-harvest crop sale. We conduct our experiment on smallholder farmers who are visiting GADC stores to sell other crops, and find increased adoption of hybrid seed, especially for female farmers. This low-cost intervention is easily scalable, and has the potential to positively affect the livelihood of smallholder farmers as well as the profits of an agricultural purchaser such as GADC once initial adoption of hybrid seeds translates into permanent usage.

While our experiment shows only a modest effect size, we believe that in other contexts it could be much larger. Our results show that people who sell more crops (and therefore are less likely to be liquidity constrained) at the time of the offer to purchase seed are more likely to take up the offer. In our experiment, the average amount of sale was lower than expected, at less than five times the price of the bag of seeds. We believe that if the intervention was conducted at times of larger sales it would likely be even more effective. Also, as this was the first time GADC offered hybrid seeds for sale, many potential buyers likely did not know about the opportunity. In a context where all farmers were informed one might expect higher purchasing rates. Additionally, this evaluation's implications extend to other productive inputs, beyond hybrid maize seed. If cash availability at the time of planting is a significant barrier to the adoption of more expensive (and more productive) inputs, providing access to such inputs when farmers sell crops could lead to greater adoption of productive technology. At the same time, our findings suggest that farmers face multiple constraints to adoption of improved inputs that are not easily overcome, even when addressed simultaneously.

Selling seeds at the point of sale has a particularly large effect on female farmers. This is likely due to the fact that female farmers experience many barriers to input usage, and our intervention was successful in overcoming them. The exact mechanism is not entirely clear. Female farmers may have lower levels of trust in outside sources of seeds, but feel comfortable purchasing from a known entity such as GADC. Another explanation could be that women find it harder to save for seeds, and therefore the opportunity to purchase at a time of high liquidity is especially valuable. In either case, our results suggest that this intervention may be an effective tool in reducing the gender gap in agricultural productivity.

Chapter 2

Social Interaction Effects in Low-Income Health Insurance

2.1 Introduction

The rural poor in developing countries are particularly vulnerable to adverse health shocks (Krishna, 2007). Since conventional risk management and coping mechanisms oftentimes provide only imperfect coverage (Dercon and Krishnan, 2000), access to formal health insurance is considered a promising avenue to mitigate existential health risks (Morduch, 2006). The low uptake and renewal rates of formal insurance schemes observed in many contexts are therefore particularly concerning from a social impact perspective (Platteau et al., 2017). The literature has investigated a multitude of channels that could potentially spur insurance demand.[1] On the supply side, key determinants include the price (Chemin, 2018; Giné et al., 2011; Cole et al., 2011; Dercon et al., 2015), the quality of covered services (Dong et al., 2009), sufficient information provision about the policy (Das and Leino, 2011; Thornton et al., 2010; Platteau et al., 2013), and transaction costs (Thornton et al., 2010; Chemin, 2018). On the demand side, among others, financial literacy (Giné et al., 2011; Gaurav et al., 2011; Carpena et al., 2011; Bonan et al., 2011; Schultz et al., 2013) and trust in the insurance provider (Liu and Myers, 2016; Dercon et al., 2015; Clarke, 2011; Cai et al., 2015a; Cole et al., 2017; Townsend et al., 2010) have been studied extensively. More recently, the role of social networks as a demand side factor potentially increasing demand has gained attention (Chemin, 2018; Giné et al., 2011; Liu et al., 2014; Janssens and Kramer, 2016).

In this paper, we argue that the role of the social network in the demand for low-income health insurance is ambiguous. On the one hand, positive social interaction effects might emerge as a consequence of a desire to conform with expected choices in the group (Bernheim, 1994). In other words, when offered a new technology for which no clear behavioral norms exists, group members

[1] Refer to Platteau et al. (2017) for a recent review of both theoretical models and empirical studies of demand for indemnity as well as index based micro-insurance products.

might orient their own decision towards the predicted take-up of their group members (Festinger, 1954). As a result, a group member who expects a larger fraction of peers to take-up might decide to also demand the product. On the other hand, when insurance is offered to members of joint liability groups, the correlation of wealth distributions implies that all group members benefit from the positive externality of a single member's decision to insure against idiosyncratic risk, potentially creating an incentive to free ride (Janssens and Kramer, 2016; De Janvry et al., 2014).[2] Therefore, anticipating a higher fraction of group members to demand insurance, might inhibit the agent's take-up. At the same time, such incentives to free ride might be mitigated through repeated interactions in the group (Dal Bó and Fréchette, 2018). [3]

To test which of these channels dominates empirically, we use data from a randomized control trial through which the members of 199 jointly liable credit groups in rural Pakistan are offered one of four voluntary hospitalization insurance policies. All members of the same group are offered the same policy and the offered policies differ in their eligibility criteria. Two individual insurance policies allow the credit group member to insure any number and combination of household members. In contrast, two household insurance policies require to insure all household members. We hypothesize the effect of expected peer choices on own demand in the subgroup offered individual insurance policies to be larger in magnitude as compared to the subgroup offered household insurance policies for two reasons. First, it is more expensive to insure all dependents in the household policies. The higher price to conform with peer decisions might therefore mitigate the desire to conform. Second, the decision to take-up household insurance implies that more household members are insured on average. The positive externality from insurance is thus larger than in the individual policies, resulting in a stronger incentive to free ride.

Utilizing the framework developed by Lee et al. (2014a) and Yang and Lee (2017), we model an agent's binary insurance decision as a static, simultaneous move game under incomplete information. Agents' insurance demand depends on the expected choice of other group members, which is derived as a rational expectation given publicly observed characteristics. Given the discussion above, the sign of this social interaction effects parameter is considered as an indication of which channel dominates. The model accounts for the similarity of group members' decisions via contextual effects and can be extended to capture correlated group-level unobservables. In estimating this game, we determine the rational expectations equilibrium in each group. For this reason, the estimation procedure is based on a nested fixed point maximum likelihood estimation procedure common in the estimation of dynamic discrete choice models (Rust, 1987, 2000; Bajari et al., 2010).

[2] In joint liability groups, group members are obliged to cover outstanding loan amounts of their group members in case of default.

[3] Generally, network interactions might also lead to social learning, thereby directly or indirectly affecting priors about the value of the offered insurance product (Choi et al., 2015). The setting of the study precludes group members to directly observe their peers' decisions, ruling out the former observational learning channel. Knowledge spillovers, in contrast, might indeed lead to positive peer effects. The empirical framework allows to account for such implied correlations of decisions because of factors common to the group.

Pooling joint liability groups from all offered policies, we find a positive effect of expected peer choices on own insurance demand. This finding indicates that the conformity and repeated interactions channels dominate potential incentives to free ride. Average partial effect estimates suggest that a ten percentage point increase in expected peer take-up would increase demand by 3.5 to 4.3 percentage points. Price elasticity estimates indicate that a comparable increase in demand would require a decrease in premium price by 4.5 to 6 percent. Estimation results disaggregated by policy type reveal that the overall positive social interaction effects are driven by comparable effects of expected peer take-up on demand in the subgroup offered an individual insurance policy. For the subgroup offered a household insurance policy, in contrast, the social interaction effects estimate is negative, but estimated imprecisely. The estimated average partial effect suggests that a ten percentage point increase in expected peer demand would lead to a decrease in demand by 2.2 percentage points. This decrease in demand is comparable to a one percent increase in the insurance premium. Taking the relatively small and statistically insignificant effect of expected peer take-up on own demand by heart, conformity considerations and incentives to free ride appear to cancel each other out. This finding is in line with the hypotheses of a smaller magnitude of the social interaction effect in the subgroup offered a household insurance policy. Overall, we therefore conclude that incentives to free ride do seem to exist in the joint liability context of this study, but are likely to be dominated by social preference considerations.

We contribute to the literature in several ways. First, we add to a broader literature on the role of social networks in agents decisions such education (Sacerdote et al., 2011; Epple and Romano, 2011; Boucher et al., 2014) and health (Fortin and Yazbeck, 2015; Clark and Lohéac, 2007). In a developing country context, peer effects have been studied in the demand for innovative health services (Oster and Thornton, 2012; Miller and Mobarak, 2014) and improved agricultural products (Conley and Udry, 2010; Carter et al., 2014).

Second, we contribute to an emerging literature on the role of social networks in the demand for financial services in developing countries. In addition to savings and high stakes investment decisions (Bursztyn et al., 2014), microfinance loans (Banerjee et al., 2013) and index-based weather insurance (Cai et al., 2015b; Giné et al., 2011), the role of social networks in health insurance decisions has been studied (Chemin, 2018). Investigating the demand for voluntary, public health insurance in rural China over time, Liu et al. (2014) find positive effects of observing others' insurance choices, indicative of social learning. Instead of observed decisions, this paper focuses on the role of *expected* peer choices and a trade-off between conforming with and free-riding on these expected decisions.

Third, we extend a strand of literature relating insurance decisions to risky investment decisions in the context of joint liability (Fischer, 2013; Giné et al., 2010). Complementing existing evidence on free riding from framed insurance experiment (Janssens and Kramer, 2016), this paper provides novel evidence from actual insurance decisions. Studying actual decisions in joint liability groups allows for a more realistic description of the interplay of the various channels potentially affecting insurance demand. In addition to incentives to free ride, the setting of this paper incorporates the motifs of social norms, a taste for conformity, communication learning and repeated interactions in the group.

The remainder of this paper is structured as follows. Section 2.2 provides a theoretical motivation of the conformity and free-riding channels and discusses a unifying framework. Section 2.3 discusses how the model informs the estimation strategy. Section 2.4 discusses the institutional framework, the intervention and the sources of data used for estimation. Section 2.5 presents the results and Section 2.6 concludes.

2.2 Theoretical Framework

The purpose of this section is threefold. Section 2.2.1 briefly discusses the economic theory underlying the conformity and free riding channels. In addition, social learning is conceptualized and put in context of this study. Section 2.2.2 discusses the history of social interaction effects models. Section 2.2.3 discusses the behavioral model developed by Lee et al. (2014a) and extended by Yang and Lee (2017).

2.2.1 Social Interactions in Insurance Demand

In the context of interacting in joint-liability groups, economic models justify the existence of both positive and negative peer effects in the demand for low-income health insurance. This section discusses the various channels through which peer effects have been shown to affect behavior and rules out mechanisms not applicable in the studied context. Generally, this paper refers to peer effects as an observed correlation in agents' behavior, and defines social interaction effects as an agent's utility being directly affected by another agent's behavior (Cooper and Rege, 2011).

Social Learning Learning from peers about a new technology or product, such as health insurance, can occur in two different ways (Golub and Sadler, 2017). First, an agent can observe other agents' decisions and indirectly infer useful information that influences her own decision. Second, an agent can learn directly about other agents' beliefs or opinions and incorporate these into his decision making. Models employing the former notion of learning are often referred to as observational learning models (Choi et al., 2015). The latter type of models are called communication learning models (Choi et al., 2015) or models with knowledge spillovers (Cooper and Rege, 2011)

Observational learning models are often at the heart of studies of agricultural adoption of improved technologies. Observing the outcome of others' decision to adopt an improved technology might allow to assess the profitability of that technology, thereby influencing own adoption (Besley and Case, 1993; Goyal, 2011). Relatedly, many improved technologies are complex to use and require a specific combination of inputs to achieve optimal results. For this reason, in target-inputs models, Bayesian agents observe input-output combinations and update their input choice to reflect that of successful peers (Conley and Udry, 2010). In a similar spirit, Oster and Thornton (2012) document that school-girls in Nepal learn from their peers about the appropriate use of a new health product. As the name indicates, observational learning models require to observe other agent's actions to infer useful information.[4] In this study, a new product is introduced for the first time in a context that does not allow agents to observe their group members decisions and outcomes. While agents might have an incentive to strategically delay take-up of the product to benefit from social learning (Maertens, 2017), this is not applicable in the given context because agents face a one-shot decision.

Communication learning models exhibit direct information sharing and formalize how learning of others' beliefs about an unknown or ambiguous state of the world affects own actions.[5] In the insurance context, ambiguous states of the world could for example be the perceived value of the offered product or the perceived probability of insurer default. Perceiving an insurance provider likely to default is found to inhibit insurance demand both in theory (Liu and Myers, 2016) and in practice (Dercon et al., 2015). In a situation with high ambiguity about the perceived value of the product or probability of default, learning about others' beliefs might therefore lead the agent to update his priors and thereby change his decision. Giné et al. (2011) document social interaction effects in the demand for an index based weather insurance product. The authors exogenously vary both the price of the policy and the intensity of access to information material across villages in Kenya, leading to exogenous variation in the exposure to treated peers. They find spillovers of the information material above a specific threshold of treated peers, but no spillover of the discount voucher. Similarly, Cai et al. (2015b) document knowledge spillovers in the demand for a weather insurance product in rural China. Within a given village, the randomized study offers the product to farmers through information sessions that are held over the course of several weeks. The authors find that the effect of the information session on demand is lower for second round sessions, and that this reduction is explained by the diffusion of insurance knowledge from first round participants to their friends participating in the second round. Using an estimation approach comparable to this paper, Liu et al. (2014) provide evidence of social learning in households' decision to enroll in voluntary, public health insurance in rural China. The authors find that a 10 percentage point increase in average village enrollment leads to a five percentage point increase in the likelihood to enroll.

This study focuses on the role of social networks in demand for a health insurance product offered to credit group members of a well-known rural development organization in Pakistan.

[4] Imitation, in a sense, qualifies as a simple heuristic that is based on observational learning. Instead of inferring useful information, an imitating agent would infer something about the correctness of his decision making (Cooper and Rege, 2011).

[5] How agents update their beliefs is an ongoing field of research. DeGroot (1974) proposes a simple updating rule that averages over all beliefs. In contrast, Bayesian updating models postulate a more sophisticated decision rule (Choi et al., 2015). Grimm and Mengel (2014) tests different belief formation models in the lab and finds evidence that lies somewhere in between.

While the room for observational learning in this context is limited, communication learning might play an important role. One example is that the majority of group members is not aware of the concept of health insurance.[6]

Social Norms and Conformity Social norms and conformity considerations can be a channel for positive social interaction effects in the demand for the offered health insurance product. Social norms are defined as a set of behavioral rules that guides agents to take socially accepted decisions (Cooper and Rege, 2011). Learning about the social desirability of a decision oftentimes happens through sanctions in the form of (dis-)approval by others in the social network (Coleman, 1994). Similarly, conformity is defined as changing one's actions to align with the (expected) action of others (Cialdini and Goldstein, 2004). In situations in which no objectively acceptable behavior is defined, such as the introduction of a new product, conformity considerations and social norms operate in a comparable manner (Festinger, 1954). Social preference models postulate that agents care about the choices of others per se (Manski, 2000; Lahno and Serra-Garcia, 2015). The utility function in such models oftentimes features a loss function of own behavior in relation to others' behavior given by the distance of the agent's decision from the (expected) group decision (Bernheim, 1994; Akerlof, 1997). A conformity parameter that weighs this distance determines the magnitude of the conformity considerations. For a non-negative conformity parameter, utility is maximized if the agent's decision is as close to the expected decision of the remaining members in the group. Expecting a higher average demand in group, the conformity channel would predict that the agent is more likely to purchase insurance. Thus, the agent's decision depends positively on the average decision in the group, establishing the potential for positive social interaction effects. In a group interaction, such (simultaneous) decision making can be modeled as a non-cooperative game. Non-cooperative games, in which the agent's marginal utility depends positively on the other agents' actions, are said to exhibit strategic complementarities (Jackson and Zenou, 2015; Ballester et al., 2006).[7]

Lahno and Serra-Garcia (2015) conduct a lab experiment to test whether other agent's choices and/or others' outcomes matter in the context of making decisions under uncertainty. They find that peer effects almost double when peers make choices as compared to when peers are allocated a lottery. [8] Similarly, Bursztyn et al. (2014) conduct a large scale field experiment with a financial brokerage in Brazil to document social learning and social utility considerations in financial decision making. The study design allows the authors to separate the decision to buy an asset from the possession of that asset, thereby enabling them to separately estimate the effects of information

[6] Table 2.3 illustrates that only 22% of the credit group members in the sample have heard of the concept of health insurance. Note that positive peer effects indicate a positive correlation of own and other behavior. This might go in both ways in that an agents learning of another agents higher (lower) perceived value would lead him to positively (negatively) update his belief and potentially action.

[7] Vice versa, a game exhibits strategic substitutes if an agent's marginal utility depends negatively on other agents taking the same decision. Section 2.2.3 provides a framework that allows to study conformity considerations.

[8] For a review of experimental literature studying the role of social networks in models of other regarding preferences refer to Breza (2016).

spillovers and social preferences. In particular, clients of the investment brokerage receive either no information or are informed about both the purchasing decision and the ownership of the asset status of their friends or family members who have also been offered the asset. The authors find that both observing a connected peer expressing interest to purchase and observing a connected peer owning the asset increases the likelihood of purchasing. Moreover, the authors find that learning is more pronounced among financially sophisticated agents.

Instead of high-income brokerage clients and their decision to invest, this study focuses on low-income members of joint liability groups and their decision to insure against existential health risk. Studying the demand for index weather insurance, Cai et al. (2015a) find that participants of a training program are more likely to purchase insurance when learning about a high demand among former training participants. This study focuses on indemnity insurance and studies how group member's expected behavior influences own decision making.

Free Riding By construction, joint liability implies that group members' wealth is dependent on the wealth distribution of their fellow group members.[9] Unforeseen health expenditures for example constitute an adverse wealth shock that might lead to a group member defaulting on her outstanding loan amount. In that case, joint liability would require other group members to make up for the missing contribution. Offering voluntary insurance against idiosyncratic health risks in a joint liability context has two counteracting effects (De Janvry et al., 2014). First, insurance directly affects the distribution of the group member's own wealth. Standard insurance theory predicts that risk averse agents prefer full insurance at a fair premium price. In the case of jointly liable groups, though, there is a second, indirect effect of one member's insurance decision on the wealth distribution the remaining group members face. The reduced probability of having to cover for an insured member means that individual insurance exhibits a positive externality for other members.[10] In other words, individual insurance constitutes a public good to the group, creating an incentive to free ride (De Janvry et al., 2014; Janssens and Kramer, 2016).[11] Consequently, expecting a larger fraction of fellow group members to take up insurance might inhibit own demand, leading to negative social interaction effects.[12]

Free riding on other's insurance decision is akin to free riding on jointly liable group members when it comes to risky project choice. Fischer (2013), for example, develops a model of investment choice and risk sharing in joint liability groups to explain two inefficiencies of the conventional group lending setting. First, risk pooling allows to invest in riskier projects without having to bear the full costs in case of failure - a positive externality that encourages agents to take more risky projects. Second, peer monitoring of individual investment decisions - like

[9] If agents' utility is separable, i.e. depends only on own wealth, free riding cannot occur (De Janvry et al., 2014).
[10] Depending on the structure of the policy, insurance might only be partial.
[11] Formalizing this insurance game might lead to multiple equilibria (De Janvry et al., 2014). Section 2.2.3 provides a formal model of the insurance decision.
[12] Requiring full insurance at the group level might be one way to overcome the free riding incentives (De Janvry et al., 2014; Janssens and Kramer, 2016).

group insurance - is able to solve the free riding problem, but might lead to lower than socially optimal investment behavior. Bringing these predictions to the data, Fischer (2013) conducts lab-in-the-field experiments with microfinance clients in rural India. The results of these experiments suggest that there is substantial free riding in investment decisions, especially among more risk tolerant clients. Similarly, Giné et al. (2010) test the effects of the loan contract structure on investment behavior in a series of ten different experiments run over the course of ten months with Peruvian micro-entrepreneurs. The results provide evidence of considerably higher risk taking in jointly liable groups. At the same time, they find that dynamic incentives, in the sense of clients being excluding from future loan disbursements in the case of group default, significantly reduces risk taking behavior. These findings are in line with theoretical predictions and other experimental studies investigating the effect of repeated interaction on cooperative behavior (Dal Bó and Fréchette, 2018).

Janssens and Kramer (2016), to the best of my knowledge, are the only ones who empirically test the free riding hypotheses in the health insurance context. They conduct a framed lab-in-the-field experiment with 335 credit group members in Tanzania. For the sake of the experiment, study participants are randomly allocated to form jointly liable groups to play multiple rounds of a public good game that is framed as a health insurance decision. To test whether group insurance does indeed overcome potential free riding problems, groups are randomly offered individual insurance policies or group insurance that mandates 100% take-up among all group members. Similar to Fischer (2013), the results reveal that relatively risk averse group members are more likely to take up insurance when individual insurance is offered. In contrast, more risk tolerant group members tend to free ride on their group members insurance decisions. Since the offered insurance is optimal from an individual group member's perspective, group insurance leads to higher uptake and is found effective in overcoming the free riding problem. While these results support the free riding hypothesis, the experimental setting abstracts from several important factors. First, even though the game is dynamic, group members are not able to save and finance health expenditures through pre-cautionary savings. Second, randomly formed groups allow to overcome potential endogeneity issues in the empirical analysis[13], but might switch off the particular channel through which social norms might induce group members to conform to the average choice in the group. Third, the experiment mandates anonymous decision making, potentially reducing the taste for conformity even further.

In this paper, I study real life health insurance decisions of members of pre-existing joint-liability groups. Since these groups are not formed at random, the empirical strategy discussed below will ideally account for group unobservables that could explain similar decision taking. Further, the members of these groups are supposedly subject to social norms and a credible threat of punishment throughout future interactions. In theory, it might therefore be possible to provide the public good of insurance (Fehr and Gachter, 2000; Dal Bó and Fréchette, 2018). The confor-

[13] Refer to section 2.3 for a more detailed discussion of how endogenously formed groups can bias the empirical analysis in a social interaction framework.

mity channel in a repeated interactions context thus provides room for the existence of positive social interaction effects. At the same time, theoretical and experimental evidence suggests that agents are well aware of the strategic incentives they face when interacting in jointly liable groups. Consequently, there is grounds for the existence of negative social interaction effects. Whether conformity or free-riding considerations dominate in the context at hand is therefore an empirical question.

The theoretical framework introduced in section 2.2.3 accommodates the free riding and conformity channels through a single social interactions parameter. If conformity considerations outweigh the free riding considerations, we would expect to observe positive social interaction effects. Vice versa, if free riding considerations dominate, we hypothesize the parameter of interest to be negative. Before discussing the model in more detail, though, section 2.2.2 provides a brief history of identification in social interaction effects models.

2.2.2 Identification of Social Interaction Effects Models

The discussion of identification in social interaction models goes back to Manski (1993). In general, linear social interaction models attempt to disentangle the role of (expected) peer choices in agents' decisions from the role of own characteristics, the fact that agents with similar characteristics are likely to take similar actions, and the fact that common environmental factors can induce similar actions. A direct effect of a connected peer's (expected) choice on an agent's decision is referred to as an *endogenous* effect due to its potential spillover effects in equilibrium. The possibility that agents' take similar decisions because they have similar characteristics is referred to as *contextual* effects.[14] Analogously, agents' decisions taken in a similar environment could be similar because of factors common to this environment, a channel denoted *correlated* effects. Manski (1993) discusses the challenges of disentangling these channels due to a so-called reflection problem. Intuitively, the reflection problem arises due to a simultaneity of individual choice and average behavior in the group. More recent contributions demonstrate that the original non-identification result is implied by the particular setting of interacting in complete groups and substituting observed peer choices for expected peer choices. If instead group members are observed to be connected only to a subset of individuals in the group, the network structure provides identification conditions similar to the conditions in spatial econometrics (Kelejian and Prucha, 1998; Bramoullé et al., 2009).

This study models households' decision to purchase insurance as a binary choice. For this reason, the discussion of identification focuses on binary choice models that incorporate social interaction effects. Brock and Durlauf (2001) adapt Manski's original social network model to the context of a binary decision problem. As in the original framework, their model exhibits inter-

[14] Contextual effects can only be accounted for if the relevant characteristics influencing the decision are observable by the researcher. Unavailability of such information might lead to a spurious correlation in behavior that can in fact be explained by similarity in agent characteristics.

action in complete groups. Moreover, the authors assume that agents form rational expectations about their group members' choices by taking into account group level characteristics.[15] As a consequence, all agents attribute the same choice probability to each group member, implying that every peer exerts identical influence on others. In other words, the influence an agent exerts on other individuals is solely determined by being member of a particular group and that group's characteristics.

Lee et al. (2014a) relax this assumption in allowing agents to form heterogeneous rational expectations. Their model assumes that every agent has full information about peer characteristics and that this information is taken into account when forming expectations about peer decisions. This assumption implies that every agent has the same expectation about a peer's decision. These expectations differ across peers because of differences in peers' observable characteristics. While the original binary choice framework seems reasonable in large group settings in which the agent is interested in average behavior of the group, the extended setting seems more applicable to small group interactions in which agents know their peers better.

Yang and Lee (2017) extend this generalized binary choice framework to allow for private information in the formation of rational expectations. Intuitively, agents form heterogeneous expectations about peer choices because of (i) differences in peer observables (Lee et al., 2014a) and (ii) asymmetric information sets about privately observed peer characteristics. Accounting for private information in the formation of expectations is an interesting topic, but beyond the scope of this study. Section 2.2.3 nevertheless discusses the generalized conceptual framework in more detail.

2.2.3 Binary Choice with Social Interactions and Heterogeneous Expectations

This study employs the binary choice framework with social interactions discussed in Lee et al. (2014a) and extended by Yang and Lee (2017). The subsequent paragraphs summarize key components of that framework, adopting their notation. The components comprise the definition of social interactions, the information structure, the decision making process, and the equilibrium conditions. While introduced in a general manner, each of the component is then discussed in the context demand for low-income health insurance.

Social Interactions Suppose that there is a set of n individuals organized in G groups, where group g has size n_g, $\sum_g n_g = n$. Assuming no interactions across groups, the social-interaction matrix W_g captures connections within group g. Define $W_g = (w_{g1}, ..., w_{gn_g})'$ where $w_{gi} = (w_{gi1}, ..., w_{gin_g}), g = 1, ...G, i = 1, ...n_g$. w_{gi} captures agent i's connections and the respective

[15] A different set of studies assumes that the peer's realized outcome directly enters an agents utility function (Krauth, 2006; Soetevent and Kooreman, 2007).

weight she assigns to group members 1 to n_g. The model abstracts from self-influence, thus $w_{gii} = 0$. If individual i is not influenced by individual j they are unconnected, $w_{gij} = 0$. If individual i considers j a connection, $w_{gij} > 0$. The literature usually considers equally weighted links with $w_{gij} = 1$. In general, networks are differentiated along two dimensions: directionality and completeness. Directed networks are characterized by non-symmetric socio-interaction matrices W_g. In directed networks models it matters which agents reports to be connected to which peer. In undirected network graphs, this information is aggregated and a connection is established as soon as one part reports a link. Thus, W_g is symmetric. Directed and undirected network models differ in terms of the implicit assumptions imposed on the link formation process.[16] In terms of network completeness, interaction in complete groups implies that every member of the group is connected to every other member, $w_{gij} = \frac{1}{n_g-1}, i \neq j$. In contrast, interaction in incomplete, potentially overlapping subgroups allows for more subtle connections between members of the same group. Given the context of joint liability groups, this study assumes interaction in complete groups.Aggregating group level information, and assuming no interaction across groups, the socio-matrix W is block diagonal

$$W = \begin{pmatrix} W_1 & 0 & \dots & 0 \\ 0 & W_2 & \dots & 0 \\ \vdots & & \ddots & \\ 0 & 0 & \dots & W_G \end{pmatrix}.$$

Information Structure The social interaction matrix W_g is assumed to be common knowledge. In addition, agent i in group g is described by the set of characteristics $X_{gi} = (X_g^{g'}, X_{gi}^{c'}, X_{gi}^{p'})'$, where $X_g^{g'}$ denotes group level characteristics that are observable by all members of the group.[17] $X_{gi}^{c'}$ contains observable characteristics, such as the member's gender, age and occupation, that are common knowledge among the group members. $X_{gi}^{p'}$ denotes characteristics that are potentially known to (specific) group members, such as the number of children or household members' health status. J_{gi} is a $(n_g \times 1)$ vector that captures agents i's knowledge about other group members' private characteristics $X_{gj}^p, j \in \{1, ..., n_g\}$. $J_{gi}(j) = 1$ if i knows j's private characteristics, 0 otherwise. Thus, $J_g = (J_{g1}, ..., J_{gn_g})$ captures the information structure in group g. This information structure is assumed to be common knowledge. Define $X_{J_{gi}}^p$ as the vector of private characteristics X_{gj}^p that are in i's information set. Yang and Lee (2017) differentiate three types of information structures: (i) publicly-known characteristics, i.e. $X_{J_{gi}}^p = (X_{g1}^{p'}, ..., X_{gn_g}^{p'})', \forall i$, (ii) self-known characteristics, i.e. $X_{J_{gi}}^p = X_{gi}^p$, and (iii) socially-known characteristics, i.e. $X_{J_{gi}}^p = (X_{gj}^{p'} : j = i \vee w_{gij} \neq 0)'$. At this stage, the empirical application assumes publicly known

[16] In this study, social interactions are regarded exogenous (conditional on fixed group characteristics). Goldsmith-Pinkham and Imbens (2013) suggest a test for exogenous network formation. Johnsson and Moon (2016) propose a control function approach to model an endogenous network formation process.

[17] These group level characteristics can be either observed or unobserved by the econometrician, influencing the modeling choice later on. Ideally, the estimation will allow for unobserved correlated effects by estimating a random effects model a la Mundlak (1978) and Chamberlain (1982) (see section 2.3).

characteristics. This is considered the benchmark for potential extensions that leverage other information structures. Specifically, the study design features privately observed characteristics in the form of random premium discounts that are allocated in private.[18] The public information in group g is summarized in $Z_g = (X^g, X^c_{g1}, ..., X^c_{gn_g}, W_g, J_g)$.

Behavioral Model This paper studies agents' binary decision to insure at least one member of their household, $y_{gi} \in \{0, 1\}$.[19] This decision is modeled through a latent variable model, $y_{gi} = I\left(y^*_{gi} > 0\right)$, where $I()$ is the indicator function and the latent index y^*_{gi} is a function of the agent's characteristics X_{gi} and a weighted average of her expectation about connected peers' choices[20]

$$y^*_{gi} = \beta_0 + X^{c'}_{gi}\beta_1 + X^{p'}_{gi}\beta_2 + X^{g'}_{g}\beta_3 + \lambda \sum_{j \neq i}^{n_g} w_{gij} E\left[y_{gj} | X^p_{J_{gi}}, Z\right] - \epsilon_{gi}, \tag{2.1}$$

where $(\beta_l, \lambda), l = 0, 1, 2, 3$ are the parameter vectors of interest. β_1 and β_2 capture the direct effects of own (private) characteristics, β_3 captures correlated group effects and λ is the main social interaction effects parameter. If agent i in group g expects a higher demand among the other group members $\left(\sum_{j \neq i}^{n_g} w_{gij} E\left[y_{gj} | X^p_{J_{gi}}, Z\right]\right)$ and $\lambda > 0$, the latent index increases, making the agent more likely to demand insurance. This is in line with the conformity and repeated interactions arguments presented in section 2.2.1. Thus, if $\lambda > 0$, the model exhibits positive social interaction effects. In contrast, for $\lambda < 0$, expecting a higher demand among the (connected) group members decreases the latent index, making the agent less likely to purchase insurance. Therefore, $\lambda < 0$ implies negative social interaction effects, in line with the free riding channel. ϵ_{gi} is an iid random component drawn from a logistic density function f_ϵ. The respective draw of ϵ_{gi} is known only to agent i and assumed to be independent of the socio-matrix W_g and the observable characteristics

[18] Another reason for focusing on the case of publicly known characteristics is that the social interaction parameter of interest does not seem to be identified in the presence of group level unobserved characteristics in the cases of privately or socially known characteristics (Yang and Lee, 2017).
[19] The description of the behavioral model follows the notation of Yang and Lee (2017). Guerra and Mohnen (2017) develop an analogous multinomial choice model and provide an application to occupational choice.
[20] The empirical approach assumes publicly known characteristics and will thus include peers' observed characteristics as contextual variables. These are excluded from equation 2.1 for notational purposes. In case of socially known characteristics, for example, the agent would form expectations conditional on his information structure, accounting for a potential correlation in private characteristics.

X_{gi}. An agent's expected choice is thus given by[21]

$$E\left[y_{gi}|X^p_{J_{gi}}, Z\right] = P(y_{gi} = 1) = P(y^*_{gi} > 0)$$
$$= F_\epsilon\left(\beta_0 + X^{c'}_{gi}\beta_1 + X^{p'}_{gi}\beta_2 + X^{g'}_g\beta_3 + \lambda\sum_{j\neq i}^{n_g} w_{gij}E\left[y_{gj}|X^p_{J_{gi}}, Z\right]\right). \quad (2.2)$$

This framework can be formally described as a Bayesian game in which agents take simultaneous decisions given their information structure $X_{J_{gi}}$ and their type ϵ_{gi} (Yang and Lee, 2017). If all characteristics are publicly known, it is a complete information game. If there are privately or socially known characteristics the game exhibits (asymmetric) incomplete information.[22] Moreover, the econometrician does not observe agents' subjective expectations about peer actions.[23] Therefore, it is assumed that agents form rational expectations about the choices of their connected peers given the agent's available information. Depending on the information structure, these expectations can be heterogeneous for two reasons. First, individuals differ in their observable characteristics, X^c_{gi}, and agents take these differences into account when forming their expectations about the individuals' choices (Lee et al., 2014a). Second, information about an individual's privately observed characteristics X^p_{gi} can be asymmetrically distributed among group members. This asymmetry in information implies that group members take into account different information for the same individual when forming their expectations (Yang and Lee, 2017).[24] The empirical application currently only allows for the former type of heterogeneity because it assumes publicly known characteristics. The equilibrium condition of this game requires that every agent, as described by a specific information set $X^p_{J_{gi}}$ and private type ϵ_{gi}, chooses his best strategy $s_{gi}(X^p_{J_{gi}}, \epsilon_{gi})$ given her belief of all other (connected) agents' strategies. Formally, the consistency condition for equilibrium strategies states that $\forall i = 1, ..., n_g$

$$s_{gi}(X^p_{J_{gi}}, \epsilon_{gi}) = I\left(\beta_0 + X^{c'}_{gi}\beta_1 + X^{p'}_{gi}\beta_2 + X^{g'}_g\beta_3 + \lambda\sum_{j\neq i}^{n_g} w_{gij}E\left[s_{gj}(X^p_{J_{gj}}, \epsilon_{gj})|X^p_{J_{gi}}, Z\right] - \epsilon_{gi} > 0\right) \quad (2.3)$$

[21] Lee et al. (2014a) point out that this specification follows from a random utility framework (McFadden, 1974). Yang and Lee (2017) describe a structural model of conformity that is consistent with this framework in their appendix. Alternatively, Blume et al. (2015) suggest that a model of complementary choices, in which an agents marginal utility increases in the average (expected) choice of peer behavior, would lead to a similar estimation equation. Bajari et al. (2010) state that this set-up implies only pure strategies of the game.

[22] Agents type ϵ_{gi} will never be known by others. Privately or socially known characteristics are not observed by all agents in the group.

[23] The data collection process did not elicit subjective expectations to remain independently of the intervention. This protocol was followed to ensure that the introduction of insurance is not anticipated. For more details on data collection and roll-out refer to section 2.4. Li and Lee (2009) use subjective expectations in a binary choice model with social interactions in the context of voting decisions.

[24] Information asymmetry is relevant if characteristics are socially-known or if privately known characteristics are correlated across individuals (or with observable characteristics).

Equilibrium Expectations and Solution The solution of this game involves solving for agent i's conditional expectation of her connected peers' j strategies, $E\left[s_{gj}(X^p_{J_{gj}}, \epsilon_{gj})|X^p_{J_{gi}}, Z\right]$. In general, these expectations depend on agent i's information structure $X^p_{J_{gi}}$. In the case of publicly observed characteristics, though, every agents has the same information structure, $X^p_{J_{gi}} = (X^{p'}_{g1}, ..., X^{p'}_{gn_g})', \forall i$. Following Yang and Lee (2017), for some agent i, connected to some j, we can express her expectation of j's action as a function of that information structure J_{gi},

$$\Psi^e_{gj,J_{gi}}(x) = E\left[y_{gj}|X^p_{J_{gi}} = x, Z = z\right]. \tag{2.4}$$

It can be shown that this vector-valued function is a contraction mapping if regularity conditions hold and social interactions are not too strong (Lee et al., 2014a; Yang and Lee, 2017). The contraction mapping property implies that there is a unique Bayesian equilibrium of the simultaneous move game. The sufficient condition for a unique equilibrium in a framework with row-normalized social interaction matrices and logistic error-term distribution is $|\lambda| < 4$. In the case of complete networks, Lee et al. (2014a) establish that there is a unique solution to this equation if and only if the social interactions parameter is within a specific range, $\lambda \in \left(-\frac{(n_g-1)}{max_u f_\epsilon(u)}, \frac{1}{max_u f_\epsilon(u)}\right)$.[25]

If characteristics are publicly know, all agents have the same information set and therefore form identical expectations about any peer they have in common.[26] In the case of complete networks, this implies that all agents form identical expectations of a given group member's insurance decision. Nevertheless, these expectations differ across group members because of differences in their observable characteristics (Lee et al., 2014a). Formally, $\forall i = 1, ..., n_g, X^p_{J_i} = \left(X^p_1, ..., X^p_{n_g}\right)$ requires the equilibrium expectations

$$\Psi^e = \begin{pmatrix} E\left[y_1|X^p_1, ..., X^p_{n_g}, Z = z\right] \\ \vdots \\ E\left[y_{n_g}|X^p_1, ..., X^p_{n_g}, Z = z\right] \end{pmatrix}$$

[25] Note that the condition for a unique solution depends on the size of the respective group. In the empirical application there is considerable variation in group sizes and thus variation in the condition for a unique equilibrium solution. Note, that given a particular value of the social interactions parameter, variation in group size might lead to multiple equilibria for some groups, but not others. In the empirical application the occurrence of multiple equilibria is mitigated by focusing on groups with more than 3 members attending.

[26] For more information on the cases of self and or socially known characteristics see Appendix B.1. For a more detailed discussion of the numerical methods required to obtain solutions these cases refer to Yang and Lee (2017). Note that in the case of interaction in complete networks there is no room for socially known characteristics, while there would be room for privately known characteristics.

to satisfy the consistency condition

$$\Psi_i^e = E\left[I\left(\beta_0 + X_{gi}^{c'}\beta_1 + X_{gi}^{p'}\beta_2 + X_g^{g'}\beta_3 + \lambda\sum_{j\neq i}^{n_g} w_{gij}\Psi_j^e - \epsilon_{gi} > 0\right)|X_1^p, ..., X_{n_g}^p, Z = z\right],$$
$$\forall i = 1, ..., n_g. \tag{2.5}$$

As stated above, a unique solution of the equilibrium consistency condition exists if the social interactions parameter λ is within a specific range. In case the numerical procedure described in section 2.3 leads to multiple equilibria, a random selection rule is implemented. The random selection rule assigns a probability of one to one of the equilibria and probability zero to all others. If the selection rule is correctly specified, this leads to consistent point estimates (Krauth, 2006; Soetevent and Kooreman, 2007).[27]

Reparameterization Following Lee et al. (2014a), the behavioral model proposed in equation 2.2 is reparameterized. The reparameterization allows the authors to establish that the identifying assumption on the social interaction effects parameter λ is no stronger than the assumption invoked in the case of homogeneous equilibrium expectations (Brock and Durlauf, 2001) or in the case of a linear social interactions model with continuous outcome variable (Bramoullé et al., 2009; Kelejian and Prucha, 2010).[28] To show this equivalence the authors define $\tilde{y}_{gi} \in \{-1, 1\}$ as $\tilde{y}_{gi} = 2y_{gi} - 1$ and rewrite equation 2.2 as

$$P(\tilde{y}_{gi} = 1) = P(\tilde{y}_{gi}^* > 0) = F_\epsilon\left(\tilde{\beta}_0 + X_{gi}^{c'}\tilde{\beta}_1 + X_{gi}^{p'}\tilde{\beta}_2 + X_g^{g'}\tilde{\beta}_3 + \tilde{\lambda}\sum_{j\neq i}^{n_g} w_{gij}E\left[\tilde{y}_{gj}|X_{J_{gi}}^p, Z\right]\right). \tag{2.6}$$

Agent i' expected choice is then given by $E\left[\tilde{y}_{gi}|X_{J_{gi}}^p, Z\right] = P(\tilde{y}_{gi} = 1) - P(\tilde{y}_{gi} = -1) = 2P(\tilde{y}_{gi} = 1) - 1$. In a further step, it can be shown that $\lambda = 2\tilde{\lambda}$.[29] For the Bayesian game with logistic type distribution ϵ and row-normalized socio-interaction matrix W_g this implies that a unique Bayesian Nash equilibrium exists if $|\tilde{\lambda}| < 2$. Writing out the logistic cumulative distribution function in equation 2.6 and rearranging we have

$$P(\tilde{y}_{gi} = 1) = \frac{exp\left(\tilde{k}\right)}{1 + exp\left(\tilde{k}\right)} = \frac{exp\left(\tilde{\tilde{k}}\right)}{exp\left(\tilde{\tilde{k}}\right) + exp\left(-\tilde{\tilde{k}}\right)} = \frac{1}{1 + exp\left(-2\tilde{\tilde{k}}\right)} \tag{2.7}$$

[27] Lee et al. (2014a) hypothesize that their estimation approach should be robust to this a procedure.
[28] Moreover, specifying $y_{ig} \in \{0, 1\}$ implicitly assumes that $y_{ig} = 0$ does not exert any peer effects (Soetevent and Kooreman, 2007). [29] The relationship between β and $\tilde{\beta}$ depends on $\tilde{\lambda}$ and is derived in Lee et al. (2014a).

where

$$\tilde{k} = \tilde{\beta}_0 + X_{gi}^{c'}\tilde{\beta}_1 + X_{gi}^{p'}\tilde{\beta}_2 + X_g^{g'}\tilde{\beta}_3 + \tilde{\lambda}\sum_{j\neq i}^{n_g} w_{gij} E\left[\tilde{y}_{gj}|X_{J_{gi}}^p, Z\right]$$

and

$$\tilde{\tilde{k}} = \tilde{\tilde{\beta}}_0 + X_{gi}^{c'}\tilde{\tilde{\beta}}_1 + X_{gi}^{p'}\tilde{\tilde{\beta}}_2 + X_g^{g'}\tilde{\tilde{\beta}}_3 + \tilde{\tilde{\lambda}}\sum_{j\neq i}^{n_g} w_{gij} E\left[\tilde{y}_{gj}|X_{J_{gi}}^p, Z\right]$$

with $\tilde{\beta}_t = 2\tilde{\tilde{\beta}}_t, t = 0, 1, 2, 3$ and $\tilde{\lambda} = 2\tilde{\tilde{\lambda}}$. Consequently, $|\tilde{\tilde{\lambda}}| < 1$ emerges as the necessary restriction on the reparameterized social interactions parameter. Moreover, using equation 2.7, agent i's expected value can be expressed as

$$E\left[\tilde{y}_{gi}|X_{J_{gi}}^p, Z\right] = \frac{2}{1+exp(-2\tilde{\tilde{k}})} - 1 = \frac{1-exp(-2\tilde{\tilde{k}})}{1+exp(-2\tilde{\tilde{k}})} = \frac{exp(\tilde{\tilde{k}})-exp(-\tilde{\tilde{k}})}{exp(\tilde{\tilde{k}})+exp(-\tilde{\tilde{k}})} = tanh(\tilde{\tilde{k}}) \quad (2.8)$$

2.3 Estimation Strategy

This section discusses how to obtain parameter estimates for the model discussed in section 2.2.3. The estimation strategy focuses on the case of publicly observed characteristics because it is a benchmark for potential extensions and because the parameters are not identified for other information structures in presence of group effects unobservable by the researcher (Yang and Lee, 2017).[30] Therefore, the model in equation 2.7 can be adapted to include contextual effects without having to solve for the conditional expectation of privately or socially known characteristics. As discussed in section 2.2.2, contextual effects account for the possibility that agents take the same decision because they exhibit similar characteristics.[31] Households that both exhibit higher health risks for example might both be more likely to take-up insurance. Following the literature, such contextual effects are incorporated for by allowing agent i's choice to depend on average observed characteristics of her connected peers j, $\sum_{j\neq i}^{n_g} w_{gij}X_{gj}$.

Moreover, members of the same joint liability group g might take similar decisions because they are exposed to the same environmental factors or common shocks (Manski, 1993).[32] The choice model described in section 2.2.3 accounts for such environmental factors through observable group characteristics $X_g^{g'}$. The estimation approach could account for such observable group characteristics. However, additional group level determinants that are potentially unobservable to the econometrician might influence the group members' general tendency to enroll in insurance.

[30] Yang and Lee (2017) provide a discussion of the estimation approach for the cases of privately and socially known characteristics in absence of correlated group effects.

[31] In addition to the observability of the relevant characteristics by the research (as stated in section 2.2.2), the insurance game specified in section 2.2.3 requires that the characteristics are observable by other group members. For the case of publicly observed characteristics the information structure guarantees this by assumption.

[32] In the setting at hand, insurance is introduced by social organizers in a community meeting. Since all group members interact with the same social organizer, α_g could capture effects specific to the social organizer. Further, the group formation process could be driven by considerations that are shared among the potential group members, such as a taste for risk taking (Attanasio et al., 2012; Cooper and Rege, 2011).

At the same time these group level characteristics might be correlated with group members' characteristics (Mundlak, 1978). Neglecting the possibility of group unobservables could therefore result in biased estimates even when accounting for observable group characteristics (Lee et al., 2014a; Wooldridge, 2010). One way to account for the possibility of unobserved correlated group effects would be to include group level fixed effects in the decision model (Lin, 2010).[33] Estimating group fixed effects in a non-linear discrete choice model, however, is likely to result in biased estimates due to the incidental parameters problem (Lee et al., 2014a; Greene, 2004; Wooldridge, 2010). Instead, the estimation approach could follow Lee et al. (2014a) and Liu et al. (2014) in leveraging a correlated random effects model to overcome potential endogeneity concerns (Mundlak, 1978; Chamberlain, 1982). While such a correlated random effects approach is not implemented in the estimation of this paper yet, a formal discussion is provided. The correlated random effects framework can be modeled through a composite error term, $\epsilon_{gi} = u_g + v_{gi}$, that comprises of group and individual level innovations, u_g and v_{gi} respectively. For a logistic choice model, the individual level innovations v_{gi} are independent draws from a logistic distribution. The group level component u_g is modeled as a linear projection of average group characteristics and a group level projection error (Bajari et al., 2010)[34]

$$u_g = \bar{X}_g \beta_g + \alpha_g, \tag{2.9}$$

where $\bar{X}_g$ contains average values of observable characteristics across all group members and α_g is the projection error. By construction, α_g is uncorrelated with the linear projection. Moreover, the parameter estimates of the contextual effects and individual characteristics absorb the linear projection term. Furthermore, assuming that the projection error α_g follows a normal distribution with unknown variance for all groups g, $\sigma\alpha_g \sim N(0,1)$, the correlated random effects approach introduces only one additional parameter to estimate (Lee et al., 2014a). Consequently, we can re-write the linear index in equation 2.7 as

$$\tilde{\tilde{k}} = \tilde{\tilde{\beta}}_0 + X_{gi}^{c'} \tilde{\tilde{\beta}}_1 + X_{gi}^{p'} \tilde{\tilde{\beta}}_2 + \tilde{\tilde{\gamma}} \sum_{j \neq i}^{n_g} w_{gij} X_{gj} + \tilde{\tilde{\lambda}} \sum_{j \neq i}^{n_g} w_{gij} E\left[\tilde{y}_{gj} | X_1^p, ..., X_{n_g}^p, Z = z \right] + \sigma\alpha_g, \tag{2.10}$$

.

where $\tilde{\tilde{\gamma}}$ provides the vector of contextual effects parameters and σ is the unknown standard deviation of the group random effect. Note that the current estimation approach does not account for the group random effect $\sigma\alpha_g$ yet.[35]

[33] The inclusion of group level fixed effects might only partially solve the endogeneity problem in the case of incomplete networks, because peer-to-peer link formation might still be influenced by unobservable characteristics common to the respective pair of peers (Bramoullé et al., 2009; Lin, 2010; Johnsson and Moon, 2016).
[34] In the original panel data setting, the group level component is modeled as a linear projection of average individual level characteristics across all time periods (Mundlak, 1978). In the social interaction context, time periods are replaced with group members exposed to the same environment (Liu et al., 2014). [35] If the estimation accounted for the group random effect, a reparameterization of σ as e^{ω} would ensure $\sigma > 0$.

Given the distributional assumptions above, it is possible to obtain parameter estimates through maximum likelihood estimation. As seen in equation 2.10, these estimates depend on endogenously formed expectations about group members' behavior. For this reason, the estimation strategy incorporates a nested fixed point routine to solve the equilibrium consistency condition (Lee et al., 2014a).[36] Intuitively, the first step of the iterative procedure is to obtain values for peer expectations through numerically solving the equilibrium consistency condition in equation 2.5. The resulting expectations are then used in a second step as an input in the maximum likelihood estimation. In subsequent iterations, these parameter estimates serve as updated starting values to solve for the expectations term. If a unique rational expectations equilibrium exists, this approach can be followed until the vector of parameter estimates converges.[37]

The log-likelihood function is given by[38]

$$lnL(\tilde{\tilde{\beta}}_0, \tilde{\tilde{\beta}}_1, \tilde{\tilde{\beta}}_2, \tilde{\tilde{\gamma}}, \tilde{\tilde{\lambda}}, \sigma; \tilde{Y}|X_1^p, ..., X_n^p, Z) = \sum_{i=1}^{n} \left(\frac{\tilde{y}_{gi}+1}{2} ln\left[P(\tilde{y}_{gi}=1)\right] + \frac{\tilde{y}_{gi}-1}{2} ln\left[P(\tilde{y}_{gi}=-1)\right] \right) \tag{2.11}$$

where Z is the vector of publicly observed information and $X_1^p, ..., X_n^p$ is the vector of privately observed information as discussed in section 2.2.3. In the case of publicly observed characteristics, every group member is assumed to have full information about all other group members' characteristics. For this reason, the estimation procedure includes household level characteristics in X that are thought to be both observable by other group members and important determinants of insurance demand. In particular, the estimation procedure controls for household-level socio-demographic information such as education, age or household size, the household's economic situation as measured for example by asset ownership, and the household's health history.[39]

To assess the importance of controlling for contextual and correlated group effects, I follow Lee et al. (2014a) and estimate models in which some of the social interaction parameter vectors are restricted to 0.[40]

[36] Iterative nested fixed point algorithms are commonly used in the estimation of dynamic discrete choice models (Yang and Lee, 2017; Rust, 2000, 1987). An alternative approach would be a two-step estimation procedure (Bajari et al., 2010). The first step would be to obtain (non/semi-parametric) estimates the choice probability. These estimates can be used in the second step to obtain unbiased estimates. Generally, the first stage of this approach requires an exclusion restriction to overcome potential endogeneity. Liu et al. (2014) create such an exclusion restriction by assuming no contextual effects.

[37] In case multiple rational expectations equilibria exist for at least some groups, I implement an equilibrium selection rule that randomly assigns a probability of one to one of these equilibria. In the estimation, multiple equilibria do not appear regularly.

[38] The individual likelihood contributions are independent since the agent's type v_{gi} is iid and independent of observed characteristics and the socio-matrix. Obtained estimates for the random effects coefficient σ, the estimation approach would employ a simulated maximum likelihood estimation approach in which the choice probabilities in equation 2.11 would be replaced with simulated choice probabilities. These simulated choice probabilities would result from averaging predicted choices over D draws of α_g from a standard normal distribution.

[39] Table 2.3 provides a detailed list of household-level characteristics accounted for in the analysis. Refer to section 2.4.2 for a more detailed discussion on the available sources of data.

[40] The estimation is implemented in the statistical software R and partly based on the MATLAB routine provided alongside the original paper (Lee et al., 2014b; R Core Team, 2014; Henningsen and Toomet, 2011).

Model 1 No social interaction effects: $\tilde{\tilde{\gamma}} = \tilde{\tilde{\lambda}} = \sigma = 0$

Model 1 serves as a benchmark and constitutes a conventional binary choice model in which the demand decision is solely determined by own characteristics.

Model 2 Endogenous social effects only: $\tilde{\tilde{\gamma}} = \sigma = 0$

Model 2 allows for endogenous social interaction affects, but excludes contextual and correlated group effects. If the either of these channels matters, omitted variables bias could lead to biased estimates of the endogenous social interactions parameter.

Model 3 Contextual effects only: $\tilde{\tilde{\lambda}} = \sigma = 0$

Model 3 allows to assess the importance of contextual effects, while excluding endogenous social interaction effects and random group effects. As for model 2, omitted variable bias could lead to biased estimates if endogenous or correlated social effects are relevant.

Model 4 Endogenous and contextual effects only: $\sigma = 0$

Model 4 allows for both endogenous social interaction and contextual effects, thereby partially overcoming the potential concerns of omitted variable in models 2 and 3. If unobserved group effects are present, this model might still result in biased estimates. A model that, in addition, accounts for such unobserved effects would therefore allow to mitigate such concerns.

While the estimation of these models provide parameter estimates, the interpretation of these estimates as marginal effects is complicated by two factors. First, the non-linearity of the model implies that the marginal effects depend on the level of individual characteristics and peer characteristics. Second, the parameter estimates depend on endogenously formed equilibrium expectations. Since these expectations are also based on peer characteristics, a change in any of these characteristics affects the choice probability both through a change in the direct or contextual effect and through an indirect effect via a change in equilibrium expectations. Moreover, the presence of direct and indirect effects implies that, in general, marginal effects differ for individuals whose own characteristics change and individuals that only experience this change. Lee et al. (2014a) derive marginal effects formulas that explicitly account for these channels.

In this paper, the main parameter of interest is the endogenous social interactions parameter. A negative social interactions parameters suggests that an increase in an agent's expectation of his group members' insurance decision leads to a lower probability of take-up, in line with the free riding argument. A positive social interactions parameter in contrast suggests that an increase in expected demand among group members' leads to a higher probability to purchase. Being agnostic about the underlying reason for a change in equilibrium expectations, the conventional marginal effect is then given by the partial derivative of equation 2.7 with respect to the agent's expectations,

$$\frac{\partial P(\tilde{y}_{gi} = 1)}{\partial M} = 2P(\tilde{y}_{gi} = 1)\left[1 - P(\tilde{y}_{gi} = 1)\right]\tilde{\tilde{\lambda}}, \tag{2.12}$$

where $M = \sum_{j \neq i}^{n_g} w_{gij} E\left[\tilde{y}_{gj} | X^p_{J_{gi}}, Z\right]$. Using equation 2.12, it is possible to obtain average partial effect estimates of the endogenous social interactions terms by averaging individual level marginal effects estimates.

2.4 Empirical Setting and Data

This paper uses data from a randomized control trial in rural Pakistan. While Pakistan is classified as a lower-middle income country, in 2013, about one third of the population lived below the national poverty line.[41] For this reason, adverse health shocks and the resulting financial burden pose an existential risk to a large part of the population (Heltberg and Lund, 2009a). The government attempts to mitigate this risk through its system of free public health facilities. Due to low public spending on health[42], many expensive treatments and drugs provided in these facilities are not covered (MoH, 2009). Further, formal private health insurance plays little to no role in poor household's risk management portfolio.[43] At the start of this study, our implementation partner, the National Rural Support Programme of Pakistan (NRSP), was the only non-governmental institution that offered low-income hospitalization insurance with significant outreach (SECP, 2012).

NRSP is the largest rural development program in Pakistan, reaching more than 2.5 million households. In rural areas, most activities are implemented through community organizations (*COs*), groups of 9 to 15 members living in the same village.[44] Members of COs are eligible to apply for NRSP agricultural and livestock loans. These loans exhibit joint liability meaning that group members will have to cover outstanding loan amounts of defaulting members. In urban areas, NRSP operates as a micro-finance organization extending enterprise loans to credit groups comprised of three to five members.

As of 2005, NRSP credit products are bundled with mandatory hospitalization and disability insurance for microcredit clients and their spouses. The main benefit of this insurance policy is the coverage of inpatient hospitalization expenditures accrued during the loan period up to a threshold of PKR 15,000 ($\sim$ USD 150) per person insured. The coverage threshold is at about 65% of available monthly household income and suffices to finance a minor surgery with a four

[41] If not stated otherwise, information in this section is based on the World Bank Indicators 2015, `http://data.worldbank.org/country/pakistan`. Fischer et al. (2017) provide a similar description of the background and intervention.

[42] The Government of Pakistan spends about one percent of its GDP on health, one of the lowest fractions in the world.

[43] Existing insurance schemes predominantly target formal and public sector employees.

[44] COs are formed in a four stage mobilization process. In a first step, a NRSP social organizer identifies and introduces the organization and its program to social activists in the community. These activists inform the community about NRSP and its program in an informal, unstructured way. In a third step, the NRSP social mobilizer formally introduces the organization and its operations to the community in a program induction meeting. After this meeting, the CO forms as a group of self-selected individuals that share the intention to collect savings. NRSP policies permit members of the same CO to come from the same household. In the inaugural CO meeting, the members of the group select a CO president and a CO manager who share administrative responsibilities and act as contact persons for NRSP staff.

day stay in the hospital.[45] The total premium of PKR150 is automatically deducted from the loan amount before disbursement. Note that in the mandatory policy, only a fraction of the household is insured against unforeseen health expenditures.

2.4.1 Intervention and Sampling

In 2014, our implementation partner engaged in a randomized control trial (RCT) to test the scope for expanding the existing mandatory insurance coverage. In collaboration with the University of Mannheim, NRSP developed four low-income health insurance policies that allow its credit clients to cover additional household members against unforeseen health expenses. In the RCT, one of these four policies is offered in a randomized manner to members of community organizations and credit groups from the same village. Table 2.1 summarizes the characteristics of the four policies.[46] The offered policies exhibit either individual eligibility (policies P1 and P2) or household eligibility (policies P3 and P4). In the individual eligibility policies the client is allowed to enroll any number and combination of dependents in his household. In contrast, in the household eligibility policies, the client is required to insure either all dependents or none. The group policy (P4), in addition, requires minimum take-up of 50% among the group members present during the community meeting through which insurance is offered. The benefits of the offered policies are comparable to the benefits of the mandatory policy described above. The coverage threshold for hospitalization expenses (in policies P1, P3 and P4) is PKR15,000 per person insured for a contract length of 12 months. The corresponding premium per person for these policies is PKR100. The individual policy P2 exhibits a coverage threshold of PKR30,000 and therefore a higher premium of PKR150 per person.

The insurance innovations are rolled out through community meetings held by NRSP social organizers. These sessions are structured into three phases. In the first phase, the social organizer conducts an interactive awareness session to recap the concept of insurance and explain the existing, mandatory insurance contract. This first phase of the meeting takes about 30 to 40 minutes.[47] In the second phase, the social organizer introduces the new, voluntary insurance policy that has been randomly determined to be offered in that village. The third phase is given by the enrollment procedure that is held with each group member in private. During enrollment, group members play a lottery that randomly assigns a discount of PKR 0, 10, 20 or 30 on the per person insurance premium. Since this third phase is held with each group member in private, enrollment is sequential. At the same time, there is considerable uncertainty about other group members' demand when deciding about own take-up, making the decision effectively simultaneous.[48]

[45] The mandatory policy also covers accidental death and disability of the household's main breadwinner. Furthermore, the policy includes a life insurance element in that the outstanding loan amount is written off in case of main breadwinner's death. Refer to Fischer et al. (2017) for a more detailed description. [46] This table along with more detailed information on the policies can also be found in Fischer et al. (2017). [47] During this first phase, the social organizer confirms the attendance of the group members. [48] Even if a group member was aware of realized take-up of the peers deciding before him, uncertainty about the

The sampling frame for this study is determined by the set of NRSP clients in Sargodha district in the Punjab province of Pakistan who apply for a loan with our implementation partner between December 2014 and March 2015. Observing clients who apply for a loan, the sampling frame is given by all active members of joint liability groups with at least one incoming credit application in the sampling window (Fischer et al., 2017).[49] We attempt to sample approximately 13 households per village. The sampling frame consists of both smaller credit groups and larger community organizations.[50] Due to their small group size, credit groups are excluded from the analysis.[51]

Table 2.1 – Insurance Innovations

	Individual (P1)	**Individual High (P2)**	**Household (P3)**	**Group (P4)**
Eligibility	Individual		Household	
Add. Requirement				50% Uptake in the group
Coverage Limit (pp)	15,000	30,000	15,000	15,000
Premium (pp)	100	150	100	100
Premium discounts (pp)	0 - 30	0 - 30	0 - 30	0 - 30

Numbers are in PKR; USD 1 ≈ PKR 101, PKR 15,000 ≈ USD 148 (in February 2015), pp = per person.
Individual Eligibility: Insure any number and combination of dependents.
Household Eligibility: Insure either all or none of the HH members.
Premium Discounts: Vouchers of PKR 0, 10, 20 and 30 (pp); randomized with equal probability at the household level.

2.4.2 Data

This study leverages three different sources of household and individual level data of both administrative and survey nature. First, client level administrative data obtained from the implementation partner's management information system (MIS) provides unique identifiers for households, groups and villages. This information allows to map clients to groups and groups into villages.

demand of peers deciding after remains. For this reason, the decision process can be modeled as a simultaneous game. Observing some group members' realized demand would potentially introduce some room for observational learning.

[49] Members of joint liability groups generally take loans at the same time with our implementation partner, making this approach equivalent to sampling all members of the joint liability group.

[50] In urban and peri-urban locations, NRSP provides business and entrepreneurship loans to members of so-called credit groups that consist of three to five members. The members of these groups apply for individual loans as a group.

[51] The sampling procedure would select complete groups until at least 13 households are sampled per village and consider the village as fully sampled thereafter, thus ignoring later incoming credit applications. Effectively, the focus on community organizations leads to sampling all active members of one or two COs per village. For more information on the sampling procedure refer to Fischer et al. (2017).

The administrative data contains information on incoming credit applications, thereby facilitating the sampling procedure described above. Furthermore, the administrative data includes a household roster that defines the dependents eligible for insurance.[52] After roll-out, administrative data collected from the MIS system is supplemented with information on the sampled dependents' insurance status, including the type of policy offered and the premium paid.

Second, this study leverages information from a baseline survey conducted between December 2014 and March 2015.[53] The survey is administered to the client registered in our implementation partner's system to align with the captured insurance decisions. The survey is administered through computer-assisted personal interviews (CAPI) by independent enumerators operating in the name of University of Mannheim, Germany.[54] The survey modules capture both household level and individual level information. Among others, the collected household-level information comprises socio-demographic and economic indicators and psychological well-being. Individual-level information is collected on further socio-demographic indicators, income generating activities, and health status. The health module contains detailed information on subjective health status, the history of both in- and outpatient treatments, and coping strategies in case of a health shock.

Third, we collect additional information through a bi-monthly phone survey over the course of one year. The phone survey is administered remotely through independent enumerators and attempts to capture higher-frequency information about the occurrence of health shocks in the household. The phone survey collects dependent level information on health status, the history of inpatient and outpatient health shocks (since the last call), health expenditures incurred, and coping strategies utilized. Fischer et al. (2017) use the information on dependent level health expenditures to predict dependents' expected health expenditures given their baseline characteristics. The empirical application aggregates these individual level expected cost measures as a proxy for households' perceived health risk.

Insurance Demand The administrative data provides information about the insurance status of all eligible dependent's for all sampled households.[55] This information is aggregated on the household level to define a dichotomous indicator of a household insuring at least one eligible member.

[52] The household roster is collected by the implementation partner's field staff as part of the credit application process and elicited before roll-out of the intervention. Information from this household roster is incorporated in the CAPI software to facilitate the data collection process and to improve data quality. The MIS data also contains information about which clients take administrative positions within the joint liability group. In general, every group has both a president and a group manager, positions that could proxy an individual's influence in the group.

[53] The baseline survey is conducted before program implementation. All sampled households from a given village must be interviews before the village is eligible to receive the intervention. In practice, there is a two to three week waiting period between baseline survey and program implementation.

[54] The CAPI system included both instantaneous in-field quality assurance and more sophisticated, regular data quality checks on the enumerator level. These data quality checks are anticipated to prevent logical errors and serious measurement error, especially of sensible data.

[55] The administrative data is back checked to align with the data provided by the social mobilizers introducing the insurance policy.

This extensive margin indicator provides the coarsest level of information about a household's insurance decision. Note that the amount of information contained in this dichotomous indicator varies by policy. For this reason, the analysis reports results both for pooling all policies regardless of the offered insurance policies and separate by type of offered policy. Implicitly, the extensive margin indicator is assumed to be the key information group members use in their decision making. At the same time, more nuanced, extensive and/or intensive margin indicators might be driving household decision making.[56] On the intensive margin, agents might consider the marginal effect of insuring an additional household member (of a particular age group and/or gender), and how this affects other group members' behavior. While the estimation approach could be adjusted to account for other extensive margin outcome indicators, assessing intensive indicators would require a modified estimation procedure.[57]

Social Interactions This study defines the relevant peer group as the members of the joint liability group. While group members might have broader social circles in their respective village and beyond, the roll-out procedure used to introduce the insurance innovations prevents inter-group interactions from influencing demand decision.[58] Corresponding socio-matrices can be constructed from the group membership information contained in the administrative dataset.

2.4.3 Descriptive Statistics

Table 2.2 provides the number of villages and groups in which insurance is offered. In total, insurance policies are offered in 334 villages and 1025 groups. As mentioned above, we focus on the subset of community organizations (COs). These 199 jointly liable groups are located in 161 villages and have about 2100 members in total (average group size of 10.5 members).[59] About 75% of the group members attend the community meetings through which the respective insurance policy is introduced. Attending group members have about 4950 dependents eligible for insurance (average of 3.18 eligible dependents per group member).[60] Figure 2.1 depicts the distribution of group members and members attending the group meeting. We observe that there are four groups with only one or two members attending the group meeting. These groups are excluded from the analysis.[61]

[56] In a social learning framework, for example, agents might form expectations on whether peers insure dependents of particular age groups or gender and integrate this into their decision making.

[57] At this point, the empirical application focuses on extensive margin indicators of a household's insurance status.

[58] The roll-out protocol specifies that community meetings can be attended by members of one community organization at most. Therefore, all community organizations considered in the empirical application have been offered the insurance policy in separate meetings.

[59] Note that the number of COs offered the respective policy seems to systematically increase from P1 to P4. This might be because the sampling process was not stratified on the number of COs in each village. Instead, the sampling approach solely focused on the total number of households sampled per village.

[60] Eligible dependents exclude the client's spouse but includes any other dependent mentioned in the household listing.

[61] Group members with no eligible dependent reported at baseline have been excluded during data cleaning as they do not face an active insurance decision.

Socio-Demographic Information Table 2.3 provides household level information for the subset of group members attending the community meetings. As mentioned in section 2.3, we include the set of household-level characteristics that is thought to both influence insurance demand and to be observable by other group members. Households have 3.18 eligible dependents on average. This number differs from the number of dependents reported in the survey due to mismatches with the administrative database.[62] Clients' average age is approximately 39 years, and about 40% of clients in the sample have not attained any formal education. 12% of clients in the sample are female. Total monthly household income amounts to about PKR $22,000$ ($\sim$ $190)[63] and total savings amount to about 70% of monthly income. Outstanding liabilities in form of loans (credit) amount to about twice monthly household income. Since monetary measures tend to be noisy, as indicated by their large variances, the baseline survey captured household's ownership of a set of durable assets. This asset ownership information is used in a principal components analysis to construct a standardized index that indicates socio-economic status (*wealth index*) (Vyas and Kumaranayake, 2006; Kolenikov and Angeles, 2009).[64] Considering health indicators, 11% of households had to admit one of their dependents for treatment in a hospital within the last 12 months (inpatient treatment). The average cost for inpatient treatment is PKR 4,461 ($\sim$ $40), but heavily skewed to the right. Note that costs for treatment of health conditions without being admitted to a hospital (outpatient costs) exhibit both a higher mean and a higher variance than inpatient costs. As discussed in section 2.4.2, we use baseline survey data and phone survey follow-up information about the occurrence of health shocks to predict expected health expenditures on the individual level. Aggregating these individual level predictions, the average household faces expected inpatient health expenditures of about PKR300 (Expected Cost Index).[65] Table B.1 in Appendix B.2 provides summary statistics and balance tests for the set of socio-demographic characteristics across the different policies offered. While there appear to be statistical imbalances in some of the descriptive variables considered, balance is achieved on key variables related to the households economic and health status.

[62] Dependent-level matches are constructed using a fuzzy merge routine that is based on the dependents' name, age and gender reported both in the survey and administrative data.
[63] Exchange rate: $1 = PKR101
[64] The wealth index is constructed using information from the complete sample of credit group and community organization members. The positive mean in column 1 indicates that the subsample of community group members has a higher socio-economic status than the sample of credit groups and COs combined.
[65] For more information on the construction of the expected cost index refer to Fischer et al. (2017). In the estimation procedure, the monetary variables for income, savings, credit and inpatient and outpatient costs are standardized to log-measures in PKR'000 to make the expected parameter space smoother.

Table 2.2 – Overview and Treatment Allocation

	P1	P2	P3	P4	Total
Villages	82	84	82	86	334
Groups	260	262	246	257	1025
Villages with COs	35	39	42	45	161
COs	41	48	54	56	199
HHs in COs	433	490	560	614	2097
HHs Attending in COs	338	368	417	434	1557
Dependents in COs	1212	1512	1783	1780	6287
Attending Dep. in COs	997	1187	1397	1375	4956

Note: This table provides an overview of the treatment allocation and the study sample. Overall, insurance policies are offered to more than 1000 groups in 334 villages. This study focuses on the decision to insure of the 1557 households attending community meetings in the subsample of about 200 jointly liable community organizations (COs) offered insurance in 161 villages.

Table 2.3 – Summary Statistics

	Mean (SD)	
Socio-Demographics		
Dependents (Survey)	3.96	(1.76)
Dependents (Matched)	3.18	(1.70)
Group_Leader_(D)	0.18	(0.38)
Client_Female_(D)	0.12	(0.33)
Client No Education (D)	0.40	(0.49)
Client_Age	38.73	(11.07)
Economic		
Wealth Index	0.29	(2.51)
Income (month)	21846.39	(23435.35)
Savings	15396.26	(84632.82)
Credit	43404.42	(89539.38)
Health & Insurance		
Knows Health Insurance (D)	0.22	(0.42)
Any Inpatient (D)	0.11	(0.32)
Total Inpatient Cost	4461.46	(23875.02)
Total Outpatient Cost	6954.99	(34842.52)
Expected Cost Index (HH)	304.29	(306.53)
Insurance Demand		
HH Insured	0.54	(0.50)
No. Insured Dependents	1.28	(1.64)

Note: The table provides means and standard deviations (SD) of the respective variables. Binary variables are indicated with (D).

Outcome Data The lower panel of table 2.3 summarizes intensive and extensive measures of insurance demand. On the extensive margin, 54% of households in the sample insure at least one eligible dependent. On the intensive margin, about 1.3 dependents are insured per household on average. Figure 2.2 plots intensive and extensive margin insurance demand for the two types of policies across the different discount levels. As expected, as the discount increases, insurance demand increases for each policy type both in terms of extensive and intensive measures of demand.[66] Due to the difference premium price per person for the individual policies, Figure 2.2 possibly summarizes demand at different points along the demand curve. Figures 2.2b and 2.2a in Appendix B.3 therefore verify the same patterns for each of the policies. Comparing demand for individual and household level policies, extensive margin demand is higher for individual level policies across almost all price levels. Vice versa, intensive level demand is higher for household level policies at all price levels. Moreover, note that the intensive demand pattern for household policies can be explained by household size. Larger households appear less likely to buy household insurance at higher premium prices. In general, insurance demand seems rather price sensitive. In the household policies, for example, a 30 percent decrease in premium price almost doubles the share of households insured. Figure B.3 in Appendix B.3 provides own price elasticity estimates for the two types of policies and reveals that these elasticity estimates are larger than one in absolute terms for both types of policies.

So far, we have mainly looked at household level demand. The focus of this paper is how household level demand is affected by expected take-up decisions of other members in the group, possibly resulting in aggregated patterns of group level demand. To study such patterns descriptively, Figure 2.3 graphs the distribution of group-level demand pooling groups from both types of policies. The histogram plots the number of groups with a fraction of group members taking up insurance in the respective decile. The fraction of insured members within a group varies from 0 (29 groups with no member taking up) to 100 (15 groups with all members taking up) with some groups in each of the deciles. The policy-wise distributions presented in Figure 2.4 allow to explain the shape of the overall distribution. We observe a more or less uniform distribution of group-level demand for policies P2 and P3, whereas group-level demand for the individual policy P1 seems to be slightly skewed to the left. For group policy P4, the 50% uptake criterion explains the large number of groups with no member insured and the missing probability mass in deciles up to 50% of members insured. Six groups appear to have positive demand despite not meeting the 50% group uptake requirement.

Overall, we observe a high level of variation in average group take up across groups and policies. As laid out in section 2.2.3, these differences can potentially be explained by differences in group level characteristics, differences in individual group members' characteristics, and the that fact group members take into account expectations about their peers insurance decision in their own decision making.

[66] Table B.2 in Appendix B.2 provides evidence on balanced distributions of discount levels across the different policies. While there seems to be some missing probability mass for zero discounts, especially for policy P1, we cannot reject the null hypothesis of a uniform distribution across the discount levels.

Figure 2.1 – Distribution of Group Size

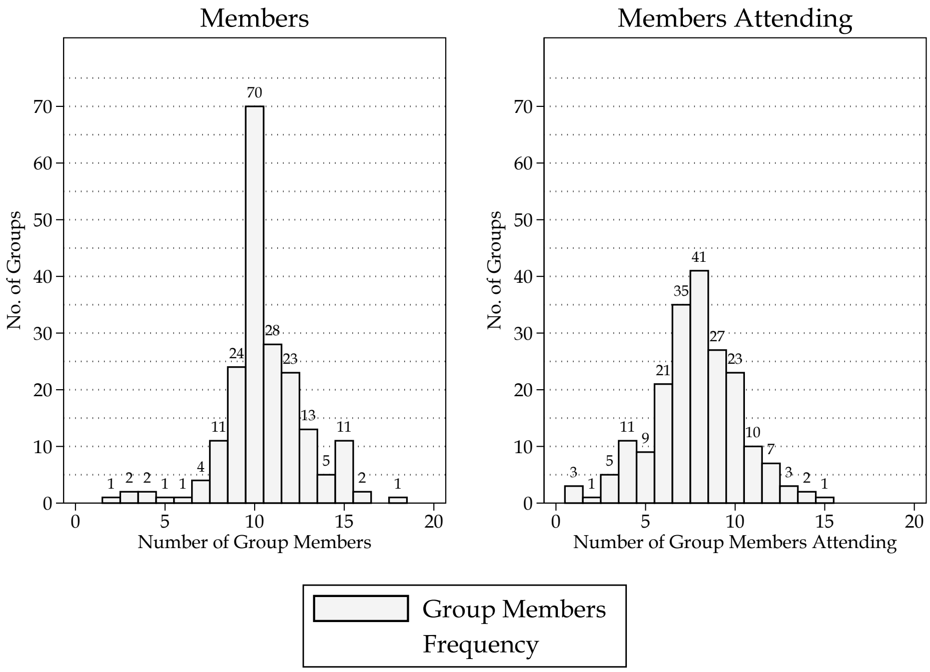


Figure 2.2 – Insurance Demand

(a) Intensive Margin

(b) Extensive Margin

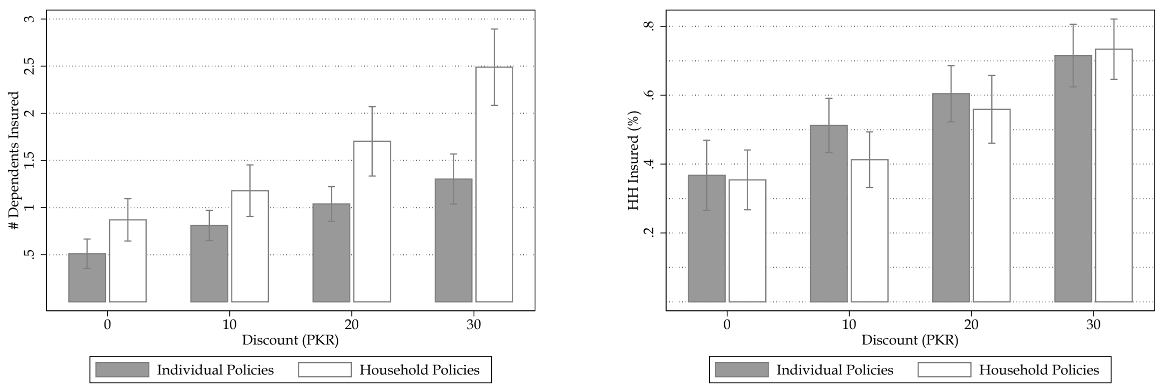


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Figure 2.3 – Average Take-Up across Groups

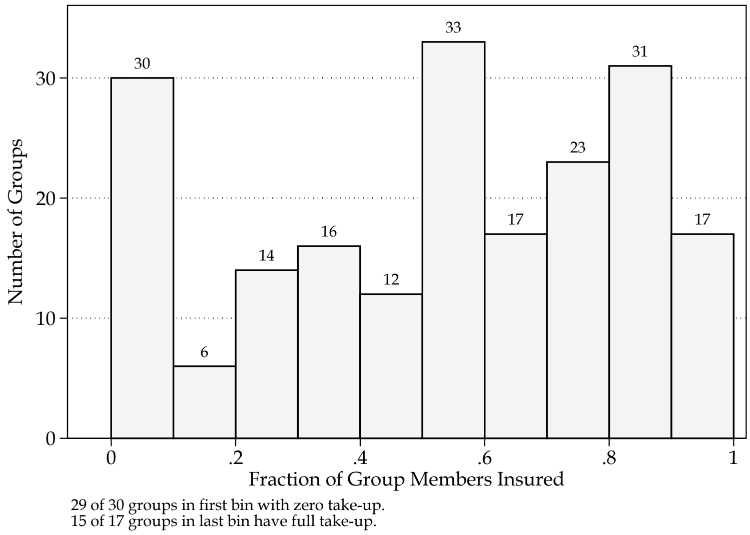
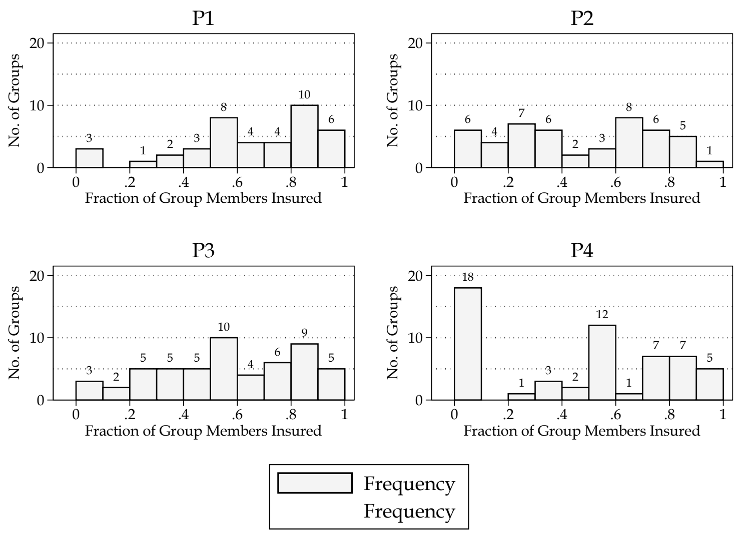


Figure 2.4 – Average Take-Up across Groups



2.5 Results

This section presents the estimation results for Models 1 to 4 discussed in section 2.3. Table 2.4 provides results of pooled estimations including all groups regardless of the offered insurance policy. Column 1 contains the results of the baseline specification that does not account for any social effects (Model 1). As expected, we observe that a decrease in price in the form of a higher discount increases demand. Moreover, group members with some formal education and higher savings seem more likely to purchase insurance. Also, group leaders are more likely to purchase insurance. Larger households, in contrast, appear less likely to purchase insurance. Accounting for endogenous social interaction effects, columns 2 and 3 reveal that an increase in the propensity with which other group members are expected to take-up positively affects own demand. The positive coefficient on the endogenous social interactions parameter suggests that conformity considerations and repeated interactions dominate potential free riding concerns. The difference between the two sets of results comes from the different optimization algorithms used in the maximum likelihood estimation. While the coefficient estimates are very similar for both specifications, the estimates based on a BFGS optimization algorithm are slightly less precise, explaining the the difference in the level of significance for some of the coefficients.[67]

Model 3 excludes the endogenous social interactions parameter and only accounts for contextual effects. The coefficient estimates of the individual characteristics are comparable to those in Models 1 and 2. Assessing contextual effects, the results for Model 3 suggest that (average) peer characteristics related to health and insurance directly influence group member's take-up decision. A given group member seems for example more likely to demand insurance if her group members have received higher discounts or have spent more on inpatient treatment. At the same time, a group member appears less likely to demand insurance if a higher fraction of her peers know the concept of insurance or have admitted a household member to the hospital during the last 12 months. While the signs of the latter contextual effects coefficients seem somewhat in contradiction to common hypotheses at first, the results of Model 4 seem to clarify these.

Model 4, in addition to contextual effects, accounts for equilibrium expectations in the insurance decision. We observe an even stronger positive relationship between group member's expected take-up and own demand than in model 2. At the same time, the coefficient estimates of the contextual effects parameters change considerably and, with the exception of average peer discount, are no longer statistically significant. The change in point estimates might be related to the two channels through which peer characteristics can influence a given group member's take-up decision. First, there is a direct channel through contextual effects. Second, there is an indirect channel through equilibrium expectations, which are in turn derived using all publicly

[67] The models in columns 2 and 3 of Table 2.4 are presented side-by-side because they resulted in very similar values of the log-likelihood function, which serves as a measure of model fit within a given class of models. For models 1 and 3 only one result is presented in Table 2.4 because the different optimization algorithms lead to identical results. This can be seen in Table B.4.

observed characteristics. As Model 3 only accounts for the direct channel, the resulting coefficient estimates absorb any indirect effect that would operate through the equilibrium expectations term. The change in contextual effects parameter estimates indicates the estimates in Model 3 pick up a spurious correlation that is in fact attributable to this equilibrium expectations term. The results from Model 4 reveal that it is in fact the expectation of group members take-up that affects demand, while peers' characteristics do not seem to matter above and beyond their influence on these expectations. The finding that higher peer discounts positively affect own demand is surprising because - by design - group members should not know their peers' discount draw. A possible extension of the model would therefore modify the information structure to allow for private information.[68] Taking the fining by heart, though, the positive coefficient estimate suggests that group members with a higher discount draw do exert some direct influence on their peers that makes these more likely to take up. This effect is in the opposed direction of a potential anchoring effect in which group members might be less likely to take up if their peers have received a higher discount than themselves. In general, the absence of broader contextual effects are in line with those in Liu et al. (2014) who study the role of social networks in the demand for voluntary, public health insurance in rural China. The authors therefore use peer characteristics as additional, exogenous variation in their two-step estimation approach (Bajari et al., 2010).

Given the theoretical discussion in section 2.2.1 and the observed positive coefficient estimate of the social interactions term, we might conclude that the conformity and repeated interactions channels dominate potential incentives to free ride. At the same time, the coefficient estimates in Table 2.4 do not directly allow to interpret the magnitude of the social interaction effects. To this end, as discussed in section 2.3, the last row of Table 2.4 provides an estimate of the average partial effect (APE) of the social interactions parameter for the relevant models. We observe that the APE estimates range between 35 and 43 percentage points, meaning that a 10 percentage point increase in the propensity of peer take-up leads to an increase in demand by 3.5 to 4.3 percentage points. It is possible to obtain a relative measure of the magnitude of this social interaction effect by translating it into a price effect. Figure B.3 in Appendix B.3 facilitates such a comparison by providing price elasticity estimates of the offered types of policies. Given an own price elasticity estimate of -0.783 across all policies, an increase in demand comparable to a 10 percentage point increase in the propensity of expected peer take-up would require a reduction in price by 4.5 to 6 percent.

[68] Since all group members face the same probability distribution over discount levels, the more sophisticated estimation approach would imply that the peer discount effect is effectively absorbed in the constant. For more information refer to Appendix B.1 or Yang and Lee (2017).

Table 2.4 – Estimation Results

row	Model.1	Model.2a	Model.2b	Model.3	Model.4
Discount	0.026187 ***	0.011808 ***	0.012417 **	0.025520 ***	0.010774 ***
	(0.002551)	(0.002835)	(0.005374)	(0.002604)	(0.002704)
Client Age	0.002057	0.001310	0.000830	0.002172	0.001031
	(0.002589)	(0.001410)	(0.002244)	(0.002648)	(0.002786)
client No Education (D)	-0.147861 **	-0.061902 **	-0.060166	-0.111981 **	-0.036208
	(0.059647)	(0.032386)	(0.056338)	(0.062776)	(0.066619)
HH Size	-0.045407 ***	-0.021037 **	-0.024405	-0.045526 ***	-0.024445
	(0.016637)	(0.010126)	(0.016166)	(0.016753)	(0.017174)
Wealth Indicator	-0.001827	0.002307	0.002833	-0.003093	-0.000862
	(0.013246)	(0.006533)	(0.011028)	(0.014027)	(0.014763)
HH Income (Log Rs '000)	0.017875	-0.011244	-0.004391	0.007150	-0.004670
	(0.048603)	(0.025797)	(0.043910)	(0.051658)	(0.054724)
HH Savings (Log Rs '000)	0.035382 **	0.015860 **	0.014318	0.030537	0.016954
	(0.020876)	(0.009487)	(0.015448)	(0.023207)	(0.024245)
Group Leader (D)	0.329395 ***	0.210666 ***	0.224517 ***	0.416087 ***	0.132945 **
	(0.072917)	(0.066064)	(0.075634)	(0.078708)	(0.072529)
Knows Insurance (D)	-0.089529	-0.063773 **	-0.077783	-0.052573	-0.028131
	(0.069703)	(0.035471)	(0.057027)	(0.073847)	(0.076959)
Total Inpatient Cost (Log Rs '000)	0.083083	0.062502	0.074844	0.073147	0.013511
	(0.079743)	(0.052752)	(0.067540)	(0.081600)	(0.081888)
Total Outpatient Cost (Log Rs '000)	0.007216	-0.004190	0.000139	0.014091	0.011835
	(0.023353)	(0.011920)	(0.021663)	(0.024299)	(0.025728)
HH Any Inpatient (D)	-0.204233	-0.154714	-0.187609	-0.167144	0.002014
	(0.263742)	(0.168847)	(0.214445)	(0.271227)	(0.273015)
HH Exp Cost Index (Log Rs '000)	0.033487	-0.008294	-0.008109	0.110217	0.065968
	(0.176052)	(0.085506)	(0.151498)	(0.182367)	(0.190104)
(del) Discount				0.016209 ***	-0.006671 **
				(0.005850)	(0.003547)
(del) Client Age				0.003017	-0.000348
				(0.006237)	(0.002906)
(del) client No Education (D)				-0.161632	0.007613
				(0.126960)	(0.068940)
(del) HH Size				0.010224	0.015945
				(0.039427)	(0.017756)
(del) Wealth Indicator				0.020900	0.003424
				(0.029432)	(0.015349)
(del) HH Income (Log Rs '000)				-0.030365	-0.007852
				(0.117589)	(0.056879)
(del) HH Savings (Log Rs '000)				0.023525	-0.009026
				(0.042026)	(0.025081)
(del) Group Leader (D)				0.886143 ***	-0.002090
				(0.300274)	(0.106279)
(del) Knows Insurance (D)				-0.260973 **	-0.004380
				(0.140444)	(0.079171)
(del) Total Inpatient Cost (Log Rs '000)				0.392174 **	0.016919
				(0.202786)	(0.089348)
(del) Total Outpatient Cost (Log Rs '000)				-0.062247	-0.016259
				(0.053203)	(0.026802)
(del) HH Any Inpatient (D)				-1.183809 **	-0.071974
				(0.666233)	(0.292379)
(del) HH Exp Cost Index (Log Rs '000)				-0.467138	-0.099256
				(0.386308)	(0.196817)
Endogenous		0.855774 ***	0.792326 ***		0.967280 ***
		(0.053362)	(0.187533)		(0.064600)
Constant	-0.320531 **	-0.114560	-0.136062	-0.567074	-0.017029
	(0.170925)	(0.092822)	(0.171814)	(0.420666)	(0.058680)
Unobserved					
value LogLik	-991.8327	-977.5561	-977.8521	-974.0990	-969.6540
Share Mult. Eq.	0.0000	0.0000	0.0000	0.0000	0.0000
Iterations	2	39	5	2	9
Stop Reason	0	0	0	0	0
Convergence Code	2	3	0	2	3
Method	BHHH	BHHH	BFGS	BHHH	BHHH
Gradient	Analytical	Analytical	Analytical	Analytical	Analytical
APE		0.3689	0.3476		0.4234

Note: This table provides parameter estimates of the iterative MLE approach. *value LogLik* is the value of the log-likelihood. *Share Mult. Eq.* gives the fraction of groups with multiple equilibria (if any).
Iterations: number of iterations until convergence. *Stop Reason* = 0: successful convergence of the iterative approach. *Convergence Code* of latest MLE iteration. *Method*: optimization approach (BHHH,BFGS).
Gradients for BHHH and BFGS approaches are provided analytically.
APE: Average partial effect of the endogenous social interaction effects calculated using equation 2.12.

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

2.5.1 Results by Eligibility

So far, the discussion has omitted the fact that the offered policies vary in terms of eligibility and that this variation might lead to differences in the direction and the strength of social interaction effects. For this reason, Table 2.5 provides separate estimation results for individual and household policies, respectively. The first four columns of Table 2.5 provide estimation results of Models 1 to 4 for the individual policies. Analogously, the last four columns contain the results for the household policies.

Considering the individual policies, the results from the baseline specification in column 1 reveal that, besides the premium price, only the group leader status seems to influence own demand. Accounting for equilibrium expectations of peer take-up, in column 2, shows that an increase in expected group member take-up positively affects own demand. This effect is statistically significant at the 1% level. Similar to the pooled estimation results, the results for Model 3 suggest that some peer characteristics directly affect own demand. Yet, with the exception of the average peer discount, these direct effects vanish once equilibrium expectations are accounted for in Model 4. The coefficient of the social interactions term is positive and statistically significant at the 1% level. The corresponding average partial effect estimate, contained in the final row of Table 2.5, varies between 38 and 42 percentage points. In other words, a ten percentage point increases in the propensity of expected peer take-up would increase demand by 3.8 to 4.2 percentage points.

Looking at the household policies, the results of the baseline specification in column five suggest that more household level characteristics than for the individual policies affect demand. In particular, households who receive a higher discount, are more educated or have more savings exhibit a higher demand. Also, group leaders are more likely to take-up. At the same time, demand decreases for larger households, confirming the descriptive pattern found in Figure 2.2. Moreover, better knowledge of the concept of insurance seems to decrease insurance demand. While the hypothesis would be that better understanding fosters insurance demand, the negative coefficient estimate could suggest distrust in the insurance provider or a low perceived value of the offered household insurance policies among those with a better understanding of the contract.

Accounting for equilibrium expectations, the results of Model 2 reveal a positive and statistically significant estimate of the social interactions term. Thus, expecting a larger proportion of group members to take-up insurance seems to increase own demand, in line with the conformity and repeated interactions channel dominating potential incentives to free ride. Controlling for contextual effects only, the results for Model 3, similar to the pooled estimation results, suggest that several peer characteristics related to health and insurance directly affect demand. Accounting in addition for equilibrium expectations of peer take-up, the results of Model 4 reveal that, in contrast to the results from the pooled estimation, the contextual effects remain statistically significant and even increase in absolute terms. The social interaction effects parameter, instead of positive and statistically significant as in Model 2, turns negative but is estimated imprecisely. Even though not statistically significant, the corresponding average partial effect is estimated at

-0.22, meaning that a ten percentage point increase in the propensity of peer take-up leads to decrease in demand of 2.2 percentage points.

Note that the patterns observed in the household policy results are in line with omitted variable bias. Both the overestimation of the social interaction effect in Model 2, and the underestimation of the contextual effects coefficients (in absolute terms) in Model 3.[69] Therefore, Model 4 reveals the importance of controlling for both equilibrium expectations and contextual effects.

The presence of contextual effects implies a direct effect of average peer characteristics on own insurance demand. The positive effect from group leaders on their group members' demand, for example, could be explained by group leaders directly advertising to take up the policy. The negative effect of a larger fraction of peers knowing the concept of insurance might indicate the presence of communication learning. Group members who know the concept of insurance are less likely to demand insurance, and might share their concerns in the group, thereby directly reducing their peers propensity to take up. The interpretation of the remaining two contextual effects variables found statistically significant is less obvious.[70] Direct effects are expected to be of higher relevance in particular in the group policy because it requires a minimum uptake of 50% among the group members. Compared to the other policies, this requirement might result in stronger incentives to directly communicate or even convince group members to (not) take up insurance.

To assess the relative magnitude of the positive social interaction effect in the individual policies and the negative social interaction effect in the household policies, we can engage in a similar exercise as for the pooled estimation results to determine a corresponding price effect. For the individual policies, the own price elasticity estimate in Figure B.3 is given by -1.08. Therefore, to achieve an increase in demand comparable to a 10 percentage point increase in expected peer demand, a decrease in price by 3.5 to 4 percent would be required. For the household policies, a 10 percentage point increase in expected peer take-up would lead to a decrease in demand by about 2.2 percentage points. To achieve a similar decrease in demand given an estimated own price elasticity of -2.13, the policy price would have to increase by about one percent.

While the economic effect of peer take-up on own demand in the subgroup offered a household policy seems limited, another interpretation is that conformity considerations and incentives to free ride to seem to cancel each other out. These findings can be explained by two effects. First, the price to conform with the expected choice of other group members is larger in the household policy, reducing the taste to conform. Second, a group member's decision to take-up when of-

[69] The contextual effects that exhibit a negative coefficient estimate are found to be negatively correlated with equilibrium expectations. Vice versa, contextual effects with positive coefficient estimates are found to exhibit a positive correlation with equilibrium expectations.

[70] The negative direct effect on own demand from having a higher fraction of group members that had to admit a household member to the hospital in the last twelve months is in the opposite direction as expected from an availability bias argument. The positive direct effect on own demand from higher risk peers might also be in line with communication learning. At the same time, this seems implausible since a household's own risk type does not seem to affect own demand.

fered a household policy exhibits a larger externality on other group members due to the higher number of dependents insured on average. Taken together, these two effects appear to reduce the dominance of the social preference channel.

Further extensions might leverage inter-group variation in household size and riskiness among group members. For groups with larger than average household size, for example, an expected insurance decision would imply that the remaining pool of non-insured individuals is relatively small. This reduces the risk posed by these individuals, potentially resulting in stronger incentives to free ride as compared to groups with lower than average household size. Likewise, for groups with low variation in group members' riskiness, an expected insurance decision reduces the pool of non-insured individuals but leaves the risk distribution more or less unchanged. In groups with a higher variation in group members' riskiness, in contrast, insurance take-up might be expected in particular for higher risk group members, leading to a better risk distribution of non-insured members and potentially increasing incentives to free ride.

Table 2.5 – Estimation Results by Policy Eligibility

row	IND.M1	IND.M2	IND.M3	IND.M4	HH.M1	HH.M2	HH.M3	HH.M4
Discount	0.023890 ***	0.010712 ***	0.024463 ***	0.010617 ***	0.030607 ***	0.014159 ***	0.030812 ***	0.052711 ***
	(0.003856)	(0.003543)	(0.004108)	(0.004059)	(0.003556)	(0.004168)	(0.003751)	(0.018230)
Client Age	0.003452	0.000137	0.004240	0.003517	-0.000316	0.000640	-0.001706	-0.003509
	(0.003863)	(0.001846)	(0.004098)	(0.004181)	(0.003669)	(0.002288)	(0.003763)	(0.003910)
client No Education (D)	0.103577	0.053050	0.107463	0.042351	-0.343181 ***	-0.144412 **	-0.262275 ***	-0.432889 **
	(0.089748)	(0.043500)	(0.097608)	(0.101703)	(0.083281)	(0.064631)	(0.089368)	(0.172197)
HH Size	0.007990	-0.002724	0.020330	0.010753	-0.085730 ***	-0.036206 **	-0.095427 ***	-0.161011 ***
	(0.024618)	(0.011069)	(0.025415)	(0.025819)	(0.023920)	(0.017906)	(0.025041)	(0.060169)
Wealth Indicator	-0.021481	-0.005299	-0.015114	-0.008233	0.015577	0.008342	0.005084	0.007935
	(0.019103)	(0.008504)	(0.020749)	(0.021659)	(0.019406)	(0.011544)	(0.021524)	(0.021456)
HH Income (Log Rs ’000)	0.075556	0.026258	0.026414	0.008012	-0.029701	-0.027411	0.021880	0.042266
	(0.064983)	(0.028603)	(0.071277)	(0.074740)	(0.077524)	(0.050580)	(0.084551)	(0.084984)
HH Savings (Log Rs ’000)	0.015329	-0.006479	0.007289	0.005758	0.054566 **	0.024112	0.040148	0.066342
	(0.029426)	(0.011520)	(0.033457)	(0.034126)	(0.032184)	(0.016463)	(0.037695)	(0.043040)
Group Leader (D)	0.353674 ***	0.215059 **	0.449988 ***	0.177429 **	0.272256 ***	0.185145 **	0.435515 ***	0.696647 ***
	(0.107391)	(0.092656)	(0.116681)	(0.107608)	(0.103241)	(0.094753)	(0.117379)	(0.245649)
Knows Insurance (D)	0.090572	0.015410	0.102886	0.033316	-0.227284 **	-0.112416 **	-0.154110	-0.249753 **
	(0.101525)	(0.044667)	(0.108907)	(0.112293)	(0.100236)	(0.063914)	(0.110294)	(0.132145)
Total Inpatient Cost (Log Rs ’000)	0.148585	0.060413	0.131619	0.098549	0.010283	0.024807	-0.023668	-0.058527
	(0.110099)	(0.063268)	(0.116830)	(0.119911)	(0.118329)	(0.095345)	(0.125434)	(0.130762)
Total Outpatient Cost (Log Rs ’000)	0.005659	-0.000698	0.018221	0.009559	0.001063	-0.014286	0.019246	0.043042
	(0.034885)	(0.015320)	(0.037626)	(0.039352)	(0.033515)	(0.020434)	(0.035358)	(0.036534)
HH Any Inpatient (D)	-0.207525	0.028439	-0.125616	-0.253075	-0.122501	-0.150154	-0.000632	0.065378
	(0.368674)	(0.214305)	(0.391931)	(0.405993)	(0.385768)	(0.306089)	(0.409663)	(0.420338)
HH Exp Cost Index (Log Rs ’000)	-0.113995	-0.173984	0.068850	0.182533	0.019651	0.214173	-0.035494	-0.183058
	(0.239360)	(0.119686)	(0.243835)	(0.247776)	(0.318700)	(0.204838)	(0.344926)	(0.364841)
(del) Discount			0.021366 **	-0.007708 **			0.017202 **	0.016151
			(0.009421)	(0.004588)			(0.008201)	(0.010949)
(del) Client Age			-0.014852	-0.004362			0.010250	0.016884
			(0.010174)	(0.004549)			(0.008824)	(0.012430)
(del) client No Education (D)			0.258885	-0.016370			-0.280204	-0.326164
			(0.217378)	(0.105595)			(0.177455)	(0.238162)
(del) HH Size			-0.007138	-0.016319			0.080897	0.147963
			(0.062325)	(0.027511)			(0.059847)	(0.100292)
(del) Wealth Indicator			-0.006005	0.010588			0.012827	0.015267
			(0.048192)	(0.023249)			(0.042795)	(0.057387)
(del) HH Income (Log Rs ’000)			0.151692	-0.010913			-0.117073	-0.187738
			(0.157114)	(0.078815)			(0.206375)	(0.285061)
(del) HH Savings (Log Rs ’000)			-0.091624	-0.007017			0.062652	0.086524
			(0.065490)	(0.035249)			(0.063057)	(0.082806)
(del) Group Leader (D)			0.942478 **	-0.111110			1.320582 ***	1.849473 **
			(0.452524)	(0.140555)			(0.423805)	(0.723795)
(del) Knows Insurance (D)			0.160182	-0.027607			-0.393336 **	-0.559462 **
			(0.214896)	(0.115591)			(0.211885)	(0.309109)
(del) Total Inpatient Cost (Log Rs ’000)			-0.103447	-0.074555			0.477615	0.716698
			(0.300937)	(0.125096)			(0.328903)	(0.482680)
(del) Total Outpatient Cost (Log Rs ’000)			0.007342	-0.009238			-0.123425	-0.181358
			(0.079926)	(0.042990)			(0.080674)	(0.120415)
(del) HH Any Inpatient (D)			1.754529	0.249236			-2.165621 **	-3.138696 **
			(1.134353)	(0.448991)			(1.050096)	(1.622608)
(del) HH Exp Cost Index (Log Rs ’000)			-2.181202 ***	-0.269306			2.034412 **	3.051237 **
			(0.573064)	(0.262702)			(0.805008)	(1.319085)
Endogenous		0.926475 ***		1.034153 ***		0.814044 ***		-0.540546
		(0.049285)		(0.038310)		(0.086950)		(0.430910)
Constant	-0.769866 ***	-0.240228 **	-0.682571	0.017988	0.100761	-0.008993	-1.042319	-1.582720
	(0.241730)	(0.131806)	(0.625728)	(0.089667)	(0.255666)	(0.160903)	(0.675437)	(1.019551)
Unobserved								
value LogLik	-450.9305	-438.9729	-430.3994	-421.0321	-519.7075	-509.8393	-496.0593	-495.4132
Share Mult. Eq.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Iterations	2	36	2	25	2	5	2	20
Stop Reason	0	0	0	0	0	0	0	0
Convergence Code	2	3	2	3	2	3	2	2
Method	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH
Gradient	Analytical	Analytical	Analytical	Analytical	Analytical	Analytical	Analytical	Analytical
APE		0.3863		0.4202		0.3406		-0.2168

This table provides parameter estimates of the iterative MLE approach. *value LogLik* is the value of the log-likelihood. *Share Mult. Eq.* gives the fraction of groups with multiple equilibria (if any).
Iterations: number of iterations until convergence. *Stop Reason* = 0: successful convergence of the iterative approach.
Convergence Code of latest MLE iteration. *Method*: optimization approach (BHHH,BFGS).
Gradients for BHHH and BFGS approaches are provided analytically.
APE: Average partial effect of the endogenous social interaction effects calculated using equation 2.12.

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

2.6 Conclusion

The demand for formal low-income health insurance has been found to be low in many contexts. In this paper, we investigate the role of the social network in the demand decision. From a theoretical point of view, interaction groups can both increase or decrease insurance demand. On the one hand, social norms might create a desire to conform with the expected choice in the group, leading to positive social interaction effects. On the other hand, an incentive to free-ride on others' insurance decision might arise when insurance is offered to jointly liable groups, implying negative social interaction effects. At the same time, such potential incentives to free ride might be mitigated through repeated interactions in the group.

To test which of these channels dominates empirically, we use data from a randomized control trial in rural Pakistan in which voluntary hospitalization insurance is offered to members of pre-existing jointly liable credit groups. The binary insurance decision is modeled as a static, simultaneous move game under incomplete information. Agents' take-up decision depends on the expected choice of other group members, which is derived as a rational expectation given publicly observed characteristics. In addition, the model accounts for contextual effects and can be extended to capture correlated group effects. The estimation is based on a nested fixed point maximum likelihood approach commonly used in the estimation of dynamic discrete choice models.

The findings indicate that the social norms and repeated interactions channels dominate potential incentives to free ride in the subgroup offered an individual policy that allows to insure any number and combination of dependents. Average partial effect estimates suggest that a ten percentage point increase in expected peer take-up would increase demand by 3.8 to 4.2 percentage points. This effect is comparable to a decrease in the premium price by about 4 percentage points. For the subgroup offered a household insurance policy, in contrast, the social interaction effects estimate is negative, but estimated imprecisely. The estimated average partial effect suggests that a ten percentage point increase in expected peer demand would lead to a decrease in demand by 2.2 percentage points. This decrease in demand is comparable to a one percent increase in the insurance premium. Taking these results by heart, conformity considerations and incentives to free ride appear to cancel each other out.

The smaller effect of expected peer decisions in household policies can be explained by several factors. First, being offered a household policy requires to insure a larger number of dependents on average, therefore increasing the household's total premium compared to an individual policy. Consequently, it is more expensive to conform with expected peer decisions, lowering the desire to do so. Second, a larger number of dependents insured in the household policies constitutes a stronger positive externality from expecting a peer to purchase insurance than in the individual policies. The larger externality from insurance in the household policies therefore results in stronger incentives to free ride. Overall, we may conclude that incentives to free ride seem to exist in the joint liability context of this study, but are likely to be dominated by social preference considerations.

This paper adds to an emerging literature on the role of social networks in the demand for financial services in developing countries. Moreover, the findings complement existing evidence on free riding in insurance decisions in a joint liability context from framed field experiments by studying actual insurance decisions and allowing for other motifs to affect demand.

Chapter 3

Adverse Selection in Low-Income Health Insurance Markets: Evidence from a RCT in Pakistan

3.1 Introduction

Poor households around the world are plagued by financial risk, and health shocks are often the most important type of unexpected events that could lead poor families into severe financial distress (e.g. Heltberg and Lund, 2009b). Effective insurance solutions not only promise to protect households from falling into a poverty trap, but might also improve long-term health and productivity. Given the deficiencies of public health systems and inefficient public health insurance in many developing countries, the potential for market-based solutions is large.[1] From an economist's perspective, however, the question whether private insurance schemes can attain efficiency largely depends on the extent of adverse selection. If adverse selection is present, equilibrium demand may be below the social optimum, and in the worst case markets might even break down (Arrow, 1963; Akerlof, 1970; Rothschild and Stiglitz, 1976).

The empirical debate about adverse selection in low-income health insurance is relatively recent and controversial. Some authors find evidence for more risky individuals selecting into health insurance (Zhang and Wang, 2008; Clement, 2009; Lammers and Warmerdam, 2010; Yao, Schmit, and Sydnor, 2015), but there are also studies which find no evidence of adverse selection (Jütting, 2004; Dror et al., 2005; Nguyen and Knowles, 2010; Banerjee et al., 2014). Other scholars even argue that demand for health insurance of poor households often does not follow classical economic principles and is rather determined by community norms (Dror and Firth, 2014). The available

[1] The Swiss Reinsurance Company estimates that the microinsurance (i.e. low-income insurance) market comprises approximately 4 billion potential customers (Swiss Re, 2010). Only about 500 million people were covered under any microinsurance contract in 2013, but most of the major insurance companies currently engage in microinsurance activities to expand this market share (ILO Microinsurance Innovation Facility, 2014).

evidence is limited in several dimensions, though. First, many studies correlate uptake decisions with ex-post measures of health risk, and hence suffer from a discrimination problem between adverse selection and moral hazard (Chiappori and Salanie, 2000). Those papers which use ex-ante health measures rarely show the relevance of these measures in terms of actual health events *after* insurance take-up. Second, none of these research settings allows a rigorous assessment of the welfare consequences of adverse selection. Third, there exists no systematic comparison of different insurance designs regarding adverse selection and welfare.

This paper addresses these limitations by analyzing a large-scale cluster randomized control trial (RCT) on hospitalization insurance conducted in rural Pakistan. The RCT tests different insurance schemes that are randomized across more than 500 villages. We exploit baseline health measures as well as detailed data on health events after the introduction of insurance to analyze adverse selection. Additionally, the experiment induces exogenous price variation which enables us to estimate demand and cost curves. Identifying these curves permits us to conduct a welfare analysis similar to the approach of Einav and Finkelstein (2011). To the best of our knowledge, this study is the first to apply their method with experimentally controlled price variation. Finally, we test three insurance designs that are supposed to allow for different degrees of adverse selection, and conduct a comparative welfare analysis. We construct a measure for the insurers' expected reimbursement costs for each individual's inpatient expenditures based on detailed baseline health status, health history, ex post hospitalization expenses and claim behavior.

Our results provide strong evidence that hospitalization insurance schemes for individuals suffer from adverse selection. In particular, selection becomes more pronounced with higher premium prices, creating a trade-off between cost recovery and the quality of the insurance pool. When bundling insurance policies at the household or group level, however, adverse selection is mitigated. A welfare analysis suggests that bundled policies are also able to sustain higher quantities and lower prices than individual policies. Further, the welfare consequences of adverse selection seem less severe in relative terms for household policies.

The setup of our experiment has high relevance for the design of insurance in developing countries. Compared to insurance markets in high-income countries, contracts in the low-income context need to maintain low premiums, exhibit a simple design and keep administrative costs low. These requirements imply a limited potential for ex-ante risk screening (Brau et al., 2011). In addition, providers often lack management capacity or cannot attract qualified staff, which prohibits working with a portfolio of products. On the demand side, offering a single and easily understandable insurance product (pooling contract) simplifies marketing to a target group which is often exposed to formal insurance for the first time. The drawback of policies which do not separate different risk types and furthermore abstain from ex-ante risk screening is that they are highly vulnerable to selection. We therefore explore simple measures against adverse selection in pooling contracts which are widely applicable in low-income insurance markets, i.e. bundling individual policies on different levels. Also the context of our study is typical for many low-income countries: The Pakistani government spends little resources on public health care provision; a universal social security system does not exist; the informal sector without any access to health insurance products is large and health expenses as a consequence cause high financial stress for low-income households. These challenges are shared by many countries in Africa and Asia, underpinning the need for scalable insurance solutions.

The remainder of the paper proceeds as follows. Section 3.2 explains the approach we use to analyze adverse selection and welfare in more detail. Section 3.3 describes the context of the experiment, the different insurance innovations and the hypotheses linked to their implementation. Section 3.4 contains information about the data collection process and provides summary statistics. Section 3.5 briefly discusses the demand for the offered insurance policies. Section 3.6 presents empirical results on adverse selection and Section 3.7 discusses welfare consequences. Section 3.8 concludes.

3.2 Identification of Adverse Selection

The theory of adverse selection had its origin in the contributions of Arrow (1963), Akerlof (1970), and Rothschild and Stiglitz (1976). All these models (and many subsequent ones) hinge on the assumption that agents select into insurance policies based on their individual risk type and premium prices. In case of adverse selection, agents with the highest expected costs are those with the highest willingness to pay. This implies that the expected costs caused by the insured should always be higher than for non-insured. Further, it implies that individuals at the margin exhibit lower expected costs than the pool of individuals already insured, which leads to a downward sloping marginal cost curve. Similarly, products with higher risk coverage should attract higher risk types, creating a positive correlation between coverage and riskiness of the insurance pool. From an empirical point of view, however, it is difficult to establish the presence of adverse selection due to the discrimination problem (Chiappori and Salanie, 2000). An observed positive correlation between insurance coverage and loss incidences can either be caused by more risky individuals selecting higher coverage (adverse selection) or by higher coverage causing behavioral changes (moral hazard).

Cohen and Siegelman (2010), who summarize the empirical literature in a developed country context, describe various approaches that go beyond a simple positive correlation test. These methods include exploiting dynamic claim behavior and comparing positive correlation patterns between subgroups with different potential for selection. Most of the reviewed studies on health insurance, however, only provide some form of the positive correlation test.

Another possibility to test for selection is to correlate *ex-ante* measures of risk, such as subjective health status or medical history before enrollment, with insurance uptake (e.g. Wang et al., 2006). Relying on ex-ante risk proxies prevents potential confounding with moral hazard, as those ex-ante risk proxies cannot be affected by the insurance status. The drawback of using ex-ante measures is the uncertainty about how they map into future costs faced by the insurer, especially in the absence of data on ex-post health events and costs. Yao et al. (2015) discuss recent evidence from low-income health insurance markets and document several studies using ex-ante measures, but only few relate the results to actual health expenditures after the insurance choice (one exception is Banerjee et al., 2014). However, without reliable evidence that ex-ante proxies indeed have predictive power for ex-post costs, those studies without ex-post costs may be of little value since a lack of adverse selection found in the data could simply be an artifact of a bad proxy.

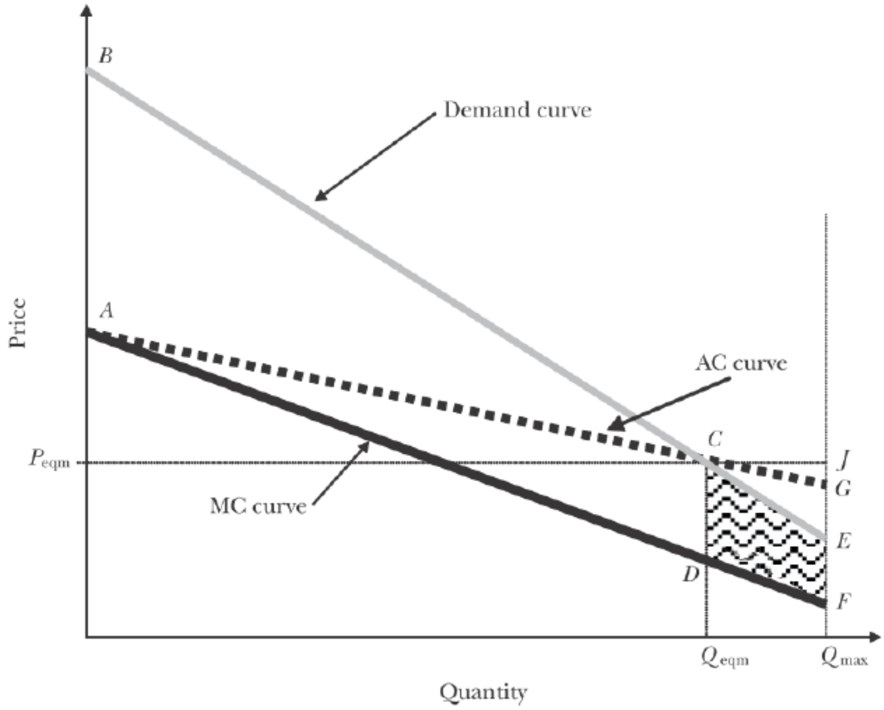
Another approach to identify and quantify adverse selection is to estimate the average cost curve faced by the insurer (Einav and Finkelstein, 2011). As depicted in Figure 3.1, the marginal cost curve decreases if higher risk types exhibit a higher willingness to pay for insurance. Consequently, the insurer faces decreasing average costs with increasing demand, i.e. adverse selection. Knowledge of the marginal and average cost curves and the demand curve not only identifies adverse selection, but also allows for welfare analyses: The intersection of demand and average cost curves determines the market allocation (under the assumption of perfect competition). A welfare loss can be observed if the willingness to pay for insurance in the market equilibrium is higher than the marginal costs of providing insurance. In Figure 3.1, this welfare loss is illustrated as the shaded rectangle CDEF.

Insurance theory, therefore suggests a straightforward test of the presence of adverse selection that relies on the slope of the marginal cost curve. Rejecting the null hypothesis of a flat marginal cost curve, i.e. no relationship between insurance price and the claim ratio, constitutes evidence for selection. Moreover, the direction of selection can be tested: A decreasing marginal cost curve suggests adverse selection, while an increasing one suggests advantageous selection.[2] The presence of moral hazard does not confound this identification approach, as the slope after the upwards shift of the average cost curve still reflects the degree of adverse selection.[3]

[2] The finding of advantageous selection would not be in line with classical adverse selection model but could result e.g. if highly risk-averse individuals purchase insurance but at the same time also take precautionary health actions, e.g. preventive health efforts, or have unobserved characteristics that also make them care about future health, which would result in the insurance-buying individuals having below-average costs.

[3] In its simplest form, moral hazard should shift the average cost curve upwards by a constant. Even in case of 'selection on moral hazard' the slope still identifies adverse selection based on costs after the insurance choice, which is the most important from the insurer's perspective. This view is in line with Einav and Finkelstein (2011) who consider the selection component in moral hazard as part of adverse selection.

Figure 3.1 – Analysis of Adverse Selection and Welfare



Source: Figure 1 from Einav and Finkelstein (2011)

A necessary pre-requisite for applying this approach is exogenous variation in the premium prices for the same insurance contract. Such exogenous variation in policy premiums allows estimating demand curves and at the same time observing average costs at different demand points. Providing credible exogenous price variation, however, is challenging in most settings. Einav et al. (2010) are the first ones utilizing this identification approach. They investigate the presence of adverse selection and its implied welfare costs in the context of employer provided health insurance in the US. Using countrywide data from a large US employer, they are able to exploit differences in regional pricing to estimate both demand and average cost curves of the provided health insurance schemes. The authors find a downward sloping marginal cost curve, which constitutes evidence for the presence of adverse selection, but relatively small implied welfare cost. While several other recent studies from developed insurance markets make use of the same identification approach (e.g. Hackmann et al., 2012, 2015; Finkelstein et al., 2017; Panhans, 2017), we are not aware of any studies using experimental variation in premium prices.

Within our RCT, we introduce exogenous price variation via random premium discounts. Demand and average cost curves for different insurance products can hence be estimated without any further exogeneity assumption. The costs for the insurer are calculated from ex post health events, expenditure and claim behavior. This cost data is then used to predict expected costs for each individual based on detailed baseline health and demographic information. Predicting costs for each individual provides us with sufficient statistical power to compare the quality of the risk pool in different subsamples, while preserving the interpretation of the average cost curve in an expected value sense.[4] We provide further details on the available data in Section 3.4, discuss the ‘expected cost index’ in Section 3.6.1 and provide more details on its construction in Appendix C.4.

3.3 Setup of the Experiment

This section contains details on the RCT and its context. We first describe the public health context in Pakistan and the role of our implementation partner in Subsection 3.3.1. The second subsection explains the interventions as well as the most important hypotheses linked to each policy. Subsection 3.3.3 presents our sampling strategy as well as the randomization procedures employed for treatment allocation.

3.3.1 Background

Pakistan is a lower-middle income country with a population of 189 million and a GDP per capita of USD 1,429 (2015). Almost one third of the population lives below the national poverty line (2013).[5] Furthermore, a majority of households faces the risk of remaining or falling into poverty (World Bank, 2007, 8). The government spends less than one percent of its GDP on health, which is low even compared to other developing countries. Public health expenditure hence accounts for only about 35% of total health expenditure, while 87% of private expenditure has to be paid out-of-pocket (2014). Free public health facilities exist, but service quality is perceived as low and many expensive treatments and drugs are not covered (Pakistan Ministry of Health, 2009). Given the absence of a universal health insurance system, the poor are hence exposed to considerable financial risk in case of health events (Heltberg and Lund, 2009b). Existing schemes predominantly target public and formal sector employees, thus excluding the rural poor, who most often work in the informal sector. A small number of NGOs and microfinance institutions provide low-income insurance policies – so-called microinsurance – to their clients, but the majority of these are life insurance products bundled with a loan.

Until very recently, the National Rural Support Programme of Pakistan (NRSP), our implementation partner, was the only microinsurance provider in Pakistan offering hospitalization insurance at significant scale (World Bank, 2012, 11).[6] NRSP is the largest of twelve Rural Support Programmes in Pakistan with an outreach of more than 2.5 million households. It supports poor

[4] In principle, it would be straightforward to conduct the analysis with realized claim costs only. However, hospitalization is a rare event and despite our relatively large sample size, statistical power is too low to estimate average cost curves based on realized/reimbursed claims directly. In particular, it is difficult to obtain precise estimates at different demand points and for different products.
[5] See World Bank Indicators 2015 at http://data.worldbank.org/country/pakistan. Subsequent figures on public health spending and out of pocket expenditures are also drawn from this source.
[6] Specific national and provincial government programs lately started to roll out similar hospitalization insurance packages in selected districts. The Prime Minister’s National Health Program started in three out of 23 pilot districts until August 2016 (http://www.pmhealthprogram.gov.pk). Also in 2016, the Social Health Protection

households through community development activities and microfinance. NRSP is the leading provider of microcredit and the largest holder of savings among the Rural Support Programmes (Rural Support Programmes Network, 2015). In rural areas, NRSP usually works with community organizations (COs), which consist of 12 to 15 member households. Members of these COs are eligible for NRSP agricultural and livestock loans that exhibit joint liability on the group level. Furthermore, NRSP offers micro-enterprise development loans to smaller, jointly liable credit groups that usually consist of three to six members.

Since 2005, NRSP complements its micro-credit products with mandatory hospitalization and disability insurance for its credit clients and their spouses. This policy offers three benefits. First, it covers inpatient hospitalization expenditures up to a threshold of PKR 15,000 per person during the loan period, which is equivalent to about USD 150. This is a significant amount relative to households' total monthly income (on average less than PKR 23,000 in our sample) and sufficient for about four days in hospital including minor surgery. Second, it separately covers accidental death and disability of the main breadwinner up to a maximum threshold of PKR 15,000.[7] Third, the outstanding loan amount is written off and a contribution of PKR 5,000 towards funeral charges is paid to the family in the case of a normal death of the main breadwinner. The annual premium of PKR 150 for both client and spouse is automatically deducted from the loan amount before disbursement. The covered expenses during hospitalization range from room charges, doctor fees, lab tests and prescribed drugs to transportation costs. For maternity-related expenses, the reimbursement threshold is set to PKR 10,000. Pre-existing conditions are not covered under the policy. The claim process depends on the availed health facility. In each district, NRSP has created a panel of hospitals that are approved and whose quality is certified. In these so-called panel hospitals, treatment expenditures up to the maximal threshold of PKR 15,000 are billed directly to the insurance company, after confirmation of the insurance status by NRSP. Expenditures exceeding the maximal threshold have to be covered by the patient. In all other facilities, the patient has to bear medical expenses first and will be reimbursed by NRSP after approval of the claim.

3.3.2 Intervention

With the insurance innovations tested in this experiment NRSP aims to increase the resilience of its clients towards adverse health shocks, while also striving for a sustainable product. At the same time, the local context restricts the range of possible innovations. NRSP's large-scale operations on the grass-root level heavily depend on simple routines and on recruiting staff from local communities. NRSP's field staff has on average nine years of formal education and its target population is mostly poor and uneducated. Any scalable insurance solution therefore needs to focus on simple contracts that are easy to administer in the field.

Initiative was initiated in four districts of the province Khyber Pakhtunkhwa (http://www.healthkp.gov.pk/SHPInitiative.asp).

[7] The maximal benefit depends on the degree of disability caused by the accident.

This study tests three simple policies that expand mandatory insurance described above by offering voluntary coverage for additional household dependents. A fourth policy, which was also included in the RCT but is not directly comparable to the other three designs, is also described here for completeness. The benefits and claim procedure of the offered insurance policies are similar to the existing mandatory insurance policy. All policies cover hospitalization expenditure and accidental death or disability up to a specific threshold. Treatment in panel hospitals is cashless up to the coverage threshold. Expenditures from non-panel facilities are reimbursed ex post. NRSP already implemented a similar coverage innovation for dependents of their credit clients in Hyderabad between 2009 and 2011. This earlier pilot led to promising social impacts, which are in (Landmann and Frölich, 2015; Frölich and Landmann, 2018).

Table 3.1 provides an overview of the insurance innovations. The *Individual* policy (P1) allows clients to enroll any number and combination of dependents in the insurance scheme. It covers hospitalization expenditures of the insured individuals up to a threshold of PKR 15,000 for a premium of PKR 100 per person insured. In addition, death or disability resulting from an accident is covered up to a maximum of PKR 15,000. The *Household* policy (P3) differs from the individual products in that the client is required to enroll all dependents of the household to obtain additional insurance. This policy provides the same coverage as the individual product (P1) for each insured dependent. The *Group* policy (P4) furthermore requires at least 50% uptake within the respective credit group or community organization. Specifically, for any household of the group to be eligible, at least half of the group members present in the meeting need to enroll all their dependents. The *Individual High* policy (P2) is supposed to increase protection of clients against more expensive health events. Its coverage limits are increased to PKR 30,000 per person insured, which also justifies the higher insurance premium [8]. Note that in contrast to all other schemes, the high coverage policy changes the expected reimbursement costs for a given individual and is furthermore offered at a higher price. So while the observations under this policy might help to understand how baseline characteristics translate into health behavior, the demand and claim patterns are not comparable to the other policies. We therefore focus on policies P1, P3 and P4 in our main results.

In each village, one of these four policies is offered in a community meeting. The community meeting starts with an introduction to the concept of insurance and explains in detail the benefits of the existing, mandatory health insurance policy. These awareness sessions are held by trained social organizers and take about 30 to 40 minutes. Afterwards, social organizers introduce the policy which has been randomly allocated to the community. During the sign-up phase for the insurance they also offer each client a discount vouchers in private. The resulting discount (0, 10, 20 and 30 PKR) applies to the per person premium for all of the eligible household members.

In terms of hypotheses, we expect a high level of adverse selection in the individual policy

[8] About 80% of claims from the mandatory insurance in 2014 were above the coverage threshold of PKR 15,000. Based on these numbers and expected increases in reimbursements, the fair premium was estimated at PKR 150.

Table 3.1 – Insurance Innovations

	Individual (P1)	Individual High (P2)	Household (P3)	Group (P4)
Eligibility	Individual	Individual	Household	Household
Add. Requirement				50% uptake in the group
Coverage Limit (pp)	15,000	30,000	15,000	15,000
Premium (pp)	100	150	100	100
Premium Discounts (pp)	0-30	0-30	0-30	0-30

Notes: Numbers are in PKR, USD 1 ≈ 101 PKR, 15'000 PKR ≈ USD 148 (in February 2015), pp = per person.
Individual Eligibility: Client allowed to insure any number and any combination of dependents.
Household Eligibility: Client has to insure either all or none of the dependents.
Premium Discounts: Discount vouchers of 0, 10, 20 and 30 PKR (pp) were randomized with equal probability at the household level.

(P1), as clients can cherry pick insurance coverage for 'risky' household members. Compared to Individual insurance, the household policy (P3) is expected to impede selection of high risk individuals, and the group policy (P4) additionally impedes selection of specific high risk households into the scheme. By construction, both bundled products should mitigate adverse selection (P4 even more than P3). How much adverse selection is decreased depends on the clustering of health risks within households and groups, as well as on the extent to which clients possess and use information about aggregated financial risk at the level of these respective clusters.

The welfare implications of such risk bundling policies are ambiguous from a theoretical point of view. On the one hand, we expect risk bundling to mitigate adverse selection, and thereby increase overall welfare. On the other hand, limiting the choice of clients could in some cases decrease welfare. Imagine, for example, that the marginal willingness to pay is above the uniform household price for some and below this price for other dependents. This would imply an inefficient level of coverage under the household insurance (assuming that the von Neumann-Morgenstern axioms hold). The resulting demand might both be higher or lower compared to the individual product at the same price. Furthermore, liquidity constraints might be more of an issue in products P3 and P4, especially for large households, as premiums for all household members need to be paid. We assess demand, selection into the insurance policies and overall welfare effects in Sections 3.5, 3.6 and 3.7.

3.3.3 Sampling and Randomization

We chose the 'revenue village' or 'mouza', which is best described as a collection of settlements forming a village, as the level of randomization. This means that only one out of four interventions described above is made available to clients living in the same village. We choose this level of randomization because it is sufficiently small to allow for the required number of clusters, while at the same time being sufficiently large to reach the optimal number of observations per cluster. Further, given the considerable distance between villages, this choice minimizes the potential for information spillovers, which could contaminate the treatment effect estimates. A map of the villages included in the experiment can be found in Appendix C.2.

The sampling procedure focuses on clients from groups whose loan application had been approved just before the introduction of the innovation in December 2014. This approach guarantees that the group composition and household structure are exogenous to the introduction of the innovations. Moreover, this procedure allows the coverage periods of the mandatory and extended insurance policies to overlap for most of the time. For sampling purposes, we first generate a unique order of credit applications from the timing in which they appear in NRSP's management information system. In a second step, we select *all* members with active loans from the pool of groups for which there is at least one credit application. New groups are added following this procedure until at least 13 client households per village are sampled to achieve an optimal cluster size.[9] Sampling from incoming credit applications implies that we do not know the set of villages with incoming credit applications ex-ante. We therefore employ a permuted block randomization procedure for dynamic treatment assignment (McEntegart, 2003) and additionally stratify the treatment assignment across a set of ex-ante village characteristics.[10] Premium discounts are randomized on the level of the household during the sign-up procedure. The discount is determined through a lottery in which clients have to choose one of four seemingly identical cards. These discount cards are drawn with replacement, hence giving each household an identical chance for each discount level. The result is captured on a specifically developed sign-up sheet that contains unique household level identifiers.

Table 3.2 presents the resulting allocation of treatments. In total, there are 502 villages with 6,461 client households, which are each allocated to one of the four insurance innovations or two control groups. The first set of control villages constitutes a pure control group. In these villages no intervention in addition to the usual procedures takes place. The sampled credit groups in the second control group, labeled "Awareness", receive a standardized session in which the contract of the already existing mandatory insurance for clients and spouses is explained.[11] In most of our analysis, we focus on the 334 villages in which the four insurance innovations have been implemented with policies P1, P3 and P4 being of particular interest. As expected by design, the number of villages across treatment arms is balanced and each treatment cluster on average comprises 13 households.

[9] In general, this translates into sampling one complete community organization per village, which is sometimes amended by a smaller credit group. Alternatively, we sample four to five smaller credit groups per village.
[10] More details on the randomization procedure can be found in Appendix C.2.
[11] This session is also conducted in the treatment villages in which an additional insurance policy is offered.

Table 3.2 – Treatment Allocation

	Control	Awareness	P1	P2	P3	P4	Total (Policies)	Total
Villages	86	82	82	84	82	86	334	502
Groups	283	230	268	266	252	264	1050	1563
HHs	1154	1026	1022	1083	1058	1120	4283	6463
HHs Attending	0	822	856	870	830	877	3433	4255
Dependents (Dep.)	4183	3539	3560	3920	3797	4085	15362	23084
Attending Dep.	0	2798	2981	3209	2938	3156	12284	15082

3.4 Data

To facilitate the understanding of our analyses, the data sources and the data itself are described in the following.

3.4.1 Data Sources

In the analysis below, we combine household and individual level data from three different sources. First, we use client level information captured in our implementation partner's management information system (MIS). Second, we collect household and individual level data from the sample households through computer assisted personal interviews (CAPI). Third, we augment this information with bi-monthly phone surveys for the subset of households that consented in the baseline survey.

The MIS data includes unique client, group and village identifiers that we rely on in the randomization process. In addition, our implementation partner's credit procedure involves the collection of household rosters for incoming credit clients. We use these household rosters in two ways: On the one hand, it determines insurance eligibility of the dependents at the time of the insurance offer.[12] On the other hand, we incorporate these household rosters in the survey software to facilitate the survey process. Moreover, we will have access to detailed claim data for the introduced policies. The claim data will contain information on the type of claim (hospitalization vs. accidental death/disability), the claim amount and details on the disease diagnosed.

The household survey consists of several modules capturing socio-demographic, psychological, economic, and health indicators. The health module contains individual level information on subjective health status, history of both in- and outpatient treatments and detailed information on coping strategies. Baseline data was collected between December 2014 and March 2015 before the implementation of the intervention. Externally hired enumerators operating in the name of the University of Mannheim were engaged in data collection. To maximize data quality, our CAPI

[12] This procedure also ensures that the household structure is exogenous to the introduction of insurance.

system included both instantaneous in-field quality assurance and regular, more sophisticated data quality checks on the enumerator level.

The phone survey captures high-frequency information on health events. In general, there is the concern that information on more regular shocks such as visits to the doctor and corresponding expenditures become inaccurate for longer recall periods. In order to collect complete and accurate information on health shocks, we call respondents on a bi-monthly basis and ask about the health status of their household members. The phone survey instrument captures both inpatient and outpatient events along with the costs incurred and coping strategies. The phone survey data collection covers the complete product cycle of the insurance innovation (one year).

3.4.2 Summary Statistics

Table 3.3 shows some basic summary for the 4283 households in the four insurance treatment arms. The average household size reported in the baseline survey is close to six. The average number of household members for whom the take-up information can be matched is about 5.4 and the number of eligible dependents in the household is about 3.6. The average age of the client is about 38.5 years old and about 53% of the clients are female. The majority of clients have no formal education. The second panel of Table 3.3 (a) contains economic indicators. Average monthly income of households is about PKR 22,700 (USD 220) and on average they own about 1.4 acres of land. Further, credit obligations are about three times as large as the savings stock, which amount to about 30,000 and PKR 12,000, respectively. The third panel contains household level health indicators. In about 12% of the sampled households, at least one member was admitted to a medical facility for inpatient treatment in the last 12 months prior to the survey. In case of hospitalization, average expenditure amounts to approximately PKR 37,000 per household. On average, 18% of the sampled households have heard about insurance. 16% of the dependents in the household consulted a doctor in the last month, whereas 2% of household members were hospitalized in the past 12 months. Part (b) of Table 3.3 describes data gathered via the phone survey (93% of respondents in the baseline agree to be contacted via phone). During the 12 months covered, 15% of households report that some dependents experienced an inpatient event, while two thirds of households sought outpatient treatment for some of their dependents in the last month. On the dependent level of the, reported inpatient and outpatient incidences are comparable to those of the baseline survey (2% and 16% respectively).

Table 3.3 – Summary Statistics
(a) Baseline Characteristics

	N	Mean	SD
Socio-Demographics - HH			
HH Size (Survey)	4283	5.99	2.12
HH Size (Matched)	4283	5.37	1.91
Dependents (Matched)	4283	3.59	1.87
Age of Client	4283	38.62	10.89
Client Female (D)	4283	0.53	
Client No Education (D)	4283	0.55	
Economic - HH			
Income (month)	4283	22691	24695
Asset Index	4283	0.06	2.42
Savings	4283	12085	67986
Credit	4283	30439	71910
Health & Insurance - HH			
Any Inpatient (D)	4283	0.12	
Total Inpatient Cost	4283	4446	24475
Knows Health Insurance (D)	4283	0.18	
Health - Dependents			
Health Step (1-5)	15361	4.76	0.63
Outpatient Experience (D)	15361	0.14	
Inpatient Experience (D)	15361	0.02	
Outpatient Cost	15361	609.99	7920.43
Inpatient Cost	15361	506.36	7520.87

(b) Phone Survey

	N	Mean	SD
Consent	4283	0.93	
Health - HH			
Any Inpatient (D)	3973	0.14	
Any Outpatient (D)	3973	0.65	
Health - Dependents			
Inpatient Experience (D)	14246	0.02	
Outpatient Experience (D)	14246	0.14	
Inpatient Cost	14246	371.59	5537.91
Outpatient Cost	14246	702.79	5415.12

Notes: The table provides means and standard deviations (SD) of the respective variables. Binary variables are indicated with (D). Monetary amounts are in Pakistani rupees (PKR), where 101 PKR $\approx$ USD 1.

Balancing tests for these (and other) characteristics are shown in Appendix C.3. They indicate that the randomization achieved a very good balance of covariates across treatment arms. Also the share of the four discount types distributed during insurance roll-out is not significantly different from 25%, consistent with our uniform distribution scheme. Levels of discounts furthermore do not seem to systematically differ by recipient characteristics.

3.5 Insurance Demand

Figure 3.2 depicts demand for the three insurance policies of interest. For each policy, demand is plotted at the four different premium levels. The dark bar illustrates the share of households insuring at least one dependent, while the lighter bar illustrates the share of eligible dependents becoming enrolled in the insurance scheme.[13] For all offered policies uptake decreases in the premium. The fraction of households covering some of their members is relatively high in the individual policy (P1: 42-77%) compared to the household (P3: 26-74%) and the group level policy (P4: 28-72%). In terms of the fraction of dependents covered, however, the bundled policies achieve higher uptake (P3: 18-71%, P4: 19-68%) compared to the individual policy (P1: 17-39%). Table C.2 in Appendix C.1 provides elasticity estimates assuming a linear demand curve. The resulting estimates vary between -0.6 for the individual policies to -1.6 for the household policies.

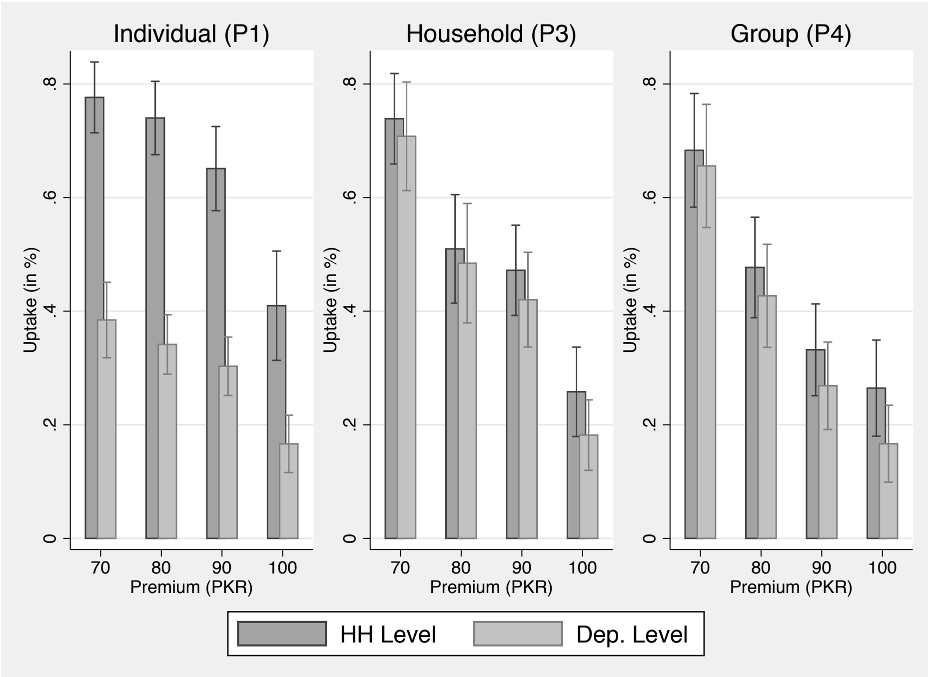
In the individual product P1, we observe a large gap between the share of households and the share of individual becoming insured at any premium level. This gap illustrates that households to large extent insure only partially and we will analyze in the next section whether the insured individuals differ from the non-insured with respect to their expected health costs. The gap between household and individual level uptake is much lower in the household and group policies P3 and P4. This is not surprising and shows that our eligibility criteria of ensuring all dependents in the household have actually been enforced in the field. The remaining gap exists because smaller households are more likely to purchase, which again suggests that clients face difficulties to pay the amount necessary to insure many dependents.

Comparing the individual policy P1 and policies with the household eligibility criterion (P3 and P4), we further observe that fewer households buy insurance if enrollment of all dependents is required. On the other hand, the share of insured dependents is larger with the requirement. This suggests a trade-off between a larger pool of insured dependents and a larger pool of insured households. In other words, some households that buy (partial) insurance when offered the individual policies would not do so when they were required to insure the whole household.

Appendix Table C.3 sheds further light on the determinants for households to enroll in the different insurance products. In the individual product (P1) household size does not play a role in whether to engage in some form of insurance, but larger households insure a smaller fraction of their members. Individuals selecting into the scheme tend to have lower health status and worse health history. Furthermore, children – especially the oldest son – are more likely to be enrolled. In the household and group policies (P3 and P4) individual characteristics have less predictive power. Instead, factors which might aggravate liquidity constraints of households (household size, female gender of the client and household experience of a hospitalization) correlate with lower take-up.

[13] Note that the figure is based on households attending the group meeting. Overall, the attendance in the meeting is around 80%. We do not find any statistical differences in terms of observable characteristics between households attending the meeting and households not attending the meeting (refer to Table C.11 in Appendix C.3). The shares depicted in Figure 3.2 as well as the number of households attending the meetings (and their eligible dependents) are provided in Table C.1 of Appendix C.1.

Figure 3.2 – Insurance Demand, by product type



Notes: The bars indicate average uptake ratios on the household and dependent level respectively. The depicted 95% confidence intervals account for clustered standard errors at the village level. Small differences between dependent and household level uptake in policies P3 and P4 occur because of the smaller size of insured households.

3.6 Adverse Selection

In the previous section, we estimated how many households or individuals purchase insurance as a function of the price, which exogenously varies as part of the RCT. In this section, we examine *who* purchases insurance and if these individuals systematically differ from those who do not. Thereby we analyze the relationship between insurance demand and health risk in terms of expected reimbursement costs to learn more about adverse selection

3.6.1 Measuring Health Risk: The Expected Cost Index

Expected reimbursement costs at different demand points are of central importance for the identification of adverse selection in our setup. To measure these costs, we construct an expected cost index capturing the insurer's expected reimbursement costs for each individual given baseline covariates. To translate baseline covariates into expected costs we link characteristics to observed health events, costs and claim behavior after insurance was introduced. Even though this mapping is based on the costs observed in reality after the introduction of the insurance innovation, the cost index remains purely a function of ex ante characteristics.[14] We follow this approach for several reasons:

First, moral hazard can create a correlation between insurance demand and health costs after the insurance decision even in the absence of adverse selection. For example, people may change their behavior after having purchased insurance and take such behavioral changes into account before buying insurance.[15] Specifying the cost index as a function of baseline values avoids any such confounding.[16] Imagine a case where moral hazard exists and increases hospitalization costs incurred. In this case, the mapping would predict higher costs, but it would do so for all individuals with the same baseline variables – irrespective of their insurance status. The comparison between insured and non-insured hence remains unbiased. Note that even though the index does not suffer from a discrimination problem, our experimental setup allows investigating moral hazard further. Specifically, we can compute predictive models for health care costs using the 162 control villages included in the RCT. Since insurance was not made available in these villages, moral hazard cannot enter into this alternative index. In contrast, estimating predictive cost models using data from the treatment villages incorporates the overall cost shift due to potential moral hazard as well. Appendix C.4 reveals that both approaches lead to similar empirical results. For this reason, we regard adverse selection as the main channel, while selection on moral hazard seems to be of less relevance in our setting.[17] The main analysis presented below hence uses the predictive model that includes data from all villages in the experiment in order to maximize precision of the estimation.

Another reason to compute an expected cost index for each individual rather than using insurer reimbursement costs is that the latter relies on few claim observations. An assessment of selection across different policies and further subgroups requires a sufficient number of observations, though. Comparing individuals with respect to a large set of baseline characteristics ensures that we can effectively use all individuals for analysis and furthermore differentiate them sufficiently. A drawback of using baseline characteristics is that their interpretation is usually not trivial. Many studies employing baseline risk measures face uncertainty about how well their measures relate to the occurrence of health events in the future. Such limitations of the relevance do not apply here, as our risk measure is based on a mapping of baseline risk factors into inpatient costs aris-

[14] See Appendix C.4 for further details on the parametric prediction models. Note that results are robust to other prediction models.

[15] In our case, preventive behavior may change or patients might visit more expensive facilities, both leading to an increase in the expected cost distribution of insured individuals as compared to uninsured individuals.

[16] All baseline covariates are fully exogenous in the sense that they could not be causally affected by the insurance policies offered because at the time of data collection, households were not aware of the upcoming insurance innovations. Furthermore, the household roster used to determine eligibility for insurance was collected before the innovations were introduced. Otherwise, households might have answered strategically when being asked about who belongs to their household (particularly for the household and group insurance policies P3 and P4). Table C.8 reveals that there is no statistically significant difference in the household size reported at baseline.

[17] This is in line with our expectations because the insurance only covers in-patient expenses which are mostly related to emergencies and acute illnesses, where we expect moral hazard to be less relevant.

ing during the product cycle. The model used for this mapping is strongly prognostic with many coefficients and the overall model being highly significant (compare Appendix C.4). [18]

For the main analysis below, the health risk index is computed in the same way for all individuals under the policies P1, P3 and P4, which share the same coverage limit of PKR 15,000. The average predicted cost per individual in these policies is PKR 71.42. Appendix C.4 documents that the index is balanced between policies P1, P3 and P4.

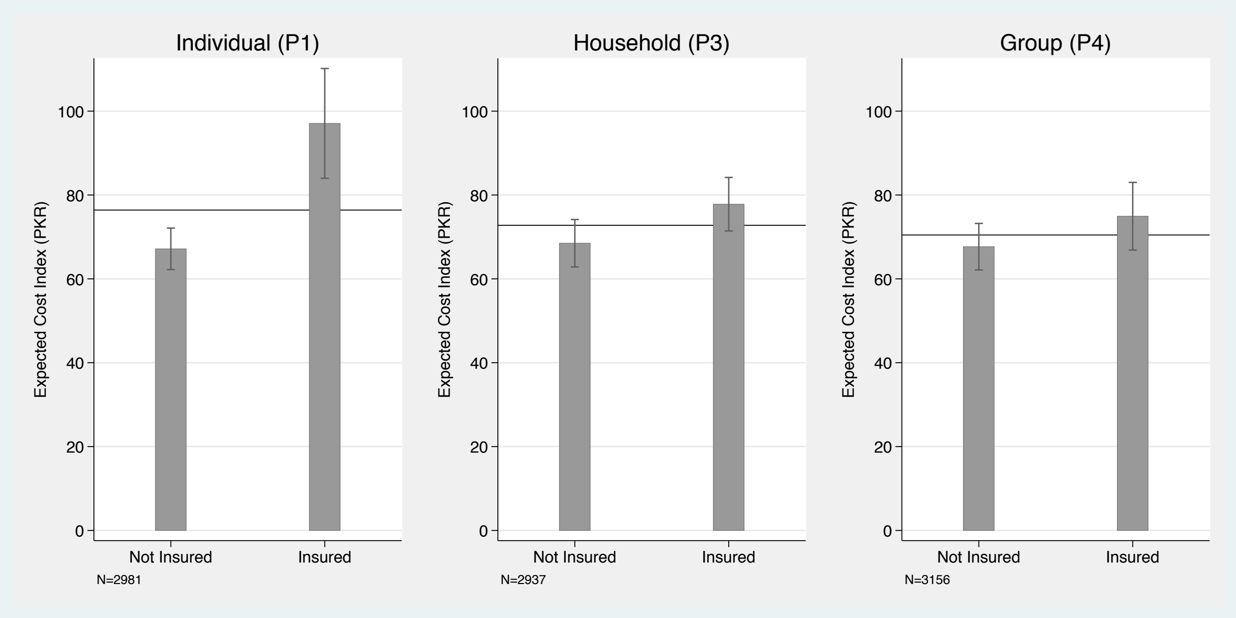
3.6.2 Presence of Adverse Selection: Positive Correlation Test

As described in Section 3.2, adverse selection leads to a situation in which high risk types choose higher insurance coverage than lower risk types. In a first step, we therefore assess the existence of such a relationship by implementing a conventional positive correlation test (Chiappori and Salanie, 2000). The individual's insurance status is given by a binary indicator for insurance uptake. Further, we proxy individuals' health risk by the expected cost index described before. Figure 3.3 plots coefficient estimates (and corresponding 95% confidence bounds) from a bivariate regression of the expected cost index on the binary insurance status for each of the offered policies. The horizontal line indicates the overall mean of the cost index. For the individual policy P1, we observe a large and statistically significant difference in the average cost index of insured versus uninsured individuals. The average cost index is almost 50% larger for insured individuals and the difference is highly significant (p-value $\ll 0.0001$). For household policies P3 and P4, on the other hand, we find that the difference in health risk between insured and uninsured individuals is much smaller. Average predicted costs are between 10-15% higher for insured compared to uninsured. This difference is statistically significant at the 5% level for policy P3 and insignificant for P4.

The pattern observed in Figure 3.3 is in line with the presence of adverse selection. Higher risk individuals are more likely to become insured, in particular if given the choice in the individual insurance policies. The requirement to enroll all household members appears to mitigate such cherry picking and therefore could be considered a promising tool in alleviating adverse selection. Note that the observed pattern can also explain the partial insurance uptake within the household established in Section 3.5. The corresponding demand analysis in Appendix Table C.3 confirms that idiosyncratic health risk factors are a much better predictor for insurance uptake in the individual than in the household or group products. In the absence of positive assortative matching within the household this result is mechanical in the sense that there is simply no more scope for adverse selection in the household products. On the other hand, it is possible that clients are less likely to exploit the scope for selection, for example because they have difficulties to obtain a good estimate of the household's riskiness as a whole.

[18] Not surprisingly, the predictive power is not perfect since health shocks are generally hard to predict. The non-explained part reflects pure randomness as well as unobserved health risks.

Figure 3.3 – Positive Correlation Test: Expected Cost Index and Take-up, by policy



Notes: Bars indicate mean values of the health cost index by insurance status and policy. Confidence intervals are derived from OLS regression of the health risk index on a binary insurance status indicator. Standard errors clustered at the village level.

While the presented evidence of the positive correlation test seems conclusive, the behavior explaining these results remains less clear. Insurance demand is a conscious decision, but the choice might well be related to other characteristics besides expected inpatient costs. If these characteristics – such as risk aversion or income – are related to the measure of riskiness, the interpretation as deliberate selection on the basis of costs might be misleading. More risk-averse clients for example are expected to be more likely to insure their dependents. If these clients are at the same time more likely to be located in households with higher health risk, a similar result as in Figure 3.3 could arise without intentional selection based on expected costs. In Appendix Table C.4, we investigate this issue by explaining the demand-risk correlation with non-health related characteristics on the one hand and health history on the other hand. Even though the non-health variables are able to explain some of the insurance effect, there remains a large and significant effect that can only be explained by variables related to past health events. The classical explanation for adverse selection thus appears to be at least part of the story.

From an insurer's perspective, the behavior explaining the selection process is not the key issue, though. For the provider it is more interesting to know the costs caused by adverse selection and how these change at different price and demand levels. Furthermore, changes in the cost distribution across prices shed additional light on the origins of adverse selection; classical explanations for adverse selection imply a decreasing average cost curve which is caused by a transition of relatively less risky individuals out of the insurance pool with increasing prices. The setup of our

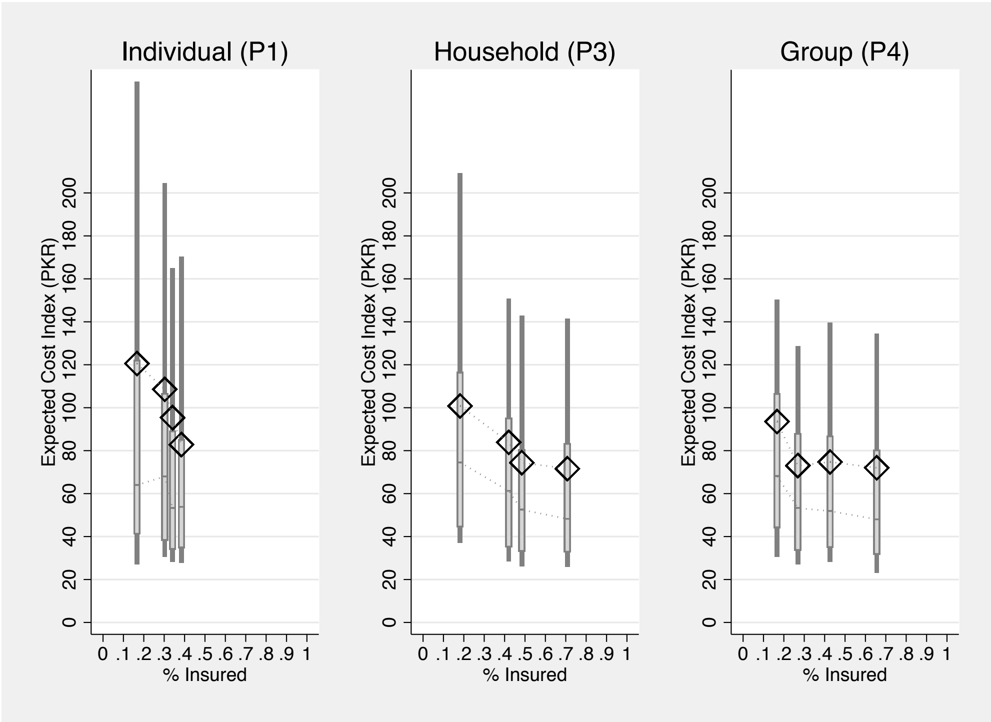
RCT allows investigating such dynamics caused by price changes specifically, and we discuss the corresponding analyses in the following section.

3.6.3 Presence of Adverse Selection: Slope of (expected) Marginal Cost Curve

In this section we move beyond the purely correlational approach and analyze the distribution of risk types' at different points of the demand curve. As illustrated in Figure 3.1 and discussed in Section 3.2, the slope of the insurance providers' marginal cost curve directly indicates the presence of adverse selection (Einav and Finkelstein, 2011). In the absence of adverse selection, the marginal cost curve would be flat. Thus, the risk type distribution of the insurance pool would be independent of the insurance premium. In contrast, if adverse selection were present, the marginal cost curve would be upward sloping in price.

Figure 3.4 illustrates the distribution of the cost index in the pool of insured individuals at different demand levels using box plots. The box indicates the interquartile rage (IQR), with the median indicated by the line separating the box. The lower (upper) adjacent line indicates the 90^{th} (10^{th}) percentile, respectively. The diamond represents the mean of the distribution. For the individual level policy P1 the mean costs associated with the insurance pool decrease with demand, i.e. with lower premiums. While all depicted moments of the distribution tend to shift downward, the shift is most pronounced at the upper tail. For the household (P3) and group (P4) policy there also seems to be an upwards shift in the cost distribution with increasing premiums, but this shift is smaller than under the individual policy (P1). Table C.5(a) shows the result of testing for a trend in the mean cost index of insured individuals by policy. Findings lack precision, in particular when there are fewer observations in the insurance pool, but the downward slope of the average cost curve tends to be stronger in the individual policy (P1) than in the household and group policies (P3, P4).

Figure 3.4 – Distribution of Expected Cost Index of Insured over Demand, by policy



Notes: The box plot illustrates the interquartile rage (IQR), with the median indicated by the line separating the box. The lower (upper) adjacent line shows the 90th (10th) percentile, respectively. The diamond indicates the value of the mean.

Appendix C.1 provides further robustness checks and comparisons within the different policy regimes. Figure C.1 shows the distribution of costs across demand levels amongst the non-insured. For the individual policy, there appears to be a downward shift in the cost distribution when the share of insured becomes larger. Marginal individuals switching the insurance status in response to a change in price hence seem to be high risk relative to the non-insured but low risk relative to the insured. This is fully in line with the economic theory on adverse selection discussed in Section 3.2. In contrast, such a pattern for non-insured is not observed under household (P3) and group (P4) policies. Table C.5(b) provides a formal test for the relationship between the cost index of non-insured and the share insured. The estimated slope is significantly negative for the individual policy P1 and insignificantly positive for household and group policies (P3, P4).

We conduct several robustness checks. For instance, we employ an alternative health risk measure which is constructed by a principal component analysis of baseline health measures. Further, we repeat the analyses for the main baseline health measures separately. Our primary finding that adverse selection is much more pronounced in individual versus household and group insurance policies is robust across all these analyses.[19] Finally, we validate our analysis by comparing *real* hospitalization costs, claim incidences and claimed amounts amongst the insured during the

[19] The results for these robustness checks are available upon request.

product cycle between policy types. All three measures are significantly higher in the individual policies' insurance pool (see Table C.13).

3.7 Welfare Analysis of Adverse Selection

In the previous sections we established the existence of adverse selection in particular in products for which clients can select individual members to become insured. The selection is less pronounced when complete households or groups of households have to enroll. This section investigates the welfare consequences of adverse selection under the different policies. As discussed in Section 3.2, the exogenous price variation induced by the RCT setting identifies both the demand and the average cost curves. To analyze welfare consequences, we need to connect the demand estimates from Section 3.5 with the analyses on the slope of the average cost curve in the previous Section 3.6.3. Different to the above demand and cost analyses, however, we use priors to constrain our estimates to exhibit reasonable features. First, we restrict the slope of the demand curve to yield full coverage at price zero or above.[20] Second, we know that with 100% take-up, average costs of the scheme must equal the mean of the cost index in the sample. We therefore restrict the average cost curve to pass through this point. This approach is in line with the analyses in Einav et al. (2010). Given these restrictions, we estimate the demand curve via a linear regression of a dependent level take-up indicator on the exogenously varied premium price. The cost curve estimates result from linear regressions of the individual-specic cost index on aggregate demand for the corresponding policy at the respective price. The marginal cost curve can easily be derived afterwards in the linear case $(MC' = 2 \times AC')$. The result of the exercise is shown in Figure 3.5 . It plots the average demand at different premium prices, the average cost index at these respective demand points as well as the estimated demand, average cost and marginal cost curves for the three policies. As discussed in Section 3.2, the intersection of the demand and average cost curve determines the market equilibrium, while the intersection of demand and marginal cost curve determines the efficient allocation.

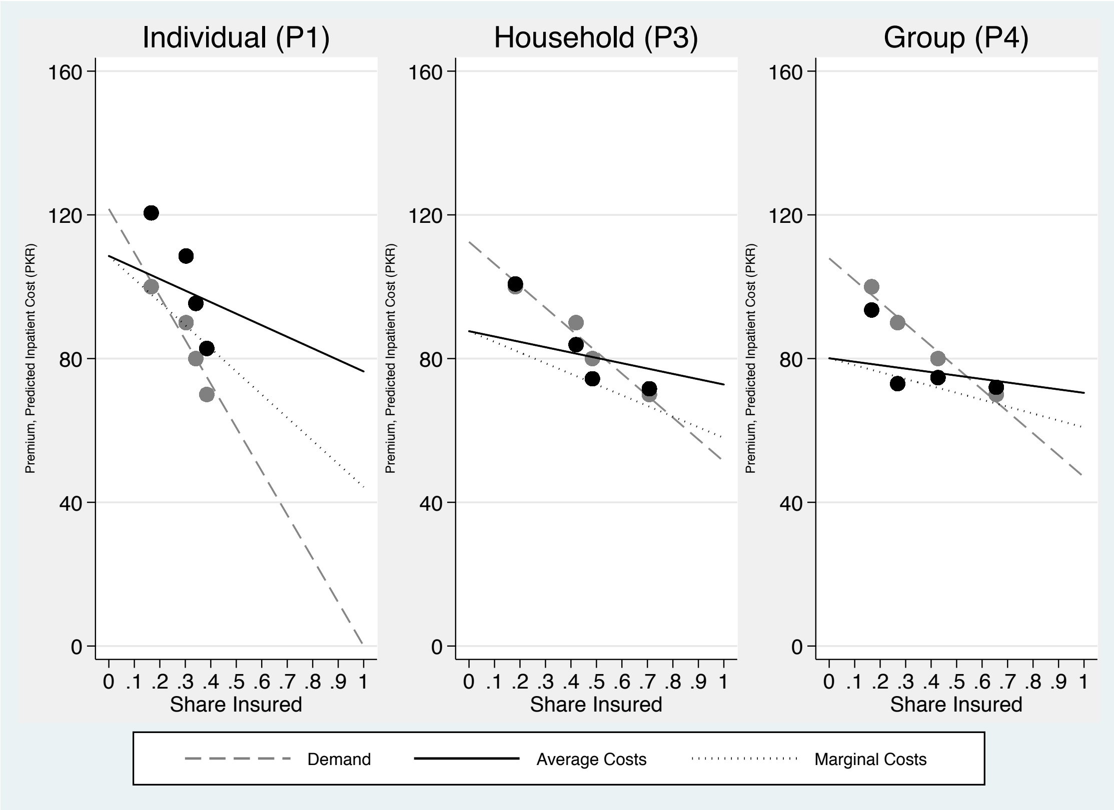
Even though the linear approximation with restrictions does not fit the data points perfectly, Figure 3.5 clearly shows that sustaining insurance supply is much harder under the individual policy (P1). Both linear approximations as well as the visual inspection of data points suggest that the market for individual insurance is close to a breakdown. In the case of the bundled policies (P3, P4), however, the average cost curves are less steep and more often situated below the demand curve. This leads to higher equilibrium demand, higher aggregate welfare and lower prices compared to the individual policy. This result is to some extent driven by the higher demand for insurance coverage in bundled policies (estimates shown in Table C.6), but shifts in the average cost curves (parameter estimates in Table C.7) also play a role. The slope of the cost curve is

[20] In other words, we assume full take-up if the product was offered for free. This restriction is binding in only one case (P1), but the fit still appears to be very good.

relatively large and highly significant for the individual policy P1 (-32.228). Figures are smaller and less significant for household policy P3 (-14.884, significant at 5% level) and group policy P4 (-9.302, insignificant). When comparing the slopes, we find significant differences between P1 vs. P4 (p-value: 0.0751).

Another important aspect to consider is how close the respective policies are to the efficient allocation. Table 3.4 shows the equilibrium as well as the efficient allocations under the different policies and calculates the resulting welfare losses from adverse selection. Despite the lower gradient of the average cost curves for the bundled policies, losses in quantity caused by adverse selection (0.11-0.15) are higher than for the individual policy (0.09). Also the calculated welfare loss is higher for the household and group insurance (P3: 1.00, P4: 0.33) than in the individual insurance policy (P1: 0.21). There are two reasons for the higher losses despite lower adverse selection in bundled policies. First, the gradient of the demand curve is lower and second, equilibrium allocations are at a higher quantity. Both factors ceteris paribus extend the 'loss triangle'. We therefore also calculate the relative welfare loss, indicated in the last row of Table 3.4. Relative to overall welfare, losses are indeed lower in the household and group policies (10.16% and 3.50%) compared to individual policy (14.40%).

Figure 3.5 – Market Equilibrium and Efficient Allocation, by policy



Notes: The figure plots the demand, average and marginal cost curves for the respective policies. Average demand for the corresponding premium is given by the dots in light grey. The slope of the demand curve is estimated from a linear regression of an individual take-up indicator on the premium for which a restriction of a constant larger or equal than 1 is imposed. Average costs of the insured for the corresponding demand are given by the dots in black. The slope of the average cost curve is estimated from a linear regression of the individual level expected cost index on average take-up at the corresponding premium level. The estimation is restricted to pass through the average cost index for the respective policy at a demand level of 1. The regressions predicting the both curves are shown in Tables C.6 and C.7 and account for clustering of standard errors at the village level.

Table 3.4 – Welfare Analysis

	Individual (P1)	Household (P3)	Group (P4)
Equilibrium			
Price	103.41	79.48	75.02
Quantity	0.15	0.54	0.54
Welfare	1.32	8.84	8.95
Efficient			
Price	93.67	64.20	67.11
Quantity	0.23	0.79	0.67
Welfare	1.49	9.83	9.29
Loss			
Quantity	0.08	0.25	0.13
Welfare	0.18	0.99	0.34
%Welfare	11.75	10.06	3.67

The welfare results presented above should be interpreted with caution, as they are sensitive to the parametric fit of the demand and cost curves. In particular, the cost estimates are based on insured individuals only and lack precision when demand is low. The restricted linear regressions smooth such fluctuations, but they also smooth away local slopes. For this reason, the quality of this parametric fit seems somewhat limited, in particular for the individual policy P1. As a robustness check, we allow for a quadratic average cost curve that accounts for the analogous restriction of passing through the mean of the expected cost index at full demand. Appendix Figure C.2 suggests an even more pronounced contrast between individual (P1) and bundled policies (P3, P4): the market for individual policies breaks down completely.[21] We therefore interpret the linear specification as a conservative estimate of the difference between the different policies.

Another central element of the welfare analysis is the interpretation of the demand curve. The neoclassical welfare analysis above assumes that the willingness to pay measures utility derived by coverage. There might be many reasons why this interpretation is flawed, such as wrong beliefs about insurance benefits, liquidity constraints, or simply irrational behavior. We indeed find uptake patterns consistent with liquidity constraints for household and group policies (refer to the discussion on demand in Section 3.5 for more details). At the same time, these findings cannot explain why demand for bundled policies is *higher* than for the corresponding individual policy. This finding of higher average willingness to pay for household than for individual insurance is not easy to reconcile with simple neoclassical theory under perfect information. In such an environment, average willingness to pay should be similar for individual and bundled policies, even though the shape of the curves might differ.[22] Finally, the interpretation of the demand curve

[21] The market for individual insurance (P1) breaks down in equilibrium, even though insurance take-up would be positive in the efficient allocation. In case of the bundled policies (P3, P4), equilibrium prices and quantities remain very similar and the equilibria are even closer to the efficient situation than in the linear specification. [22] Assuming constant absolute risk aversion (CARA) for example, it is straightforward to show that the sum of the

might be distorted by the implementation of price variation through discount vouchers. Receiving a positive discount might for example induce more uptake than other forms of price variation. While we do not observe deviations from the linear demand predictions at particular discount levels, we cannot exclude that there are effects on demand. To severely bias our results, though, such effects would have to be different across policies.

3.8 Discussion and Conclusion

This paper provides robust evidence on adverse selection in low-income health insurance markets. We analyze a randomized control trial which was conducted in more than 500 villages of rural Pakistan and where hospitalization insurance for household members of microfinance clients was offered by a large local NGO. The setup of the RCT allows us to separate adverse selection from moral hazard, to estimate how selection changes at different points of the price curve and to test different mechanisms against adverse selection. Our analysis of adverse selection is based on individual health characteristics at baseline which we translate into an idiosyncratic expected cost index using realized costs during the product cycle.

The results suggest that there is substantial adverse selection if specific individuals within the household can be enrolled in the health insurance. In particular, adverse selection becomes worse with higher premium prices, suggesting a trade-off between cost recovery and the quality of the insurance pool. Bundling policies on the household level is effective in mitigating adverse selection to a large extent. Additional bundling of policies on the level of microfinance groups further improves the risk pool and no significant adverse selection remains in this policy.

Our main analysis assumes that the expected cost index is a good proxy to construct cost curves. An alternative and more direct approach would be to estimate average and marginal cost curves using claim data from the insurance provider only. Given that hospitalization is a rare event with a high unexplained error component, following this strategy would yield very imprecise results in our sample. Using the best predictor for expected claim costs given baseline covariates as a measure of health risk has several desirable properties in this context: It is highly relevant for expected costs, easy to interpret and at the same time its value is less affected by random health shocks at the respective price/policy points. The drawback of this measure is that we lose the selection based on health risk that is not explained by observable baseline characteristics. In that sense, results based on the cost index might represent a lower bound for true selection.

Nevertheless, the results show that (a function of) baseline health information does play a role for rural microfinance clients in Pakistan when they decide about insurance uptake. Moreover, a household's ability to sort high risks into the insurance to a large extent is limited to selection within households. There does not seem to be much selection on higher levels, such as the house-

willingness to pay for each individual household member as indicated by the demand curve is equal to the willingness to pay for the whole household.

hold or the micro-finance group. These findings add to the controversial debate about classical assumptions in the developing country context. While community level demand factors might be important (Dror and Firth, 2014), they apparently do not preclude microfinance clients in our sample from specifically enrolling more risky individuals within their households.

The exogenous price variation induced in the RCT enables us to conduct a comparative welfare analysis for the different insurance schemes by merging the analyses of demand and costs curves. This exercise – which naturally rests on some assumptions – suggests that equilibrium allocations under bundled products are characterized by higher quantities, lower prices and higher welfare than under individual policies. An increased demand and decreased average cost curves under bundled policies jointly explain the result. The conclusions related to welfare are subject to some reservations, though. In addition to the difficulty to precisely identify cost and demand curves, the neoclassical assumptions needed to interpret the willingness to pay as welfare might not be fulfilled. In particular, liquidity constraints, peer effects, a lack of financial literacy or biased beliefs about future benefits could lead to uptake decisions which do not reflect the true utility derived by insurance. Furthermore, equilibrium allocations might not be relevant for a market where little supply exists so far. Irrespective of the welfare interpretation and equilibrium allocations, however, there are important observations to be drawn from the analysis. It suggests that it is easier for insurers to operate sustainably when offering bundled policies, given that the spread between willingness to pay and average costs is larger. Further, lower adverse selection under household and group policies makes entering the market less risky for insurance providers when they do not know costs and demand at specific premiums.

This paper focuses on simple pooling products. This means that only one policy is offered and no additional measures against adverse selection, such as co-payments or ex-ante screening are included. Our results show that even under these circumstances household policies might be able to achieve a sustainable pool of insurance clients. This is good news for organizations interested in patching imperfect social security systems via insurance products for the low-income market. Such organizations might prefer a simple pooling contract to alternative solutions – such as contract portfolios with separating equilibria, screening, or risk classification based on observables – since the former are simple to market to low-income clients under difficult supply conditions and might exhibit lower administrative costs.

Appendix A

Appendix to Chapter 1

Table A.1 – Robustness Checks of Outcome Definition

	(1) ITT	(2) ITT	(3) ITT	(4) TOT	(5) TOT	(6) TOT
Seeds Offered	0.057*	0.069**	0.060**			
	(0.030)	(0.028)	(0.025)			
Accepted Offer				0.353*	0.422**	0.371**
				(0.182)	(0.166)	(0.152)
Store FE	Yes	Yes	Yes	Yes	Yes	Yes
N	974	974	974	974	974	974
R^2	0.098	0.093	0.073	0.125	0.135	0.097
Control Mean	0.39	0.26	0.18			

Note: This table reports robustness checks for the outcome definition. Column (1) and (4) report impact estimates on the self-reported measure to have planted hybrid maize seeds. Columns (2) and (5) report impact estimates for an outcome that - in addition to (1) & (4) - considers the source of hybrid seeds (governemnt, NGO, store), but does not impose a price threshold. Columns (3) and (6) consider an outcome variabel that - in addition to (2) and (4) considers a price cutoff of 2000 UGX/kg and requires the reported hybrid seed variety to be of type Longe. Robust standard errors are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%

Table A.2 – ITT and TOT Estimates of Hybrid Seed Adoption - Cluster Wild Bootstrap

	ITT	ITT	TOT	TOT
Seeds Offered	0.082***	0.084***		
Accepted Offer			0.505***	0.517***
Store Fixed Effects	Yes	Yes	Yes	Yes
Control Variables		Yes		Yes
Bootstrap P-value	[.031]	[.02]	[.011]	[.005]

Note: This table reports Intention-to-treat and treatment-on-the-treated estimates based on linear linear probability / TSLS models. The outcome is an indicator for whether the farmer reliably planted hybrid maize at endline. The p-values come from the STATA cluster-wild bootstrap procedure boottest with 1000 bootstrap samples. Control variables are identical to those reported in Table 1.4. * significant at 10%, ** significant at 5%, *** significant at 1%

Table A.3 – ITT and TOT Estimates of Hybrid Seed Adoption - Split by Survey Week

	ITT Week1	ITT Week 2	ITT Week 3	TOT Week 1	TOT Week 2	TOT Week 3
Seeds Offered	0.135**	0.139***	-0.040			
	(0.053)	(0.046)	(0.043)			
Accepted Offer				0.551***	0.857***	-0.434
				(0.201)	(0.273)	(0.468)
Growing Maize	-0.124	-0.034	0.096	-0.130	-0.041	0.086
	(0.087)	(0.071)	(0.060)	(0.082)	(0.068)	(0.061)
Grew Hybrid Maize	0.123*	0.014	-0.027	0.078	0.032	-0.034
	(0.068)	(0.055)	(0.062)	(0.061)	(0.055)	(0.061)
Age	0.001	-0.002	0.000	0.000	-0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Gender: Male	0.043	0.098*	0.102**	0.046	0.084	0.111**
	(0.068)	(0.056)	(0.052)	(0.062)	(0.056)	(0.053)
Completed Primary Education (or above)	-0.053	-0.010	0.014	-0.077	0.023	0.021
	(0.066)	(0.053)	(0.053)	(0.061)	(0.054)	(0.052)
Reachable by Phone	0.211**	-0.070	-0.027	0.244***	-0.031	-0.005
	(0.096)	(0.082)	(0.110)	(0.087)	(0.079)	(0.119)
Owns Phone	-0.110	0.095	-0.056	-0.157*	0.023	-0.057
	(0.091)	(0.084)	(0.113)	(0.083)	(0.082)	(0.129)
Crop Sold: Cotton	-0.269	0.006	-0.462*	-0.276	-0.049	-0.525*
	(0.193)	(0.186)	(0.259)	(0.176)	(0.162)	(0.293)
Crop Sold: Sesame	-0.291	0.024	-0.514**	-0.287*	0.002	-0.592**
	(0.194)	(0.170)	(0.232)	(0.172)	(0.142)	(0.274)
Crop Sold: Maize	-0.260	-0.009	-0.499**	-0.221	-0.033	-0.556**
	(0.221)	(0.166)	(0.227)	(0.193)	(0.142)	(0.262)
Log(Revenue, UGX)	0.002	0.016	-0.010	-0.012	-0.007	-0.010
	(0.025)	(0.021)	(0.019)	(0.026)	(0.023)	(0.019)
Plot Size planted with Maize (Acres)	-0.008	0.011	-0.006	-0.004	0.010	-0.006
	(0.021)	(0.010)	(0.009)	(0.021)	(0.009)	(0.009)
Grow: Beans	0.003	0.047	-0.015	-0.006	0.039	-0.031
	(0.084)	(0.058)	(0.073)	(0.077)	(0.054)	(0.077)
Grow: Cassava	0.107	0.012	-0.008	0.123**	-0.002	0.005
	(0.066)	(0.057)	(0.060)	(0.061)	(0.054)	(0.063)
Grow: Cotton	-0.038	0.019	-0.162*	-0.011	0.043	-0.180**
	(0.079)	(0.087)	(0.091)	(0.073)	(0.085)	(0.088)
Grow: Groundnuts	-0.032	0.015	-0.010	-0.026	0.031	-0.003
	(0.057)	(0.052)	(0.055)	(0.050)	(0.053)	(0.056)
Grow: Pigeon Peas	0.076	0.074	0.012	0.074	0.094	0.022
	(0.089)	(0.070)	(0.059)	(0.080)	(0.067)	(0.057)
Grow: Sesame	-0.043	-0.009	0.058	-0.010	-0.048	0.078
	(0.077)	(0.065)	(0.080)	(0.069)	(0.063)	(0.084)
Grow: Sorghum	0.030	0.043	-0.043	0.018	0.046	-0.049
	(0.073)	(0.054)	(0.053)	(0.065)	(0.055)	(0.052)
Grow: Soya	-0.031	0.002	0.098	-0.049	0.013	0.114
	(0.074)	(0.086)	(0.074)	(0.069)	(0.081)	(0.080)
Grow: Sweet Potato	-0.008	0.065	-0.021	-0.035	0.046	-0.013
	(0.065)	(0.048)	(0.050)	(0.062)	(0.050)	(0.048)
Grow: Vegetables (Salad,Greens)	-0.080	-0.038	-0.004	-0.042	-0.032	0.006
	(0.106)	(0.067)	(0.059)	(0.102)	(0.064)	(0.057)
Constant	0.375	-0.103	0.708**	0.202	0.182	1.016**
	(0.365)	(0.313)	(0.329)	(0.400)	(0.296)	(0.400)
Store Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	307	332	335	307	332	335
R^2	0.202	0.192	0.157	0.231	0.105	0.054

Note: This table reports Intention-to-treat and treatment-on-the-treated outcome estimates based on linear linear probability / TSLS models, using robust standard errors. The outcome is an indicator for whether the farmer reliably planted hybrid maize at endline. The coefficient from missing revenue indicator is omitted. Missing standard error estimates for *Revenue Missing for the Week 2* estimates are explained with no variation in the variable for that subsample. Coefficient estimates of an indicator for missing revenue are not reported, but not statistically significant.
* significant at 10%, ** significant at 5%, *** significant at 1%

Appendix B

Appendix to Chapter 2

B.1 Solution of Equilibrium Expectations

If private characteristics are self-known, an agent's information set contains only her own private characteristics, $X^p_{J_i} = X^p_i$. Any individual k connected to i is assumed to know the (conditional) distribution of private characteristics given her own realization, $X^p_k = x$. Thus, agent k forms her expectation about i's choice by integrating over all possible realizations of this distribution (and the type distribution ϵ_{gi}). Formally, k's expectation of i's decision is

$$\Psi^e_{i,k} = \int\int I\left(\beta_0 + X^{c'}_{gi}\beta_1 + X^{p'}_{gi}\beta_2 + X^{g'}_{g}\beta_3 + \lambda\sum_{j\neq i}^{n_g} w_{gij}\Psi^e_{j,i}(x^p_i) - \epsilon_{gi} > 0\right) f_\epsilon \quad \text{(B.1)}$$

$$f_{p,ik}\left(x^p_i | X^p_k = x, Z = z\right) d\epsilon dx^p_i$$

$$= \int F_\epsilon\left(\beta_0 + X^{c'}_{gi}\beta_1 + X^{p'}_{gi}\beta_2 + X^{g'}_{g}\beta_3 + \lambda\sum_{j\neq i}^{n_g} w_{gij}\Psi^e_{j,i}(x^p_i)\right) f_{p,ik}\left(x^p_i | X^p_k = x, Z = z\right) dx^p_i \quad \text{(B.2)}$$

where $f_{p,ik}\left(.|X^p_k = x, Z = z\right)$ denotes the conditional distribution of i's private characteristics given k's realization of private characteristics x and observable information z.[1] In principle, each of the n_g group members forms $(n_g - 1)$ expectations this way. Yang and Lee (2017) propose two ways to reduce the dimension of this problem. First, agents can be classified into subgroups based on publicly observed characteristics. Agents in the same subgroup could be assumed to face identical distributions of private characteristics. Alternatively, the (conditional) distribution of private characteristics can be assumed to be exchangeable. Intuitively, this assumption ensures

[1] Define $x_{gi} = \beta_0 + X^{c'}_{gi}\beta_1 + X^{p'}_{gi}\beta_2 + X^{g'}_{g}\beta_3 + \lambda\sum_{j\neq i}^{n_g} w_{gij}\Psi^e_{j,i}(x^p_i)$. Then, the inner part of equation B.1 simplifies to

$$\int I(x_{gi} - \epsilon_{gi} \geq 0) f_\epsilon(\epsilon) d\epsilon = \int I(\epsilon_{gi} \leq x_{gi}) f_\epsilon(\epsilon) d\epsilon = \int_{-\infty}^{x_{ig}} f_\epsilon(\epsilon) d\epsilon = P(\epsilon \leq x_{gi}) = F_\epsilon(x_{gi})$$

that given a public information structure only the realization of k's private characteristics, not her identity though, influences her expectation about any i's decision (Yang and Lee, 2017). As a consequence, only n_g equilibrium expectation functions need to be determined. This study is particularly interested in the case of independently distributed private characteristics.[2] In that case, the consistency condition for equilibrium expectations in equation B.1 simplifies to the constant function

$$\Psi_i^e = \int F_\epsilon \left(\beta_0 + X_{gi}^{c'} \beta_1 + X_{gi}^{p'} \beta_2 + X_g^{g'} \beta_3 + \lambda \sum_{j \neq i}^{n_g} w_{gij} \Psi_{j,i}^e(x_i^p) \right) f_{p,ik}\left(x_i^p | Z = z \right) dx_i^p \quad \text{(B.3)}$$

Socially known, private characteristics are defined as every agent i knowing her own private characteristics and those of her connected peers j. Therefore, the information structure depends on the social interaction matrix W_g. Moreover, agent i takes into account all information available to her when forming expectations about her connected peers, while information about non-connected peers is integrated out as in (ii).[3] Consistent equilibrium expectations of agent k about peer i's decision are thus given by

$$\begin{aligned} \Psi_i^e(X_{J_k}^p) &= \Psi_{iJ_k}^e(X_k^p, X_i^p, (X_l^p : l \neq i, n \neq k, W_{k,l} \neq 0)) \\ &= \int F_\epsilon \left(\beta_0 + X_{gi}^{c'} \beta_1 + X_{gi}^{p'} \beta_2 + X_g^{g'} \beta_3 + \lambda \sum_{j \neq i}^{n_g} w_{gij} \Psi_{j,J_i}^e(X_i^p, (X_{l'}^p : W_{k,l'} \neq 0)) \right) \\ &\quad f_p \left(X_{l'}^p : l' \neq k, w_{gil'} \neq 0, w_{gkl'} = 0 | Z = z \right) d(X_{l'}^p : l' \neq k, w_{gil'} \neq 0, w_{gkl'} = 0) \end{aligned} \quad \text{(B.4)}$$

[2] The case of independently distributed private characteristics can be solved using the approach proposed by Lee et al. (2014a). Solving the equilibrium consistency condition in the case of correlated private characteristics requires approximating integrals of the joint distribution. Refer to Yang and Lee (2017) for a discussion of both discrete and continuous joint distributions.

[3] See Appendix C in Yang and Lee (2017) for an example of both independent and correlated private characteristics. This study will focus on independent private characteristics.

B.2 Balancing Tests

Socio-Demographics Table B.1 provides summary statistics and balance tests for the set of socio-demographic characteristics across the different policies offered. We observe that there are imbalances in some of the variables considered (such as the share of female clients offfered the respective policy). As briefly discussed above, such imbalances can arise due to the differing number of COs sampled from the respective villages per policy. It is reassuring that there are no imbalances in the variables related the household members' health status, expenditures or insurance knowledge.[4]

Discount Checks Discounts are assigned on the household level through a private lottery with replacement played during the community meeting. Since every household faces the same probability of drawing a particular discount, we expect a uniform distribution across discount levels. Table B.2 provides evidence such uniform distributions. It illustrates the relative frequencies of the discount level for each of the offered policies. Moreover, the table reports the p-value from Pearson's Chi-squared test of uniform distributions. The results indicate that we are not able to reject the null of uniform distributions.

[4] The imbalance in the expected cost index measure is per design because policy P2 exhibits a higher coverage, thus leading higher expected costs for the insurance provider.

Table B.1 – Summary Statistics by Policy and Balancing Tests

	Overall	P1	P2	P3	P4	P-val
Socio-Demographics						
Dependents (Survey)	3.96	3.69	4.04	4.13	3.92	0.05
	(1.756)	(1.631)	(1.848)	(1.800)	(1.705)	
Dependents (Matched)	3.18	2.95	3.23	3.35	3.17	0.09
	(1.696)	(1.590)	(1.750)	(1.763)	(1.649)	
Group Leader (D)	0.18	0.19	0.19	0.17	0.16	0.13
	(0.381)	(0.392)	(0.391)	(0.376)	(0.370)	
Client Female (D)	0.12	0.11	0.05	0.13	0.19	0.03
	(0.328)	(0.316)	(0.210)	(0.336)	(0.392)	
Client No Education (D)	0.40	0.38	0.35	0.41	0.45	0.15
	(0.490)	(0.486)	(0.476)	(0.493)	(0.498)	
Client Age	38.73	38.89	39.24	38.18	38.69	0.74
	(11.066)	(10.976)	(11.301)	(10.831)	(11.172)	
Economic						
Wealth Index	0.29	0.38	0.46	0.29	0.06	0.38
	(2.514)	(2.650)	(2.565)	(2.418)	(2.443)	
Income (month)	21846.39	20354.54	25441.86	21623.50	20173.73	0.10
	(23435.351)	(14528.240)	(38570.359)	(18021.314)	(14860.815)	
Savings	15396.26	18837.42	23738.46	12426.29	8496.34	0.04
	(84632.817)	(93812.261)	(141161.883)	(35835.945)	(25340.921)	
Credit	43404.42	42712.61	49230.89	43613.67	38801.73	0.77
	(89539.377)	(77562.727)	(105801.773)	(97944.202)	(73304.521)	
Health & Insurance						
Knows Health Insurance (D)	0.22	0.22	0.27	0.21	0.21	0.29
	(0.417)	(0.416)	(0.443)	(0.405)	(0.406)	
Any Inpatient (D)	0.11	0.11	0.12	0.11	0.12	0.64
	(0.319)	(0.309)	(0.328)	(0.317)	(0.322)	
Total Inpatient Cost	4461.46	3652.66	6960.60	3400.48	3991.71	0.17
	(23875.019)	(15655.299)	(38920.854)	(14081.248)	(19392.472)	
Total Outpatient Cost	6954.99	8327.31	6756.85	6089.70	6885.63	0.86
	(34842.523)	(53667.298)	(27419.991)	(22194.569)	(31752.083)	
Expected Cost Index (HH)	304.29	281.35	426.56	258.01	262.93	0.00
	(306.531)	(278.997)	(470.120)	(185.058)	(199.877)	
N	1557	338	368	417	434	.

Note: This table provides summary statistics and balance tests of the main baseline characteristics by treatments arm. The columns contain means and standard deviations (in parentheses) of the respective characteristic. Column 1 provides overall information, while columns (2) to (5) indicate the respective policy. The last column contains the p-value of a balancing test with the null of equal mean across the four insurance policies. The test is based on a linear regression of the respective characteristics on the set of policy indicators and strata fixed effects. Standard errors are clustered at the village level. Binary variables are indicated with (D). Monetary amounts are in Pakistani rupees (PKR), where 101 PKR = USD 1.

Table B.2 – Discount Checks

	P1	P2	P3	P4	Overall
0	0.18	0.24	0.24	0.22	0.22
10	0.30	0.28	0.27	0.28	0.28
20	0.25	0.27	0.23	0.23	0.24
30	0.28	0.21	0.27	0.27	0.26
Pearson Chi2 P	0.1518	0.4236	0.7272	0.4238	0.2612
HHs	338	368	417	434	1557

Note: Relative frequencies of discounts given the respective policy. Pearson Chi2 p provides the p-value from a chi-square test with H0 of a uniform distribution.

B.3 Additional Results

Figure B.1 – Insurance Demand - Fraction of Households Insured

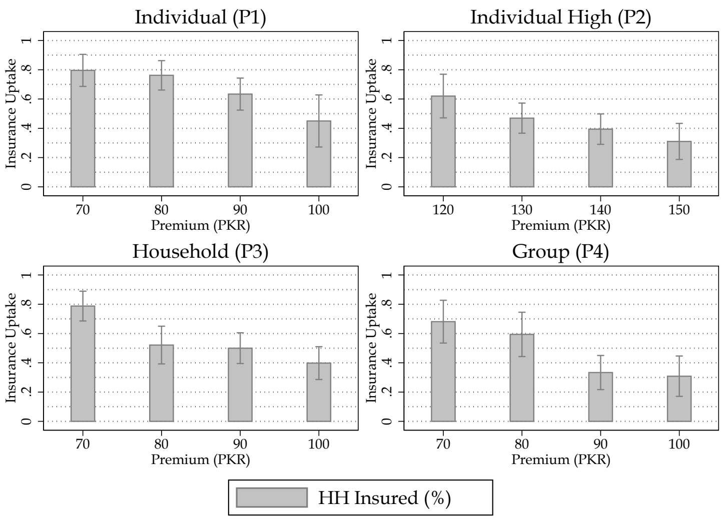


Figure B.2 – Insurance Demand - Number of Dependents Insured

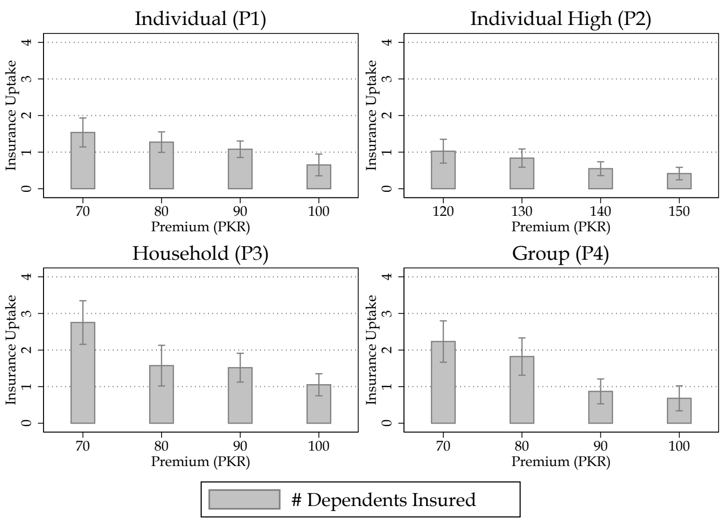


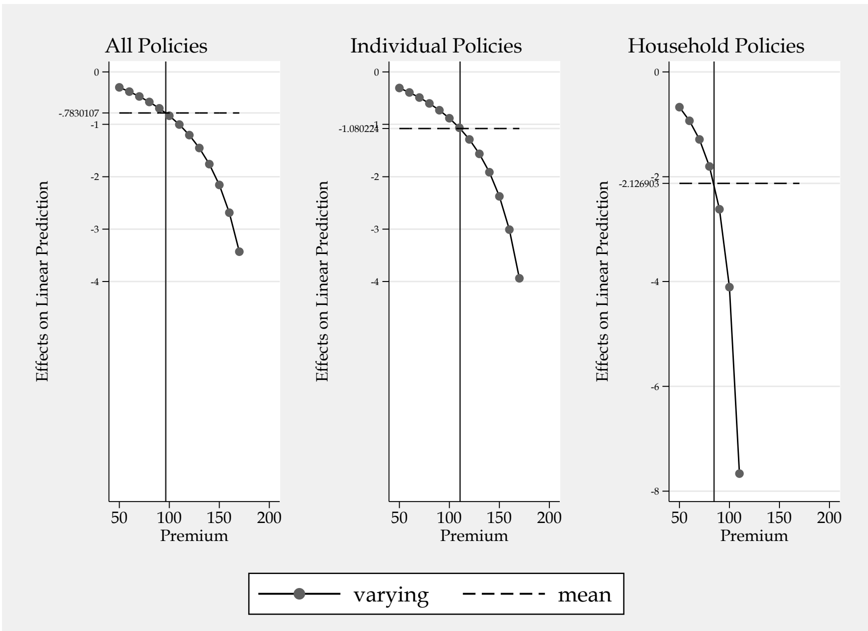
Table B.3 – Demand and Own Price Elasticity

	All	IND	HH
Premium	-0.0043***	-0.0054***	-0.0131***
	(0.0007)	(0.0008)	(0.0019)
Constant	0.9551***	1.1550***	1.6241***
	(0.0788)	(0.0900)	(0.1607)
N	1557	706	851

Note: This table provides parameter estimates from OLS regression of the dichotomous insurance indicator on the policy premium. For policies P1, P3 and P4 the coefficient estimate provides an estimate of the own price elasticity for the respective policy since the base premium is PKR100 per person. For policy P2

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

Figure B.3 – Own Price Elasticities of the Insurance Policies



This figure provides (mean) own price elasticity estimation of pooled across all policies and by eligibility. The elasticity estimates are derived as (average) partial effect estimates from OLS regression of a binary indicator of whether the household is insured on the premium price per person paid.

Table B.4 provides parameter estimates of equation 2.11 for the benchmark model that does not account for any social interaction effects (Model 1), and the model that only accounts for contextual effects. For each model, results from two different optimization algorithms used in the maximum likelihood estimation are presented. It is apparent that the results are (almost) identical for both models in terms of point estimates, precision and value of the log-likelihood function at the optimum. Moreover, as the model does not require the computation endogenously formed expectations, the gradient based methods - as expected - converge in 2 iterations.

Table B.4 – Estimation Results - Models 1 and 3

row	M1.a	M1.b	M3.a	M3.b
Discount	0.026187 ***	0.026187 ***	0.025520 ***	0.025520 ***
	(0.002551)	(0.002529)	(0.002604)	(0.002576)
Client Age	0.002057	0.002057	0.002172	0.002172
	(0.002589)	(0.002589)	(0.002648)	(0.002648)
client No Education (D)	-0.147861 **	-0.147861 **	-0.111982 **	-0.111978 **
	(0.059647)	(0.059759)	(0.062776)	(0.063125)
HH Size	-0.045407 ***	-0.045407 ***	-0.045526 ***	-0.045525 ***
	(0.016637)	(0.016919)	(0.016753)	(0.017280)
Wealth Indicator	-0.001827	-0.001827	-0.003093	-0.003092
	(0.013246)	(0.013347)	(0.014027)	(0.014197)
HH Income (Log Rs '000)	0.017875	0.017875	0.007150	0.007150
	(0.048603)	(0.051261)	(0.051658)	(0.054493)
HH Savings (Log Rs '000)	0.035382 **	0.035382 **	0.030537	0.030536
	(0.020876)	(0.021134)	(0.023207)	(0.023530)
Group Leader (D)	0.329395 ***	0.329396 ***	0.416089 ***	0.416080 ***
	(0.072917)	(0.073769)	(0.078708)	(0.080460)
Knows Insurance (D)	-0.089529	-0.089529	-0.052575	-0.052575
	(0.069703)	(0.066923)	(0.073847)	(0.070141)
Total Inpatient Cost (Log Rs '000)	0.083083	0.083083	0.073147	0.073145
	(0.079743)	(0.076619)	(0.081600)	(0.078056)
Total Outpatient Cost (Log Rs '000)	0.007216	0.007217	0.014092	0.014092
	(0.023353)	(0.024541)	(0.024299)	(0.025673)
HH Any Inpatient (D)	-0.204233	-0.204232	-0.167145	-0.167138
	(0.263742)	(0.252126)	(0.271227)	(0.257651)
HH Exp Cost Index (Log Rs '000)	0.033487	0.033490	0.110216	0.110214
	(0.176052)	(0.182172)	(0.182367)	(0.189835)
(del) Discount			0.016209 ***	0.016209 ***
			(0.005850)	(0.005866)
(del) Client Age			0.003017	0.003016
			(0.006237)	(0.006225)
(del) client No Education (D)			-0.161634	-0.161629
			(0.126960)	(0.126334)
(del) HH Size			0.010225	0.010226
			(0.039427)	(0.039628)
(del) Wealth Indicator			0.020901	0.020901
			(0.029432)	(0.029098)
(del) HH Income (Log Rs '000)			-0.030367	-0.030368
			(0.117589)	(0.116982)
(del) HH Savings (Log Rs '000)			0.023525	0.023524
			(0.042026)	(0.041537)
(del) Group Leader (D)			0.886158 ***	0.886150 ***
			(0.300274)	(0.299603)
(del) Knows Insurance (D)			-0.260976 **	-0.260970 **
			(0.140444)	(0.138398)
(del) Total Inpatient Cost (Log Rs '000)			0.392181 **	0.392181 **
			(0.202786)	(0.197423)
(del) Total Outpatient Cost (Log Rs '000)			-0.062247	-0.062246
			(0.053203)	(0.054072)
(del) HH Any Inpatient (D)			-1.183825 **	-1.183824 **
			(0.666233)	(0.643778)
(del) HH Exp Cost Index (Log Rs '000)			-0.467151	-0.467158
			(0.386308)	(0.389762)
Endogenous				
Constant	-0.320531 **	-0.320531 **	-0.567072	-0.567057
	(0.170925)	(0.175823)	(0.420666)	(0.428431)
Unobserved				
value LogLik	-991.8327	-991.8327	-974.0990	-974.0990
Share Mult. Eq.	0.0000	0.0000	0.0000	0.0000
Iterations	2	2	2	2
Stop Reason	0	0	0	0
Convergence Code	2	0	2	0
Method	BHHH	BFGS	BHHH	BFGS
Gradient	Analytical	Analytical	Analytical	Analytical
APE				

Note: This table provides parameter estimates of the iterative MLE approach. *value LogLik* is the value of the log-likelihood. *Share Mult. Eq.* gives the fraction of groups with multiple equilibria (if any).
Iterations: number of iterations until convergence. *Stop Reason* = 0: successful convergence of the iterative approach. *Convergence Code* of latest MLE iteration. *Method*: optimization approach (BHHH,BFGS).
Gradients for BHHH and BFGS approaches are provided analytically.
APE: Average partial effect of the endogenous social interaction effects calculated using equation 2.12.

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

B.3.1 Additional Results by Policy Eligibility

Table B.5 provides parameter estimates of equation 2.11 for the benchmark model that does not account for any social interaction effects (Model 1), and the model that only accounts for contextual effects separately for individual and household policies. For each model, results from two different optimization algorithms used in the maximum likelihood estimation are presented. It is apparent that the results are (almost) identical for both models in terms of point estimates, precision and value of the log-likelihood function at the optimum. Moreover, as the model does not require the computation endogenously formed expectations, the gradient based methods - as expected - converge in 2 iterations.

Table B.5 – Heterogeneity by Eligibility - Model 1

row	M1.Ind.a	M1.Ind.b	M3.Ind.a	M3.Ind.b	M1.HH.a	M1.HH.b	M3.HH.a	M3.HH.b
Discount	0.023890 ***	0.023890 ***	0.024463 ***	0.024463 ***	0.030607 ***	0.030607 ***	0.030812 ***	0.030812 ***
	(0.003856)	(0.003845)	(0.004108)	(0.004027)	(0.003556)	(0.003522)	(0.003751)	(0.003667)
Client Age	0.003452	0.003452	0.004240	0.004240	-0.000316	-0.000316	-0.001706	-0.001706
	(0.003863)	(0.003937)	(0.004098)	(0.004114)	(0.003669)	(0.003588)	(0.003763)	(0.003759)
client No Education (D)	0.103577	0.103575	0.107462	0.107462	-0.343181 ***	-0.343180 ***	-0.262278 ***	-0.262276 ***
	(0.089748)	(0.090404)	(0.097608)	(0.096116)	(0.083281)	(0.082627)	(0.089368)	(0.089171)
HH Size	0.007990	0.007990	0.020330	0.020330	-0.085730 ***	-0.085730 ***	-0.095426 ***	-0.095426 ***
	(0.024618)	(0.025181)	(0.025415)	(0.026088)	(0.023920)	(0.024652)	(0.025041)	(0.025579)
Wealth Indicator	-0.021481	-0.021482	-0.015114	-0.015113	0.015577	0.015577	0.005080	0.005083
	(0.019103)	(0.019419)	(0.020749)	(0.020685)	(0.019406)	(0.019170)	(0.021524)	(0.021141)
HH Income (Log Rs ’000)	0.075556	0.075559	0.026411	0.026409	-0.029701	-0.029701	0.021879	0.021879
	(0.064983)	(0.069016)	(0.071277)	(0.074177)	(0.077524)	(0.078980)	(0.084550)	(0.085395)
HH Savings (Log Rs ’000)	0.015329	0.015329	0.007288	0.007288	0.054566 **	0.054566 **	0.040153	0.040150
	(0.029426)	(0.029661)	(0.033457)	(0.033558)	(0.032184)	(0.031243)	(0.037695)	(0.036052)
Group Leader (D)	0.353674 ***	0.353672 ***	0.449989 ***	0.449991 ***	0.272256 ***	0.272256 ***	0.435503 ***	0.435515 ***
	(0.107391)	(0.107269)	(0.116681)	(0.119928)	(0.103241)	(0.103998)	(0.117379)	(0.117859)
Knows Insurance (D)	0.090572	0.090570	0.102888	0.102889	-0.227284 **	-0.227283 **	-0.154089	-0.154101
	(0.101525)	(0.099258)	(0.108907)	(0.106520)	(0.100236)	(0.095473)	(0.110294)	(0.102201)
Total Inpatient Cost (Log Rs ’000)	0.148585	0.148583	0.131624	0.131628	0.010283	0.010284	-0.023661	-0.023661
	(0.110099)	(0.114242)	(0.116830)	(0.122280)	(0.118329)	(0.108996)	(0.125434)	(0.113724)
Total Outpatient Cost (Log Rs ’000)	0.005659	0.005660	0.018221	0.018221	0.001063	0.001063	0.019244	0.019244
	(0.034885)	(0.036611)	(0.037626)	(0.038673)	(0.033515)	(0.034638)	(0.035358)	(0.037253)
HH Any Inpatient (D)	-0.207525	-0.207519	-0.125634	-0.125653	-0.122501	-0.122504	-0.000659	-0.000659
	(0.368674)	(0.384426)	(0.391931)	(0.413010)	(0.385768)	(0.350830)	(0.409663)	(0.370310)
HH Exp Cost Index (Log Rs ’000)	-0.113995	-0.113991	0.068851	0.068857	0.019651	0.019653	-0.035510	-0.035511
	(0.239360)	(0.238305)	(0.243835)	(0.251305)	(0.318700)	(0.331538)	(0.344926)	(0.345240)
(del) Discount			0.021367 **	0.021367 **			0.017200 **	0.017201 **
			(0.009421)	(0.009649)			(0.008201)	(0.008097)
(del) Client Age			-0.014853	-0.014853			0.010250	0.010251
			(0.010174)	(0.009861)			(0.008824)	(0.009076)
(del) client No Education (D)			0.258893	0.258899			-0.280200	-0.280210
			(0.217378)	(0.214385)			(0.177455)	(0.177230)
(del) HH Size			-0.007142	-0.007148			0.080892	0.080890
			(0.062325)	(0.064921)			(0.059847)	(0.058762)
(del) Wealth Indicator			-0.006003	-0.006001			0.012828	0.012826
			(0.048192)	(0.048078)			(0.042795)	(0.041312)
(del) HH Income (Log Rs ’000)			0.151689	0.151684			-0.117052	-0.117056
			(0.157114)	(0.158290)			(0.206375)	(0.196972)
(del) HH Savings (Log Rs ’000)			-0.091625	-0.091624			0.062651	0.062650
			(0.065490)	(0.063655)			(0.063057)	(0.062098)
(del) Group Leader (D)			0.942475 **	0.942462 **			1.320558 ***	1.320575 ***
			(0.452524)	(0.453759)			(0.423805)	(0.442477)
(del) Knows Insurance (D)			0.160176	0.160170			-0.393325 **	-0.393338 **
			(0.214896)	(0.215864)			(0.211885)	(0.204621)
(del) Total Inpatient Cost (Log Rs ’000)			-0.103446	-0.103428			0.477583	0.477554
			(0.300938)	(0.304497)			(0.328903)	(0.314424)
(del) Total Outpatient Cost (Log Rs ’000)			0.007340	0.007338			-0.123425	-0.123434
			(0.079926)	(0.085106)			(0.080674)	(0.079292)
(del) HH Any Inpatient (D)			1.754527	1.754470			-2.165561 **	-2.165467 **
			(1.134353)	(1.111124)			(1.050096)	(0.981964)
(del) HH Exp Cost Index (Log Rs ’000)			-2.181207 ***	-2.181216 ***			2.034430 **	2.034595 **
			(0.573064)	(0.574972)			(0.805009)	(0.795633)
Endogenous								
Constant	-0.769866 ***	-0.769872 ***	-0.682518	-0.682463	0.100761	0.100760	-1.042307	-1.042363
	(0.241730)	(0.253647)	(0.625728)	(0.658175)	(0.255666)	(0.256443)	(0.675437)	(0.660516)
Unobserved								
value LogLik	-450.9305	-450.9305	-430.3994	-430.3994	-519.7075	-519.7075	-496.0593	-496.0593
Share Mult. Eq.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Iterations	2	2	2	2	2	2	2	2
Stop Reason	0	0	0	0	0	0	0	0
Convergence Code	2	0	2	0	2	0	2	0
Method	BHHH	BFGS	BHHH	BFGS	BHHH	BFGS	BHHH	BFGS
Gradient	Analytical	Analytical	Analytical	Analytical	Analytical	Analytical	Analytical	Analytical
APE								

This table provides parameter estimates of the iterative MLE approach. *value LogLik* is the value of the log-likelihood. *Share Mult. Eq.* gives the fraction of groups with multiple equilibria (if any).
Iterations: number of iterations until convergence. *Stop Reason* = 0: successful convergence of the iterative approach.
Convergence Code of latest MLE iteration. *Method*: optimization approach (BHHH,BFGS).
Gradients for BHHH and BFGS approaches are provided analytically.
APE: Average partial effect of the endogenous social interaction effects calculated using equation 2.12.

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

Appendix C

Appendix to Chapter 3

C.1 Supplementary Tables and Figures

Table C.1 shows the fractions of individuals and households who bought insurance under the different insurance policies and different discount levels (D0: no discount, D10: discount of 10 PKR, D20: discount of 20 PKR and D30: discount of 30 PKR). Table C.2 analyzes trends and non-linearity in insurance demand.

Table C.1 – Insurance Uptake and Enforcement of Eligibility

	Individual (P1)		Household (P3)		Group (P4)	
	Dependents	HH	Dependents	HH	Dependents	HH
D0	0.166	0.410	0.182	0.258	0.167	0.265
	(0.025)	(0.048)	(0.031)	(0.040)	(0.034)	(0.043)
D10	0.303	0.651	0.420	0.472	0.269	0.332
	(0.026)	(0.037)	(0.042)	(0.040)	(0.039)	(0.041)
D20	0.341	0.740	0.484	0.510	0.427	0.477
	(0.026)	(0.032)	(0.053)	(0.048)	(0.046)	(0.044)
D30	0.385	0.776	0.708	0.739	0.656	0.683
	(0.033)	(0.031)	(0.048)	(0.040)	(0.055)	(0.050)
N	2981	856	2937	830	3156	877

Notes: Standard errors in parentheses are clustered at the level of the village.

Table C.4 shows the result of regressing the expected costs index on individual insurance uptake under the different insurance policies. The first specification implements a simple positive correlation test. It reveals that the difference between insured and non-insured individuals is substantially larger in the individual (P1) than in the household (P3) and group (P4) insurance schemes. Specification (2) tests whether the positive correlation can be explained by selection based on non-health factors. The idea is that the purchase decision might be influenced by non-health factors which also correlate with health risk, thus creating a positive correlation without the intention of adverse selection. Controlling for such confounding factors would therefore lead to a change in the esti-

Table C.2 – Insurance Uptake and Demand Elasticities

	P1	P1	P3	P3	P4	P4
Premium	-0.0066***	0.0320*	-0.0164***	-0.0110	-0.0164***	-0.0701**
	(0.0013)	(0.0173)	(0.0017)	(0.0337)	(0.0020)	(0.0276)
Premium^2		-0.0002**		-0.0000		0.0003**
		(0.0001)		(0.0002)		(0.0002)
Constant	0.8636***	-0.7413	1.8408***	1.6162	1.7726***	4.0090***
	(0.1133)	(0.7422)	(0.1613)	(1.4046)	(0.1825)	(1.1887)
N	2981	2981	2937	2937	3156	3156

Notes: Results are from OLS regression. Standard errors in parentheses are clustered at the level of the village.

mated coefficient compared to the first specification. The results from specification (2) show that some of the differences between insured and non-insured individuals can indeed be explained by non-health factors. Nonetheless, most of the correlation remains in policy P1, for which the coefficient is still highly significant. As a next step, we control for characteristics that are relatively easy to observe and verify. The idea of this exercise is to test whether an insurance company could in principle separate risk types when using information that is available and reliable in a low-income setting under realistic conditions. Specification (3) controls for such (mainly demographic) variables. Similar to the specification before, the coefficient remains positive and significant for the individual level policy P1, suggesting that classifying individuals based on observable baseline characteristics might not solve the adverse selection problem. For illustrative purposes, specification (4) uses all control variables – essentially the ones used to create the index. The correlation disappears as to be expected.

Figure C.1 shows the distribution of costs across demand levels amongst the non-insured. For the individual policy, there appears to be a downward shift in the cost distribution when the share of insured becomes larger. Marginal individuals switching the insurance status in response to a change in price hence seem to be high risk relative to the non-insured but low risk relative to the insured. This is fully in line with the economic theory on adverse selection discussed in Section 3.2. In contrast, such a pattern for non-insured is not observed under household (P3) and group (P4) policies.

Table C.3 – Insurance Demand: Individual vs. Household Policies

	Household Level Uptake			Individual Level Uptake		
	Individual (P1)	Household (P3)	Group (P3)	Individual (P1)	Household (P3)	Group (P3)
Household Level						
Discount	0.011***	0.015***	0.015***	0.007***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
HH size	0.003	-0.048***	-0.055***	-0.055***	-0.034***	-0.038***
	(0.011)	(0.010)	(0.009)	(0.006)	(0.010)	(0.008)
Income (in 1000 PKR)	-0.000	-0.000	0.001	0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Saving (in 1000 PKR)	0.000	0.000	0.000	-0.000*	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Index	-0.005	0.018*	0.003	0.004	0.014	0.003
	(0.008)	(0.009)	(0.008)	(0.005)	(0.010)	(0.008)
Head Female	0.012	-0.133***	-0.098	-0.020	-0.123**	-0.096*
	(0.042)	(0.047)	(0.060)	(0.033)	(0.049)	(0.055)
No Education	-0.060	-0.047	-0.061	-0.043*	0.004	-0.049
	(0.051)	(0.044)	(0.043)	(0.024)	(0.034)	(0.033)
High Education	-0.042	-0.095*	-0.029	-0.052*	-0.022	0.004
	(0.050)	(0.052)	(0.057)	(0.029)	(0.028)	(0.039)
Any Inpatient	0.085*	-0.022	-0.093*	-0.012	-0.042	-0.082
	(0.045)	(0.054)	(0.051)	(0.030)	(0.058)	(0.054)
Dependent Level						
Female				-0.109***	-0.025	-0.004
				(0.019)	(0.017)	(0.018)
Age (0-4)				0.125***	0.071	0.084
				(0.036)	(0.049)	(0.052)
Age (5-9)				0.067*	0.049	0.056
				(0.038)	(0.045)	(0.045)
Age (10-14)				0.057	-0.006	0.070
				(0.036)	(0.040)	(0.043)
Age (15-19)				0.061**	-0.005	-0.003
				(0.030)	(0.033)	(0.031)
Age (20-29)						
Age (30-49)				0.038	-0.045	0.037
				(0.042)	(0.047)	(0.039)
Age (50-59)				0.061	0.115*	0.100*
				(0.070)	(0.068)	(0.054)
Age (60-69)				0.044	-0.019	0.066
				(0.057)	(0.060)	(0.064)
Age (70+)				0.112	0.035	0.168*
				(0.082)	(0.074)	(0.092)
Low Health				0.183**	0.009	0.013
				(0.083)	(0.099)	(0.089)
Medium Health				0.084**	-0.003	-0.006
				(0.040)	(0.038)	(0.043)
Inpatient Treatment				0.153***	-0.038	-0.078
				(0.056)	(0.090)	(0.052)
Outpatient Treatment				0.066**	0.051	0.003
				(0.032)	(0.034)	(0.034)
First Son				0.058**	0.017	0.015
				(0.027)	(0.020)	(0.020)
First Daughter				0.027	-0.023	0.034
				(0.029)	(0.021)	(0.023)
Working				-0.066**	-0.029	0.002
				(0.032)	(0.028)	(0.027)
Constant	0.473***	0.530***	0.476***	0.421***	0.404***	0.313***
	(0.058)	(0.060)	(0.062)	(0.050)	(0.070)	(0.072)
N	856	830	877	2981	2937	3156
R^2	0.07	0.17	0.16	0.13	0.19	0.19

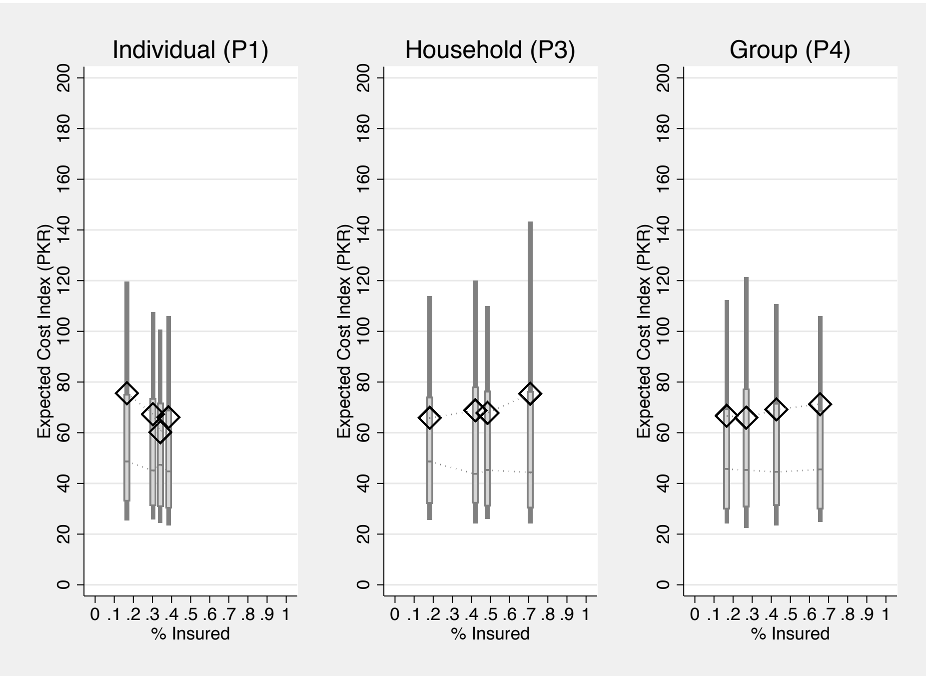
Notes: Point estimates result from OLS regression with standard errors clustered at the village level.

Table C.4 – Correlation between Insurance Demand and Expected Costs Index

	(1)	(2)	(3)	(4)
Controls	none	non-health covariates^	observable by insurer∼	all
P1 (N=2981)	29.927***	19.841***	19.431***	2.318
	(6.722)	(5.582)	(5.782)	(3.121)
P3 (N=2937)	9.307**	0.291	1.057	-0.323
	(3.854)	(3.102)	(3.181)	(1.470)
P4 (N=3156)	7.264	-2.805	-3.197	0.107
	(4.793)	(3.364)	(3.347)	(1.624)

Notes: Result from OLS regression of the expected costs index on individual insurance uptake with standard errors clustered at the village level. Covariates are: HH size, client gender, client education level dummy, age category dummies, HH income, HH savings, HH asset index, individual work status, individual health status, inpatient and outpatient treatment experience and related costs.
^ All variables except: individual health status, inpatient and outpatient treatment experience and related costs.
∼ HH size, client gender, client education level dummy, age category dummies.

Figure C.1 – Change in Risk Distribution across Discounts, Non-Insured



Notes: This figure illustrates shifts in the expected cost distribution by discount level and policy regime. The box depicts the interquartile range (IQR). The middle line indicates the median. The upper (lower) adjacent line depicts the 90% (10%) quantile, respectively. The diamond indicates the mean.

Table C.5(a) shows the result of testing for a trend in the mean cost index of insured individuals by policy. Findings lack precision, in particular when there are fewer observations in the insurance pool, but the downward slope of the average cost curve tends to be stronger in the individual policy (P1) than in the household and group policies (P3, P4). Table C.5(b) tests the relationship between the cost index and the share insured for the noninsured. The estimated slope is negative for individual policies (significant for P1), which is in line with adverse selection theory, and insignificantly positive for household and group policies (P3, P4).

Table C.5 – Trend in Expected Costs
(a) Insured

	P1	P3	P4
Uptake (%)	–186.817*	–47.110***	–20.854
	(100.028)	(16.653)	(13.326)
Constant	158.372***	102.984***	84.670***
	(34.875)	(10.534)	(7.376)
N	922	1350	1211

(b) Non-Insured

	P1	P3	P4
Uptake (%)	–56.068	15.623	10.941
	(34.851)	(13.745)	(17.763)
Constant	84.027***	62.314***	64.043***
	(10.762)	(5.567)	(5.761)
N	2059	1587	1945

Notes: Point estimates result from OLS regression of expected cost index on average demand for relevant policy at respective discount, standard errors clustered at the village level.

Table C.6 – Slope of the Demand Curve, restricted

	Individual (P1)	Household (P3)	Household (P4)
Premium	–0.008***	–0.016***	–0.016***
	(0.000)	(0.002)	(0.002)
Constant	1.000	1.841***	1.773***
	(.)	(0.161)	(0.182)
N	2981	2937	3156

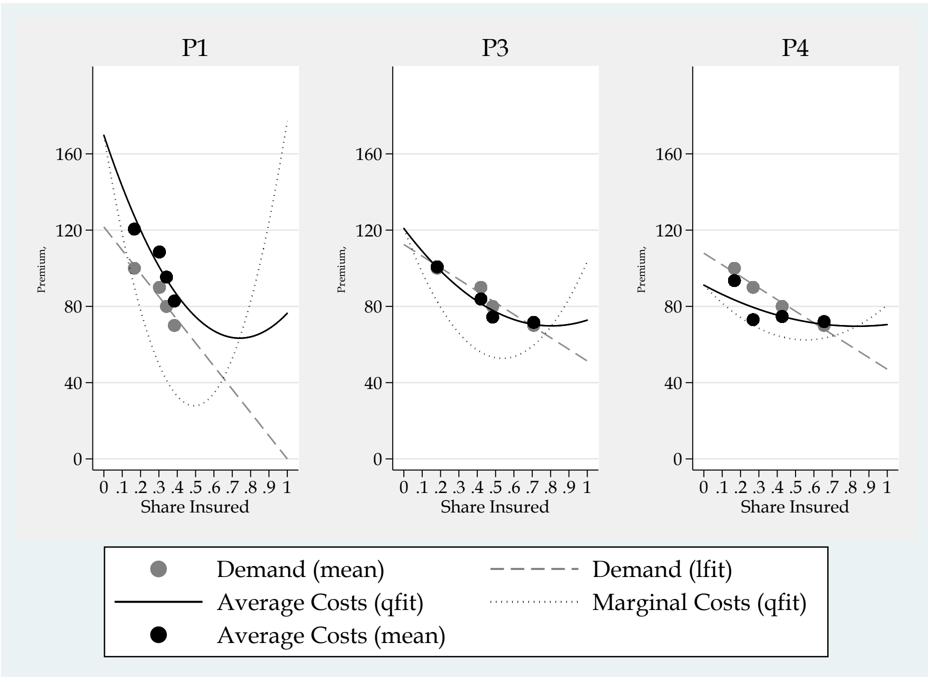
Notes: The slope of the demand curve is estimated from a linear regression of an individual take-up indicator on the premium, and a restriction of a constant larger or equal than 1 is imposed. Standard errors are not reported if the restriction is binding (only the case for P1). Standard errors are clustered at the village level.

Table C.7 – Slope of the Average Cost Curve, restricted

	Individual (P1)	Household (P3)	Household (P4)
Demand	−32.146***	−14.841**	−9.617
	(9.924)	(7.088)	(6.955)
Constant	108.560***	87.621***	80.081***
	(9.924)	(7.088)	(6.955)
N	922	1350	1211

Notes: The slope of the average cost curve is estimated from a linear regression of the individual level expected cost index on average take-up at the corresponding premium level. The estimation is restricted to pass through the average cost index for the respective policy at a demand level of 1. Standard errors are clustered at the village level.

Figure C.2 – Market Equilibrium and Efficient Allocation (Quadratic Cost Curve), by policy



Notes: The figure plots the demand, average and marginal cost curves for the respective policies. Average demand for the corresponding premium is given by the dots in light gray. The slope of the demand curve is estimated from a linear regression of an individual take-up indicator on the premium for which a restriction of a constant larger or equal to 1 is imposed. Average costs of the insured for the corresponding demand are given by the dots in black. The slope of the average cost curve is estimated from a quadratic regression of the individual level expected cost index on average take-up at the corresponding premium level. The estimation is restricted to pass through the average cost index for the respective policy at a demand level of 1.

C.2 Randomization Procedure

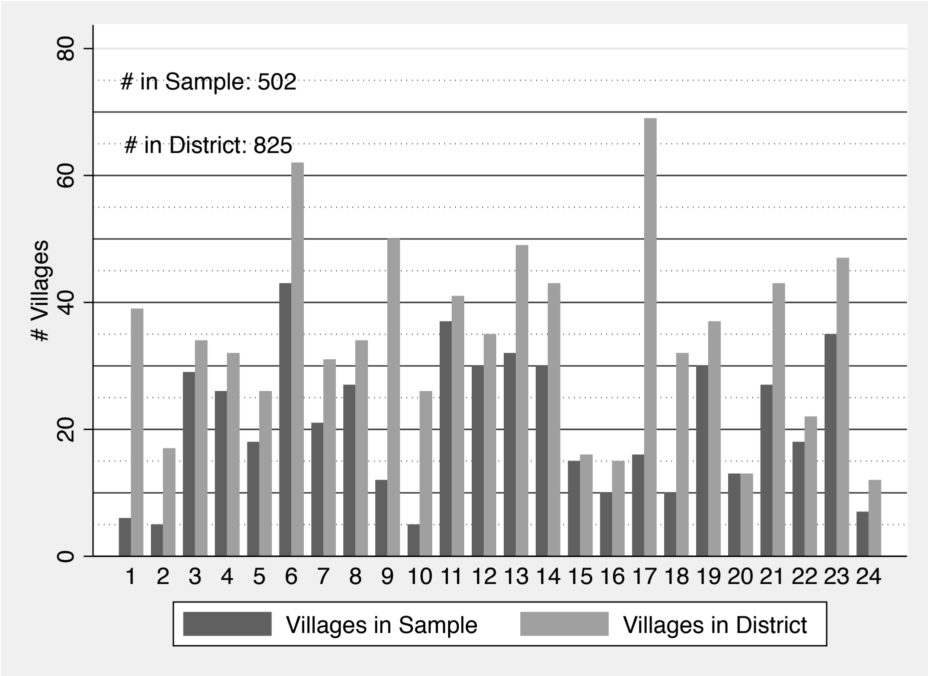
Sampling from incoming credit applications implies that we do not know the set of villages with incoming credit applications ex-ante. Instead, we start with a census of all villages in which our implementation partner operates. To achieve a balanced treatment allocation we employ a permuted block randomization procedure for dynamic treatment assignment. This procedure is used frequently in medical studies facing similar problems of patients stochastically entering the trial (McEntegart, 2003). In addition, we stratify the treatment assignment across a set of ex-ante village characteristics to improve balance between treatments along a set of important characteristics.

Specifically, we condition the randomization on the rural/urban status (4 categories), the historical origin of the village (2 categories) as well as the distance to the next hospital under NRSP's panel (3 categories). This leaves us with a categorization of villages into 24 strata. The treatment assignment proceeds as follows: In a first step, we generate a set of randomly permuted blocks of the six main treatment indicators for each of the 24 strata. In a second step, we produce a unique order in which the villages have entered the experiment. For this purpose, we rely on the timing of loan applications entered in the management information system (MIS). Using the list from step two, we create strata specific lists of villages that are ordered according to the date and time they entered the MIS. In a final step, each village on this strata-specific list is matched with the corresponding treatment from the strata-specific permuted block of treatments.

This procedure guarantees a balanced distribution of treatments in each cluster, in particular when there are sufficient villages per strata entering the experiment to cover full blocks. The reason is that within a full block, there is one village assigned to each treatment and no imbalance can occur. Hence, the more full blocks are covered, the fewer imbalances can remain. Figure C.3 shows the total number of villages in the district where the RCT takes place by strata as well as the number of villages finally entering the experiment. In only three out of 24 strata there are less than six villages to create at least one full block.

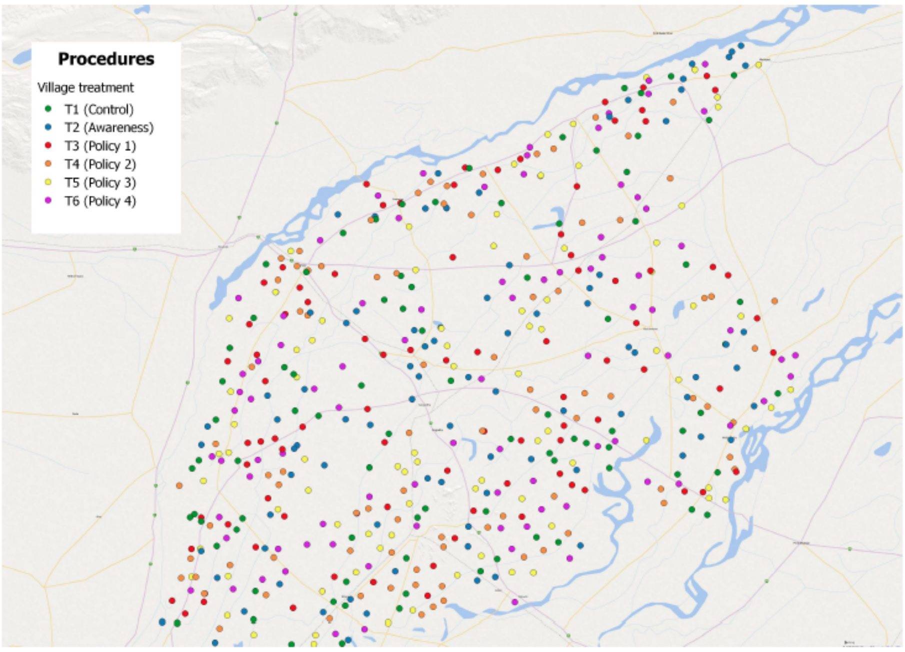
Figure C.4 also shows the geographical distribution of treatments. The different treatment arms appear to be well balanced across the whole district suggesting that the randomization procedure worked as expected.

Figure C.3 – Distribution of Clusters across Strata



Notes: The figures illustrates the distribution of treatment clusters across strata. The 24 strata are generated from ex-ante village level information on location (distance to closest panel hospital, 3 categories), historical origin (chak vs. no chak, 2 categories) and rural/urban status (percentage of agricultural loans, 4 categories).

Figure C.4 – Treatment Allocation in Sargodha District



Notes: The figure illustrates the distribution of treatments across Sargodha district. The dots capture the center of the respective village. The legend gives the corresponding treatment. The average minimum distance between the villages is about 4 km and the average distance about 50 km.

C.3 Balancing Tests

In the following we present balancing tests that assess whether our randomization indeed results in a similar distribution of covariates across treatment arms. The balancing tables have the following structure: The first column shows the overall means (standard deviations are in brackets). Subsequent columns provide means and standard deviations for each treatment arm separately. The final column contains the p-value from a joint test for model significance from the following estimation equation:

$$X_{iv} = \alpha + \beta_2 I_{\{T_{iv}=P2\}} + \beta_3 I_{\{T_{iv}=P3\}} + \beta_4 I_{\{T_{iv}=P4\}} + d_s S_v + \varepsilon_{iv}, \qquad \text{(C1)}$$

where X_{iv} is the respective covariate, $I_{\{T_{iv}=Pk\}}$, k=2,3,4 are indicators for the respective treatments P2, P3 and P4 (P1 is the omitted category) and S_v with $v \in \{1, ..., 24\}$ represents strata dummies.[1] The error term ε_{iv} is clustered at the village level. The test for joint significance of β_2, β_3 and β_4 , is thus equivalent to a test for equal means in the treatment arms P1 to P4.

Table C.8 (a) provides summary statistics and balance tests for sociodemographic, economic and health indicators on the household and individual level from the baseline survey. Comparing the means of sociodemographic indicators across treatment groups (first panel), we observe no significant differences. This is confirmed by the relatively high p-values of the joint test for model significance. Also the economic indicators (second panel), household level health indicators (third panel) and individual level health indicators (fourth panel) show no statistically significant differences across treatment groups. Table C.8(b) provides summary statistics and balance tests for the bi-monthly phone survey data. Overall consent to the phone survey is above 90% and balanced across the different treatments.[2] About 2% of dependents report an inpatient event, leading to 15% of households having some dependent admitted. These numbers are similar to the health seeking behavior at baseline. Again, all variables appear to be balanced across treatment arms. Balancing also holds when including the two control groups of villages where no additional insurance was available in the comparison.

In a next step, we provide evidence for a balanced distribution of discount vouchers. Random assignment through household level lotteries with replacement implies an expected uniform probability distribution of discounts. Table C.9 illustrates the frequencies of the four discount levels across insurance policy as well as overall. In addition, we test the null-hypothesis of the expected uniform distribution by Pearson's Chi-square test, the p-value of which is reported in the second to last row. Overall, our test does not reject the null hypothesis of a uniform distribution, even though the share of zero discounts is lower than 25%. This holds true also for policy P1 for which we observe a stronger deviation from the expected uniform distribution.

[1] Note that strata fixed effects are included only in the balance tests for the main treatments P1 to P4. Discounts are randomized on the level of the household and thus not stratified. [2] We conduct a separate attrition analysis, but do not find any systematic differences in drop-out across the treatments.

Table C.8 – Balance Tests across Insurance Policy Treatments

(a)Baseline Survey

	Overall	P1	P2	P3	P4	P-val
Socio-Demographics - HH						
HH Size (Survey)	5.99	5.95	5.95	6.03	6.03	0.57
	(2.117)	(2.093)	(2.072)	(2.054)	(2.237)	
HH Size (Matched)	5.37	5.26	5.43	5.37	5.42	0.37
	(1.912)	(1.872)	(1.956)	(1.822)	(1.986)	
Dependents (Matched)	3.59	3.48	3.62	3.59	3.65	0.44
	(1.869)	(1.834)	(1.876)	(1.791)	(1.961)	
Age of Client	38.62	38.85	38.57	38.24	38.82	0.69
	(10.887)	(10.918)	(10.934)	(10.741)	(10.955)	
Client Female (D)	0.53	0.57	0.51	0.50	0.54	0.33
	(0.499)	(0.495)	(0.500)	(0.500)	(0.499)	
Client No Education (D)	0.55	0.56	0.52	0.55	0.56	0.37
	(0.498)	(0.496)	(0.500)	(0.498)	(0.497)	
Economic - HH						
Income (month)	22691.3	21634.4	24515.1	22627.0	21953.0	0.28
	(24695)	(20018)	(34658)	(20225)	(20379)	
Asset Index	0.06	0.06	0.20	0.07	-0.09	0.37
	(2.422)	(2.433)	(2.539)	(2.319)	(2.387)	
Savings	12085.1	13548.5	13092.2	10147.2	11606.5	0.64
	(67986)	(71670)	(85948)	(31357)	(70158)	
Credit	30438.7	27602.8	33056.8	30112.4	30803.1	0.35
	(71910)	(54074)	(79531)	(78197)	(72204)	
Health & Insurance - HH						
Any Inpatient (D)	0.12	0.11	0.13	0.12	0.12	0.51
	(0.327)	(0.316)	(0.338)	(0.325)	(0.328)	
Knows Health Insurance (D)	0.18	0.20	0.19	0.18	0.16	0.62
	(0.385)	(0.397)	(0.390)	(0.383)	(0.369)	
Health - Dependents						
Health Step (1-5)	4.76	4.75	4.76	4.75	4.77	0.97
	(0.631)	(0.631)	(0.644)	(0.648)	(0.602)	
Outpatient Experience (D)	0.14	0.14	0.15	0.15	0.14	0.96
	(0.351)	(0.349)	(0.355)	(0.353)	(0.346)	
Inpatient Experience (D)	0.02	0.02	0.02	0.01	0.02	0.60
	(0.126)	(0.124)	(0.135)	(0.121)	(0.124)	
Outpatient Cost	609.99	302.63	706.62	491.23	895.49	0.00
	(7920.4)	(2198.5)	(9268.9)	(5763.7)	(10873.5)	
Inpatient Cost	506.36	404.38	747.68	429.66	434.93	0.39
	(7520.9)	(5261.3)	(11433.7)	(6260.5)	(5164.3)	
N (Dependents)	15361	3560	3920	3796	4085	
N (HHs)	4283	1022	1083	1058	1120	

(Continued on next page)

(Table C.8, continued)

(b)Phone Survey

	Overall	P1	P2	P3	P4	P-val
Consent	0.93	0.92	0.93	0.93	0.93	0.82
	(0.259)	(0.269)	(0.254)	(0.261)	(0.253)	
Health - HH						
Any Inpatient (D)	0.14	0.15	0.13	0.15	0.15	0.46
	(0.351)	(0.353)	(0.334)	(0.360)	(0.355)	
Any Outpatient (D)	0.65	0.66	0.66	0.64	0.65	0.85
	(0.476)	(0.475)	(0.473)	(0.480)	(0.478)	
Health - Dependents						
Inpatient Experience (D)	0.02	0.02	0.01	0.01	0.02	0.96
	(0.124)	(0.130)	(0.121)	(0.120)	(0.124)	
Outpatient Experience (D)	0.14	0.14	0.14	0.14	0.14	0.88
	(0.348)	(0.348)	(0.349)	(0.350)	(0.344)	
Inpatient Cost	371.59	438.46	452.54	371.85	237.36	0.12
	(5537.914)	(5116.372)	(8022.091)	(4937.016)	(2872.399)	
Outpatient Cost	702.79	569.42	769.31	638.28	812.38	0.07
	(5415.117)	(3154.431)	(5475.952)	(5350.682)	(6772.168)	
N (Dependents)	14246	3275	3641	3496	3834	
N (HHs)	2256	504	583	600	569	

Notes: The table provides means and standard deviations (in parentheses) of the respective variables. Column 1 provides overall measures, while other columns indicate the respective policy. The last column contains the p-value from a joint test for model significance of equation (C1). Standard errors are clustered at the village level. Binary variables are indicated with (D).

Table C.9 – Balance Check: Discount Allocation

	P1	P2	P3	P4	Overall
0	0.19	0.23	0.22	0.22	0.22
10	0.27	0.27	0.26	0.28	0.27
20	0.27	0.28	0.25	0.27	0.27
30	0.27	0.23	0.27	0.23	0.25
Pearson Chi2 P	0.2268	0.4632	0.5998	0.2290	0.2144
HHs	856	870	830	876	3432

Notes: Relative frequencies of discounts given the respective policy. Pearson Chi2 p provides the p-value from a chi-square test with H0 of a uniform distribution. The difference in number of observations to the main balance checks is explained by the fact that only households attending the community meeting received a discount.

To investigate potential systematic imbalances, we provide additional tests in Table C.10. The idea is to investigate whether specific household characteristics, potentially related to health indicators and thus insurance demand, cause a jump in the probability of receiving a specific discount voucher. We replace the main treatment indicators in equation (C1) with discount level indicators, where the zero discount group serves as the reference group. We test for discontinuous jumps in the probability of receiving a specific discount by conducting a joint test for model significance. The corresponding p-value is provided in the final column. We observe that there is no statistically significant difference across discount levels for any of the health indicators. Similarly, there are no systematic differences in economic indicators. In terms of sociodemographic variables, it seems that there are statistically significant differences in the age and sex composition across discount levels. A clear, systematic pattern such as older individuals or females receiving higher discounts, however, is not visible. For this reason, we are confident that the randomization of discounts through household lotteries in the field is not subject to systematic imbalances.

Table C.10 – Balance Checks (Discounts)

	Overall	D=0	D=10	D=20	D=30	P-val
Socio-Demographics						
HH Size	5.99	5.98	5.96	6.01	6.01	0.94
	(2.103)	(2.028)	(2.048)	(2.238)	(2.080)	
Age of Client	38.72	38.33	39.52	39.02	37.86	0.01
	(10.959)	(10.916)	(11.215)	(11.186)	(10.397)	
Client Female (D)	0.53	0.50	0.52	0.57	0.54	0.03
	(0.499)	(0.500)	(0.500)	(0.496)	(0.499)	
Client No Education	0.54	0.53	0.55	0.57	0.52	0.16
	(0.498)	(0.499)	(0.498)	(0.495)	(0.500)	
Economic						
Avg. Inc. (month)	22727.4	22963.6	21588.0	24125.4	22264.7	0.12
	(25553)	(30840)	(16445)	(28186)	(25640)	
Land (acres)	1.41	1.29	1.48	1.42	1.45	0.66
	(3.264)	(2.921)	(3.288)	(3.123)	(3.649)	
Savings	12343.9	9757.7	14193.1	12840.7	12043.2	0.40
	(73131)	(33068)	(85167)	(90299)	(62996)	
Credit	30861.7	30574.9	32890.4	30272.8	29535.9	0.72
	(70148)	(80249)	(65293)	(73655)	(61565)	
Health & Insurance (HH)						
Any Inpatient (D)	0.12	0.13	0.13	0.11	0.12	0.55
	(0.327)	(0.338)	(0.335)	(0.314)	(0.325)	
Total Inpatient Cost	4379.7	4895.1	4972.6	3658.7	4060.6	0.55
	(22282)	(24975)	(26317)	(19502)	(17260)	
Knows Health Ins. (D)	0.18	0.18	0.21	0.17	0.16	0.07
	(0.386)	(0.382)	(0.408)	(0.379)	(0.371)	
N (Dependents)	12283	2643	3283	3236	3121	
N (HHs)	3432	739	927	913	853	

Notes: The table provides means and standard deviations (in parentheses) of the respective variables. Column 1 provides overall measures, while other columns indicate the respective policy. The last column contains the p-value from a joint test for model significance of equation (C1). Standard errors are clustered at the village level. Binary variables are indicated with (D).

Table C.11 provides analogous balance tests for the group meeting attendance. We observe that there are no statistically significant differences in observables between meeting attendants and non-attendants. The observed similarity supports external validity of our results for the population of credit clients in Sargodha district.

Table C.11 – Balance Checks (Meeting Attendance)

	Overall	Not Attending	Attending	P-val
Health-Dependent				
Expected Reimbursement Cost (PKR)^	82.73	82.59	82.77	0.95
	(134.352)	(138.970)	(133.176)	
Subjective Health Status (1-5)	4.76	4.77	4.76	0.41
	(0.631)	(0.625)	(0.633)	
Oupatient Treatment (D)	0.14	0.14	0.14	0.69
	(0.351)	(0.348)	(0.351)	
Inpatient Treatment (D)	0.02	0.02	0.02	0.88
	(0.126)	(0.125)	(0.127)	
Outpatient Cost (PKR)	610.0	417.1	658.3	0.06
	(7920)	(5190)	(8467)	
Inpatient Cost (PKR)	506.4	525.3	501.6	0.85
	(7521)	(6632)	(7728)	
Socio-Demographics - HH				
HH Size (Survey)	5.99	5.99	5.99	0.97
	(2.117)	(2.170)	(2.104)	
Age of Client	38.62	38.23	38.72	0.23
	(10.887)	(10.596)	(10.958)	
Client Female (D)	0.53	0.52	0.53	0.74
	(0.499)	(0.500)	(0.499)	
Client No Education (D)	0.55	0.56	0.54	0.34
	(0.498)	(0.497)	(0.498)	
Economic - HH				
Avg. Monthly Earning (PKR)	22691.3	22560.7	22723.7	0.86
	(24695)	(20900)	(25550)	
Asset Index	0.06	-0.05	0.09	0.13
	(2.422)	(2.419)	(2.423)	
Savings (PKR)	12085.1	11054.3	12340.3	0.48
	(67986)	(41200)	(73121)	
Total Credit	30438.7	28731.2	30861.5	0.41
	(71910)	(78684)	(70138)	
Health & Insurance - HH				
Any Inpatient (D)	0.12	0.12	0.12	0.87
	(0.327)	(0.325)	(0.327)	
Inpatient Cost (HH)	4445.9	4718.2	4378.5	0.76
	(24475)	(31854)	(22279)	
Knows Insurance (D)	0.18	0.18	0.18	0.73
	(0.385)	(0.381)	(0.386)	
N (Dependents)	15361	3078	12283	
N (HHs)	4283	850	3433	

Notes: The table provides means and standard deviations (in parentheses) of the respective variables. Column 1 provides overall measures, while other columns indicate the attendance of the respective household in the group meeting. The last column contains the p-value from a joint test for model significance similar to equation (C1), excluding strata fixed effects. Standard errors are clustered at the village level. Binary variables are indicated with (D). Monetary variables are in Pakistani Rupees (PKR).

^ In line with the other balancing tables, we include all treatment arms in the test – including the individual high insurance (P2), which features higher expected costs. The mean of the costs index is therefore somewhat higher than in the standard coverage treatments only (P1, P3, P4).

C.4 Construction of the Health Risk Index

The insurer's average cost curve constitutes the central element for testing adverse selection in this study. A straightforward estimate of the average cost curve would aggregate the insurer's reimbursed claims for a given insurance product and price level.[3] Since hospitalization is a rare event, we are – despite the relatively large sample size – not able to estimate the average cost curve based on these reimbursed claims directly. Instead, we use detailed baseline health and demographic information (X_{i0}) to predict the insurance provider's reimbursement costs for each individual i (C_{i1}). Time is indicated with 0 at baseline and with 1 at the end of the insurance period. We are interested in obtaining a good estimate of the conditional expectation of the provider's reimbursement cost at the end of the insurance period, i.e. $\hat{E}[C_{i1}|X_{i0}]$.

Again, a direct approach would employ observed reimbursement cost to estimate their relation to baseline characteristics. However, claims are too rare in our data to obtain a good estimate (only 39 claim cases are reported). Part of this is because claims can only be made by insured individuals, which excludes the non-insured part of our sample from such an analysis. Furthermore, not all hospitalization cases lead to a claim.[4] We therefore make use of detailed information on inpatient health events and costs incurred, gathered in our bi-monthly phone survey during the one year product cycle. Hospitalization events in the phone survey are reported for 334 of the 21,470 dependents in the phone survey sample. Based on the aggregated inpatient expenditures during the insurance period, we calculate the maximum amount for each individual that could potentially be reimbursed under the insurance policy ($\bar{C}_{i1}$). Subsequently, $\hat{E}[\bar{C}_{i1}|X_{i0}]$ can be predicted using an adequate regression. We furthermore account for the fact that not all of these costs are claimed by adjusting the final expected cost index (ECI_{i1}) as follows:

$$ECI_{i1} = \hat{E}[\bar{C}_{i1}|X_{i0}] \times \frac{\sum_P \sum_{i \in Insured} C_{iP1}}{\sum_P \sum_{i \in Insured} \hat{E}[\bar{C}_{i1}|X_{i0}]} \qquad \text{(D1)}$$

This means the prediction is made based on all potentially claimable costs, which maximizes statistical power. At the same time, the index is scaled by the ratio between actual claim amounts relative to the maximal claimable amount according to the policy (PKR 15,000 for P1, P3, and P4).

We estimate $\hat{E}[\bar{C}_{i1}|X_{i0}]$ using a Tobit model, controlling for a broad range of baseline household and individual level characteristics.[5] The household level variables account for the economic

[3] As described in section 3.3.2 of the main text, there are four different insurance products and four different price levels.

[4] To gain insights into this phenomenon we conducted in-depth interviews with some households that were insured, reported a hospitalization event and yet did not claim reimbursement of their expenses. These interviews have been conducted after the end of the insurance period to not interfere with the research study. The reported reasons for this behavior are manifold. While some incidences can be explained with unawareness about the claim procedure or frustration about the process, other cases are related to missing trust, preference for alternative (more expensive) coping strategies and recall problems about having bought the insurance product.

[5] A Tobit model is a natural choice, as maximum claimable amounts cannot be lower than zero and are restricted to PKR 15,000 in policies P1, P3 and P4.

situation, the household size and client characteristics. The individual level characteristics include demographic information such as age, gender and whether the individual is contributing to the household income as well as detailed health information. The latter includes individual's subjective health status, inpatient and outpatient health history, associated costs, type of health events experienced and subjective magnitude of the shocks experienced. Table C.12 reports the estimated coefficients in the Tobit regression for eligible dependents. The estimated coefficients suggest that dependents in lower age groups cause lower reimbursable claims as compared to the reference group of 30 to 49 year olds. Further, better subjective health and better self-reported health history result in lower reimbursable costs.

Column 2 of Table C.12 reports the results of an identical estimation that only considers the eligible dependents in the control groups. The idea of this additional regression is to assess the robustness of our results to the existence of moral hazard. As described in Section 3.3.2 the control groups are not offered any additional insurance and hospitalization expenditure for dependents in this group hence should not be affected. Thus, comparing the coefficient estimates in column 1 and 2, shows whether moral hazard changes the mapping from baseline characteristics to hospitalization expenditures. The resulting coefficient estimates are mostly similar to the ones in reported in column 1 in terms of sign and magnitude. Based on a Hausman specification test we cannot reject that both models are equivalent (p-value: 0.57). This is consistent with the fact that there is no significant treatment effect of the insurance treatments on inpatient expenditures (see Table C.14). The choice between including all observations and using the control groups only hence does not make a large difference. To maximize precision of our estimates, we include all observations (i.e. specification 1).

Table C.12 – Predicting Inpatient Expenditure using Baseline Characteristics

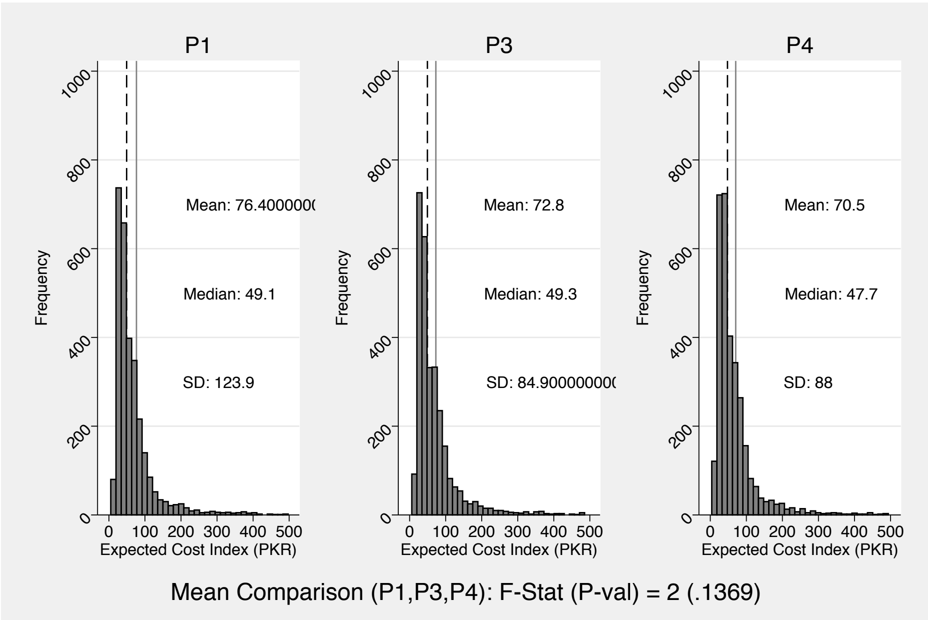
	All T	Controls Only
Household Level Info		
HH Size	-2117.81***	-2157.93*
	(616.24)	(1157.82)
Income (in 1000 PKR)	56.33	-0.41
	(43.62)	(50.86)
Saving (in 1000 PKR)	15.27	20.89
	(10.48)	(22.90)
Asset Index	178.60	-565.30
	(519.33)	(748.02)
Client Female	-2693.87	-3971.38
	(2501.32)	(3516.04)
Client has no education	-225.60	-1862.40
	(2464.48)	(3787.29)
Individual Level Info		
Age (0-4)	-11284.12**	-2515.22
	(5128.38)	(7817.78)
Age (5-9)	-23400.18***	-16939.28**
	(5535.32)	(8145.62)
Age (10-14)	-25454.44***	-17694.00**
	(5849.77)	(8555.38)
Age (15-19)	-12717.43***	-8448.89
	(4826.51)	(7032.81)
Age (20-29)	-8764.89*	-9052.73
	(5133.15)	(7650.28)
Age (50-59)	1512.15	-539.27
	(6570.36)	(10119.70)
Age (60-69)	-5043.40	-5590.26
	(6590.69)	(9704.61)
Age (70+)	-4342.60	-478.83
	(7169.47)	(10114.03)
Working	-14635.29***	-16080.74**
	(4194.80)	(6587.80)
Female	266.71	-1961.23
	(2447.19)	(3387.72)
Subjective Health Status (1-5)	-6667.32***	-7474.08***
	(1659.26)	(2535.78)
Outpatient Treatment	8348.97*	90.09
	(4355.64)	(6834.38)
Inpatient Cost (PKR)	0.06	0.02
	(0.07)	(0.07)
Outpatient Cost (PKR)	0.07***	0.06***
	(0.02)	(0.01)
Chronic Inpatient Disease	31643.95***	12698.73
	(9441.58)	(12701.57)
# Inpatient Cases	2157.61***	7044.08*
	(826.55)	(4194.29)
# Neglected Inpatient Care	-1061.03	-967.46
	(2798.62)	(3883.62)
Drop in Subj. Health (Inpatient)	-5246.08**	-3710.95
	(2505.71)	(4309.28)
Drop in Subj. Health (Outpatient)	339.89	-1550.96
	(1624.50)	(2371.66)
Constant	-48526.07***	-30326.65*
	(10454.33)	(15573.63)
sigma	49197.76***	42658.61***
	(3485.41)	(4775.13)
N	21473	7227
F-Value	6.30	4.60
P-Value	0.0000	0.0000

Notes: The table provides results from a Tobit model that explains the maximal claimable costs as a function of household and individual level variables. Standard error in parentheses are clustered at the village level. Monetary amounts are in Pakistani rupees (PKR), where 101 PKR $\approx$ USD 1.

We predict expected claimable inpatient expenditures $\hat{E}[\bar{C}_{i1}|X_{i0}]$ for each individual using specification 1 of Table C.12 above. Consistent with Equation (D1), we then apply a scaling factor of 0.4588 to predict the expected cost index ECI_{i1} for each individual under the respective policy.[6]

Figure C.5 illustrates the distribution of the expected insurer costs across policies P1, P3, and P4. The mean and median of the respective distribution are shown as a grey solid and a black dashed line respectively. The figure reveals that the cost distribution is right-skewed in a similar way for all policies. A test for equality of their means cannot be rejected (p-value: 0.1369).

Figure C.5 – Histogram of the Expected Cost Index, by Policy



Notes: The figures shows histograms of the provider's expected reimbursement costs across the four policies. The mean and median are illustrated through the solid and dashed line respectively. The predicted reimbursement costs are measured in Pakistani rupees (PKR), where 101 PKR ≈ USD 1.

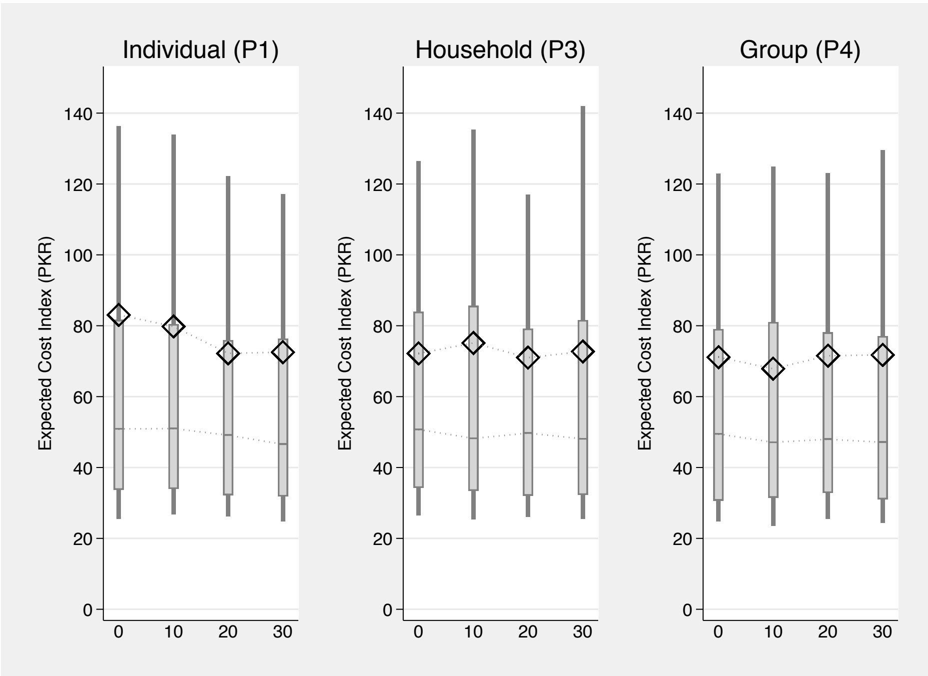
Figure C.6 shows the balancing of the cost index across policies and prices. The box plots illustrate the interquartile rage (IQR), as well as the 10$^{\text{th}}$ and the 90$^{\text{th}}$ percentile of the distribution. The distributions appear to be relatively balanced across prices in all policies.

Table C.13 summarizes and compares hospitalization costs up to the theoretical coverage limit ("Claimable Inpatient Costs"), number of claims reimbursed and average payouts under the different insurance policies. Reimbursed claims are based on all observations in the insurance data set. Claimable costs are based on the self-reported information from the bi-monthly phone survey and restricted to the observations that can be matched with insurance data (the dataset used in the paper). Matched and non-matched observations from the survey data are not significantly different, though. Besides illustrating the ratio between insurance payouts and potentially claimable amounts (0.3885), the table reveals that there are indeed strong differences in paid claims between

[6] The scaling factor is based on hospitalization expenditure and claim data during the insurance period which are summarized in Table C.13.

products. The payout frequency tends to be higher in individual policies (P1, P2) than in households or group policies (P3, P4) and despite the limited number of cases, several comparisons via two-sample proportion tests are significant: P1 vs. P4 (p-value: 0.0782), P2 vs. P3 (p-value: 0.0216) , P2 vs. P4 (p-value: 0.0133) and P1+P2 vs. P3+P4 (p-value: 0.0054). Comparisons between P1 vs. P2 and P3 vs. P4 are all insignificant.

Figure C.6 – Distribution of Risk across Discounts and Policy Regimes



Notes: This figure illustrates the distribution of the expected cost index by discount level and policy regime. The box plot illustrates the interquartile range (IQR), with the median indicated by the line separating the box. The lower (upper) adjacent line shows the 90^{th} (10^{th}) percentile, respectively. The diamond indicates the value of the mean.

Table C.13 – Summary Statistics of Inpatient Expenditure and Claim Behavior

	N Insured	N Insured (Matched)	Mean Claimable Inpatient Costs^	Mean Predicted Claimable Inpatient Costs^	N Claims (Total)∼	Mean Amount Claimed ∼
P1	1054	921	349.59	212.11	12	114.18
P2	663	615	450.90	316.72	11	202.36
P3	1505	1350	166.80	169.62	9	59.21
P4	1344	1212	122.69	163.10	7	55.04
Total	4566	4098	235.55	199.36	39	91.46

Notes: Monetary amounts are in Pakistani rupees (PKR), where 101 PKR ≈ USD 1. 'Insured' are all individuals appearing the insurance management information system, 'Insured (Matched)' are those Insured that can be matched with our survey data. ^ Based on 'Insured (Matched)', ∼ based on 'Insured'.

Table C.14 – Treatment Effect of Insurance Policies on Reported Inpatient Cost

	Inpatient Cost (PKR)
P1	158.3321*
	(92.7487)
P3	109.9905
	(106.1380)
P4	–44.5723
	(62.1140)
Strata FE	yes
N	17832
R^2	0.0014
Wald	1.6900
p(Wald)	0.1685

Notes: Reported inpatient costs are in Pakistani rupees (PKR), where 101 PKR $\approx$ USD 1. The control group serves as the reference group. The OLS regression includes strata fixed effects and standard errors are clustered at the village level. The Wald test statistic is from a joint test of significance of the main treatment indicators. The estimation sample contains eligible dependents of all policies, excluding policy P2, for which there exists information from the follow-up phone survey.

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Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig angefertigt und mich keiner anderen als der in ihr angegebenen Hilfsmittel bedient zu haben. Insbesondere sind sämtliche Zitate aus anderen Quellen als solche gekennzeichnet und mit Quellenangaben versehen.

Mannheim, 03.08.2018: ____

Torben Fischer