Adverse Selection in Micro-Health Insurance Markets: Evidence from a Randomized Control Trial in Pakistan $^{\perp}$

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Abstract: We provide robust evidence on adverse selection in low-income health insurance markets from a randomized control trial 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 price curve and to test different measures against adverse selection. Our results suggest that there is substantial adverse selection if health insurance coverage can be individually assigned. In particular, adverse selection becomes 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 through bundling insurance policies at the household or higher levels. The results for our sample suggest that insurers should abstain from offering individual policies to avoid adverse selection, which should allow them to focus on simple and comprehensive products for the low-income market.

Keywords: Adverse selection, Health Insurance, Pakistan

JEL: I13, D82, O12

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I. Introduction

Adverse selection is a central concept in (insurance) economics and a potential impediment for efficient insurance solutions. In its worst forms, it may lead to the breakdown of markets (Arrow 1963; Akerlof 1970; Rothschild and Stiglitz 1976). In practice, therefore, insurers intend to establish separating equilibria and thus mitigate the problem, e.g. by offering contracts with varying residual risk exposure or by pricing products based on observable information about clients' risk types. Despite its importance, empirical studies of adverse selection are challenging due to a discrimination problem (as discussed by Chiappori and Salanie 2000): An observed positive correlation between insurance coverage and loss incidences could be caused by more risky individuals selecting higher coverage (adverse selection) or by higher coverage causing behavioral changes (moral hazard). This observation has led to a controversial discussion about the presence of adverse selection and the implied welfare loss in various insurance markets (Cohen and Siegelman 2010). In this paper, we contribute to the literature by providing robust evidence on the presence of adverse selection in the health insurance sector in Pakistan. We exploit a randomized control trial (RCT) to evaluate a hospitalization insurance scheme in more than 500 villages of rural Pakistan. The RCT involves a variety of insurance products, which aim at mitigating adverse selection. These products are offered with randomly varying prices. Moreover, our baseline data includes individual health indicators measured before the introduction of insurance. Within this setting, we can separate adverse selection from moral hazard, estimate selection at different premiums and compare adverse selection across different product variants.

Our results have high policy relevance. Health events are a top financial hazards for poor households and often the most important type of unexpected events (e.g. see Heltberg and Lund 2009). In absence of universal social insurance systems, an overwhelming share of health expenses is financed through out of pocket expenditure (Fafchamps 2003). In order to cope with these shocks, which sometimes amount to a multiple of the available monthly income, households rely on a combination of strategies such as precautionary savings, selling productive assets, credit and other informal risk sharing. These informal risk management arrangements are often imperfect, expensive and leave the household vulnerable to poverty (Dercon 2002). Microinsurance, i.e. formal insurance contracts targeted to the poor, in theory have the potential to mitigate the adverse effects of severe financial shocks, thus providing a welfare improving risk coping mechanism.[1] Compared to traditional insurance markets, though, microinsurance providers face a peculiar environment, which leaves offered policies even more vulnerable to information asymmetries. First, this is due to the need of maintaining low administrative costs and the resulting limited potential for ex-ante risk screening (Brau, Merrill, and Staking 2011). Second, there is a requirement for simple policy design. On the supply side, insurance providers often have limited capacity to work with a portfolio of products, either because they lack management capacity or because they cannot work with qualified and more expensive staff. On the demand side, the target group is oftentimes exposed to formal insurance for the first time. Therefore, offering a single and easy to understand variant (pooling contract) is the only way to market an insurance scheme successfully. For these reasons, investigating both the presence and the magnitude of information asymmetries as well as exploring optimal design features under a pooling equilibrium are important areas of research.

At the same time, there is an ongoing discussion about the presence of adverse selection in microinsurance markets and part of the literature questions whether standard assumptions regarding insurance demand actually hold in this context (Dror and Firth 2014). The empirical evidence is mixed. While some results suggest the presence of adverse selection (Zhang and Wang 2008; Clement 2009; Lammers and Warmerdam 2010; Yao, Schmit, and Sydnor 2015), other studies conclude that adverse selection is absent (Jütting 2004; Dror et al. 2005; Nguyen and Knowles 2010; Banerjee, Duflo, and Hornbeck 2014). Most of the literature relies on purely correlational approaches though and is therefore neither able to solve the discrimination problem nor to eliminate potential omitted variable bias problems. Only few studies use (quasi) experimental designs and provide evidence that is more reliable.

In this paper, we contribute to the literature by providing robust evidence on the presence of adverse selection in the health microinsurance sector in Pakistan. Our experimental setup 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 measures against adverse selection. Our results suggest that there is substantial adverse selection if health insurance coverage can be individually assigned. In

[1] The potential of formal micro insurance is captured by recent increases in the number of persons insured under low premium products to about 500 million in 2013 (ILO Microinsurance Innovation Facility 2014).

particular, adverse selection becomes worse with higher premium prices, creating a trade-off between cost recovery and the quality of the insurance pool. In contrast, adverse selection virtually disappears when bundling insurance policies at the household or higher levels. The results for our sample suggest that insurers should abstain from offering individual policies to avoid adverse selection, which should allow them to focus on simple and comprehensive products for the low-income market. Additional data collection expected to complete in March 2016, will allow us to assess whether the presence of adverse selection threatens the financial sustainability of the products and ultimately leads to market breakdown. Following Einav and Finkelstein (2011), this setting in addition allows us to estimate the implied welfare costs of adverse selection.

From a methodological point of view, we analyze the presence of adverse selection in several steps. First, we conduct a conventional positive correlation test between individual's ex-ante measure of riskiness and the probability of insurance take-up (Chiappori et al. 2006). Baseline characteristics are used to construct the proxy of riskiness, which rules out moral hazard after insurance uptake as a confounding explanation. Still, a positive correlation between uptake and risk type could be explained by other unobservable factors driving the insurance decision. Therefore, in a second step, we follow a more structural approach proposed by Einav and Finkelstein (2011) and investigate the change in average riskiness of the insurance pool for different policy prices. Since policy prices vary exogenously by design, this approach produces causal evidence.

The results of the positive correlation test indicate that insured individuals exhibit significantly higher risk than uninsured individuals do. Exploiting random discounts, we find that the average riskiness of the pool of insured individuals increases in policy price as long as households are free to choose which dependents to insure. The observed pattern is in line with the theoretical prediction of adverse selection (Akerlof 1970): Individuals on the margin of becoming insured exhibit less riskiness. This relationship between riskiness and insurance price disappears once household level enrolment to the insurance is required.

The remainder of the paper proceeds as follows. Section II explains our approach to identify adverse selection in more detail. Section III describes the context of the experiment, the different insurance innovations and the hypotheses linked to their implementation. Section IV contains information about the data collection process and provides summary statistics. Section V presents empirical results on the presence of adverse selection and Section VI concludes.

II. Identification of Adverse Selection

The theory of adverse selection was established in the 1970's by the seminal papers of Arrow (1963), Akerlof (1970) and Rothschild and Stiglitz (1976). All these models (and many subsequent ones) hinge on the assumption that agents will select into the insurance based on their individual risk type and premium price. In case of adverse selection, the resulting slope of the marginal cost curve should be negative, and expected costs for insured should always be higher than for non-insured.

From an empirical point of view, it is more 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). Further, there might be other, possibly unobserved factors influencing both insurance coverage as well as the risk indicator (omitted variable bias). The empirical literature on adverse selection has utilized identification approaches with varying robustness and generated mixed results (Cohen and Siegelman 2010).

From a methodological point of view, the majority of studies establishes a simple positive correlation between a measure of insurance coverage and an indicator of risk, usually measured after the insurance decision (Yao, Schmit, and Sydnor 2015).[2] For example, comparing health expenditures incurred by insured and non-insured individuals does not necessarily identify adverse selection if the insurance status changes the loss distribution through behavioral changes. Few studies instead use *ex-ante* measures of risk, such as subjective health status or medical history at baseline to analyze selection (e.g. Wang et al. 2006). The advantage of relying on baseline risk proxies is that the potentially confounding moral hazard channel is prevented. A potential drawback of using ex-ante risk measures, on the other hand, might be the interpretation of results if these

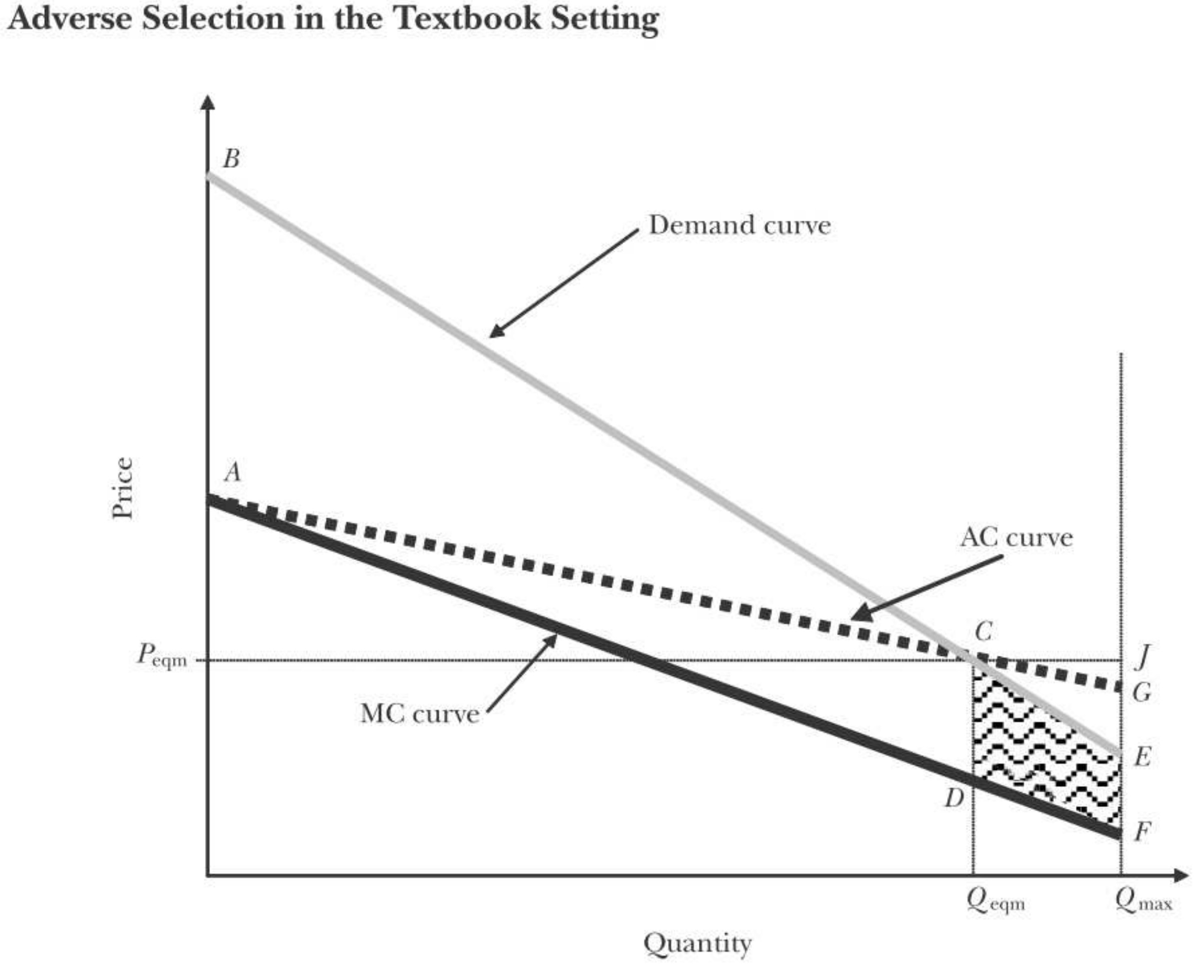
[2] Most studies use ex-post claim or accident realizations as proxies for individual riskiness.

measures are imperfect proxies for future risk. Moreover, the problem of omitted variable bias remains.

A more structural identification approach of adverse selection can be derived from the predicted decrease in the quality of the insurance pool for increased insurance premiums (Einav and Finkelstein 2011). Figure 1 illustrates this approach. Let us assume that insurance is a normal good, and thus the fraction of the population-insured increases as the price falls. Note that providers' cost curves are interlinked with individuals' risk types through the occurrence of claims. If higher risk types exhibit a higher willingness to pay for insurance, we would expect to observe the decreasing marginal cost curve depicted in Figure 1. Consequently, the insurer faces decreasing average costs as premiums decrease. Given perfect competition, the intersection of demand and average cost curves determines the market allocation. We observe a welfare loss since the willingness to pay for insurance is higher than the marginal costs of providing insurance for the whole population, while in equilibrium only a share of the population will be insured. In Figure 1, this welfare loss is illustrated as the shaded rectangle CDEF. Insurance theory, therefore allows for a straightforward test of the presence of adverse selection that relies on the slope of the marginal cost curve. Empirically, a necessary pre-requisite for this approach is a (plausibly exogenous) variation in premiums for the *same* insurance contract. If it is possible to reject the null of a flat marginal cost curve, i.e. no relationship between insurance price and the claim ratio, this provides evidence for selection. Moreover, this approach allows testing the direction of the selection: An increasing marginal cost curve (in insurance price) suggests adverse selection, while a decreasing one suggests advantageous selection. Furthermore, note that the presence of moral hazard does in general not confound this approach when a specific insurance contract is considered.[3] Therefore, the behavioral response of the insurance status is likely to be similar across varying prices, leaving the slope of the marginal cost curve unaffected.[4]

[3] Note that selection on moral hazard might threaten the validity of this identification approach.
[4] In other words, moral hazard would shift the position of the marginal cost curve, but leave its slope unaffected.

Figure 1 Adverse Selection (Figure 1 in Einav & Finkelstein, JEP 2011)



In praxis, providing credible exogenous variation in policy premiums is challenging in most settings. To the best of our knowledge, Einav, Finkelstein, and Cullen (2010) is the only study utilizing this identification approach. The authors investigate the presence of adverse selection and the implied welfare costs thereof 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.

III. Background, Intervention and Hypotheses

III.1 Background

Pakistan is a lower-middle income country. While GNI per capita was $1,400 in 2014, more than one third of the population, corresponding to more than fifty million individuals, lives below the poverty line.[5] According to the World Bank (2007, 8), the majority of households can be classified as vulnerable. Individual level factors related to health shocks are a major determinant of this vulnerability.

On a macro level, public health expenditure accounts for about 37% of total health expenditures, while 55% is from by private out-of-pocket expenditures. Free public health facilities exist on the national level, but provide limited protection. The reasons are multiple and range from offered services to be perceived of low quality, to not covering expensive treatment and drugs (Pakistan Ministry of Health 2009). This often leaves the poor with little choice, except for consulting more expensive private healthcare providers. While some health insurance schemes do exist on the provincial level, they lack universality. The existing schemes predominantly target public and formal sector employees, thus leaving the rural poor mostly working in the informal sector with limited options. A small number of NGOs and microfinance institutions do provide microinsurance policies to their clients, but the majority of these microinsurance schemes contain only life insurance and are bundled along with a credit product. Since such life insurance covers are often designed to include both outstanding loans as well as an assured sum, they provide protection for the MFI and the client simultaneously. Considering health microinsurance specifically, the National Rural Support Programme of Pakistan (NRSP), which is our implementation partner, is regarded the only provider with significant outreach (World Bank 2012, 11).

NRSP is the largest of twelve rural support programmes in Pakistan with an outreach of more than 2.5 million households. Its ambition is to support poor households through community development activities and microfinance. NRSP microfinance is the largest provider of microcredit and the largest holder of savings among the Rural Support Programmes (Rural Support Programmes Network 2015). In remote, rural areas, NRSP usually works with community organizations (COs), which consist of 18 to 20 member households. Members of these community organizations 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.

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[5] Compare the World Bank Indicators 2013 at: http://data.worldbank.org/country/pakistan .

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. Second, it separately covers accidental death and disability of the main breadwinner up to a maximum threshold of PKR 15,000.[6] Third, the outstanding loan amount is written off and a contribution of PKR 5,000 towards funeral charges is paid to the family in case of normal death of the main breadwinner. The premium of PKR 150 for both client and spouse is automatically deducted from the loan amount before disbursement. The covered expenses in case of hospitalization range from room charges, doctor fees, lab tests and prescribed drugs to transportation costs. For maternity related expenses, the 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 which 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.

III.2 Intervention

Our implementation partner aims at increasing resilience of its clients towards adverse health shocks by providing them with additional insurance coverage. At the same time, the local context restricts the range of possible innovations. In particular, the large-scale operations of NRSP on the grass-root level depend heavily on proven, but simple routines and recruiting staff from local communities in the area of operation. The field staff's educational background in general equals matriculation, which is equivalent to 9 years of education. NRSP's target population is mostly poor and uneducated.[7] Simulating realistic rollout conditions for scalable insurance solutions, the proposed innovations focus on simple pooling contracts that are easy to administer in the field. Due to the scarcity of robust empirical evidence on the optimal design of simple insurance policies, this collaboration pilots different insurance solutions in a way that allows a rigorous analysis of adverse

[6] The maximal benefit depends on the degree of disability caused by the accident.
[7] Average household income amounts to PKR 22,000 ($220) and about 50% of clients have no formal education.

selection, financial sustainability and social impact. In total, we test four policies that expand the mandatory insurance by offering voluntary coverage of additional dependents of the household. 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.

Table 1 provides an overview of all insurance innovations. *Individual* policy (P1) allows the client to enroll any number and combination of dependents in the insurance scheme. It covers hospitalization expenditures of the insured individual 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. We expect a high level of adverse selection in this policy, as the clients can specifically choose 'risky' household members to be covered. We therefore implemented two alternative treatments that we believe to be less vulnerable to adverse selection.

The *Household* policy (P3) differs from *Individual* insurance in that the client is required to enroll all dependents of the household if he intends to buy insurance. This policy provides the same coverage for each insured dependents as the Individual product. The Group policy (P4) additionally 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 their dependents. Compared to Individual insurance, the Household policy is expected to improve the risk pool of insured persons, thus leading to an improved financial viability of the scheme. The trade-off is given by higher premium payments for household coverage, which might result in lower demand. Analogously, the group eligibility is expected to further increase the risk pool and financial viability of the scheme, potentially at the expense of even lower demand.

The rationale behind the Individual High policy (P2) is not to affect adverse selection but to increase social efficiency. It is similar to the individual policy (P1), but its coverage limits are increased to PKR 30,000 per person insured, which also justifies the higher insurance premium.[8] The design change might nevertheless have interesting consequences for adverse selection. While the same eligibility criterion as for P1 applies, the Individual High policy offers higher effective coverage at a lower price per coverage and should hence be more attractive for high risk types.

Table 1- Insurance Innovations

	Individual (P1)	Individual High (P2)	Household (P3)	Group (P4)
Eligibility	Individual		Household	
Add. Requirement				50% Uptake in the group
Coverage Limit (p.P)	15,000	30,000	15,000	15,000
Premium (p.P)	100	150	100	100
Premium Discounts	✔	✔	✔	✔

Notes: Numbers are in PKR, $1 ≈ 101 PKR, 15’000 PKR ≈ $148 (in February 2015).
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.

In each village, one out of these four policies is offered in a community meeting. This community meeting starts with an introduction about the concept of insurance and explains in detail the benefits of the existing, mandatory health insurance policy. All awareness sessions are held by specifically trained social organizers and take about 30 to 40 minutes. Afterwards, the social organizer introduces exactly one out the four insurance policies. During the sign-up procedure the social organizers randomly allocate one of four discount vouchers (0, 10, 20 and 30 Rupees) to each client. The discount is allocated to each client independently and applies to the per person premium for all of the eligible household members. For the assignment, the social organizers show the client four equally looking cards, from which the latter has to choose exactly one. The resulting discount is captured on a specifically developed sign-up sheet that contains unique household level identifiers.

III.3 Randomization Procedure and Sampling

As the level of randomization, we chose the ‘revenue village’ or ‘mouza’, which is an administrative level similar to (a collection of) villages. This means that exactly one out of the four

[8] The motivation for offering P2 derives from the fact that 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 around PKR 150.

interventions described above is made available to groups of 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 level of randomization minimizes the potential for information spillovers, which could contaminate the treatment effect estimates.

The total sample contains about 6,500 households. We aim to sample approximately 13 credit clients in each of the randomization clusters to achieve an optimal cluster size. The sampling procedure focuses on clients from groups whose loan application has been approved just before the introduction of the innovation in December 2014. This guarantees that the group composition and household structure are exogenous to the introduction of 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 the organization's management information system. In a second step, we select all members with active loans from the pool of applying groups until at least 13 clients per village are sampled.[9]

Note that the representativeness of the sample generated in this way for the population of interest, i.e. all credit clients of our implementation partner, is maintained.[10] This holds even if selection into credit was driven by characteristics related to demand for the mandatory insurance product. The reason is that anticipation of the interventions as a driving factor of selection into credit can be ruled out by design, thus generating no differential selection between treatment arms.[11]

Concerning the treatment allocation, sampling from incoming credit applications implies that we do not know the set of villages with incoming credit applications ex-ante. In order to achieve a

[9] In general, this translates into one community organization, sometimes amended by a smaller credit group, or four to five smaller credit groups per village. In rare cases, it might be that a community organization is taking loans in cycles. In such cases, there might be clients with disbursed loans at the time of loan application. We define the "group" as all members of the group with currently disbursed or applied loans.

[10] Representativeness for the population of Pakistan is not given since selection into credit might be driven by unobservable characteristics.

[11] One threat to representativeness might be the correlation of individual health risks within the household. The magnitude of such a correlation is an empirical question and therefore testable.

balanced allocation of treatments in this dynamic setting, we therefore employ a permuted block randomization procedure. 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. 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 then 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 use the timing of loan applications in the management information system (MIS). In a third step, we create strata specific lists relying on the list from step two. In a final step, the treatment status results from assigning each village in the strata specific order the correspondingly ranked status from the strata specific permuted block.

Table 2 presents the allocation of treatments resulting from this randomization procedure. In total, there are 502 randomization clusters. In the analysis below, we will focus on information from the 334 villages in which the four insurance innovations have been implemented. As expected, we observe a balanced number of villages of across treatment arms. We can confirm the average cluster size of 13 households per village by dividing the number of households per treatment arm by the number of villages.

Table 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	1153	1025	1023	1083	1058	1119	4283	6461
HHs Attending	0	822	857	870	830	876	3433	4255
Dependents (Dep.)	4182	3542	3561	3921	3796	4084	15362	23086
Attending Dep.	0	2801	2982	3210	2937	3157	12286	15087

IV. Data

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

IV.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 as well as villages 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 will 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 that are administered to the sampled clients through computer assisted personal interviews (CAPI). The modules capture socio-demographic, psychological, economic and health indicators. The health module contains information on individuals' subjective health status, her history of both in- and outpatient treatments as well as detailed information on coping strategies. Baseline data was collected between December 2014 and March 2015. Externally hired enumerators operating in the name of the University of Mannheim were engaged in data collection. To maximize data quality, our CAPI system included both instantaneous in-field quality assurance and regular, more sophisticated data quality checks on the enumerator level.

[12] This procedure also ensures that the household structure is not endogenous to the introduction of insurance.

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. Phone survey data collection started in February 2015 and is ongoing.[13]

IV.2 Summary Statistics and Balance Tests

In the following we present summary statistics and balancing tests that assess whether our randomization indeed results in a similar distribution of covariates across treatment arms. The balancing tableshave 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:

$$X_{iv} = \alpha + \beta_2 I_{\{T_{iv}=P2\}} + \beta_3 I_{\{T_{iv}=P3\}} + \beta_4 I_{\{T_{iv}=P4\}} + \varepsilon_{iv} \quad , \qquad (1)$$

where X_{iv} is the respective covariate and $I_{\{T_{iv}=Pk\}}$, k=2,3,4 are indicators for the respective treatments P2, P3 and P4 (P1 is the omitted category). The error term ε_{iv} is clustered at the village level. The test for joined 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 3 provides summary statistics and balance tests for sociodemographic, economic and health indicators on the household and individual level. The first panel shows that the average household size in the sample of 4283 households to which insurance is offered is close to 6. The average age of the client is about 38.5 years old and about 53% of the clients are female. The majority of household heads have no formal education. Comparing the means of these indicators across treatment groups, we observe that there are no significant differences. This is confirmed by the relatively high p-values of the joint test for model significance.

[13] This version of the paper includes phone survey data up to the 14th of April 2016.

The second panel of **Table 3** contains economic indicators. Average monthly income of households is about PKR 22,700 (USD 220), and has a relatively high standard deviation. On average households own about 1.4 acres of land. Further, credit obligations are about three times as large as the savings stock, which amount to about PKR 9,000. Again, as indicated by the p-values in the last column, there seem to be no statistically significant differences across treatment groups.

The third panel of **Table 3** is split into two parts. The first part contains household level health indicators, whereas the second part presents individual level information. 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. On average, expenditures for such inpatient cases amount to about PKR 2,800 per household. Looking at the standard deviation, we deduce that inpatient expenditures are skewed. On average, about 20% of the sampled households have heard about insurance. The final row provides an individual-level health risk index for the sample of eligible dependents. This index is constructed as the first principal component (PCA) of baseline information on individuals subjective health status, self-reported health history and health expenditures.[14] It is a standardized measure capturing individuals' health risk, which we will use as a proxy for individual riskiness.

[14] Table 6 in Appendix A provides balance tests and factor loadings for the components used in the index.

Table 3- Balance Tests (Insurance Policies)

	Overall	P1	P2	P3	P4	P-val
Socio-Demographics – HH						
HH Size	5.99	5.95	5.95	6.03	6.03	0.73
	(2.118)	(2.095)	(2.072)	(2.054)	(2.238)	
Client Age	38.62	38.83	38.58	38.22	38.83	0.64
	(10.891)	(10.925)	(10.941)	(10.737)	(10.959)	
Client Female (D)	0.53	0.57	0.51	0.51	0.54	0.72
	(0.499)	(0.495)	(0.500)	(0.500)	(0.499)	
Client No Education (D)	0.55	0.56	0.52	0.55	0.56	0.58
	(0.498)	(0.496)	(0.500)	(0.498)	(0.497)	
Economic – HH						
Avg. Inc. (month)	22691.10	21622.03	24515.11	22627.03	21963.72	0.25
	(24694.733)	(20012.031)	(34658.332)	(20224.808)	(20384.801)	
Land (acres)	1.38	1.02	1.51	1.52	1.45	0.07
	(3.230)	(2.403)	(3.509)	(3.236)	(3.564)	
Savings	9231.70	9685.67	9371.95	9298.46	8617.81	0.90
	(24724.301)	(25495.292)	(26221.785)	(22356.826)	(24667.702)	
Credit	27839.61	26542.08	29763.20	26473.94	28455.33	0.76
	(47581.811)	(41791.826)	(51546.915)	(47344.613)	(48752.036)	
Health & Insurance – HH						
Any Inpatient (D)	0.12	0.11	0.13	0.12	0.12	0.72
	(0.327)	(0.316)	(0.338)	(0.325)	(0.328)	
Total Inpatient Cost	2793.31	2325.61	3219.67	2725.43	2872.41	0.34
	(9595.441)	(8386.123)	(10747.891)	(9292.777)	(9722.447)	
Knows Health Ins. (D)	0.18	0.20	0.19	0.18	0.16	0.63
	(0.385)	(0.397)	(0.390)	(0.383)	(0.369)	
Health – Dependents						
Health Index	0.05	0.06	0.03	0.05	0.06	0.81
	(0.915)	(0.872)	(0.971)	(0.885)	(0.925)	
N (Dependents)	15361	3560	3921	3796	4084	
N (HHs)	4283	1023	1083	1058	1119	

Notes: The table provides means and standard deviations (in parentheses) of the respective variables. Column 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 (1). Standard errors are clustered at the village level. Binary variables are indicated with (D).

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 4 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.

To investigate potential systematic imbalances, we provide additional tests in Table 5. 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 (1) 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 socio-demographic 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 4 - 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	0.26	0.28	0.25	0.27	0.27
30	0.27	0.23	0.27	0.23	0.25
Pearson Chi2 P	0.2325	0.4632	0.5998	0.2290	0.2153
HHs	857	870	830	876	3433

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.

Table 5 - Balance Checks (Discounts)

	Overall	D=0	D=10	D=20	D=30	P-val
Socio-Demographics – HH						
HH Size	5.99	5.97	5.96	6.01	6.01	0.94
	(2.10)	(2.03)	(2.05)	(2.24)	(2.08)	
Age of Client	38.70	38.31	39.52	39.01	37.84	0.01
	(10.96)	(10.92)	(11.22)	(11.19)	(10.39)	
Client Female (D)	0.53	0.50	0.52	0.57	0.54	0.03
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Client No Education (D)	0.54	0.53	0.55	0.57	0.52	0.15
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Economic – HH						
Avg. Inc. (month)	22723.40	22944.73	21587.96	24125.41	22264.71	0.12
	(25549.93)	(30823.18)	(16445.10)	(28186.03)	(25640.41)	
Land (acres)	1.40	1.29	1.47	1.40	1.41	0.68
	(3.26)	(2.91)	(3.29)	(3.12)	(3.63)	
Savings	9193.49	8598.57	9964.99	9075.05	8997.92	0.70
	(24760.13)	(21275.03)	(26549.99)	(25393.97)	(24890.35)	
Credit	28383.48	27013.33	31030.07	27170.44	27994.30	0.31
	(47987.53)	(47362.55)	(53642.26)	(43790.32)	(46253.15)	
Health & Insurance – HH						
Any Inpatient (D)	0.12	0.13	0.13	0.11	0.12	0.55
	(0.33)	(0.34)	(0.33)	(0.31)	(0.32)	
Total Inpatient Cost	2828.21	2979.05	3182.95	2240.31	2941.07	0.12
	(9648.45)	(9699.37)	(10413.59)	(8140.04)	(10201.21)	
Knows Health Ins. (D)	0.18	0.18	0.21	0.17	0.16	0.07
	(0.39)	(0.38)	(0.41)	(0.38)	(0.37)	
Health – Dependents						
Health Index	0.05	0.05	0.03	0.06	0.05	0.70
	(0.92)	(0.91)	(0.96)	(0.87)	(0.95)	
N (Dependents)	12286	2644	3285	3236	3121	
N (HHs)	3433	740	927	913	853	

Notes: The table provides means and standard deviations (in parentheses) of the respective variables. Column 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 (1). Standard errors are clustered at the village level. Binary variables are indicated with (D).

V. Results

We analyze the presence of adverse selection in two steps. First, we investigate relationship between individuals' ex-ante measure of riskiness and the probability of insurance take-up, following the conventional positive correlation test approach proposed by Chiappori et al. (2006). In a second step, we investigate changes in the risk distribution of the insurance pool by implementing the more structural approach proposed by Einav and Finkelstein (2011). Before shedding light on the presence of adverse selection in Pakistan's micro-health insurance market though, we provide necessary insights about insurance demand.

V.1 Insurance Uptake & Eligibility Criteria

The demand for the different insurance policies offered by our implementation partner is expected to depend on the product characteristics. If households are cash constrained for example, economic theory predicts more households to insure (some of their) dependents in the individual insurance policies as compared to the household policies. Which product achieves the largest coverage of dependents, on the other hand, is an empirical question. Furthermore, having randomly assigned discounts, we can assess the sensitivity of insurance demand with respect to price. In general, we expect the insurance policies to be normal goods and thus demand to increase in the discount amount.

Figure 2 depicts demand for the four different insurance policies. For each policy, demand is plotted at the four different discount levels. For each discount level, the figure shows two bars. The orange bar illustrates the share of households buying any insurance offered the respective policy at a given discount.[15] The green bar illustrates the share of eligible individuals or dependents becoming enrolled in the insurance scheme given the respective policy and discount level. The product specific uptake ratios are obtained from a regression of a household or individual uptake indicator on the set of discount levels respectively. The corresponding confidence intervals are constructed using clustered standard errors at the village level.

[15] Note that the figure only includes information on households attending the group meeting. Overall, the attendance in the meeting is around 80%. Further, we do not find any statistical differences between households attending the meeting and households not attending the meeting. A household is considered as buying any insurance if at least one dependent becomes insured.

For all offered policies, we observe the law of demand: Uptake increases in the level of the discount amount. For product P1, for example, demand increases from about 40% of households buying any insurance at a price of 100 Rs. per person to about 80% at a discount level of 30 Rs. In other words, decreasing the price by 30% leads to an increase in demand by about 100%.[16] Similarly, the share of eligible dependents becoming insured increases from about 18% to around 38% at a discount level of 30 Rs. per person. A similar sensitivity of demand with respect to price can be observed for the other policies.

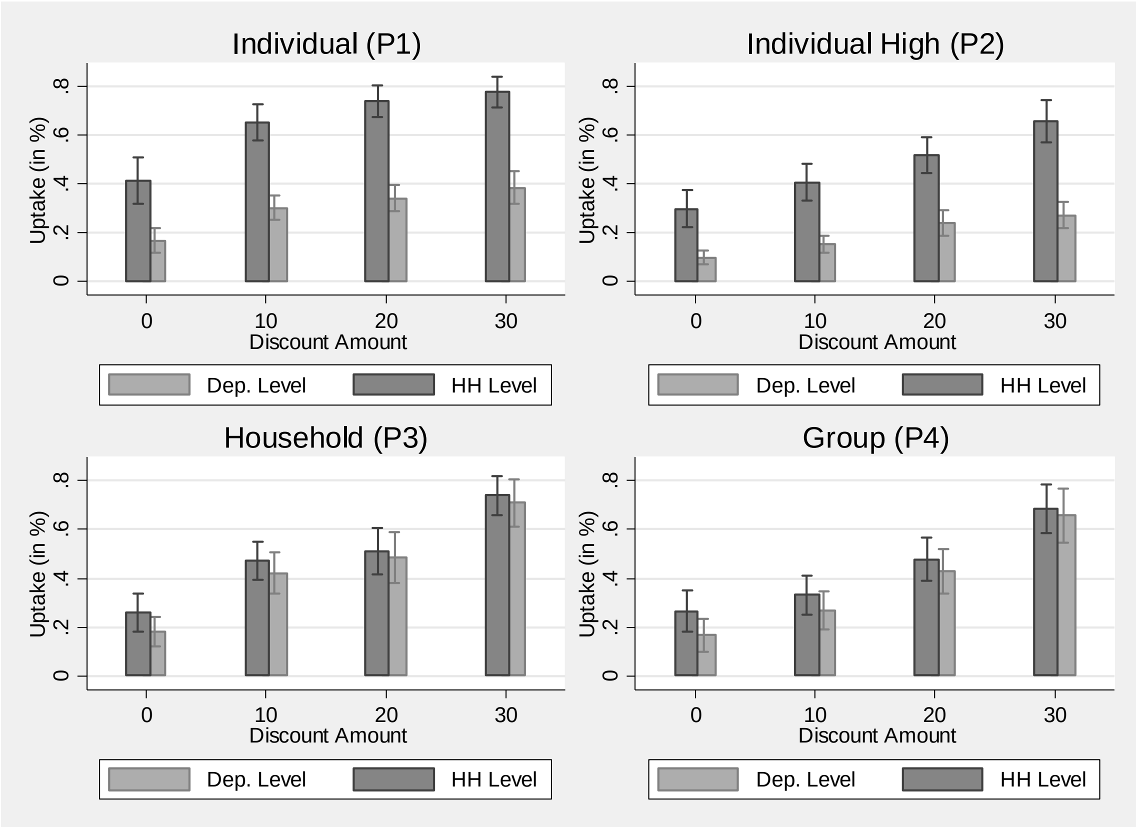
Comparing household and individual level uptake for the individual insurance policies depicted in the top panel, we observe that the share of household buying any insurance is significantly higher than the share of eligible dependents becoming insured at any discount level. In other words, there is large gap between the number of households buying any insurance and the number of individuals becoming insured. This gap indicates partial uptake of insurance within households. In the next section, we will analyze whether this gap is due to individuals with specific characteristics being more or less likely to become insured. In contrast, the gap between household and individual level uptake diminishes for the household level policies P3 and P4 displayed in the lower panel. This indicates that the eligibility criteria of ensuring all dependents in the household have been actually enforced in the field.[17]

Comparing household level uptake between the individual policy P1 and household level policies P3 and P4, we observe that the share of households buying any insurance decreases under the requirement for household insurance. In contrast, the share of dependents being insured is larger for the household insurance policies. This observation 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 offered household insurance. Table 8 in Appendix A sheds further light on the determinants for households (not) to enroll in household insurance.

[16] Note that there are several ways of calculation exact price elasticities in this scenario. These ways differ in assuming a linear demand curve or not.

[17] Minor discrepancies between individual and household level enrolment result from imperfect matching of survey and take-up data. Even though the mechanism is evident by construction, this confirmation is crucial for the interpretation of the results on adverse selection.

Figure 2- Insurance Demand and Enforcement of Eligibility



Notes: The bars indicate average uptake ratios on the household and dependent level respectively. A household is considered as taking up if at least one dependent is insured. The confidence intervals are based on an OLS regression of the corresponding demand indicator on a set of discount indicators with standard errors clustered at the village level.

V.2 Presence of Adverse Selection: Positive Correlation Test

As described in section II, we define adverse selection as a situation in which a high risk types choose higher insurance coverage than lower risk types. The previous section revealed partial uptake of insurance for households that are offered individual level insurance policies. This section investigates to which extend we can explain this partial insurance pattern through a relationship between individuals' riskiness and their insurance status. In a first step, we assess the existence of such a relationship by implementing a conventional positive correlation test (Chiappori and Salanie 2000).

The idea of the positive correlation test is to establish a difference in average riskiness between insured and not-insured individuals. Finding insured individuals to exhibit higher health risks, would be in line with the presence of adverse selection. In the following, the individual's insurance status is given by a binary indicator for insurance uptake. Further, we proxy individuals' ex-ante health risk by the health index described before. The advantage of using a baseline proxy is the exclusion of potentially confounding moral hazard effects. Moral hazard is characterized as a behavioral change (after being covered by insurance) that leads to an increased individual riskiness.[18] The presence of moral hazard would equally result in a positive relationship between individual riskiness and insurance status if an ex-post measure of riskiness were used. Thus, a positive correlation test relying on ex-post measures of riskiness is generally not suited for differentiating between adverse selection and moral hazard. On the downside, the constructed health index might not accurately capture individuals' riskiness if it is unrelated to the occurrence of health events in the future. We validate the quality of our risk measure using information on health shocks collected through a bi-monthly phone survey, which started after product rollout. Table 9 establishes a significant partial correlation between the health index and an indicator for any inpatient treatment in the follow-up period, which suggest some predictive power of the baseline risk measure for future health shocks.

Figure 3 plots means (and corresponding 95% confidence bounds) of the health index by insurance status across the offered policies. Recall that higher values of the index are associated with less health risk. The horizontal line at zero indicates the overall mean of the health index. For individual policies P1 and P2, we observe a large and statistically significant difference in the average health index of insured versus uninsured individuals. On average, uninsured individuals exhibit a positive health index. In contrast, insured individuals exhibit a strongly negative health index on average. This difference is statistically significant at the 1% level and therefore suggests that insured individuals exhibit more health risk than not insured individuals do. For household policies P3 and P4, on the other hand, we find no difference in health risk between insured and uninsured individuals. Average risk for the two groups in both insurance policies is close to the overall average of zero. Table 10 illustrates that the same pattern is found for each of the components of the health index.

The pattern observed in Figure 3 is in line with the prediction of adverse selection. Higher risk individuals are more likely to become insured if given the choice in the individual insurance

[18] In our case, this might be given by changes in preventive behavior that lead to a change in the expected cost distribution of insured individuals as compared to uninsured individuals.

policies. The requirement to enroll all household members, in contrast, appears to mitigate such cherry picking and therefore could be considered a promising tool in preventing adverse selection. Note that the observed pattern can also explain the partial insurance within the household established in the previous section. Households seem to insure particular dependents that exhibit higher health risks. Moreover, the absence of adverse selection under risk bundling could be interpreted as evidence against positive assortative matching within the household. This is because there appears to be a balanced distribution of risk types within the household.

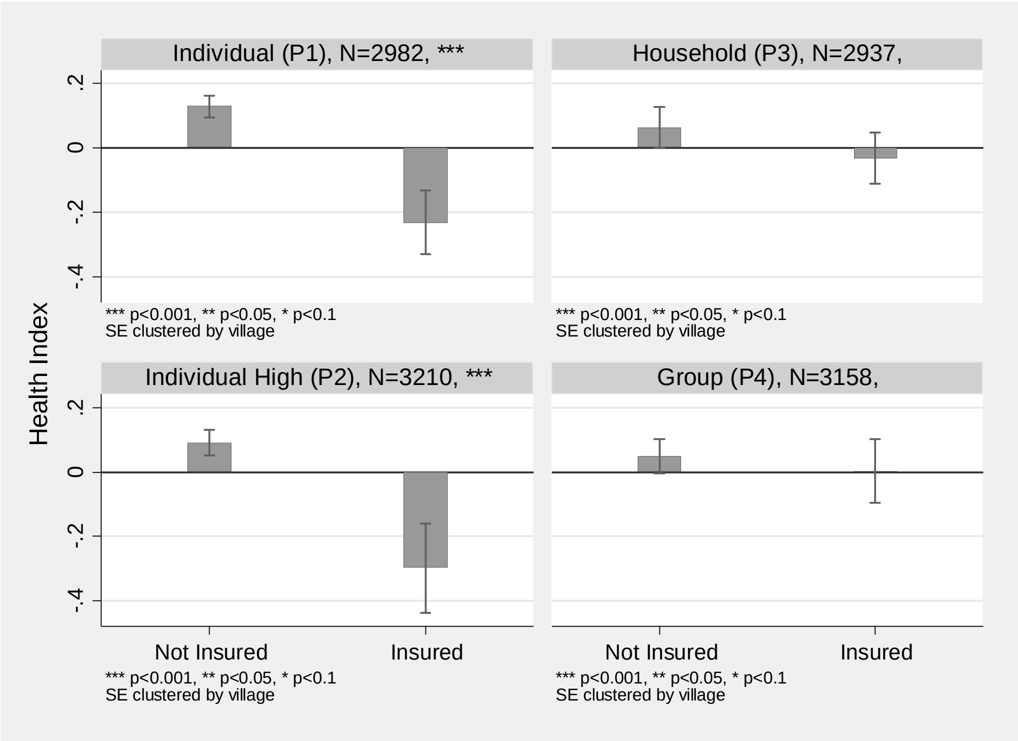
While the presented evidence of the positive correlation test seems conclusive, some concerns remain. Most importantly, the conclusions derive from a simple mean comparison of characteristics between insured and uninsured individuals. Since insurance demand is a conscious decision, this choice might well be related to other unobserved characteristics such as households' risk aversion or income. If these unobserved characteristics are related to the measure of riskiness, the above analysis might be flawed due to omitted variable bias. More risk averse people for example are expected to be more likely to insure their dependents. If more risk averse people are at the same time more likely to be located in households with higher health risk, a similar result as in Figure 3 could establish without implying the presence of adverse selection.

Table 11 provides results from including additional, potentially correlated household level variables. It can be see that the general pattern is maintained and that the point estimates on the insurance status indicator are stable. Furthermore, Figure 4 allows for a comparison of (residual) risk type distributions across insurance status for the two different policy regimes. The residual health risk index takes the residuals from a regression of the health index on the set of control variables reported in Table 11.[19] Intuitively, this residual risk measure partials out variables that could be related to insurance uptake and the health index simultaneously. The residual health risk index therefore considers the risk that cannot be explain by those confounds. Figure 4 illustrates distributional changes in the residual health measure by insurance status and policy regime. 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 individual level policies, we observe lower quantiles of the risk measure distribution for insured individuals. The Kruskal Wallis test reports evidence

[19] Corresponding regression results are reported in Table 12.

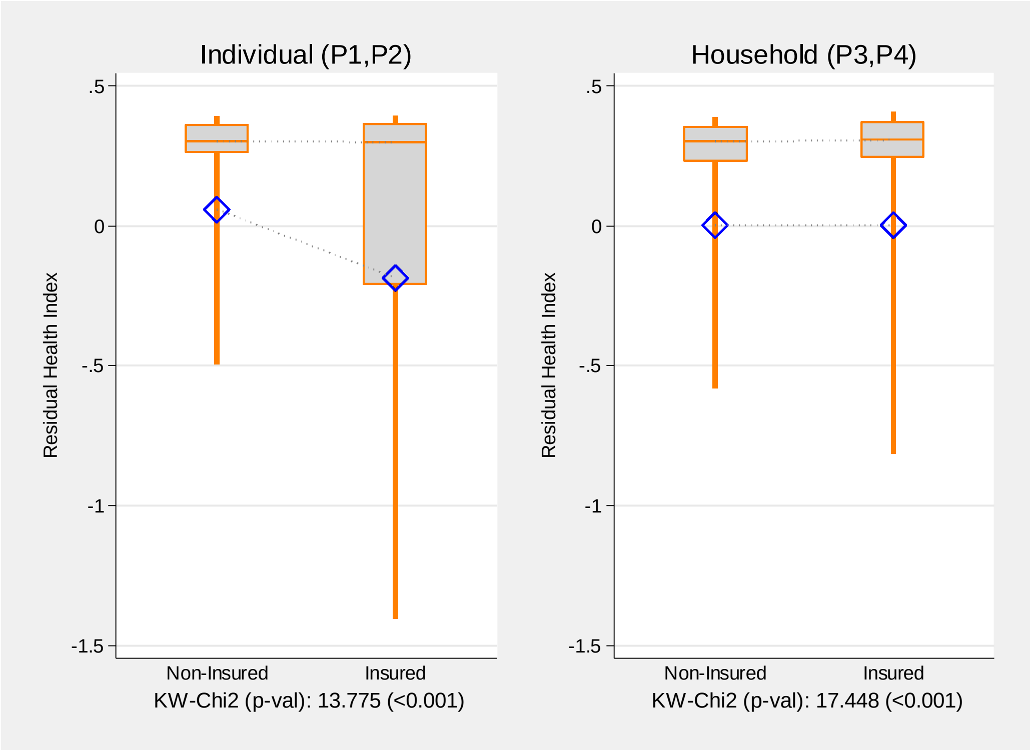
against the null of these distributions stemming from the same population. This means that there is a statistically significant difference between the risk distributions of insured and uninsured individuals. For the household level policies, we confirm the pattern from Figure 3 since the mean risk does not differ across insurance status. However, we observe a modest upward shift in the interquartile range of the risk distribution, while the lower quantile decreases. The positive shift in the interquartile range is sufficient to provide evidence against similarity of the risk distributions. This finding underpins the potential of risk bundling as a solution for adverse selection problems.

Figure 3 - Positive Correlation Test: Health Index



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

Figure 4 - Positive Correlation Test: Residual Health Index



Notes: This figure illustrates shifts in the residual health measure distribution by insurance status and policy regime. The box depicts the interquartile range (IQR), where the median is indicated by the middle line. The upper/lower adjacent depicts the 90%/10% quantile respectively. The diamond indicates means. The KW-Chi2 (p-val) gives the p-value from a Kruskal Wallis test with H0 that the respective samples (separated by insurance status) come from the same population.

V.2 Presence of Adverse Selection: Slope of (expected) Marginal Cost Curve

Given the drawbacks of the purely correlational approach described above, we present results from the alternative approach of identifying adverse selection discussed in section II. We exploit the connection between different risk types' willingness to pay and resulting (expected) costs of the insurance provider. As illustrated in Figure 1, the slope of the insurance providers' marginal cost curve allows for a direct test for the presence of adverse selection (Finkelstein and Einav, 2010). 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 is upward sloping in price. Rather than observing the insurers cost curve directly, we rely on the subjective, ex-ante individual risk measure as a measure for the expected cost curve.[20] Specifically, we deduce the slope of this expected cost curve from distributional changes in the risk distribution of the insurance pool across discounts.

Figure 5 plots this health risk distribution for insured individuals across discounts and policy regimes. For individual insurance policies (left panel), we observe an upward shift in the lower quantiles of the risk distribution and the mean as the discount level increases. This distributional shift is significant at the 5% level. For household level policies (right panel), there is a similar, but less pronounced shift in the lower tail of the risk distribution, accompanied with modest increase in the mean as the discount level increases. This shift is marginally not statistically significant at the 10% level. The observed pattern for individual policies in line with the theoretical prediction of adverse selection. As discounts increase, there is a larger fraction of the insurance pool with a better health risk. Consequently, we expect average claim ratios and costs to decrease. At the same time, the extent to which clients react to their dependents health risk is less pronounced in the household level policies.

Appendix A provides further robustness checks and comparisons within the two policy regimes. Figure 6 in the appendix provides evidence that the risk distributions are similar across exogenously determined discount levels and insurance regimes. Figure 7 illustrates a similar upward shift in the lower quantile of the distribution in the pool of uninsured individuals. This means that uninsured individuals on the margin of being insured are more risky than uninsured counterparts not on the margin. At the same time, individuals on the margin of being insured are less risky than those already insured.

Figure 8 reveals that adverse selection in the individual policies mainly comes from selection into the low coverage policy, while there seems to be no selection for the higher coverage policy. Note that this finding is at odds with our hypotheses of finding stronger selection for the higher coverage product. Figure 9 shows that there is a similar pattern in the distributional shift across the household level policies. Furthermore, Figure 10 compares the distributional shift across discounts for the residual and original health risk measures. We find that the presence and magnitude of selection does not depend on the choice of risk measure

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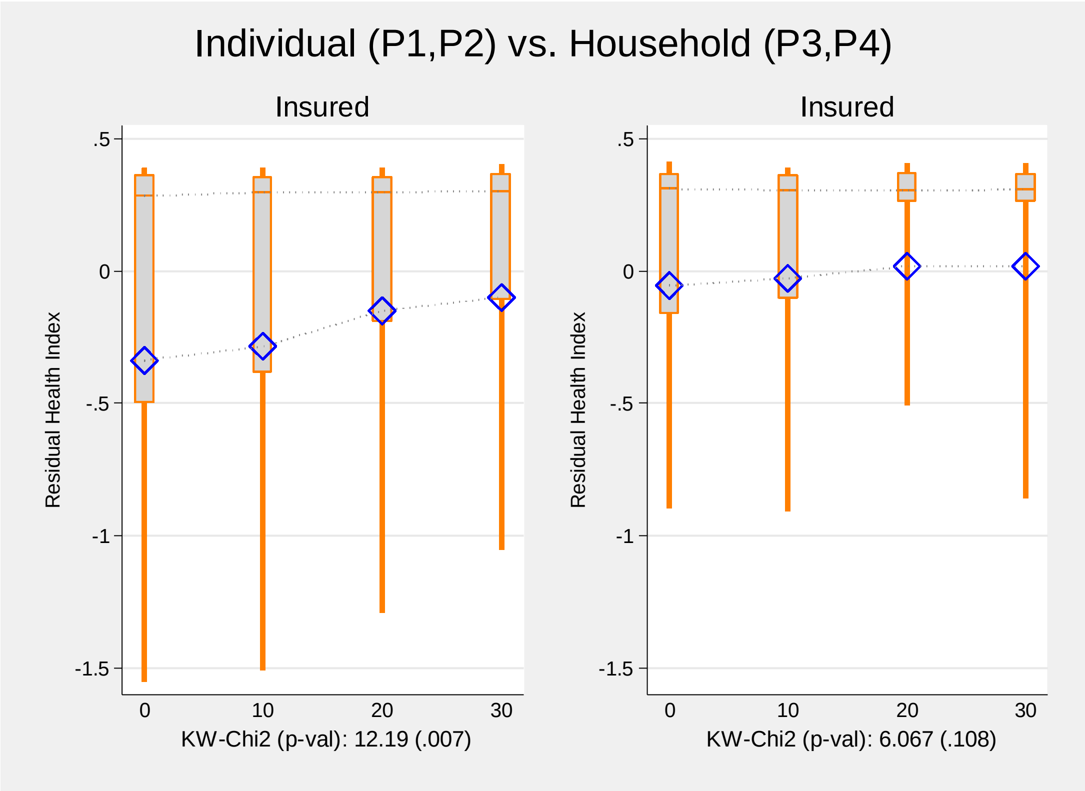
[20] Once the insurance cycle is completed, our implementation partner will share administrative data about claims and their reimbursement. Therefore, we will be able to investigate the insurer's cost curve at a later point in time.

Figure 5 –Shift in Risk Distribution across Policy Regimes



Notes: This figure illustrates shifts in the residual health measure distribution by discount level and policy regime. The box depicts the interquartile range (IQR), the middle line the median and the upper (lower) adjacent line the 90% (10%) quantile, respectively. The diamond indicates mean. The KW-Chi2 (p-val) gives the p-value from a Kruskal Wallis test with H0 that the respective samples come from the same population.

VI. Discussion and Conclusion

This paper provides robust evidence on adverse selection in low-income health insurance markets. We implement a randomized control trial in rural Pakistan that 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 results are based on subjective individual health measures at baseline. This prevents behavioral changes and thus rules out moral hazard effects. Our results suggest that there is substantial adverse selection if health insurance coverage can be assigned individually. In particular, selection becomes worse with higher premium prices, suggesting 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 level. Additional bundling of policies on the level of microfinance groups does not improve the risk pool further – which is not surprising given that policies on the household level already seem to countervail selection.

Comparing individual level policies with different coverage levels, our results seem less intuitive at first glance. Even though insured individuals with high coverage exhibit higher health risk on average, selection does not seem to change across prices. At the same time, the high coverage policy has a higher base premium of PKR 150 per person and faces lower demand. Comparing the demand pattern, the share of dependents insured in the high coverage policy with a discount of PKR 30 (or 20%) is slightly lower than the fraction insured in the standard individual policy with a discount of PKR 10 (10%). At these levels of demand, the risk distribution of the insured seems very similar across policies. Therefore, relative discounts in the high coverage policy might not be large enough to stimulate increases in demand among less risky individuals.

The policy relevance of this analysis hinges on the assumption that worse baseline health indicators translate into higher health costs. In general, one would like to estimate average and marginal cost curves using actual data incurred by the insurance provider. Instead, we show that subjective baseline health measures correlate with the occurrence of inpatient health events measured in a bi-monthly phone survey after insurance uptake. Still, we should interpret these results with caution. Irrespective of the relevance for real costs of insurance providers, we show that rural microfinance clients in Pakistan consider private health information when making insurance decisions. This finding adds to the controversial debate about classical assumptions in the developing country context (Dror and Firth 2014). Further, we show that households' ability to sort high risks into the insurance is limited to selection *within* households. There does not seem to be selection on higher levels, such as the household or the micro-finance group.

If one were to draw a policy recommendation from this research, it would be that offering contracts at the household level (or higher) is preferable to individual level policies in terms of adverse selection. Under these circumstances, even simple pooling contracts 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 microinsurance products. Such organizations might prefer a simple pooling contract to alternative solutions for adverse selection – 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.

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A. Appendix I – Additional Results

Table 6 – Balance Tests (Policies) – Construction of Health Index

	Overall	P1	P2	P3	P4	P-val	Factor Loading
Health Index	0.05	0.06	0.03	0.05	0.06	0.81	
	(0.915)	(0.872)	(0.971)	(0.885)	(0.925)		
Health Step (1-5)	4.76	4.75	4.76	4.75	4.77	0.93	0.7068
	(0.631)	(0.631)	(0.644)	(0.648)	(0.602)		
Outpatient (D)	0.14	0.14	0.15	0.15	0.14	0.87	-0.5794
	(0.351)	(0.348)	(0.355)	(0.353)	(0.346)		
Inpatient (D)	0.02	0.02	0.02	0.01	0.02	0.72	-0.7319
	(0.126)	(0.124)	(0.135)	(0.121)	(0.124)		
Outpatient Cost	356.96	284.12	386.37	325.26	421.67	0.17	-0.4962
	(2304.007)	(1825.368)	(2389.800)	(2134.181)	(2708.974)		
Inpatient Cost	305.72	279.38	378.45	267.65	294.25	0.60	-0.7206
	(3035.742)	(2898.294)	(3441.172)	(2804.362)	(2942.982)		
N	15361	3560	3921	3796	4084		

Notes: The table provides means and standard deviations (in parentheses) of the respective variables. Column 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 (1). Standard errors are clustered at the village level.

Table 7 - Insurance Uptake and Enforcement of Eligibility

	Individual (P1) Dependents	Individual (P1) HH	Individual (P2) Dependents	Individual (P2) HH	Household (P3) Dependents	Household (P3) HH	Household (P4) Dependents	Household (P4) HH
D0	0.166	0.415	0.099	0.299	0.182	0.261	0.190	0.287
	(0.025)	(0.048)	(0.014)	(0.038)	(0.031)	(0.040)	(0.036)	(0.043)
D10	0.302	0.645	0.153	0.410	0.421	0.476	0.309	0.382
	(0.026)	(0.038)	(0.018)	(0.038)	(0.042)	(0.040)	(0.039)	(0.039)
D20	0.343	0.746	0.241	0.522	0.484	0.522	0.438	0.494
	(0.026)	(0.032)	(0.026)	(0.038)	(0.053)	(0.049)	(0.045)	(0.043)
D30	0.385	0.773	0.272	0.658	0.708	0.742	0.683	0.721
	(0.033)	(0.032)	(0.027)	(0.043)	(0.048)	(0.040)	(0.049)	(0.042)
N	2979	847	3210	853	2938	820	3155	870

Notes: OLS regression, standard errors in parentheses are clustered at the level of the village.

Table 8 - Insurance Demand: Individual vs. Household Policies

	Individual (P1,P2)	Household (P3,P4)
Discount	0.007***	0.017***
	(0.001)	(0.001)
Female	-0.080***	-0.011
	(0.012)	(0.011)
Age (0-4)	0.124***	0.071**
	(0.025)	(0.030)
Age (5-9)	0.096***	0.054*
	(0.024)	(0.028)
Age (10-14)	0.072***	0.039
	(0.023)	(0.027)
Age (15-19)	0.068***	-0.000
	(0.019)	(0.023)
Age (30-49)	-0.009	-0.006
	(0.027)	(0.030)
Age (50-59)	0.032	0.107**
	(0.043)	(0.044)
Age (60-69)	0.000	0.023
	(0.041)	(0.041)
Age (70+)	0.011	0.100*
	(0.051)	(0.056)
Low Health	0.170***	0.056
	(0.052)	(0.070)
Medium Health	0.089***	-0.002
	(0.028)	(0.028)
Inpatient	0.157***	-0.133**
	(0.043)	(0.057)
Outpatient	0.062***	0.022
	(0.020)	(0.024)
HH Size	-0.033***	-0.040***
	(0.006)	(0.006)
Income (in 1000 Rs.)	-0.000	0.001
	(0.000)	(0.001)
Saving (in 1000 Rs.)	0.000	0.000
	(0.000)	(0.000)
Land Quintile	0.004	-0.007
	(0.006)	(0.009)
Head Female	-0.026	-0.149***
	(0.026)	(0.040)
No Education	-0.008	-0.035
	(0.016)	(0.024)
High Education	-0.011	-0.006
	(0.020)	(0.024)
Constant	0.347***	0.634***
	(0.062)	(0.077)
N	6191	6095
r2	0.10	0.20

Notes: Point estimates result from OLS regression with standard errors clustered at the village level. Variables below the dash are HH level variables.

Table 9 - Validity of the Ex-Ante Risk Measure

	Inpatient (0,1)	Inpatient (0,1)	Inpatient (0,1)	Inpatient (0,1)
Health Index	-0.017***		-0.017***	
	(0.003)		(0.003)	
Res. Health Index		-0.017***		-0.017***
		(0.003)		(0.003)
HH Size			-0.001	-0.001**
			(0.001)	(0.001)
Income (in 1000 Rs.)			0.000*	0.000*
			(0.000)	(0.000)
Saving (in 1000 Rs.)			-0.000**	-0.000**
			(0.000)	(0.000)
Land Quintile			-0.000	-0.000
			(0.001)	(0.001)
Head Female			-0.004	-0.003
			(0.003)	(0.003)
No Education			0.002	0.007**
			(0.003)	(0.003)
High Education			-0.002	-0.001
			(0.003)	(0.003)
High Risk Aversion			-0.005*	-0.004*
			(0.002)	(0.002)
Constant	0.016***	0.015***	0.028***	0.027***
	(0.001)	(0.001)	(0.007)	(0.007)
N	12284	12284	12284	12284
r2	0.02	0.02	0.02	0.02

Notes: OLS regression of an individual level indicator for any inpatient case reported in the follow-up period on the ex-ante measure of riskiness. The standard errors in parentheses are clustered at the village level.
*** p<0.01, ** p<0.05, * p<0.1.

Table 10 - Positive Correlation Test: Components

	Individual (P1)	Individual High (P2)	Household (P3)	Group (P4)
Health Step	-0.149***	-0.164***	-0.020	0.007
	(0.039)	(0.043)	(0.036)	(0.035)
Constant	4.804***	4.790***	4.748***	4.763***
	(0.022)	(0.018)	(0.028)	(0.026)
Inpatient	0.017***	0.022***	-0.002	-0.006
	(0.006)	(0.008)	(0.005)	(0.005)
Constant	0.011***	0.014***	0.016***	0.018***
	(0.002)	(0.003)	(0.004)	(0.003)
Outpatient	0.074***	0.096***	0.036**	0.010
	(0.015)	(0.022)	(0.016)	(0.019)
Constant	0.120***	0.128***	0.129***	0.137***
	(0.010)	(0.010)	(0.012)	(0.010)
Health Exp. (Inp.)	388.079***	665.890***	-75.875	-182.880*
	(143.102)	(220.006)	(111.288)	(104.896)
Constant	168.367***	224.354***	304.224***	370.504***
	(43.652)	(49.197)	(80.570)	(84.832)
Health Exp. (Out.)	260.311**	311.845**	96.896	266.800*
	(109.475)	(144.838)	(80.352)	(140.427)
Constant	213.985***	358.885***	294.899***	334.681***
	(32.109)	(53.044)	(62.583)	(62.045)
N	2981	3210	2937	3158

Notes: Each panel represent an OLS regression of the respective health indicator (reported in the first row) on a binary insurance status indicator. Standard errors reported in parentheses are clustered at the village level.
*** p<0.01, ** p<0.05, * p<0.1.

Table 11 - Positive Correlation Test

	Individual (P1,P2)	Individual (P1,P2)	Household (P3,P4)	Household (P3,P4)
Insured	-0.253***	-0.265***	-0.014	-0.006
	(0.041)	(0.040)	(0.032)	(0.031)
HH Size		-0.001		0.017***
		(0.006)		(0.006)
Income (in 1000 Rs.)		0.000		0.002***
		(0.001)		(0.001)
Saving (in 1000 Rs.)		0.000		-0.000
		(0.001)		(0.001)
Land Quintile		-0.006		-0.020*
		(0.010)		(0.011)
Head Female		0.021		-0.040
		(0.037)		(0.041)
No Education		-0.329***		-0.237***
		(0.046)		(0.041)
High Education		-0.075*		-0.001
		(0.038)		(0.034)
High Risk Aversion		-0.017		-0.038
		(0.030)		(0.027)
Constant	0.109***	0.179**	0.056***	0.069
	(0.014)	(0.087)	(0.021)	(0.098)
N	6190	6190	6094	6094
r2	0.01	0.03	0.00	0.02

Notes: OLS regression of the health risk index on insurance status and control variables. Standard errors are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1.

Table 12 Residual Health Risk Indicator

	Health Index
Income (in 1000 Rs.)	0.001**
	(0.001)
Saving (in 1000 Rs.)	0.000
	(0.000)
Land Quintile	-0.014*
	(0.007)
Client Female	-0.014
	(0.025)
Client has no education	0.079***
	(0.022)
Constant	0.003
	(0.027)
N	12271
r2	0.00

Notes: OLS regression of the health risk index on potential confounders. Standard errors are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 6 - Distribution of Risk across Discounts and Policy Regime

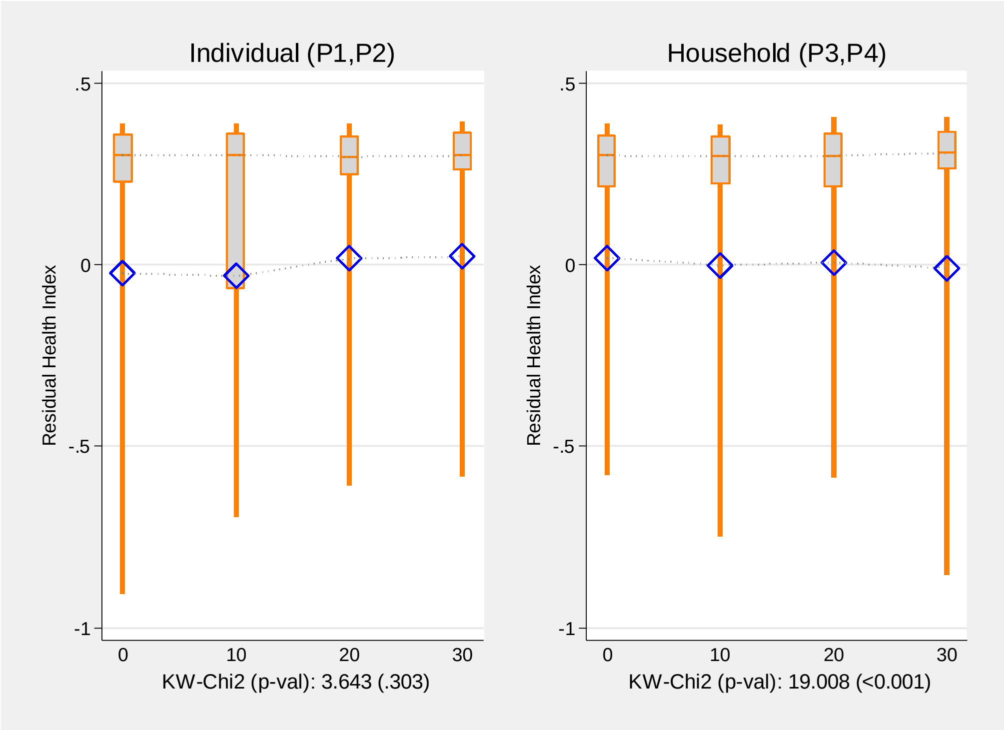
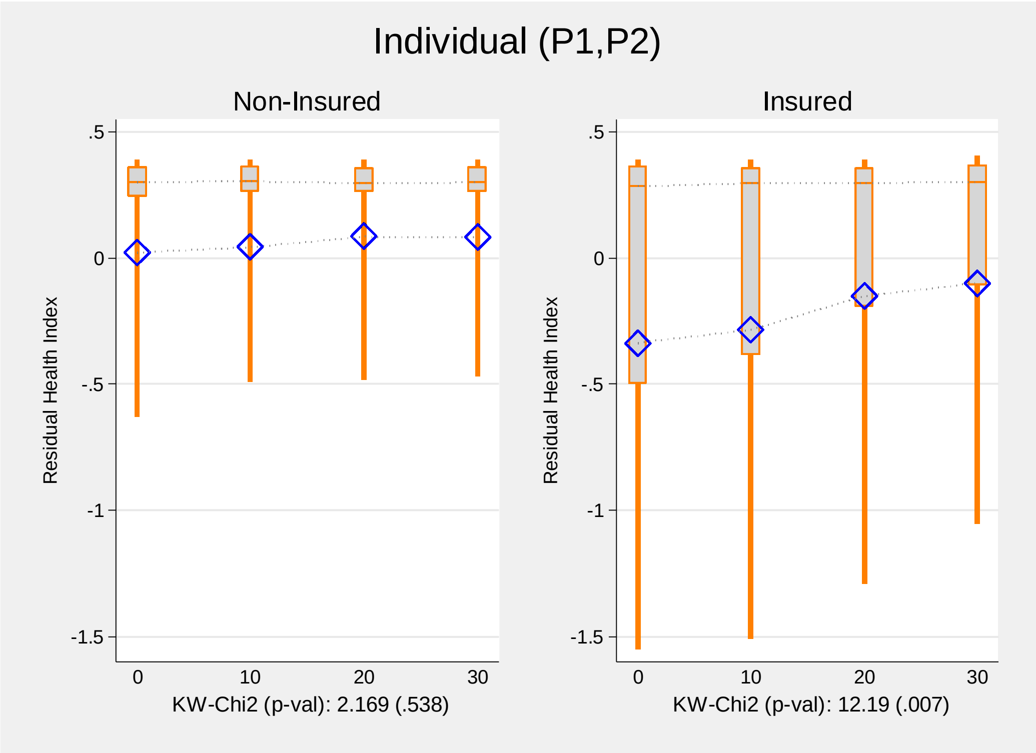


Figure 7 - Change in Risk Distribution across Discounts



Notes: This figure illustrates shifts in the residual health measure 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. The KW-Chi2 (p-val) gives the p-value from a Kruskal Wallis test with H0 of the respective samples coming from the same population.

Figure 8 - Comparison across Policies (Individual Policies)

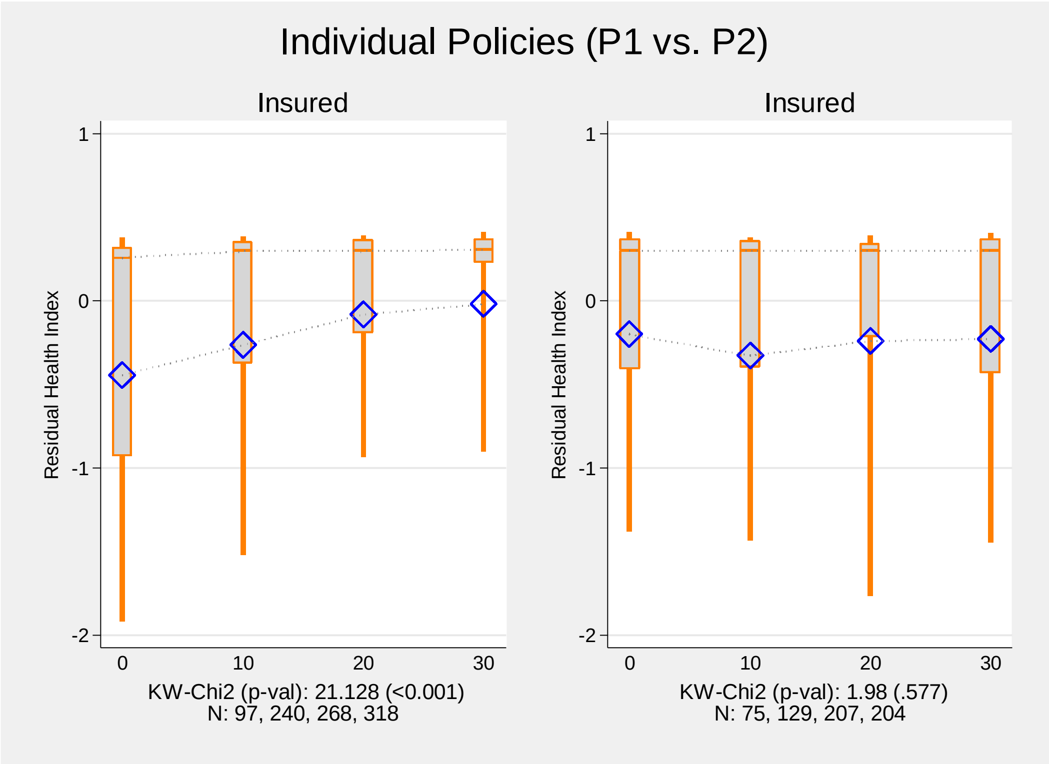
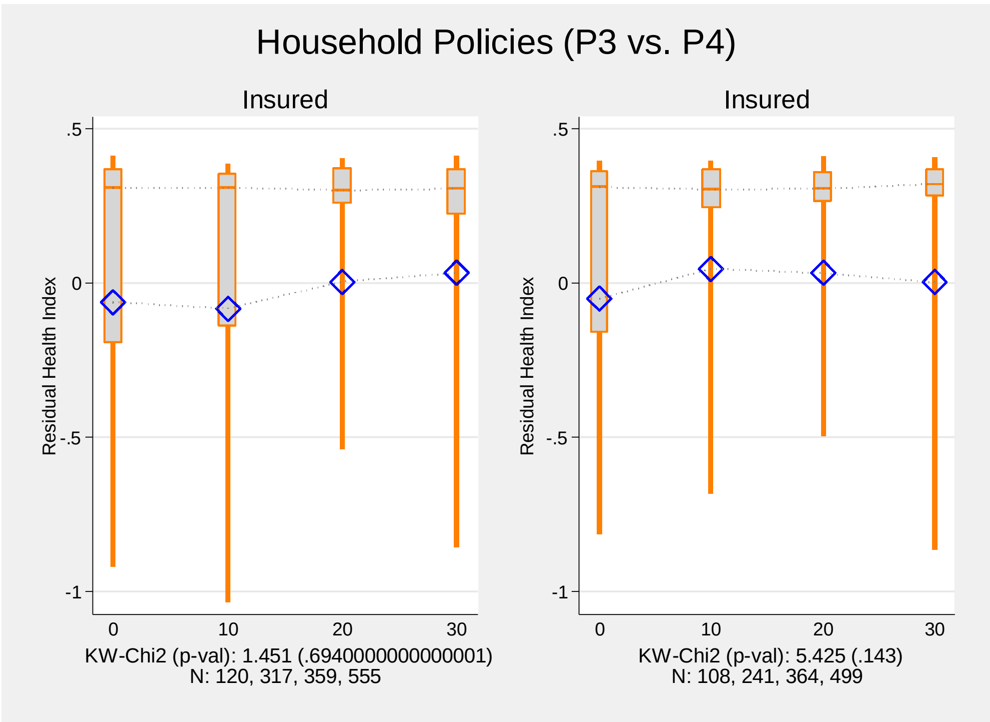
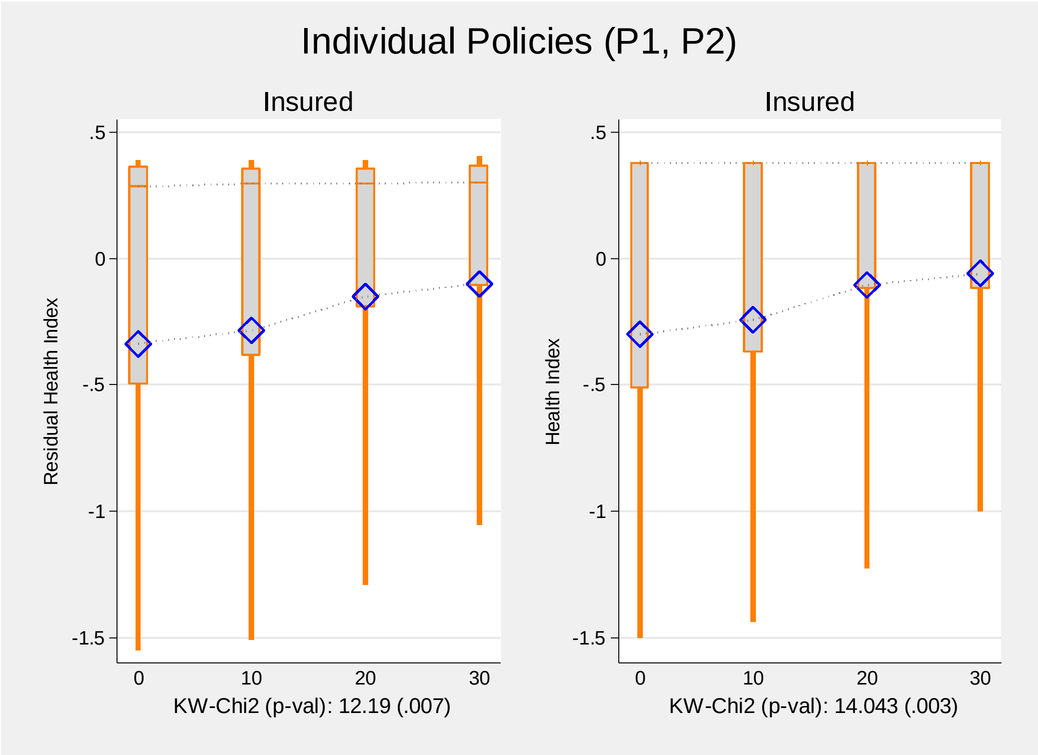


Figure 9 - Comparison across Policies (Household Policies)



Notes: This figure illustrates shifts in the residual health measure 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. The KW-Chi2 (p-val) gives the p-value from a Kruskal Wallis test with H0 of the respective samples coming from the same population.

Figure 10 - Comparison of Risk Measures



Notes: This figure illustrates shifts in the residual health measure 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. The KW-Chi2 (p-val) gives the p-value from a Kruskal Wallis test with H0 of the respective samples coming from the same population.