Health Insurance Preferences for Outpatient Care – A Discrete Choice Experiment in Pakistan[⊥]

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Abstract

State-funded health insurance schemes are increasingly implemented in the Global South, but utilization and acceptance often remains lower than desired for Universal Health Coverage. Including features that address the beneficiary population's preferences could improve this. We conducted a Discrete Choice Experiment to elicit preferences for a new public outpatient health insurance for low-income households in Pakistan at scheme design stage. We included five attributes that reflected the dimensions of real policy trade-offs during scheme design: healthcare providers, services, health conditions, coverage amount and premium. The main effects reveal relevance of all attributes and strong preferences for including higher-level healthcare providers as well as telemedicine and for covering chronic disease needs. We see suggestive evidence that even in a setting with low insurance literacy, choices regarding which health conditions to cover were made to maximise benefits along known, pre-existing health complaints and risk-factors. We do not detect substantial heterogeneity in preferences across socio-demographic strata, respondent and household health status, indicating rather homogenous preferences.

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1 Introduction

A strong primary health care system is crucial for progressing towards Universal Health Coverage (UHC) and the Sustainable Development Goals (Hanson et al., 2022; The World Bank, 2021). On this path, many governments in Low- and Middle-Income Countries (LMIC) have introduced state-funded health insurance programs, which are now increasingly being expanded to also cover outpatient department (OPD) services (Das & Do, 2023; Reich et al., 2016) . However, acceptance and utilization levels of those schemes often remain below levels needed to achieve Universal Health Coverage. One potential reason is the inability of schemes to effectively cater to the beneficiary population's needs and preferences. A limiting factor to address this barrier is the limited empirical evidence regarding health insurance preferences of such low-income population groups, especially the very poor, who have had little exposure to other insurance products. Typically, there is little or no revealed preference data available for populations without previous access to health insurance. If revealed preference data is not available, one can resort to stated preference data, which is growing but also remains rather scarce.

In this paper, we study health insurance preferences for a new OPD health insurance scheme of a low-income population with low insurance literacy in Khyber Pakhtunkhwa (KP), Pakistan. We first seek to answer the question which insurance elements are important for the population. Then, we seek to explore whether the inferred preferences reflect the household's observable health risk profiles, i.e. whether choices are made to maximize benefits along known, pre-existing self-reported health complaints. Finally, we want to answer whether different population groups value insurance elements differently and thereby shed some light on the potential for one homogeneous insurance package rather than more tailored solutions for different population groups.

At the time of our study, the government of KP was about to launch a new OPD health insurance scheme for the lowest wealth quintile of the population in selected pilot districts. To shed light on insurance preferences in that setting, we conducted a discrete choice experiment (DCE) with 359 respondents in four districts in KP to elicit preferences for hypothetical OPD insurance plans that contain real policy tradeoffs. Within our experiment, we asked respondents to make nine choices between two hypothetical OPD insurance plans and an opt-out option. The plans comprised five different attributes which were selected in a careful process including literature review and stakeholder consultations: providers covered, health conditions covered, services covered, annual coverage amount, and yearly premium. Each attribute could take on three different levels. We used a mixed logit model to estimate the preferences for the OPD insurance. To examine heterogeneities in preferences we draw on rich data from our household survey which contains detailed information on household health and recent health care utilization patterns (see Shaukat et al., 2024).

We find that almost all included insurance attributes and their respective levels significantly influence the respondents' choices. Regarding health conditions, respondents prefer chronic disease coverage over including infectious diseases or pre- and postnatal care. Furthermore, respondents strongly prefer to have higher-level facilities covered compared to only primary care providers. They also value telemedicine to be included on top. Concerning services, we find a positive, yet not statistically significant preference for covering medication expenditures compared to only diagnostic tests and fees. The preference for additionally paying for transportation costs is rather strong.

Our results suggest that the inferred preferences for the OPD insurance at least partly reflect the household's observable self-reported health problems and risks. For the health conditions attribute, we find a significantly higher preference for including chronic diseases if the family recently had more healthcare visits related to chronic diseases. Besides, we find female respondents to value the coverage of pre- and postnatal care less than male respondents but do not find significant differences in preferences for different gender compositions of the household. For the provider and services attributes, we find only light evidence that preferences are driven by the explored health risk factors. Differences in preferences are mainly statistically insignificant.

We find almost no significant and economically meaningful differences in preferences for the hypothetical insurance attributes in terms of socio-demographics, location, and respondent as well as household health status. We do detect some significant but unsystematic preference heterogeneity in terms of location. Therefore, we would expect a rather homogeneous acceptance of a new OPD insurance scheme which offers the same benefits for all among the beneficiary population.

Empirical evidence on the population's stated health insurance preferences in LMICs is still rather scarce. Previous studies report population preferences mainly for micro health insurance (e.g. Abiiro et al. 2014; Wakamatsu, Fukui, and Miwa 2019), or community-based health insurance (e.g. Sydavong et al. 2019; Ozawa et al. 2016), but less so for the newly emerging national schemes (e.g. Kalyango, Kananura, and Kiracho 2021 for Uganda). We hence add to the literature by providing evidence on population preferences for a public insurance scheme and are – to the best of our knowledge – the first study to examine insurance preferences for OPD services in particular. Furthermore, little is known about the health needs of low-income populations and empirical evidence on their insurance preferences is particularly scarce. Our study hence contributes to the literature by providing evidence on insurance preferences of households in a low-income country (Pakistan) from the lowest income segment (among poorest 21%) with low levels of health and insurance literacy.

In a broader sense, our study also relates to the literature on adverse selection in low-income health insurance markets (e.g. Banerjee et al., 2014; Eling et al., 2017; Fischer et al., 2018; Kinnan et al., 2020; Yao et al., 2017). Similarly to Vroomen & Zweifel (2011), we presume that preferences for insurance attributes depend on health risks, more specifically we expect respondents to prefer the insurance plan that cover their household's known health risks more than other plans. Vroomen & Zweifel (2011) provide evidence from two DCEs in the Netherlands and Germany and find that individuals suffering from chronic diseases value attributes of health insurance differently from other individuals. Such evidence from LMICs is scarce: studies from Malawi (Abiiro et al., 2016) and Cambodia (Wakamatsu et al., 2019) detect significant heterogeneity in preferences for health insurance along the lines of recent health care seeking behaviour. Abiiro et al. (2016) find coverage of transportation costs to be particularly attractive to those who reported recent health-related out-of-pocket expenditures. They also detect signs for adverse selection effects into the market for health insurance as this group expressed a preference for covering only individuals (presumably those at higher risk) instead of the whole family as unit of enrolment. Similarly, in their latent class analysis, Wakamatsu et al. (2019) find that only the group with more reported recent illnesses exhibits a significant willingness to pay for any of the insurance attributes in their DCE. We extend this literature by testing a comprehensive set of attribute-specific risks.

Furthermore, our study contributes to the DCE literature that explores heterogeneities for health insurance preferences in LMICs. Similar to other studies, with our heterogeneity analysis we investigate which groups can be expected to be more or less accepting of different insurance features (Abiiro et al., 2016; Wakamatsu et al., 2019) and account for the beneficiary population's diversity (Kalyango et al., 2021; Kamara et al., 2018).

Our DCE results directly informed the policy makers in KP, Pakistan, such that population preferences could be taken into account in the design phase of a new pilot OPD health insurance scheme.

The rest of the paper is structured as follows. Section 2 describes the study setting, DCE design and methods used for analysis. Section 3 presents the results regarding the insurance preferences including heterogeneities. Section 4 discusses results and limitations of this study and concludes.

2 Design and method

2.1 Policy background and study setting

The Pakistani health care system consists of several levels of care in public and private ownership (Hassan et al., 2017; WHO, 2018). Despite the extensive network of public primary facilities, most outpatient treatment is delivered by the more costly private providers (Hassan et al., 2017). Currently, out-of-pocket expenditure compose the majority of Pakistani health care financing, out of which the largest component is related to OPD treatment (60% of health costs) (Khalid et al., 2021; Pakistan Bureau of Statistics, 2018). As the majority of the population does not have insurance covering OPD services, adequate OPD health care is frequently unattainable especially for the poor population (Kurji et al., 2016).

Our study is set in Khyber Pakhtunkhwa (KP), a province in the North of Pakistan. The province introduced an inpatient insurance scheme in 2015 and pursued a rollout that started with the poorest quintile of the population and later expanded coverage to the whole province (GIZ, 2017). We fielded our DCE among households from the lowest wealth quintile of the population in four districts in KP in early 2022 (for more details see section 2.4). These districts were purposefully selected to be pilot recipients of a new public health insurance scheme covering outpatient care, which was not yet launched or announced at the time of data collection. The DCE was fielded directly after a broader household survey on health needs and previous health care experiences. We collected information on recent health care visits for inpatient care (within past year) as well as outpatient care (within past month) and also inquired about neglected health needs. For the most recent health care visits, we also elicited the respective expenditures. We are hence in the position to draw upon rich data for our heterogeneity analyses. For instance, we see that despite the hospitalization insurance scheme, out-of-pocket expenditures for health remain high and especially high-frequency expenditures for outpatient care pose a substantial financial burden for low-income households.

2.2 Discrete choice experiment

We employed a discrete choice experiment, which is a stated-preference elicitation method, often used when revealed preferences are unavailable or unfeasible to elicit for various reasons (Mangham et al., 2009; Watson et al., 2019). DCEs are widely and increasingly applied in health care preference research (Clark et al., 2014; Soekhai et al., 2019; Wang et al., 2021). DCEs present respondents to a series of hypothetical choices with varying attributes and allow for inference on the underlying preferences from the choices observed (Lancsar & Louviere, 2008).

2.2.1 Attribute and levels

To define the attributes and levels of the hypothetical OPD insurance, we pursued a sequential approach in defining and refining the attributes and levels. Note that the chosen attributes and levels represented real trade-offs that were under consideration for the planned pilot OPD insurance scheme. Following usual DCE protocols, our attribute selection was based on a review of literature, followed by consultations with local public health experts and important policy stakeholders (Lancsar & Louviere, 2008; Mangham et al., 2009).

First, we conducted a literature review in September and October 2021, where we reviewed related studies published between 2010 and 2021 that were either DCEs on health insurance in a LMIC or provided other evidence on health insurance preferences in Pakistan and neighboring countries (appendix A1). From this review, we selected frequently occurring attributes (appendix A2) which were applicable to our study context:, healthcare provider choices, services, health conditions covered, annual insurance premium, and the annual coverage amount. Additionally, we identified possible levels for the aforementioned attributes from specific literature on the Pakistani context (e.g., Dror et al.,2007; Khalid et al., 2021; Jahangeer & Ul Haq,2015), which were then validated by local health experts. Next, in late October 2021, we had two stakeholder consultation sessions via video call: one with two representatives of the implementing provincial health department unit (Social Health Protection Initiative) and one with an employee of the commissioned consulting firm contracted to design and implement the new OPD insurance scheme. Prior to the consultation, we provided the stakeholders with information on the five selected attributes and a range of possible levels and asked them for their judgment. The stakeholders confirmed the selected attributes to be relevant and of interest in this context without the need for addition or replacement of one dimension. Furthermore, four attributes were designed with additive levels, while the conditions attribute remained non-additive, to match the policy trade-offs communicated by the stakeholders. To avoid a potential bias due to a different number of levels per attribute (Kjaer, 2005) , we set three levels for each attribute. The levels displayed in Table 1 were selected to be the most relevant trade-offs that were under consideration for the scheme design. In addition, we display the hypothesized direction based on prior evidence. See appendix A4 for the complete attribute and level description as it was presented to the respondent.

Table 1: Final Selection of Attributes and Levels

Attribute	**Description**	**Level**	**Modeling**	**Hypoth. Direction**
1. Premium	Premium to be paid per family member per year.	1) 50 PKR / person /year 2) 100 / person /year 3) 500 / person /year	Continuous	-
2. Provider	Coverage of the outpatient health expenses in the following type of health facilities.	1) Primary 2) Primary + secondary + tertiary 3) Primary + secondary + tertiary + telemedicine	Categorical	(base) ++ +
3. Health conditions	Coverage of the outpatient health expenses for the following health conditions/diseases.	1) Chronic 2) Pre- and postnatal care 3) Infectious	Categorical	(base) - -
4. Services	Coverage of the outpatient health expenses for the following services.	1) Doctor’s fee and diagnostic tests 2) Doctor’s fee and diagnostic tests + medication 3) Doctor’s fee and diagnostic tests + medication + transportation	Categorical	(base) ++ +
5. Amount	Coverage of the outpatient health expenses up to the following annual amount per family.	1) 100,000 PKR / family / year 2) 150,000 PKR / family / year 3) 250,000 PKR / family / year	Continuous	+

2.2.2 Hypothetical insurance packages

From these attributes, we constructed hypothetical insurance packages using a Bayesian d-efficient[1] design in the Ngene software. We conducted three pilot rounds in order to test and, in an iterative process, refine the experimental design and supportive materials. The pilots were conducted among 42 respondents with similar characteristics as the target population, but selected from villages that did not form part of the main study. One purpose of piloting was to elicit priors. In the first round, we followed the convention of assuming zero priors to construct the design (De Bekker-Grob et al., 2012; Pérez-Troncoso, 2020), and used the prior information from the pilots for the final design. Our design encompassed nine unblocked choices, mirroring the approximate average number of choices found in our literature review and the trade-off between sample size requirements and respondent burden (Hensher et al., 2015). We used main effects modeling and reached a d-error of around 0.010[2]. Since we are interested in attribute preferences only and not two different schemes per se, we used an unlabeled (or generic) design (Hensher et al., 2015). To avoid biased estimates through forced choices (Lancsar & Louviere, 2008), we added an opt-out alternative, framed as choosing

[1] A d-efficient design is a frequently-used approach to obtain efficient estimates while reducing the number of choices (Pfarr et al., 2014).
[2] In general, a lower d-error indicates a more efficient design. However, there is no cutoff on what a ‘good’ d-error is as this varies by the design properties (Hensher et al., 2015).

“neither of the plans”, as a third alternative. Adding a status quo option was not possible as there was no current state funded outpatient insurance in place. Moreover, to test internal consistency, in the first pilot round we included a dominant choice-set in which one alternative was explicitly better than the other in terms of all attribute levels (Hensher et al., 2015). This dominance test was passed by more than 80% of the respondents, which we interpret as a positive sign that the majority of respondents understood the DCE and made a ‘rational’ choice. We only implemented the dominance test in the first pilot round.

We address hypothetical bias as it is recommended for DCEs (Haghani et al., 2021), and particularly relevant for our context as all respondents had no previous experience with OPD insurance. We implemented a consequentiality script, stressing the importance of making realistic choices[3] and further added an opt-out option as well as a follow-up question in case of serial non-participation. A reminder of the consequentiality and the opt-out alternative was placed in the middle of our experiment to increase salience of this information.

To familiarize respondents with the choice task and avoiding invalid first responses (Kjaer, 2005), we initiated the DCE with an informative introduction (see appendix A5) and a practice choice. To further facilitate understanding of the study population with limited insurance exposure and little or no formal education, we used visual aids that depicted the different hypothetical insurance packages (example in appendix A3). Moreover, as the concept of level of care for the providers covered[4] may be difficult to comprehend, we added local (district-specific) facility names and pictures as examples for the levels in the provider attribute.

2.3 Model and estimation strategy

2.3.1 Main effects

As it is standard in DCE literature, we analyzed the DCE responses based on the specification of a random utility maximization model. More specifically, for the approximation of preferences for the attributes of the OPD insurance, we employed a mixed logit model. The mixed logit model is an extension of the conditional logit model, which is the basic analytical model frequently used in stated preference experiments (e.g. Ozawa et al. 2016; Abiiro et al. 2014; Eshetu and Seyoum 2019). The mixed logit model partially loosens some of the assumptions of the conditional logit model, making it more flexible. Importantly, while the conditional logit restricts variation in preferences to be independent across the sequence of choices, the mixed logit model allows the attribute preferences to be random and vary across individuals. The mixed logit is hence the appropriate model for a discrete choice experiment where the same respondents make repeated choices, which induces correlation between answers (de Bresser

[3] We asked respondents to choose the option which they would prefer in real life and told them that this was important to the success of our research and that, ultimately, their honest answers would help to improve the health situation of the people in their province (see appendix A5 for exact wording).
[4] We distinguished between primary, secondary, and tertiary care providers.

et al., 2022). For example, a respondent might prefer covering medication costs in all insurance plans where this attribute level is offered, while another might have a strong preference for coverage of chronic diseases.

Formally, individual i's utility associated with alternative j in the choice situation s is given by:

Equation 1

$$U_{ijs} = \alpha_i \cdot p_{ijs} + \beta_i{}' X_{ijs} + \varepsilon_{ijs}\ ;\ \ j = 1,2,3; \quad s = 1,2,\dots,9$$

Here p_{ijs} is the yearly premium per family member, our price attribute, with the associated preference parameter α_i ; X_{ijs} is a vector of the other relevant attributes of the OPD insurance plan j, β_i is a vector of preference parameters for attributes other than premium, and error ε_{ijs} is assumed to follow a type 1 extreme value distribution. To account for left-right reading bias, we include alternative-specific constant among X_{ijs} in our main model (Ryan et al., 2018).

As preferences are easier to interpret when expressed in monetary terms, we are particularly interested in the Willingness To Pay (WTP) estimates of our model. For this purpose, we included costs (premium) to be one of our health insurance attributes j and computed the marginal WTPs. Marginal WTPs are obtained by computing the marginal rate of substitution between the attribute of interest and the premium attribute by dividing the coefficient of interest by the coefficient of the cost attribute (Lancsar et al., 2017; Ryan et al., 2008). There are two common approaches for estimating marginal WTP in mixed logit models: estimation in preference space and estimation in WTP space. For our main analysis, we use the latter, imposing assumptions on the distributions of WTP directly and deriving the distributions of the coefficients in a next step (Hole & Kolstad, 2012; Train & Weeks, 2005). We opted for estimation in WTP space as this approach yields a better model fit in our data and to avoid too large standard deviations which are often observed when estimating in preference space (Hole & Kolstad, 2012). As robustness check, we additionally report the results of the generally equivalent, but practically different estimation in preference space in the appendix, where one specifies the distributions of the coefficients in the utility function and derives the WTP as ratio of two coefficients, thereby deriving the distribution of WTP (Hole & Kolstad, 2012).

We reformulate Equation 1 as:

$$U_{ijs} = -\alpha_i\left(-p_{ijs} + \gamma_i{}' X_{ijs}\right) + \varepsilon_{ijs}$$

Where $\gamma_i = \frac{\beta_i}{\alpha_i}$ contains the WTPs for all attributes except monthly per person premium and $-\alpha_i$ is assumed to follow a log-normal distributions, meaning preferences for premium are restricted to be negative.

As further robustness checks, we compare the estimation results of the mixed logit to the ones of a conditional and a nested logit model. We test the conditional logit model because it is the basic approach for analysis of DCE data (but restricted by relatively strong assumptions e.g. homogeneity of preferences) and we test the nested logit model because due to the opt-out option, we have two “nests” of choices: choosing one of the two insurance plans versus choosing neither of them (which is very different to choosing one of the presented plans).

We conducted all analysis in Stata 16. For estimation of the mixed logit model we used the mixlogit-command and for estimating the mixed logit model in WTP space we use the mixlogitwtp-command.

2.3.2 Preference heterogeneities

Beyond the main effects, we analyzed heterogeneities in preferences. The detailed household survey in which our DCE was embedded offers a wide range of individual, household characteristics, and covariates on individual health needs.

To explore preference heterogeneities, we followed de Bresser et al.(2022)’s approach and combined mixing distribution and observed choices to approximate preferences for each individual. In order to obtain a single taste coefficient per attribute-level by individual, we conditioned the mixing distribution on the choices made by a specific individual and approximated individual-specific preferences by the means of these posterior distributions. To explore heterogeneities, we then analysed how preferences vary with observed characteristics using simple linear regressions. (For more details, see de Bresser et al., 2022) Our simple estimation strategy is formally given by:

Equation 2

$$Y_i = \gamma_0 + \gamma_j{}' X_{ij} + \varepsilon_i \;\; ; i = 1, \ldots, n$$

Here, Y_i is the individual specific preference for an attribute level of individual i, γ_j is a vector of coefficients, X_{ij} is a vector of j individual and household characteristics, and ε_i the error term.

In Stata 16, we used the mixlbeta command to store the individual posteriors.

In a first step, we developed twelve hypotheses related to specific attribute levels to check whether choices are made to maximize benefits from the hypothetical insurance along known, pre-existing health complaints and attribute-specific health risk factors (see Table 2). For this, we regressed specific health complaints and risk factors (from our household survey) on the preference for including the corresponding benefit in the insurance package.

We hypothesized that respondents from families which recently experienced cases of chronic (infectious) diseases would have a higher preference for chronic (infectious) diseases to be covered by the OPD insurance benefit package, as they might deem it more likely that their family would again experience such cases in the future. (Hypothesis 1+2) Furthermore, we hypothesized that households with (more) females, especially in reproductive age, would value including pre- and postnatal care differently. In Pakistan, there are already state as well as NGO provided services in place where women can seek pre- and postnatal care free of costs. Therefore, we expected female respondents and male respondents with many females in their family to value the inclusion of these services (which are already provided for free) in a hypothetical insurance plan less. (Hypothesis 3) Besides, we hypothesized that families that recently incurred high costs for OPD care at higher level facilities would have a larger preference for them to be included in the insurance plan. (Hypothesis 4) We further hypothesized that telemedicine services would be preferred by those who have more issues in accessing in-person care and who would hence benefit more from the relief of access barrier via telemedicine. (Hypothesis 6) Similarly, we hypothesized those with worse access and hence higher costs to reach health care to prefer the coverage of transportation costs. (Hypothesis 9) Also, we hypothesized that the possession of a smartphone would facilitate access and younger respondents / families to have less fear of contact with new technology and therefore be more likely to prefer the inclusion of telemedicine to the benefit package. (Hypothesis 5) Regarding services included in the hypothetical insurance plan, we hypothesized that families who recently incurred high costs for a certain service would prefer this to be included as the financial shock experienced would still be more salient. (Hypothesis 7, 8, 10, 12) Besides, we hypothesized families with repeated OPD visits in the past month as well as with chronic patients who usually require regular care would have a higher preference for the OPD insurance to cover costs for medication and transport as these are the costs occurring repeatedly. (Hypothesis 11)

Table 2 Twelve hypotheses on health risks and insurance preferences

#	**Hypothesis**
1	Chronic diseases in family associated with preference for including chronic diseases.
2	Recent occurrence of infectious diseases in family associated with preference for including infectious diseases.
3	Gender composition of household influences preference for including pre- and postnatal care and family planning.
4	Families who spend more on higher-level care facilities have a larger preference to include them in insurance plan.
5	Younger people and families with smartphone are more open to telemedicine usage.
6	Telemedicine is preferred by families with higher transportation need (for whom it is harder to access in person care).

7	Recent occurrence of high medication costs within family associated with preference for including medication coverage.
8	People with high diagnostic costs during recent health care visits are already more content with the base level (that covers that) and have smaller preference for including medication on top.
9	Transport coverage is more preferred by families with higher transportation need (for whom it is harder to access in person care)
10	Recent occurrence of high costs for medication and/or transport within family associated with preference for including medication and transportation coverage.
11	Chronic diseases in family and repeated OPD visits within past month associated with preference for including medication and transport coverage (as these are costs that occur repeatedly).
12	People with high diagnostic costs during recent health care visits are already more content with the base level (that covers that) and have smaller preference for including more services.

In a second step, in a series of multivariate regressions, we estimated heterogeneities in preferences along characteristics that are commonly used in the literature, namely gender of respondent, respondent's education (dummy whether s/he has at least primary education), socio-economic status (wealth quintile from asset index), household size, and location (district). We furthermore included covariates that indicate a generally higher risk for a health need of the respondent or in the household.

2.4 Sampling and data collection

The sample comprises respondents who were randomly drawn from the population of low-income households in the four districts Mardan, Malakand, Kohat and Chitral in the KP province. The DCE respondents were drawn as a subset of a larger sample of households that completed a survey on health care needs (see appendix A6 for details). The sampling frame was the list of households in the poorest income quintile as recorded in the beneficiary registry of the BISP program[5] that is commonly used for poverty targeting. Respondents were drawn in three stages: First, we determined union councils (UCs) that were accessible to our enumerators and randomly selected four UCs within each district. Within the UCs, we identified villages that had more than 40 poor households and were within a one-hour radius to the closest rural health center. Finally, the DCEs were conducted with 395 respondents and we used DCE responses of 359 respondents for our analysis[6].

Data collection was semi-digitalized: the choice sets were presented to the respondents on laminated sheets, the instructions were read from and choices were recorded on enumerator-

[5] Note that the poverty classification was conducted in 2010 and hence includes only households that were below the poverty line, and no new households that formed later. We opted to use this dataset nevertheless as it is also expected to be used by the program at implementation stage.
[6] Exclusions (36) due to quality concerns.

administered tablets using ODK collect. Data collection took place from January until March 2022 and interviews were conducted by trained local staff. The interviewers were graduates and students of a local medical university who were extensively trained in the survey tool.

3 Results

3.1 Sample characteristics

As displayed in Table 3, the 359 respondents were in most cases those persons who can take decisions related to money in the household. They were on average slightly over 50 years old, to a higher proportion male and only 31% had any formal primary education. They lived in households with on average six members and the average monthly household expenditure highlights the poverty status of the households as this means around 1€ per day and household member.

Table 3 Sample characteristics (household and respondent level)

	Mean	SD	Min	Max	N
Number of hh members	6.21	2.38	1	18	359
Average monthly household expenditure in PKR[7]	35,955.79	16,858.62	1,500	120,400	350
Age of respondent	50.46	14.10	16	86	359
Respondent female	0.27	0.44	0	1	359
Respondent educated (at least primary education)	0.31	0.46	0	1	359
Respondent is money decision-maker[8]	0.82	0.39	0	1	359

3.2 Choice responses

In total 9,438 choices were included in analysis. See Supplementary Tables

Table A 1 for the distribution of choices among plan A, B and the neither option. The alternative plans were chosen with very similar frequencies and in only 2.5% of the choice situations, respondents opted to choose neither. Around half of the opt-out choices stem from respondents that selected this alternative for the majority of their choices. The follow-up question, however, indicates that these were valid responses (as opposed to serial non-participation), as unattractiveness of the alternatives or inability to pay for a premium were stated as justifications. In only 9 situations, the respondent could not decide for one of the three and chose “don’t know”, this choice is then excluded from the analysis.

[7] Respondents were asked how much their household usually spends monthly on the following items: electricity, fuel, house rent, food, guests, children, books, clothing, travelling (within town), milk, amount of instalments, health related expenses. Item expenditures were summed up and top-coded at the 90th percentile.

[8] Respondents were asked whether they are responsible for decisions about money in their household.

3.3 Mixed logit estimates

In Table 4 we report the estimates of the mixed logit model that we use to map the observed choices from the DCE into preferences for different types of OPD insurance. We find that almost all included insurance attributes and levels significantly influence respondents' choices since the coefficients associated with each of them are statistically different from zero at the 1% level. The attribute-levels that do not significantly influence the package choice are adding medication to the fees and diagnostic services to be covered, and covering pre- and postnatal care versus the base category of infectious diseases. Besides, the coefficients of all attribute-levels have the expected signs (compare Table 4), confirming the theoretical validity of our estimates. As the constant terms are also statistically significant ($p<0.01$) we find that the respondents prefer the presented OPD insurance plans over opting out.

When examining specific attribute-levels, the results suggest that respondents have a higher preference for having higher-level care providers covered on top of only primary care providers. Additionally including telemedicine[9] yields another significant increase in preference. Compared to including infectious diseases, respondents strongly prefer to have chronic diseases included in the benefit package. We find no statistically significant difference in respondents' preferences between covering infectious diseases or pre- and postnatal care in the OPD insurance plans. There is also no statistically significant preference change if medication expenditures are covered on top of diagnostic services and fees alone, but there is a strong and positive preference for including both medication and transportation costs. As expected, respondents prefer higher coverage amounts and increasing premium levels are negatively associated with the preference for the respective OPD insurance package.

Panel b. of Table 4 shows that the attribute levels for the health conditions, providers, and services covered by the OPD insurance are fairly strongly correlated with each other, ranging between correlations of 0.15 and 0.72 in absolute terms. Most are also positively correlated with each other. The positive correlations indicate that respondents who value one dimension of the insurance plan highly tend to also place a higher value on other aspects. For example, respondents who tend to highly value the inclusion of the highest provider level (primary and higher-level providers and telemedicine) also tend to value the inclusion of the highest service level (diagnostics and fees, medicine, and transport). But there are two exceptions: the preference for including higher-level providers is correlated negatively with the preference for including medicine (on top of diagnostic tests and fees) and with the preference for inclusion of pre- and postnatal care (as compared to infectious diseases) respectively. This shows that respondents who prefer higher-level providers to be included on top of primary providers (but no telemedicine) tend to be the ones who value the inclusion of pre- and postnatal care as well

[9] Telemedicine was explained as any "consultation and prescription through a telephone call".

as the inclusion of only medicine on top of diagnostics and fees (and not transport) less. The correlations between a higher coverage amount and the other attribute levels are less strong (between 0.03 and 0.25 in absolute terms) and mixed in directions. We find positive correlations between a higher coverage amount and services included, but a negative correlation between a higher coverage amount and provider levels. Price sensitivity is negatively related to tastes for most attribute levels, most strongly with pre- and postnatal care services (-0.79). However, price sensitivity is positively correlated with coverage amount, chronic disease coverage, and inclusion of higher-level providers.

As preferences are easier to interpret in monetary terms, we estimated the mixed logit in WTP space. Figure 1 shows a graphical illustration of mean WTP for the different attributes in terms of a yearly insurance premium per family member[10]. While respondents are inclined to pay around 31 Pakistani rupees (PKR) more for the inclusion of pre- and postnatal care compared to infectious diseases to the benefit package, they would pay 259 PKR more to have chronic diseases covered instead (as compared to the package including infectious diseases), which corresponds to around 0.7% of the average household's monthly expenditures (according to the data collected in our household survey). Respondents were willing to pay 242 PKR to extend the coverage from only primary to secondary and tertiary care providers, which corresponds to around 0.4% of the average household's monthly expenditures. For additionally including telemedicine respondents were willing to pay 105 PKR more. Their WTP for covering expenditures for medication in addition to only fees and diagnostics was 57 PKR. For covering medication and transportation costs on top of only fees and diagnostics, they would on average pay 390 PKR (in terms of yearly premium per person) more. For rising the yearly maximum coverage amount per family by 100,000 PKR, respondents would be on average willing to pay around 145 PKR in terms of annual premium per family member more.

[10] For the full table of results of the mixed logit estimation in WTP space see

Table A 2.

Table 4 Estimates of the mixed logit model

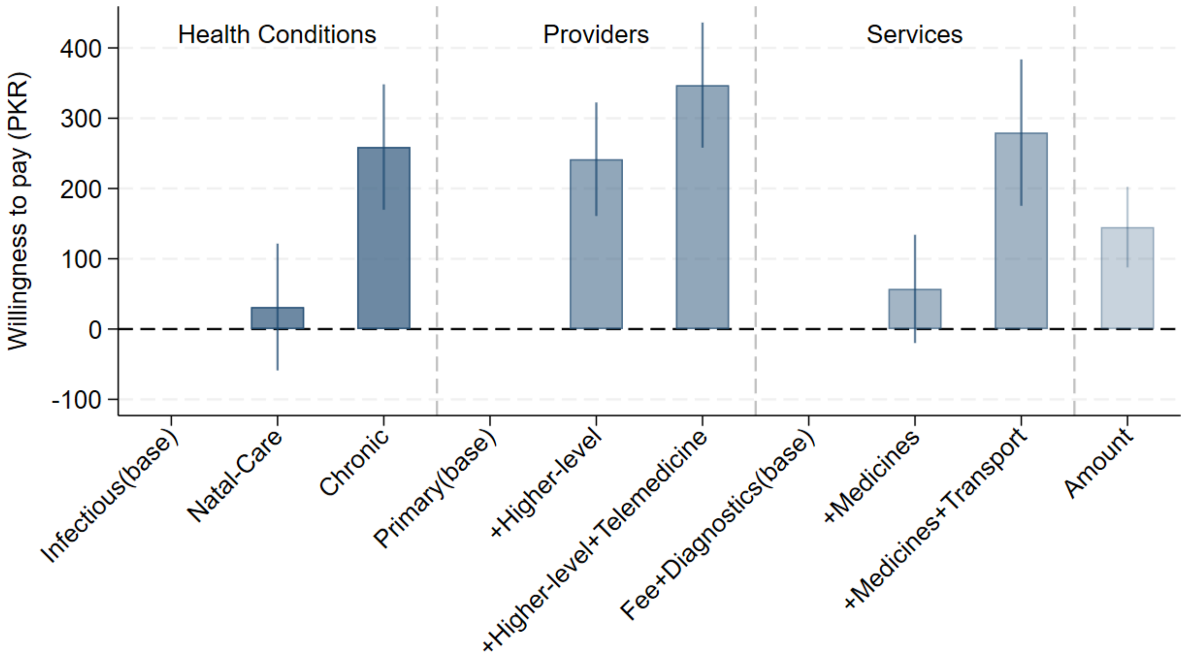
a) Mixed logit estimates (dummy coded)		Mean	Standard Deviation
Constant Plan A		3.7936***	
		(0.2718)	
Constant Plan B		3.8363***	
		(0.2711)	
Premium		-6.4034***	1.5980***
		(0.1379)	(0.0882)
Provider	(base: Primary)		
	Primary + Higher level	0.6318***	0.0196
		(0.0910)	(0.2305)
	Primary + Higher + Telemedicine	0.8495***	0.7541***
		(0.1194)	(0.1584)
Services	(base: Fees incl. Diagnostics)		
	Fees + Medication	0.1015	0.6646***
		(0.0974)	(0.1270)
	Fees + Medication + Transport	0.6180***	0.7801***
		(0.1060)	(0.1438)
Conditions	(base: Infectious)		
	Natal	-0.1416	1.1639***
		(0.1065)	(0.1192)
	Chronic	0.7580***	0.9282***
		(0.1173)	(0.1289)
Amount		0.3067***	0.5245***
		(0.0534)	(0.0705)
No. choices		9,426	
No. individuals		359	
Log-likelihood		-2,041.8144	

b) Correlation matrix

	+Higher-level	+Telemed	+Medicine	+Transport	Natal care	Chronic	Amount	Premium
+Higher-level	1							
+Telemed	0.5520***	1						
+Medicine	-0.2321***	0.6821***	1					
+Transport	0.1505***	0.7215***	0.5232***	1				
Natal care	-0.3466***	0.1772***	0.5514***	0.5405***	1			
Chronic	0.4258***	0.3448***	0.3108***	0.3915***	0.4630***	1		
Amount	-0.2502***	-0.0499***	0.2351***	0.2210***	-0.0364***	0.0474***	1	
Premium	0.4285***	-0.0628***	-0.4941***	-0.3936***	-0.7879***	0.2354***	0.0567***	1

Estimates using mixed logit, likelihood simulated using 50 Halton draws. The data consists of 9 choices between two hypothetical insurance plans and an opt-out. Robust standard errors in parentheses; Amount in 100,000 PKR; *** p<0.01, ** p<0.05, *p

Figure 1 Main effects in WTP



Mean estimates from equation 1 using mixed logit in WTP space with 95% confidence interval. Amount in 100,000 PKR (per family per year).

3.4 Quality and robustness of (WTP) estimation

To test the robustness of the results from the mixed logit model, we compared the results against estimating equation 2 using other commonly used estimation models, the conditional logit and nested logit models.

Firstly, we compared the conditional logit to the nested logit model estimations. Both models yielded very similar coefficients (see appendix *Table A 3*) and almost identical explanatory power in terms of log-likelihood (-2002.99 (conditional logit) vs. -2002.61 (nested logit)). Hence, the nested logit model was not an improvement as compared to the conditional logit model for the analysis of our DCE results. Comparing the estimation results of the mixed logit and conditional logit models, the mixed logit model results yielded similar (but slightly different) coefficients (see appendix *Table A 3*) but a better model fit than the conditional model (-1895 (mixed logit) vs. -2002 (conditional logit)). Moreover, the standard deviations of the estimated mixed logit model are significantly different from zero for almost all attribute levels (see Table 4), indicating that heterogeneity in preferences is present (Hole & Kolstad, 2012). As the conditional model assumes homogeneous preferences, the mixed logit is hence the more appropriate model for our analysis.

As the mean coefficients of the alternative-specific constants for plan A and B were of similar size and statistical significance, we do not suspect a left–right reading bias as described in (Ryan et al., 2018) to be at play.

3.5 Heterogeneity in Preferences

3.5.1 Attribute specific health risk indicators

We explored twelve hypotheses to check whether preferences for attribute levels differ in terms of observable pre-existing health complaints and other risk factors. We found that inferred preferences for the hypothetical insurance reflected the household's observable health risks in their choices in the health conditions attribute, but not so in their provider and services choices.

Health conditions

We found evidence for the hypothesis that having chronic disease patients in the family affects the respondent's preference for the benefit package in terms of which conditions would be covered by the insurance plan. More healthcare visits in the family related to chronic diseases was positively associated with a higher WTP for including chronic diseases in the benefit package. Every additional visit due to a chronic disease resulted on average in a rise in WTP of around 18 PKR in monthly per person premium. If the respondent himself/herself suffered from a chronic disease, this was associated with a higher WTP but the difference was not statistically significant. We do not see a significant difference in preference for those families having any member with chronic disease compared to those who don't have a member with a chronic disease. We also find no evidence for respondents who recently had a case of infectious disease in their household to prefer the inclusion of infectious diseases in the benefit package more. Besides, there was heterogeneity in preferences for including pre- and postnatal care and family planning. Female respondents had a significantly lower WTP of on average 27 PKR than male respondents. We did not find significant differences in preferences of respondents with different gender compositions of their households.

Table 5 Hypotheses 1-3 (Health conditions)

	WTP chronic		WTP natal care	
	Coeff	Std Err	Coeff	Std Err
Hypothesis 1				
Chronic (respondent)	25.9133	(18.9721)		
Chronic (any member)	-9.1479	(20.6098)		
# chronic visits (family)	17.7193*	(10.5306)		
Hypothesis 2				
Infectious(respondent)	-25.1115	(17.8235)		
Infectious (any member)	-7.2471	(13.8265)		
# infectious visits (family)	0.5767	(5.2721)		
Hypothesis 3				
Female respondent			-27.1934**	(11.9879)
Any female reproductive age			8.0529	(15.7637)

# females reproductive age			-3.0084	(6.5718)
N	359			

robust standard errors in parentheses, significance levels: * 0.1 ** 0.05 *** 0.01

Providers

We did not find evidence that respondents from families whose members recently experienced above median costs at higher-level care facilities preferred covering this facility level more. Besides, we did not see that respondents, for whom it would be easier to use telemedicine (being younger, household owns a smartphone) had a higher preference for including telemedicine on top of primary and secondary providers. Also, respondents from families with a higher transportation need (for whom it is expected to be more difficult or expensive to access in-person health care) did not exhibit a significantly higher WTP for covering telemedicine as additional provider option. In contrast, families who lived further away from the closest health care facility even had a significantly lower WTP, but the magnitude of less than 2 PKR each is economically negligible.

Table 6 Hypotheses 4-6 (Providers)

	WTP Higher		WTP Higher+Telemed	
	Coeff	Std Err	Coeff	Std Err
Hypothesis 4				
High cost at sec/ter (respondent)	1.7728	(0.3811)		
High cost at sec/ter (any member)	2.0870	(2.2150)		
N	162			
Hypothesis 5				
Smartphone			-0.2866	(0.8992)
Age(respondent)			-0.0158	(0.0318)
Any young member (hh)			0.7042	(1.2095)
Hypothesis 6				
Large distance facility			-1.6380*	(0.9395)
High transport costs			-0.2819	(0.9374)
Any high transport cost (family)			0.3676	(0.9566)
# females (hh)			-0.1288	(0.3013)
N			344	

robust standard errors in parentheses, significance levels: * 0.1 ** 0.05 *** 0.01

Services

We found no empirical evidence for any of our hypotheses regarding the included services. Our results indicated that coverage of transportation costs is not preferred by households with a presumed higher transportation need. Households with an above median distance to the nearest health care facility had no significantly different WTP for including the transport attribute level. Whether they owned a transportation medium (like car, motorcycle, bicycle) and whether recent high transportation costs occurred did not significantly influence preferences, neither did the family composition. Households with more elderly members and/or more female members did not have a different WTP for including transportation in the benefit package. Our results did not indicate that respondents from families who recently incurred high medication expenditures during an OPD visit have a higher preference for including medication coverage in the insurance plan. We also did not find respondents from families with above median costs for diagnostic tests to be more content with the base level (covering only diagnostics and fees) as compared to including medication or medication and transport on top. We also found no evidence of people with chronic diseases and/or repeated OPD visits within the past month to have significantly higher preference for including transportation costs in the OPD insurance plan.

Table 7 Hypotheses 7-12 (Services)

	WTP Medication		WTP Medicaton+Transport	
	Coeff	Std Err	Coeff	Std Err
Hypothesis 7				
High med cost (respondent)	0.1183	0.1562		
High med cost (any member)	-0.0033	0.1590		
Hypothesis 8				
High diagn cost (respondent)	0.1019	0.1780		
High diagn cost (any member)	0.0540	0.1541		
N	359			
Hypothesis 9				
Large distance facility			1.4906	1.2391
Hh owns any transport medium			0.9630	1.4311
High trans cost (any member)			-0.1456	1.1581
# females in hh			0.1969	0.4080
# elderly in hh			-0.4571	0.7021
N			344	
Hypothesis 10				
high transport cost (respondent)			2.1929	1.9902
high trans cost (any member)			-0.2898	1.1298
N			359	
Hypothesis 11				
Chronic (respondent)			-0.3631	2.0318
Chronic (any member)			-0.1956	1.4982
Multiple visits (respondent)			-0.3631	2.0318
Multiple visits (any member)			-0.1956	1.4982
N			341	
Hypothesis 12				
High diag cost (respondent)			-0.3631	2.0318
High diag cost (any member)			-0.1956	1.4982
N			359	

robust standard errors in parentheses, significance levels: * 0.1 ** 0.05 *** 0.01

3.5.2 General household characteristics and health indicators

We found almost no significant and economically meaningful differences in preferences for the hypothetical insurance attributes in terms of socio-demographics, location, and respondent as well as household health status indicators.

Socio-demographics

In terms of gender, we found little differences in preference between female and male respondents. Besides, we found almost no differences regarding education, except that educated respondents had a lower WTP (of around 5 PKR) for including transport costs, while respondents from wealthier households have a slightly higher WTP for this attribute level. Respondents from larger households had a slightly smaller WTP for including pre- and postnatal care as compared to infectious diseases in the benefit package of the hypothetical OPD insurance.

Location

We found some significant but unsystematic differences in preferences for the insurance attributes in the different districts of our study area. Regarding the conditions covered by the hypothetical insurance, respondents from Chitral had a significantly higher WTP for including pre- and postnatal care (base level: infectious disease coverage) as compared to respondents from Mardan and the difference is meaningful in economic terms (around 70 PKR). For including higher-level providers on top of only primary providers, respondents from Chitral and those from Kohat also had significantly larger WTP compared to respondents from Mardan. However, the difference in mean WTP is small in economic terms (less than 10 PKR).

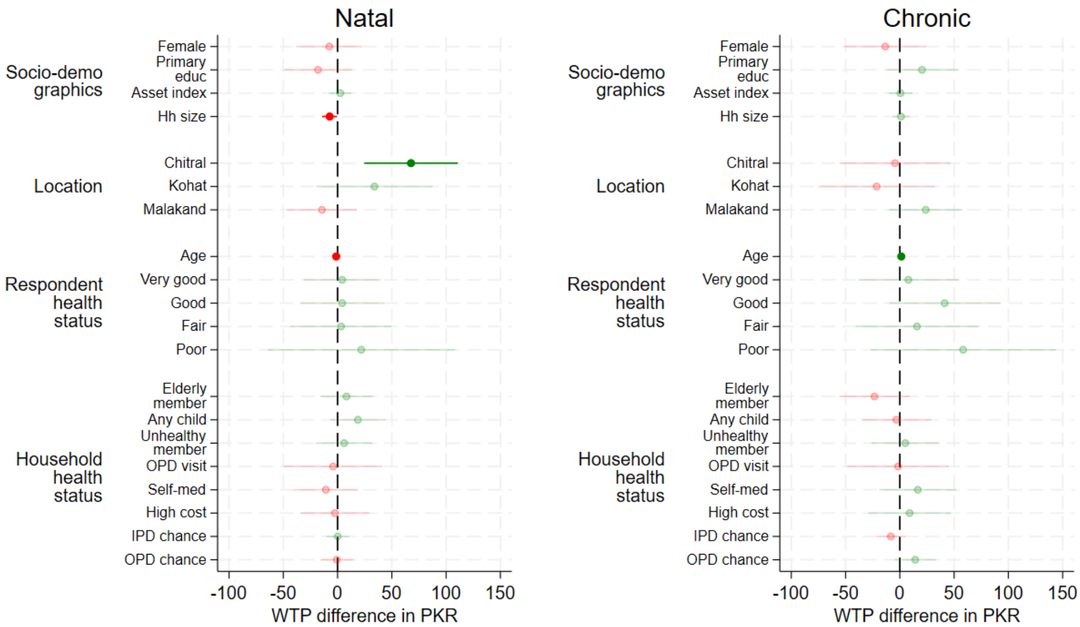
Respondent health status

We found a small age gradient: Older respondents had a slightly higher preference for chronic disease coverage and a slightly lower preference for pre- and postnatal care (base level: infectious disease coverage). Furthermore, respondents with a worse health tended to exhibit a larger WTP for including higher-level providers in the hypothetical insurance plan.

Household health status

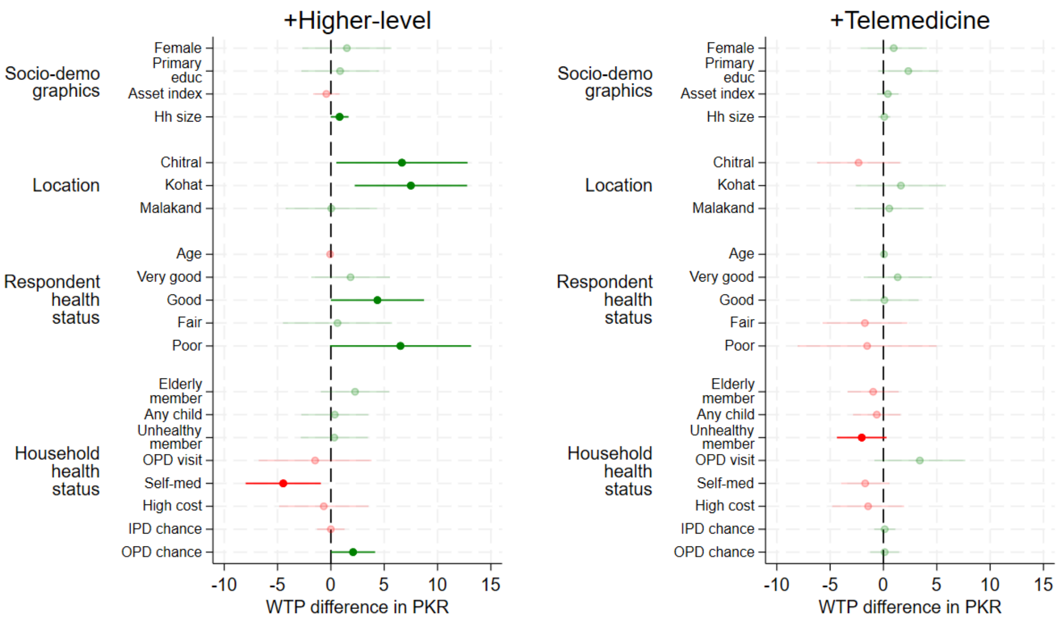
We find no significant differences in preferences regarding the age structure of the household, i.e. whether or not respondents had at least one elderly person or child in their household. We also found almost no differences regarding the health status of family members, except that respondents from families with at least one unhealthy member had a slightly smaller mean WTP for telemedicine, but the difference is negligible in economic terms. We found no significant differences in whether or not there where recent OPD visits nor recently incurred high costs for OPD visits. In those households where cases of self-medication where reported, the respondent exhibited a slightly lower WTP for including higher-level providers but a higher WTP for including transport costs. Considering expectations of future health events, we found few differences but that those respondents who expected a higher likelihood of their household to experience the need of an OPD visit in the future had significantly higher WTP for including higher-level providers but the economic size of the differences are again small.

Figure 2 Preference heterogeneities for conditions covered



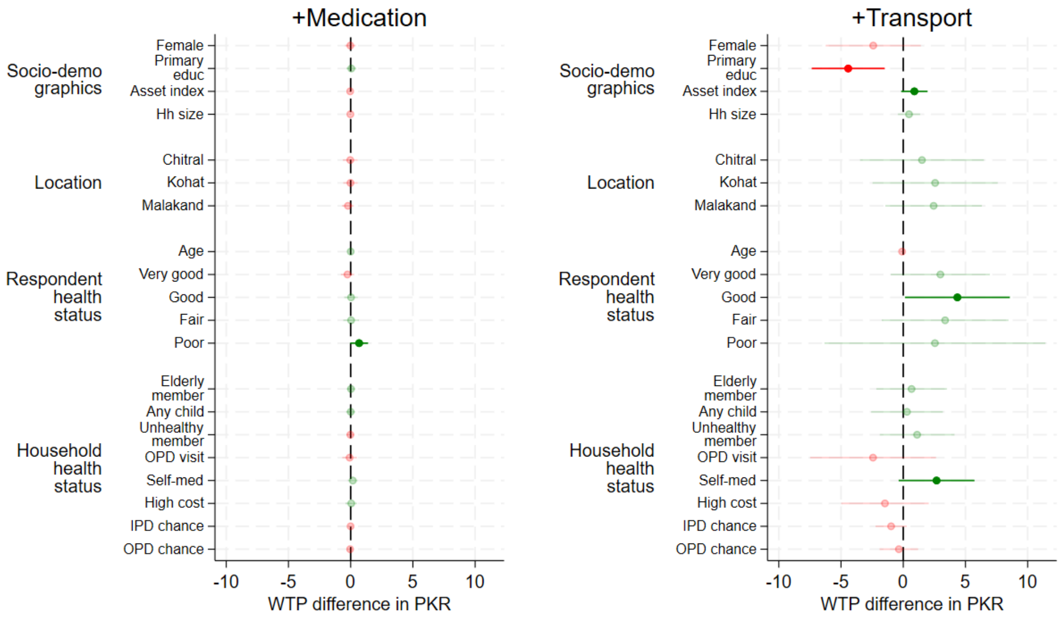
Coefficient plot of Equation 2 with 95% confidence interval, green indicates a higher and red a lower mean willingness-to-pay (WTP) point estimate for the respective group; darker colors indicate p<0.1

Figure 3 Preference heterogeneities for providers covered



Coefficient plot of Equation 2 with 95% confidence interval, green; green indicates a higher and red a lower mean willingness-to-pay (WTP) point estimate for the respective group; darker colors indicate p<0.1

Figure 4 Preference heterogeneities for services covered



Coefficient plot of Equation 2 with 95% confidence interval, green; green indicates a higher and red a lower mean willingness-to-pay (WTP) point estimate for the respective group; darker colors indicate p<0.1

4 Discussion and conclusion

To increase acceptance and utilization of state-funded health insurance schemes that are expanding across the Global South, it is important that their design corresponds to the beneficiary population's needs and preferences. This paper contributes to our understanding of the preferences of a low-income population in the context of a planned OPD insurance scheme in Pakistan. For this purpose, we conducted a DCE with the prospective beneficiary population.

Overall, we found a clear preference for covering needs associated with chronic care and non-communicable diseases as well as covering costs that go beyond fees and diagnostic tests, more specifically medication and transport costs. Furthermore, respondents prefer higher-level as compared to only primary facilities and exhibit a strong preference for including telemedicine into the package. We did not detect substantial preference heterogeneity across socio-demographic strata, as well as over respondent and household health status. This suggests that different population groups in our setting might be similarly accepting of the same OPD insurance scheme elements.

The preference to include chronic diseases as compared to infectious diseases or pre- and postnatal care in the benefit package is highly significant and rather strong. This result is in line with other stated preference studies in low-income countries. For example, Wakamatsu et al. (2019) found that respondents in rural Cambodia had a strong preference for including long-term treatment of chronic diseases in the insurance benefit package and Kalyango et al. (2021) found that respondents in non-slum communities in Kampala, Uganda, preferred insurance plans that covered chronic illnesses to other plans. The result is also not surprising in our context, considering both the age of our respondents (on average 50 years old, median age was 52 years) and the prevalence of chronic diseases in their families: our household survey shows that more than 30% of the families had at least one OPD visit of a family member related to a chronic disease within the past month (self-reported). Besides, national statistics on disease burden and causes of deaths illustrate the structural change and growing importance of non-communicable diseases (NCDs) in Pakistan. While in 1990 the five leading causes of premature mortality in Pakistan were all communicable, in 2019 two of the five leading causes were NCDs (Hafeez et al., 2023). Hence, the clear preference for including chronic diseases in the benefit package of the OPD insurance scheme points towards the growing burden of NCDs in the region, the growing awareness of the population thereof, and the need to increase their protection in this regard.

We do not find a preference for including pre- and postnatal care as well as family planning in the insurance benefit package. As our respondents were to a larger fraction male and rather old, this could have led to a certain bias towards chronic diseases and away from maternal and child healthcare. However, we find that female respondents value the inclusion of pre- and postnatal care even significantly less than male respondents. The underlying mechanism for the lower preference could be that females are better informed regarding the already available free-of-cost or low cost maternal and child health services which are provided in the area. For example, there is a state-funded inpatient insurance scheme which already covers deliveries at empanelled hospitals. Besides, some services related to pre- and postnatal care are already available free of cost or for a small fee at public primary healthcare facilities in KP. Hence, childbirth related services seem to be covered comparatively well in our context and it hence seems like a rational choice to prefer coverage of a category with currently rather low protection, namely chronic diseases.

We furthermore find that the population’s preference for inclusion of higher-level as compared to only primary care providers is quite strong. Aligning with our findings, Kamara et al. (2018) in Sierra Leone and Zuhair & Roy (2022) in India find a positive preference for higher-level providers. In contrast, in Uganda Kalyango et al. (2021) find a higher preference for covering higher-level versus primary-level services only in non-slum but not in slum areas. The clear preference towards higher-level providers, not only in Pakistan but also other LMICs, might point out a challenge in the efforts to strengthen primary care in LMICs which is considered crucial for progressing towards UHC (Hanson et al., 2022). If the population preferences are not fully aligned with this goal, for example because people do not believe to receive quality service provision at lower level care facilities, policy makers should consider to accompany measures to strengthen the primary care system with measures to improve its quality and the population's acceptance.

We saw a rather strong preference for including telemedicine as an additional provider option on top of primary and higher-level in-person care providers. As among other benefits eHealth is seen as a cost-effective opportunity to make healthcare more accessible it plays a crucial role in achieving UHC(World Health Organization, 2016). We consider the preference for including telemedicine services as a signal of the population's willingness to engage in this new opportunity and as promising chance for future advances of UHC in Pakistan, if the necessary infrastructure is made available and accompanied by educational measures.

We did not find a significantly higher preference for covering medicines on top of costs for diagnostic tests and fees alone. We did, however, find a strong preference for covering costs for both medication and transport in addition to only diagnostic tests and fees. The valuation of transportation costs hence seems rather strong in our setting. Evidence on this in the literature is mixed. A positive preference for transportation that is larger than for medication coverage is also found by several other studies on stated health insurance preferences in different contexts in LMICs (Abiiro et al., 2014; Ozawa et al., 2016; Sydavong et al., 2019; Zuhair & Roy, 2022). In contrast, Habib & Zaidi (2021) and Dror et al. (2007) report a larger preference for medication coverage than for transport for low-income households in Pakistan and India respectively. Preferences regarding medication coverage seem context-dependent, which in itself is not surprising. As medication accounted for the largest proportion of out-of-pocket expenditures for healthcare visits recorded in our household survey (Shaukat et al., 2024), it is surprising we did not find a stronger preference for covering medication alone but only in combination with transport. However, according to our household survey data, transport costs also made up a substantial share of overall out-of-pocket expenditures. Besides, reaching a healthcare facility is crucial for receiving treatment and not being able to afford the respective costs can be prohibitive of accessing any potential insurance benefit, which the population might be well aware of. Policy-makers should hence bear in mind the full spectrum of out-of-pocket expenditures that are related to a healthcare visit and consider for insurance programs to cover components like medication and transport in addition to diagnostic tests and fees to offer a better health protection of the beneficiaries.

Our results further suggest that even in our setting where health and insurance literacy is relatively low, the DCE choices were partly made to maximise benefits along (self-reported) known, pre-existing health problems and risk factors. This was especially true for the health conditions to be covered and less the case for which providers and services were spreferred to be covered. The health problems and risk factors drove the DCE choices to some degree despite the hypothetical nature of the experiment and respondents being unfamiliar with OPD health insurance at the time our study.

One of the limitations of this study is, that ideally, one would also collect primary, qualitative evidence for the attribute and level design in DCEs (Mangham et al., 2009). This was however, not feasible in our case due to time restrictions related to the design process of the pilot OPD insurance scheme. Furthermore, it was not possible to randomize the order of choices, as one would ideally do to reduce a potential bias (Kjaer, 2005) since the choices were presented on paper to enhance the participants' understanding. This measure also served to reduce interview fatigue to make the exercise more engaging. We furthermore reduced the number of choice sets to the smallest possible while still reflecting all relevant trade-offs in our design. A further limitation is the rather small sample size. However, the sample size is sufficient for analyzing the main effects and the heterogeneities are rather precise and small.

Our results provide insights on the population's preferences regarding a new OPD health insurance scheme in KP, Pakistan, which was not yet implemented at the time of data collection. The generated evidence informed this new and innovative policy during the scheme design phase. In addition to informing this concrete policy in Pakistan, our results point towards several chances as well as challenges in the context of moving towards UHC in Pakistan and beyond.

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Appendix

A1 Overview of Collected Insurance-Related DCE Studies in LMICs

Overview of Collected Insurance-Related DCE Studies in LMICs

Author(s) and date	**Study setting**	**Study population**	**Study subject**	**Special notes**
Abiiro, Torbica, et al. (2014)	Malawi	Rural community	MHI	Note accompanying papers Abiiro2014 (development of attributes and levels) and Abiiro2016 (heterogeneity analysis)
Eshetu and Seyoum (2019)	Ethiopia	Eligible areas of CBHI	CBHI	-
Habib and Zaidi (2021)	Pakistan	Women, low-income beneficiaries of BISP	GHI	Not DCE, but descriptive, cross-sectional study
Kalyango, Kananura, and Kiracho (2021)	Uganda	Slum and non-slum communities in Kampala city	NHI	-
Kamara, Bonet, and Mesnard (2018)	Sierra Leone	Informal sector workers	SHI	-
Kananurak (2014)	Thailand	Retired workers in and around Bankok	SHI	-
Karyani, Sari, and Woldemichael (2019)	Iran	Tehran area	GHI	Note accompanying paper Karyani2018 (development of attributes and levels).
Nanna (2011)	Thailand	Covered areas of NHI	NHI	Doctoral Thesis
Obse et al. (2016)	Ethiopia	Formal sector employees	SHI	-
Ozawa, Grewal, and Bridges (2016)	Cambodia	Eligible households of CBHI	CBHI	-
Sydavong et al. (2019)	Laos	Rural, informal sector households	CBHI	-
Haar (2013)	Nepal	Women who participated in microfinance program and repaid their loans	MHI	Master's Thesis
Wakamatsuzu, Fukui, and Miwa (2019)	Cambodia	Rural provinces	MHI	-

Sorted alphabetically.
CBHI=Community Based Health Insurance; GHI=General (not further specified) Health Insurance; MHI=Micro Health Insurance; NHI=National Health Insurance; SHI=Social Health Insurance

A2 Attributes in Reviewed Studies

Attribute Title	Details (if applicable)	Count	Abiiro et al. 2014	Eshetu and Seyoum 2019	Habib and Zaidi 2021	Kalyango et al. 2021	Kamara et al. 2018	Kananurak 2014	Karyani et al. 2018	Nanna 2011	Obse et al. 2016	Ozawa et al. 2016	Sydavong et al. 2019	van der Haar 2013	Wakamatsu et al. 2019
(Monthly) Premium		**12**	x	x		x	x	x	x	x	x	x	x	x	x
Choice of provider	Public, private, faith-based	**7**		x		x	x		x	x	x				x
Benefit package	Benefit package / Coverage	**5**	x	x		x	x								x
	Type of health benefits package	1			x										
	Dental coverage	1							x						
	Rehabilitation/ Physical therapy benefits	1							x						
	Public hospital benefits	1							x						
	Private hospital benefits	1							x						
	Medical devices benefits	1							x						
	Paraclinical benefits	1							x						
	Long-term care	**2**						x	x						
	Medicines / Pharmaceuticals	**2**									x		x		
	Coverage inpatient / Hospitalization	**3**						x			x		x		
	Coverage outpatient	**2**						x			x				
	Coverage tests	1									x				
	Covers medical consultation	1											x		
	Covers traffic accidents	1											x		
Copayment levels / OOP		**4**	x		x							x		x	
Unit of enrolment		**4**	x			x					x			x	
Transport coverage		**3**	x									x	x		

Management structure		**2**	x												x
Waiting time		**2**					x			x					
Exclusion	Exclusion of Services	1									x				
Work compensa-tion	During hospitalization	1						x							
Meal coverage	For family members	1										x			
Communica-tion frequency		1										x			
Contract duration		1													x
Participation on non-poor hhs and discount		1													x
Payment frequency		1										x			
Timing & Duration of Payment		1													x
Pre-payment discount		1											x		
Average number of attributes:	**5.4**		6	3	2	4	4	5	9	3	8	6	7	3	7

A3 Example of Visual DCE Presentation, District Chitral and Urdu

Choice 1

	صحت منصوبہ الف
یہ منصوبہ درج نیل قسم کی صحت کی سہولیات میں بیرونی مریضوں کے صحت کے اخراجات ادا کرے گا۔	بنیادی سہولیات (مثلاً، BHU Broze، BHU Koghuzi، RHC Ayun، پرائیویٹ کلینک، ...) اور ثانوی اور ترتیری سہولیات (مثلاً، DHQ، THQ، خصوصی ہسپتال، جیسہ زچگی کہ ہسپتال، ...) 
اس منصوبےسے او پی ڈی مریضوں کے لئے درج ذیل سہولیات فراہم ہوں گی۔	ڈاکٹر کی فیس، تشخیصی ٹیسٹس،ادویات اور ٹرانسپورٹ کے اخراجات 
اس منصوبے سے او پی ڈی میں درج ذیل بیماریوں کے علاج کے اخراجات کی ادائیگی ہوگی۔	بچے کی زچگی سے قبل اور بعد کی دیکھ بھال)ماں اور نوزائیدہ بچے کے لئے مثلاً خوراکی سپلیمنٹ، معائنہ، علاج(اور خاندانی منصوبہ بندی)مانع حمل ادویات اور آلات وغیرہ(۔ 
اس منصوبے سے آپ کے درج ذیل حد تک علاج کی ادائیگی ہوسکے گی۔ یہ پورے خاندان کے لئے ایک سال تک زیادہ سے زیادہ حد ہوگی۔	ایک لاکھ روپے تک علاج کے اخراجات 
رقم جو آپ کے خاندان کے ہر فرد کی طرف سے ادا کی جائے گی۔	روپے 100 

A4 Final Attribute and Level Framing, English

Attribute and Level Framing, English

Attribute Description	Level No.	Level Framing (EN)
The plan will pay the outpatient health expenses in the following type of health facilities.	0 1 2	Primary facilities (e.g., BHU, RHC, private clinics, …) Primary facilities (e.g., BHU, RHC, private clinics, …) and secondary and tertiary facilities (e.g., DHQ, THQ, specialized hospitals, such as maternity hospitals, …) Primary facilities (e.g., BHU, RHC, private clinics, …), secondary and tertiary facilities (e.g., DHQ, THQ, specialized hospitals, such as maternity hospitals, …), and telemedicine (i.e., consultation and prescription through telephone call)
The plan will pay the outpatient health expenses for the following services.	0 1 2	Doctor's fee and diagnostic tests Doctor's fee, diagnostic tests, and medication Doctor's fee, diagnostic tests, medication, and transportation coverage
The plan will pay the outpatient health expenses for the following diseases.	0 1 2	Diseases that stick with you for a long time, namely, disease of veins of heart, shortness of breath disease, and diabetes (Increasing sugar level) Care before and after childbirth (for the mother and the newborn child, e.g., nutrition supplements, examination and treatment, …) and family planning (e.g., contraceptives) Diseases that are infectious (caused by bacteria, viruses, fungi, or parasites, e.g., Malaria, Dengue fever, Tuberculosis, Hepatitis, Flu …)
The plan will pay the health expenses up to the following annual amount. This will be the maximum amount for the whole family per year.	100000 150000 250000	Up to 100,000 PKR Up to 150,000 PKR Up to 250,000 PKR
Amount you will contribute per family member per year. The total amount will depend on the number of members in your family, as the whole family will be enrolled.	50 100 500	50 PKR 100 PKR 500 PKR

A5 Introductory Text

"In the following, you will be presented with a series of imaginary health plans. In reality, these plans would pay the medical bills for you, in case you get ill, and in return require you to make smaller and regular payments. Thus, they protect against a high financial burden caused by large medical bills. We will ask you to choose between two different imaginary health plans at a time, which will differ in what and how much they cover and how much they require you to contribute in turn. We will ask you to take a few of those choices in a row. Note that we are interested in your true opinion and there are no right or wrong answers. Please note that these are purely imaginary choices and that you will not face any consequences (neither risks nor benefits) from your decisions in real life. However, we kindly ask you to imagine yourself in a real-life situation where you would choose between two such health plans and to tell us how you would decide in real life. *Consider what implications this would have for yourself and your family members if you were facing the decision in real life and try to choose the best option in your view. That you really choose the option which you would prefer is very important to the success of our research. Ultimately, your participation and honest answers will provide important information and help to improve the health situation of the people in our province.*

In a moment, I will show you several printed sheets and ask you to imagine that you would have to choose between the two health plans they show. You can choose between Health Plan A, Health Plan B, or not choosing any of them. Imagine that both health plans cover medical bills for outpatient services only (i.e., no procedures requiring admittance to a facility) which you can access in selected private and public health care facilities all over the province. Further, please imagine that when choosing the health plan, your whole family would be covered (i.e., your wife/husband and unmarried children)."

A6 Sampling Procedure

Out of the eligible households (52,703) who live in the accessible UCs, the sample was selected in three stages as follows. The procedure is described for households

1. UC-level: We randomly drew four accessible union councils per district.
2. Village-level: Within the UCs, we excluded all villages with less than 40 poor households on our sampling list and those that are farther than one hour by car away from the closest RHC.[11] Out of the resulting list of villages per district, half was again randomly selected to do the discrete choice experiment in addition to the household survey. This yielded up to two villages per UC and a total of 22 villages (Chitral: 7, Kohat: 7, Malakand: 3, Mardan: 5).
3. Household-level: If there were two villages in a UC, we sampled 40 households from each. If there was only one village, we sampled 80 households still reach the number of 80 households per UC. Re-sampling of some villages became necessary for Kohat (within and outside the district) due to a worsened security situation. We drew 4 times as many households from the sampling frame as we aimed to interview as the list was old and imprecise so we expected to on the one hand not find many households, but also exclude some due to death or migration. In total, 1,423 households were sampled to conduct a DCE.

A7 Variable Selection for Heterogeneity Analysis

Alongside common socio-demographics and location, we include various health status indicators in our heterogeneity analysis. We based our indicator selection on indicators used by previous literature to proxy health risk.

Literature health risk indicators (DCEs)				
Health risk indicator	**Author, year**	**Study method**	**Study area**	**Indicator definition**
Chronic diseases				

[11] For district Chitral, we included all accessible UCs and the respective villages to reach the desired sample size.

	Abiiro et al. (2016)	DCE	Malawi	chronic illness present in household (yes/no)
	Determann et al. (2016)	DCE	Netherlands	number of chronic diseases & individual has chronic illness (yes/no)
	Leukert-Becker & Zweifel (2014)	DCE	Germany + Netherlands	individual has chronic illness (yes/no)
	Pendzialek et al. (2017)	DCE	Germany	individual has chronic illness (yes/no)
	Trujillo et al. 2012	DCE	Colombia	individual has chronic illness (yes/no)
	Zweifel and Vroomen (2011)	DCE	Germany + Netherlands	individual has chronic illness (yes/no)
Age				
	Abiiro et al. (2016)	DCE	Malawi	younger age (<55 years) / older age (>= 55 years)
	Honda et al. (2016)	DCE	South Africa	age groups: 18-34 years, 35-49 years, >=50 years
Perceived health status				
	Jiang & Ni (2019)	cross-sectional analysis	China	self-reported health status (5-point Likert scale)
	Leukert-Becker & Zweifel (2014)	DCE	Germany + Netherlands	subjective health status (healthy / ill)
	Wakamatsu et al. (2019)	DCE	Cambodia	perceived health (5-point Likert scale)
Previous healthcare needs / expenditures				
	Abiiro et al. (2016)	DCE	Malawi	household health expenditure (none / any)

	Leukert-Becker & Zweifel (2014)	DCE	Germany + Netherlands	physician visit during past 12 months (yes/no)
	Wakamatsu et al. (2019)	DCE	Cambodia	experience of illness (yes/no) & experience of injury (yes/no)

Heterogeneity analysis variable definitions			
Category	**Level**	**Indicator**	**Variable definition**
Sociodemographics			
Gender	respondent	respondent's gender	male/female
Education	respondent	respondent's education	respondent has any (at least primary) vs. no formal education
Wealth	household	asset index	continuous (between -2.902224 and 2.307704, higher values indicating higher wealth)
Household size	household	number of household members	continuous (1-10)
Location			
District	household	district of residence	base level: Mardan, others: Chitral, Kohat, Malakand
Health risk indicators			
Age	respondent	respondent's age	continuous (in years)
	respondent	any elderly member in household	any household member >=55 years
	household	any child in household	any household member <15 years
Perceived health status	respondent	respondent's self-reported health status	5-point Likert scale (excellent to poor)
	household	any unhealthy household member	any household member reported health status fair or poor

Previous healthcare needs / expenditure	household	recent OPD visit	any household member had a OPD visit within past month
	household	self-medication	any household member had used self-medication within past month
	household	Household experienced recent high healthcare costs	any household member had above median costs for most recent healthcare visit (for OPD within past month, for IPD within past year)

A8 Further information

The study received ethical clearance from Heidelberg University (Germany) and Khyber Medical University (KMU) Peshawar (Pakistan).

A9 Supplementary Tables

Table A 1 Choice responses

Plan chosen	**Freq.**	**Percent**	**Cum.**
Health Plan A	4581	48.54	48.54
Health Plan B	4611	48.86	97.39
Neither	234	2.48	99.87
Refused	3	0.03	99.90
Don't know	9	0.10	100
Total	9438	100	

Table A 2 Estimates of the mixed logit model in WTP space

		Mean	Standard Deviation
Constant Plan A		1,404.0835***	
		(142.7674)	
Constant Plan B		1,427.4182***	
		(142.8075)	
Premium		-6.0615***	0.6968***
		(0.0756)	(0.0864)
Health Conditions	(base: Infectious)		
	Natal	31.3463	468.3869***
		(46.0427)	(52.5072)
	Chronic	258.9987***	291.1688***
		(45.5136)	(54.4270)
Providers	(base: Primary)		
	Primary + Higher level	241.6243***	265.5303***
		(41.2024)	(30.8674)
	Primary + Higher + Telemedicine	347.0780***	91.4414*
		(52.7774)	(47.7568)
Services	(base: Fees incl. Diagnostics)		
	Fees + Medication	57.1428	247.8069***
		(39.2762)	(34.2681)
	Fees + Medication + Transport	279.5316***	389.5028***
		(53.1347)	(51.4407)
Amount		145.0587***	298.6590***
		(29.2503)	(30.2262)
No. choices		9,426	
No. individuals		359	
Log-Likelihood		-2,120.4860	

* amount in 100,000 PKR

Table A 3 Robustness checks

		Mixed	Conditional	Nested
	Constant Plan A	3.1151***	2.3685***	1.8328***
		(0.2215)	(0.2028)	(0.6567)
	Constant Plan B	3.0216***	2.3775***	1.8395***
		(0.2178)	(0.1999)	(0.6617)
	Premium	-0.0034***	-0.0018***	-0.0026***
		(0.0004)	(0.0002)	(0.0010)
Provider	(base: Primary)			
	Primary + Higher level	0.5240***	0.3644***	0.5179***
		(0.0897)	(0.0551)	(0.1998)
	Primary + Higher + Telemedicine	0.7527***	0.5804***	0.8373***
		(0.0961)	(0.0665)	(0.3221)
Services	(base: Fees incl. Diagnostics)			
	Fees + Medication	0.1073	0.1329**	0.1844*
		(0.0927)	(0.0593)	(0.1091)
	Fees + Medication + Transport	0.5434***	0.4557***	0.6331***
		(0.0857)	(0.0618)	(0.2255)
Conditions	(base: Infectious)			
	Natal	-0.0869	0.0276	0.0160
		(0.1137)	(0.0639)	(0.0900)
	Chronic	0.5254***	0.4723***	0.6698***
		(0.0919)	(0.0649)	(0.2485)
	Amount	0.2554	0.1639***	0.2385**
		(0.0596)	(0.0355)	(0.1039)

* amount in 100,000 PKR