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Consumer access to high quality primary healthcare, which is one of the United Nation's Sustainable Development Goals, is known to improve health outcomes (Panday et al., 2007). The two distinct, but related, issues of supply and quality are fundamental to promoting equitable access to quality primary healthcare. The limited supply of qualified healthcare providers in rural areas is a widespread problem. Internationally, a range of government incentives are used to induce qualified healthcare providers to practice in rural communities (Dussault and Franceschini, 2006; Holte et al., 2015). In developing economies, particularly, however, pluralistic and heterogeneous healthcare provider quality varies considerable among Bachelor of Medicine and Bachelor of Surgery (MBBS) qualified providers and between MBBS and non-MBBS providers (Chang and Trivedi, 2003; Das and Hammer, 2007; Das et al., 2016; Das et al., 2012b; Pinto, 2004). The problem of under-supply of qualified healthcare providers in rural areas is exacerbated by government MBBS provider absenteeism.

Government MBBS provider absenteeism is a major weakness of health systems across developing economies. The unaccounted absence of government MBBS providers from their government posts is measured at between 25 and 40 percent (Banerjee et al., 2004; Chaudhury et al., 2006). The combination of institutional regulatory weakness and financial incentives motivates government employed MBBS providers to 'moonlight' and practice in the private sector. Recent estimates of 'dual practice' from rural North India and urban centres in three African countries suggests that over half of government MBBS providers have identifiable and active private practices (Das et al., 2016; McPake et al., 2014).

Studies evaluating the effectiveness of interventions aimed at reducing the level of government MBBS provider absenteeism indicate that the presence of strong accountability mechanisms are important. A community accountability intervention in Uganda reduced government doctor absenteeism by 13 percentage points (Björkman and Svennson, 2009). However, in contexts were local communities are disempowered the challenge of creating and sustaining public sector accountability mechanisms is greater. The effect of financial disincentives on government nurse absenteeism in India showed positive results while supervisors adhered to the program. Once the strength of the institutional accountability mechanism weakened the effect of the salary penalties on nurse absenteeism was negligible (Banerjee et al., 2008).

The quality of healthcare service provision within health systems in developing economies is also important when considering access to high quality healthcare. Sustained research by Das and colleagues has established the use of Standardised Patients as a method for measuring the quality of primary healthcare. The utilisation of government outpatient care in India is estimated at between 10 to 20 percent (Das et al., 2016; NSSO, 2015). Among healthcare providers who practice in both private and government outpatient sectors, the effort exerted by providers when working in the government sector was lower than when they practiced in their private clinics (Das et al., 2012b). More interestingly, Das and colleagues record lower levels of treatment effort from government MBBS providers operating at their government post, relative to their private practice (Das et al., 2016). These results support the thesis that reducing government MBBS provider absenteeism is necessary, but not sufficient, to ensuring consumer access to high quality primary healthcare in developing economies.

The work of Das and others has also helped map the full spectrum of primary healthcare providers in North India (Das and Hammer, 2007; Das et al., 2012a,b; Das et al., 2016; Goodman et al., 2017). A range of non-MBBS healthcare providers operate in the parallel informal[1] sector (Das et al., 2012a,b; Pinto, 2004). In North India, the estimated percentage of informal and unqualified doctors, of all available primary healthcare providers, is between 45 and 80 percent (Das et al., 2016; The WorldBank, 1998). The use of the Standardised Patient methodology has estimated that while the knowledge of unqualified providers is low, surprisingly their treatment effort and practices are comparable to those exerted by qualified government MBBS providers (Das et al., 2012b). This suggests that, while there is reason for concern about the practices of the unqualified provider, the standard of treatment practices among qualified government MBBS providers is also concerning.

The current study evaluates how important doctor absenteeism is to explaining the low level of utilisation of public sector outpatient healthcare services in rural Uttar Pradesh, India. Demand estimates for outpatient treatment for fever symptoms are provided under status quo and the counterfactual scenario of zero government MBBS provider absenteeism. Demand for healthcare services targeting fever symptoms was selected for this study due to the high

[1] The informal healthcare sector is defined as producers who are not State authorized or registered (Bloom et al., 2008).

prevalence of fever symptoms in rural North India (fever is a common symptom for malaria, TB and Dengue) and the relative ease with which respondents would identify these symptoms prior to any diagnosis (Wangdi et al., 2016; Law et al., 2018; Shepard et al., 2016). Results of this research inform on-going policy debate concerning the structure of India's health system. The announcement in 2018 of - 'Modicare' - an expanded health insurance scheme in India provides few details concerning the role of unqualified providers. Results of the counterfactual demand estimates, presented here, highlight the considerable role played unqualified healthcare providers in outpatient care settings. Consideration of expanding health coverage by incorporating unqualified providers as 'front-line' ambulatory community providers, under the agency of universal health care, is needed.

In addressing the above question, this paper makes several contributions to the literature. It offers the first estimates of demand for outpatient services provided by unqualified private healthcare providers. Secondly, Word-of-Mouth recommendations are incorporated into the model as a proxy for expected health outcomes. This paper also presents an innovative approach to estimating public policy treatment interventions using joint modelling of revealed preference (RP) survey and experimental stated preference (SP - self-stated preference for goods or services) discrete choice data. Using the behaviourally rich Stated Choice (SC) data (a form of SP data), the demand estimates and associated price elasticities provide new insights into the credence nature of demand for government MBBS doctor and unqualified private healthcare provider supplied outpatient care in a developing economy.

This work uses the SC experimental design in two ways. Firstly, the counterfactual assumption is introduced that zero government doctor absenteeism is present in the market. When the choice alternatives are the same across self-reported RP and the experimental SC data, the contrasting assumptions of government doctor availability, when modelling the data separately and jointly, enables analysis of counterfactual scenarios. Secondly, incorporating perceptions of healthcare provider quality as a qualitative variable in the experimental design allows respondents to make quality trade-offs against other service attributes. Allowing respondents to trade-off important, but otherwise unobservable preferences, in SC data represents an advantage over structural demand models.

The counterfactual scenario presented mixes the current expected level of absenteeism of government MBBS doctors with the hypothetical setting when these same doctors were always present. The current expected level of absenteeism within the sample villages - across 1 Community Health Centre (CHC) and 2 Primary Health Centres (PHC) - is assumed to be 50%. This level is higher than estimates in the literature from more than 10 years ago (Banerjee et al., 2004; Chaudhury et al., 2006), but appears realistic based on qualitative data analysis from districts in the relatively underdeveloped state of Uttar Pradesh. In addition, across each of the three villages that had either a CHC or PHC, approximately 20 percent of people stated that they did not consult such government centres due to absenteeism (see Table S5). Based on this assumption, the counterfactual scenario price elasticities portray a health system with absenteeism at 33%. The sensitivity of the results to the assumed current expected level is tested by increasing the weighting of the SC tasks. This sensitivity analysis portrays absenteeism at approximately 17 percent. This level of absenteeism is below the 25-40 percent estimate from Rajasthan, India (Banerjee et al., 2004) and representative over 20 Indian states (Chaudhury et al., 2006). Elasticity results are uniform using both weighting levels.

The use of jointly modelled RP-SC data to evaluate counterfactual policies removes problems of time differences associated with ‘before and after’ studies and the assumption that consumers respond to policy treatments identically in observational data (Manski 2013). The careful use of randomised control trials (RCT) remains a robust way to evaluate policy treatment effects. However, the ability for policy related RCT use in settings with weak governing and regulatory institutions is limited, particularly in cases where the intervention requires regulatory oversight (see Banerjee et al., 2008 for details). Therefore, second-best research methodologies designed to test the effectiveness of a policy intervention are required in developing economy contexts. The use of Stated Choice (SC) experiments and the joint modelling of RP-SC datum is a practical and informative alternative to RCTs.

The utility framework and functional form used are outlined in Section 1, and the joint revealed and stated preference modelling is explained in Section 2. Section 3 provides a description of the data, including the construction of outpatient provider alternatives in both data sets, and a rationale for using Word-of-Mouth recommendation as a proxy for patient expected health outcomes. Sections 4 and 5 contain demand estimation results and the associated price elasticities. Ethics approval for this research was granted by Griffith University Human Ethics Committee.

1. Economic Model

Estimation of unconditional demand using RP and SC data utilises the same systematic, stochastic utility structure. The systematic component of the random utility model used is non-linear in parameters and linear in the attributes. The log of household income enters the function twice with the second entry being a squared term. This allows for the testing of the convexity of the relationship between income and health. Prices enter the utility function independently of income. Despite earlier concerns about the lack of stability in utility maximisation estimates due to independent price parameters (Gertler et al., 1987), more recent work demonstrates that stability is maintained with the inclusion of price parameters (Dow, 1995). The deterministic component of the random utility function for the model is given below

$$V_{qj} = \beta_0 + \boldsymbol{\beta}_1^{'} \boldsymbol{X}_q + \boldsymbol{\beta}_2^{'} \boldsymbol{Z}_j + \alpha_1 \ln(Y) + \alpha_2 \ln(Y)^2 + \alpha_3 P_j + u, \qquad (1)$$

where V is the deterministic component of utility, and subscripts *q*, *j* denote consumers and provider alternatives. The vectors ***X*** and ***Z*** represent consumer and healthcare provider characteristics, while Y and P represent household income and prices. A discussion of vectors X and Z is presented in Section 3.

Healthcare quality is an important component in the derived demand for healthcare. In the utility function defined in (1), healthcare provider quality retains its place via the use of qualitative measures of consumer perceptions of quality. However, it has become standard for empirical work in developing economies to allow provider quality to drop out of a reduced form random utility model (Borah, 2006; Gertler et al., 1987; Sahn et al., 2003). However, healthcare quality has been modelled as a random component by Chang and Trivedi (2003). The inclusion of consumer perceived measures of 'quality' in the utility function (1) is important for several reasons. Due to the low level of clinical quality regulation in the Indian healthcare market and the credence nature of healthcare, objective measures of provider clinical quality are difficult for consumers to assess (Dulleck and Kerschbamer, 2006).

Word-of-Mouth recommendations of heterogeneous healthcare providers are important in informing consumers' prior beliefs of provider quality. These prior beliefs reflect consumers' perceptions of expected health outcomes (Cronin and Taylor, 1992; Panchapakesan et al., 2009). A series of papers by Das and colleagues has shown that the relationship between outpatient healthcare provider effort and knowledge systematically varies according to provider type in North India (Das et al., 2007, 2012b, 2016). Patients are assumed to have a consistent rank ordering of provider effort. Word-of-Mouth recommendations from social networks, particularly immediate family networks[2], are viewed as an important mechanism to reduce consumers' diagnostic search costs (Campbell, 2013; Erden and Keane, 1996). Therefore, assuming that consumers select a provider prior to any consultation, based on the joint perception of personal and family network provider experiences, controlling for these prior believes in the utility function, is important.

We hypothesise that consumers expect relatively lower health outcomes when treated by unqualified providers, and that the expected health outcomes of government MBBS providers are lower than private MBBS providers but higher than that given by unqualified providers. As a result, the trust of consumers, as generated through Word-of-Mouth recommendations, is likely to capture relative measures of outpatient fever treatment quality.

2. Data

Four 'doctor' type categories are used in this study. These are 1) unqualified providers[3], 2) private MBBS doctors, 3) government MBBS doctors and 4) Other provider category representing a collection of self-medication, government nurses, traditional forms of medicine and no treatment. This choice set was defined following a census and qualitative interviews with key informants within and surrounding the sample villages. The key informants (community health workers, elected village leaders, private healthcare providers and drug retailors) helped enumerators to identify private and government healthcare providers servicing the village (both within the village and immediately surrounding). This qualitative work from each of the eight sample villages revealed that all villages: i) either had a resident set of unqualified providers or at least one unqualified provider who regularly

[2] In addition to the role of word-of-mouth recommendations in providing consumers with information about provider quality, it helps to weaken the implicit modelling assumption that all respondents in North India make autonomous healthcare decision. The culturally dominant practice that daughters-in-law are subservient to their mothers-in-law, within an intergenerational household, is expected to help generate non-autonomous financial and healthcare decision-making.

[3]The Hindi phrase *jhola chhaap* is used to refer to unqualified allopathic healthcare providers. It carries negative connotations. As a result, it may be likened to the term 'quack'. The phase 'unqualified provider' used in this study implies the meaning associated with the Hindi pharse '*jhola chhaap*'.

consulted each week in the village and ii) three out of the eight villages had a government health facility where at least one MBBS doctors was nominally posted (see Supplementary S3 for details of sampling frame, choice set creation, attributes of surveyed providers). This uniformity of the availability outpatient healthcare provider groups supported the use of a fixed choice set in each the RP and choice experiment data across all respondents.

Survey responses from a total sample of 1173 individuals are used in the current analysis. All respondents answered a set of nine choice tasks (experimental data) and completed a recall survey of fever treatment consultations. Respondents were selected to participate in the survey without regard to the time interval since their last episode of fever. The following proportion of respondents reported experiencing fevers within the specified time interval: 47 percent within 30-days, 68 percent within 6-months, 83 percent within 12-months and 100 percent within 5 years. The recall survey framed a series of direct questions concerning treatment for fever symptoms that had lasted for between 1-3 days prior to seeking treatment. This definition of mild-severe fever acknowledged the results of preliminary qualitative work revealing that many people waited at least a day prior to seeking treatment.

The survey contained two components. The first collected basic demographic and socio-economic details. The second collected recent treatment history. Sequentially enumerators asked respondents about provider characteristics and prices paid (with or without medicine) for each provider consulted, for a single episode of mild-severe fever. In turn, this treatment history contained three sections: i) most recent mild-severe fever (defined by high temperature and shivers), ii) reasons for consultation or non-consultation with government MBBS doctor (i.e. visiting a Community or Primary Health Centre), and iii) a series of questions defining what type of healthcare provider, if any, they consulted during their most recent fever. The following provider categories where used: non-MBBS doctor (including a range of sub-types), private MBBS doctor and government MBBS doctor. When defining the healthcare provider consulted the following information was also collected: cost of treatment, distance (km) from home, whether return visits were made for the same episode of fever, frequency of return visits and associated payments for return visits.

The descriptive statistics of the full data, including prices, are shown in Table I. The attributes used in the SC choice tasks are i) prices, ii) travel distances, iii) Word-of-Mouth recommendations and iv) mode of treatment for unqualified providers and whether extra medicine charges are expected when seeing government MBBS providers (Iles and Rose, 2014). The SC choice task included four alternatives: Unqualified provider, private MBBS provider, government MBBS provider and 'none-of-the-above'. The price attribute included three levels for each alternative. The levels were: INR 50, 100 and 150 for unqualified providers, INR 1, 25 and 50 for government MBBS doctors, and INR 100, 200 and 300 for private MBBS doctors. The attribute - travel distance - was; 'at-home' or 'in-village' for the unqualified provider alternative, 'in-village' or '5-15 kms' for each of the MBBS doctor alternatives. The 'word-of-mouth recommendation' attribute was defined by three categorical levels: 'positive', 'negative' or 'no recommendation' for each alternative. The forth attribute related to medicines received. In the unqualified alternative two levels were used to define the mode of treatment: 'pill' or 'pill and injection'. This attribute was defined to relate to whether medicines received from the government MBBS doctors were 'free' or required an 'extra-charge'. An example of the presentation of the SC task is presented in Figure I.

[Insert Table I here]

[Insert Figure I here]

The experimental design of the choice task were informed by prior analysis of 13 interviews with consumers and 14 interviewers with private healthcare providers within the sample villages. The consumer interviews included several ranking exercises to elicit preference for health provider attributes (including 'trust') and sources of 'trust'. All tools and a summary of the interview data are provided in Iles (2014). Prior to completing the choice experiment respondents were instructed to assume that government MBBS providers were always available at the government health centres. The magnitude of this counterfactual assumption across sample villages appears to differ. Qualitative data from the recall survey indicates that the location of the government health centre and the perceived availability of government MBBS providers are the two most important reasons why respondents don't attend government centres for fever treatment (see Table S5). Within sample villages that had a functioning government health centre with MBBS providers the proportion of respondents who did not select to consult a government MBBS provider as their first choice source of treatment due to non-availability was: 25, 21 and 18 percent. No instructions were given concerning the use of informal payments to government MBBS providers above the one rupee (INR 1) administration fee.

A qualitative data collection and analysis process assisted in identifying important SC variables, which contributed to the elimination of omitted variable bias in joint estimation (see S3). The use of this qualitative process ensured that the price and distance values used in the SC design were appropriate. Although the SC and RP data were collected during a single 'interview' with a respondent, the price and distance levels correspond well - see Table I. The use of four provider alternatives in the SC tasks are the same as used in the RP survey. The pricing of outpatient treatment in the selected villages typically includes the cost of medicine and a consultation fee or 'margin'. This is the case for the majority of unqualified and government doctors in rural areas who supply their own prescribed medicine. Approximately 30 percent of government consultations were priced at the prescribed INR 1 fee.

The choice experiment analysis consists of 587 respondents who answered Efficient design choice tasks[4], while the RP datum is from the same SC respondents and an additional 586 respondents who answered Orthogonal design SC choice tasks (see Iles and Rose, 2014). The unequal number of RP and SC respondents causes the data to be unbalanced and follows Brownstone, Bunch and Train (2000) who use a RPL (EC) model in a combined analysis of revealed and stated preference data. The combined effect of having a larger number of RP respondents and the weighting of the SC data ensures that the RP data effectively has twice the implicit weight on parameter estimates. The results presented are based on each of the nine SC choice tasks receiving a weighting of 0.1111. Sensitivity analysis using a weighting of 0.222 is presented in Figures S6.1 through S6.5.

RP datum for non-selected alternatives is drawn from data provided by the same individuals who, for the same episode of fever, consulted other providers (see Iles, 2018 for details of repeat visit behaviour). This additional consultation data are available for 65 percent of non-selected unqualified providers and 35 per cent of non-selected government providers. The remaining non-selected data are imputed using a Multivariate Imputation by Chain Equation (MICE) method to estimate price and distance values (see S4 for details). The R packages *MICE* and *Countimp* are used to fill the missing values following a series of univariate imputations (Kleinke and Reinecke, 2013; van Buuren and Groothuis-Oudshoorn, 2013).

[4]See Iles and Rose (2014) for a description and discussion of alternative SC experimental designs and their impact on literate and illiterate respondents' behaviour.

With the assumption of missing at random (MAR) applicable to the missing data there are no reason to believe that results are biased due to the imputation. The MAR assumption for the missing data associated with the non-selected alternatives holds. Within each healthcare provider alternative, the probability of the data being non-selected has an equal probability. This set of missing data are associated with whether consumers sought treatment from multiple providers. The association between whether the initial provider was an unqualified provider or a government MBBS provider is not a determining factor in whether additional providers were sought. As a result, this data may also be considered MAR. The RP private MBBS provider category, which constitutes approximately 10 percent of all RP provider choice, is merged with the residual None (Other) category. This merger is due to insufficient data to impute values for the approximate 90 percent of cases when this provider type is a non-selected alternative.

The vectors representing consumer and healthcare provider characteristics (**X**, **Z** in equation 1) include a range of demographic and socio-economic variables: caste, literacy level, employment category, travel distance, perceived provider quality, and government and unqualified specific determinants, respectively. The qualitative measures included in the SC data are i) Word-of-Mouth recommendations as a proxy for trust (Ahmed et al. 2014; Leonard et al. 2009), ii) perceived quality of mode of medicine administration (Kermode and Murani, 2006), and iii) the perceived need to make payments (either informal or to private chemists) for medicines prescribed by government doctors (Dasgupta et al., 2015) (see S5 for a summary of perceived reasons for not using government doctors from the sample data).

The practice of price discrimination by individual healthcare providers (private and public) has not been previously tested. With the weak governance oversight of the public and private health sectors in North India, price discrimination is highly likely due to the credence nature of healthcare. The median charge of consulting a government MBBS provider (without imputed values) is INR 15 for consumers in the first (lowest) income quartile and decreasing to INR 3 in the fourth (highest) income quartile. It might be expected that households in the higher income quartiles have a greater ability to pay, and therefore, would be discriminated against by a high price. However, these higher income households are on average more educated, and by extension, more aware that government providers are regulated to only charge a INR 1 administration fee that covers the consultation and prescribed medicines. This would account for the charging of lower informal payments among higher income households.

The Job variable, Job1, denotes the respondents whose primary occupation was farming. Job2 denotes respondents who self-identified labouring as their primary occupation, while Job9 captures respondents who identified unpaid domestic work as their primary occupation. The Other Job category includes respondents who self-identified as: unemployed, unclassified, tradesperson, shopkeeper, government employee, market seller, and business person. The fever duration variables have the following meanings corresponding to length of time: Dur1 - 1-3 days, Dur2 - 4-6 days, Dur3 - 7-9 days, and Dur4 - 10+ days.

Analysis was performed using the full data set, which includes eight villages from three districts, and a reduced data set that included a sub-set of 6 villages from two districts. Although the districts selected for sampling reflect a representative sample of Uttar Pradesh's districts (using an interquartile range of aggregate household income and religious composition) the RP survey data for choice of providers, corresponding prices charged, and household income estimates indicate that the two villages in District 2 (Lalitpur) were significantly different from the sample villages in districts 1 (Fatehpur) and 3 (Balrampur). Table II and Figure II present a summary of data highlighting the difference. The sample villages in district 2 reported: a higher level of government MBBS provider consultations for fever symptoms (40.6 vs 17.5 percent), statistically significant lower mean household annual income (INR 6527 vs INR 10000), and a lower proportion of households reporting payment of the INR 1 for government MBBS provider fever consultation (20 vs 40 percent). The proportion of district 2 respondents indicating that they first sought treatment for fever symptoms from a government MBBS provider (40.6 percent) is significantly higher than the national rural average of 11.5 percent for all symptoms (NSSO, 2015). The combined effect of differences in government MBBS provider choice and the higher mean price charged by government MBBS providers unduly, in a small sample, change the parameter estimate for government MBBS price. The exclusion of district 2 data provides a more accurate aggregate profile of rural North Indian outpatient healthcare market.

[Insert Table II here]

[Insert Figure II here]

3. Model Estimation

The estimation of consumer utility includes data collected using two distinct sources. Recall survey data constitutes a form of RP data. This forms of RP data are considered relatively weak compared to barcode or insurance claim data, due to the likely presence of recall bias and measurement errors (Das et al., 2012a). Despite being a relatively weak form of RP data, recall survey data reflects actual healthcare utilization decisions made in functioning markets. However, RP data does not capture many qualitative variables that may have affected consumers' healthcare utilisation decision. One such qualitative variable is 'word-of-mouth' recommendations. The use of non-market experimental SC data allows for the inclusion of such unobservable data (Hensher et al., 1999).

The SC data used in this research involved experimentally defining a choice situation that reflected actual market features. Once defined, respondents were asked to selected their preferred alternative from a set of four alternatives. Each alternative was defined by provider type (private or government, qualified or unqualified), price, travel distance, word-of-mouth recommendation and medicine characteristics. Each respondent answered nine different choice scenarios (i.e. tasks). The design of each scenario is unique requiring the respondent to make trade-offs among attributes according to varying attribute levels - prices, distances, positive or negative recommendations. The inclusion of common price and distance measures in the RP and SC data enables the joint modelling of data to account for scale differences. The econometric models outlined below catalogue different approaches that control a range of structural and behavioural features of the data.

Consumer demand estimates for healthcare providers in developing economies has widely utilised Maximum Likelihood estimators for qualitative response data. The Random Parameter Logit (RPL) model extends standard Multinomial Logit (MNL) estimations by introducing β estimates that vary across individuals, which allows for control of preference heterogeneity. The RPL model is well suited to jointly model RP and SC data. Parameters are estimated using either or both data sources in utility functions specified for each alternative and for each data source. Several econometric techniques have been developed to control for a range of important scale and heteroscedastic characteristics that vary across the data sources. The remainder of this section details the RP-SC unified choice modelling approach proposed by Bhat and Castelar (2002), which is applied in the current study.

The greater flexibility of the RPL also carries favourable behavioural characteristics. This modelling approach enables four important issues to be adequately managed when modelling RP-SC data jointly: i) error structure, ii) scale difference, iii) unobserved heterogeneity effects and iv) state-dependence effects (Bhat and Castelar, 2002). Error Components (EC) are a set of independent individual terms that are added to the utility function. The inclusion of error components (EC) to RPL is one way of accounting for the differences in error variance across healthcare provider type. The non-IID error structure is maintained in the RPL (EC) from the base RPL model.

Equation (2) shows the probability that a consumer chooses provider q at time t is a function of the relationship between the characteristics of the selected alternative, relative to all possible alternatives. The use of exponential terms follows random utility specifications. Equation (2) extends the standard random utility specification by including the EC term to a RPL probability function with the inclusion of a scale parameter λ_{qt}

$$Prob(c_{qt} = j) = \frac{e^{\lambda_{qt}(z'_{qjt}\beta_q + \sum_{m=1}^{M} d_{jm}\theta_m E_{qm})}}{\sum_{a=1}^{J_q} e^{\lambda_{qt}(z'_{aqt}\beta_q + \sum_{m=1}^{M} d_{am}\theta_m E_{qm})}}, \qquad (2)$$

where c_{qt} is the index of the choice, E represents the 'error component', θ represents the standard deviation, d represents a binary value denoting the presence of E for a given healthcare provider alternative and the subscript m denotes the number of Es. The combined use of RPL (EC) model provides a flexible framework to jointly model RP and SC data.

The scale parameter(s) is estimated as part of the error terms and is defined as $\lambda_{qt} = [(1-\vartheta_{qt,RP}) \times \lambda] + \vartheta_{qt,RP}$ (Bhat and Castelar, 2002; Hensher, 2012). The term $\vartheta_{qt,RP}$ is equal to 1 if an RP is observed and zero otherwise. The parameter estimate for $(1 - \vartheta_{qt,RP})$ captures the state dependence effect of the association between the RP alternative choice and those in the corresponding SC data (Bhat and Castelar, 2002). Heterogeneity across income is controlled through the random parameters in the RPL model. The unified RP-SC modelling approach of Bhat and Castelar (2002) is a common modelling practice (Cherchi and Ortuzar, 2011; Hensher, 2012).

The price and income values are all positive, so distributions allowing only for positive draws are appropriate. Triangular distributions anchored at zero are used for income random parameters and unqualified providers, private MBBS and government MBBS prices (Hensher, 2012). As a result of the mixing of distributions in the residual, interpretations of the coefficients are not the same as in the base MNL model. The RPL model results are based on the simulated maximisation of the log-likelihood. Two hundred Halton draws are made from the distributions of the random variables. The RPL (EC) model fit the data better than the Generalized Mixed Multinomial Logit (Fiebig et al., 2010) (see S1). Parameter estimates of the separate RP and SC data are presented in Supplementary material S2.

Parameter estimates are based on five additive utility functions - three related to SP choices and two for RP choices. In general, the utility functions in each dataset type uses only its own data. For the purposes of estimating the counterfactual scenario of zero government MBBS provider absenteeism this is required. However, the price parameter estimates are based on both data types. This ensures that the price estimates and related elasticities have as much realism as possible and, as such, reflect current market realities. The income parameter estimate is used jointly to provide further anchoring between the estimates of both data and a basis for estimating scale effects.

4. Results

4.1 Unconditional estimates

The results of joint modelling of RP and SC data using a RPL (EC) model are presented in Table III (model fit results using full sample are presented in S1). The parameter estimates that use both datasets reflect cases where selected variables are listed in each of the two utility functions for the nominated healthcare provider alternative (RP and SC). Price and log of income variables are estimated jointly. The log of household income squared was estimated separately using RP and SC data due to the apparent large scale difference in individual estimates (see S2). The Distance variables are estimated separately due to the use of different categorical variables in the RP data compared to the SC data. The corresponding unqualified provider SC Distance coefficient reflects preferences towards zero travel (i.e. at home consultation) relative to the base of travel within the immediate village (i.e. less than 1km). The Distance coefficient in the SC government MBBS provider utility function is negative and reflects preferences towards travelling 5-15 km, relative to the base of in village travel (only two of the six sample villages had a government MBBS provide posted within the immediate village). All covariate data used to estimate the coefficients in the SC utility functions are also used in the RP utility functions, except for duration of fever. This was done to ensure stability of the estimates.

Several salient coefficient estimates are apparent from Table III. Firstly, the government MBBS provider price coefficient is negative when excluding the villages in district 2. The Medicine coefficients in the SC unqualified provider utility function measures respondents' preference for a combine pill and injection mode of treatment, relative to a pill only. This positive coefficient contrasts to the negative coefficient in the government MBBS provider function. The Medicine coefficient in the SC government MBBS utility function reflects respondents' preference towards paying for medicine (at the government clinic or in the private sector) relative to accessing free medicine at the government clinic. The negative Medicine coefficient in the government MBBS provider utility function reflects a strong preference for accessing free government medicine, as per government policy.

[insert Table III here]

Results in Table III shows that Word-of-Mouth recommendation for private providers are perceived differently by consumers for unqualified and MBBS qualified providers when treating fever symptoms. The coefficient for positive recommendation for unqualified providers is positive and significant at the one percent level. The corresponding negative recommendation coefficient is negative, and is significant at the 10 percent level. The inclusion of interaction coefficients for distance and negative recommendation for the private MBBS provider is negative and statistically significant at the one percent level. However, the inclusion of the interaction terms for private MBBS provider reduces the significance of the positive recommendation coefficient, highlighting the negative Word-of-Mouth recommendation are statistically more meaningful for providers who are assumed to be sources of high quality of care. The recommendation coefficients for the government MBBS provider are correctly signed and statistically significant at the one percent level.

These model estimates confirm the hypothesis that consumers' ranking of expected health outcomes by provider type reflect the relative measures of clinical treatment of unqualified, government MBBS and private MBBS providers provided by Das et al. (2016). Positive recommendations increase the likelihood consulting an unqualified provider to treat a mild-severe fever. The lack of corresponding importance in negative recommendations for the same providers suggests that healthcare consumers have a prior expectation that unqualified providers offer relatively low quality care. However, the dual importance of positive and negative recommendations for government MBBS providers suggests consumers weigh both positive and negative recommendations. This confirms that consumers' prior expectation is that government MBBS providers may or may not offer higher quality healthcare, relative to unqualified providers.

The results in Table III provide the basis for the counterfactual market share estimates. Once the counterfactual assumption of zero government MBBS provider absenteeism is applied expected utilisation of government MBBS provider fever services increases from 17.5 to 49.6 percent. Table IV also shows that the market share of unqualified primary healthcare providers decreases from 66.2 to 35.2 percent under the counterfactual scenario of zero government MBBS provider absenteeism. Constraint on the growth of the counterfactual market share for government MBBS provider is due to consumers' negative perceptions of government MBBS provider service quality. These include: perceived poor quality of medicines, perceived need to pay informal payments and other factors (see S5).

[Insert Table IV here]

5. Simulated demand elasticities

The own-price demand elasticities for unqualified providers and government MBBS providers are calculated using the unconditional RP and joint RP and SC demand estimations from Table S2 and Table III. The two sets of estimates are provided: i) the current level of healthcare provider competition in selected areas of rural Uttar Pradesh and ii) counterfactual market demand. Figure III communicates the aggregate effect of the counterfactual assumption that all government MBBS providers are present at their post on own-price elasticities for government MBBS and unqualified providers. The right-hand panel reflects an unchanged own-price elasticity of -0.06 for government MBBS provider fever services when moving from the current market to the counterfactual market. In contrast, the own-price elasticity for unqualified private providers for fever treatment increases from -0.24 to -0.56 under the counterfactual market scenario. Equivalent mean own-price elasticities are presented in Figure S6.1 using a revised weighting of 0.222 per SC choice task. The relative lack of movement in the own-price elasticity for government MBBS providers supports the argument (and experimental design) that respondents made counterfactual choices based on current pricing practices. The greater level of competition in local markets under the counterfactual assumption is expected to increase consumers price sensitivity for substitute services, particularly those that may be viewed as of lower quality.

[Insert Figure III]

The mean own-price demand elasticities for government MBBS providers, by income quartile, under the counterfactual scenario are presented in Figures IV and V. For government MBBS providers, the elasticity point estimates increase (decrease in absolute value) from QR_1 (-0.07) to QR_4 (-0.05). The elasticities at QR_1 and QR_4 are statistically different. This same pattern in the mean point estimates is also reflected in the arc estimates across three price intervals. Figure V depicts the own-price arc elasticities for the intervals INR 1-50, 51-100 and 101-150. The arc estimates for the interval INR 1-50 reflect those presented in Figure IV. Over the price interval 51-100 the arc estimates are -0.20 for QR_1 and increase to -0.13 for QR_4. While estimates of -0.27 for QR_1 and -0.18 for QR_4 are shown for the price interval INR 101-150. Equivalent own-price elasticities are presented in Figures S6.2 and S6.3 using the revised weighting of 0.222 per SC choice task. The decreasing elasticity estimates (in absolute terms) across income quartiles is as expected. Those with higher income, on aggregate, are less price sensitive to low single visit fees.

[Insert Figure IV & V]

The unqualified provider counterfactual own-price elasticity estimates, by income quartile, are presented in Figures VI and VII. Higher unqualified provider estimates, under the counterfactual scenario of greater certainty of availability of government MBBS providers, reflect consumers’ greater price sensitivity due to a more reliable supply of lower single-visit cost government providers. Figure VI communicates an increasing price sensitivity from lower to higher income quartiles. The mean estimate of -0.50 for respondents in the lowest income quartile (QR_1) is statistically different from -0.61 for those in the highest quartile (QR_4). The arc estimates for price intervals below and above the mean price are consistent. In Figure VII the arc own-price elasticities for the interval INR 1-50 commence at -0.22 in QR_1 and decrease to -0.27 for QR_4. Across quartiles, estimates for the interval INR 101-150 fall from -0.62 in QR_1 to -0.78 in QR_4. The same pattern is evident in the own-price elasticity estimated for unqualified providers present in Figures S6.4 and S6.5, using the higher weighting of SC choice tasks of 0.222. In both these figures the elasticity range is greater between QR_1 and QR_4. The range for mean own-price is -0.43 to -0.70, while over the price interval INR 101-150 the range is -0.51 to -0.93. This pattern is counter to microeconomic theory and is contrasting to the results for the government MBBS providers.

[Insert Figure VI & VII]

Taking the assumption, which is supported by Word-of-Mouth recommendation parameter estimates presented earlier, that consumers expect unqualified providers to offer lower quality care, the increasing price sensitivity among higher income groups stands to reason. Consumers with higher incomes, who are generally more educated in rural North India, are more sensitive to paying higher prices for health services that are expected to be of lower quality, compared to those provided by qualified providers.

Elimination of government MBBS provider absenteeism in North India would increase consumers' price sensitivity for unqualified provider fever treatments (cross-price elasticities are provided in Table S6.1 and S6.2). The results in Figure III demonstrate that, based on the assumption of zero government absenteeism and current market prices, the price sensitivity of consumers for fever outpatient treatment services by unqualified private providers is expected to increase two-fold. This increased price sensitivity is most pronounced among higher income groups.

6. Concluding Comments

The proceeding results demonstrate that the removal of government MBBS provider absenteeism in rural North India would increase the market share of the public sector for fever treatment services. The estimated increase would provide the public sector with parity relative to the private sector for fever treatment. Due to the high prevalence of communicable diseases, such as malaria, tuberculosis and dengue fever, across the North Indian states of

Uttar Pradesh, Bihar and Madhya Pradesh, fever symptoms treatment demand may be considered as a proxy for outpatient demand, in general. However, the treatment of chronic conditions such as tuberculosis, and for more specialised conditions, the demand for government MBBS provider outpatient services may be greater than for fevers. Therefore, generalising the current results beyond the immediate consideration of undiagnosed fever is not warranted. The other side of this parity indicates that the unqualified primary healthcare provider would continue to play an important role in outpatient service delivery. An estimated market share of 35 percent would ensure that unqualified providers continue to provide a large quantity of healthcare to rural communities.

Demand estimates presented here indicate that uncertainty of government MBBS provider availability is a barrier to increasing the market share of government health centres in treating outpatient fever patients in Uttar Pradesh. However, the increased market share of government MBBS providers is not as large as one might expect. The expected marginal benefit of better health offered by government MBBS providers is outweighed by the combined expected marginal cost of paying informal fees and travel costs. Although not tested in this paper, latent perceptions of continued low levels of effort among government MBBS providers may limit the potential counterfactual demand for qualified provider services.

The hypothesis that consumers perceive the quality of care of unqualified providers as being lower than that provided by government MBBS doctors is affirmed. The findings that consumers' predominantly use positive recommendations in choosing to access fever treatment from unqualified providers, while using both positive and negative recommendations when choosing to seek fever treatment from government MBBS providers, attests to an aggregate expected lower quality of care offered by unqualified providers. These results indicate that consumers in low-middle income countries, particularly in this case in rural North India, are not naïve about differences in outpatient service quality among the unqualified or the public sectors. This is despite the difficulty for consumers to objectively measure clinical quality. Improvement in the quality of health services received by the poor and marginalised in low-middle income countries requires improved provider behaviour across the market, not just among unqualified providers.

The role of unqualified providers in the current and counterfactual Indian market remains vital. Therefore, policy options towards formalising the role of unqualified outpatient providers within the health system (i.e. community level ambulatory health providers) warrants further consideration. Ways of incorporating these informal providers into any universal health scheme appears a justifiable avenue for further consideration and research.

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Tables

Table I: Descriptive Statistics for Revealed Preference and Stated Choice Variables – Full Sample

	Full sample Vill 1-8		Partial sample Vill 1-4,7-8	
	Mean/ Proportion	St. Dev	Mean/ Proportion	St. Dev
Stated Choice				
Price - unqualified	79.81	34.1	80.25	32.0
Price - private MBBS	144.30	56.9	143.11	54.9
Price - government MBBS	23.43	17.9	23.75	17.6
Revealed Preference				
Price - unqualified	82.29	85.8	63.16	69.5
Price - government MBBS	63.39	244.0	47.22	68.8
Distance - unqualified (categorical variable)	1.33	1.9	1.35	1.8
Distance - government MBBS (categorical variable)	7.31	5.4	6.15	6.2
Lnhinc - log household income per person	8.83	0.7	8.93	0.7
Lnhinc2 - log household income per person squared	78.51	12.2	80.29	12.3
Household size	6.90	3.2	6.88	3.1
Religion				
Low caste	0.593		0.526	
Middle caste	0.418		0.370	
High Caste	0.118		0.123	
Jain	0.003		0.002	
Muslim	0.198		0.286	
Literacy				
Illiterate	0.433		0.453	
Literate	0.370		0.343	
Highly Literate	0.195		0.204	
Employment				
Farm (Job1)	0.257		0.161	
Labour (Job2)	0.242		0.324	
Unpaid (Job9)	0.289		0.271	
Other	0.212		0.244	
Duration (percent)				
Dur1 (1-3 days)	0.404		0.460	
Dur2 (4-6 days)	0.304		0.286	
Dur3 (7-9 days)	0.116		0.102	
Dur4 (10+ days)	0.048		0.037	

Table II:

	Revealed Preference provider choices (percent)			Household income per capita				Religious Identity (percent)		Education levels (percent)		
	Unqualified	Gov't MBBS	Pvt MBBS / None	Mean	St. Dev	t-test	p-value	Hindu	Muslim	Illiterate	≤ Primary	≤ High School
District 1	63.5	17.4	19.1	10,001	13232	1:2	<0.001	81.5	18.3	40.8	16.9	23.1
District 2	44.9	40.6	14.5	6,527	4314	2:3	<0.001	99.7	<0.1	39.6	25.8	33.8
District 3	72.0	17.5	10.5	10,132	7933	1:3	0.861	48.8	50.8	55.0	24.8	17.1

Table III: Unconditional Estimates - Joint Revealed Preference and Stated Choice

	Unqualified		Government MBBS		Private MBBS	
	Coefficient	(St.error)	Coefficient	(St.error)	Coefficient	(St.error)
Price [RP,SC]	R_1 : -0.013	(0.003)	R_1 : -0.041	(0.009)	R_1 : -0.015	(0.003)
Ln Income (household pp) [RP,SC]	R_1 : 0.324	(0.217)	R_1 : 0.324	(0.217)	R_1 : 0.324	(0.217)
Ln Income Sq (household pp) [RP]	R_1 : -0.222	(0.072)	R_1 : -0.222	(0.072)	R_1 : -0.222	(0.072)
Ln Income Sq (household pp) [SC]	R_1 : -0.152	(0.039)	R_1 : -0.152	(0.039)	R_1 : -0.152	(0.039)
Distance [SC] *	0.135	(0.077)	-1.741	(0.109)	-2.418	(0.091)
Distance [RP] *	-0.028	(0.059)	-0.043	(0.024)	-	-
Recom. +ve (base: none) [SC]	0.579	(0.093)	0.819	(0.124)	0.011	(0.165)
Recom. -ve (base: none) [SC]	-0.206	(0.121)	-0.728	(0.122)	-0.706	(0.195)
Dist. x Recom. (+ve) [SC]	-	-	0.054	(0.103)	0.115	(0.174)
Dist. x Recom. (-ve) [SC]	-	-	0.094	(0.130)	-0.859	(0.201)
Medicine [SC@]	0.334	(0.072)	-1.098	(0.111)	-	-
Demographic Variables						
Job1[b] (base: all other jobs) [RP,SC]	-0.097	(0.319)	0.460	(0.378)	-	-
Job2[b] (base: all other jobs) [RP,SC]	0.676	(0.284)	0.346	(0.302)	-	-
Job9[b] (base: all other jobs) [RP,SC]	0.363	(0.327)	0.304	(0.338)	-	-
Illiterate[b] (base: highlit) [RP,SC]	0.707	(0.234)	-	-	-	-
Literate[b] (base: highlit) [RP,SC]	0.505	(0.220)	-	-	-	-
Health Variables						
CHC[b] (base: all other villages) [RP,SC]	-0.492	(0.274)	-	-	-	-
PHC1[b] (base: all other villages) [RP,SC]	-0.695	(0.178)	-	-	-	-
Constant [RP]	-	-	-2.546	(0.341)	-	-

	Coefficient	(St.error)
Scale Parameters		
JC (RP, SC)	R_2 : 0.509	(0.294)
Gdr (RP, SC)	R_2 : 1.007	(0.206)
None (RP, SC)	R_2 : 1.529	(1.188)
State Dependence	R_2 : 0.291	(0.055)
Heterogeneity in Mean		
Price - Unqualified	-0.001	(<0.001)
Price - gov't MBBS	-0.001	(0.001)
Price - pvt MBBS	-0.003	(0.001)
Ln Income	1.257	(0.574)
Ln Income Sq. [RP]	-0.075	(0.039)
Ln Income Sq. [SC]	-0.062	(0.031)
Distribution of Random Parameters		
Price - Unqualified	0.013	(0.003)
Price - gov't MBBS	0.041	(0.009)
Price - pvt MBBS	0.015	(0.003)
Ln Income	0.324	(0.217)
Ln Income Sq. [RP]	0.222	(0.072)
Ln Income Sq. [SC]	0.152	(0.039)
State Dependence	0.043	(0.133)
Error Components		
Unqualified (SC) + Unqualified (RP)	0.596	(0.277)
Gdr (SC) + Gdr (RP)	1.064	(0.215)
Model Fit		
LL	-2766.5	
AIC	5634.9	

R_1 random parameter with triangular distribution; R_2 random parameter with a normal distribution

[SC] State Choice parameter; [RP] Revealed Preference paramater

Table IV: Utilisation of healthcare provider according to survey type

Full recall - unconditional		
	RP	**SC***
	percent	percent
Unqualified 'doctor'	66.2	35.2
Private MBBS doctor	-	13.8
Government MBBS doctor	17.5	49.6
None (Other)	16.3	1.4
TOTAL	**100**	**100**

Note: * A central assumption of the SC survey was that government MBBS doctors were always present and available in and/or surrounding each village.

Figures

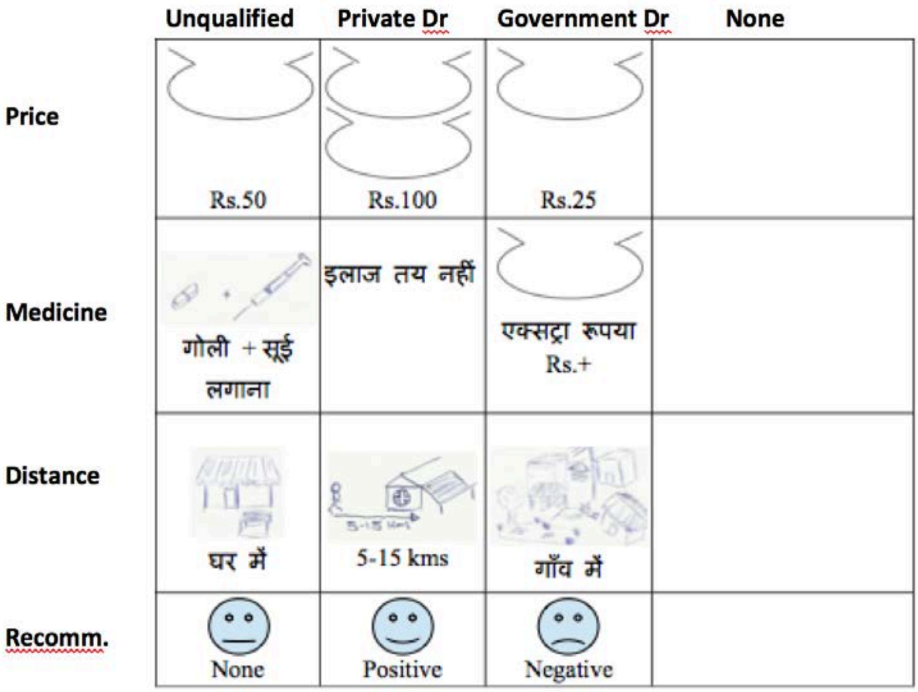

Figure I: Example presentation of SC task

Figure II: Histogram of Government MBBS provider priced for fever treatment, by District

Figure III: Own-price Mean elasticities for Unqualified and Government MBBS providers for market and counterfactual scenarios in Districts 1 and 3.

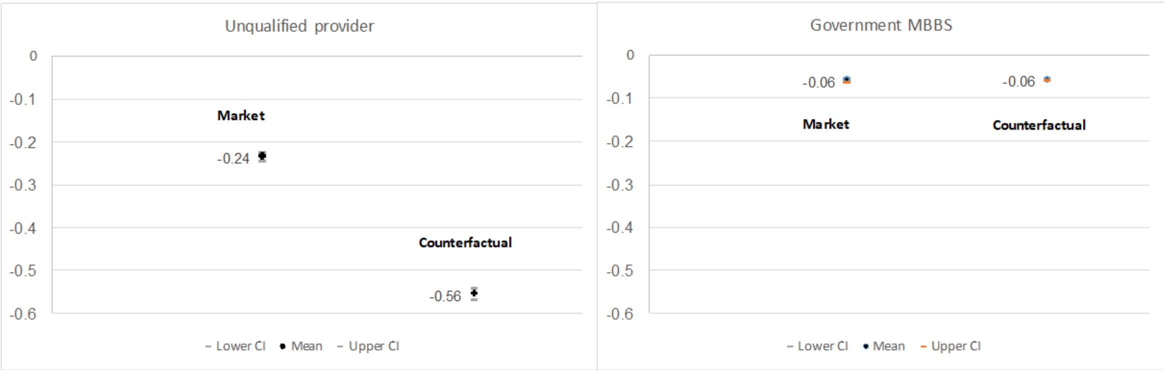

Figure IV: Own-price Mean elasticities for Government MBBS provider fever treatment in Districts 1 and 3 by income quartile.

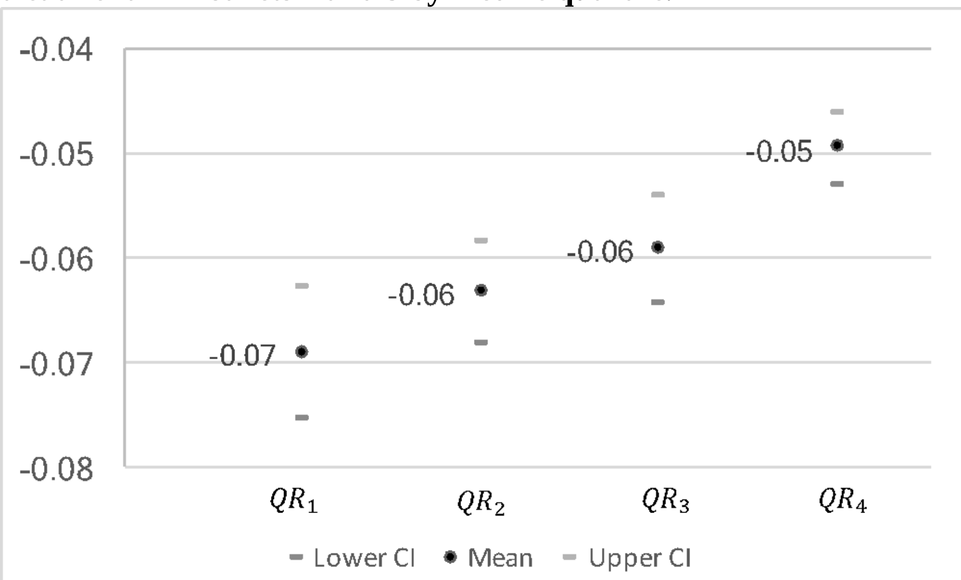

Figure V: Own-price arc elasticities for government MBBS provider fever treatment in Districts 1 and 3 by income quartile.

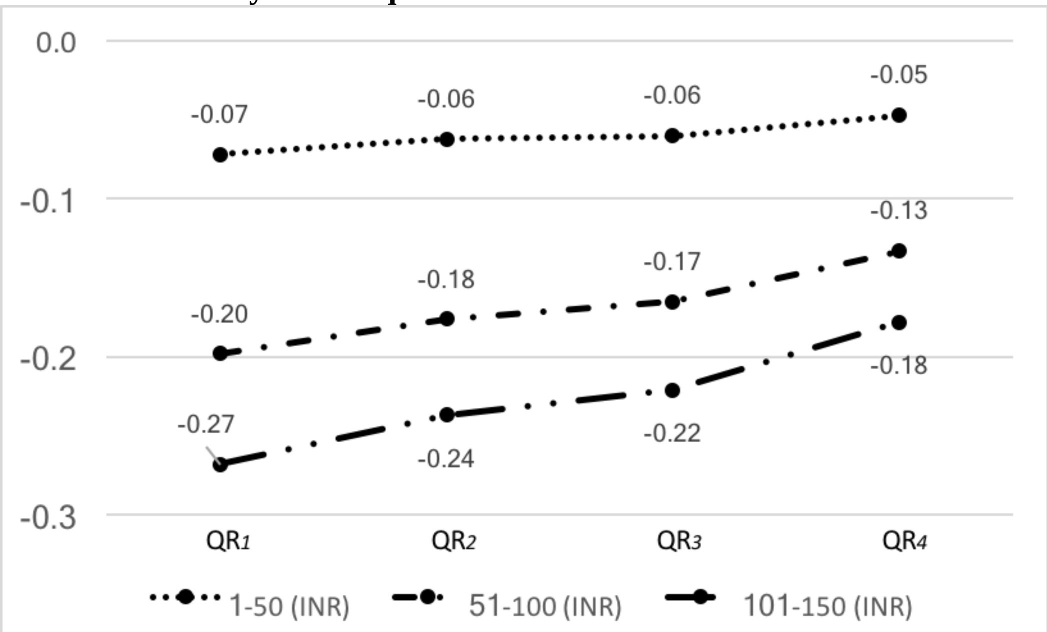

Figure VI: Own-price Mean elasticities for Unqualified provider fever treatment in Districts 1 and 3 by income quartile.

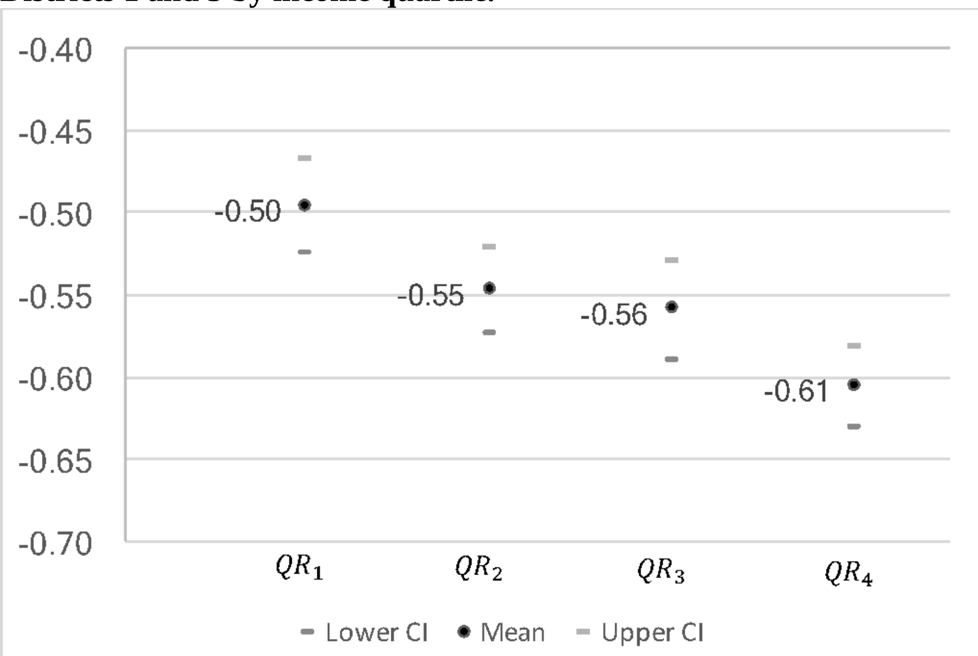

Figure VII: Own-price Arc elasticities for Unqualified provider fever treatment by income quartile.