School of Economic Sciences

Working Paper Series
WP 2017-9

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October 2017

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GOVERNMENT DOCTOR ABSENTEEISM AND ITS EFFECTS ON CONSUMER DEMAND IN RURAL NORTH INDIA.

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Abstract

Government doctor absenteeism from their public posts is a sizable problem across developing economies. The consumer demand estimation for outpatient fever treatment presented in this paper investigates the interrelationship between government doctor absenteeism and the large informal healthcare sector. Using a counterfactual framework this paper estimates treatment effect of eliminating government doctor absenteeism. The effects are measured by changes to the market share of government MBBS providers and resulting own-price elasticities of demand for government MBBS providers and unqualified providers. Modelling incorporates patients expected health outcomes, by provider, via the use of a qualitative measure of word-of-mouth recommendations. Results indicate that eliminating government MBBS provider absenteeism in North India would increase utilisation of government outpatient fever treatments from 25 to 50 percent.

Keywords
Consumer demand, Absenteeism, Counterfactual, India

JEL: I11, I32

* This research was supported by Griffith University (Australia) and the Centre for Development Economics, Delhi School of Economics (India) who hosted the author as a Visiting Scholar in 2012. Helpful comments on earlier drafts of this paper were provided by Tim Powell-Jackson, Ben Cowan and from participants of the Indian Statistics Institute 2015 Development Conference in Delhi. All mistakes are the sole responsibility of the author.

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 between 20 to 30 percent (Das et al., 2016; NSSO, 2015). The differential treatment effort exerted by government MBBS providers, relative to private MBBS providers, is low (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 equally 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 are provided under status quo and the counterfactual scenario of zero government MBBS provider absenteeism. Results inform policy debate concerning how health systems in developing economies should consider expanding coverage under the agency of universal health care.

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

In addressing the above question, this paper makes several contributions to the literature. It offers the first estimates of demand for unqualified private healthcare provider outpatient services. 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 data 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 and private unqualified 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 sets 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 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 data is a practical and informative alternative to RCTs.

The utility framework and functional form used are outlined in Section 1, 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, a rationale for using word of mouth recommendation as a proxy for patient expected health outcomes and an explanation for lower informal patient payments for higher income households. 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

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

where subscripts q,j denote consumers and provider alternatives. The vectors $\boldsymbol{X}$ and $\boldsymbol{Z}$ 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 of 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. Model Estimation

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 greater flexibility of the RPL also carries favourable behavioural characteristics. This

[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.

modelling approach enables four important issues to be adequately managed when modelling RP-SP 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. The unified RP-SC modelling approach of Bhat and Castelar (2002) is a common modelling practice (Cherchi and Ortuzar, 2011; Hensher, 2012).

Equation (2) shows the inclusion of EC to a RPL probability function with the inclusion of a scale parameter λ_{qt}

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

where 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).

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 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 (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.

3. 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 used following a survey of providers within and surrounding the sample villages (see Supplementary S3 for details of sampling frame, choice set creation, attributes of surveyed providers).

Survey responses from a total sample of 1173 individuals are used in the current analysis. The SC data uses 587 respondents who answered Efficient design choice tasks[4], while the RP data is from the same SC respondents and an additional 586 respondents who answered Orthogonal design SC choice tasks. 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 qualitative data. The aggregation of the RP data (no assumption of government doctor absenteeism) with the SC data (assuming zero absenteeism) involves applying an exogenous weighting to account for the number of surveyed villages with government facilities. Further details of this assumed availability under the counterfactual scenario are provided in S4.

RP data 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, 2015 for details of repeat visit behaviour). This additional consultation data is available for 65 percent of non-selected unqualified providers and 35 per cent of non-selected government providers. The remaining non-selected data is imputed using a Multivariate Imputation by Chain Equation (MICE)

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[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'*.

[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.

method to estimate price and distance values (see S5 for details). 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 S6 for a summary of perceived reasons for not using government doctors from the sample data).

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 (see Iles and Rose, 2014 for further details). A qualitative data collection and analysis process assisted in identifying important SC variables, which assist in eliminating omitted variable bias in joint estimation (see S3). 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.

[Insert Table I here]

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 who primary occupation was farming. Job2 denotes respondents who 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 identified as a: unemployed (5.3%), unclassified (3.6%), tradesperson (3%), shopkeeper (2.7%), government employee (2%), market seller (1%), and business person (1%). 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.

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 II (model fit results are presented in S1). The parameter estimates that use both data sets reflects cases where variables are listed in each of the two utility functions for the nominated healthcare provider alternative (RP and SC). 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 closeness of these parameter estimates in Table II provides a measure of the model's ability to account for scale difference. The Distance variables are estimated separately due to the use of continuous variables in the RP data and a qualitative variable in 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. All covariate data is used to estimate the coefficients for the RP utility functions, except for duration of fever. This was done to ensure stability of the estimates. Where possible, the covariates are used in the RP and SC utility function estimates.

Several salient coefficient estimates are apparent from Table II. Firstly, the government MBBS provider price coefficient is positive. This reflects the fact that i) lower income households report paying more for government services than did higher income households and ii) lower income households are more likely to access locally available and known healthcare providers (33% respondents in QR_1, 25% in QR_2, 18% in QR_3 and 24% in QR_4). 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 II here]

Results in Table II shows that the *positive recommendation* coefficient for unqualified providers is positive and significant at the one percent level. The corresponding *negative recommendation* coefficient is negative, but it is not significant at the 10 percent level. Both the *recommendation* coefficients for the government MBBS provider are correctly signed and statistically significant at the one percent level. The inclusion of interaction coefficients for *distance* and *positive recommendation* for the private MBBS provider is positive and statistically significant at the one percent level. However, the inclusion of the interaction terms for private MBBS provider alternative reduces the significance of the *positive recommendation* coefficient. The inclusion and statistical significance of the interaction term *Distance* x *Recommendation* for private MBBS providers supports the hypothesis that healthcare consumers are willing to bypass local outpatient providers to access perceived higher quality, but more distant private providers.

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 II 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 24.6 to 51.1 percent. Table III also shows that the market share of unqualified primary healthcare providers decreases from 59.6 to 34.4 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 consumer 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 S6).

[Insert Table III 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 II. The two sets of estimates are provided: i) the current level of healthcare provider competition in rural Uttar Pradesh and ii) counterfactual market demand.

The RP own-price demand elasticities in Table IV are relative inelastic and reflect the scale found in earlier studies (see Borah, 2006). At the lowest price interval for government MBBS providers (INR 1-25) the estimates range between -0.01 to -0.02 across the four income quartiles (QR_1 - lowest to QR_4 - highest). In addition, the elasticities increase within each income quartile as prices increase. At the interval INR 126-150, the range of elasticities range between -0.03 to -0.04. The own-price elasticities for unqualified providers are larger. Within Table IV, the estimates at the lowest price interval (INR1-50) are -0.03 to -0.04. This increases to a range of -0.10 to -0.11 at the interval INR 251-300. For both providers, little or no change is evident across income quartiles.

[Insert Table IV here]

The RP own-price demand elasticity estimates of Table IV are higher for unqualified providers than for government MBBS providers. The own-price demand elasticities are expected to be higher because of i) greater level of village-based competition among fever services and ii) generally perceived lower levels of clinical quality among these providers. Relative to government MBBS services, the clinical quality of unqualified providers is generally considered lower. Thus, price increases for low-quality services would see some consumers demand more alternative fever treatment services from within the village.

The unqualified provider counterfactual estimates are presented in Table Va and are greater than those estimated for the RP only data. These 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. The table shows that as the price interval increases, the degree of own-price elasticity increases within each income quartile. In the first income quartile (QR_1), the elasticities increase from -0.20 at the price interval INR 1-50 to -0.85 at the price interval INR 251-300, and the corresponding elasticities for the fourth quartile (QR_4) range from -0.21 to -0.83. This pattern is consistent with microeconomic theory. However, own-price elasticities for unqualified providers remain stable as incomes increase within each price interval. The stable own-price elasticity of demand for unqualified providers reflects a fixed level of utilisation of unqualified provider fever services across income quartiles (ranging between 23.9% in QR_2 to 26.6% in QR_4)

[Insert Table V here]

The corresponding own-price demand elasticities for government MBBS providers under the counterfactual scenario are presented in Table Vb. For government MBBS providers, the elasticity point estimates are also higher at each price interval compared to the RP estimates. However, the mean own-price elasticities for government MBBS providers are not statistically different (see S7). With respect to the counterfactual elasticity estimates, within an income quartile, the elasticities rise. In QR_1, the own-price elasticities rise from -0.02 for the INR 1-25 interval to -0.10 for the INR 126-150 interval. Within each income quartile, the pattern of increasing own-price elasticity is consistent. The results from Table Vb show the counterintuitive result that own-price elasticities increase for a given price interval as incomes rise. The increasing own-price elasticities among higher income groups reflects the combined effects of decreasing levels of utilisation as incomes rise and greater sensitivity to the need to pay informal payments for government services that should be effectively free.

The above demand estimation result in two principle policy outcomes. 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 S8). The results in Figure I demonstrate that at an approximate fixed mean prices of INR 80 mean own-price elasticity for unqualified provider fever treatment is estimated to increase from -0.24 under the current market scenario to -0.40 when government MBBS providers are fully available. The second policy related outcome is that own-price elasticity for government MBBS provider fever treatments may not change even if reduced absenteeism was associated with reduced informal payments.

[Insert Figure I here]

6. Concluding Comments

The proceeding results demonstrate that the removal of government MBBS provider absenteeism in rural North India is not sufficient to ensure the demise of the unqualified primary healthcare provider. 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.

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 counterfactual demand for these 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.

Jointly modelling RP and SC data offers market-based predictions of demand while allowing for a wider set of trade-offs under a counterfactual scenario. The assumed complete availability of government MBBS providers in the SC data, combined with the RP data, provided market scenarios akin to a situation where all current CHCs and PHCs have consistent availability of allocated government MBBS providers. This method of counterfactual estimation does not assume that consumers' trade-offs across attributes are fixed between the two scenarios. As a result, the approach allows for more behavioural accuracy in estimating consumer demand under the counterfactual scenario.

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Tables

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

Variable	Mean (percent)	St. Dev	Median	Min	Max
Stated Choice					
Price – unqualified (INR)	79.8	42.6	-	50	150
Price – private MBBS (INR)	144.3	56.9	-	100	300
Price – government MBBS (INR)	23.4	17.9	-	1	50
Reveal Preference					
Price – unqualified (INR)[#]	82.2	85.8	60	1	4000
Price – government MBBS (INR)[#]	63.4	244	20	0	600
Distance – unqualified (km)[#]	1.3	2.7	1	0	17
Distance – government MBBS (kms)[#]	7.3	5.2	7	0	32
Lnphinc – log per person household income	8.8	0.7	-	-	-
Lnphinc2 – log per person household income Sq	78.1	12.7	-	-	-
Hhsize - Household size	6.8	2.8	-	1	17
Sample (percent)					
D1 - District A[b]	46.9				
D2 - District B[b]	31.2				
D3 - District C[b]	21.8				
Religion (percent)					
Low-caste - (Tribal + Shudra)[b#]	12				
Medium-caste - (Vaisya + Kshatriya)[b#]	44.1				
High-caste - (Brahmin)[b#]	23.7				
Jain[b]	0.2				
Muslim[b]	19.9				
Literacy (percent)					
Illiterate[b]	43.4				
Literate[b]	36.3				
Highly Literate[b]	20.3				
Employment (percent)					
Job1[b]	25.9				
Job2[b]	23.9				
Job9[b]	27.8				
Other *Job*[b]	22.4				
Duration (percent)					
Dur1[b] (1-3 days)	40.5				
Dur2[b] (4-6 days)	30.7				
Dur3[b] (7-9 days)	11.7				
Dur4[b] (10+ days)	17.1				

Note: [b] dummy variable; [#] imputed values

Table II: 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 : -0.019	(0.003)	R_1 : 0.037	(0.002)	R_1 : -0.013	(0.003)
Ln Income (household pp) [RP,SC]	R_1 : 0.497	(0.115)	R_1 : 0.497	(0.115)	R_1 : 0.497	(0.115)
Ln Income Sq (household pp) [RP]	R_1 : -0.241	(0.064)	R_1 : -0.241	(0.064)	R_1 : -0.241	(0.064)
Ln Income Sq (household pp) [SC]	R_1 : -0.217	(0.036)	R_1 : -0.217	(0.036)	R_1 : -0.217	(0.036)
Distance [SC] *	0.150	(0.062)	-2.245	(0.067)	-1.701	(0.092)
Distance [RP] *	-0.062	(0.044)	-0.021	(0.021)	-	-
Recom. +ve (base: none) [SC]	0.387	(0.073)	0.711	(0.093)	0.033	(0.128)
Recom. -ve (base: none) [SC]	-0.024	(0.099)	-0.668	(0.094)	-0.397	(0.142)
Dist. x Recom. (+ve) [SC]	-	-	0.134	(0.084)	0.440	(0.125)
Dist. x Recom. (-ve) [SC]	-	-	0.087	(0.100)	-0.340	(0.141)
Medicine [SC@]	0.290	(0.054)	-1.061	(0.070)	-	-
Demographic Variables						
Job1[b] (base: all other jobs) [RP,SC]	0.371	(0.239)	0.815	(0.295)	-	-
Job2[b] (base: all other jobs) [RP,SC]	0.752	(0.259)	0.341	(0.278)	-	-
Job9[b] (base: all other jobs) [RP,SC]	0.099	(0.237)	0.228	(0.267)	-	-
Low-caste[b] (base: Brahmin) [RP]	-0.574	(0.237)	-	-	-	-
Medium-caste[b] (base: Brahmin) [RP]	0.421	(0.220)	-	-	-	-
Illiterate[b] (base: highlit) [RP,SC]	0.757	(0.188)	-	-	-	-
Literate[b] (base: highlit) [RP,SC]	0.679	(0.177)	-	-	-	-
Health Variables						
Dur1[b] (base: Dur4) [SC]	-	-	-0.233	(0.227)	-	-
Dur2[b] (base: Dur4) [SC]	-	-	-0.653	(0.242)	-	-
Dur3[b] (base: Dur4) [SC]	-	-	-0.118	(0.345)	-	-
CHC[b] (base: all other villages) [RP,SC]	-0.815	(0.257)	-	-	-	-
PHC1[b] (base: all other villages) [RP,SC]	-0.678	(0.188)	-	-	-	-
PHC2[b] (base: all other villages) [RP,SC]	-0.221	(0.300)	-	-	-	-
Geographic Variables						
District 2 (base: District 1) [RP]	-	-	0.389	(0.229)	-	-
District 3 (base: District 1) [RP]	-	-	-0.051	(0.303)	-	-
Constant [RP]	-	-	-2.503	(0.337)	-	-

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

[SC] State Choice parameter; [RP] Revealed Preference paramater; [b] imputed missing values

Table III: Utilisation of healthcare provider according to survey type

	Full recall (Unconditional)			
	RP		SC*	
	Number	percent	Number	percent
Unqualified 'doctor'	699	59.6	1815	34.4
Private MBBS doctor	-	-	702	13.3
Government MBBS doctor	289	24.6	2698	51.1
None (Other)	185	15.8	68	1.3
TOTAL	**1173**	**100.0**	**5283**	**100.0**

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

Table IV: Unconditional RP own-price elasticities for unqualified – *jhola chhaap* – providers and government MBBS providers

IVa: Own-price RP Unqualified

Price interval (INR)	QR_1	QR_2	QR_3	QR_4
1-50	-0.04	-0.04	-0.03	-0.03
101-150	-0.06	-0.07	-0.07	-0.07
251-300	-0.11	-0.10	-0.10	-0.10

IVb: Own-price RP gov't MBBS

Price interval (INR)	QR_1	QR_2	QR_3	QR_4
1-25	-0.01	-0.02	-0.01	-0.01
51-75	-0.02	-0.03	-0.02	-0.02
126-150	-0.03	-0.04	-0.03	-0.03

Table V: Unconditional pooled and weighted own-price elasticities for unqualified –*jhola chhaap*– providers (Va) and government MBBS providers (Vb)

Va: Own-price Unqualified ^{RP}

Price-interval (INR)	QR_1	QR_2	QR_3	QR_4
1-50	-0.20	-0.20	-0.21	-0.21
51-100	-0.26	-0.26	-0.26	-0.26
101-150	-0.45	-0.45	-0.45	-0.45
151-200	-0.69	-0.69	-0.69	-0.69
201-250	-0.78	-0.78	-0.78	-0.77
251-300	-0.85	-0.84	-0.84	-0.83

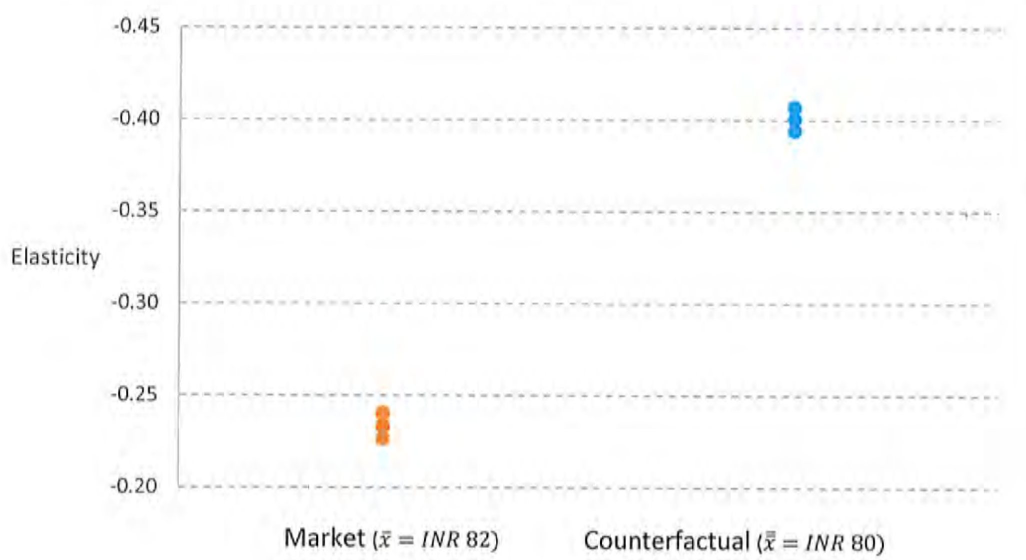
Vb: Own-price Gov't MBBS ^{RP}

Price-interval (INR)	QR_1	QR_2	QR_3	QR_4
1-25	-0.02	-0.03	-0.04	-0.05
26-50	-0.03	-0.04	-0.05	-0.07
51-75	-0.06	-0.09	-0.11	-0.15
76-100	-0.07	-0.11	-0.14	-0.19
101-125	-0.08	-0.13	-0.16	-0.23
126-150	-0.10	-0.15	-0.19	-0.26

Note: *the above are* arc-elasticities using only the RP variable estimates of Table III

Figures

Figure I: Unqualified provider mean own-price elasticity scenarios - current market and counterfactual (point estimate and confidence interval)



Supplementary Material

S1

	Random Parameter Logit – (EC) Model A			Generalised Mixed MNL Model B		
	Coefficent		St.error	Coefficent		St.error
Unqualified						
Price^{RP,SC}	R_1: -0.019	***	0.002	R_1: -0.025	***	0.002
Ln Income (household pp)^{RP,SC}	R_1: 0.497	***	0.114	R_1: -0.332	***	0.119
Ln Income Sq. (household pp)^{RP}	R_1: -0.241	***	0.064	R_1: -0.351	***	0.102
Ln Income Sq. (household pp)^{SC}	R_1: -0.217	***	0.036	R_1: -0.231	***	0.029
Dist.At Home (base:in village)^{SC}	0.150	**	0.061	0.110	*	0.059
Distance^{RP}	-0.062		0.044	-0.062		0.042
Med.Pill & Inject. (base: Pill)^{SC}	0.290	***	0.053	0.296	***	0.051
Recom. + ve (base: none)^{SC}	0.387	***	0.073	0.336	***	0.067
Recom. – ve (base: none)^{SC}	-0.024		0.099	-0.053		0.086
CHC^{c} (base: all other villages)^{RP,SC}	-0.815	***	0.257	-0.474	**	0.204
PHC1^{b} (base: all other villages)^{RP,SC}	-0.678	***	0.188	-0.707	***	0.136
PCH2^{b} (base: all other villages)^{RP,SC}	-0.221		0.300	-0.315		0.250
Job1^{b} (base: all other jobs)^{RP,SC}	0.371		0.239	0.582	**	0.271
Job2^{b} (base: all other jobs)^{RP,SC}	0.752	***	0.259	1.030	***	0.278
Job9^{b} (base: all other jobs)^{RP,SC}	0.099		0.237	0.159		0.258
Low-caste^{b} (base: Brahmin)^{RP}	-0.574	**	0.237	-0.619	***	0.225
Medium-caste^{b} (base: Brahmin)^{RP}	0.421	*	0.220	0.438	**	0.207
Illiterate^{b} (base: highlit)^{RP,SC}	0.757	***	0.188	0.633	***	0.135
Literate^{b} (base: highlit)^{RP,SC}	0.679	***	0.177	0.661	***	0.131
Constant^{RP}				2.386	***	0.282
Government MBBS						
Price^{RP,SC}	R_1: 0.037	***	0.002	R_1: -0.031		0.020
Ln Income (household pp)^{RP,SC}	R_1: 0.497	***	0.114	R_1: -0.332	***	0.119
Ln Income Sq. (household pp)^{RP}	R_1: -0.241	***	0.064	R_1: -0.351	***	0.102
Ln Income Sq. (household pp)^{SC}	R_1: -0.217	***	0.036	R_1: -0.231	***	0.029
Dist.5-15 kms (base: in village)^{SC}	-2.245	***	0.067	-1.919	***	0.057
Distance^{RP}	-0.021		0.021	-0.031		0.020
Med.Medicine cost (base: free)^{SC}	-1.061	***	0.070	-0.945	***	0.065
Recom. + ve (base: none)^{SC}	0.711	***	0.093	0.536	***	0.085
Recom. – ve (base: none)^{SC}	-0.668	***	0.094	-0.509	***	0.085
Dist. x Recomm. (+ve)^{SC}	0.134		0.084	0.151	**	0.077
Dist. x Recomm. (-ve)^{SC}	0.087		0.099	-0.023		0.095
Job1^{b} (base: all other jobs)^{RP,SC}	0.815	***	0.295	0.831	***	0.259
Job2^{b} (base: all other jobs)^{RP,SC}	0.341		0.278	0.780	***	0.250
Job9^{b} (base: all other jobs)^{RP,SC}	0.228		0.267	0.198		0.226
Dur1^{b} (base: Dur4)^{SC}	-0.233		0.227	-0.289	***	0.110
Dur2^{b} (base: Dur4)^{SC}	-0.653	***	0.242	-0.588	***	0.117
Dur3^{b} (base: Dur4)^{SC}	-0.118		0.345	-0.287	*	0.169
District 2 (base: sample1)^{SC}	0.389	*	0.229	0.389	*	0.229
District 3 (base: sample1)^{SC}	-0.051		0.303	-0.051		0.303
Constant^{RP}	-2.503	***	0.337	-2.503	***	0.337
Private MBBS						
Price^{SP}	R_1: -0.013	***	0.003	R_1: -0.011	***	0.003
Ln Income (household pp)^{SC}	R_1: 0.497	***	0.114	R_1: -0.332	***	0.119
Ln Income Sq. (household pp)^{SC}	R_1: -0.217	***	0.036	R_1: -0.231	***	0.029
Dist.5-15 kms (base: in village)^{SC}	-1.701	***	0.092	-1.661	***	0.091
Recom. + ve (base: none)^{SC}	0.033		0.128	-0.011		0.121
Recom. – ve (base: none)^{SC}	-0.397	***	0.141	-0.470	***	0.139
Dist. x Recomm. (+ve)^{SC}	0.440	***	0.125	0.355	***	0.125
Dist. x Recomm. (-ve)^{SC}	-0.340	**	0.141	-0.350	**	0.141
None						
Constant^{RP,SC}	17.877	**	7.537	22.963	***	7.988

S1 continued

	Mixed MNL – (EC) weighted Model A			Generalised Mixed MNL (weighted) Model B		
	Coefficent		St.error	Coefficent		St.error
	Scale Parameters					
JC (RP, SC)	R_2: 0.535	***	0.162			
Gdr (RP, SC)	R_2: 1.201	***	0.125			
None (RP, SC)	R_2: 0.448		0.329			
Tau				0.121	***	0.038
	State Dependence					
State Dependence	R_1: 1.805	***	0.378	R_1: -3.115	***	0.335
	Heterogeneity in Mean (income)					
Price-JC	<0.001	*	<0.001	0.001	***	<0.001
Price-GDr	-0.001	**	-0.001	-0.001	***	<0.001
Price-PDr	-0.005	***	0.001	-0.005	**	0.002
Ln Income	1.117	***	0.380	1.661	***	0.392
Ln Income Sq. ^{RP}	-0.066	**	0.026	-0.103	***	0.029
Ln Income Sq. ^{SC}	-0.043	**	0.022	-0.095	***	0.026
	Distribution of Random Parameters					
Price-JC	0.019	***	0.002	0.024	***	0.002
Price-GDr	0.037	***	0.007	0.011	***	0.003
Price-PDr	0.013	***	0.003	0.017	***	0.002
Ln Income	0.497	***	0.114	0.332	***	0.119
Ln Income Sq.^{RP}	0.241	***	0.064	0.231	***	0.029
Ln Income Sq.^{SC}	0.217	***	0.036	0.351	***	0.102
State Dependence	1.805	***	0.378	3.115	***	0.335
Error Components						
$JC^{(SC)} + JC^{(RP)}$	0.429	***	0.171			
$GDr^{(SC)} + GDr^{(RP)}$	1.035	***	0.127			
Heterogeneity in GMXL scale factor (SC)				-0.371	***	0.026
LL	-4313.9			-4460.2		
AIC	8749.8			9034.5		
BIC	9162.9			9420.5		

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

^{SC} Stated Choice data; ^{RP} Revealed Preference data.

S2

Variables	Revealed Preference		Stated Choice		
	Unqualified Coefficient (St. Err.)	Government Coefficient (St. Err.)	Unqualified Coefficient (St. Err.)	Private Coefficient (St. Err.)	Government Coefficient (St. Err.)
Price.	-0.001	-0.001	R_1: -0.026	R_1: -0.021	R_1: -0.020
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Travel Dist.[a]	-0.074	-0.016	0.037	-1.799	-2.140
	(0.028)	(0.015)	(0.064)	(0.091)	(0.064)
Ln Income (per cap).	3.673	3.673	R_1: 3.538	R_1: 3.538	R_1: 3.538
	(1.451)	(1.451)	(0.434)	(0.434)	(0.434)
Ln Income sq (per cap).	-0.249	-0.249	R_1: -0.091	R_1: -0.091	R_1: -0.091
	(0.087)	(0.087)	(0.012)	(0.012)	(0.012)
Medicine[a]	-	-	0.318	-	-0.994
			(0.049)		(0.064)
Recomm. positive[a]	-	-	0.430	0.355	0.417
			(0.072)	(0.124)	(0.088)
Recomm. negative[a]	-	-	-0.213	-0.538	-0.617
			(0.094)	(0.133)	(0.086)
Recomm x Travel positive[a]	-	-	-	0.454	-
				(0.121)	
Recomm x Travel negative[a]	-	-	-	-0.278	-
				(0.134)	
CHC[b] (base: all other villages)	-0.743	-	0.093	-	-
	(0.274)		(0.363)		
PHC1[b] (base: all other villages)	-0.284	-	-1.004	-	-
	(0.208)		(0.243)		
PCH2[b] (base: all other villages)	0.188	-	-0.228	-	-
	(0.287)		(0.447)		
Job1[b] (base: all other jobs)	0.287	0.530	0.328	-	0.647
	(0.258)	(0.281)	(0.396)		(0.288)
Job2[b] (base: all other jobs)	0.555	0.098	1.025	-	0.818
	(0.262)	(0.306)	(0.438)		(0.303)
Job9[b] (base: all other jobs)	0.454	0.526	0.218	-	0.021
	(0.250)	(0.274)	(0.415)		(0.281)
Low-caste[b] (base: Brahmin)	-0.361	-	-	-	-
	(0.156)				
Medium-caste[b] (base: Brahmin)	0.311	-	-	-	-
	(0.151)				
Illiterate[b] (base: highlit)	0.570	-	0.434	-	-
	(0.191)		(0.248)		
Literate[b] (base: highlit)	0.437	-	0.623	-	-
	(0.184)		(0.239)		
Hhsize	-	-0.056	-	-	-
		(0.024)			
Dur1[b] (base: Dur4)	-	-	-	-	-0.308
					(0.160)
Dur2[b] (base: Dur4)	-	-	-	-	-0.717
					(0.176)
Dur3[b] (base: Dur4)	-	-	-	-	-0.353
					(0.244)
D2[b] (base: D1)	-	1.192	-	-	0.889
		(0.209)			(0.173)
D3[b] (base: D1)	-	0.265	-	-	-0.093
		(0.279)			(0.236)
Constant	0.825	-	0.102	-	-0.536
	(0.303)		(0.463)		(0.364)
None	13.099			-1.292	
	(6.195)			(0.149)	

S2 continued

Variables	Revealed Preference		Stated Choice		
	Unqualified Coefficient (St. Err.)	Government Coefficient (St. Err.)	Unqualified Coefficient (St. Err.)	Private Coefficient (St. Err.)	Government Coefficient (St. Err.)
Heterogeneity in mean of random parameters (Dur2, D1,D3)					
Price:Dur2	Fixed	0.002 (0.001)	-	-	-
Ln Income:D1	-0.528 (0.293)	-0.528 (0.293)	-	-	-
Ln Income:D3	-1.301 (0.475)	-1.301 (0.475)	-	-	-
Ln Income Sq:D1	0.064 (0.033)	0.064 (0.033)	-	-	-
Ln Income Sq:D3	0.153 (0.053)	0.153 (0.053)	-	-	-
Distributions of Random Parameters					
Price	-	-	0.026 (0.002)	0.021 (0.002)	0.020 (0.003)
Ln Income[1]	-	-	3.538 (0.434)	3.538 (0.434)	3.538 (0.434)
Ln Income Sq.[1]	-	-	0.091 (0.012)	0.091 (0.012)	0.091 (0.012)
Error Component					
JC + GDr				1.292 (0.149)	
JC + None				1.367 (0.102)	
N	1173			5283	
LL	-1022.1			-3265.4	
AIC/N	1.8			1.3	
Pseudo. R2	0.552			0.554	

Note: RI random parameter with a triangular distribution anchored at zero; [a] effects coded qualitative variable; [b] dummy variables.

S3

A multi-stage clustering sampling frame was used in Stages One and Two of the data collection. Stage One included 48 surveys with consumers, healthcare providers and local level key informants (Community Health Workers, *ASHAs* and Village Leaders, *pradhans*). Stage Two encompassed the delivery of the RP and SC surveys. An important constraint surrounding the data collection process was the need to control for potential seasonal effects associated with fever treatment demand. For example, the monsoon season is expected to generate a high level of fever treatment demand in North India. Stage One data was collected during April and May in the dry-season of 2012. Stage Two data was collected during the North Indian monsoon season, which usually runs from mid-June to mid-September. However, in 2012, the monsoon onset was delayed by three-four weeks in North India. As a result, the average rainfall during the first 2-months of the season was below average (Government of India, 2013). This contracted the duration of the monsoon and limited the window of opportunity. However, Stage Two data was still collected during the monsoon season.

Sampling frame

The primary sampling units of the study were three districts from Uttar Pradesh (UP). Purposeful sampling was employed in selecting the three districts. Districts were selected due to their representative mean income profiles and for accessibility reasons (Government of Uttar Pradesh, 2006). The district mean incomes of the three districts cover the interquartile range of UP. In addition, one known Non-Governmental Organisation (NGO) hospital from the Emmanuel Hospital Association was in each district. While the data were collected independently of the NGO hospitals, logistical support was provided by these hospitals throughout Stages One and Two.

The sampling units used in this study were district level development blocks. These were selected at random from a list of development blocks available on district websites. At the tertiary level, Gram Panchayats from the select block(s) were stratified according to the Hindu and Muslim religious majority of the Gram Panchayats. Assistance in stratifying was obtained from district Block Development Offices. In total, eight Gram Panchayats were selected: four from Fatehpur and two each from Lalitpur and Balrampur. The location of Fatehpur in UP's central region allowed for proportional sampling of Hindu and Muslim individuals (three Hindu majority Gram Panchayats and one Muslim majority). The small proportion of Muslim residents in Lalitpur from the Bundelkhand region limited the ability to sample Muslim respondents. This was balanced by sampling an equal number of Gram Panchayats in Balrampur, which has a strong Muslim representation.

Sampling of village households within all villages except Village Two (Fatehpur), systematically covered all geographic sections in a quasi-random process. Maps of the villages were not available, so local knowledge of the village was used to ensure that enumerators sampled evenly across the whole village. This approximately even sampling across any given village was important, as many villages are informally divided according to religion and caste. Enumerators also selected the households and individuals to survey. As a check on the micro-level sampling by enumerators, sampling profiles for each enumerator of their survey respondents was monitored during each day of data collection. This monitoring of sampling profiles included consideration of mean age and gender proportions. Based on this information, the sampling of individuals conformed to a quota method. Village Two was the first village sampled. The village *pradhan* organised the recruitment of villagers according to our representative sample request.

Choice set creation

The three choice alternatives used in the surveys reflect the full range of alternative outpatient allopathic healthcare providers available in North India. Given the high prevalence of fever symptoms in North India (NSSO, 2006), the catchment area of providers was limited to those available at the village level. Consumer surveys, as part of Stage One, confirmed that household members suffering from mild-sever fever symptoms often consulted village based unqualified healthcare providers before consulting qualified providers (public and private) further away should no relief be experienced following the treatment of the unqualified healthcare provider *jhola chhaap* (Iles, 2014). A survey of providers was also completed as part of Stage One of the study to help verify the range of provider characteristics available in the local outpatient market. Village level healthcare providers were identified by local key informants. Table S5 provides a summary of the providers' surveys and their attributes.

Table S3: Summary of provider survey results

Village No.	1	1	1	2	2	3	3	4
Description	Jhola Chhaap	Pharmacist	Jhola Chhaap	Ayurvedic	Jhola Chhaap	Jhola Chhaap	Jhola Chhaap	'Wardboy'
Gov't Facility	0	1	0	0	0	0	0	1
Nearest gov't facility	< 1km		< 1km	< 1km	< 1km	7 km	7 km	
Gender	male	male	male	male	male	male	male	male
Age	50-54	45-49	25-29	65+	45-49	30-34	20-24	45-49
Religion	hindu	hindu	hindu	hindu	hindu	hindu	hindu	hindu
Experience (years)	25		2	54	20	8	1	
Type of clinic	Drug store	CHC	informal	informal	drug store	informal	informal	CHC
size of clinic			1	1	2	1	1	
Average Price – fever	denied	1	50-100	cost of injection + margin	40	40	35	
Margin/Fees	denied		50%	10 INR	15 INR	5 INR	10 INR	
Validity		15 days	5 days		1 visit	1 visit	1 visit	
Patients per day*		100	12	2	6	10	7	
Consult Length		4 mins	5 mins	15 mins +	2 mins^		10 mins	
Patient Travel distance radius			10 km	10 km	2 km	2 km	1 km	
Top Ailments		Fever (50%) Diarrhea (10%) Skin Diseases (4%) Other (36%)	Fever (80%) Diarrhea (20%)	Fever - most	Fever (50%) Diarrhea (25%) Other (25%)	Fever (70%) Diarrhea (25%) Other (5%)	Fever (70%) Diarrhea (20%) Other (10%)	
Advertising			Word-of-mouth	Word-of-mouth		Word-of-mouth	Word-of-mouth	
Perception - Why patie attend?		Price Location Recommendation	Location Availability of Medicine Price	Qualification Location Personal Experinece	Location Price Personal Experience	Personal Experinence Price Recommendation	Location Personal Experience Price	
Comments	Respondent claimed to not prescribe medicine. This was in opposition t the claim ofvillage residents.	Respondents indicate that doctors lived 2 hours away (x 2 Drs) and 30 minutes away (1) in district centres.						No Drs avalable. Respondent indicated that Drs were often not present - living 2+ hours away (x 2) and 45 mins away (x 1).

* patients per day doesn't necessarily refer to at home visits

^ observed

Table S3: (con't)

Village No.	non sample	5	5	7	7	7	8	8
Description	MBBS Dr	MBBS Dr	Jhola Chhaap	Nurse	Jhola Chhaap	Jhola Chhaap	Pharmacist	Jhola Chhaap
Gov't Facility	1	1	0	1	0	0	1	0
Nearest gov't facility			5 km		10 km	10 km		< 1 km
Gender	male	male	male	female	male	male	male	male
Age	35	25-29	36	50	22	50-54	45-49	
Religion	hindu	hindu	hindu	hindu	hindu	hindu	hindu	hindu
Experience (years)	10	2	2	30	3	30	20	27
Type of clinic	CHC	PHC	informal	CHC	shop front	shop front	PHC	shop front
size of clinic			1		1	1		
Average Price – fever	1	1	40		50-60	50	1	50
Margin/Fees			10 INR		10 INR	10 INR		10 INR
Validity	15 days	15 days	1 visit		1 visit	1 visit		1 visit
Patients per day*	100	80	5		12	15		15
Consult Length	4 mins	5 mins	10 mins		5 mins^			3 mins^
Patient Travel distance radius	up to 40 kms	up to 20 kms	1 km		1 km			2 km
Top Ailments	Fever (50%)	Fever (50%)	Fever (50%)		Diarrhea (50%)	Diarrhea (40%)		Diarrhea (40%)
	Diarrhea (15%)	Women's health (25%)	Diarrhea (20%)		Fever (40%)	Fever (40%)		Fever (40%)
	Lung (20%)	Diarrhea (20%)	Lung (20%)		Lung (10%)	Other (20%)		Injury + Other (20%)
	Women's health + Other (15%)	Lung (5%)	Other(10%)					
Advertising	Word-of-mouth and past experience				Word-of-mouth & past experience	Word-of-mouth & past experience		Word-of-mouth & past experience
Perception - Why patie attend?	Price Trust in Hospital Medicines	Price Recommendation Personal experience	Price Distance Personal experience		Location Price Recommendation	Experience Location Price		Price Location Personal Experience
Comments				No Drs available. Claimed that Drs often back dated records to give the appearance that they were present. Translator was an old acquance of the nurse.			Dr Not available. Translator was an old acquance of pharmacist.	

* patients per day doesn't necessarily refer to at home visits

^ observed

The price information collected from Government health centres is generally unreliable in the presence of known widespread informal payment made by patients directly to government health workers or indirectly via private medical stores. Consequently, not all neighbouring government health centres were surveyed. In addition, taking a census of all private healthcare providers is challenging due to the large share of informal unqualified providers who may i) operate as a drug store and/or ii) are itinerant and difficult to identify, and/or iii) unwilling to respond due to the illegal nature of their work. As all sample 'villages' had at least one *jhola chhaap*, provider surveys were administered to a subset of these where *pradhans* (village leaders) introduced us. Copies of the survey tools are provided are available (Iles, 2014). Broad uniformity among surveyed unqualified *jhola chhaaps* is evident from Table S3, and average stated prices range between 40–60 rupees for a single visit, which a margin of 10 rupees was added to the cost of medicine by providers. Word-of-mouth recommendation were widely seen to be the main mechanism to grow one's business, and no direct advertising was employed by unqualified *jhola chhaaps* providers. All providers cited that fever symptoms were one of the leading complaints by patients. Based on the survey result of healthcare providers, it is assumed that in the treatment of mild-severe fevers, the attributes of unqualified providers were homogeneous. However, the survey provides limited insight into the attributes of government MBBS doctors, as location and behaviour of these doctors of the counterfactual underpinning of the study lack of knowledge of true attributes is not expected to bias the results.

S4

Combining the RP and SC data creates a new village-level hypothetical market. If village-level government MBBS provider availability is measured using an index, the SC data assumes full availability in half the villages. The two distance attribute levels i) in village and ii) 5–15 km away averages out to equate to half of the villages having a government MBBS provider. By contrast, the RP accounts only for the three sample villages with government MBBS providers. The actual availability of these government providers is not known. However, over repeated visits to the three government health centres, the MBBS providers were not present. In calculating the availability index, it is assumed that at these three government health centres MBBS providers are available 33 percent of the time. This equates to an availability score of 0.124 (i.e. 3/8*0.33).

Pooling the RP and SC data with and without the weights provides intermediate availability scores. These intermediate scores are calculated by multiplying the above SC and RP base availability score by the proportion of each data type and weighting them accordingly. The availability score formulas for pooled data are as follows:

$$\text{Availability score}^{\text{pooled}} = \underline{(\text{observation}^{SC}/\text{total observation}^{RP+SC})} \times \underline{\text{baseavailability}}^{SC} + \underline{(\text{observation}^{RP}/\text{total observation}^{RP+SC})} \times \underline{\text{baseavailability}}^{RP}, \text{ and}$$

$$\text{Availability score}^{\text{weighted pooled}} = \underline{((\text{observation}^{SC}/9)/(\text{total observation}^{RP+SC/9})} \times \underline{\text{baseavailability}}^{SC} + \underline{(\text{observation}^{RP}/\text{total observation}^{RP+SC/9})} \times \underline{\text{baseavailability}}^{RP}$$

The pooled availability score is $0.432 = (0.8183 \times 0.5)^{SC} + (0.1817 \times 0.124)^{RP}$. The proportion of SC and RP observations within the data set are 0.8183 = 5283 / 6456 and 0.1817 = 1173 / 6456, respectively. By contrast, the weighted pooled availability score is $0.249 = (0.3335 \times 0.5)^{SC} + (0.6665 \times 0.124)^{RP}$. The proportion of the data from each data type changes in the weighted pooled calculation. The SC number of observations is divided by nine to scale the number of SC observation per respondent to equal 1. As a result, the proportion of SC data is 0.3335 = (5283/9) / (5283/9 + 1173), and the proportion of RP data is 0.6665 = 1173 / (5283/9 + 1173).

The range of government MBBS provider availability are estimated at the levels 0.124 (RP only), 0.249 (RPSC pooled and weighted), 0.432 (RPSC pooled) and 0.5 (SC only). The socially optimal availability score in the short run where all government MBBS providers are fully available in the three village government health centres is 0.375 = 3/8. This optimal short-run score is between the RPSC pooled and the RPSC pooled and weighted.

S5

The price and distance variables of the non-selected healthcare provider alternative are not recorded in the original survey. However, due to the number of survey respondents who consulted more than one type of provider, where this data is available, the attributes of subsequent providers are used to populate the non-selected provider attributes in the RP data. Despite the prevalence of multi-provider consultations for a given fever episode, imputation of provider attributes for non-selected providers was necessary. This corresponds to approximately 35 percent of unqualified providers and 65 percent of government MBBS doctors. A Multivariate Imputation by Chain Equation (MICE) method is used to estimate and fill these missing values. 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). The MICE algorithm, also known as fully conditional specifications (FCS), employs a Markov Chain Monte Carlo (MCMC) method by using conditional densities to run the multivariate imputation model for each variable individually (see Appendix D for more details).

Due to the sequential nature of the MICE algorithm, each variable with missing data may use a different distribution from which to draw imputations.

A Bayesian procedure is used to update the prior distributions from the preceding posteriors. This iterative approach is completed over a given number of cycles. The number of iterations used in this study ranged between five and seven. This number is sufficient due to low levels of autocorrelation among regression variables and the limited amount of memory occupied in MICE algorithm while running the imputation model (van Buuren, 2012). The work of Brand (1999) and van Buuren et al. (1999) used between five and twenty iterations.

Evaluating the convergence of the MCMC process is necessary to ensure that a stationary distribution is reached. Reviews of convergence testing methods find that machine generated tests are unreliable (Cowles and Carlin, 1996; El Adlouni et al., 2006). Cowles and Carlin (1996) conclude that machine generated tests should be avoided. As such, visual inspection of the plots of the mean and standard deviations of the individual imputed variables at each iteration is used to check that free movement across the iterations occurs.

The missing data imputed as part of this chapter includes the price and categorical distances for the alternative (non-selected) doctors for respondents and the caste affiliation of respondents in Fatehpur. The assumption of Missing At Random (MAR) appears relevant to the case of the missing caste data from all respondents in Fatehpur. Within the sub-sample of Fatehpur respondents, all caste data has an equal probability ($p = 1$) of being missing (van Buuren, 2012). In this case, knowledge of the mechanism of *missingness* makes the assumption of MAR clear.

The MAR assumption for the missing data associated with the non-selected alternatives also holds. Within each healthcare provider alternative, the probability of the data being non-selected has an equal probability. This second set of missing data is associated with whether consumers sought treatment from multiple providers. The association between whether the initial provider was an unqualified *jhola chhaap* 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.

<u>Price</u>

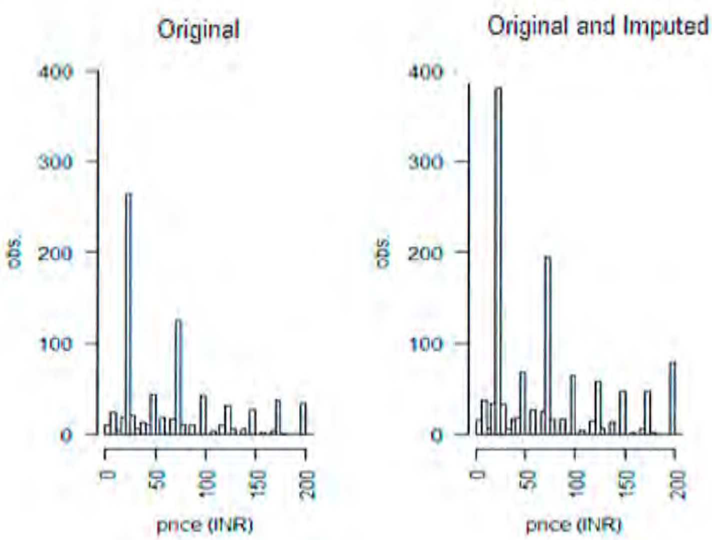


Figure S5-1: Frequency distribution of unqualified *jhola chhaap* price, original responses and combined original and imputed

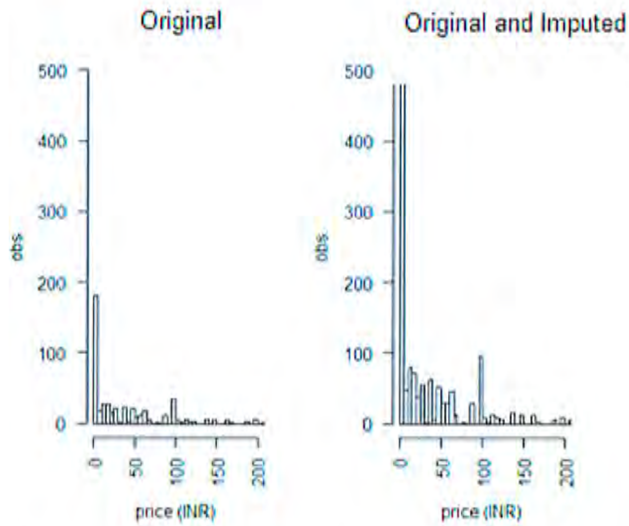


Figure S5-2: Frequency distribution of government MBBS doctor price, original responses and combined original and imputed prices

The price of INR 5000 for a single consultation to a government doctor, depicted in Figure 8.3, is an outlier. This value is dramatically greater than all other values. As such, this observation was deleted reducing the number of observations from 1174 to 1173.

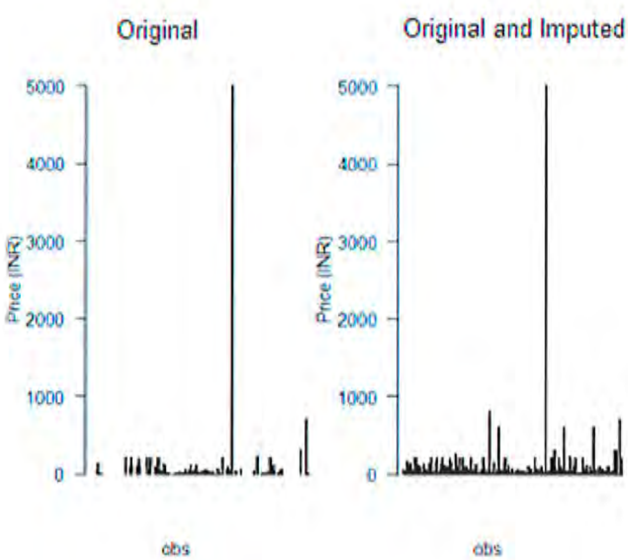


Figure S5-3: Distribution of government MBBS doctor prices, original and combined original and imputed prices

Distance

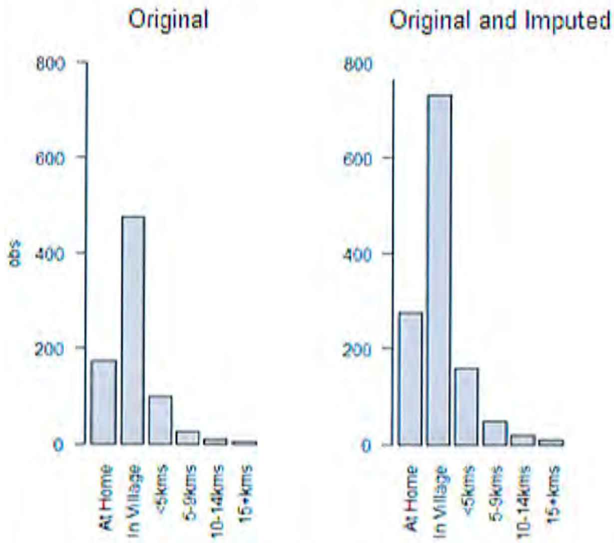


Figure S5-4: Frequency distribution of distance to unqualified *jhola chhaap* provider original responses and combined original and imputed prices

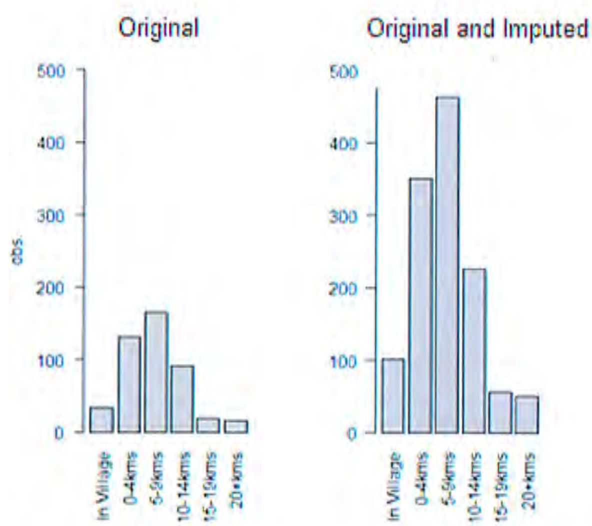


Figure S5-5: Frequency distribution of distance to government MBBS doctor, original responses and combined original and imputed

S6

Table A1 provides data on perceived reasons for non-government MBBS doctor service utilisation. The seven reasons for non-use are i) government doctor not in village, ii) government doctor not available in village, iii) need to pay for medicines, iv) need to pay for consultation, v) poor quality of government medicines, vi) too far to travel, and vii) other reason. On average, 63.7 percent of respondents nominated that they did not utilise government MBBS provider services. The two most cited reasons were i) government MBBS doctor not in village at 19.3 percent, and ii) government MBBS doctor not available in village at 13.1 per cent. These two respondent fields measure in differing ways the widespread problem of government doctor absenteeism within the sample.

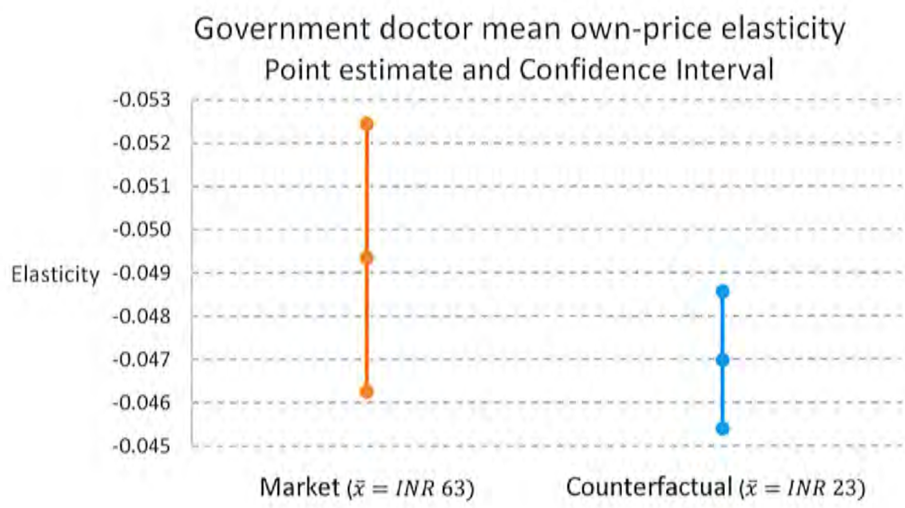
Villages One and Eight, which had a government Community Health Centre (CHC) and Primary Health Centre (PHC), both recorded zero percent for this first category. In Village One, 25.3 percent of respondents indicated that the unavailability of government doctors was the primary reason for their non-use of government MBBS outpatient services. In Village Eight, the percentage was 18.0 percent in the same category of non-availability. However, Village Two, which also had a PHC, had 18.5 percent of respondents nominate 'government doctor not in village' and 21.2 percent nominate 'government doctor not available' as the primary reasons for not utilising government MBBS outpatient services. Key-informant interviews with the elected village leader from Village Two indicated that the PHC was generally closed. Across three visits to this village, the PHC was closed on each occasion. This continual closure of the PHC in Village Two helps explain the high percentage of respondents who recorded 'government doctor not in village' despite having a government PHC located there.

Table S6: Reasons for non-use of government doctors by village (% of all respondents).

Reasons	Village One^	Village Two*	Village Three	Village Four	Village Five	Village Six	Village Seven	Village Eight*
Gov't Dr not in village	0.2	18.5	26.7	22.9	26.8	27.7	18.0	0.0
Gov't Dr not available in village	25.3	21.2	24.1	15.7	6.8	0.0	1.5	18.1
Pay for medicines	0.0	0.2	1.6	1.1	1.2	1.0	17.2	15.1
Pay for consultation	0.2	2.9	0.0	0.0	0.0	0.1	8.0	14.3
Poor quality medicines	20.5	10.4	3.5	1.2	8.1	1.3	6.7	25.9
Too far to travel	0.0	5.3	10.6	17.3	6.7	8.9	18.6	0.0
Other	12.0	11.4	11.9	9.9	1.2	0.0	12.1	3.0
sub-total	**58.2**	**69.9**	**78.5**	**68.1**	**50.7**	**38.9**	**82.0**	**76.4**
N	77	190	110	174	168	197	123	135

Note: ^ denotes the presence of a Community Health Centre (CHC); * denotes the presence of a Primary Health Centre (PHC).

S7



Government doctor mean own-price elasticity
Point estimate and Confidence Interval
-0.053
-0.052
-0.051
-0.050
Elasticity -0.049
-0.048
-0.047
-0.046
-0.045
Market ($\bar{x} = INR\ 63$)
Counterfactual ($\bar{x} = INR\ 23$)

S8

S8a: Cross-price: Gdrrp, Other (given demand for JCrp)

	QR_1		QR_2		QR_3		QR_4	
Price-interval (INR)	Gdrrp	Other	Gdrrp	Other	Gdrrp	Other	Gdrrp	Other
1-50	0.48	0.16	0.51	0.14	0.49	0.12	0.53	0.09
101-150	0.50	0.20	0.58	0.19	0.60	0.17	0.63	0.13
201-250	0.51	0.22	0.55	0.20	0.60	0.19	0.65	0.15

S8b: Cross-price: JCrp, Other (given demand for Gdrrp)

	QR_1		QR_2		QR_3		QR_4	
Price-interval (INR)	JCrp	Other	JCrp	Other	JCrp	Other	JCrp	Other
1-25	0.02	0.01	0.03	0.01	0.04	0.01	0.05	0.01
51-75	0.03	0.01	0.04	0.02	0.05	0.01	0.06	0.01
101-125	0.03	<0.01	0.04	0.02	0.05	0.01	0.06	0.01

Note: *JCrp* and *Gdrrp* refer to arc-elasticities only using the RP variable estimates of the jointly modelled SC and RP data.