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RESEARCH PAPER

On willingness to pay for Covid-19 vaccines: a case study from India

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ABSTRACT

In this paper, using survey data from 1251 respondents from peri-urban parts in the Bhopal district of India, we estimated the willingness-to-pay (WTP) for hypothetical Covid-19 vaccines. We use open-ended questions along with the discrete choice contingent valuation method for two vaccines, one with full efficacy and the other with 70% efficacy. While no major evidence of vaccine hesitancy was observed, we found a WTP of about Rs. 141 ($1.9) for the former type vaccine and about Rs. 116 ($1.6) for the latter. From the contingent valuation method, we found about 71.9% were not willing to spend Rs. 200 ($2.7) or more for the fully effective vaccine, while this figure goes up to 77.8% for the one with 70% efficacy. Estimations from linear and probit regressions suggest that economic indicators were the most important predictors of WTP. Usage of public transport, the number of days that the respondent stepped out for work, and the presence of comorbid individuals in the household were positively associated with the WTP, while pandemic-induced income reduction was negatively correlated. The findings lend support toward the requirement of highly subsidized vaccines, and hence back the recent policy announcement toward the supply of free vaccines to all states.

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Introduction

The novel coronavirus disease (Covid-19) outbreak is the worst health crisis since the 1918 influenza pandemic, which arguably claimed at least 50 million lives globally.[1] More than a century later, Covid-19 has recorded over 227.5 million cases across the world and directly caused more than 4.6 million deaths as of September 16, 2021.[2] With no acceptable antiviral drug available for treatment, comprehensive vaccination drive has become the primary mechanism through which various countries are trying arrest the growth in cases and fatalities. However, the success of the vaccination drive depends on what percentage of the population has been inoculated, which, apart from the prevalent vaccine hesitancy and availability, also relies on the government's pricing policy. This becomes especially critical in developing countries' contexts that is typically characterized by the prevalence of poverty, which translates to unaffordability and hence low demand for private healthcare. As the infection spreads from urban to rural areas, these concerns are further accentuated as rural areas have distinctly worse health infrastructure, are economically poorer but constitute a larger share of the overall population in comparison to their urban counterparts. This paper, using household-level survey data from 1251 respondents from the Bhopal district of India, assesses the Willingness to Pay (WTP) for Covid-19 vaccines in peri-urban areas, which is the rural periphery that separates the urban agglomeration from the hinterlands and is thereby a critical spatial channel of infection spread to the rural areas. In addition, the paper also identifies the socio-economic correlates of the WTP for the vaccine.

The case of India is pertinent with respect to the research objective of affordability and the need for a fiscal intervention to facilitate rapid mass vaccination in the global south. It remains among the worst affected countries with over 33 million cases and 444000 deaths as of September 16, 2021.[2] In fact, since April 2021, India has been battered by the second wave of infection that has taken a huge toll on health and mortality figures. News reports from across the world have reported about the grim condition of health infrastructure in the country that includes oxygen supply, ventilators, and hospital beds, among others. Additionally, the devastating effects of this crisis on the economy and livelihoods are expected to further compound this misery. The Gross Domestic Product (GDP), for instance, has contracted by 7.3% in 2020–2021.[3] According to a report by the Center for Monitoring of Indian Economy (CMIE), unemployment in India has increased by more than 23.5% in the last quarter of 2019–2020. These occurrences underscore the importance of a comprehensive vaccination drive, which will not only avert the worsening of the current health crisis but will also minimize the spillover effects from another round of economic fallout of the Covid-19 crisis.

The Government of India (GoI) started its vaccination program in mid-January 2021, which allowed two vaccines initially: Covishield from the Serum Institute of India (SII) in collaboration with Oxford-AstraZeneca (OA) and the indigenous Covaxin from Bharat Biotech International (BBI) and Indian Council of Medical Research (ICMR). In the first two phases, vaccines was provided free of cost to healthcare and

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frontline workers, senior citizens (60 years of age or above) and individuals in the age group 45–59 years. Private health-care facilities were also tied up in the process to speed up the vaccination drive, albeit this necessitated out-of-pocket expenditure of Rs. 500 (about $7) for both dosages per person. In the third phase, vaccination has been opened up for all individuals above 18 years of age though this responsibility has been completely transferred to the state governments, who are now competing with each other as well as other countries and private healthcare facilities to procure vaccines directly from a handful of manufacturers. Despite other vaccines, including the Sputnik-V from Russia being approved for use, India has been able to vaccinate only about 41% of its population with at least one dose (as of September 14, 2021). In comparison to other countries, the United Kingdom has vaccinated close to 71% of its population with at least one dose, the United States of America about 63%, and Israel about 69%. Even with respect to developing countries, India has fared worse relative to Brazil (67%), Argentina (63%), and Mexico (47%), among others.[4]

Even with the availability of more efficacious vaccines in the near future, economic affordability, which has been further worsened by the Covid-19 induced lockdowns, is likely to be a major stumbling block in achieving mass vaccination. In this context, it becomes pertinent to assess acceptability and demand for vaccines and measure these through the WTP approach. Quantifying the overall WTP and studying its socio-economic and demographic correlates facilitates the understanding of the vaccine market in India, which in turn offers valuable insights for an optimal pricing and subsidization strategy. While there have been a few studies on WTP for Covid-19 vaccines in different parts of the world,[5–9] to the best of our knowledge, ours is the first one pertaining to India, which in the past few months has been arguably the worst affected country. Importantly, identification of the correlates of WTP is likely to be instrumental in formulating a policy response for expedited vaccination drive in India. Moreover, these findings may simultaneously be pertinent for the rest of the global south that also suffers from a limited fiscal capacity of a majority of its citizens.

Methods

Although urban areas constituted the initial hotspots of Covid-19 infection in India, the spread of infection to the rural areas, which are characterized by inadequate health infrastructure, was a growing public health concern.[10] Consistent with these concerns, this paper focuses on peri-urban regions, which constitute the rural periphery that is in proximity to urban spaces, thereby maintaining strong economic linkages to these regions. Thus, peri-urban regions are a critical channel of infection transmission into rural areas.

The sampling design for the study had a purposive and a random component. For the former, Bhopal (capital district) in the state of Madhya Pradesh (MP) was chosen deliberately. During the first wave of infection in India, the state reported one of the highest basic reproductive numbers (*R0*) for the infection growth of about 3.36.[11,12] Also, MP has been one of the laggard states with poor convergence in socio-economic improvements witnessed by the rest of India.[13] Moreover, MP is the fifth and second-largest state of India in terms of population and landmass, respectively.

For identification of peri-urban sites of the survey, village councils (gram panchayats) were chosen on the basis of a mapping exercise. In rural India, village councils have democratically elected local governments where the elected representative (Sarpanch) is chosen for a period of 5 years. This is as per the 73rd Amendment to the Indian Constitution. The selection of village councils was based on the following criteria: first, a distance threshold of up to 25 kilometers (km) from Bhopal Junction, the major railway station of the capital and second, qualitative interviews with village heads to identify villages where at least half of the households had a member visiting the city regularly for work before the crisis. Based on these qualifiers, six village councils consisting of 11 villages from the administrative blocks of Berasia and Phanda were identified for the survey. Sample size calculations were conducted based on a cluster randomized design with village councils serving as clusters. Within these clusters, households in villages were selected randomly on the basis of probability proportional to size (PPS). Given the unanticipated nature of the pandemic, there existed little secondary evidence on willingness to pay for vaccines that could guide the sampling strategy. This was therefore based on formative research and assumptions around certain parameters like intra-cluster correlation (ICC). With no previous WTP studies for vaccination done in the region, we relied on secondary evidence to select ICC values for sample size calculations. A cluster-randomized trial across 80 rural villages in the state found children's health outcomes to have an ICC of 0.17.[14] Using nationally representative data for India, ICC for five major cardiovascular diseases (CVD) risk was found to be less than 0.20 at the community level.[15] Based on these studies, we chose an ICC level of 0.20, and we conducted a cross-sectional survey of 1251 households, which was sufficient for the smallest detectable mean differences of 0.08. Notably, the actual value of ICC in the data is about 5%, which is well within these assumed bounds (20%), and hence our sample size is sufficiently powered. Fieldwork for the study was conducted between January 30 and February 14, 2021. Each interview was conducted in an average time span of about 32 minutes. Of the 1251 households, three households refused to participate in the survey and were replaced by their respective neighboring households. The respondent of our survey from each of these households was the household head. In the context of our study, this is the person who makes most of the household financial decisions. If we were unable to interview him/her despite three visits, we interviewed the person who is next in line in terms of financial decision-making.

To get an estimate of the WTP, we first posed the following open-ended question to our respondents, in tandem with the literature on WTP.[5,16–18] "*Assume that a corona vaccine is available which can be effective for almost all individuals who are given the vaccine. What is the maximum amount you are willing to pay for each household member on average (in Rs)?*" On similar lines, we asked the following question for vaccine with 70% efficacy. "*Assume that a corona vaccine is available which can be effective for 7 out of the 10 individuals who are* *given the vaccine. What is the maximum amount you are willing to pay for each household member on average (in Rs)?"* These two variables are our main response variables.

In addition, during the survey, we posed the following question for the respondents: *Suppose that when vaccines become available, it is priced at Rs 3000 per person (not necessary that this actually happens). Will you be willing to pay Rs. 3000 per person in your household for corona vaccine which is effective for almost each individual who are given the vaccine?* If the response to the above question is positive, a follow-up question is asked that has seven options consecutively starting from Rs. 3500, Rs. 4000, Rs. 4500, Rs. 5000, Rs. 5500, Rs. 6000, and above Rs. 6000. If the response is negative, the follow-up question with eight options is asked: Rs. 2500, Rs. 2000, Rs. 1500, Rs. 1000, Rs. 500, Rs. 300, Rs. 200, and finally less than Rs. 200. As in the earlier case, we repeated the same question for vaccines which is effective for 7 out 10 individuals who are given this. To ensure that the respondents understand the difference, the meaning of efficacy was explained repeatedly with the use of examples. In order to ensure accuracy of WTP estimates, we asked a follow-up question about the certainty of responses after each of the above open-ended questions[19,20] that were as follows: *"Suppose I were to ask you the same question one week from now, how likely is it that your answer to this above question will remain the same? (small chance/high chance)."*

The open-ended questions can be considered to have a continuous distribution in $[0, +\infty]$ and, thus, provide the most efficient estimates.[19] Nevertheless, it is possible that open-ended questions may lead to biased estimates of WTP since they may not induce respondents to reveal their preferences truthfully. The use of self-reported certainty scales after respondents have answered the open-ended question helps to minimize reporting bias, if any. Accordingly, we used the modified double-bounded dichotomous choice contingent valuation method (henceforth, discrete choice CV experiment) based on the above questions as the robustness check for our WTP measures. The use of this method has been outlined in recent WTP literature.[6,21,22] Looking at the distribution of the responses (less than Rs. 200 constitute about 72% and 78% of the samples for vaccines with full and 70% efficacy, respectively), we fix Rs. 200 as the cutoff, where the variable takes the value of "1" if the respondent is willing to pay Rs. 200 or above and "0" if the quoted value is below Rs. 200. One further justification of choosing Rs. 200 as the cutoff came from the Government of India, who stated just before the rollout that the average vaccine cost would be from Rs. 200 to Rs. 295.[23]

Apart from these questions on WTP, we gathered information about the presence of vaccine hesitancy, if any, apart from a number of socio-economic and demographic individual and household level information. Based on this, we used a set of predictor variables in the regression models. Among the socio-demographic characteristics, we included age, gender, gender of the household head, education, highest education in the household, number of earning members, number of elderly, number of children of 5 years or lesser, and main occupation of the household (whether engaged as a agricultural/non-agricultural laborer). Because caste as a social group forms an important ingredient of the Indian social structure, we considered this as one of the determinants. From historicial times, Scheduled Castes (SC) and Scheduled Tribes (ST) have suffered from severe social deprivation behind the Other Backward Castes (OBC) and Upper Castes (UC) in terms of different indicators of welfare though the former is more disadvantaged than the latter.[24] With respect to economic variables, apart from the number of mobile phones possessed by the household, an asset possession index was developed using possession of a set of assets that include television, air-conditioner/cooler, computer/laptop, two-wheeler, car, washing machine, and mixer grinder. The asset index is constructed in the following way: we first standardize each of these assets indicators across all the respondents, sum them up, and then standardize the total. This method of aggregation has been used by a number of studies in different contexts.[25]

During the survey, we also collected information on an important indicator of the financial vulnerability of the household where we asked if they faced any loss of income due to Covid-19 in the last year. In cases where this was answered in affirmative, we also enquired about the share of loss of income with respect to the preceding year, before the Covid-19 crisis. This share was included in the regression as a dummy variable that takes the value of 1 if the reported income reduction has been over 50% and 0 otherwise. The health vulnerability was captured through usage of public transport and the presence of comorbid individuals in the household, along with the number of days the respondent had to go out in a week. The details of each of predictor variables on how they had been incorporated in the regression models in given in Table 1.

To estimate the determinants associated with WTP as discussed, we used the Ordinary Least Square (OLS) regression model. We performed a number of diagnostic tests to ensure that the assumptions of OLS surrounding multi-collinearity, homoscedasticity, and residual normality hold. We used the Variance Inflation Factor (VIF) to analyze the multi-collinearity and a tolerance value ($\frac{1}{VIF} > 0.1$) was used as the cutoff point that indicates the absence of multi-collinearity between the predictors.[26] Homoscedasticity and residual normality assumptions were also checked using the White test for homoscedasticity[27] and the Shapiro Wilk test, respectively.[28] A rejection of the null hypothesis in these two tests indicates that the residuals are homoscedastic (have a constant variance) and are distributed normally, respectively. Our initial analysis indicated that the assumptions surrounding homoscedasticity and normality of residual assumptions were violated. Hence, a natural logarithm function was used, whereby because the WTP can be 0, we take $\ln(WTP + 1)$ as the response variable. Also, for estimation, we use robust standard errors to account for violation of the assumption of independently distributed error structure, and accordingly correct for the potential concerns on heteroscedasticity and residual non-normality. Accordingly, we present the 95% confidence interval (CI) for each independent variable in the model calculated from robust standard error.

For robustness check, we estimated the probability of the vaccine WTP being less than Rs. 200 using a probit regression as our response variable is binary in nature. Please note that because we are categorizing the information on WTP here into two groups (WTP of less than Rs. 200 and Rs. 200 or more),

Table 1. Descriptive statistics

Variables	Definition	Mean/ Proportion	Standard deviation	Minimum	Maximum
WTP (fully effective)	WTP for fully effective vaccine from open ended question	Rs. 140.61	209.01	0	3000
WTP (70% effective)	WTP for 70% effective vaccine from open ended question	Rs. 115.90	176.25	0	2000
Less than Rs. 200 (fully effective)	1 if WTP is less than Rs. 200 for fully effective vaccine from discrete choice CV method; 0 otherwise	0.281		0	1
Less than Rs. 200 (70% effective)	1 if WTP is less than Rs. 200 for 70% effective vaccine from discrete choice CV method; 0 otherwise	0.223		0	1
Female	1 if the respondent is female; 0 otherwise	0.168		0	1
Age	Age of the respondent (in years)	42.155	13.471	18	92
Household head	1 if the household head is male; 0 otherwise	0.804		0	1
Years of education	Education of the respondent (0 to 17 in order)	6.497	4.720	0	17
OBC	1 if the respondent belongs to OBC group; 0 otherwise	0.622		0	1
SC/ST	1 if the respondent belongs to SC/ST group; 0 otherwise	0.285		0	1
Upper caste	1 if the respondent belongs to Upper caste group; 0 otherwise	0.094		0	1
Highest education in household	Highest education in the household (0 to 17 in order)	10.331	3.587	0	17
Number of earning members	Number of earning members in the household	1.438	0.833	0	8
Laborer	1 if the respondent is an agricultural or non-agricultural casual laborer; 0 otherwise	0.426		0	1
Television	1 if there is a television in the household; 0 otherwise	0.862		0	1
Air conditioner/cooler	1 if there is an air conditioner/ cooler in the household; 0 otherwise	0.002		0	1
Computer/laptop	1 if there is a computer/ laptop in the household; 0 otherwise	0.023		0	1
Two-wheeler	1 if there is a two-wheeler in the household; 0 otherwise	0.743		0	1
Car	1 if there is a car in the household; 0 otherwise	0.049		0	1
Washing machine	1 if there is a washing machine in the household; 0 otherwise	0.016		0	1
Mixer grinder	1 if there is a mixer grinder in the household; 0 otherwise	0.170		0	1
Number of mobile phones	Number of mobile phones in the household	1.062	0.904	0	6
Income reduction	1 if the income reduction has been more than 50%; 0 otherwise	0.656		0	1
Frequency of going out	Number of days the respondents has to go out for work in a week	3.179	3.210	0	7
Uses public transport	1 if the respondent uses public transport for traveling; 0 otherwise	0.094		0	1
Comorbid	1 if the household has at least one member suffering from either asthma, heart disease, diabetes, hypertension, liver problems, any other chronic disease or had a surgery in the past one year.	0.114		0	1
Elderly	Number of elderly in the household (60 years of age or above	0.436	0.694	0	6
Children	Number of children in the household (5 years of age or lesser)	0.402	0.708	0	6
Observations	1251				

Proportion within the sampled respondents is given for the categorical variables. For continuous variables, mean, standard deviation, maximum and minimum values are presented.

there is a loss of information. Hence, we do not expect the determinants to be exactly similar and treat the response on open-ended WTP questions as the primary response variable. The estimates of the determinants of WTP from the discrete choice CV method are presented to ensure that our inferences from the earlier method are qualitatively robust and also obtain the strongest predictors.

Results

During our survey, as mentioned, we asked some basic questions about the vaccination drive that the government started initiating during the survey. About 42% of the respondents (N = 524) said they had heard of this drive. Out of these 524 respondents, 456 reported that they had heard that the vaccines would be given free of cost. Over 85% of the sampled respondents (N = 1068) felt that the government should entirely subsidize the vaccine cost. We did not find any major evidence of vaccine hesitancy as more than 97.4% of the respondents (N = 1219) informed us that they would be willing to take the vaccine with full effectiveness, and over 90.2% (N = 1128) of them were willing to accept the one with 70% efficacy. Hence, to estimate the determinants of WTP, we dropped the vaccine-hesitant respondents and considered only those who were willing to accept the respective vaccine. For regression estimations, 1219 respondents were considered for analysis of WTP of the fully effective vaccine, and 1128 were considered for the one with 70% effectiveness.

Notably, we included those who were willing to take the vaccine only if it is free, as their WTP would essentially be zero. The reason for the inclusion of this set of respondents is that the concept of WTP operates within the confines of the budget constraint, and hence it is possible that these individuals may not have the financial ability to pay for vaccines. This becomes especially relevant given the context we are studying. Our study is based on India, which is a developing country and according to the data from the World Bank, it has a GDP per capita of $1961 (at 2010 constant prices) in 2020. This is lesser than countries that include Nigeria, Congo, or Papua New Guinea, among others. Even within India, we conducted the survey in rural parts of Madhya Pradesh, which is among the poorest states economically.[29] Moreover, evidence suggests that rural consumption in India was declining even before the pandemic, which further exacerbated the economic component of this crisis.[30] Post-pandemic, as even our data suggests, there has been a considerable income loss because of subsequent lockdowns and low economic activity. Hence it is likely that a significant proportion of the population would not have the financial ability to pay for the Covid-19 vaccine. Therefore, if we drop these individuals, our sample would no longer be considered random, rather it will systematically exclude the most vulnerable and economically poor, and accordingly, the WTP correlate estimates might be biased. Importantly, previous studies on WTP suggest that those respondents who have zero WTP because of inability to pay should be retained in the analysis.[31]

The average willingness to pay for a vaccine with full efficacy was found to be about Rs. 141 ($1.9) with 15% reported their unwillingness to pay any money (N = 183). About 43.8% (N = 534) reported that they were not willing to pay over Rs. 70 (~$1) for the vaccine. Notably, the figures for the WTP reduced considerably for vaccines with lesser efficacy (70%). The average WTP here stood at Rs. 116 ($1.6) with 17.2% (N = 194) reporting of their unwillingness to pay money. 54.5% of the respondents were found to be unwilling to pay over Rs. 70 (~$1) for this vaccine. Importantly, this is much lesser than the amount of the first set of vaccines given to the elderly and those above 45 years, which has been fixed by the government for private immunization, (about Rs. 250 or $3.4). Overall, we observed low willingness to pay among the respondents not only for the vaccine with lower efficacy but also with full effectiveness. This underscores the importance of significant subsidization from the government to ensure higher take up of vaccines, something that is paramount to stem the transmission of the virus as well as its severity. Importantly, vaccine hesitancy was found to be low, hence pricing can to a large extent determine the success of the vaccination drive.

From the discrete choice CV experiment as well, we found that about 876 respondents (71.9%) reported being willing to pay less than Rs. 200 ($2.75) for the fully effective vaccine. Just about 3.8% (N = 46) of the respondents were willing to pay Rs 1000 ($13.7) or more for this vaccine. For the vaccine with 70% efficacy, this figure fell to 2.8% (N = 31). About 77.8% of the respondents are reported to be willing to pay less than Rs. 200 (N = 877) for this vaccine. This largely ensures that WTP we estimate is robust to the various measures taken to elicit the response and is found to be less than Rs. 200 consistently. Among respondents who responded that their WTP for the fully effective vaccine was very likely to remain unaltered, 69.6% (N = 609) said it is lower than Rs. 200 whereas the figure is 77.6% (N = 267) for the ones who said it is likely to alter. For the vaccine with 70% effectiveness, these figures were 75.1% (N = 610) and 84.5% (N = 267), respectively.

Determinants of WTP

The descriptive statistics that include the mean and standard deviation for the continuous variables, and proportion for the binary/categorical variables used in the regression are given in Table 1. This is for the full sample of 1,251 respondents. We also included the range (minimum and maximum) values for each of these variables. In addition, the table presents a clear description of how each of them had been defined. 210 respondents out of the 1251 surveyed respondents were females (16.8%). The average age was around 42 years with education of about 6.5 years. Over 62% of the respondents were from the OBC groups (N = 778) with 28.5% from the SC/ST community (N = 356) and 9.4% from the upper caste groups (N = 117). Over 86% of the respondents were from a household that had a television (N = 1078) and 74% of them owned a two-wheeler (N = 930). The average number of mobile phones in each of the sampled households was found to be 1. About 9.4% of the respondents used public transport (N = 118). Notably, the average reduction of income among the respondents was about 61.9% since the outbreak, with 65.6% reporting that this reduction had been more than 50%. This signifies the staggering impact of the pandemic on income and livelihoods among the people.

Results from multivariate regression to estimate the WTP is presented in Table 2. We included the two types of indicators of WTP as our dependent variable: the one obtained directly (column 2 and column 3) and the other through discrete choice CV experiment (columns 4 and 5) for both types of vaccine: 70% and full effectiveness, respectively. For the later indicator, as indicated earlier, we estimated the probability of willing to pay more than Rs. 200 for the vaccine. Please note that for estimation of the first indicator, we presented the OLS regression coefficients, and for the second, the marginal effects derived from the probit regression model.

We find no association of age of the respondent, number of elderly, number of children, or household headship with WTP. However, female respondents were likely to be willing to pay lesser and so were the households from SC/ST social group. One level increase in education of the respondent was associated with a 4% (95% CI: 1.2–6.9) and 3.8% (95% CI: 1.0–6.5) increase in WTP for the vaccine with 70% and full effectiveness, respectively. Importantly, the highest education within the household was also found to be a significant predictor. Variables that capture income or wealth stock of the respondent were found to be significant predictors of WTP. For example, one standard deviation in asset possession index is found to be linked with a 25.6% on average (95% CI: 11.3–40.0) increase in the WTP for the vaccine with full efficacy, and for the one with 70% efficacy, the increase is 24.9% (95% CI: 10.2–39.6). If there is an income reduction since the outbreak of the pandemic by more than 50%, we found the reported WTP for the fully effective vaccine to reduce by 22.5% (95% CI: 2.2–42.8). For the one with 70% effectiveness, this reduction is 30.2% (95% CI: 8.9–51.5) on average. The presence of comorbid individuals was likely to raise the WTP for the fully effective vaccine by 33.7% (95% CI: 5.1–62.2) and by 29.4% (95% CI: 0.8–58.1). The number of days in a week that the respondent needed to go out for work purposes and usage of public transport was also found to be strong correlates of the WTP.

The estimations for WTP from the discrete choice CV method indicated to some extent similar findings. As in the earlier case, we found that one standard deviation increase in asset index was associated with about 5.0 (95% CI: 1.1–8.9) and 7.0 percentage point (95% CI: 03.5–10.5) increase on average in the likelihood of WTP to be Rs. 200 or above for the vaccines with 70% and full effectiveness, respectively. Importantly, after controlling for economic status, we also found respondents from educated households to report higher WTP underscoring the importance of education of awareness in enabling higher demand for vaccines. One standard increase in education of the respondent was observed to be associated with 0.7 (95% CI: 0.1–1.3) and 0.6 (95% CI: 0–1.3) percentage point increase in the reported WTP being Rs. 200 or more, on average. Indicators like age, gender, household headship, presence of comorbid individuals, number of elderly or children in the

Table 2. Regression estimation of WTP.

	Open-ended question (OLS regression)		Discrete choice CV (probit regression)	
	WTP (70% effective)	WTP (fully effective)	WTP (70% effective)	WTP (fully effective)
(1)	(2)	(3)	(4)	(5)
Female	−0.465*	−0.462*	−0.034	−0.035
	(−0.830 – −0.100)	(−0.826 – −0.098)	(−0.114–0.047)	(−0.115–0.045)
Age	0.001	−0.003	−0.000	0.000
	(−0.009–0.011)	(−0.012–0.006)	(−0.003–0.002)	(−0.002–0.002)
Household head	0.006	0.094	0.028	0.020
	(−0.366–0.378)	(−0.267–0.454)	(−0.051–0.108)	(−0.061–0.100)
Education	0.040**	0.038**	0.007*	0.006*
	(0.012–0.069)	(0.010–0.065)	(0.001–0.013)	(0.000–0.013)
Ref. OBC				
SC/ST	−0.261*	−0.311*	−0.024	−0.017
	(−0.505 – −0.016)	(−0.552 – −0.071)	(−0.079–0.032)	(−0.074–0.040)
Upper Castes	−0.122	−0.118	−0.055	0.009
	(−0.488–0.244)	(−0.485–0.249)	(−0.132–0.022)	(−0.080–0.098)
Highest education in the household	0.041*	0.046**	0.007	0.012**
	(0.006–0.076)	(0.011–0.080)	(−0.002–0.015)	(0.003–0.021)
Number of earning members	−0.232**	−0.258**	−0.026	−0.047**
	(−0.392 – −0.071)	(−0.421 – −0.096)	(−0.058–0.006)	(−0.082 – −0.013)
Agricultural/ Non-agricultural laborer	−0.269*	−0.288*	−0.076**	−0.062*
	(−0.507 – −0.031)	(−0.522 – −0.055)	(−0.132 – −0.021)	(−0.119 – −0.006)
Asset index (standardized)	0.249***	0.256***	0.050*	0.070***
	(0.102–0.396)	(0.113–0.400)	(0.011–0.089)	(0.035–0.105)
Number of mobile phones	0.277***	0.281***	0.038*	0.059***
	(0.144–0.411)	(0.145–0.417)	(0.006–0.069)	(0.025–0.092)
Over 50% income reduction in last one year	−0.302**	−0.225*	−0.033	0.010
	(−0.515 – −0.089)	(−0.428 – −0.022)	(−0.080–0.014)	(−0.040–0.059)
No. of days out for work	0.168***	0.126***	0.012**	0.005
	(0.134–0.202)	(0.093–0.159)	(0.003–0.020)	(−0.003–0.013)
Uses public transport/ pool for work	0.534**	0.467**	0.004	0.096*
	(0.205–0.863)	(0.114–0.821)	(−0.088–0.095)	(0.009–0.183)
Comorbid household members present	0.294*	0.337*	0.060	0.050
	(0.008–0.581)	(0.051–0.622)	(−0.010–0.130)	(−0.024–0.123)
Number of elderly (>60 years)	−0.068	−0.092	−0.007	−0.008
	(−0.224–0.089)	(−0.244–0.061)	(−0.042–0.029)	(−0.044–0.028)
Number of children (<5 years)	0.070	0.086	0.015	0.011
	(−0.074–0.214)	(−0.054–0.225)	(−0.017–0.046)	(−0.024–0.045)
GP fixed effects	Yes	Yes	Yes	Yes
Observations	1,128	1,219	1,128	1,219
R-squared	0.279	0.246	0.148	0.144

Marginal effects from OLS and probit regressions are presented with 95% CI calculated using robust standard errors given in the parentheses. Significance level: *** $p < .001$, ** $p < .01$, * $p < .05$.

household, caste, and income reduction because of the pandemic did not bear any significant relationship. The highest education within the household, public transport usage, and number of days that the respondents needed to go out were significant determinants for only the fully effective vaccine.

As pointed out earlier, India faced devastating economic shock in the aftermath of the outbreak of the pandemic. This loss has been disproportionately higher among casual laborers or informal or formal workers employed in shops or manufacturing units. Studies have reported significant levels of distress across dimensions such as employment, sales, and credit uptake for the Micro, Small, and Medium Enterprise (MSME) sector, one of the largest sources of employment outside agriculture.[32] Accordingly, residents of peri-urban areas similar to our survey area where many have been engaged in these sectors have been hit tremendously by the pandemic. From our data, we find that 66% of the respondents reported a loss of over 50% of income since the outbreak. 37% report that this loss had been more than 70%. From our regression results, we found respondents reporting more than 50% decline in incomes because of the pandemic were more likely to report a lower WTP. This result, however holds true only for the open-ended WTP outcome and not the discrete choice CV experiment.

Importantly, respondents who perceive themselves to be vulnerable to infection also reported higher WTP. For example, we find the WTP to be significantly and positively related to the number of days the respondent had to go out for work every week. This finding captures the notion of a risk premium that the respondents are willing to pay and underscores the importance of urgent vaccines for a broad category of frontline workers, who are more exposed to the virus as they have to move out more frequently for livelihood. Furthermore, as one would expect, respondents from households with comorbid individuals are, on average, more likely to have a higher WTP for the vaccine. Therefore, we observe health-wise vulnerable individuals who have to travel frequently for work or those having a comorbid individual in their household have higher WTP for the vaccines. Nevertheless, no such relationship is observed for households with at least one elderly above 60 years of age.

Importantly, in our analysis, we further use the question we posed on the likelihood of the respondent to change his/her answer. We ran separate probit regressions of WTP through discrete choice CV method controlling for a dummy variable that takes the value of "1" if the respondent reported "high chance" and "0" if he/she reported "low chance." This exercise would control for the likelihood of changing WTP response along with the aforementioned predictor variables. The regression results, which are shown in Table A1 that presents the marginal effects indicate similar findings to what we reported in columns 4 and 5 of Table 2. For example, agricultural/non-agricultural laborers have a significantly lower WTP. Economic indicators like asset possession and the number of mobile phones are found to be important predictors. The dummy indicating a change in response is found to be significantly associated with the WTP. Notably, we also present separate regressions for respondents who reported high and low chances of changing response (columns 2, 3, 5, and 6). However, we avoid interpreting the results because of the low sample size, which is given in the last row of Table A1.

Discussion

Historically, rural India has by and large been characterized by systematically poor health infrastructure in comparison to its urban counterparts. However, the severity of the crisis during the second wave was such that even the urban health infrastructure was largely overwhelmed with a sudden spike in cases and deaths. Given that a predominant share of Indian population resides in rural spaces that are under-resourced, residents here are additionally vulnerable to the spread of Covid-19 infection. In this paper, we have focused on a peri-urban region, a spatial entity that constitutes a likely source of transmission from urban to rural areas, and assessed the magnitude and correlates of WTP for the two variants of Covid-19 vaccines.

We find negligible vaccine hesitancy amongst surveyed households, which is quite encouraging. This is particularly because the field survey for this study (a) started within a fortnight of the commencement of India's vaccine drive and (b) was completed before the commencement of the devastating second wave of the pandemic in India. Despite the fact that there was a considerable lack of information among non-urban residents' regarding Covid-19 vaccines (only 42% were about the vaccine drive started by the Government of India) during this time period, more than 97.4% of the respondents were willing to accept a vaccine with full effectiveness and over 90.2% were willing to accept the one with 70% efficacy. Interestingly, these numbers are even higher than those reported from England,[33] Italy,[34] Denmark, France, Germany, Sweden, Hungary, United States,[35] and Malaysia,[8] and are comparable to those from Ecuador[7] and Kenya.[36]

Our analysis of WTP has demonstrated that, though people are not hesitant to get vaccinated, their WTP is quite low. On average, a person was willing to pay about $1.9 only for a vaccine with full efficacy and about $1.6 only for a vaccine having 70% efficacy, while about 56% and 46% of households were willing to pay more than $1 per person for full and 70% effective vaccine, respectively. We compare our results with existing studies, we find that the mean WTP for the sample households was much less than that reported for other countries. For example, the reported mean WTP was $30.66 in Malaysia,[8] $57.20 in Indonesia,[6] more than $147.41 in Ecuador,[7] more than $49.81 in Kenya,[36] and $184.72 in Chile.[37] While a part of the difference in WTP in our study from those reported from other countries may be due to differences in methods of scopes of surveys, our stratified random sampling and in-person survey of households form a peri-urban region in India vis-à-vis countrywide online sample survey in existing studies, our findings highlight that "one-fits-for-all" policy toward vaccination across countries is likely to be sub-optimal.

Furthermore, we have demonstrated that level of education, wealth, frequency of going out for work, and reliance on public transport for travel have a significant positive association with WTP, as found in existing studies.[6–8,36,37] Therefore, greater awareness regarding benefits of vaccines, higher ability to pay and a higher level of perceived exposure to the virus (indicated by the number of days that the respondent has to step out for work and usage of public transport) seems to induce individuals to be willing to pay more for a vaccine. On the other hand, our results also pointed out that female respondents and households from socially disadvantaged groups (SC/STs) are willing to pay lesser amounts for Covid-19 vaccines compared to male respondents and others, respectively, ceteris paribus. Lower willingness to pay by females is also found in the case of other countries such as Kenya. It suggests that appropriate gender and socio-economic background sensitive vaccine policy is necessary to ensure equal access to health by all. Surprisingly, unlike as in existing studies,[6,8,37] a positive and significant effect of perceived health risk (proxied by the variable indicating the presence of comorbid individuals in the household) does not appear to be robust. This is, perhaps, because the variable used in this study to measure health risk does not directly concern the respondent but her/his family as a whole. Our analysis also provides limited evidence for the relationship between income loss due to the pandemic and WTP. While income loss due to pandemics may reduce respondents' ability to pay, the possibility of recovering lost income in the future by getting vaccinated might induce higher WTP.

To sum up, our findings underscore the necessity for massive subsidization of vaccines. This becomes especially pertinent for India and also for the Global South as the average level of education is low, with high dependence on informal jobs that require workers to go out frequently. This becomes even more relevant because of the adverse economic effects of the pandemic that has been disproportionately higher for informal workers. 66% of the respondents from our survey revealed that they faced above 50% reduction in income over the last year because of the pandemic. For these respondents, the reported WTP for vaccines is just about Rs. 95.5 ($1.3), which increases to Rs. 119.5 ($1.6) for those with 70% and full effectiveness, respectively. Our results suggest that unless the government continues to offer Covid-19 vaccine for free for all adult Indians, as it is being done at present through public health facilities, and extends the same to the younger population (below 18 years), achieving the target of "fully vaccinated India" is likely to remain a distant dream.

Our study has certain limitations. We note here that this study is based on a survey that is representative of a peri-urban region in India and need not be representative for the whole country. Thus, our results should be interpreted with caution. We had conducted the survey just before the second wave of the pandemic started in India, and the vaccination drive in the country was at a nascent stage. While our results seem to suggest that greater devastating effect of the second wave is likely to further reduce WTP, it is necessary to collate more recent data to be more confident about such inferences since perceptions of people regarding their vulnerability to the disease and usefulness of vaccines might also have changed over time. Nonetheless, to the best of our understanding, the qualitative results of multivariate analysis of this paper are likely to hold true.

Conclusion

This paper offers insights into peri-urban households' WTP for Covid-19 vaccines, and its correlates from primary survey data collected from rural peripheral regions across the city of Bhopal in India. To the best of our knowledge, this is one of the first studies on this issue of paramount importance for India. In the study, we find little vaccine hesitancy but quite low levels of WTP for Covid-19 vaccines, something that needs to be accounted for in the nationwide vaccine policy.

India's vaccine policy has undergone several changes, from a fully centralized to complete decentralized and then to the partially centralized system of procurement and distribution, since its inception in January 2021. However, the stipulated price of vaccines at private health care facilities has steadily increased. Currently, the minimum price of the vaccine stands at ₹780 ($10.5) per dose per person, which is about 81% of pre-crisis monthly household incomes as calculated from the latest available National Sample Survey (NSS) round from 2017 to 2018 conducted by the Government of India. This suggests that the private healthcare facilities may be out of reach of average Indians even for the purpose of Covid-19 vaccination.[38]

Furthermore, analysis of correlates of WTP suggests that the economic well-being of the household and respondents' education were strong predictors. While respondents who need to go out frequently for work purposes and use public transport were willing to pay more for the vaccine, on average, there is some evidence to suggest that the degree of economic shock experienced by households was negatively associated with the WTP. With India coming to terms with the devastating second wave of Covid-19, our findings offer critical insights for public health policy on vaccination in India. Preliminary evidence suggests that the second wave has had a debilitating impact on the economy and has further disrupted livelihoods, thereby adversely affecting people's ability to pay for the vaccine.[39] In light of these facts, our estimates may in fact, be an upper bound of WTP, thereby highlighting an urgent requirement for fiscal intervention that subsidizes vaccines and promote mass vaccination.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, [UD], upon reasonable request. (https://authorservices.taylorandfrancis.com/data-sharing/share-your-data/data-availability-statements/)

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1. Marginal effects from probit regressions considering the reported likelihood for altering the response on WTP.

(1)	Fully effective (Small chance) (2)	Fully effective (High chance) (3)	Fully effective (With dummy) (4)	70% effective (Small chance) (5)	70% effective (High chance) (6)	70% effective (With dummy) (7)
Female	0.002 (−0.130–0.135)	−0.037 (−0.133–0.059)	−0.030 (−0.110–0.050)	−0.033 (−0.173–0.107)	−0.015 (−0.110–0.080)	−0.029 (−0.108–0.050)
Age	0.000 (−0.004–0.005)	−0.000 (−0.003–0.002)	0.000 (−0.002–0.002)	0.002 (−0.001–0.006)	−0.002 (−0.004–0.001)	−0.000 (−0.002–0.002)
Household head	0.073 (−0.068–0.214)	−0.019 (−0.115–0.077)	0.017 (−0.064–0.097)	−0.024 (−0.154–0.105)	0.032 (−0.062–0.126)	0.021 (−0.059–0.101)
Education	0.000 (−0.011–0.011)	0.008* (0.001–0.016)	0.006 (−0.000–0.013)	0.010* (0.001–0.020)	0.005 (−0.002–0.012)	0.007* (0.001–0.013)
Ref. OBC						
SC/ST	0.016 (−0.077–0.110)	−0.021 (−0.091–0.049)	−0.014 (−0.071–0.044)	0.035 (−0.050–0.120)	−0.025 (−0.094–0.044)	−0.019 (−0.075–0.036)
Upper Castes	−0.019 (−0.179–0.142)	0.022 (−0.083–0.128)	0.010 (−0.079–0.099)	−0.118** (−0.196 – −0.041)	−0.018 (−0.117–0.081)	−0.051 (−0.127–0.026)
Highest education in the household	0.014* (0.001–0.028)	0.009 (−0.002–0.020)	0.012** (0.003–0.021)	0.010 (−0.000–0.021)	0.005 (−0.005–0.016)	0.007 (−0.002–0.015)
Number of earning members	−0.053 (−0.118–0.012)	−0.054** (−0.095 – −0.014)	−0.048** (−0.083 – −0.014)	−0.025 (−0.076–0.025)	−0.034 (−0.072–0.004)	−0.026 (−0.058–0.005)
Agricultural/ Non-agricultural laborer	−0.020 (−0.119–0.078)	−0.076* (−0.146 – −0.007)	−0.066* (−0.122 – −0.009)	−0.035 (−0.124–0.055)	−0.097** (−0.165 – −0.029)	−0.082** (−0.138 – −0.026)
Asset index (standardized)	0.073** (0.026–0.119)	0.071** (0.024–0.117)	0.072*** (0.037–0.107)	0.047* (0.009–0.085)	0.049 (−0.003–0.101)	0.052* (0.011–0.092)
Number of mobile phones	0.102** (0.027–0.177)	0.046* (0.006–0.086)	0.056** (0.023–0.090)	0.053 (−0.003–0.108)	0.031 (−0.009–0.070)	0.034* (0.002–0.066)
Over 50% income reduction in last one year	0.013 (−0.071–0.098)	0.001 (−0.061–0.062)	0.004 (−0.045–0.053)	−0.048 (−0.117–0.021)	−0.049 (−0.108–0.010)	−0.045 (−0.091–0.002)
No. of days out for work	−0.005 (−0.022–0.011)	0.007 (−0.003–0.016)	0.005 (−0.004–0.013)	0.003 (−0.011–0.017)	0.012* (0.003–0.022)	0.011** (0.003–0.019)
Uses public transport/ pool for work	0.052 (−0.140–0.243)	0.091 (−0.008–0.189)	0.093* (0.006–0.179)	0.059 (−0.147–0.266)	−0.026 (−0.130–0.079)	−0.003 (−0.094–0.088)
Co-morbid household members present	0.029 (−0.110–0.168)	0.046 (−0.038–0.131)	0.046 (−0.027–0.118)	−0.008 (−0.122–0.106)	0.068 (−0.016–0.151)	0.059 (−0.010–0.127)
Number of elderly (>60 years)	0.016 (−0.050–0.082)	−0.011 (−0.053–0.031)	−0.009 (−0.045–0.027)	0.001 (−0.054–0.057)	−0.007 (−0.049–0.034)	−0.009 (−0.044–0.026)
Number of children (<5 years)	0.036 (−0.027–0.100)	0.002 (−0.038–0.041)	0.011 (−0.023–0.045)	0.040 (−0.009–0.090)	0.005 (−0.032–0.042)	0.014 (−0.018–0.046)
High chance of same response			0.058* (0.006–0.109)			0.088*** (0.041–0.136)
Observations	344	875	1,219	316	812	1,128

Marginal effects from probit regressions are presented with 95% CI calculated using robust standard errors given in the parentheses. Significance level: *** p < .001, ** p < .01, * p < .05.