Is the Demand for Clean Air Too Low? Experimental Evidence from Delhi*

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Abstract

Do hazardous levels of air pollution in developing countries reflect low demand for air quality or imperfect information about its benefits? This paper implements an experiment to estimate the demand for clean air in a low-income country and tests for several possible market failures in information that may affect it. Combining randomized price variation for low-cost pollution masks with day-to-day variation in ambient air quality, we estimate an average marginal willingness-to-pay (MWTP) for an annual 10 unit reduction in $PM_{2.5}$ of $1.14 (USD) among low-income residents of Delhi, India. This estimate is low in global terms, but increases more than five times for respondents who are treated with a description of the health effects of air pollution prior to demand elicitation. These findings suggest limited demand for clean air may partly reflect limited information about its benefits.

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1 Introduction

Residents of the world's largest cities endure levels of air pollution well beyond public health recommendations (WHO 2018).[1] The combination of high population density and low air quality has dire consequences: published estimates put the global number of deaths from air pollution at or above five million annually (Burnett et al. 2018; Lelieveld et al. 2019), in addition to the substantial morbidity and productivity impacts (Graff Zivin and Neidell 2013). In Delhi alone, around 30,000 lives are estimated to be lost each year from ambient air pollution (Burnett et al. 2018). Why do particulate pollution concentrations remain high despite such large public health costs?

Clean air is a public good. One explanation for low levels of air quality in many major urban areas is that poor households have a high marginal utility of consumption spending; in other words, that people with very limited resources rationally value consumption in the current period of future health improvements. Under this hypothesis, high levels of air pollution in poor areas is the natural consequence of limited public demand among the population. As people become wealthier, demand for health-improving goods, including clean air, should rise (Hall and Jones 2007). The implication of this explanation, often described as the "Environmental Kuznets Curve" (Kuznets 1955; Grossman and Krueger 1995), is that only after substantial economic growth will the costs of environmental regulation justify its benefits.

Richer explanations hold that low observed demand for air quality could also be the consequence of market failures, such as misinformation, that are frequently observed in developing country settings (Greenstone and Jack 2015).[2] Revealed preference measures of demand for air quality could be biased downward if individuals are either uninformed or inattentive to the benefits of air quality. For example, several studies demonstrate that informing households about the either presence of risk of water pollutants made them more likely to purify their water (Jalan and Somanathan 2008; Bennear et al. 2013). With respect to air quality, Ahmad et al. (2022) demonstrate that providing air pollution forecasts makes individuals more responsive to air pollution and increases their demand for protective air filtering masks.[3] If information provision can be shown to shift not only the demand for defensive expenditures (such as masks), but also the demand for air quality itself, then it cannot be the case that air quality levels are merely reflections of high marginal utility of consumption for poor populations.[4] Other market failures could also limit the

1. As of 2019, all ten of the largest cities in the world had $PM_{2.5}$ averages that were exceeded the World Health Organization's Air Quality Guidelines WHO (2018).

2. Greenstone and Jack (2015) also note that market failures, such as the absence of credit or risk markets or perceptions of political failures could be implicated in limiting public demand for environmental goods. Because we focus on mask purchase behavior, we do not investigate these additional explanations, but refer the reader to that paper for additional detail.

3. Ahmad et al. (2022) do not, however, demonstrate that information increases demand for air quality *per se*, a point we return to later in this section.

4. The effectiveness of information provision on public demand for environmental quality has historical precedent. The environmental movement in the United States is said to have been precipitated by a series of high-profile events including Rachel Carson's publication of *Silent Spring* and the Cuyahoga River in Ohio catching fire, among others. These events

expression of demand for air quality. In particular, misperceptions of social disapproval of technologies that limit pollution exposure or limited experience with improved air quality could also dampen expressions of demand for clean air.

Assessing the credibility of these competing explanations raises several challenges. First, estimates of the demand for clean air among the urban populations that currently face the globally highest levels of air quality are scarce. Second, understanding whether the demand for clean air is limited by the candidate explanations above requires targeted interventions to relieve the effects of information, peer disapproval, or limited experience with improved air quality.

To help answer these questions, this paper considers the demand for clean air and its drivers in Delhi, India, a city of more than 25 million people and where wintertime $PM_{2.5}$ concentrations regularly exceed 120 $\mu g/m^3$, 24 times higher than the World Health Organization (WHO) guideline of 5 $\mu g/m^3$. India, as of recently the largest country in the world, is an important place to understand the demand for air quality. With GDP per capita just below \$2,100 (World Bank, 2021), India is a relatively low-income country. However, as a democracy with a robust set of pollution laws at the national, state, and district level, its states and cities should be well-positioned to respond to demand for air quality improvements. Understanding whether the provision of air quality is limited by political constraints or by the degree to which citizens are demanding improvements is an empirical question of policy interest.

We present the first experimental estimates of the demand for clean air, as revealed by individual decisions to purchase pollution masks, the primary mode of defense against the harmful effects of air pollution in our study setting.[5] We also examine how both our own experimental interventions designed to rectify potential information gaps around air pollution and a city-wide program designed to increase the use of pollution masks affect measured demand.

Between October 2018 and March 2019, a period coinciding with the peak air pollution season in Delhi, we conducted a field experiment in which we repeatedly offered pollution masks at randomly varying prices (0, 10, 30, and 50 Indian Rupees) to lower-income households in Delhi. We focus on lower-income households in order to capture demand for air quality for a population that is both understudied and more representative of the average Delhi resident.[6] Using experimental variation in prices combined with natural variation in ambient air pollution, we develop a discrete choice model of mask demand to identify the marginal willingness-to-pay (MWTP), or demand,

contributed to a growing public awareness of the dangers of environmental pollution and provided public support for nascent United States environmental policy (Shapiro 2022). More recently, Barwick et al. (2019) demonstrate that China's rollout of real-time air quality monitoring led to large increases in the degree to which individuals sought to avoid air pollution.

5. Prior to the onset of COVID-19 in 2020, face masks were primarily associated with air pollution in Delhi. For example, in one of the first public demonstrations for clean air in 2015, an Indian Member of Parliament wore a pollution mask into the Indian Lok Sabha, garnering substantial media coverage (Times of India 2015).

6. In India and in many other countries around the world, poor households are have fewer options to defend against air pollution (Banzhaf, Ma, and Timmins 2019), but little work of which we are aware studies preferences for air quality specifically among lower-income populations.

for clean air. We cross-randomized the variation in prices with additional experimental variation in two more treatments (administered prior the mask offer), which we refer to jointly as the "non-price interventions." The first is an information treatment, which highlighted the long-run health implications of high levels of air pollution, and the second is a peer belief treatment, which revealed to the respondent that average levels of peer disapproval of mask-wearing are low.

We document three primary findings. First, we show that average demand for clean air is low in absolute terms. On average, we measure a MWTP of $1.14 USD (23.0 INR) for a 10 unit (μg/m^3) reduction in annual $PM_{2.5}$ concentrations.[7]

Second, we document that providing information on the health impacts of air pollution leads to a large increase in the demand for clean air. We show that respondents who are given a handout and shown a short video discussing the long-run health impacts of air pollution before the mask offer are much more responsive to the level of ambient air pollution when deciding whether to purchase a mask. For those respondents, we estimate a MWTP of $6.24 per 10 unit annual reduction in $PM_{2.5}$, more than five times higher than those respondents who did not receive the information intervention.[8]

Third, we find that demand for clean air increases substantially with income and education. Among informed respondents, moving from the 25th to the 75th percentile of household income and individual years of school raises MWTP by roughly 50% and 140%, respectively. Although low in an absolute sense, after adjusting for household income and providing information, the MWTP for clean air that we estimate nearly matches an analogous estimate in Ito and Zhang (2020), the only other study of which we are aware to estimate demand for clean air in a lower-income country. We also show that while the information treatment increases demand for air quality among both lower and higher income respondents in our sample, its effects are concentrated among respondents with fewer years of schooling. This finding suggests that information provision is especially relevant in contexts where education levels are low.

This study primarily contributes to the small body of work estimating demand for clean air through revealed preferences. Appendix Table A.1 provides a summary of papers that estimate the demand for air pollution reductions, obtained through both revealed and stated preference approaches. Numerical estimates of demand for clean air vary substantially by context, method, and pollutant observed, but generally, studies have found households are willing to pay between $10 and $100 USD annually per unit of particulate matter reduced. [9] These studies have contributed

7. The experiment was conducted using Rupees, but in the paper we discuss the results primarily in USD to facilitate comparison to other contexts where results have also been reported in USD. We convert Rupees to USD using the PPP-adjusted exchange rate for 2019 reported by the World Bank: 20.13 INR = $1 USD.

8. In addition, we find little evidence of two other behavioral frictions in mask takeup: informing respondents that mask-wearing in public is not widely disapproved of has no effect on mask demand, and prior experience using a mask actually reduces the likelihood that a respondent will purchase another. This experiment was carried out prior to the onset of Covid-19. In our piloting activities, a commonly cited reason for why people did not wear masks despite Delhi's extreme pollution levels was the fear of "looking strange."

9. Chay and Greenstone (2005) find that an annual unit decrease in total suspended particulates is valued at about $19

considerably to our understanding of the public's value of clean air across the world. With few exceptions, however, they rely on backing out information on preferences for clean air through location or home purchasing decisions, which necessarily means that these estimates are derived by examining cross-sectional relationships between location choices, air pollution levels, and the cost of location decisions. This raises three important concerns. First, such cross-sectional relationships could be confounded by other, difficult-to-observe factors that covary with both pollution and location values, such as neighborhood desirability.[10] The second concern, which applies across the existing literature, is that estimating demand for clean air among low-income populations is virtually impossible using these approaches. Homes and large durable expenditures like air purifiers are expenditures that are currently unavailable to most of the low-income urban populations that face high levels of air pollution. Third and finally, in all cases the existing literature relies on observed variation in home value, income, or the price of defensive expenditures against air pollution to back out a monetary measure of the demand for clean air; we are not aware of any existing work that leverages truly random variation to estimate the demand for clean air.

Our primary contribution to this line of research is providing the first experimentally-derived estimates of the demand for clean air and by using experimental variation to examine how imperfect information and other market failures affect that demand. Importantly, this estimate of demand focuses specifically on respondents living in low-income settlements in Delhi, India. The key to our approach is that we combine unpredictable natural variation in local air pollution levels with offers of pollution masks whose (subsidized) price we randomly vary across respondents.[11] As described above, Ahmad et al. (2022) provide evidence that is complementary with respect to this paper: they show that information about future pollution increases respondents' demand for masks in Lahore, Pakistan, whereas this paper uncovers the demand for clean air in general. To the best of our knowledge, ours is the first to directly estimate demand for clean air using any method among a low-income population or in the country of India.

We also contribute to the literature on the takeup of defensive health technology in developing countries. In rural Kenya, two existing studies document limited demand, even at below-

(2019 USD) by housing markets in the United States. Bayer, Keohane, and Timmins (2009) directly model relocation decisions using a discrete choice approach and find that the median household would pay \$368–\$457 (2019 USD) for a unit decrease in PM10. Finney, Goetzke, and Yoon (2011) estimate a discrete choice model using data from households moving into Riverside and San Bernardino counties. They find that middle-income households are willing to pay \$51 (2019 USD) to have 10% more days meeting air quality standards. Notably for our setting, they find that high-income households pay more, while low-income households (by U.S. standards) have a negative willingness to pay. Outside of the United States, Gonzalez, Leipnik, and Mazumder (2013) estimate a hedonic model and find a unit reduction in PM10 is valued at \$48 (2019 USD) by residents of Mexico City. Freeman et al. (2019) estimate MWTP in China using discrete choice model similar to Bayer, Keohane, and Timmins (2009) and derive a value of \$29 (2019 USD) for a unit reduction in PM10. In the most recent and similar setting to ours, Ito and Zhang (2020) compare variations in regional pollution in China with air purifier purchases to derive a value of \$1.34 USD (in 2020 dollars) for a unit reduction in household PM_{10} exposure per year.

10. Ito and Zhang (2020) are an important exception to this concern: because their estimate is derived from air purifier purchases, they can control for unobservables at the location level.

11. This approach builds on previous non-experimental evidence from Greenstone et al. 2022 and Barwick et al. (2019) that greater information on air pollution increases online searches for pollution masks and air purifiers.

market prices, of mosquito nets and water filtration technology (Cohen and Dupas 2010; Kremer et al. 2011). We provide an analogous estimate of the demand curve for pollution masks in India, which allows us to project the social benefit of its free provision. We also add to this line of work by experimentally quantifying the degree to which non-price considerations suppress demand.

This paper is organized as follows. Section 2 describes the background context and the sample we study; Section 3 describes the experimental design; Section 4 presents a model of mask demand and our methodology for estimating the MWTP for clean air; Section 5 presents the main empirical findings; Section 6 evaluates the subsequent government distribution campaign; and Section 7 discusses further implications.

2 Context

This section describes the study setting of Delhi, its air pollution problem and the countermeasures available against it, and the composition of the sample from which we draw the respondent pool for this study.

2.1 Delhi, India

Delhi, or the National Capital Territory (NCT) of Delhi, is the capital of India. Located in the north, Delhi is one of its largest cities, with nearly 28 million people living in its metropolitan area. Delhi is a relatively wealthy city relative to India as a whole, but still relatively poor by global standards: GDP per capita of around $12,000 (Brookings 2015). Within Delhi, there are significant disparities in income. Many of the lowest-income residents live in a category of low-income settlements areas called Jhuggi Jhopri Settlements (informally known as "JJ clusters").[12] By some estimates, nearly half the city population resides either within a JJ cluster or other forms of temporary, low-income settlements spread throughout the city (Times of India 2012).

The climate in Delhi is warm and subtropical, with the hottest temperatures usually occurring between April and July, but even the coolest months, December and January, still have mean temperatures around 15° C.

2.2 Air Pollution in Delhi

In 2019, the average $PM_{2.5}$ concentration in the NCT of Delhi was 114.5 $\mu g/m^3$, nearly 23 times the WHO guideline. Since 2015, Delhi has consistently ranked as one of these most polluted cities in the world. The sources of air pollution in the area include transportation, industrial emissions,

12. Journalists, government officials, and some academic articles sometimes refer to these areas using the catch-all term "slums". In this paper, we describe the areas from which we sample respondents as either "JJ clusters" in the specific case, or "low-income settlements" in the general case.

electricity generation, residential emissions, and biomass burning, among others (Jalan and Dholakia 2019). The relative importance of these sources varies seasonally. The winter months tend to have the highest pollution levels as a result of seasonal biomass burning and meteorological conditions.

At the time of our study in 2018, regulation of air pollution in Delhi was primarily conducted through the Graded Response Action Plan (GRAP), where increasingly high levels of particulate matter trigger a range of government responses. These can include bans on the use of diesel generators and fireworks, closing coal-fired power plants, limitations on construction activities, and reductions on truck and automobile traffic (Chatterji 2021). In spite of these efforts, air pollution levels have remained high in the winter seasons following the implementation of GRAP.

There are two modes of air pollution defense available to the average Delhi resident: air purifiers and pollution masks. Due to the high upfront and operational cost of air purifiers, however, ownership levels are low. In a survey of medium and high socioeconomic status (SES) Delhi households, Greenstone, Lee, and Sahai (2021) find that only 5% of households reported owning an air purifier. In contrast, pollution masks are inexpensive and have been shown to filter more than 90% of airborne particles (Langrish et al. 2012, Cherrie et al. 2018). At the time of this study, disposable "N90/N95" masks cost roughly 100 Rs ($4.97), making them accessible to the majority of the population, although their use is typically limited to two weeks of daily usage.[13]

Previous work indicates large potential increases in life expectancy would result if air pollution were reduced in Delhi. For instance, Burnett et al. (2018) calculate life expectancy impacts of 1.53 years for all of India, while Ebenstein et al. (2017) calculate that Delhi alone stands to gain a collective 180 million years of life expectancy if $PM_{2.5}$ concentrations were reduced to the WHO standard. It is likely that within the city there is meaningful heterogeneity in exposure to these high levels of air pollution; anecdotal reporting suggests that poor households, who often live in homes that are poorly sealed to outside air, are exposed to substantially higher levels of air pollution on a day-to-day basis (Wu et al. 2020).

2.3 Sample Composition

We study preferences for air quality by repeatedly surveying residents of low-income settlements throughout the city of Delhi. The sample consists of individuals living in low-income neighborhoods (n = 3,533). To construct the sample, we selected 324 "sampling points" at random from among the JJ cluster areas. Fig. 1 maps the Delhi region and its wards, and the 324 sampling points included in the study.

13. Pollution masks are are commonly used in response to high pollution episodes across the world. For instance, mask purchases tend to increase during periods of heavy pollution (Zhang and Mu 2018). In addition, multiple governments have undertaken mass mask distribution campaigns in responses to air quality crises, including in Malaysia (2019), South Korea (2019), and the United States (2012) (see Table [A3]).

[FIGURE 1 ABOUT HERE]

At each sampling point, hired enumerators surveyed adults at every other household with a small survey incentive of 50 Rs ($2.48 USD). The sampling process was carried out between October and December 2018. To our knowledge, this construction results in the largest and most representative sample of Delhi low-income settlements ever collected.[14]

Table 1 compares the characteristics of our sample to the Delhi and India averages, obtained from the 2017-18 round of the Periodic Labour Force Survey (PLFS) administered by the Government of India.

[TABLE 1 ABOUT HERE]

The average respondent was split equally between male and female, had a weekly income of roughly 1100Rs per week ($2900 USD per year, PPP), completed 7 years of school, and was around 37 years old. On average, our sample has lower income and less education than Delhi residents as a whole, but is more similar along these dimensions to the India average. Notably, few (17%) respondents report ever having worn a mask prior to the intervention. This is consistent with observations by the research team that relatively few Delhi residents are observed wearing masks, even during periods of very high pollution.

3 Experiment Design

This section describes the field experiment we ran to obtain the key parameters required to estimate the demand for clean air. We first illustrate the timeline of the four rounds of the main experiment. Second, we discuss the collection of demographic and health data. Third, we describe the randomized interventions we used to test for the existence of informational failures affecting demand for clean air. Finally, we describe the process we used to offer respondents masks at randomized prices in order to elicit demand for pollution masks over the course of the study.

3.1 Timeline

Enumerators conducted repeated surveys with the originally sampled respondents in four rounds over the course of our initial study, with each round spaced roughly two weeks apart. Fig. 2 shows the timeline of experimental rounds against the ambient concentration of air pollution in Delhi ($PM_{2.5}$).[15] Each dark gray tile represents one experimental round.[16]

14. Additional details on the sampling procedure are given in Appendix Section 1.

15. For the first two rounds starting in November 2018, all cells but the peer belief interventions were included and individuals were not re-randomized. In the third round, we re-randomized information and prices, and in the fourth round we re-randomized information and prices and also added the final belief treatment.

16. Rounds overlapped because of the time required for enumerators to locate as many of the previously surveyed individuals as possible.

[FIGURE 2 ABOUT HERE]

3.2 Survey Design

Within each experimental round, our survey proceeded in three stages. First, enumerators elicited demographic and health information, as well as beliefs about air pollution and participation in other defensive health actions. Second, the respondents in the non-price intervention arms were provided with the corresponding interventions (first the PM2.5 health information then the peer belief information, if applicable). Finally, enumerators offered respondents in the mask groups the opportunity to purchase a mask for a subsidized price.

Respondents were surveyed on a rich vector of characteristics documenting socio-economic status and short-term health outcomes. Socio-economic characteristics include age, gender, family size, occupation, income, asset holdings, etc. Health outcomes include self-reported symptoms (pollution and non-polluted related, randomly ordered), and administered biometrics by enumerators including blood oxygen levels, blood pressure, and lung capacity.[17] In addition, we asked about beliefs regarding air pollution and past defensive health behavior (e.g., hand-washing, and mask, helmet, and seat-belt usage).

3.3 Non-price Interventions

In order to both estimate the demand for clean air and the degree to which that demand is affected by non-price limitations, the experimental design included several layers of randomized variation. We varied the price that respondents were offered for masks and whether they were provided with information on the health effects of pollution and/or data on the degree to which pollution masks should expect to face social disapproval. Fig. 3 illustrates how survey respondents were randomized across treatment arms.

The sample was split into three arms: pollution mask offers (hereafter mask arm), control, and placebo. In round 1, individuals in the mask arm were randomly assigned to receive the information treatment or not and were offered a pollution mask at a randomly assigned price p of 0, 10, 30, or 50 INR ($0, $0.50, $1.49, or $2.48 USD). In round 2, those in the mask arm again received the information treatment (or lack thereof) assigned in round 1 and were offered the mask at the same price as in round 1. In round 3, those in the mask arm were re-randomized across information/no information and were offered a mask at another randomly assigned price. In round 4, those in the mask arm were again re-randomized across information/no information and also were randomly assigned to receive the peer belief treatment (or not). They were offered a mask at another randomly assigned price. Individuals in the control arm were randomly assigned to either receive

17. We chose these in particular as they are signals of broader cardiovascular health and are shown to be negatively impacted by air particulate matter in the public health and medicine literature.

information or not in round 1 and received the same treatment again in round 2. They were then re-randomized to receive information or not in rounds 3 and 4. The placebo group was offered a non-N90 mask in all rounds, never received the information treatment and randomly received the peer belief treatment in round 4.

[FIGURE 3 ABOUT HERE]

In total, each respondent-survey was randomized into a total of 24 treatment cells[18], depicted in Table D.1. Appendices D.2 and D.3 conduct tests for balance and attrition during the experiments. We find that baseline observables do not differ in meaningful ways across treatment arms and rounds, and that the round-to-round attrition we observe does not occur differentially across treatment arms.

We compare across treatment arms to identify demand for clean air and the degree to which various interventions influence demand. First, we leverage the randomization of mask prices and quasi-random variation in ambient air pollution to estimate the MWTP for clean air. Next, we test to what degree information and peer beliefs lead to distortions in the demand we observe. Third, we use the multiple randomizations of mask prices within the same customer to identify the effect of prior mask takeup on future demand. Fig. 4 illustrates the materials used for the interventions.

[FIGURE 4 ABOUT HERE]

Information Treatment The information intervention consisted of two components designed to reduce knowledge gaps on the harm air pollution causes to human health: a printed handout, documenting the same as well as information on pollution-avoidance activities and a short, two-minute video on the health effects of air pollution. Both were developed and constructed by the research team in Delhi and presented in Hindi. In other settings, similar market failures have been found to bias estimates of demand for environmental goods towards zero. For example, Ito and Zhang (2020) find that MWTP for clean air is higher after government information interventions, suggesting that prior to the intervention, individuals were undervaluing clean air. Fig. 4 documents the handout in (a1) and stills from the video in (a2). At the time of intervention, the video was played in front of the enumerator to ensure the respondent's attention and audible sound from the video. The handout was then given to the respondent and the enumerator read over each portion out-loud. Both the video screening and the out-loud reading of the handout were to ensure comprehension even among illiterate respondents. By comparing those with and without the in-

18. Cell probabilities were uniform as this experiment was repeated over four rounds, with re-randomizations and interventions included at different stages. As described above, some respondents could be represented in more than one treatment arm, since they might receive different randomized price offers or information treatments in different rounds. In addition, we oversampled the control group that did not receive information and the group that received both information and a free mask offer to increase statistical power for detecting health impacts.

formation intervention, we are then able to measure the effect of updating knowledge about the health effects of air pollution on demand.

Peer Belief Treatment Pollution masks were unusual at the time of the study (i.e., prior to the COVID-19 pandemic), and anecdotal reports indicated that many residents internalized a social stigma against wearing them in public, though these same residents also reported that they themselves did not stigmatize others who wore masks. Similar to Bursztyn, González, and Yanagizawa-Drott (2020), our strategy to correct this potential distortion of demand for masks was to first measure actual perceptions of masks and then to reveal that the true percent at random to survey respondents.[19] In the third round of our survey, we displayed pictures of an individual wearing a mask to respondents in our control group, and asked "does this person look strange?" [20] On average, 36% said yes, they thought masks looked strange.

In the fourth round of the experiment, we again asked respondents whether they thought the person wearing a mask in the image looked strange. Then, we update treated respondents with the fraction of peers that believe masks look strange. Specifically, we stated the following, prior to the mask offer:

> [English-translated] *Did you know that only 36% of your peers believe that masks look strange?*

By comparing those with and without the peer belief intervention, we are then able to measure the effect of updating peer beliefs on demand.

3.4 Pollution Mask Offer

We procured thousands of high-quality, low-cost pollution masks from well-known manufacturer 3M. The mask model we offer (3M 9001V, depicted in Appendix Figure A6) is KN90 certified: tests from the manufacturer ensure that these masks filter 90% of $PM_{2.5}$ particles.[21] Informal tests of usage suggest that masks such as these can last for roughly 2 weeks of daily usage in high-pollution environments (Talhelm 2017), and low-cost 3M masks have been shown to provide cardio-respiratory benefits even after 1 day of usage in Beijing among those with pre-existing conditions (Langrish et al. 2012).

19. Bursztyn, González, and Yanagizawa-Drott (2020) show that men in Saudi Arabia generally support women working outside the home, but underestimate the degree to which other men do so as well. They show that providing men with correct information regarding the actual degree of support leads them to increase their support for their wives' job-search efforts.

20. We showed three images in total to each respondent: one of a person wearing sunglasses, the second of a person in a masks, and the third having green hair. 27, 36, and 87% responded yes, respectively. The bottom panel of Fig. 4 includes the three images.

21. Cherrie et al. (2018) provide empirical tests of these manufacturer claims. They find that most pollution masks perform better than advertised, i.e., they filter a higher proportion of particulates than is claimed by manufacturers.

We offered masks to respondents at the end of the survey after administering the non-price interventions. To ensure the effectiveness of masks were communicated to each respondent, we stated the following at the time of the offer:

> [English-translated] *This is an N90 pollution mask manufactured by 3M. According to 3M, this mask will block 90% of particulate matter (PM) air pollution. Would you be willing to buy the mask at [0/10/30/50] rupees?*

If the respondent agreed, then she paid the enumerator and received the new mask immediately. To capture a large portion of the demand curve, we randomized prices to be either 0, 10, 30 or 50 Rs (approximately \$0,\$0.50, \$1.49, or \$2.48 USD). All of these prices represented some degree of subsidization, since masks were typically available in the retail market for 100 Rs.

4 Model and Estimation

This section describes the procedure we use to estimate the demand for clean air using observed takeup of pollution masks in response to randomized prices and variation in pollution exposure over time. We start with a model of the choice of whether to purchase a pollution mask in order to illustrate the method to back out demand for clean air. We then discuss how we estimate this model and test for the existence of several possible market failures that could limit the demand for clean air that we measure.

4.1 Model of Mask Purchase Decision

Individuals weigh the cost of the mask purchase against the protection from pollution they expect to obtain from it. The utility of a mask purchase by individual i in round t is given by u_{it}, a function of the price faced by the individual p_{it}, the expected reduction in air pollution exposure EPR_{it}, and an error term ϵ_{it}:[22]

$$u_{it} = \alpha - \beta p_{it} + \gamma_1 \mathrm{EPR}_{it} + \eta X_i + \epsilon_{it} \tag{1}$$

The utility of mask purchase falls as its price rises and increases when expected pollution is higher, i.e., both β and γ are positive. They are also the partial derivatives of u_{it} with respect to expected pollution and price: $\frac{\partial u_{it}}{\partial \mathrm{EPR}_{it}} = \gamma_1$ and $\frac{\partial u_{it}}{\partial p_{it}} = -\beta$. Since purchasing a mask reduces

22. An alternative formulation, following Train (2009), would model the mask purchase as a decision that increases utility but reduces the respondent's available income for other expenditures. In the setting we study, the two yield equivalent formulations for the demand for clean air, but the model we present here does so more parsimoniously. Readers should also note that this model is an individual-level panel analogue of the aggregated market-level models described in Ito and Zhang (2020) and Deschenes, Greenstone, and Shapiro (2017).

income, the negative of the ratio of these two is the marginal willingness-to-pay (MWTP) for a 1 unit reduction in pollution, or the demand for clean air:

$$\text{MWTP} = -\frac{\partial u_{it}/\partial \text{EPR}_{it}}{\partial u_{it}/\partial p_{it}} = \frac{\gamma_1}{\beta}$$

In words, the strategy we use to uncover the demand for clean is to compare how individuals change mask purchase behavior in response to (1) randomized price variation (represented by β) and (2) as-good-as-random variation in expected pollution levels (represented by γ_1).

Perfect Information Assumption Implicitly, this model of mask demand assumes individuals have perfect information on how air pollution affects their utility denoted by γ_1. Under this assumption, if individuals were provided education on the health consequences of air pollution Information$_i$, we would expect γ to be unchanged. Utility is therefore assumed to be:

$$u_{it} = \alpha - \beta p_{it} + \gamma_1 \text{EPR}_{it} + \gamma_2 \text{EPR}_{it} \times \text{Information}_i + \eta X_i + \epsilon_{it} \tag{2}$$

where $\gamma_2 = 0$ under full information. Estimating this interacted model with a randomized information intervention thus serves as a test against this assumption.

4.2 Estimation

Because we do not directly observe EPR$_{it}$, each individuals' expected reduction in the level of pollution from the mask purchase, we construct a proxy that is the product of recent pollution levels, the advertised effectiveness of the mask they are offered, and an estimate of the amount of time they will be using the mask. We then write EPR$_{it}$ as follows:

$$\text{EPR}_{it} = \underbrace{\text{PM}_{it}}_{\text{Expected PM}_{2.5}\text{ Level}} \times \underbrace{0.9}_{\text{Mask Efficiency}} \times \underbrace{\text{EU}_{it}}_{\text{Expected Usage}} \tag{3}$$

For PM$_{it}$, we assume that expectations about the ambient air pollution level in the near future are informed by air pollution levels in the recent past.[23] Specifically, at the time of the mask offer, we compute the preceding seven-day mean pollution level that is spatially averaged across the city.[24] We use the Delhi average instead of residence-specific location for two reasons: first, indi-

23. Fig. 6 below provides supporting evidence for this assumption: as pollution swings week-to-week, local news responds in-kind, suggesting that information on air pollution is relatively salient in our sample period.

24. Data on ambient $PM_{2.5}$ concentrations collected by a network of monitors across the city operated by the Delhi Government's Central Pollution Control Board (CPCB). These data captures high-quality, near real-time $PM_{2.5}$ readings over

viduals may commute or travel throughout the city in any given day, so measuring air quality at the residence may not fully capture total exposure; and second, using purely temporal variation in the Delhi mean helps mitigate endogeneity concerns explained in detail below. We provide results using alternative specifications of pollution in the Appendix, with qualitatively similar findings.

Mask efficiency is fixed at 90%, which we take as given since it is a manufacturer claim of the product we distribute (it is also stated at the time of offer). For EU_i, we leverage the reported mask usage data (of those that take-up) we collect as part of the experiment.[25] Our followup data indicates that individuals use masks for 8 days with an average of 1.8 hours per day during the study period.

For estimation, we replace EPR_{it} with pollution level PM2.5_t in Eq. (1) and then convert it into appropriate units following Eq. (3). To allow users who receive the information treatment to respond differently to pollution levels, we also interact PM2.5_t with the randomized information treatment Information_{it}. The resulting coefficients on PM2.5_t, γ_1, is the effect of pollution mask demand among the uninformed group, while $\gamma_1 + \gamma_2$ is the effect for the informed group. The information treatment only enters the utility function through its effect on responsiveness to pollution levels, since additional information about the health effects of pollution should not change either individuals' value of money (the price coefficient) or their mask purchase choice when pollution is at zero.

Estimating Equation The discrete choice model implies that individuals takeup (or purchase) a mask if the utility of the mask purchase $u_{it} > 0$:

$$\text{Takeup}_{it} = 1\{\alpha - \beta p_{it} + \gamma_1 \text{PM2.5}_t + \gamma_2 \text{PM2.5}_t \times \text{Information}_{it} + \eta X_i + \phi_{st} + \epsilon_{it} > 0\} \tag{4}$$

To absorb variation in the error term, our preferred specification includes controls X_i, which we select using the double-LASSO method (Urminsky, Hansen, and Chernozhukov 2016), taking p_{it} and PM2.5_t as the focal independent variables. We similarly include surveyor-by-round fixed effects ϕ_{st}. We assume that ϵ_{it} follows a type-1 extreme value distribution and estimate the model with maximum likelihood (Logit). All specifications use three-way cluster standard-errors by sampling point-round (the randomization unit for the price of the mask), date (the unit at which pollution levels are assigned), and respondent (as respondents are surveyed in multiple rounds) (Abadie et al. 2022; Cameron, Gelbach, and Miller 2011).[26]

42 monitors spread across the city. We assign each household to their sampling point, from which households are chosen nearby. We then take the network of hourly $\text{PM}_{2.5}$ readings and interpolate values across time and space using a Gaussian process regression (kriging) as in Wong, Yuan, and Perlin (2004). Using this panel of pollution measurements by sampling point and day, we average across sampling points to obtain a single Delhi-wide average pollution reading per day. We then link each survey with the 7 day mean Delhi pollution level preceding the date of the survey.

25. Appendix Section 4 describes a model of optimal mask usage and survey data that is consistent with the assumption that expected usage is the same for those who do and do not take up masks.

26. In Appendix H, we perform several robustness tests including alternative fixed effect specifications, alternative win-

Measuring MWTP and Testing Against Full Information By re-scaling model parameters from Eq. (4), we can estimate the MWTP for clean air, which we characterize as the WTP for a $1\mu g/m^3$ reduction in annual $PM_{2.5}$, separately for those with and without the information treatment:

$$\begin{aligned} \text{MWTP}|_{\text{Without Information}} &= \frac{\gamma_1}{\beta} \times \frac{1}{0.9} \times \frac{24}{1.8} \times \frac{365}{8}, \\ \text{MWTP}|_{\text{With Information}} &= \frac{\gamma_1 + \gamma_2}{\beta} \times \frac{1}{0.9} \times \frac{24}{1.8} \times \frac{365}{8}. \end{aligned} \tag{5}$$

The first term in each expression the marginal rate of substitution between weekly pollution and prices, and the third, fourth, and fifth terms reflect the mask efficiency, mean usage hours per day, and day-to-annual scaling, respectively. To examine the welfare gains of pollution reduction policy, this MWTP estimate can then be scaled by changes in annual pollution levels required to meet national and international health standards. Finally, a sufficient test against a full information assumption is whether $\gamma_2 = 0$.

Other Frictions in Mask Takeup Beyond imperfect information in the MWTP for clean air, there may exist other frictions that could suppress takeup of these defensive investments. These may include, for example, beliefs about peer disapproval of mask-wearing in public or a lack of prior experience with masks. To assess this, we specify a richer discrete choice model than that given by the benchmark Eq. (4). To examine whether beliefs about disapproval of mask-wearing are suppressing demand, we add Peer Belief$_{it}$, an indicator for respondents in round 4 who were informed about the relatively low proportion (37%) of previous respondents who find mask-wearing unusual. To examine whether masks are an experience good, we test whether past mask usage distorts current mask demand. More specifically, we let Past Takeup$_{it}$ be whether i took up a mask offer in any prior round or had worn a mask before the experiment started, which we will call their takeup in round 0.[27] In other words: Past Takeup$_{it}$ $= \max\left\{\{\text{takeup}_{ij}\}_{j=0}^{t-1}\right\}$. Including this term in the specification with distortions yields:

$$\begin{aligned} \text{Takeup}_{it} = 1\{&\alpha - \beta p_{it} + \gamma_1 \text{PM2.5}_t + \gamma_2 \text{PM2.5} \times \text{Information}_{it} + (\eta + \xi)X_i + \\ &\theta_1 \text{Peer Belief}_{it} + \theta_2 \text{Past Takeup}_{it} + c_i + e_{it} > 0\} \end{aligned} \tag{6}$$

Identification of θ_1, the impact of the peer belief intervention, is straightforward. However, the identification of θ_2, the effect of previous experience wearing a mask, requires some additions to

dows for which we define pollution, and reweighting observations to account for attrition. Our qualitative results are unchanged.

27. We specify round 0 as being before the experiment started, as opposed to our first round, for 2 reasons: (1) It provides an intuitive understanding of the coefficient θ_2 in Eq. (6) as the causal effect of *ever* having worn a mask previously on current demand, and (2) it allows us to make use of our full sample instead of having to drop the ~17% of respondents with only one experimental round.

the empirical approach. Since Past Takeup$_{it}$ is potentially a function of an unobserved individual characteristics or of other persistent correlates within the error term, including it directly in the estimating equation could bias θ_2 upward. We solve this problem by instrumenting past takeup with the minimum price of all past offers made to the survey respondent. The logic of this strategy is that previous price offers, which are given at random, are uncorrelated with any unobserved correlates of mask demand. We use the minimum of these price offers since it has the strongest relationship with past takeup. Appendix G.2 discusses this approach in greater detail.

4.3 Identification

Our estimates of MWTP relies on the causal identification of two key parameters β and γ. The demand response to prices β is identified through the random variation in prices employed in our experimental design.

The demand response to air pollution γ is driven by a combination of the randomized timing of each survey with temporal variation in average pollution levels in Delhi. After controlling for round fixed effects, our estimates are identified from day-to-day swings in air pollution in the city within each survey round of roughly 4-6 weeks. The round fixed effects capture seasonal patterns of air pollution that may be correlated with unobservables.

A common threat to identification of γ is the endogeneity of individual characteristics with air pollution (e.g., due to sorting, high income respondents have systematically higher demand but lower pollution levels, which may bias γ downward). Because the variation in pollution we use is purely week-to-week (averaged across the city), fixed observed and unobserved characteristics of respondents are uncorrelated with this pollution variation and will not bias our estimates of MWTP.

The model estimate of MWTP is identified from substitution patterns between weekly variation in ambient air pollution and the price for pollution mask offers. Under the identification assumptions, any non-price or non-pollution determinants of demand will be captured in the error term and will not affect MWTP. For example, some users of pollution masks may find them uncomfortable or bad looking. So long as the degree of discomfort is not driven by the price paid for a mask or the ambient pollution level, these features may shift *levels* of mask demand but will not influence the marginal rate of substitution between prices and pollution exposure (MWTP).

5 The Demand for Clean Air

This section documents the demand for clean air among our sample. We begin by estimate demand for the pollution masks among the sample. Next, we use the model from the previous section to infer demand for clean air from the responsiveness of mask purchase with respect to price and ambient $PM_{2.5}$. We then test for non-price limitations that may limit the expression of the demand for clear. We conclude the section by documenting how the demand for masks changes with respect to income, education, and gender.

5.1 Demand for Pollution Masks

Before proceeding to our estimates of the demand for clean air, we first document the underlying estimates of the demand for masks in our sample. Fig. 5 shows how the average probability of takeup varies with price, pollution level, and across respondents who did and did not receive the information treatment.

[FIGURE 5 ABOUT HERE]

Panel (a) shows that just under 80% of respondents take a mask when it is offered for free. At positive prices, demand for masks is relatively low. At a price of \$0.50 per mask, just over 30% of respondents purchase. That figure falls to around 15% at \$1.49 USD and 10% at \$2.48 USD. This is consistent with low rates of mask usage in this setting. Overall, at these observed levels of demand, this suggests masks provide limited value for recipients.[28]

Panel (b) documents how mask purchase choices vary with the level of pollution that day. We find that pollution levels increase demand for masks. During low pollution days – when $PM_{2.5}$ concentrations are in the lowest quartile (50-100$\mu g/m^3$) – just under 30% of the respondents purchase a mask. During high pollution days in the highest quartile (>210$\mu g/m^3$), over 40% purchase. Panel (c) separates average takeup with respect to pollution by respondents that did and did not receive the health information treatment before the mask offer. We find that providing information leads to an increase in the likelihood a respondent purchased a mask.

The descriptive facts captured in Fig. 5 indicate that the respondents, who come from some of Delhi's poorest areas, value the protection from air pollution offered by pollution masks. That levels of demand decline to close to zero as the price increases is consistent with the low levels of mask usage observed in everyday life. They also demonstrate that mask usage is responsive to the threat of air pollution. These facts are consistent with the assumptions of the model and preview the formal analysis to follow in Section 5.2. The final panel provides descriptive evidence that information problems may be an important factor in determining demand for masks, a suggestion we return to in Section 5.3.

28. Indeed, we find that those who takeup masks use them for less than 2 hours per day and find limited effects of mask takeup on observed health outcomes. In a subgroup analysis detailed in Appendix I, we leverage the control group that received no mask offers to examine whether mask uptake leads to measurable health improvements. In general, we do not find evidence that mask takeup improves several short-term health outcomes 2-4 weeks after treatment.

5.2 Demand for Clean Air

To estimate the average demand for clean air across the sample, we employ the logit model described by Eq. (4). Table 2 documents the results. The outcome variable is whether or not a respondent purchased a mask during that round. The first panel includes the model coefficients on the price of the mask, the level of pollution that day, and the level of pollution interacted with an indicator for the information treatment. The second panel uses the estimates to compute the demand for clean air, which we characterize as the MWTP per annual unit of $PM_{2.5}$ for the average respondent. The "Information = 0" row is the MWTP for respondents who did not receive the information treatment, and the "Information = 1" row is the MWTP for respondents who did.

[TABLE 2 ABOUT HERE]

Column (1) estimates a benchmark logit model that includes only the effects of price, pollution, and pollution interacted with a treatment indicator for respondents placed into the information group, as well as surveyor-by-round fixed effects. Increases in price reduce the demand for masks, while ambient pollution does not significantly impact it for respondents who did not receive the information treatment. By contrast, respondents who do receive the information treatment become more likely to buy a mask when pollution is high. We combine these estimates following Eq. (5) to obtain the demand for clean air across the two groups. We find a sharp divergence in MWTP for clean air among respondents who did not and did receive the information treatment. Baseline respondents have an MWTP of $1.92 per 10 unit reduction in annual $PM_{2.5}$ that is imprecisely estimated and not statistically distinguishable from zero. By contrast, respondents treated with information are willing to pay $7.28 for each 10 unit reduction, an estimate that is more precisely estimated and statistically different from zero.

Column (2) adds the double-LASSO controls following Urminsky, Hansen, and Chernozhukov (2016) and is the preferred specification.[29] The point estimates do not change substantially. MWTP for clean air in this specification is $1.14 (and not statistically distinguishable from zero) for individuals who do not receive the information treatment. For those who do receive the information treatment, MWTP is $6.24, a nearly six-fold increase in the point estimate.

Column (3) is a sensitivity check that allows the information treatment to enter the utility function directly. As discussed in Section 4, this is not the preferred specification because it requires that respondents value information about air pollution even when the level of air pollution is zero. We include the specification here for completeness. As might be expected, including information in this (arguably) mis-specified way adds noise to the estimate, of the effect of ambient air pollution

29. The double-LASSO procedure selects the following controls: Female, Age, asinh(Personal Income), Years of school, Occupation is driver, Owns bike or car, Has Air Conditioning, Asbestos roof, In the last week had pollution symptoms, In the last week had non-pollution symptoms, In the last week had burning eyes, In the last week had joint pain, In the last week had numbness or tingling in hands, In the last week had vision impairment, Wears a helmet or seatbelt when in vehicle, and Has worn a mask ever.

on the purchase decision. The overall result is a near-zero estimate of MWTP for clean air among the respondents who do not receive information, as before. and a slightly larger ($0.67) but less precise point estimate of the difference in MWTP for clean air between those who did and did not receive the information treatment.

Columns (4) and (5) estimate linear probability models. Column (4) is the LPM analogue of column (2), and the estimates are virtually identical. In column (5) we introduce individual fixed effects, which are not estimable in the logit approach due to incidental parameter limitations. The qualitative findings regarding demand for clean air are identical to the preferred specification: demand for clean air is near-zero for individuals in the baseline treatment, and substantially larger and statistically different for those that receive information. We show in Appendix H that these results are qualitatively robust to alternative fixed effect specifications, alternative windows for which we define pollution, and reweighting observations to account for attrition.

In general, we find the the demand for clean air is low in absolute terms among the sample we study: for respondents who are provided information on the health impacts of clean air prior to demand elicitation, we measure a MWTP of $6.24 per 10 unit reduction in annual $PM_{2.5}$. This is around 27% of the estimate in Ito and Zhang (2020) and well below comparable estimates in wealthier countries given in Appendix Table A.1. We return to the question of whether this estimate is low in a relative sense, i.e., in comparison to income, in Section 5.4.

5.3 Effects of Peer Beliefs and Prior Mask Usage on Mask Demand

Beyond information frictions in the MWTP for clean air, there may be other limitations that could suppress takeup of these defensive investments even conditional on MWTP. Accordingly, we test for two additional potential biases that could limit respondents' likelihood of mask purchase and, as a result, our measure of their demand for clean air. First, we examine whether mask purchasing could be suppressed by beliefs about peer judgement of wearers. Second, we test whether the respondents may become accustomed to masks over time, i.e., if masks are a type of "experience good". We estimate Eq. (6) to incorporate the test of the peer belief intervention and the effect of having experience with a mask into the discrete choice model. Table 3 documents the findings.

[TABLE 3 ABOUT HERE]

Column (1) reproduces the second column in Table 2 for comparison. The next two columns add the peer belief treatment and the instrumented measure of previous mask usage described by Eq. (6) sequentially. In column (2), we find that informing respondents about the low level of disapproval regarding mask usage in public does not shift the mask purchase decision. Column (3) shows that prior experience with masks actually reduces demand in our experiment. We interpret this finding as evidence that, if there is an experience effect of using masks, it is either negative or more than fully compensated by respondents' continued use of the previous masks. In either case, we do not find strong support for the contention that merely exposing users to the benefits of mask usage is a sufficient policy step to generate widespread adoption, nor do we find that it substantively influences demand for clean air. This finding suggests that large-scale programs of mask distributions will have, at most, temporary effects on usage, a question we return to in Section 6.

To summarize, our pooled estimates indicate that the low-income population we study in Delhi has zero detectable demand for clean air in the absence of information provision.[30] When information is provided prior to mask purchase, demand rises substantially and is statistically larger than zero. For the remainder of this section, we focus primarily on respondents in the information condition, since we view that condition as most reflective of the benefit a fully-informed respondent perceives for reductions in $PM_{2.5}$.

However, even the mean estimates under the information condition are comparatively low in global terms: we measure an average MWTP per annual $10\mu g/m^3$ $PM_{2.5}$ of over \$6 USD. In the following section, we examine whether the demand for clean air is correlated with income, gender, and education levels to better understand the source of both the increases due to the information treatment and differences in income.

5.4 Correlates of the Demand for Clean Air

India, like many developing countries, is experiencing rapid demographic change. As the population urbanizes, average levels of income and education are increasing, and women are becoming more involved in the workforce. This section documents to what degree key demographics predict heterogeneity in demand for clean air. We estimate how MWTP varies along three important dimensions: income, education, and gender. Theory and evidence suggest that demand for environmental quality increases with income. Second, education is a measure of permanent income and information failures are likely to be concentrated among those with low levels of human capital. To estimate how these differences relate to MWTP, we allow key model parameters to vary by household income, education, and gender measured at baseline (full estimation details are reported in Appendix G.1).

Because income, education, and gender are not randomly assigned, we interpret these as estimates of the demand for clean air *conditional* on individual characteristics. Table 4 reports our findings at specific fixed levels of income, gender, and years of schooling.

[TABLE 4 ABOUT HERE]

30. In Appendix I, we also report on whether mask receipt, driven by randomized mask pricing, led to meaningful improvements in reported health outcomes two to six weeks later. We do not find evidence in support of this hypothesis.

For household income, we find that estimates of the demand for clean air increase with income, though the degree of this increase is limited. We predict demand for clean air at household income levels of $0, $10,000, and $18,000 USD. Estimated MWTP for clean air increases from around $0 to $5.1 for respondents in the uninformed condition (though none of these estimates are statistically different from zero), and up to $11.5 for informed respondents. We also find that female respondents have lower estimated demand for clean air than men, and that the effects of information seem to be centered on these female respondents.

Finally, we find that education levels have a strong positive association with the demand for clean air, but the strength of that association falls if respondents are informed about the health effects of pollution. Among respondents with little or no education, demand for clean air is negative and not statistically different from zero in the no-information condition, but around $3.40 USD if respondents are informed. Among respondents with eight years of schooling, uninformed respondents have a positive (but still statistically zero) demand for clean air while informed respondents are willing to pay around $7.30. Respondents with a full fifteen years of schooling report the highest levels of demand for clean air in our sample at $12.70 in the uninformed condition. Most notably, for these respondents, information has virtually no effect. This finding is consistent with well-educated respondents already having fully internalized the health costs of air pollution in their decisions to protect themselves, and suggests that policies targeting information on the health impacts of air pollution might be most fruitfully targeted towards lower-education households.[31]

6 Interpretation: Delhi's 2019 Mask Distribution Program

Our findings to this point document that demand for clean air is low among the sample of low-income households we study, but that it is substantially larger when those households are treated with information about the health impacts of air pollution. We also find that demand for masks is insensitive to a treatment that reports low levels of disapproval of mask wearing to respondents and that it is actually reduced by prior experience with masks. Finally, we show that respondents with higher incomes are more likely to value clean air, and that information provision appear to be a substitute for increasing levels of education when it comes to the determination of the demand for clean air.

However, our study is necessarily limited in the sense that we could only administer treatments that were randomized by respondent; the nature of the research design means that it was not possible to, for example, treat entire communities with the opportunity to purchase a mask or with an information campaign to (potentially) shift community-wide beliefs about mask-wearing and its benefits. In that case, one possible explanation for our findings is that interventions at the indi-

31. These patterns of heterogeneity across each covariate are qualitatively robust to controlling for interactions with other covariates as described in Fig. G.1.

vidual level are insufficient in the face of a strong no-mask norm among most of the population. In this case, it is possible that a larger public health effort to popularize masks might lead to large effects on mask usage, either by providing a more credible source of information on their benefits or by reducing the strength of anti-mask wearing norms.[32]

6.1 2019 Mask Distribution Campaign

Coincidentally (with respect to this study), the Delhi government rolled out a large public health campaign to distribute five million pollution masks across Delhi a few months after we concluded our initial data collection described above. This policy was unprecedented at the time and provided masks to nearly a quarter of the residents of the city. This rollout, however, was limited to Delhi proper, and did not include its neighboring cities. We make use of this feature of the policy to estimate standard difference-in-differences models using the rollout timing and the treated (Delhi) and control (non-Delhi, or the cities of Noida and Gurgaon) areas as our combined sources of variation.

The rollout included a significant media campaign, captured notably by the Twitter post, documented in Appendix Fig. J.1 by Chief Minister of Delhi Arvind Kejriwal. On November 1st 2019, the Delhi began distributing 5 million N95 pollution masks to a network of government and private schools in the city of Delhi (but not outside), with the intention of providing masks to 1 in 4 individuals in the city. Children attending schools received two masks, which they were told to bring home and give to their head of household. Fig. J.1 depicts a Tweet by the Chief Minister describing the mask distribution, showing the packet of two N95 masks that was given to children during this campaign. Appendix Table A3 lists past mask distribution campaigns implemented by government entities around the world (as of November 2019), the largest of which is the Delhi campaign.

6.2 Survey Procedure

In anticipation of this distribution, we surveyed respondents at bus stops in the cities of Delhi (treated), Gurgaon, and Noida (untreated), a few weeks before and several weeks after the distribution date, and provide mask offers (randomized at \$0.50 and \$1.49) and the health information intervention.[33] Because the respondents were largely commuting to work, the sample is primarily employed men. In general, the Delhi and non-Delhi samples are similar to each other (the Delhi sample has slightly higher income and more education). Compared to our main sample, this sam-

32. In fact, several such interventions have been implemented in Malaysia, South Korea, Singapore, the United States, and elsewhere. See Table C.1.

33. Appendix Figure J.2 shows a map of all bus stops within Delhi as well as outside the city in neighboring areas of Gurgaon and Noida we were able to survey (dots). In Appendix Table A1 and A2, we describe this sample, split between the Delhi and the non-Delhi sample (for two different location definitions).

ple captured a larger share of working men. By some metrics, Delhi's public bus system captures nearly 60% of total transportation demand in the city (Planning Department, Government of India). This sample is thus largely representative of working adults on the lower half of the income distribution.

In addition to mask offers, we also collect self-reported mask usage and individual characteristics. In order to track the rollout of masks, we also survey administrators from a sample of more than 600 schools (across Delhi and non-Delhi) around the distribution period to collect the date of first mask receipt from the government.

Finally, we scrape tweets from the top 50 news outlets in the Delhi region, which re-post headlines of articles in print and online. Roughly 40% of all Indians across the income distribution read print newspapers at a regular basis (India Readership Survey). We categorize these Tweets by parsing whether the text contains pollution-related keywords. We interpret this as a proxy for exposure to local information related to air pollution.

Because the government mask distribution campaign occurred inside the city of Delhi and not outside (Gurgaon and Noida), we are able estimate the effects of the policy with a "difference-in-differences" approach: comparing surveys from respondents in treated and untreated cities, before and after the treatment date.

6.3 Effects of the Campaign

If the impediment to mask-wearing is insufficient credible information or a strong anti-mask social norm, then a large-scale government-funded intervention is likely the best policy instrument to reduce this frictions and encourage widespread mask adoption. A successful policy should lead to both raised awareness and increased long-run usage of masks.[34] In this section we examine the effects of the campaign in Delhi by comparing responses from commuters in Delhi to those in neighboring Noida and Gurgaon (where masks were not distributed).

We begin by showing that the intervention was indeed effective in providing masks and in raising social awareness of masks. The first panel of Fig. 6 shows the proportion of schools in each area that received masks. We sampled over 600 schools across both Delhi and Non-Delhi and called their administrators to inquire on when they received masks from the government and distributed to children. We plot the cumulative distribution of these over time. We see that within 4 weeks the distribution campaign was fully rolled out in Delhi, while not a single school in Non-Delhi received government masks. This suggests that Delhi residents received a large quantity of masks during peak episodes of air pollution, while residents just outside the city did not.

[FIGURE 6 ABOUT HERE]

34. Barwick et al. (2019), in related work, find that simply making pollution information available led to changes in the degree to which individuals seemed to protect themselves from its effects in China.

In the second and third panels, we plot weekly averages from our repeated cross-sectional surveys of nearly 3 thousand respondents in both Delhi and Non-Delhi. In the seconds panel, while pre-trends are both parallel and overlapping, we see that self-reported mask usage (fraction of respondents that report using masks that day) increases in Delhi after the mask distribution date and falls back to the Non-Delhi placebo. At its peak, magnitudes are large and statistically significant, where by late November the fraction in Delhi is twice that of Non-Delhi. In the third panel, we see that the demand for masks (fraction that take subsidized mask offers) is statistically equal between Delhi and Non-Delhi both before and after the mask distribution campaign.

In Appendix J.2, we present difference-in-difference estimates. We also report estimates for different definitions of treatment assignment (neighborhood of bus stop vs. of residence), which are qualitatively similar. Our preferred estimates using the home (residence) definition are consistent with the descriptive patterns above, with self-reported usage increasing by up to 20% one to three weeks following treatment and falling to zero by five weeks post-treatment. Meanwhile, mean takeup (averaged across prices \$0.50 and \$1.49) does not increase post-treatment (and if anything falls).

Our surveys suggest that while the mask distribution campaign may have increased the short-run usage of pollution masks, it did so only temporarily, even during a period of very high ambient $PM_{2.5}$ levels in Delhi. This is consistent with our findings in the preceding sections of the paper: mask takeup is responsive to recent air quality, but its effects are short-lived. Moreover, the limited effect of the campaign and our findings in Section 5.3 are consistent in the sense that it does not appear that social approbation is the primary driver of limited demand for clean air in this setting.

7 Discussion

In this paper, we document results from a field experiment designed to study the demand for clean air in Delhi, a city with one of the world's highest concentrations of damaging air pollution. Using randomized prices and quasi-random pollution variation, we estimate a model of mask demand to provide the first experimental estimate of the marginal willingness-to-pay (MWTP) for clean air. For respondents who are informed about the costs of air quality prior to the mask offer, we find a mean estimate of about \$6.2 USD for a 10 $\mu g/m^3$ reduction in $PM_{2.5}$, which is on the lower end of prior comparable estimates in the literature. Even so, given the very-high levels of air pollution and the population of Delhi, these estimates suggest large public benefits from reductions in air pollution: our estimates imply that, for those who received the information treatment, residents are willing to pay roughly \$47 USD per person to reduce levels of air pollution to the Indian standard. This is in stark contrast to those who do not receive the information treatment, who would be willing to pay only \$8.7 USD for such a reduction.

We believe that the stark difference in demand for clean for respondents who receive information on the health effects of pollution versus not is worth emphasizing. With many other day-to-day concerns, households with lower incomes and limited education may simply not have the capacity to internalize the threat of air pollution in day-to-day decision-making. That these households become more responsive to recent air quality changes when provided information on its health impacts suggests realized air pollution levels in these settings could be inefficiently low. That information provision seems to be a substitute with years schooling further suggests additional benefits of education – it enables households to more accurate reflect their demand for public goods (though we emphasize that the latter "effect" is an correlative association, not a causal finding).

The relationship between the demand for clean air and income merits consideration. If clean air is a normal good, standard economic theory suggests that increases in income should yield higher demand for air quality. That our own estimates of the demand for clean air increase with income suggests that the proper comparison to other settings involves an income adjustment. Accordingly, we extend the heterogeneity analysis in Section 5.4 by plotting MWTP as a function of income in Fig. 7. The bottom panel captures the distribution of household income in our sample, while the top panel projects MWTP per annual 10 μ/m^3 $PM_{2.5}$ as light blue (uninformed) and dark blue (informed) lines. Vertical lines show average household incomes for Bihar (one of the poorest states in India), India as a whole, our sample in Delhi, and China as a whole. Focusing on the informed line, we find that income increases MWTP for clean air by a factor of roughly two when moving from our sample's level of income ($10,000 USD per year) to $60,000 per year. This latter level allows us to compare to the revealed preference measure for the demand for clean air produced by Ito and Zhang (2020), who leverage the decision to purchase an air purifier as their revealed market decision. The two estimates are comparable at similar income levels, and for respondents in our sample who have been informed.

[FIGURE 7 ABOUT HERE]

To summarize, our results indicate that if there is an absence of demand for clean air, it is likely explained by either a lack of information or a lack of salience in its health effects. That information provision results in measurably positive demand for clean air and that those changes are primarily centered on low-income, low-education individuals is relevant for considerations of the benefits of public good provision in settings where poor households are the primary constituency. The methodological approach we describe in this paper could be exported to other settings where credible revealed preference measures of the demand for public goods are urgently needed.

The limited effect of public health campaigns (like the one described in Section 6) to make defensive measures such as masks available suggests that the question of how to make the salience of the benefits of clean air long-lasting remains a fruitful topic for future research. At the least, one implication of our findings is that as incomes and education in India continue to rise, policymakers should expect commensurate increases in the demand for clean air.

Tables and Figures

Tables

Table 1: Sample Characteristics at Baseline

	Main Sample	Delhi	India
	(1)	(2)	(3)
Annual Personal Income (USD)	2,936.40	3,676.64	1,487.93
	(8,285.73)	(8,763.69)	(4,329.80)
Annual Personal Income = 0	0.61	0.70	0.79
	(0.49)	(0.46)	(0.41)
Annual Household Income (USD)	7,944.37	9,665.89	6,139.14
	(15,087.20)	(0.00)	(0.00)
Below Poverty Line	0.20		
	(0.40)		
Female	0.52	0.46	0.49
	(0.50)	(0.50)	(0.50)
Age ($\geq$ 18)	36.51	36.98	39.70
	(12.76)	(14.46)	(15.77)
Years of School	7.37	7.45	5.90
	(5.01)	(5.50)	(5.18)
Household Size	5.50	3.86	4.18
	(2.40)	(1.99)	(1.97)
Ever Worn Mask	0.17		
	(0.38)		
Has Air Purifier	0.02		
	(0.14)		
Owns Bike or Car	0.39		
	(0.49)		
Has Air Conditioning	0.11		
	(0.32)		
Observations	2,466	3,956	433,339

Notes: This table reports means and standard deviations (in parentheses) for the study sample (column 1) against those of Delhi and India (columns 2 and 3), across several covariates of interest at the individual level. Statistics for Delhi and India come from the 2017-18 round of the Periodic Labour Force Survey (PLFS) administered by the Government of India. For PLFS data we use sub-sample weights. For PLFS household size data we use the household survey instead of the individual level survey. India Household Income taken from India Human Development Survey (IHDS), and Delhi Household Income set to urban average from IHDS.

Table 2: The Demand for Clean Air

	Logit			LPM	
	(1)	(2)	(3)	(4)	(5)
Model Coefficients					
Price (USD)	-1.823^{***}	-1.860^{***}	-1.860^{***}	-0.254^{***}	-0.262^{***}
	(0.095)	(0.091)	(0.091)	(0.008)	(0.012)
$PM_{2.5}$ $(10\mu g/m^3)$	0.005	0.003	0.001	0.001	0.001
	(0.012)	(0.012)	(0.014)	(0.002)	(0.002)
× Information	0.014^{***}	0.014^{***}	0.018	0.002^{***}	0.003^{***}
	(0.005)	(0.005)	(0.011)	(0.001)	(0.001)
Information			-0.085		
			(0.204)		
Marginal Willingness to Pay per annual $10\mu g/m^3$ *$PM_{2.5}$ (USD)*					
Information = 0	1.92	1.14	0.42	1.66	1.61
	(4.51)	(4.20)	(5.04)	(4.06)	(4.41)
Information = 1	7.28*	6.24	7.09*	7.19*	10.10**
	(4.30)	(4.05)	(3.97)	(4.13)	(4.39)
p-value of difference	0.004	0.004	0.109	0.008	0.005
Surveyor-by-Round FEs	Yes	Yes	Yes	Yes	Yes
Individual FEs					Yes
LASSO Controls		Yes	Yes	Yes	
Observations	6,465	6,465	6,465	6,465	6,465

Notes: The table shows how price, pollution, and health information affect demand for masks, and the resulting estimated demand for clean air. Each observation is one respondent in a survey round. The dependent variable is whether the respondent bought a mask. Price (2019 USD) is the level of the randomized price offer made to the recipient, $PM_{2.5}$ (10 $\mu g/m^3$) is the average level of $PM_{2.5}$ measured in Delhi over the preceding day in 10 $\mu g/m^3$, and Information is a dummy for whether they received information in that round on the negative health impacts of particulates exposure. The MWTP panel shows the marginal willingness to pay for clean air for those who did and did not receive health information. Surveyor by Round FEs are fixed effects for each surveyor-round combination. LASSO controls are the set of controls selected by the Double-LASSO method. Standard errors are given in parentheses and are three-way clustered: at the level of price randomization (survey point by round), at the level of pollution averaging (day), and at the respondent level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of Peer Belief and Past-Takeup

	Logit		
	(1)	(2)	(3)
Model Coefficients			
Price (USD)	-1.860^{***}	-1.861^{***}	-1.952^{***}
	(0.091)	(0.091)	(0.109)
$PM_{2.5}$ ($10\mu g/m^3$)	0.003	0.003	0.006
	(0.012)	(0.012)	(0.013)
$\times$ Information	0.014^{***}	0.014^{***}	0.016^{**}
	(0.005)	(0.005)	(0.006)
Peer Belief		0.122	0.148
		(0.184)	(0.276)
Previous Mask Usage			-1.081
			(0.701)
Marginal Willingness to Pay per annual $10\mu g/m^3$ *$PM_{2.5}$ (USD)*			
Information = 0	1.14	1.16	1.95
	(4.20)	(4.20)	(4.57)
Information = 1	6.24	6.27	7.43*
	(4.05)	(4.05)	(4.34)
p-value of difference	0.004	0.004	0.010
Surveyor-by-Round FEs	Yes	Yes	Yes
LASSO Controls	Yes	Yes	Yes
Control Fnc.			Yes
Observations	6,465	6,465	6,465

Notes: The table shows how price, pollution, health information, peer belief and past mask usage affect demand for masks, and the resulting estimated demand for clean air. Each observation is one respondent in a survey round. The dependent variable is whether the respondent bought a mask. Price (2019 USD) is the level of the randomized price offer made to the recipient, $PM_{2.5}$ (10 $\mu g/m^3$) is the average level of $PM_{2.5}$ measured in Delhi over the preceding day in 10 $\mu g/m^3$, Information is a dummy for whether they received information in that round on the negative health impacts of particulates exposure, Peer Belief is a dummy for whether they were received the treatment on how peers view masks, and Previous Mask Usage is a dummy for whether they had ever worn a mask prior to that experimental round. The MWTP panel shows the marginal willingness to pay for clean air for those who did and did not receive health information. Surveyor by Round FEs are fixed effects for each surveyor-round combination. LASSO controls are the set of controls selected by the Double-LASSO method. Standard errors are given in parentheses and are three-way clustered: at the level of price randomization (survey point by round), at the level of pollution averaging (day), and at the respondent level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: MWTP Heterogeneity

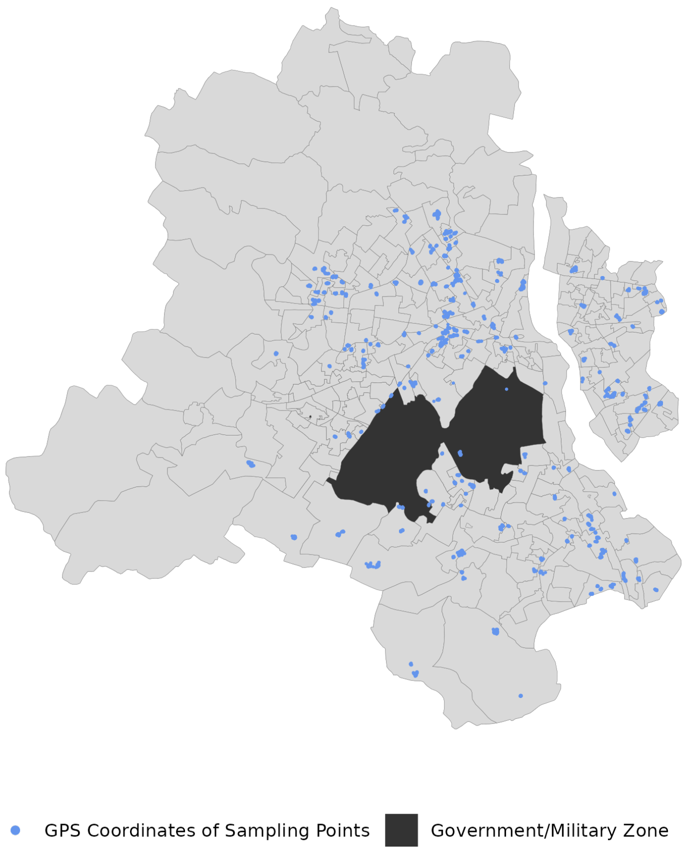
	Annual Household Income (USD)			Gender		Years of School		
	0	10,000	18,000	Female	Male	0	8	15
Information = 0	−0.23	3.03	5.11					
	(4.19)	(4.98)	(6.52)					
Information = 1	4.87	8.89*	11.45*					
	(4.11)	(4.87)	(6.58)					
p-value of difference	0.042	0.005	0.051					
Information = 0				−1.10	3.44			
				(4.16)	(4.87)			
Information = 1				6.14	6.41			
				(3.86)	(4.96)			
p-value of difference				0.001	0.211			
Information = 0						−6.14	2.00	12.70**
						(4.44)	(3.97)	(5.63)
Information = 1						3.36	7.32*	12.54**
						(4.42)	(3.90)	(5.61)
p-value of difference						< .001	0.003	0.956

Notes: This table shows how MWTP, and the impact of health information on MWTP, varies across observables. Values are marginal willingness to pay per annual $10\mu g/m^3$ $PM_{2.5}$ (USD) if the entire sample counterfactually had the given covariate value and did (not) receive health information in that round on the negative health impacts of particulates exposure. Standard errors and p-values are calculated using the delta-method from three-way clustering: at the level of price randomization (survey point by round), at the level of pollution averaging (day), and at the respondent level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

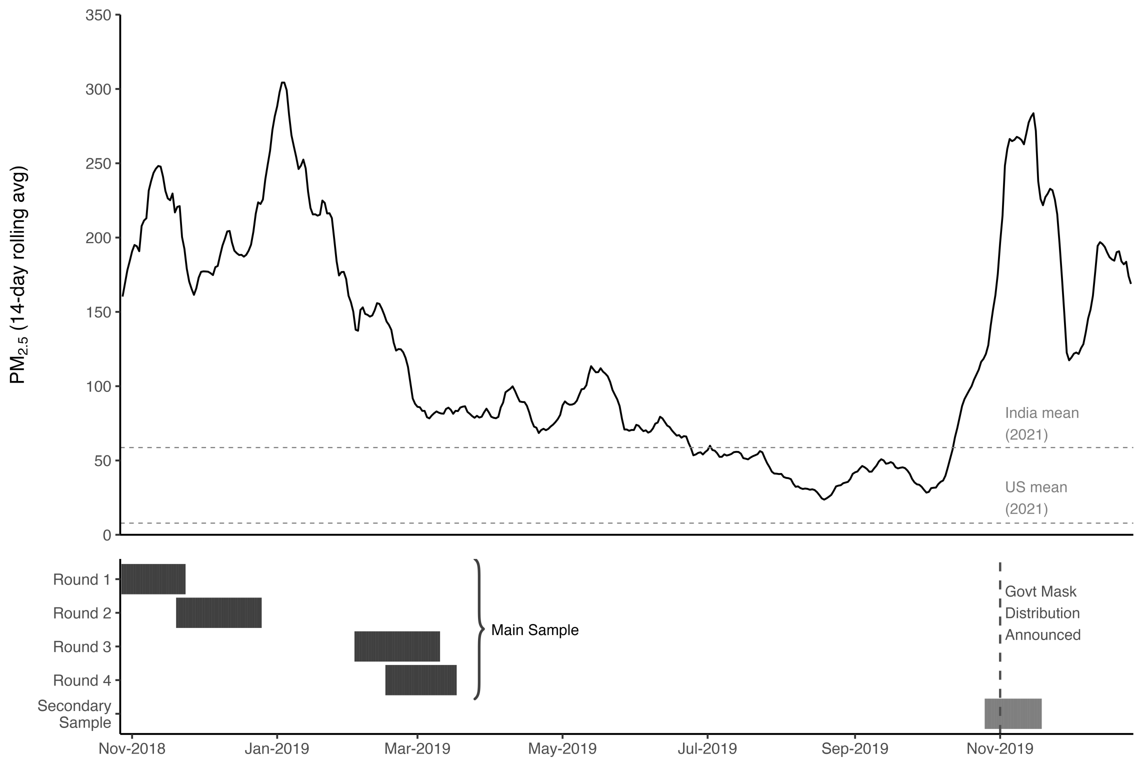
Figures

Figure 1: Map of Sample in Delhi



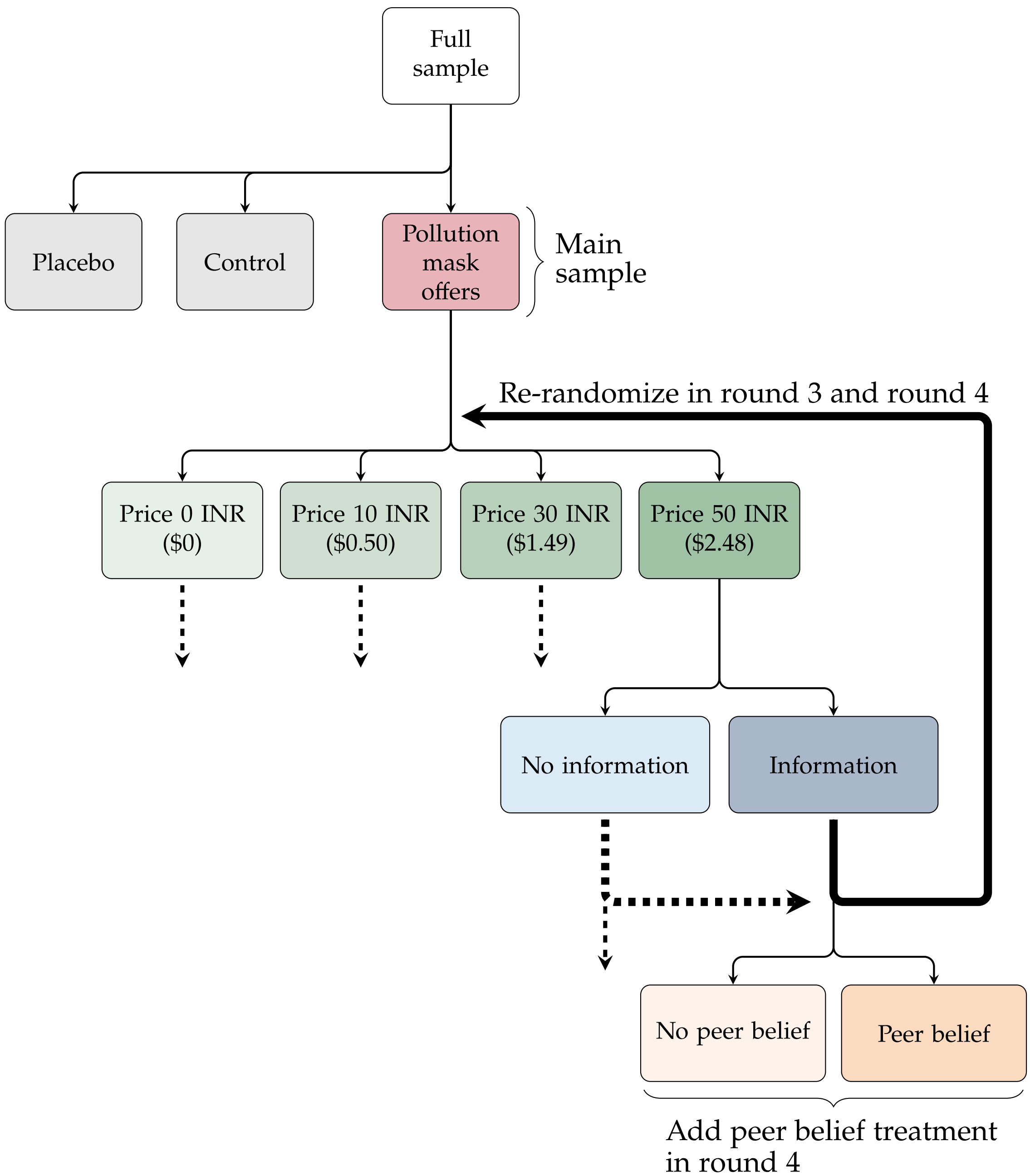
Notes: This map shows the 324 sampling points (blue), where surveys were conducted for the main sample. Grey regions demarcate Delhi Government and Military Zones that largely do not contain residents.

Figure 2: Experimental Timeline



Notes: This figure shows the timeline of our experiments and surveys against the bi-weekly rolling average of ambient air pollution ($PM_{2.5}$,$\mu g/m^3$) in Delhi. There were four rounds of our main experimental sample, and then a secondary sample overlapping the government mask distribution programming..

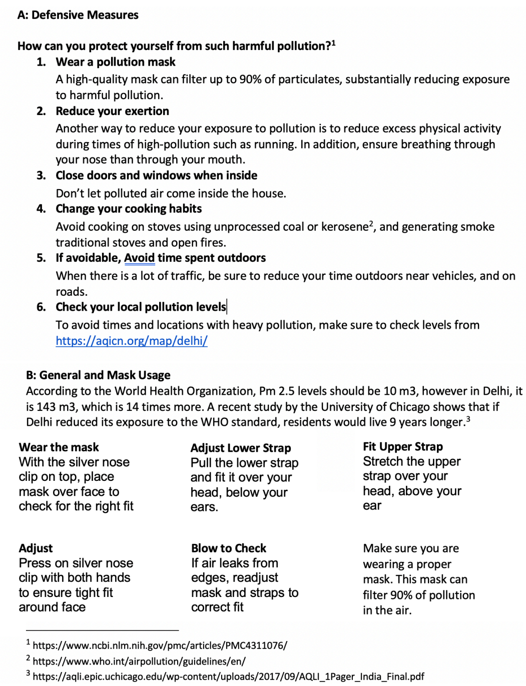
Figure 3: Experiment Flowchart



Notes: This diagram depicts the experimental design. Respondents were cross-randomized across the subsidized price offer they received, whether they received information on the health impacts of pollution or not, and whether they were informed about the level of peer disapproval of mask wearing or not. Respondents in the control group did not receive a subsidized price offer, while respondents in the placebo group received a non-N90 mask for free. See text for more details.

Figure 4: Non-Price Treatment Materials

(a) Information Treatment



A: Defensive Measures

How can you protect yourself from such harmful pollution?[1]

1. **Wear a pollution mask**
   A high-quality mask can filter up to 90% of particulates, substantially reducing exposure to harmful pollution.
2. **Reduce your exertion**
   Another way to reduce your exposure to pollution is to reduce excess physical activity during times of high-pollution such as running. In addition, ensure breathing through your nose than through your mouth.
3. **Close doors and windows when inside**
   Don't let polluted air come inside the house.
4. **Change your cooking habits**
   Avoid cooking on stoves using unprocessed coal or kerosene[2], and generating smoke traditional stoves and open fires.
5. **If avoidable, Avoid time spent outdoors**
   When there is a lot of traffic, be sure to reduce your time outdoors near vehicles, and on roads.
6. **Check your local pollution levels**
   To avoid times and locations with heavy pollution, make sure to check levels from https://aqicn.org/map/delhi/

B: General and Mask Usage
According to the World Health Organization, Pm 2.5 levels should be 10 m3, however in Delhi, it is 143 m3, which is 14 times more. A recent study by the University of Chicago shows that if Delhi reduced its exposure to the WHO standard, residents would live 9 years longer.[3]

Wear the mask
With the silver nose clip on top, place mask over face to check for the right fit

Adjust Lower Strap
Pull the lower strap and fit it over your head, below your ears.

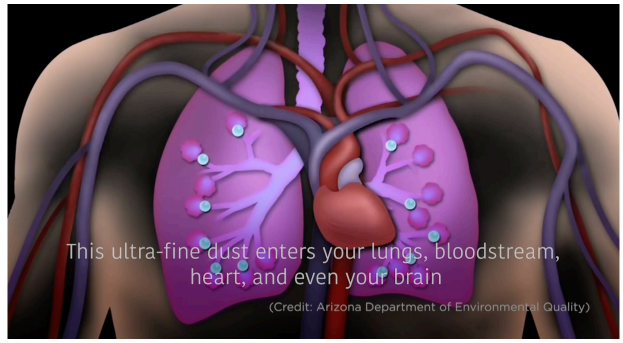
Fit Upper Strap
Stretch the upper strap over your head, above your ear

Adjust
Press on silver nose clip with both hands to ensure tight fit around face

Blow to Check
If air leaks from edges, readjust mask and straps to correct fit

Make sure you are wearing a proper mask. This mask can filter 90% of pollution in the air.

[1] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4311076/
[2] https://www.who.int/airpollution/guidelines/en/
[3] https://aqli.epic.uchicago.edu/wp-content/uploads/2017/09/AQLI_1Pager_India_Final.pdf

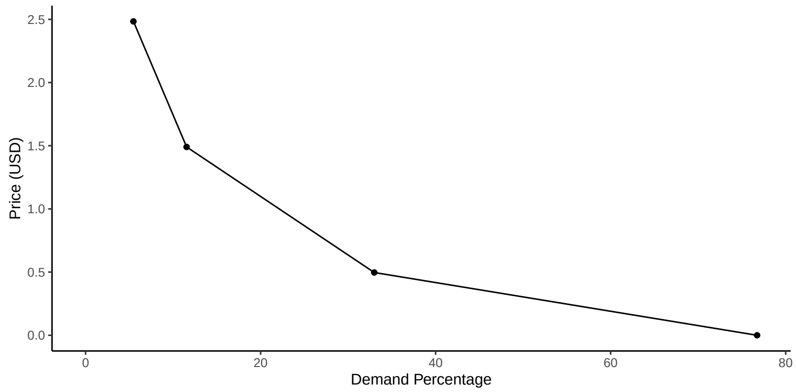


(b) Peer-Belief Treatment

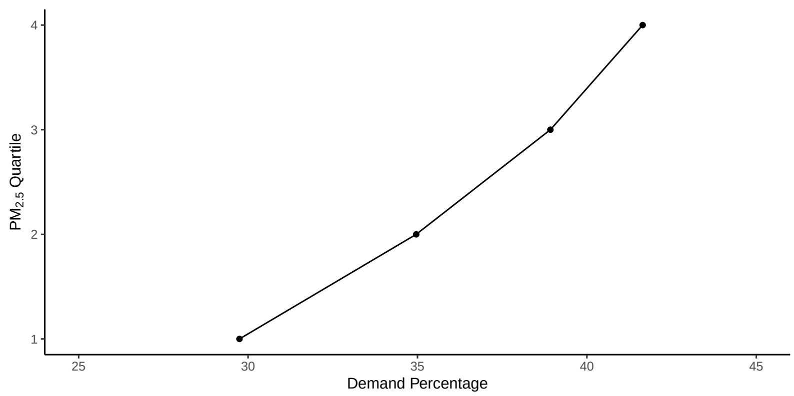
Notes: This figure depicts the two non-price interventions in the experiment. Panel (a) is the health information treatment, with the right panel showing the (english-translated) handout shown to respondents and the left sub-panel showing two scenes from the (english-translated) video shown to respondents. Panel (b) depicts images that were shown to respondents to solicit private beliefs regarding mask appearance: respondents were asked to respond yes or no to the question "do you think this person looks strange?"

Figure 5: Demand for Masks

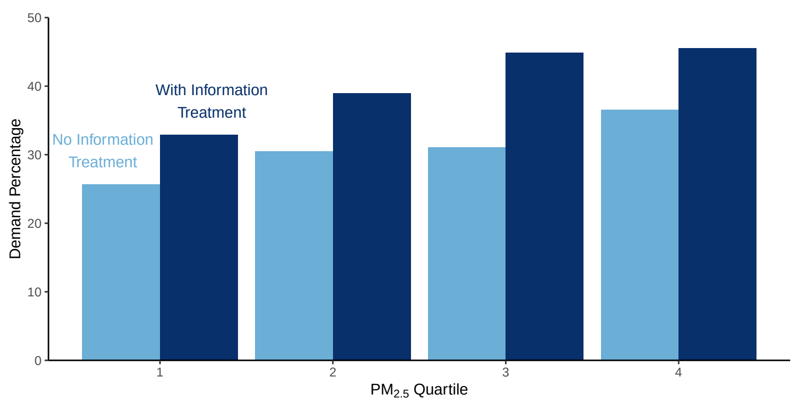
(a) Randomized Prices and Mask Demand



(b) Ambient Particulate Matter and Mask Demand

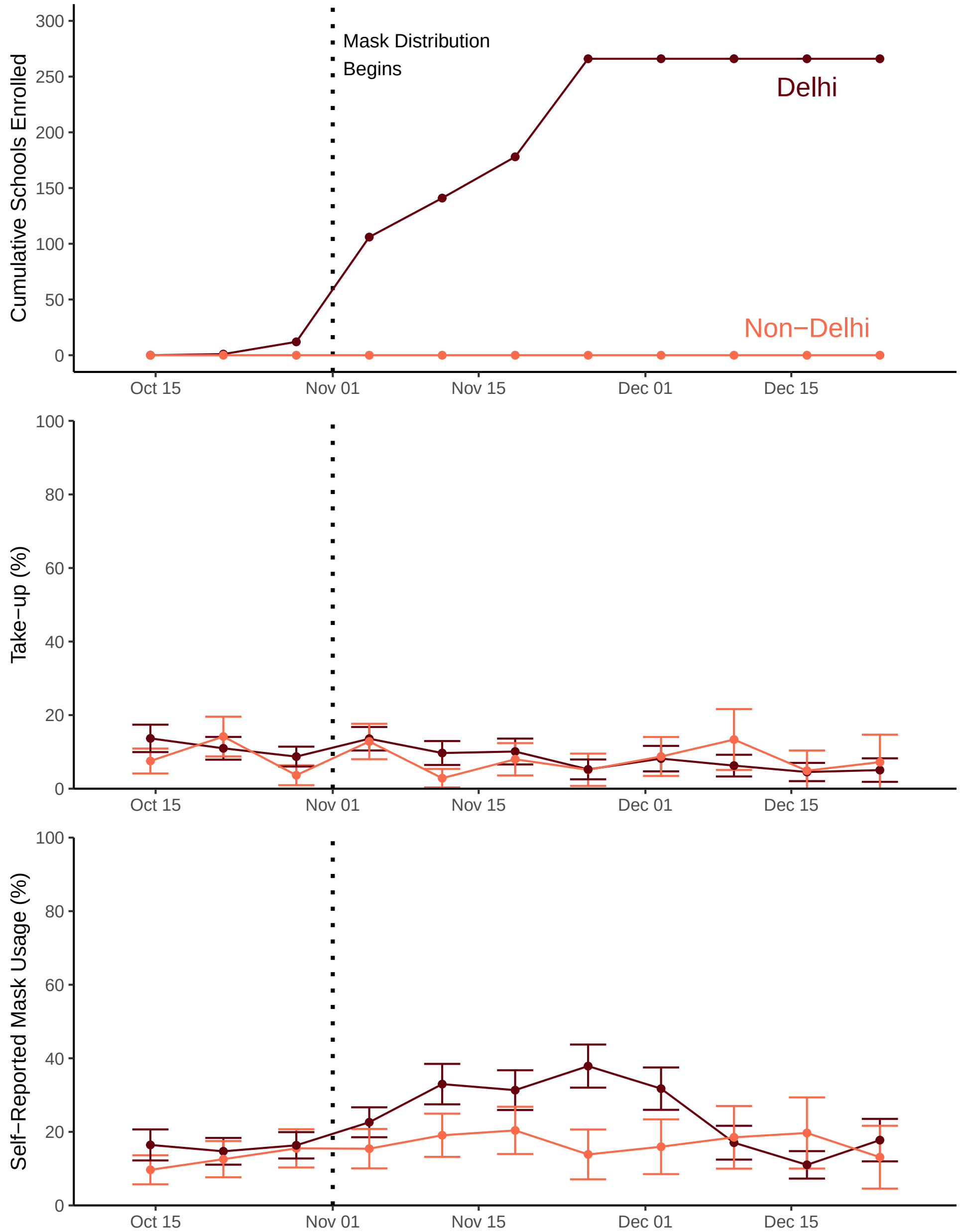


(c) Ambient Particulate Matter and Mask Demand, by Information Treatment



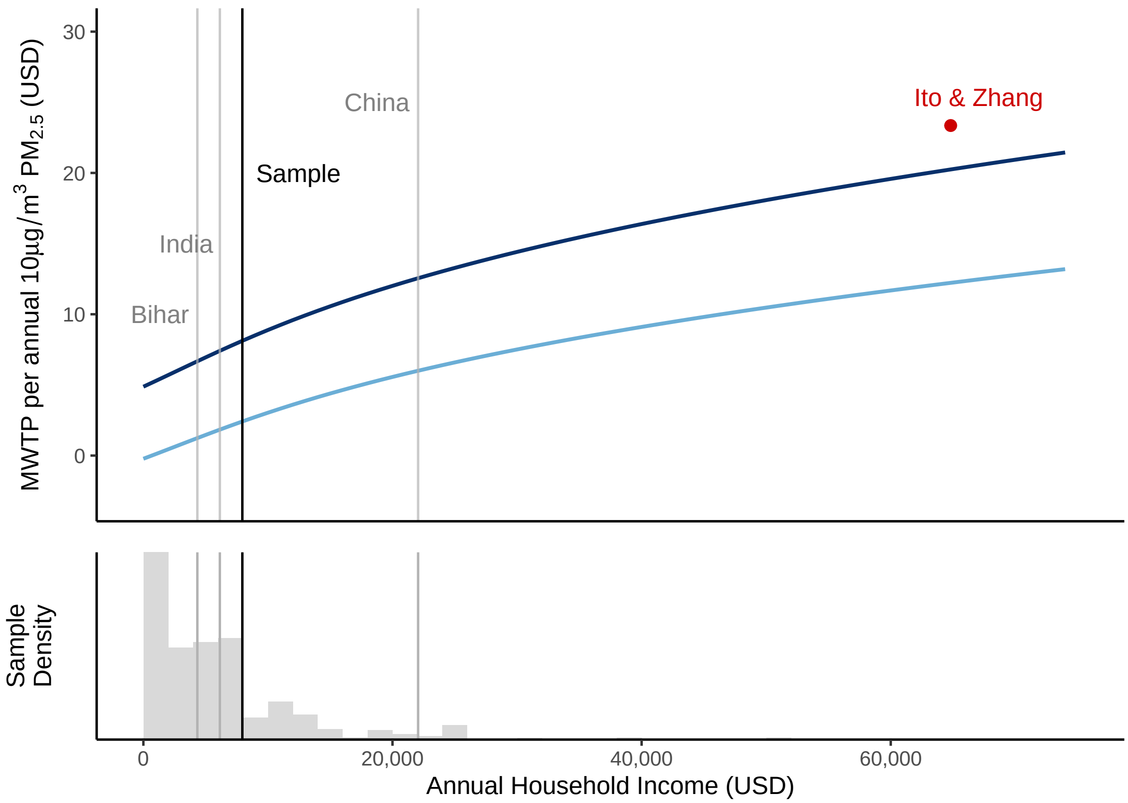
Notes: This figure shows the observed relationship between mask take-up and the randomly assigned prices offered (panel a) as well as the relationship between mask take-up and ambient city-wide PM (panel b). Panel (c) separates the relationship between ambient PM and demand by whether the respondent received the health information treatment that round.

Figure 6: Effect of Government Program



Notes: This figure plots the time series of treated and untreated units in event time by week. The three panels plot the time trends of the fraction of school that received masks from the government campaign, the fraction of respondents that reported using masks, and the fraction of respondents that took subsidized mask offers in Delhi (dark red) and Non-Delhi (orange), respectively.

Figure 7: Income and the Marginal Willingness-to-Pay for Clean Air



Notes: This figure plots the estimated MWTP at each level of income from the demand model with income heterogeneity modeled as in Eq. (7). The red dot corresponds to the annual household income and estimated MWTP from Ito and Zhang (2020); We adjust their original 2014 USD dollar value as follows: Undo the currency exchange rate they use (through correspondence with authors), convert to 2019 USD through purchasing power parity data from the World Bank, adjust to go from their household mwtp to individual level, adjust for time usage spent in home and thus exposed to air filter (using 2008 Chinese National Bureau of Statistics time use data), adjust for air filter efficiency, and lastly convert PM10 reduction to PM2.5 reduction. The vertical lines for Bihar, India, and China are average household incomes in each area: Bihar value comes from survey data in Burgess et al. (2023), India value comes from the 2004 India Human Development Survey purchasing power parity adjusted to 2019, and the China value comes from 2019 Chinese National Bureau of Statistics data purchasing power parity adjusted.

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Appendix

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A Literature Estimates of Demand for Clean Air

Table A.1: WTP for Clean Air Literature Review

Citation	Location	Time period	Original WTP estimate	Original WTP units	Standardized WTP estimate (PPP 2018 USD)	Standardized WTP units	Notes
Category 1 – Discrete choice model incorporating disutility from migration							
Bayer, Keohane, and Timmins (2009)	US metro areas	1990, 2000	$149 - $185	Annual, household level, WTP for a one unit reduction in average PM10 concentrations	$360 - $447 *base year:1984	Annual, household level, WTP for one unit reduction in average PM10 concentrations	The estimate ranges between $360 and $447 depending on the set of covariates used.
Freeman et al. (2019)	China	2005	$21.70	Annual, household level, WTP for a one unit reduction in average PM2.5 concentrations	$28 *base year: 2005	Annual, household level, WTP for a one unit reduction in average PM2.5 concentrations	This paper uses a residential sorting model incorporating migration disutility to recover the implicit value of clean air.
Category 2 – Conventional hedonic pricing							
Yusuf and Resosudarmo (2009)	Jakarta, Indonesia	1997-1998	$28 - $85	Cumulative, household level, WTP for 25 years reduction of a unit of pollutant	$1.8 - $5.3 *base year: 1997	Annual, household level, WTP for a unit reduction of a pollutant	The annual per family value of clean air ranges from $1.8 (SO2) to $5.3 (THC) in Jakarta.
Finney, Goetzke, and Yoon (2011)	Southern California	1999-2000	$44.8 - $72.8	Monthly, household level, WTP for 10% increase in number of days air quality standards are met	$783 - $1,273 *base year: 2000	Annual, household level, WTP for 10% increase in number of days air quality standards are met	$783 corresponds to the WTP for middle-income households and $1,273 for high-income households.
Gonzalez, Leipnik, and Mazumder (2013)	Mexico - 3 cities	2003 - 2004	$41.73	Cumulative, individual level, WTP for a unit reduction in PM10 levels	$55.47 *base year: 2004	Cumulative, individual level, WTP for a unit reduction in PM10 levels	The estimate is for Mexico City.
Nishitateno and Burke (2021)	Japan	1995-2015	$8	Cumulative, individual level, WTP per square meter of land area for total reduction in SPM concentration	$8.48 *base year: 2015	Cumulative, individual level, WTP per square meter of land area for total reduction in SPM concentration	This paper uses the introduction of the diesel vehicle registration restriction in Japan in 2001 to study the reduction in suspended particulate matter (SPM) concentrations.
Category 3 – Other							
Zhang and Mu (2018)	China - 190 cities	2013 - 2014	$100,000	Cumulative, population level, cost of one severely polluted day (AQI ≥ 301)	$106,070 *base year: 2014	Cumulative, population level, cost of one severely polluted day (AQI ≥ 301)	The paper elicits the marginal effect of air pollution on mask purchases controlling for relevant variables.
Deschenes, Greenstone, and Shapiro (2017)	USA	1997-2007	$2.6 billion	Annual, population level, WTP for reduction of 1 million tons of NOx emissions	$20.25 *base year: 2015	Annual, individual level, WTP for reduction of 1 million tons of NOx emissions	The estimate is derived from counties with NOx emissions in the NOx Budget Training Program participating states with an estimated population of 136 million people.
Gao, Song, and Timmins (2023)	China	2011-2016	171, 336 Chinese Yuan	Cumulative, individual level, MWTP for a one unit reduction in PM2.5 concentration	$48, $95 *base year: 2014	Cumulative, individual level, MWTP for a one unit reduction in PM2.5 concentration	The paper uses an unexpected program to disclose pollution data in China in 2012 to estimate a WTP of $48 under imperfect information and a WTP of $95 under accurate information.
Maarraoui et al. (2023)	UK	2004-2019	PM10: £60 PM2.5: £103 NO2: £62.5	Monthly, household level, WTP to avoid a one unit increase in PM10/PM2.5/NO2	PM10: $1,041 PM2.5: $1,788 NO2: $1,085 *base year: 2019	Annual, household level, WTP to avoid one unit increase in PM10/ PM2.5/No2	This paper uses a life satisfaction regression.
Category 4 – Contingent valuation models							
Carlsson and Johansson-Stenman (2000)	Sweden	1996	2000 SEK	Annual, individual level, WTP for a 50% reduction of harmful substances	$346.17 *base year: 1996	Annual, individual level, WTP for a 50% reduction of harmful substances	This study uses the contingent valuation method.
Vlachokostas et al. (2011)	Thessaloniki, Greece	2009	€920	Annual, individual level, WTP to save one year of life loss	$1,354 *base year: 2009	Annual, individual level, WTP to save one year of life loss	This study uses the contingent valuation method to elicit the WTP for reducing the risk of premature mortality attributed to air pollution.
Donfouet, Cook, and Jeanty (2015)	Douala, Cameroon	2011	225 CFA Francs	Monthly, household level, WTP for a 25% reduction in air pollution	$12.63 *base year: 2011	Annual, household level, WTP for a 25% reduction in air pollution	This study uses the contingent valuation method in a hypothetical referendum scenario.
Ndambiri, Mungatana, and Brouwer (2015)	Nairobi, Kenya	2015	$4.67	Monthly, individual level, WTP for motorized emission reductions	$59 *base year: 2015	Annual, individual level, WTP for motorized emission reductions	This study uses the contingent valuation method.
Filippini and Martinez-Cruz (2016)	Mexico City	2007-2008	$262	Annual, individual level, WTP for improved air quality	$305.5 *base year: 2008	Annual, individual level, WTP for improved air quality	This paper elicits WTP for improved air quality by means of a single-bounded, referendum format contingent valuation question.
Poder and He (2017)	Quebec and France	2009	CAD 5440	Cumulative, population level, WTP for cleaner cars for a 62.2% reduction in exhaust gases	$5,297 *base year: 2009	Cumulative, population level, WTP for cleaner cars for a 62.2% reduction in exhaust gases	The estimate refers to the average WTP across respondents from Quebec and France.

Table A.1 continued from previous page

Citation	Location	Time period	Original WTP estimate	Original WTP units	Standardized WTP estimate (PPP 2018 USD)	Standardized WTP units	Notes
Akhtar et al. (2017)	Lahore, Pakistan	2016	$118	Annual, individual level, WTP to decrease level of air contamination by 50%	$123.4 *base year: 2016	Annual, individual level, WTP to decrease level of air contamination by 50%	This study uses the contingent valuation method
Ligus (2018)	Poland	2015	21.172 PLN	Monthly, individual level, WTP for overall reduction in air pollution	$152.4 *base year: 2015	Annual, individual level, WTP for overall reduction in air pollution	This study uses the contingent valuation method.
Tantiwat, Gan, and Yang (2021)	Thailand	2020	2,275 Baht	Annual, individual level, WTP for improved air quality	$179 *base year: 2020	Annual, individual level, WTP for improved air quality	This study uses the contingent valuation method.

B Sampling Procedure

Our sampling frame consists of mostly poor and non-migrant workers living in Delhi, and some of the surrounding urban areas. The main sample, which we refer to as "low-income neighborhoods" (n = 3,533) captures individuals residing in poor, informal settlements across Delhi. To create this sample, we obtained a list of Jhuggie Jhopri (J.J.) Squatter Settlements ("clusters") provided by the Delhi Government's Urban Shelter Improvement Board. To our knowledge, this is the most comprehensive list of slum clusters or squatter settlements available in Delhi. We randomly generated sampling points (i.e., locations where enumerators could begin administering in-person surveys) located around the center of each J.J. cluster. We excluded sampling points that were deemed to no longer be slums or squatter settlements (due to urban development), using a combination of satellite images and in-person checks. This resulted in 324 sampling points, around which our team of enumerators enrolled individuals into our sample. Upon arriving at the sampling point, the enumerator would survey adults at every other household with a small survey incentive of 50Rs ($0.73 USD). The sampling process was carried out between October and December 2018. To our knowledge, this construction results in the largest and most representative sample of Delhi slum settlements ever collected.

C Experiment Documentation

C.1 Peer Belief Information Treatment

Figure C.1: Soliciting Beliefs on Mask Appearance

Notes: This figure depicts pictures that were shown to respondents to solicit private beliefs regarding mask appearance. Each picture was shown in succession and the binary question "do you think this person looks strange" was asked to respondents. The picture in the left shows someone with sunglasses, the middle shows someone with a pollution mask, and the right shows someone with green hair.

C.2 Pollution Masks Offered

Figure C.2: 3M Pollution Mask

Notes: This figure depicts the mask that was offered to respondents in our experiment. The mask is manufactured by 3M and filters 90% of particulate matter (PM) according to manufacturer tests. The retail price across our surveys was roughly 100INR on average and wholesale prices were roughly 50INR.

C.3 Mask Distribution Campaign

Table C.1: Historical protective mask distribution efforts (as of 2019)

Location	Period	Scale	Issue	Details
Delhi, India	2019	5,000,000	Pollution	In advance of the annual winter pollution season, N-95 pollution masks distributed to schoolchildren in both public and private schools.
Malaysia	2019	500,000	Pollution	During a particularly severe smog episode, the National Disaster Management Agency (NADMA) distributed masks to people in the worst-affected areas.
Suwon, South Korea	2018	36,000	Pollution	For a two-day period starting on March 26, 2018, Gyeonggi province placed 36,000 free masks on 185 buses after excessive fine dust triggered emergency response.
Singapore	2013	1,100,000	SARS	Similar kits were distributed for free once again. Volunteers went door to door to distribute the kits, while others had to collect them from local centres.
Washington, USA	2012	20,000	Pollution	Free masks distributed to towns affected by wildfire smoke. The government drew upon an emergency stockpile that had originally been intended to address a swine flu epidemic.
Singapore	2003	1,100,000	SARS	The government distributed a free SARS toolkit (which included N-95 protective masks) to all households.

This table describes historical government mask distribution efforts around the world as of 2019. Delhi's mask distribution policy was more than 4 times larger than the largest program before (Singapore's mask program during the SARS epidemic).

D Treatment Groups, Balance and Attrition

D.1 Treatment Groups

Table D.1 describes the probability of treatment assignment in each round of the sample.

Table D.1: Probability of Assignment to Treatment Groups

	No Health Info + No Peer Belief Info	No Health Info + Peer Belief Info	Health Info + No Peer Belief Info	Health Info + Peer Belief Info	Total
0 Rps	13.99%	1.70%	20.94%	2.29%	38.92%
1 Rps	7.23%	0.87%	7.02%	0.82%	15.94%
2 Rps	6.69%	0.81%	7.21%	0.92%	15.64%
Black Mask (Free)	6.98%	1.04%	0.00%	0.00%	8.02%
No Mask	14.33%	0.00%	7.15%	0.00%	21.48%
Total	49.22%	4.43%	42.32%	4.03%	100.00%

Note: This table reports probabilities (1-100) of treatment assignment across surveys in all rounds of the sample. Rows describe types of mask offers and columns describe different information interventions.

D.2 Balance Across Treatment Arms

To test the validity of our randomization in the main experiment, we collect baseline characteristics for each individual. In this section, we report means of selected variables at baseline for all control and treatment groups, as well as p-values for differences in means across groups and rounds. We find that covariates are similarly balanced across rounds as well as for the full set of 50+ covariates. We find no statistically meaningful difference in covariates of interest across various prices and intervention arms.

The tables below describe balance in selected baseline (round 1) characteristics across treatment arms, for each round. Each cell is the mean of the corresponding baseline variable (row) for the corresponding treatment variable (column). Standard deviations are in parenthesis. The right most column reports a p-value of test of equality across means of the given variable across all treatment arms using a cluster permutation F-test: We permute the group assignments across the sampling points and see what portion of those permutations result in an F-stat greater than the one observed in the raw data.

Table D.2: Baseline Balance Across Price Arms in Round 1

	Placebo	Control	N90 0 INR	N90 10 INR	N90 30 INR	N90 50 INR	p-value
$PM_{2.5}$ ($10\mu g/m^3$)	21.663	19.964	21.035	20.940	21.245	20.133	0.802
	(7.792)	(6.241)	(6.805)	(6.394)	(6.872)	(5.618)	
asinh(Weekly-Income/1000)	2.880	3.401	3.862	3.705	3.282	3.394	0.234
	(4.286)	(4.415)	(4.583)	(4.603)	(4.410)	(4.469)	
asinh(Household-Income/1000)	7.486	8.220	8.508	8.235	8.492	8.035	0.266
	(3.887)	(3.190)	(3.144)	(3.467)	(2.888)	(3.546)	
Female	0.505	0.513	0.502	0.502	0.573	0.516	0.668
	(0.501)	(0.500)	(0.500)	(0.500)	(0.495)	(0.500)	
Age	36.910	36.670	37.273	37.011	36.811	35.302	0.499
	(13.192)	(13.968)	(12.771)	(13.152)	(13.093)	(12.514)	
Years of School	6.318	7.007	7.485	7.788	6.806	7.543	0.071
	(5.182)	(5.021)	(5.009)	(4.915)	(4.981)	(5.104)	
Ever Worn Mask	0.161	0.150	0.191	0.171	0.138	0.186	0.191
	(0.368)	(0.357)	(0.393)	(0.377)	(0.345)	(0.390)	
Pollution-Symptoms	0.743	0.673	0.691	0.649	0.646	0.651	0.122
	(0.438)	(0.469)	(0.463)	(0.478)	(0.479)	(0.477)	
Non Pollution-Symptoms	0.654	0.566	0.582	0.570	0.538	0.527	0.199
	(0.477)	(0.496)	(0.494)	(0.496)	(0.499)	(0.500)	
Observations	280	813	811	539	543	547	

Table D.3: Baseline Balance Across Information Arms in Round 1

	Health-Info	No Health-Info	p-value
$\text{PM}_{2.5}$ $(10\mu g/m^3)$	20.452	20.940	0.537
	(6.120)	(6.906)	
asinh(Weekly-Income/1000)	3.446	3.530	0.676
	(4.458)	(4.510)	
asinh(Household-Income/1000)	8.129	8.341	0.350
	(3.398)	(3.229)	
Female	0.526	0.511	0.592
	(0.499)	(0.500)	
Age	36.636	36.734	0.878
	(13.191)	(13.143)	
Years of School	7.389	7.102	0.268
	(5.017)	(5.051)	
Ever Worn Mask	0.176	0.160	0.282
	(0.381)	(0.367)	
Pollution-Symptoms	0.671	0.672	0.954
	(0.470)	(0.470)	
Non Pollution-Symptoms	0.563	0.570	0.763
	(0.496)	(0.495)	
Observations	1,619	1,914	

Table D.4: Baseline Balance Across Price Arms in Round 2

	Placebo	Control	N90 0 INR	N90 10 INR	N90 30 INR	N90 50 INR	p-value
$PM_{2.5}$ ($10\mu g/m^3$)	20.360	20.704	19.632	20.429	21.026	19.997	0.733
	(3.404)	(5.898)	(4.881)	(4.495)	(5.952)	(5.722)	
asinh(Weekly-Income/1000)	2.529	3.098	3.331	3.469	2.845	3.111	0.537
	(4.112)	(4.316)	(4.421)	(4.516)	(4.220)	(4.404)	
asinh(Household-Income/1000)	7.307	8.189	8.301	8.840	8.704	8.424	0.149
	(3.910)	(3.215)	(3.333)	(2.762)	(2.556)	(3.223)	
Female	0.594	0.555	0.572	0.570	0.645	0.545	0.472
	(0.492)	(0.497)	(0.495)	(0.496)	(0.479)	(0.499)	
Age	36.213	37.145	37.434	37.770	36.874	35.735	0.593
	(12.915)	(14.390)	(13.128)	(13.597)	(13.177)	(12.626)	
Years of School	6.044	7.056	7.309	7.791	6.663	7.503	0.048
	(5.051)	(5.035)	(5.020)	(4.818)	(4.884)	(5.078)	
Ever Worn Mask	0.128	0.170	0.184	0.160	0.109	0.169	0.080
	(0.335)	(0.376)	(0.388)	(0.368)	(0.312)	(0.375)	
Pollution-Symptoms	0.750	0.689	0.704	0.676	0.637	0.666	0.268
	(0.434)	(0.463)	(0.457)	(0.469)	(0.482)	(0.472)	
Non Pollution-Symptoms	0.683	0.580	0.607	0.582	0.536	0.541	0.139
	(0.466)	(0.494)	(0.489)	(0.494)	(0.499)	(0.499)	
Observations	180	553	560	349	366	344	

Table D.5: Baseline Balance Across Information Arms in Round 2

	Health-Info	No Health-Info	p-value
$PM_{2.5}$ ($10\mu g/m^3$)	20.057	20.560	0.387
	(4.991)	(5.564)	
asinh(Weekly-Income/1000)	3.031	3.211	0.469
	(4.294)	(4.412)	
asinh(Household-Income/1000)	8.294	8.408	0.646
	(3.175)	(3.171)	
Female	0.588	0.567	0.490
	(0.492)	(0.496)	
Age	37.074	36.912	0.840
	(13.576)	(13.304)	
Years of School	7.249	7.070	0.519
	(4.983)	(5.016)	
Ever Worn Mask	0.175	0.145	0.070
	(0.380)	(0.352)	
Pollution-Symptoms	0.693	0.676	0.451
	(0.462)	(0.468)	
Non Pollution-Symptoms	0.580	0.584	0.909
	(0.494)	(0.493)	
Observations	1,084	1,268	

Table D.6: Baseline Balance Across Price Arms in Round 3

	Placebo	Control	N90 0 INR	N90 10 INR	N90 30 INR	N90 50 INR	p-value
$PM_{2.5}$ ($10\mu g/m^3$)	10.780	11.480	12.302	11.470	11.733	12.220	0.855
	(4.398)	(4.941)	(5.252)	(4.998)	(5.698)	(5.290)	
asinh(Weekly-Income/1000)	2.420	2.757	3.215	2.926	3.231	3.121	0.624
	(4.048)	(4.182)	(4.325)	(4.280)	(4.456)	(4.416)	
asinh(Household-Income/1000)	7.828	8.214	8.176	8.351	8.139	7.856	0.945
	(3.768)	(3.109)	(3.067)	(3.239)	(3.575)	(3.757)	
Female	0.573	0.565	0.569	0.622	0.576	0.565	0.915
	(0.496)	(0.496)	(0.496)	(0.486)	(0.495)	(0.497)	
Age	35.968	36.456	37.538	34.963	37.587	37.835	0.243
	(13.821)	(14.115)	(13.436)	(11.869)	(13.190)	(12.912)	
Years of School	6.503	7.379	7.122	6.821	7.281	7.345	0.730
	(5.147)	(5.046)	(4.735)	(5.092)	(5.032)	(5.165)	
Ever Worn Mask	0.096	0.159	0.141	0.123	0.161	0.190	0.162
	(0.295)	(0.366)	(0.348)	(0.329)	(0.368)	(0.393)	
Pollution-Symptoms	0.656	0.653	0.701	0.668	0.657	0.678	0.806
	(0.477)	(0.477)	(0.458)	(0.472)	(0.476)	(0.468)	
Non Pollution-Symptoms	0.548	0.511	0.597	0.568	0.531	0.585	0.488
	(0.499)	(0.501)	(0.491)	(0.496)	(0.500)	(0.493)	
Observations	157	352	461	301	335	311	

Table D.7: Baseline Balance Across Information Arms in Round 3

	Health-Info	No Health-Info	p-value
PM$_{2.5}$ ($10\mu g/m^3$)	11.965	11.612	0.602
	(5.428)	(4.961)	
asinh(Weekly-Income/1000)	3.172	2.853	0.236
	(4.365)	(4.254)	
asinh(Household-Income/1000)	8.111	8.128	0.947
	(3.356)	(3.401)	
Female	0.566	0.588	0.506
	(0.496)	(0.492)	
Age	36.794	36.932	0.863
	(13.112)	(13.401)	
Years of School	7.157	7.113	0.893
	(5.012)	(5.003)	
Ever Worn Mask	0.140	0.158	0.385
	(0.347)	(0.365)	
Pollution-Symptoms	0.685	0.659	0.275
	(0.465)	(0.474)	
Non Pollution-Symptoms	0.579	0.541	0.210
	(0.494)	(0.499)	
Observations	928	989	

Table D.8: Baseline Balance Across Price Arms in Round 4

	Placebo	Control	N90 0 INR	N90 10 INR	N90 30 INR	N90 50 INR	p-value
$PM_{2.5}$ ($10\mu g/m^3$)	8.832	8.472	8.890	8.515	8.739	8.881	0.755
	(2.297)	(1.782)	(1.937)	(1.897)	(2.244)	(1.733)	
asinh(Weekly-Income/1000)	3.409	2.779	2.863	3.394	3.182	2.918	0.583
	(4.454)	(4.194)	(4.312)	(4.446)	(4.386)	(4.265)	
asinh(Household-Income/1000)	8.067	8.169	7.992	7.933	8.505	7.880	0.824
	(3.381)	(3.152)	(3.644)	(3.498)	(3.031)	(3.692)	
Female	0.491	0.576	0.556	0.538	0.608	0.629	0.325
	(0.501)	(0.495)	(0.497)	(0.499)	(0.489)	(0.484)	
Age	39.839	36.418	36.573	37.935	36.678	36.356	0.266
	(14.181)	(13.926)	(13.347)	(13.363)	(12.484)	(13.233)	
Years of School	6.874	7.249	7.154	7.327	6.924	6.801	0.907
	(5.256)	(5.001)	(4.916)	(5.189)	(5.020)	(4.949)	
Ever Worn Mask	0.149	0.154	0.144	0.211	0.148	0.149	0.234
	(0.357)	(0.361)	(0.351)	(0.408)	(0.356)	(0.357)	
Pollution-Symptoms	0.703	0.648	0.660	0.687	0.724	0.708	0.281
	(0.458)	(0.478)	(0.474)	(0.464)	(0.448)	(0.456)	
Non Pollution-Symptoms	0.617	0.536	0.550	0.599	0.555	0.623	0.389
	(0.487)	(0.499)	(0.498)	(0.491)	(0.498)	(0.485)	
Observations	175	403	480	342	330	342	

Table D.9: Baseline Balance Across Information Arms in Round 4

	Health Info Peer-Info	Health-Info No Peer-Info	No Health Info Peer-Info	No Health-Info No Peer-Info	p-value
$\text{PM}_{2.5}$ ($10\mu g/m^3$)	8.476	8.799	8.611	8.856	0.597
	(1.819)	(1.954)	(2.100)	(1.941)	
asinh(Weekly-Income/1000)	2.695	3.063	3.704	2.797	0.024
	(4.215)	(4.336)	(4.561)	(4.197)	
asinh(Household-Income/1000)	7.873	7.985	8.512	7.981	0.388
	(3.666)	(3.490)	(3.086)	(3.420)	
Female	0.582	0.572	0.507	0.607	0.164
	(0.494)	(0.495)	(0.501)	(0.489)	
Age	35.392	37.826	38.349	36.490	0.075
	(12.773)	(13.817)	(13.830)	(13.058)	
Years of School	7.460	7.007	7.220	6.837	0.539
	(4.970)	(5.012)	(5.001)	(5.083)	
Ever Worn Mask	0.156	0.186	0.167	0.134	0.151
	(0.363)	(0.390)	(0.373)	(0.340)	
Pollution-Symptoms	0.691	0.690	0.698	0.666	0.685
	(0.463)	(0.463)	(0.460)	(0.472)	
Non Pollution-Symptoms	0.573	0.568	0.602	0.562	0.796
	(0.495)	(0.496)	(0.490)	(0.497)	
Observations	398	548	437	689	

D.3 Attrition Across Rounds

We report attrition rates across survey rounds and treatment arms. We find that we experience roughly 30% attrition round-to-round, but that this rate is not differential across arms. The tables below describe attrition rates across treatment arms, over rounds. The first row is the number of observations in round 1 for each treatment arm (column). The subsequent rows describe the fraction of these observations that we successfully surveyed int he corresponding round (row).

Table D.10: Round-to-Round Attrition Across Price Arms

	No Mask	Black Mask 0 INR	N90 Mask 0 INR	N90 Mask 10 INR	N90 Mask 30 INR	N90 Mask 50 INR	Total
Round 1 Count	813	280	811	539	543	547	**3533**
Round 1 (%)	100	100	100	100	100	100	**100**
Round 2 (%)	68	64	69	65	67	63	**67**
Round 3 (%)	43	56	57	56	62	57	**54**
Round 4 (%)	50	62	59	63	61	63	**59**

Table D.11: Round-to-Round Attrition Across Information Arms

	No PM2.5 Health Information	PM2.5 Health Information	Total
Round 1 Count	1,914	1,619	**3533**
Round 1 (%)	100	100	**100**
Round 2 (%)	66	67	**67**
Round 3 (%)	52	57	**54**
Round 4 (%)	59	58	**59**

E A Model of Optimal Mask Usage

Given equations (1-4) on the mask takeup decision, we can further model expected usage EU_i itself as another maximization problem:

$$EU_i = \max_{u\in[0,1]} \eta + b_i u - c_i u^2,$$

where u is the fraction of time using the mask, b_i is the marginal benefit, and c_i is the marginal cost of usage.

Actual usage AU_i is then realized after some usage shock ω_i:

$$AU_i = EU_i + \omega_i$$

Note that when $E[\omega_i] = 0$ we have:

$$E[AU_i] = EU_i$$

However, we only observe actual usage for those who takeup:

$$E[AU_i|\text{Takeup}_i = 1] = \overline{AU}_1$$

Actual usage for those who do not takeup is unobserved:

$$E[AU_i|\text{Takeup}_i = 0] = \ ?$$

If EU_i is assumed to be 1, then overstating usage could result in bias:[35]

→ If true $EU_i < 1$ then MWTP would be downward biased

More generally, the selection of who takes up could result in bias depending on how the takeup unobservable ϵ_i correlates with the determinants of usage c_i, b_i:

→ If $b_i, c_i \not\perp \epsilon_i$ then $E[AU_i|\text{Takeup}_i = 1] \neq E[AU_i|\text{Takeup}_i = 0]$ and MWTP would be biased

→ If $b_i, c_i \perp \epsilon_i$ then

$$E[AU_i] = E[AU_i|\text{Takeup}_i = 1] = E[AU_i|\text{Takeup}_i = 0]$$

and MWTP would be unbiased

Note that because prices were randomly assigned, those who takeup at higher prices have higher unobserved preferences:

$$E[\epsilon_i|\text{Takeup}_i = 1, p_i = 50] > E[\epsilon_i|\text{Takeup}_i = 1, p_i = 30] > \dots$$

So if $b_i, c_i \not\perp \epsilon_i$ we should have:

$$E[AU_i|\text{Takeup}_i = 1, p_i = 50] \neq E[AU_i|\text{Takeup}_i = 1, p_i = 30] \neq \dots$$

35. e.g. Ito and Zhang (2018) assume full usage of air purifiers

In Fig. E.1 we plot ex-post means of mask usage by prices, and find that mean usage is roughly equal across all prices and we cannot reject a zero difference.[36] That is, we find that:

$$E[AU_i|\text{Takeup}_i = 1, p_i = 50] = E[AU_i|\text{Takeup}_i = 1, p_i = 30] = \dots$$

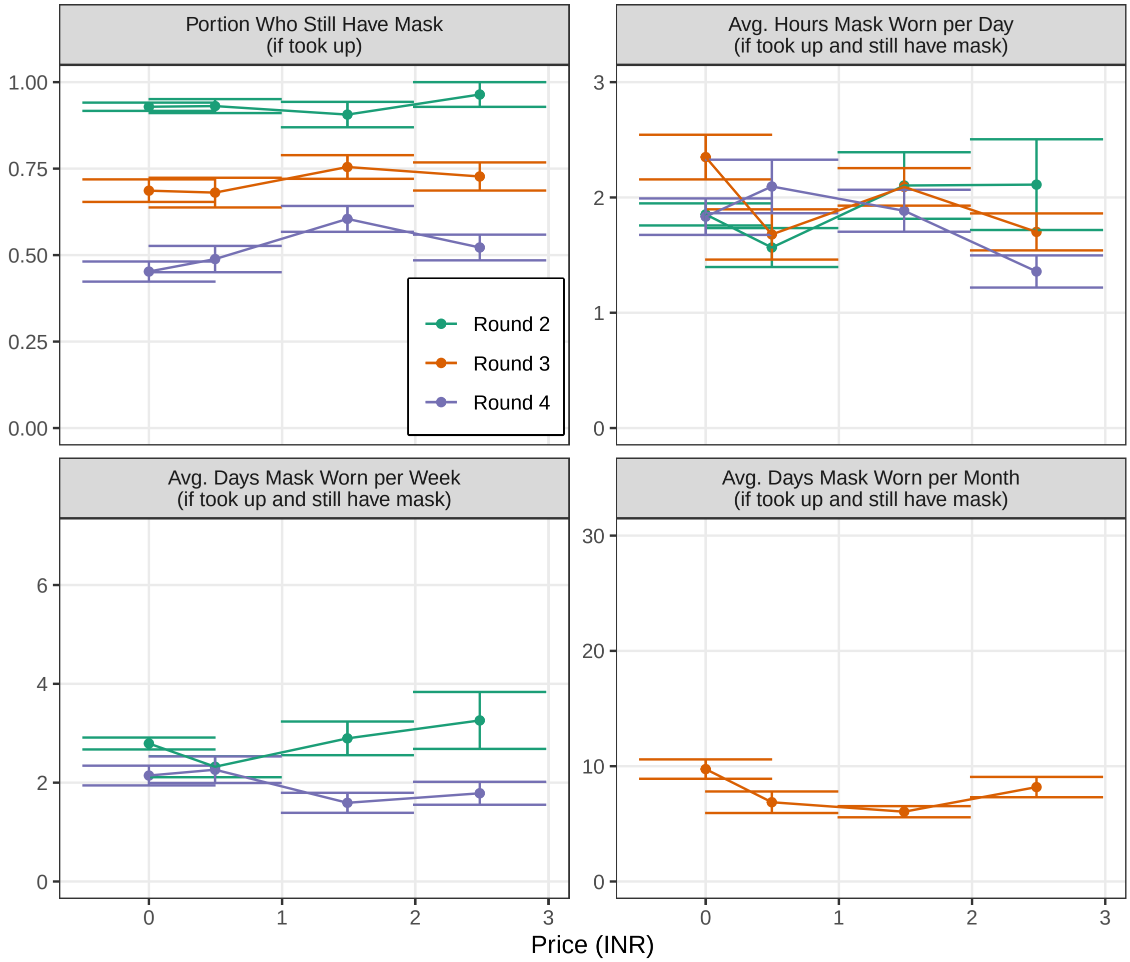
which suggests that $b_i, c_i \perp \epsilon_i$ may be a reasonable assumption. Together we then have:

$$E[AU_i] = E[AU_i|\text{Takeup}_i = 1] = \overline{AU}_1 = EU_i$$

This is thus consistent with assuming EU_i is the ex-post mean usage among those who takeup masks, which is 0.08 (1.8 hours per day).

36. Note that usage was only asked for individuals who had a mask at the time of survey. Thus, there is attrition in the fraction of respondents for which we observe usage (top-left of Fig. E.1). However, we do not observe any differences in this fraction across prices either, further suggestive of equal usage across price arms.

Figure E.1: Mask Usage by Price



Notes: This figure reports means and standard deviations of the given variable by round (color) and experimental price arm (x-axis). The top-left panel plots whether individuals still have masks conditional on taking up in a prior round. The remaining plots report self-reported usage conditional on taking up in a prior period and still having the mask: the top-right panel plots the hours in the day the respondent last used the mask; the bottom-left panel plots the days the respondent last used the mask in the last week; and the bottom-right panel plots the days the respondent last used the mask in the past month. Standard errors are in parentheses.

F Imputation

F.1 Multiple Imputation

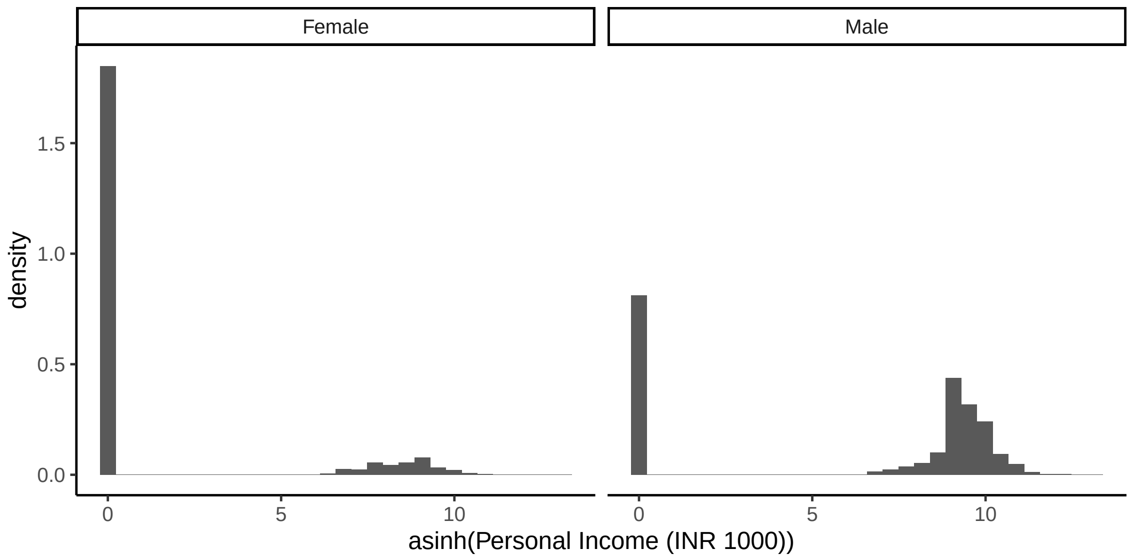
In our data we have two measures of income, personal and household. Personal income in our sample has a radically different distribution between males and females as seen in Appendix Fig. F.1, with 80% reported as 0 for females, while only 30% report 0 for males. This discrepancy, though, does not imply that males and females have such radically different sets of resources which they draw on to make their financial decisions, but instead they likely both use their household's income as the income pot from which they draw when making purchases. This reasoning suggests that to accurately understand how financial resources affect decision making, we would be interested in the interaction of MWTP with household income.

Household income, although similarly distributed across males and females in our sample as seen in Appendix Fig. F.1, is missing for 60% of individuals in our sample. Thus, we use multiple imputation (Rubin 1987, 1996): We create 30 different datasets each with a different set of imputed values, run our analysis on each of the 30 completed datasets separately, and then aggregate the results across those 30 analyses in a way accounting for variance in e.g. a parameter estimate both inside each completed dataset and across the 30 completed datasets. The intuition underlying multiple imputation is that under certain assumptions about the imputation technique, the multiple different imputed values used in each completed dataset will reflect our uncertainty about what that missing value might be, and thus we are taking into account our additional uncertainty resulting from not knowing what those true values are.

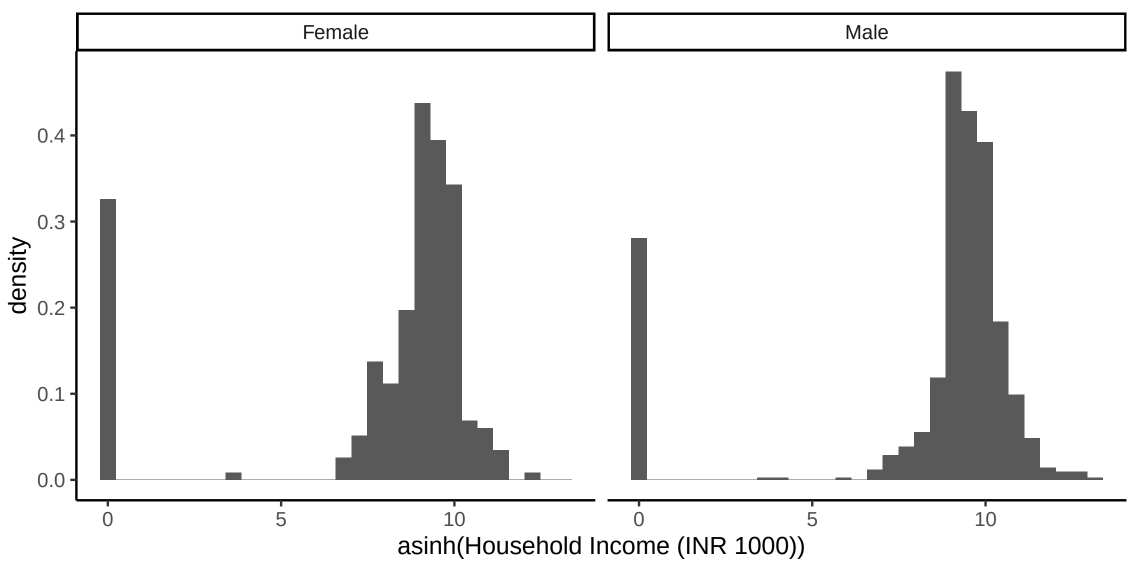
Our imputation procedure to generate each of the 30 completed datasets is to use the Multiple Imputation by Chained Equation (MICE) algorithm with random forests (Doove, Van Buuren, and Dusseldorp 2014) on each. This method imputes values for a particular variable using a "fully conditional specification" of the values of that variable conditional on all other variables. In particular, after an initial filling of missing values with other observed values at random, we then cycle through variables using the distribution of all other variables' current assigned values along with random forests to fill new values for all the observations with initially missing values of that variable. We then apply this procedure in a cycle through all variables which had any missing values, and we then iterate this whole cycle several times to achieve stability in the imputed values. We chose random forest to estimate the full conditional specification of values conditional on other variables due to its flexibility in incorporating arbitrary interactions and estimating data of arbitrary distributions due to its non-parametric nature. The key assumption for the validity of the imputation procedure is that the data is "Missing at Random" (as opposed to "Missing Completely at Random" and "Not Missing at Random") meaning that whether or not a value for a particular covariate is missing can be modelled as a function of other covariates and an i.i.d. (across individuals) distributed error term. We believe this is a reasonable assumption given the number of covariates we observe and use in the imputation procedure, but we also include our analysis restricted to only the raw data, and also using an alternative imputation procedure, below.

Figure F.1: Distribution of observed values of weekly and household incomes in raw data

(a) Personal Income

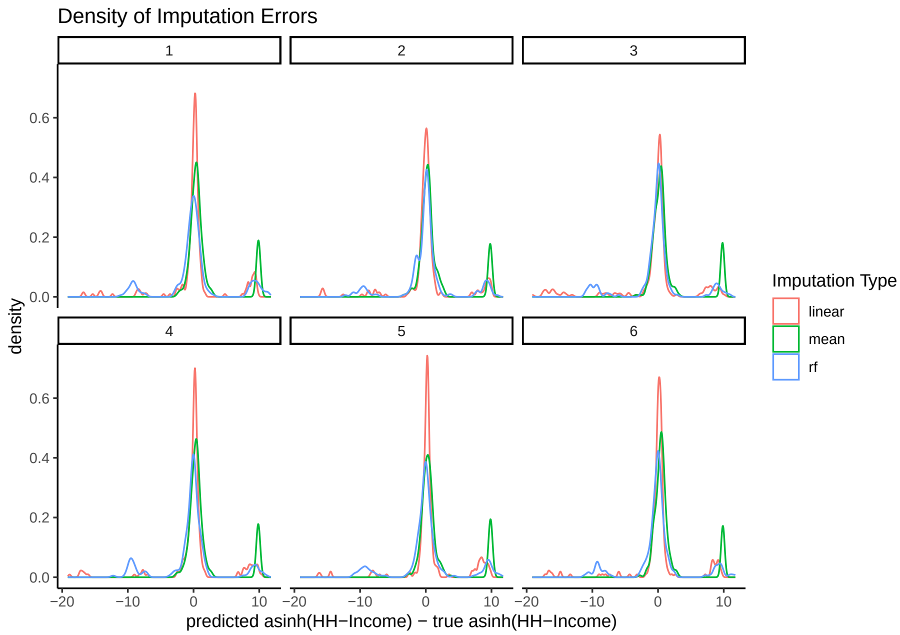


(b) Household Income



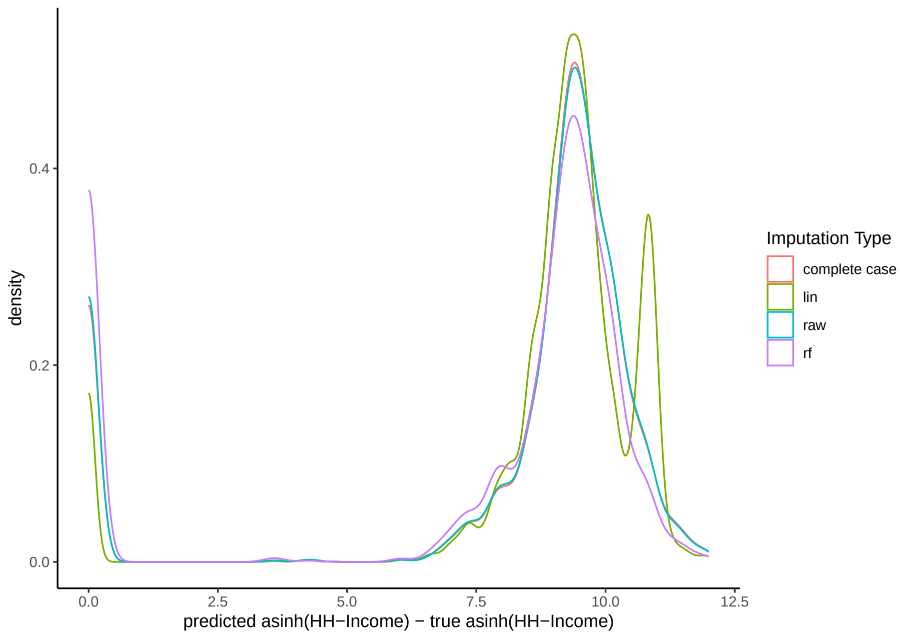
Notes: This figure plots the density histogram of the raw data distribution of weekly personal and household incomes (in 1000s Rps), with our preferred inverse hyperbolic-sine `asinh` transformation.

Figure F.2: Distribution of Test Imputation Predictions and Errors



Notes: For 6 different test datasets with amputed household income data, and using three different imputation methods (linear prediction, unconditional mean imputation, and random forest imputation) this figure plots the density of the error distributions.

Figure F.3: Distribution of observed values of weekly household income in raw data



Notes: This figure plots three distributions of weekly household incomes (in 1000s Rps), with our preferred inverse hyperbolic-sine `asinh` transformation. The green line is the raw data, the blue line is if we use our full random forest imputation procedure to create a single completed dataset, and the orange is if we use our full imputation procedure, but with linear prediction instead of random forest, to create to create a single completed dataset.

F.2 Variables Chosen For Multiple Imputation

To choose the variables which we use for multiple imputation, we look at the entire space of 63 individual level covariates collected for any of the 2645 individuals contacted. We then observe that, excluding Household income which we intend to be the centraltarget of our multiple imputation, there are only two variables (hours per day masks were worn and whether masks look strange) with more than 800 respondent's missing values (2507 and 857 missing respectively). All other covariates having fewer than 75 missing respondent values (i.e. $< 3\%$ of all respondents missing) . Thus, in our process of multiple imputation we only exclude these two variables with significant missing percentages, and include the remaining 61 in our MICE algorithm. We similarly include these 61 variables and surveyor fixed effects to predict attrition in a cross-validated relaxed lasso to generate attrition inverse probability weights.

F.3 Results using Alternate Imputation Method

Table F.1: MWTP Heterogeneity – Linear Prediction

	Annual Household Income (USD)			Gender		Years of School		
	0	10,000	18,000	Female	Male	0	8	15
Information = 0	1.14	2.06	2.58					
	(4.61)	(4.60)	(5.39)					
Information = 1	5.13	7.67*	9.11*					
	(4.49)	(4.43)	(5.26)					
p-value of difference	0.129	0.002	0.003					
Information = 0				−1.10	3.44			
				(4.16)	(4.87)			
Information = 1				6.14	6.41			
				(3.86)	(4.96)			
p-value of difference				0.001	0.211			
Information = 0						−6.14	2.00	12.70**
						(4.44)	(3.97)	(5.63)
Information = 1						3.36	7.32*	12.54**
						(4.42)	(3.90)	(5.61)
p-value of difference						$< .001$	0.003	0.956

Note: This table is similar to table 4. Here we show results from a single dataset where linear regression is used to impute missing values rather than random forest.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

F.4 Results using Raw Data

Table F.2: MWTP Heterogeneity – Raw Data

	Annual Household Income (USD)			Gender		Years of School		
	0	10,000	18,000	Female	Male	0	8	15
Information = 0	4.66	6.65	7.86					
	(5.61)	(5.82)	(7.58)					
Information = 1	5.81	12.17**	16.05**					
	(5.43)	(5.88)	(8.05)					
p-value of difference	0.748	0.034	0.039					
Information = 0				−1.10	3.44			
				(4.16)	(4.87)			
Information = 1				6.14	6.41			
				(3.86)	(4.96)			
p-value of difference				0.001	0.211			
Information = 0						−6.14	2.00	12.70**
						(4.44)	(3.97)	(5.63)
Information = 1						3.36	7.32*	12.54**
						(4.42)	(3.90)	(5.61)
p-value of difference						$< .001$	0.003	0.956

Note: This table is similar to table 4. Here we show results from a single dataset where we drop observations missing household income. Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.

F.5 Results using Personal Income

Table F.3: MWTP Heterogeneity – Personal Income

	Annual Personal Income (USD)			Gender		Years of School		
	0	10,000	18,000	Female	Male	0	8	15
Information = 0	0.08	6.33	10.84					
	(4.17)	(6.20)	(9.13)					
Information = 1	5.36	13.63**	19.62**					
	(3.89)	(6.56)	(9.93)					
p-value of difference	0.007	0.046	0.163					
Information = 0				−1.10	3.44			
				(4.16)	(4.87)			
Information = 1				6.14	6.41			
				(3.86)	(4.96)			
p-value of difference				0.001	0.211			
Information = 0						−6.14	2.00	12.70**
						(4.44)	(3.97)	(5.63)
Information = 1						3.36	7.32*	12.54**
						(4.42)	(3.90)	(5.61)
p-value of difference						$< .001$	0.003	0.956

Note: This table is similar to table 4. Here we show results from a single dataset where we use personal income rather than household income.Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.

G Additional Specifications

G.1 Heterogeneity by Income, Gender, and Education

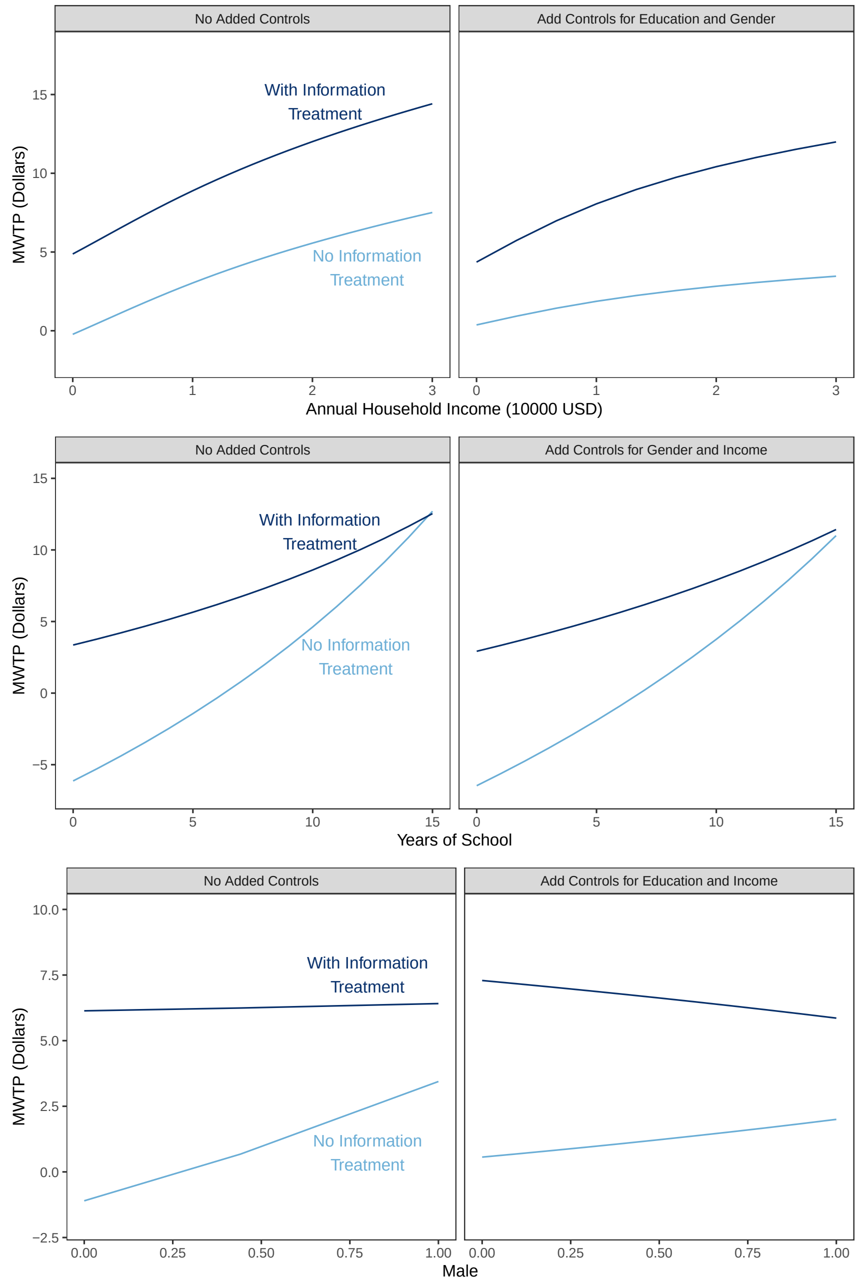
Let h_i be the covariate of interest for individual i. We modify the mask takeup decision in Eq. (4) as follows:

$$\begin{aligned}\text{Takeup}_{it} &= 1\{\alpha_i - \beta_i p_{it} + \gamma_i \text{PM2.5}_t + \phi_{st} + e_{it} > 0\},\\ c_i \mid \{\chi_{ij}\}_{j=0}^{T} &\sim_{iid} \mathcal{N}(0, \sigma_c^2)\\ \alpha_i &= \alpha_0 + \alpha_1 h_i \\ \beta_i &= \beta_0 + \beta_1 h_i \\ \gamma_i &= \gamma_0 + \gamma_1 h_i\end{aligned} \tag{7}$$

The modified expression of MWTP is therefore a function of h_i:

$$\text{MWTP}|_{h=h_i} = \frac{\gamma_0 + \gamma_1 h_i}{\beta_0 + \beta_1 h_i} \times \frac{1}{0.9} \times \frac{24}{1.8} \times \frac{365}{7}. \tag{8}$$

Figure G.1: Heterogeneity in MWTP Controlling for Other-Covariate Interactions



Notes: In each panel we allow MWTP to vary by one of three covariates (income, education, gender), while integrating over the sample distribution of the other two covariates. The overall specification allows sensitivity to price, pm, pm x info to vary by each of the three covariates.

G.2 Instrumenting Past Takeup

We use the **minimum** price of all past offers instead of just the previous price as it is a stronger instrument for takeup in **any** previous round, and equally satisfactory with respect to the exclusion restriction. We use the control function approach in Train (2009) to include the residuals in the following first-stage regression into Eq. (6):

$$\text{Past Takeup}_{it} = \alpha_1 - \beta_1 \text{Min Past Price}_i + \eta_1 X_i + \epsilon_{1it}, \tag{9}$$

This is an approximation of the true equation for Past Takeup$_{it}$ = $\max\left\{\{\text{takeup}_{ij}\}_{j=0}^{t-1}\right\}$ as it both a linear probability model and does not recognize the true dynamic nature of the model.

H Assorted Tables

H.1 LPM Models

Table H.1: The Demand for Clean Air – Fixed Effects

	Logit		LPM		
	(1)	(2)	(3)	(4)	(5)
Model Coefficients					
Price (USD)	−1.818***	−1.823***	−0.259***	−0.257***	−0.254***
	(0.096)	(0.093)	(0.008)	(0.008)	(0.008)
$PM_{2.5}$ ($10\mu g/m^3$)	0.012	0.015	0.002	0.001	0.000
	(0.011)	(0.012)	(0.002)	(0.002)	(0.002)
× Information		0.008	0.001	0.002**	0.003
		(0.005)	(0.001)	(0.001)	(0.002)
Information					−0.009
					(0.030)
Marginal Willingness to Pay per annual $10\mu g/m^3$ $PM_{2.5}$ (USD)					
Information = 0	4.49	5.51	5.37	2.13	1.07
	(4.11)	(4.17)	(4.73)	(4.52)	(4.90)
Information = 1		8.31**	8.37*	7.88*	7.89*
		(3.94)	(4.52)	(4.49)	(4.22)
p-value of difference		0.162	0.221	0.011	0.136
Round FEs		Yes	Yes		
Surveyor-by-Round FEs	Yes			Yes	Yes
LASSO Controls					Yes
Observations	6,465	6,465	6,465	6,465	6,465

Note: This table is similar to table 2. Column 1 fits a logit model with no interaction between $PM_{2.5}$ and the information treatment. The MWTP indicated by "Information = 0" is the MWTP for the full sample. Column 2 includes round fixed effects rather than surveyor-by-round fixed effects. Columns 3 and 4 compare LPM estimates with round fixed effects and surveyor-by-round fixed effects. Column 5 includes information as a demand level-shifter and LASSO controls. Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.

H.2 14 day average PM over city

Table H.2: The Demand for Clean Air – 14 day $PM_{2.5}$

	Logit			LPM	
	(1)	(2)	(3)	(4)	(5)
Model Coefficients					
Price (USD)	−1.827***	−1.864***	−1.865***	−0.254***	−0.263***
	(0.094)	(0.090)	(0.090)	(0.008)	(0.012)
$PM_{2.5}$ ($10\mu g/m^3$)	0.014	0.008	−0.003	0.001	−0.001
	(0.016)	(0.016)	(0.018)	(0.002)	(0.003)
× Information	0.016***	0.015***	0.035**	0.002***	0.003***
	(0.005)	(0.005)	(0.014)	(0.001)	(0.001)
Information			−0.380		
			(0.249)		
Marginal Willingness to Pay per annual $10\mu g/m^3$ $PM_{2.5}$ (USD)					
Information = 0	5.09	2.74	−1.00	3.23	−1.98
	(6.09)	(5.72)	(6.52)	(6.10)	(7.77)
Information = 1	10.91*	8.06	11.68*	8.91	6.62
	(6.15)	(5.78)	(6.01)	(6.27)	(7.75)
p-value of difference	0.002	0.003	0.015	0.007	0.007
Surveyor-by-Round FEs	Yes	Yes	Yes	Yes	Yes
Individual FEs					Yes
LASSO Controls		Yes	Yes	Yes	
Observations	6,465	6,465	6,465	6,465	6,465

Note: This table is similar to table 2 except that $PM_{2.5}$ is averaged over the last 14 days rather than over the last day. Statistical significance indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H.3 7 day average PM over city

Table H.3: The Demand for Clean Air – 7 day $PM_{2.5}$

	Logit			LPM	
	(1)	(2)	(3)	(4)	(5)
Model Coefficients					
Price (USD)	−1.827***	−1.863***	−1.864***	−0.255***	−0.263***
	(0.094)	(0.090)	(0.090)	(0.008)	(0.012)
$PM_{2.5}$ ($10\mu g/m^3$)	0.007	−0.001	−0.009	0.000	−0.001
	(0.012)	(0.011)	(0.014)	(0.002)	(0.002)
× Information	0.016***	0.015***	0.032**	0.002***	0.003***
	(0.005)	(0.005)	(0.013)	(0.001)	(0.001)
Information			−0.315		
			(0.227)		
Marginal Willingness to Pay per annual $10\mu g/m^3$ $PM_{2.5}$ (USD)					
Information = 0	2.50	−0.20	−3.36	1.14	−3.51
	(4.30)	(3.93)	(4.96)	(4.42)	(5.92)
Information = 1	8.41**	5.28	8.15**	6.97	5.15
	(4.14)	(3.81)	(3.93)	(4.38)	(6.09)
p-value of difference	0.001	0.002	0.014	0.005	0.006
Surveyor-by-Round FEs	Yes	Yes	Yes	Yes	Yes
Individual FEs					Yes
LASSO Controls		Yes	Yes	Yes	
Observations	6,465	6,465	6,465	6,465	6,465

Note: This table is similar to table 2 except that $PM_{2.5}$ is averaged over the last 7 days rather than over the last day. Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.

H.4 1 day average over respondent location

Table H.4: The Demand for Clean Air – Respondent Location

	Logit			LPM	
	(1)	(2)	(3)	(4)	(5)
Model Coefficients					
Price (USD)	−1.820***	−1.857***	−1.857***	−0.254***	−0.262***
	(0.094)	(0.090)	(0.090)	(0.008)	(0.012)
$PM_{2.5}$ ($10\mu g/m^3$)	0.000	0.000	0.000	0.000	0.001
	(0.011)	(0.010)	(0.013)	(0.001)	(0.002)
× Information	0.014***	0.013***	0.013	0.002***	0.003***
	(0.005)	(0.005)	(0.011)	(0.001)	(0.001)
Information			0.001		
			(0.204)		
Marginal Willingness to Pay per annual $10\mu g/m^3$ $PM_{2.5}$ (USD)					
Information = 0	0.18	0.05	0.05	1.19	1.34
	(4.23)	(3.82)	(4.61)	(3.72)	(4.04)
Information = 1	5.22	4.80	4.79	6.53*	8.98**
	(3.95)	(3.69)	(3.56)	(3.74)	(3.99)
p-value of difference	0.007	0.007	0.248	0.009	0.011
Surveyor-by-Round FEs	Yes	Yes	Yes	Yes	Yes
Individual FEs					Yes
LASSO Controls		Yes	Yes	Yes	
Observations	6,465	6,465	6,465	6,465	6,465

Note: This table is similar to table 2 except that $PM_{2.5}$ is averaged over the last day at the respondent's location rather than over the full city. Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.

H.5 Restricted to Multiple Respondent Sample

Table H.5: The Demand for Clean Air – Multiple Observations

	Logit			LPM	
	(1)	(2)	(3)	(4)	(5)
Model Coefficients					
Price (USD)	−1.816***	−1.852***	−1.852***	−0.252***	−0.262***
	(0.097)	(0.093)	(0.093)	(0.008)	(0.012)
$PM_{2.5}$ ($10\mu g/m^3$)	0.010	0.008	0.006	0.001	0.001
	(0.012)	(0.012)	(0.014)	(0.002)	(0.002)
× Information	0.013**	0.013**	0.017	0.002**	0.003***
	(0.005)	(0.005)	(0.012)	(0.001)	(0.001)
Information			−0.068		
			(0.213)		
Marginal Willingness to Pay per annual $10\mu g/m^3$ $PM_{2.5}$ (USD)					
Information = 0	3.77	2.84	2.26	2.95	1.57
	(4.46)	(4.19)	(5.05)	(4.26)	(4.41)
Information = 1	8.66**	7.67*	8.35**	8.06*	10.02**
	(4.29)	(4.07)	(4.09)	(4.32)	(4.38)
p-value of difference	0.016	0.013	0.174	0.027	0.005
Surveyor-by-Round FEs	Yes	Yes	Yes	Yes	Yes
Individual FEs					Yes
LASSO Controls		Yes	Yes	Yes	
Observations	6,053	6,053	6,053	6,053	6,053

Note: This table is similar to table 2 except that the sample is subsetted to only include respondents that are observed multiple times in the data. Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.

H.6 Attrition Weighted

Table H.6: The Demand for Clean Air – Attrition Weighted

	Logit			LPM	
	(1)	(2)	(3)	(4)	(5)
Model Coefficients					
Price (USD)	−1.816***	−1.853***	−1.852***	−0.255***	−0.263***
	(0.095)	(0.091)	(0.091)	(0.008)	(0.012)
$PM_{2.5}$ ($10\mu g/m^3$)	0.007	0.004	0.003	0.001	0.001
	(0.012)	(0.012)	(0.014)	(0.002)	(0.002)
× Information	0.013***	0.013***	0.017	0.002**	0.003***
	(0.005)	(0.005)	(0.011)	(0.001)	(0.001)
Information			−0.074		
			(0.201)		
Marginal Willingness to Pay per annual $10\mu g/m^3$ $PM_{2.5}$ (USD)					
Information = 0	2.46	1.63	1.00	2.17	1.74
	(4.52)	(4.23)	(5.04)	(4.06)	(4.49)
Information = 1	7.38*	6.33	7.08*	7.31*	10.23**
	(4.33)	(4.08)	(3.99)	(4.12)	(4.44)
p-value of difference	0.008	0.007	0.138	0.014	0.005
Surveyor-by-Round FEs	Yes	Yes	Yes	Yes	Yes
Individual FEs					Yes
LASSO Controls		Yes	Yes	Yes	
Observations	6,465	6,465	6,465	6,465	6,465

Note: This table is similar to table 2 except that observations are weighted by the inverse of the probability of staying in the sample. We compute attrition weighting using LASSO regression. Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.

I The Health Impacts of Mask Distribution

In model estimates, we find that demand for clean air and pollution masks are modest. What drives ex-ante consumer surplus from mask receipt? By exploiting our randomized assignment of pollution mask offers, we can estimate the effects of masks on ex-post short-run health outcomes. For individual i in round t we estimate

$$Y_{i,t} = \alpha + \beta \text{Takeup}_{i,t-1} + \text{HInfo}_{i,t-1} + X_i'\eta + \delta_t + \epsilon_{it},$$

where Y_{it} is the health outcome in round t, $\text{Takeup}_{i,t-1}$ is whether the individual took up the mask in round $t-1$, X_i is individual-specific controls at baseline, and δ_t is the round fixed effects. Since $\text{Takeup}_{i,t-1}$ might be endogenous, we use indicators of whether the price of mask in round $t-1$ was 0 / 10/ 30 / 50 as instruments for $\text{Takeup}_{i,t-1}$:

$$\text{Takeup}_{i,t-1} = \beta_0 + \sum_{c \in \{0,10,30,50\}} \beta_{1,p} \mathbf{1}[p_{i,t-1} = c] + \text{HInfo}_{i,t-1} + X_i'\beta_2 + \delta_t + \eta_{i,t-1}.$$

We estimate this using Two Stage Least Squares.

We estimate the model using observations in two different samples. First, we include those offered N90 masks at different prices (0, 10, 30, 50) as well as the control group. Second we include the control group and the placebo group

We use a similar specification to estimate the health impact of black masks that were offered in the placebo group. There are two main differences: 1) $\text{Takeup}_{i,t-1}$ is now instrumented with an indicator of whether the individual was assigned to the placebo group; and 2) the model is estimated using observations in the placebo and control group.

Table I.1: Health Impact of Mask Distribution

	Control Mean	Impact of N90 Takeup	Impact of Black Mask Takeup
Panel A: Self-Reported Health Outcomes			
Pollution Symptoms	0.56***	-0.02	-0.01
	(0.02)	(0.02)	(0.04)
	[813]	[3732]	[1142]
Non-Pollution Symptoms	0.46***	0.01	0.10***
	(0.02)	(0.02)	(0.03)
	[813]	[3732]	[1142]
Visited Hospital or Doctor Last 14 Days	0.36***	-0.01	0.03
	(0.02)	(0.02)	(0.04)
	[813]	[3732]	[1142]
Arcsinh(Hospital or Doctor Expenditures)	2.16***	0.01	0.27
	(0.13)	(0.15)	(0.27)
	[813]	[3723]	[1142]
Panel B: Biometric Health Outcomes			
Resting Heart Rate (BPM)	84.56***	-1.53**	0.27
	(0.73)	(0.72)	(1.46)
	[437]	[1925]	[599]
Systolic Blood Pressure	127.41***	-1.36	0.10
	(1.23)	(1.27)	(2.02)
	[429]	[1871]	[589]
Diastolic Blood Pressure	85.13***	-0.60	-1.37
	(0.79)	(0.82)	(1.46)
	[429]	[1870]	[589]
Blood Oxygen (%)	97.38***	-0.08	-0.02
	(0.18)	(0.19)	(0.31)
	[430]	[1902]	[588]
Peak Flow Lung Capacity (L/Min)	252.43***	5.06	-6.28
	(6.79)	(6.44)	(10.99)
	[412]	[1754]	[559]

Notes: Panel A reports the average of self-reported health outcomes in the control group in rounds 2, 3, and 4 and the estimated impact of N90 and black mask takeup in round $t-1$ on these outcomes in round t for $t = 2, 3$, and 4 from an IV regression as in equation (-). Panel B reports the average biometric health outcomes in the control group from round 2 and 4 and the estimated impact of N90 and black mask takeup from round $t-1$ on these outcomes in round t for $t = 2$ and 4. N90 mask takeup in last round is instrumented by indicators of whether the mask price in last round was 0/10/30/50 Rs. Black mask takeup in last round is instrumented by indicators of whether the individual is assigned to the placebo group. We assign each arm sample weights proportional to the inverse of the number of observations from that arm in that round. As a result, all arms receive equal weight inside each round. Standard errors are clustered at the level of treatment assignment (sampling point × round). Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.

We find that the provision of inexpensive pollution masks has little impact on short-run health outcomes. This seems to be driven by low self-reported usage of masks in the weeks following mask takeup: those who takeup the free mask offer report using the mask for 1.8 hours per day for 8 days. This suggests that total reductions in pollution exposure may be small for the average individual. Our sample may not have enough power to detect small differences in short-run health that would be expected with such a small reduction in air pollution exposure.

In addition, whatever value does exist in masks is a potentially large vector of short- and long-run health and productivity impacts. We test only a small subset of these potential outcomes. It is possible that (i) gains exist among unobserved dimensions and/or (ii) our sample is under-powered to detect small effects among measured dimensions. Overall, however, these results are consistent with our demand estimates which suggest MWTP and consumer surplus from mask receipt is modest.

Lastly, another interpretation of little changes to short-term health is individual disbelief in mask effectiveness. That is, if individuals do not think masks will filter $PM_{2.5}$ and improve health, they will not use them ex-post and thus experience no short-term health gain. However, as described earlier, our model parameter estimates of $\gamma > 0$ suggest that, indeed, individuals have higher demand at higher pollution levels (though imprecise), which yields a positive point estimate of MWTP. We further find that the implied one-year VSL from our MWTP estimate is roughly 19% of annual household income in our sample, similar to that of Ito and Zhang (2020).[37] This suggests that individuals are, on average, interpreting masks as defensive investments against air pollution and its associated health damages.

37. As in Ito and Zhang (2020), we can compute the implied one-year VSL from the MWTP estimate in this paper using prior estimates of the life expectancy reductions associated with $PM_{2.5}$ (Ebenstein et al. 2017).

Table I.2: Pollution vs. Non-Pollution Health Symptoms in Survey

Symptom	Air pollution related	Source (if pollution related)
Headaches	TRUE	Mukamal et. al. (2009)
Dizziness	TRUE	Künzli et. al. (2000)
Increased fatigue	TRUE	Lei et. al. (2016)
Vision impairment	FALSE	
Skin rashes	FALSE	
Joint pain	FALSE	
Numbness or tingling in hands	FALSE	
Coughing or wheezing	TRUE	Ostro (2004), Duflo et al. (2008), Afroz et al. (2003)
Stomach ache	FALSE	
Shortness of breath / chest tightness	TRUE	Ostro (2004)
Burning eyes	TRUE	Afroz et al. (2003), Guttikunda and Goel (2013)
Nausea	FALSE	
Fever	TRUE	Lei et. al. (2016)
Toothaches	FALSE	
Hearing impairment	FALSE	
Phlegm	TRUE	Ostro (2004), Afroz et al. (2003)

Notes: This table describes the construction of pollution and non-pollution related symptoms. We report various symptoms and whether or not they are related to pollution (and sources if so).

J Government Mask Distribution

Fig. J.1 documents a tweet released by Chief Minister of Delhi Arvind Kejriwal announcing the mask distribution program in 2019.

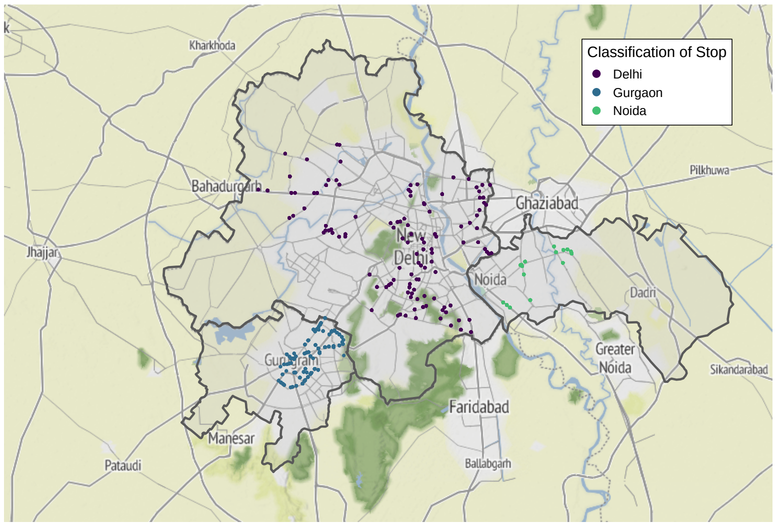
Figure J.1: Chief Minister of Delhi Tweets About Mask Distribution Campaign

Note: This figure shows a Twitter post by Chief Minister Arvind Kejriwal announcing the government mask distribution program of 5 million pollution masks in November 2019. Pictures show two masks being distributed to each child at a Delhi government school.

J.1 Sampling Procedure

The secondary sample, which we refer to as "public bus commuters" ($n = 2{,}110$), was created later in 2019 and captures individuals who use the public bus system in Delhi, and its neighboring cities Gurgaon and Noida, used for constructing a control group. To create this sample, we randomly selected 120 bus stops operated by the Delhi Transport Corporation, 18 bus stops from routes operated by the Noida Metro Rail Corporation, and 79 bus stops from routes operated by Gurgaon Metropolitan City Bus Limited. These three organizations comprise the universe of all bus stops in these three cities. Upon arriving at the bus stop, the enumerator would survey every other individual waiting at the bus stop with a small survey incentive of 50Rs ($0.73 USD). This sampling process was carried out between October and December 2019.

Figure J.2: Bus Stops Classifications in Secondary Sample



Notes: This figure maps the bus stops in Delhi (blue) and in Non-Delhi (black), where surveys were conducted for the secondary analysis of the Delhi government mask distribution campaign. Neighboring "Non-Delhi" regions include Gurgaon to the south and Noida to the east.

J.1.1 Location definition

We collect two possible location variables for whether respondents are exposed to the Delhi government mask distribution campaign. The first is the "home" address (whether the respondent has lived in Delhi for the last 10 years or more); the second is the "stop" location (where the bus stop is in Delhi). Because the mask distribution campaign offered masks to children attending schools, we use the home definition to split our sample between the Delhi and the non-Delhi sample. We provide estimates for both definitions below, and are qualitatively similar.

J.1.2 Balance

Table J.1: Secondary Sample: Delhi vs Non-Delhi (Home Definition)

	Non-Delhi (1)	Delhi (2)	p-value (3)
Age	34.31	37.34	<0.01
Female (%)	0.26	0.29	<0.01
Completed Secondary School (%)	0.59	0.60	0.31
Employed (%)	0.81	0.78	0.07
Annual Income (USD)	9,084.48	8,057.83	0.36
Obs.	1,486	3,269	

Notes: This table describes the mean of selected characteristics for the Non-Delhi and the Delhi sample using the "home" definition (column 1 and 2, respectively). Column 3 reports a p-value of test of equality across means of the given variable from the two samples.

Table J.2: Secondary Sample: Delhi vs Non-Delhi (Stop Definition)

	Non-Delhi (1)	Delhi (2)	p-value (3)
Age	36.55	36.18	0.26
Female (%)	0.24	0.34	<0.01
Completed Secondary School (%)	0.59	0.62	0.03
Employed (%)	0.73	0.87	<0.01
Annual Income (USD)	7,221.98	9,902.15	0.01
Obs.	2,747	2,016	

Notes: This table describes the mean of selected characteristics for the Non-Delhi and the Delhi sample using the "stop" definition (column 1 and 2, respectively). Column 3 reports a p-value of test of equality across means of the given variable from the two samples.

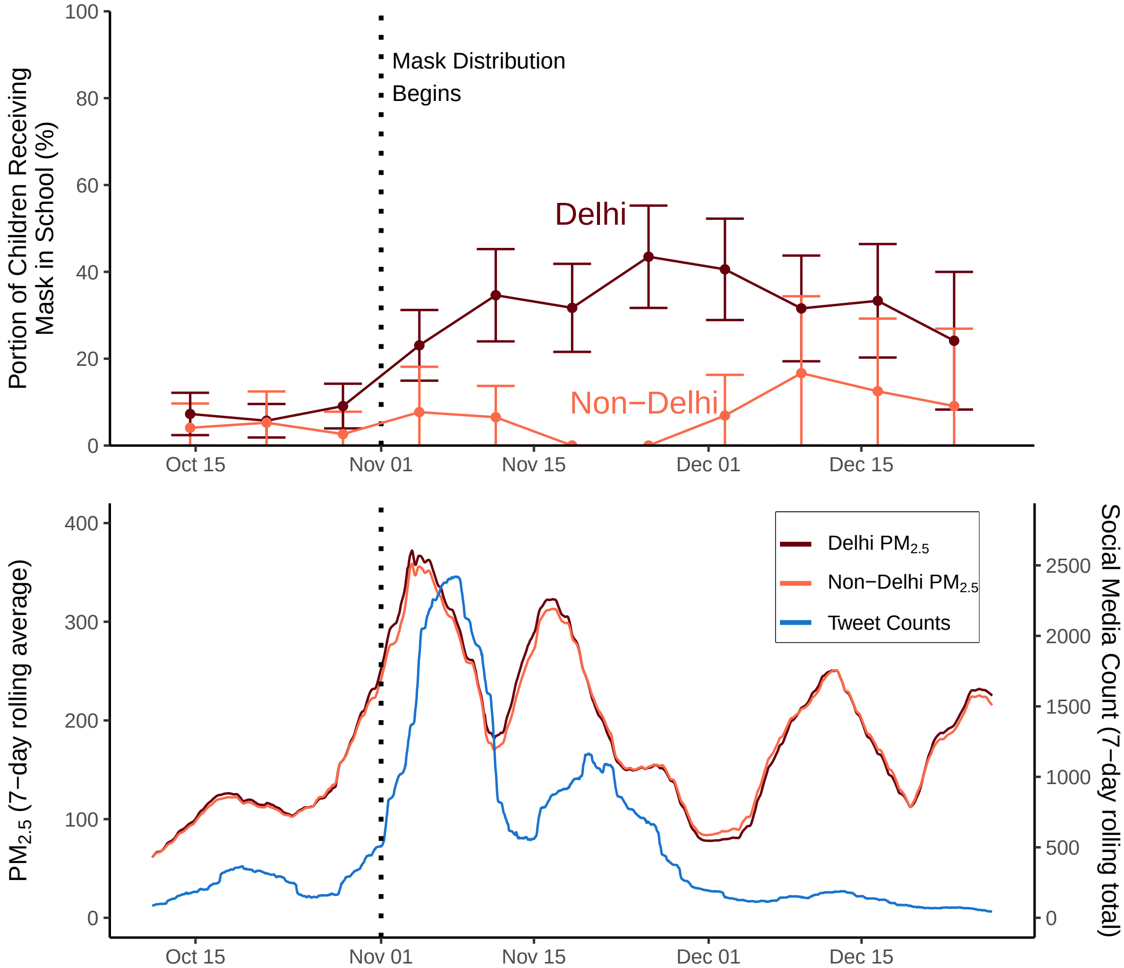
J.2 Difference-in-difference Analysis

We estimate the effect of the mask distribution policy using a difference-in-differences specification of the following form:

$$Y_{it} = \alpha_T 1(i \text{ in Delhi}) + \sum_{s=-3}^{7} \delta_s 1(t = s) + \sum_{s=-3}^{7} \beta_s 1(i \text{ in Delhi}) * 1(t = s) + \epsilon_{it} \tag{10}$$

where Y_{it} is an outcome of interest for individual i at week t. We include week fixed effects (δ_s) and allow the treatment effects (β_s) to vary among weeks. We use $s \in [-3, 7]$ to denote the event-time relative to the first week of treatment. For example, $s = -1$ is the last week of the pre-treatment period and $s = 0$ is the first week of treatment. We normalize $\beta_{-1} = 0$ so that all other β_s are treatment effects relative to the the last week of the pre-treatment period. We cluster the standard errors at the bus-stop level.

Figure J.3: Rollout of Government Mask Program

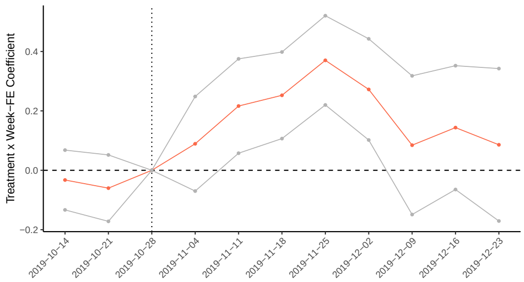


Notes: This figure plots weekly averages for children's mask receipt (fraction of children receiving a mask in school) from our repeated cross-sectional surveys of respondents in both Delhi and Non-Delhi. Here, the sample was split between the Delhi and Non-Delhi sample with the "home" definition.

Figure J.4: DID Estimates of the Government Mask Distribution Program

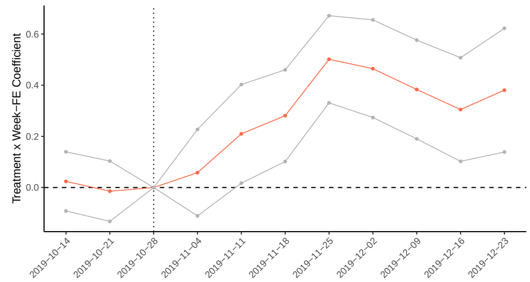
(a) Children's Mask Receipt

(Home Definition)



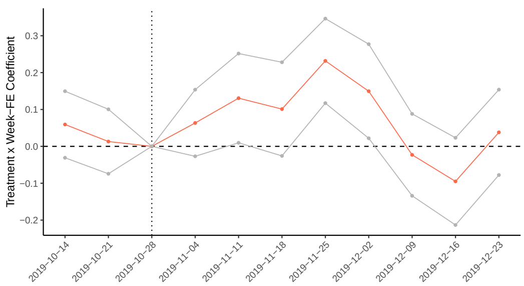
(b) Children's Mask Receipt

(Stop Definition)



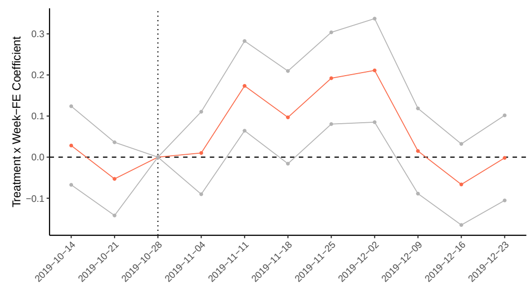
(c) Self-reported Mask Usage

(Home Definition)



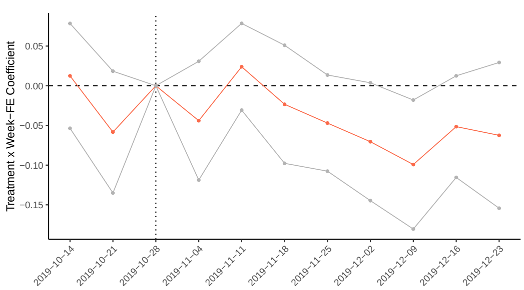
(d) Self-reported Mask Usage

(Stop Definition)



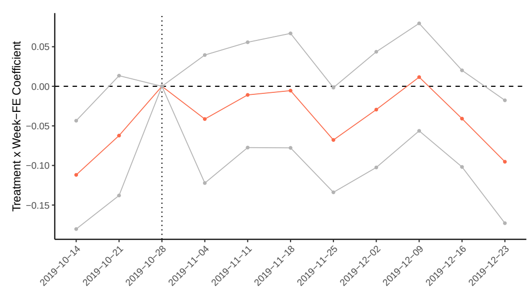
(e) Take Up

(Home Definition)



(f) Take Up

(Stop Definition)



Notes: The figure reports the estimated treatment effects (blue) from the DID specification in Eq. (10) for different binary outcome variables across definitions. "Children's Mask Receipt" is whether the respondent's children received a mask through the government policy. "Self-reported Mask Usage" is whether the respondent used a mask in the past week. "Take Up" is whether the respondent took up the mask offer (10INR or 30INR, randomized). 95% confidence intervals (black) are clustered at the bus stop level.

Table J.3: DID Estimates of Government Mask Distribution (Home Definition)

	Children's Mask Receipt (1)	Self-Reported Mask Usage (2)	Take Up (3)
t - 3	−0.033	0.059	0.012
	(0.051)	(0.046)	(0.034)
t - 2	−0.060	0.013	−0.058
	(0.057)	(0.045)	(0.039)
t	0.089	0.063	−0.044
	(0.081)	(0.046)	(0.038)
t + 1	0.216***	0.131**	0.024
	(0.081)	(0.062)	(0.028)
t + 2	0.252***	0.101	−0.023
	(0.074)	(0.065)	(0.038)
t + 3	0.370***	0.232***	−0.047
	(0.077)	(0.058)	(0.031)
t + 4	0.272***	0.150**	−0.071*
	(0.087)	(0.065)	(0.038)
t + 5	0.085	−0.023	−0.099**
	(0.119)	(0.057)	(0.041)
t + 6	0.144	−0.095	−0.051
	(0.106)	(0.060)	(0.033)
t + 7	0.086	0.038	−0.062
	(0.131)	(0.059)	(0.047)
Observations	1,243	4,745	4,755

Notes: The table reports the estimated treatment effects from the DID specification in crefeq: DID for different binary outcome variables using the "Home" definition. "Children's Mask Receipt" is whether the respondent's children received a mask through the government policy. "Self-reported Mask Usage" is whether the respondent used a mask in the past week. "Take Up" is whether the respondent took up the mask offer (10INR or 30INR, randomized). Standard errors in parenthesis are clustered at the bus stop level. Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.

Table J.4: DID Estimates of Government Mask Distribution (Stop Definition)

	Children's Mask Receipt (1)	Self-Reported Mask Usage (2)	Take Up (3)
t - 3	0.024	0.028	−0.112***
	(0.059)	(0.049)	(0.035)
t - 2	−0.014	−0.053	−0.062
	(0.060)	(0.045)	(0.039)
t	0.058	0.010	−0.041
	(0.086)	(0.051)	(0.041)
t + 1	0.210**	0.173***	−0.011
	(0.098)	(0.056)	(0.034)
t + 2	0.281***	0.097*	−0.005
	(0.091)	(0.058)	(0.037)
t + 3	0.501***	0.192***	−0.068**
	(0.087)	(0.057)	(0.034)
t + 4	0.465***	0.211***	−0.029
	(0.097)	(0.064)	(0.037)
t + 5	0.383***	0.015	0.012
	(0.098)	(0.053)	(0.035)
t + 6	0.305***	−0.066	−0.041
	(0.103)	(0.050)	(0.031)
t + 7	0.381***	−0.002	−0.095**
	(0.123)	(0.053)	(0.040)
Observations	1,243	4,751	4,763

Notes: The table reports the estimated treatment effects from the DID specification in crefeq: DID for different binary outcome variables using the "Stop" definition. "Children's Mask Receipt" is whether the respondent's children received a mask through the government policy. "Self-reported Mask Usage" is whether the respondent used a mask in the past week. "Take Up" is whether the respondent took up the mask offer (10INR or 30INR, randomized). Standard errors in parenthesis are clustered at the bus stop level. Statistical significance indicated by * p <0.10, ** p <0.05, *** p <0.01.