

Final Report



International
Growth Centre

Coping with COVID-19 in Slums

Evidence from India



Alex Armand
Britat Augsburg
Antonella Bancalari

November 2020

When citing this paper, please
use the title and the following
reference number:
COVID-19-20077-IND-1

DIRECTED BY



FUNDED BY



Final Report

November 2020

Alex Armand^{1,2}, Britta Augsburg² and Antonella Bancalari^{2,3}



Coping with COVID-19 in Slums: Evidence from India

Abstract. One of the most, if not *the* most, at-risk groups of COVID-19 is the urban poor, living in overcrowded conditions with very limited access to public (health) infrastructure. Along these hardships, misinformation about ways to prevent COVID-19 is widespread. In this study, we first evaluate slum dwellers' ability to follow governments' and scientists' advice on mitigation strategies – such as handwashing, social distancing, and the shielding of elderly and vulnerable groups – given the hardships they face on a daily basis. We next study how to debunk fake news and combat misinformation in slums. We conduct a field experiment in the context of slums in Lucknow and Kanpur, Uttar Pradesh, making use of mobile phone technology. We rely on previously collected census data of more than 30,000 households and newly collected surveys rounds through mobile phones for almost 4,000 randomly sampled households. We randomly allocate households to receiving a message from a doctor debunking fake news or not. In addition, we cross-randomize a low or high financial incentive to pay attention to the message through information technologies. We find that due to the COVID-19 crisis, slum dwellers lost their livelihoods and experienced reductions in income. In addition, the majority of slum dwellers were not able to comply with lockdown measures, mostly because of the need to search for a job daily. Hygiene measures improve over time, while willingness to vaccinate decreases. The poorest population was hit the hardest, while those with better knowledge about how to prevent COVID-19 were able to protect better. The results from our experiment suggests that doctors' messages debunking fake news about COVID-19 prevention, conditional on high financial incentives to pay attention, counter misinformation, increase the probability of sharing advice and information about how to prevent COVID-19 with others and self-isolation within slums.

¹ NOVA SBE

² Institute for Fiscal Studies

³ London School of Economics and Political Science

Table of Contents

I.	Introduction and Literature Review	5
II.	Study context.....	8
III.	Data.....	9
III.1.	Data collection	9
III.2.	Measurement.....	11
III.3.	Sampling procedure.....	12
IV.	First component: Coping with COVID-19	12
IV.1.	Economic activity	13
IV.2.	Social distancing.....	17
IV.3.	Handwashing and hygiene	19
IV.4.	Willingness to vaccinate	21
V.	Second component: Debunking Fake News	24
V.1.	Intervention	24
V.1.	Randomisation	25
V.2.	Estimation strategy	26
V.3.	Baseline balance and attrition.....	26
V.4.	Treatment effects	29
VI.	Conclusions and Policy Recommendations	32
VII.	References	34
VIII.	Appendix	37

List of Figures

Figure 1. Study area	9
Figure 2. <i>Timeline of COVID-19 restrictions in Uttar Pradesh</i>	13
Figure 3. Impacts on economic activity	15
Figure 4. Reasons for the last time they left the slum, by dwelling strength.....	18
Figure 5. Distribution of appropriate handwashing times the previous day	20
Figure 6. <i>Willingness to vaccinate when COVID-19 vaccination becomes available</i>	22
Figure 7. Relationship between willingness to pay and other factors.....	23
Figure 8. Potential sources of advice for COVID-19 vaccine, by willingness to pay	24

List of Tables

Table 1. Random allocation of households to modules – Baseline survey	10
Table 2. Results of linear regression on job loss.....	16
Table 3. Results of linear regressions on household incomes for households with job loss. 17	
Table 4. Results of linear regressions on social distancing measures.....	19
Table 5. Results of linear regression on number of appropriate handwashing times the previous day	21
Table 6. Distribution of households across treatment arms	25
Table 7. Sample characteristics and balance at baseline	27
Table 8. Attrition	28
Table 9. Treatment effects on primary outcomes.....	29
Table 10. Treatment effects on knowledge of COVID-19 prevention.....	30
Table 11. Treatment effects on acquiring and disseminating information	31
Table 12. Treatment effects on complying with government guidelines.....	32

Acknowledgments

We would like to thank Julia Loh and Kaylan Kumar for outstanding research assistance.

This project would not have been possible without the generous and insightful help of Bhartendu Trivedi, Yashashvi Singh and Tatheer Fatima, and the team of implementers, field supervisors and enumerators of Morsel Research and Development.

We gratefully acknowledge financial support from the International Growth Centre and the London School of Economics and Political Science through the COVID-19 special calls.

Ethics approval was secured from London School of Economics (REC ref. 1132). The pre-analysis plan was registered on the AEA RCT registry (RCT ID AEARCTR-0006564).

Acronyms

BL	Baseline
CT	Community Toilets
FU	Follow-up
HH	Households
IFS	Institute for Fiscal Studies
ITT	Intention-to-treat
OD	Open defecation
ppts	Percentage points
WASH	Water, Sanitation and Hygiene
WTP	Willingness to pay

I. Introduction and Literature Review

One of the most, if not *the* most, at-risk groups of COVID-19 is the urban poor, living in overcrowded conditions with very limited access to public (health) infrastructure. One billion people live in such settlements (*slums* hereafter), more than half of them in Asia and almost a fifth in India (World Bank 2020). Their ability to follow governments' and scientists' advice on mitigation strategies – such as handwashing and social distancing– has been significantly hampered by the hardships they face on a daily basis, which include lack of access to water and sanitation systems (at home) and overcrowded living conditions (Brown, Ravallion, and van de Walle 2020; Afridi, Dhillon, and Roy 2020). Social distancing is more an aspiration than an attainable reality for urban slum-dwellers (Wasdani & Prasad 2020). Moreover, slum dwellers are in general daily wage earners, which makes them more vulnerable to losing jobs when in lockdown conditions (Corburn, et al., 2020).

Along these hardships, misinformation about ways to prevent COVID-19 is widespread. While fake news spreading misinformation about COVID-19 is a global concern², it is a particular pervasive problem in India³. Examples include that eating vegetarian food can fully protect against the virus, that heat can kill it and that Indians are immune to it.⁴ Such misinformation about ways to prevent coronavirus is circulating in particular through social media.

Fake news may generate utility for some slum dwellers (e.g. eating vegetarian may be easier than keeping social distance), but it also imposes private and social costs by making it more difficult to infer the true state of the pandemic. In the presence of widespread misinformation, slum residents are at risk of falling into a false sense of protection and conduct risky behaviours. Furthermore, the pandemic has forced decision-making to take place under great uncertainty, and evidence suggests that individuals are systematically less risk averse under uncertainty compared to certainty (Callen et al. 2014). In the US, for instance, misinformation transmitted through TV shows generated harmful effects by delaying the adoption of preventive behaviour. Because of the large externalities inherent to this pandemic, just a few viewers' behaviour affected the disease transmission trajectories for the whole population (Bursztyn et al. 2020).

The aim of this study is two-fold: the first component of the study explores slum dwellers' impact of the pandemic on their economic activities and their ability to cope and follow governments' and scientists' advice on mitigation strategies – such as handwashing and social distancing– given the hardships they face on a daily basis. The second component studies how to debunk fake news about COVID-19 in slums, making use of mobile phone technology⁵.

Our study takes place in the context of slums in the cities of Lucknow and Kanpur, Uttar Pradesh. We rely on a census data we collected in 2018 of more than 30,000 households (including geo-codes and mobile phones) located in 142 slums. 1,500 of these households were subsequently interviewed a few more times as part of a completed research study. In this study, we collect two survey rounds from a random subset of the slum population (based on the 2018 census and oversample households from the previous panel survey), a total of

² The issue of fake news surrounding the COVID-19 crisis has been highlighted by UN's Secretary General Antonio Guterres (<https://www.unbonn.org/news/COVID-19-we-are-war-virus-un-secretary-general>).

³ For India, there is evidence of widespread circulation of fake news (<https://qz.com/india/1813845/coronavirus-fake-news-rife-on-indian-facebook-whatsapp-twitter/>).

⁴ The Government of India created a Fact-sheet in a website debunking the most common fake news: <https://transformingindia.mygov.in/COVID-19/?sector=myth-busters&type=en#scrolltothis>

⁵ We note that the scope of the IGC funded research included initially only the first component. Additional funding from LSE allowed for the implementation of both components.

almost 4,000 households. We refer to these survey rounds as baseline and follow-up surveys (pre- and post-intervention aimed at combating fake news) through mobile phones.

Component 1:

We collect information on how slum dwellers are coping with policy responses to mitigate the spread of COVID-19, focusing on three margins: (i) hygiene practices, (ii) containment measures, and (iii) economic activities. We use this data, to generate descriptively knowledge about a population considered most at risk and at the same time one that is rarely captured in surveys, and hence where important knowledge gaps exist. We evaluate levels, changes between lockdown and post-lockdown period, and how slum-dwellers may be differently impacted by and coping with the pandemic based on their characteristics and pre-pandemic situation.

Our first survey round (baseline) took place in March-May 2020, when the country was under lockdown and the two study cities were considered red zones, i.e. under most stringent restrictions. The second survey round was conducted in October-November of 2020, when restrictions were eased –i.e., overall lockdown lifted, offices, supermarkets and entertainment industries re-opened, and only weekend curfews in place.

We find that at the time of the first survey, first lock-down, 2% of households had at least one member who had tested positive for COVID-19, which increased to 5% about 7 months later. During the first lockdown, 41% of households had at least one member that lost their jobs, livelihoods or income sources due to the crisis, which increased to up to 79% at the time of the follow-up survey. 56% of households experienced a fall in their household income when compared to before the crisis, and this figure decreases to 42% during the follow-up survey. Results suggest that households with less educated heads were more likely to experience job loss, and households with members working as casual workers were more likely to face a decrease in income.

Our data further reveals the challenges of keeping social (or physical) distance in slums settings. Main drivers are the overcrowded conditions and the fact that most households rely on shared facilities outside the home for basic needs, including (drinking) water and sanitation places, making it impossible to stay home. Hence, we study the extent to which people stay in the slum where they live. We document that 65% left the slums (mostly to work or find a job) the week prior to the survey and 28% received visitors at the beginning of the lockdown, which increased to 89% and 72%, respectively, after the lockdown restrictions were eased.

We also find that appropriate hand-washing increased throughout the period of study, as well as the acquisition of hygiene items. Notably, better information about ways to prevent COVID-19 is positively associated with these hygiene practices.

We also analyse slum dwellers' willingness to be vaccinated against COVID-19 and find that 95% of slum dwellers were willing to be vaccinated at the beginning of the pandemic. Notably, less than 60% would get the vaccination if they had to pay for it themselves). The willingness to get vaccinated decreased to 86% by the time of the follow-up survey. Willingness to pay for COVID-19 vaccine is positively associated with a better knowledge about COVID-19 prevention, hygiene behaviour and awareness of externalities. More than 80% would rely on advice from doctors to learn about the COVID-19 vaccine.

Component 2:

The government of India, as most other governments in the World, are further seeking information about effective means through which to communicate the right ways to prevent

the spread of this lethal virus. A number of studies explore means to release information constraints that affect public health (Alatas et al. 2019), including specific to COVID-19 (Banerjee, Alsan, et al. 2020). They find that communication technologies and social media can be effective and low-cost tools.

Little however is known how to best design the message to be sent via social media, making sure it is trusted and accurate. Banerjee et al. (2020) find that a message from Nobel-prize winner Abhijit Banerjee reminding individuals in his home state of West-Bengal to comply with COVID-19 policies is effective at improving behaviour, but the external validity of this study is limited. To what extent can we translate this effect to that of receiving information from other types of messengers (e.g., health experts, religious and political leaders, celebrities)? In a pandemic, the key source of information to be trusted is doctors. Hence, our first research question (RQ) adds to filling this knowledge gap by providing evidence on:

RQ1: How effective are doctors' messages to counter misinformation about ways to prevent COVID-19?

To answer this question, we send a random subset of our sample of slum dwellers doctor messages to their mobile phones, debunking fake news, and study whether, and if so how, their beliefs about COVID-19 change due to receiving these messages.

And important challenge in this exercise is that uptake of messages via phone technologies can be extremely low and hence, the effectiveness of these tools limited. In their study in West-Bengal, Banerjee et al. (2020) achieved take up (in terms of opening the message) of only 1.14%, consistent with low rates of other click-through studies (Richardson, Dominowska, and Ragno 2007; Kanich et al. 2009). Hence, we also study:

RQ2: Can higher financial rewards lead to higher uptake of messages and hence be more effective in counteracting misinformation?

To speak to this question, we cross-randomize a financial incentive to listen to and reply to the message (in other words, to pay more attention) through information technologies. Household were allocated to participate in a 'high incentive' lottery, where they could win Rs. 5,000, or a low-incentive lottery, where the winning amount was half (Rs. 2,500).

Our experiment reveals that doctors' messages debunking fake news about ways to prevent COVID-19 can counter misinformation. Receiving a doctors' message increases the probability of disagreeing with fake news about COVID-19 – albeit only when incentivised with the high lottery amount. Interestingly, the impact is found on a fake news not directly addressed by the doctors. While the doctors discussed that “eating vegetarian does not fully protects from COVID-19”, we find that the intervention leads highly incentivised individuals to disagree more strongly with the statement that “Indians have a stronger immune system against the virus”.

At the same time, we find that receiving doctor's message, conditional on a low incentive to pay attention, crowds out private investment in getting informed about how to prevent the virus, as well as the probability of sharing information or advice to somebody about COVID-19. These effects are offset by providing high incentives to paying attention to the doctors' messages. Furthermore, receiving the doctors' messages, conditional on higher financial incentives to pay attention, decreased by 8% over high-incentive control mean the probability of leaving the slum. It is reassuring that a short message by doctors debunking fake news and a low-cost financial incentive can translate into behavioural changes that can save lives

Take-away messages:

Besides closing gaps in the literature, the results of our study are of high policy relevance. First, the description of the impact of the COVID-19 pandemic is useful information for policymakers to understand the evolving consequences of the COVID-19 crisis on the welfare of the most vulnerable population in low- and middle-income countries (LMICs) – a population on which exists limited data. Second, our findings of how, and in particular the low extent to which slum dwellers are able to comply with governments' advise and strict measures provides a warning signal to policymakers, indicating whether the implemented measures in response to the pandemic are well-suited to the most vulnerable groups, while at the same time providing information based on which future decisions can be made. Third, our findings provide guidance on the main trade-off faced globally between stopping the spread of the virus and jeopardising other welfare measures that can lead to an indirect effect on health: economic and daily hardships. Finally, we provide evidence of a low-cost tool (i.e. £0.21 per household to send a voice message and Whastapp chatbot) that policy-makers can use to debunk fake-news in these uncertain times. Low-cost voice and video messages, plus a lottery offering a financial incentive to pay attention, can be effective ways of communicating doctors' and other scientists' advice on how to prevent the spread of the virus.

II. Study context

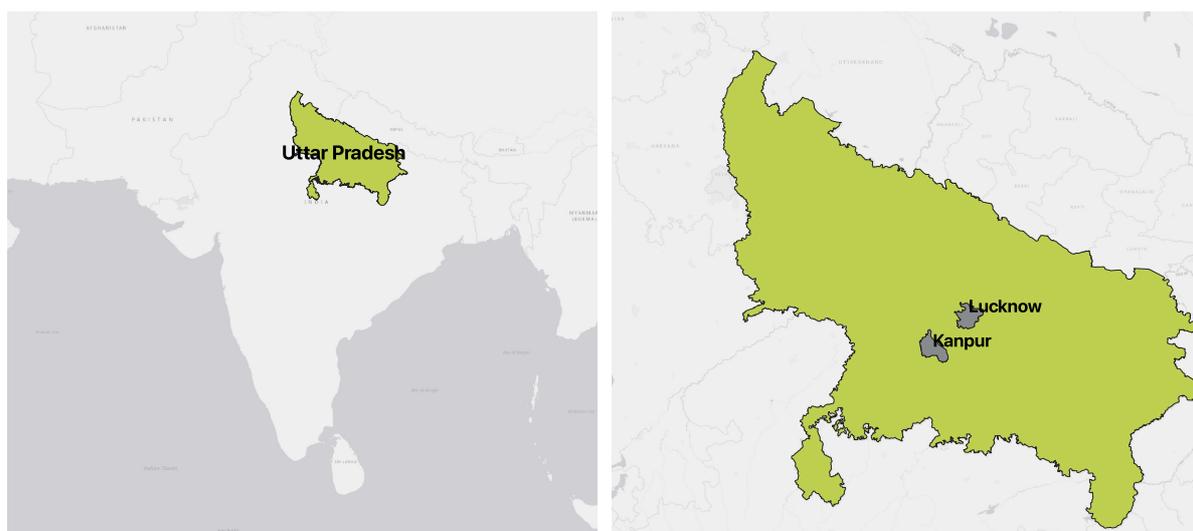
The Indian state of Uttar Pradesh is the largest (home to 200 million people), the 4th most-densely populated, and the 6th in terms of share of population living in slums (corresponding to more than 6 million people) (Ministry of Home Affairs India, 2011).

While Uttar Pradesh presents a higher poverty rate as compared to the average for India (29.43% versus 21.92%) (Reserve Bank of India, 2019), its slum population is highly comparable to the average slum population in the country (see Appendix 1). The share of adult males (0.53 in Uttar Pradesh versus 0.52 in India), of adult females (0.47 versus 0.48), and of children (0.14 versus 0.12), as well as the sex ratio (1.12 versus 1.08) and the share belonging to Scheduled Castes (0.22 versus 0.20) are indicative of close similarities between these two populations. In terms of literacy rates, the average slum in Uttar Pradesh outperforms the one of the whole India (0.69 versus 0.78).

This study focuses on the two largest urban agglomerations of Uttar Pradesh, Lucknow and Kanpur.

Figure 1 shows the geographic location of the study. Similar to many expanding cities in South Asia and Sub-Saharan Africa, Lucknow and Kanpur are characterized by a relatively large prevalence of informal settlements, and a prospect of rapid population growth. In 2015, among all urban agglomerations with more than 300,000 inhabitants, Lucknow and Kanpur were respectively the 129th and 141th worldwide (United Nations, 2018). In the period 2015-2035, Lucknow is expected to grow from 3.2 to 5.2 million (+59%), and Kanpur from 3 to 4.1 million inhabitants (+37%).

Figure 1. Study area



Source: Basemap, Esri.

Across agglomerations of similar size (1.5-4 million inhabitants), this growth prospect is similar to cities such as Accra (Ghana), Amman (Jordan), Jaipur (India), or Hyderabad (Pakistan). Among largest cities, this is similar to Karachi (Pakistan), Cairo (Egypt) or Manila (The Philippines). In terms of slum population, the share of inhabitants living in slums is 12.95% in Lucknow and 14.5% in Kanpur. This is comparable to other major cities in India, such as Delhi, where 14.66% of the urban population live in slums (Ministry of Home Affairs India, 2011).

III. Data

III.1. Data collection

Previously collected data

We recently completed a study in 142 slums. Available data includes a complete census of households within mapped slum borders, implemented in September-December 2017. The census includes basic demographics, access to water and sanitation infrastructure, dwelling characteristics, mobile phone numbers and geo-location of dwellings.

In addition, we collected a detailed household survey before the COVID-19 crisis from a subset of 1,500 slum dwellers located in 110 slums. This sub-set of households is representative of the population that rely on community toilets to fulfil their sanitation needs, either because they lack a private latrine at home, or because at least one member practices open defecation (even when owing a latrine). The data that we use in this study is the detailed baseline data collected between June-September 2018. It includes socio-demographic information, as well as characteristics of the household head, including its level of education, and additional data on sanitation and hygiene behaviour.

Newly collected data

We collect data via phone surveys targeted to the household head, spouse or the most senior household member available. From all respondents, we collect basic socio-demographic characteristics, including age, gender, religion and caste.

We also collect data on respondents' experience during the COVID-19 pandemic, such as their knowledge on how to prevent the virus, risk perceptions, symptoms and testing. Data on the availability of smartphones in the household was also obtained.

We then collected data on four different modules:

- (i) *Sources of information and trust*⁶, which included respondents' trust in various sources of information, information sources about the pandemic and confidence in identifying fake news.
- (ii) *Hygiene and health*, such as respondents' handwashing behaviour and acceptance of a vaccine, as well as household handwashing facilities.
- (iii) *Social distance*, which involved questions on shielding, and physical distancing activity in terms of leaving the slum and receiving outside visitors.
- (iv) *Economic activities*, which collected data on livelihood/job/income losses, and related occupations.

To deal with misreporting, we collect additional information. First, we measure social desirability bias of each respondent based on a short version of the Marlowe-Crowne Social Desirability Scale (Fischer and Fick 1993). Second, we ask respondents to report the behavior of an intimate neighbour similar to them along socio-demographics, which has proven effective for measuring sensitive public health behaviour (Yeatman and Trinitapoli 2011).

In order to collect detailed high-quality data about behaviour, while at the same time balancing the need for a pragmatic, short and concise surveys, we randomly allocate households to one of four modules in the baseline survey: (i) Sources of information and trust; (ii) Hygiene and health; (iii) Social distance; and (iv) Economic activities.

Table 1. Random allocation of households to modules – Baseline survey

Module	Number of households	Percentage (%)
Sources of information and trust	1,590	39.84
Hygiene and health	795	19.92
Social distance	815	20.42
Economic activity	791	19.82
Total	3,991	100.00

To ensure that the survey was concise, the follow-up survey was restricted to the data that is relevant to the intervention carried out (as will be explained in Section III). At follow-up, households allocated to the module on "Sources of information and trust" was randomly allocated to modules (ii), (iii) or (iv), with equal probability.

⁶ This module was included to investigate the process of acquiring information at the baseline, and was moved into the common section of the follow-up survey.

The baseline survey was carried out from June 17 to July 18 2020, while the follow-up survey took place between 01 October and 18 November 2020.

III.2. Measurement

Our analysis, and in particular, the evaluation of the intervention, concentrates on several key outcomes. Indicators particularly helpful to evaluate these key outcomes are as follows. The full list of indicators, along with their definitions, are included in Appendix 3.

Main outcomes:

1. *RQ1: Knowledge about COVID-19 prevention.*
 - This is measured as the extent to which the participant agrees (disagrees) with statements on different confirmed (unconfirmed) ways to prevent COVID-19; and knowledge about COVID-19 symptoms.
2. *RQ2: Exposure to intervention.*
 - Exposure is measured by whether participants listened to messages/watched videos, as well as the extent to which participants recall receiving a message through Whatsapp or voice message related to COVID-19.

Secondary outcomes:

1. *Acquiring and spreading information:*
 - Time spent in acquiring COVID-19 related information; extent of checking truthfulness of news, feeling confident in identifying fake news and discussion about COVID-19 with other people.
2. *Complying with policy guidelines:*
 - Compliance is seen as behaviour related to better hygiene and isolation within the slum (social distance).
3. *Attitudes towards vaccination:*
 - The extent to which the participant is willing to vaccinate (having to pay or not) when the vaccine for COVID-19 becomes available; attitude towards people that don't want to vaccinate.
4. *Risk perception:*
 - The extent to which respondents believe a member of the household can get COVID-19; how anxious they feel about the pandemic.
5. *Trust:*
 - The extent to which participants trust doctors in comparison to people in their State in general.

III.3. Sampling procedure

Within each slum, we sampled up to 60 households, aiming for an average of 30 households per slum. Our sampling procedure is informed by the power calculation used in the previous study registered in the AEA Registry - Number AEARCTR-0003087.

We conduct a two-step sampling procedure. First, we sample only from the households that were part of our initial study (approximately 1,500 study households). This allows us to take advantage of the wealth of data available for these households, as well as to focus specifically on more vulnerable households that are forced to leave daily their dwelling to defecate in community toilets. Second, we sample from all the remaining households in the slums that were not part of the study. To deal with high non-response (given the fact that mobile numbers are from two years ago), we randomly sample replacements. We have 1,234 households sampled in the first step and 2,757 households sampled in the second step (a total of 3,991 households).

We define slums as clusters, having a total of 142 clusters. In total, we survey 3,991 households, with a mean of 28 households per cluster.

IV. First component: Coping with COVID-19

In this section, we describe the situation of the slum population surveyed in our study during the COVID-19 crisis. We also analyzed how slum-dwellers may be differently impacted by the pandemic based on their pre-pandemic situations and highlight the key differences in this section.

We find exposure to COVID-19 comparatively high: we find that 2% of slum households have at least one member who tested positive for COVID-19. During that time period, only 0.2% of India's population had tested positive for COVID-19, and only about 0.3% of the global population. The higher percentage in positive testing can reflect both, greater testing intensity in this vulnerable population and/or their vulnerability to the spread of the virus.

The percentage of households in our sample with at least one member who tested positive for COVID-19 increased to 3% by the time of the follow-up survey in October-November 2020. For comparison, 0.6% of India's population tested positive for COVID-19 at that point in time, similar to the percentage of cases worldwide.

A key reason behind slum-dwellers' higher vulnerability towards COVID-19 may lie in their inability to adhere to guidelines set by the government and public health experts to protect from the virus. The household census that we collected in 2018 clearly shows the overcrowded conditions the slum-dwellers live in: the average slum density is 4,465 households per km² and the average household size is 5 members for a typical single-room dwelling. Further, in-house access to water and sanitation infrastructure is low: 18% of slum households lack a functional latrine at home and 28% have no access to piped water at home. These living situations can cause difficulties in adhering to COVID-19 guidelines of handwashing and physical distancing.

As our study takes place over two survey periods, which are June to August, and October to November 2020, we note that COVID-19 guidelines in Uttar Pradesh have evolved throughout this period. These guidelines provide an important context to our findings about the extent to which slum-dwellers are able to cope with the crisis.

Figure 2 shows that, from late March to the end of May 2020, Lucknow and Kanpur, where the study took place, were placed under lockdown. As COVID-19 hotspots, these cities had stricter lockdowns than other places in India at different times. India has been undergoing a phased relaxing of restrictions under the government’s Unlock initiatives since early June 2020 in all places except for containment zones which are marked within individual districts by state authorities.

The baseline survey, which took place in the months of June and July 2020, was carried out in the context of the start of the easing of restrictions. The follow-up survey in October and November 2020 was done in the context of the relaxation of most of the restrictions –i.e., self-employed allowed to work, offices, super-market and entertainment industries re-opened, and curfews only on weekend. However, guidelines of social distancing and wearing face masks remained constant throughout these periods.

Figure 2. Timeline of COVID-19 restrictions in Uttar Pradesh

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct/ Nov
Guidelines	National lockdown			Unlock 1	Unlock 2	Unlock 3	Unlock 4	Unlock 5
	<i>Lucknow and Kanpur as Red Zones</i>			<i>Red Zone districts split into containment zones</i>				
Closure of businesses	Only essential shops			Offices, super-markets reopen		Entertainment industry reopens		
Stay at home				Only in containment zones within districts				
Curfew				Weekend curfews - markets, offices, non-essential businesses close				
Social distancing	In public places, work places and on transport							
Face coverings	Wearing of face cover compulsory in public and work places							

Source: Ministry of Home Affairs India (2020); Awasthi (2020).

IV.1. Economic activity

It is generally understood that urban slum-dwellers’ economic activities are likely to be massively impacted by lockdown restrictions. This is because most slum dwellers have been found to be informal workers and daily wage-earners, implying little – if any – formal income protection (Corburn et al. 2020). Afridi, Dhillon, and Roy (2020) studied manufacturing workers in industrial estates across Delhi and found that a large majority of respondents who were employed before the lockdown have not earned any income from their main occupations. A majority of the lockdown restrictions had not yet eased during the time of their study which took place in April and May 2020. While our study looks at India at later stages of the crisis

and also focuses on a different subset of the population, we expect such hardships to be relevant for our study sample as well.

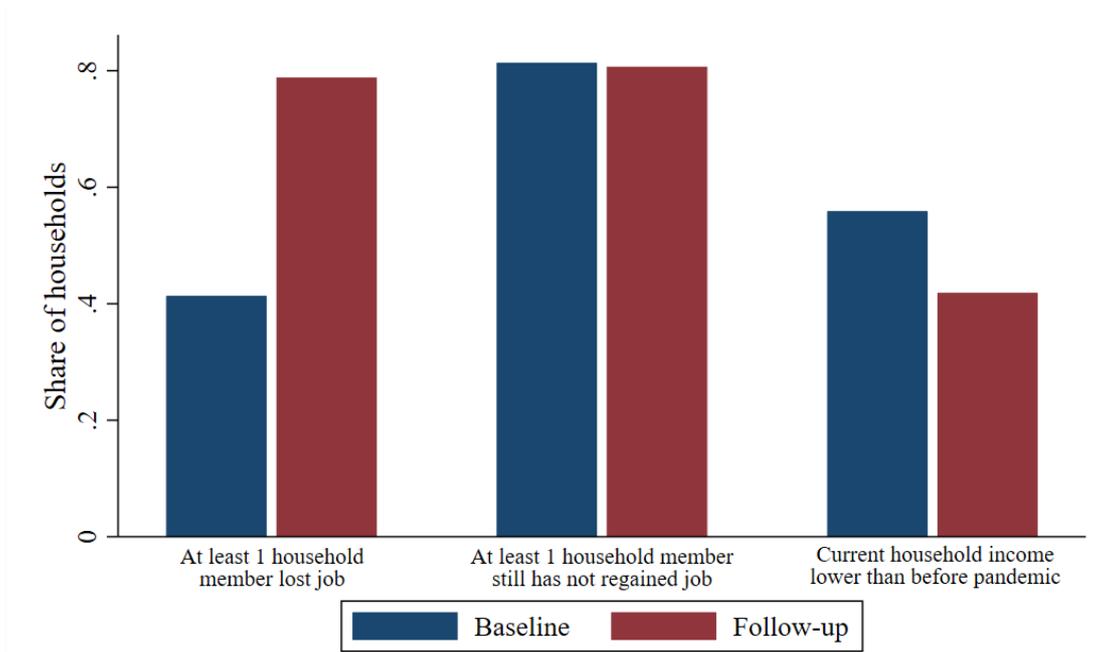
And indeed, 41% of respondents reported in the baseline survey that at least one household member had lost their job, livelihood or income source due to the crisis. This figure is lower than reported by Afridi, Dhillon, and Roy (2020), who found that 85% of respondents had lost their main income sources two months earlier. Our study finds that the percentage of households with at least one household member who has lost their job due to the crisis rises to 79% in the follow-up survey, as shown in Figure 3. The increase may be the result of the follow-up survey being a few months later and more jobs being lost over time due to the continued negative repercussions of the pandemic.

In the baseline survey, it was further found that a majority of those who lost jobs were salaried workers, followed by the self-employed. The same pattern is found in the follow-up survey. However, we cannot attribute this observation to salaried workers being hit the hardest by the pandemic, as opposed to most slum-dwellers in the sample being salaried workers, because we lack information of the distribution of occupations in our study sample pre-pandemic. The loss of jobs by casual workers may be under-reported, leading to the relatively low figures, as casual employment is characterized by irregular work, which may have been the same before and during the crisis.

Figure 3 also shows that the percentage of households who report that jobs lost earlier in the crisis have not been regained, with the rate of households with at least one member not having regained their lost economy activity being 81% in both the baseline and follow-up surveys. This provides further evidence that urban slum-dwellers' economic activity may not have recovered despite the easing of restrictions, and there is some persistence in the losses of livelihoods.

The loss of income sources is accompanied by a loss in earnings: the baseline survey found that 56% of households experienced a fall in their household income when compared to before the crisis. Interestingly, the follow-up survey finds that this percentage falls to 42%, as shown in Figure 3. Given the above findings of an increase in percentage of households with members who have lost jobs and the persistence of these losses, it is surprising that incomes have recovered to some extent.

Figure 3. Impacts on economic activity



Note: Data collected during baseline and follow-up surveys from 791 and 827 households, respectively. The sample for the follow-up survey is restricted to households allocated to the control group in our field experiment.

Among the households where at least one member has lost their job, Muslim households were more likely to report that the job still has not been regained during the baseline survey, shown in

Table 2. Using a subset of the sample for which pre-crisis data is available, we find that casual workers who lost jobs were less likely to have regained their jobs, although this is not true for the full sample. We also find that households with less educated household heads were more likely to face persistence in job losses. This indicates that some inequality due to differences in human capital may be reinforced through the lockdown, as Deshpande & Ramachandran (2020) argued.

Table 2. Results of linear regression on job loss

	(1) Current study baseline survey sample	(2) Previous study sample	(3)
Person who lost job was a casual worker	0.08 (0.05)	0.23*** (0.08)	0.24*** (0.08)
Person who lost job was self-employed	0.03 (0.05)	0.05 (0.09)	0.04 (0.09)
Muslim	0.15*** (0.05)	0.13 (0.10)	0.02 (0.10)
Household head did not complete primary education			0.19** (0.08)
Controls (current study and census)	Yes	Yes	Yes
Controls (previous study)	No	No	Yes
Mean	0.81	0.82	0.82
Obs-round	316	81	81
Slums	117	55	55

Notes: Observations limited to Hindu and Muslim respondents, who make up 99.8% of the whole baseline survey sample. Outcome: Probability that the household member who lost their job due to the crisis has not regained their job. Controls: age, age², gender, caste, relationship to household head, social desirability. Controls from 2018 census: Dwelling strength. Additional control from previous study's baseline survey: household asset level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors clustered by slum in parentheses. Column (2) represents the model in (1) used on the same samples as in (3).

Despite the fact that casual workers made up the smallest proportion of those who lost their jobs, we find that compared to other households with members who have lost jobs, households with casual workers who lost jobs were the hardest hit in terms of household incomes, as seen in

Table 3. Compared to households where a salaried worker lost their job, households where a casual worker lost their job were more likely to report that their incomes decreased since the crisis. This may be related to the finding in

Table 2, where casual workers find it hardest to regain their jobs when lost compared to salaried workers and self-employed workers, although there is no evidence that this is true for the whole sample. The fall in household incomes experienced by households where casual workers lost jobs may also reflect the lower employment protection experienced by casual workers. This is in line with studies that argue that economic inequality is reinforced through the crisis (e.g. Young Lives, 2020).

Table 3. Results of linear regressions on household incomes for households with job loss

	(1)	(2)	(3)
	Current study baseline survey sample	Previous study sample	
Person who lost job was a casual labourer	0.22*** (0.06)	0.40*** (0.11)	0.40*** (0.12)
Person who lost job was self-employed	0.09 (0.06)	0.11 (0.12)	0.10 (0.12)
HH head did not complete primary education			0.09 (0.12)
Controls (current study and census)	Yes	Yes	Yes
Controls (previous study)	No	No	Yes
Mean	0.56	0.57	0.57
Obs-round	316	81	81
Slums	117	55	55

Notes: Observations limited to Hindu and Muslim respondents, who make up 99.8% of the whole baseline survey sample. Outcome: Probability of current household income being lower than before the crisis. Reference category for variables of person who lost job: Person who lost job was a salaried worker. Controls: age, age², gender, religion, caste, relationship to household head, social desirability. Controls from 2018 census: Dwelling strength. Additional control from previous study's baseline survey: household asset level. Column (2) represents the model in (1) used on the same samples as in (3).. *** p<0.01; ** p<0.05; * p<0.1. Standard errors clustered by slum in parentheses.

IV.2. Social distancing

Earlier studies have suggested that slum-dwellers would find it difficult to comply with social distancing. Wasdani & Prasad (2020) concludes that social distancing is more an aspiration than an attainable reality for urban slum-dwellers in Bangalore. This is exacerbated by the fact that slum-dwellers are often daily wage earners and must go out to work to survive.

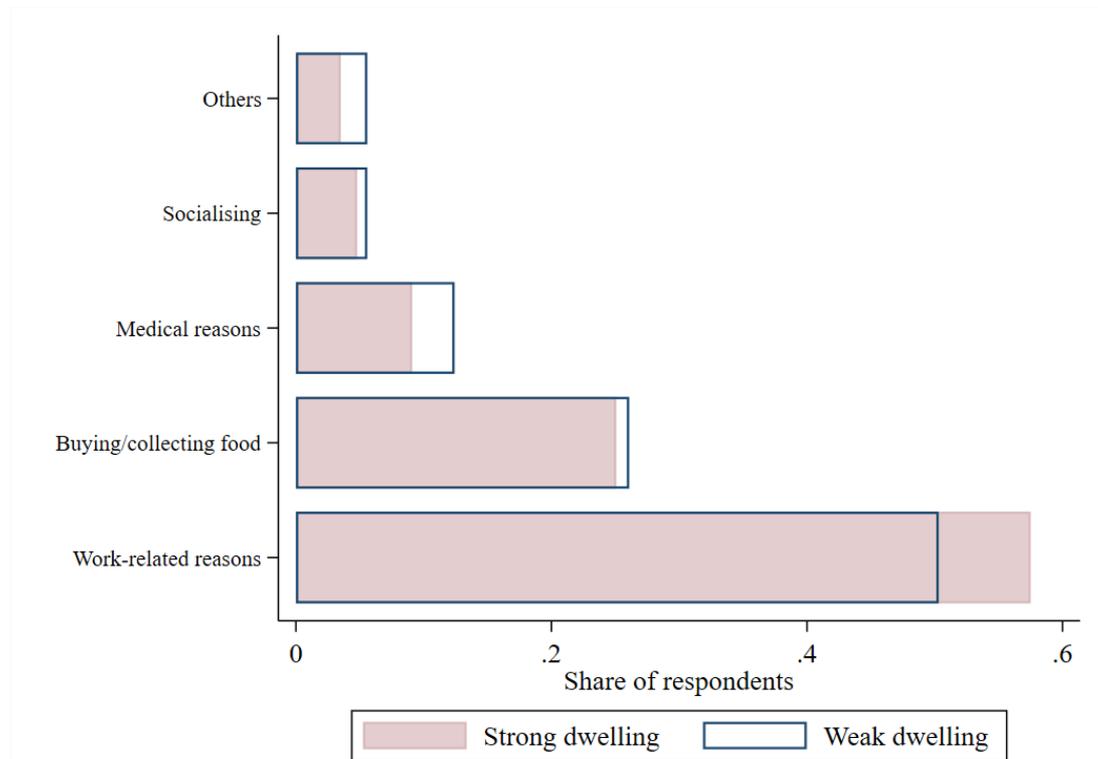
Due to their unique living situation that involves sharing basic facilities –e.g., public water sources, community toilets, kitchens – as well as physical space, we measure adherence to stay-at-home guidelines as the extent to which slum-dwellers stay in their slums, rather than in their home. .

In the baseline survey, we found that 65% of respondents said that they left their slums within the last week. This percentage increased to 89% in the follow-up survey, which is expected given the Unlock initiatives and the easing of restrictions in Uttar Pradesh during the follow-up survey period. The reasons for breaching stay-at-home guidelines are largely essential. A large majority of respondents breached stay-at-home guidelines for work-related reasons during the baseline survey, as shown in Figure 4. As previous studies have found that slum-dwellers are daily wage earners (Corburn et al. 2020), it is not surprising that more than half of those who left their slums within the last week left to work or to look for work.

Interestingly, we find that richer respondents, measured by their dwelling strengths, were more likely to have left their slums for work-related reasons, while poorer respondents were more

likely to have left for reasons such as medical purposes and food collection. This difference may be due to the fact that richer respondents may still have kept their jobs during the crisis, while poorer respondents may be more prone to health problems.

Figure 4. Reasons for the last time they left the slum, by dwelling strength



Note: Data on reasons for leaving slums collected during baseline from 787 households. Data on strong dwelling index collected in the slum census back in 2018.

As a measure of physical distancing, we also studied whether households received outside visitors the previous week. 28% of households received visitors within the previous week during the baseline survey in the months of June and July. This percentage increases substantially as lockdown restrictions are removed, as 72% of respondents stated that their household received visitors within the previous week in the follow-up survey.

When exploring different heterogeneities, we find that men were on average more likely to have left their slums within the previous week as they are more likely to be the primary breadwinners of their households.

Notably, we find that Muslims were more likely to have left slums compared to non-Muslims, possibly because Muslims in these slums are poorer on average, as measured by household asset levels. Interestingly, we find that Muslims living in slums where they are a minority are more likely to adhere to guidelines, as they are less likely to have left the slum or to have received outside visitors compared to Muslims in slums with higher percentage of Muslims. This effect is shown by the coefficient on the interaction term of Muslims and slum with low percentage of Muslims in Table 4. This is not explained by wealth, as Muslims in slums where they are a minority are also poorer on average. Hence, it may be speculated that peer effects may have an impact on adherence to guidelines. Living in a community where Muslims may be more marginalised may bring about pressures to comply with guidelines.

Our analysis in Table 4 includes social desirability as a control. It is found that respondents who gave more socially desirable responses were significantly less likely to state that they

broke social distancing rules, which highlights household's awareness of what they ideally should be doing, and the importance of accounting for this information.

Table 4. Results of linear regressions on social distancing measures

	(1) Left the slum within the last week	(2) Received outside visitors within the last week
Muslim	0.07 (0.05)	0.05 (0.06)
Slum with low % of Muslims	0.21 (0.13)	0.16 (0.13)
Muslim * Slum with low % of Muslims	-0.22* (0.11)	-0.17* (0.10)
Social desirability index	-0.03* (0.02)	-0.03* (0.02)
Dwelling strength	-0.01 (0.07)	-0.00 (0.06)
Controls (current study and census)	Yes	Yes
Mean	0.65	0.28
Obs-round	769	769
Slums	142	142

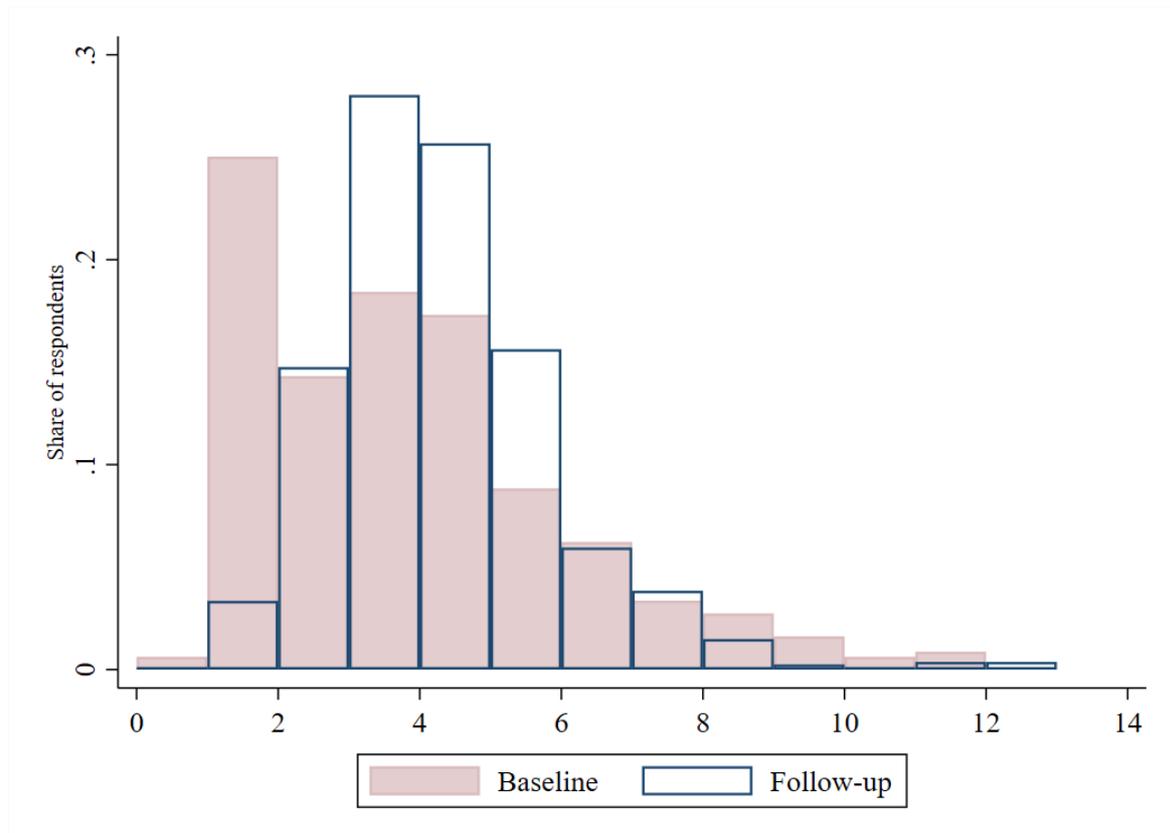
Notes: Observations include Hindus and Muslims only. Controls: age, age², gender, religion, caste, relationship to household head, anxiety about the pandemic. Controls from 2018 census: Dwelling strength, access to piped water and toilet ownership. Slums with low % of Muslims defined as slums with % of Muslims less than the median level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors clustered by slum in parentheses.

IV.3. Handwashing and hygiene

Given limited availability of water facilities within the household, and continuous access to water more generally, adherence to hand-washing is another recommendation difficult for slum dwellers, as also highlighted by Patel (2020).

Figure 5 shows that the mode for the number of appropriate handwashing occasions the previous day in the baseline survey is low at 1 occasion a day, but this increases to 3 occasions a day in the follow-up survey. The average number of handwashing situations also increased from 3 times a day to 4 times a day.

Figure 5. Distribution of appropriate handwashing times the previous day



Note: Data collected from 803 households in the baseline survey and 806 households in the follow-up survey.

In terms of the correlation between hygiene facilities and handwashing behaviour, we find that having piped water at home is positively associated with the number of correct handwashing times in a day, proving that easier access to piped water can lead to better hygiene, as found by previous literature. However, we do not find any significant association between having a latrine at home and handwashing, as shown in Table 5.

We also find that the number of handwashing items at home, such as soap and sanitizer, is positively associated with the number of handwashing times in a day. However, we do not find a significant increase in the number of handwashing items at home between the baseline and follow-up survey, which leads us to infer that the improvement in handwashing behaviour is not explained by changes in handwashing items. Notably, being more informed about COVID-19, as indicated by the knowledge of ways to prevent COVID-19 spread, is also strongly correlated with a higher number of handwashing times in a day in the baseline survey. This finding served as motivation for the experiment conducted in the second component of this study.

Further, having greater household assets is positively associated with handwashing. Columns (2) and (3) of Table 5 are restricted to a subset of the sample from Column (1) from which we have pre-COVID data. The associations found in Column (1) are robust to this change in sample in column (2), suggesting that the association found in Column (3) is not just the result of sample selection. Evidently, asset-poverty is a binding constraint to hygienic behavior due to several factors, but in particular, the capacity to buy hygienic items. In support of this proposition, we

can see that controlling for asset and education levels in Column (3) leads to a decrease in the coefficient on the number of hygienic items and its statistical significance when compared to Column (2).

Table 5. Results of linear regression on number of appropriate handwashing times the previous day

	(1) Current study baseline survey sample	(2)	(3)
Number of handwashing items available at home	0.78*** (0.19)	0.90** (0.43)	0.80* (0.43)
Household owns a latrine	-0.15 (0.18)	-0.37 (0.54)	-0.35 (0.55)
Piped water	0.36* (0.19)	0.61* (0.35)	0.62* (0.36)
Knowledge of COVID-19 prevention	0.44*** (0.09)	0.67*** (0.16)	0.68*** (0.16)
Household head did not complete primary education			-0.17 (0.32)
High household asset level			0.76** (0.33)
Controls (current study and census)	Yes	Yes	Yes
Mean	3.36	3.47	3.47
Obs-round	786	213	213
Slums	141	92	92

Note: Outcome: Number of correct handwashing times the previous day. Controls: age, age², gender, religion, caste, relationship to household head, social desirability. Column (2) is the output from running model (1) on the same sample as (3). High household asset level are asset levels above the median level. Control from 2018 census: dwelling strength. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors clustered by slum in parentheses.

IV.4. Willingness to vaccinate⁷

Willingness to vaccinate varies between populations of different countries. Lazarus, et al. (2020) found that 72% of people were willing to be vaccinated in a survey carried out in June 2020 across 19 countries, most with a high COVID-19 burden. This percentage varied quite widely, from 90% in China to only 55% in Russia. The study also finds a relatively high tendency towards acceptance of a vaccine in India.

Among Indian slum dwellers, we find that willingness to be vaccinated is particularly high, at a rate of 95% during the baseline survey in June and July 2020. The willingness decreases in the follow-up survey after restrictions are further eased, with 86% of respondents willing to be vaccinated. This is similar to the trend found in Europe, where willingness to vaccinate decreased significantly over time, evidenced by the willingness to vaccinate of Germans falling from 70% in April 2020 to 61% in June 2020, following the easing of lockdown restrictions

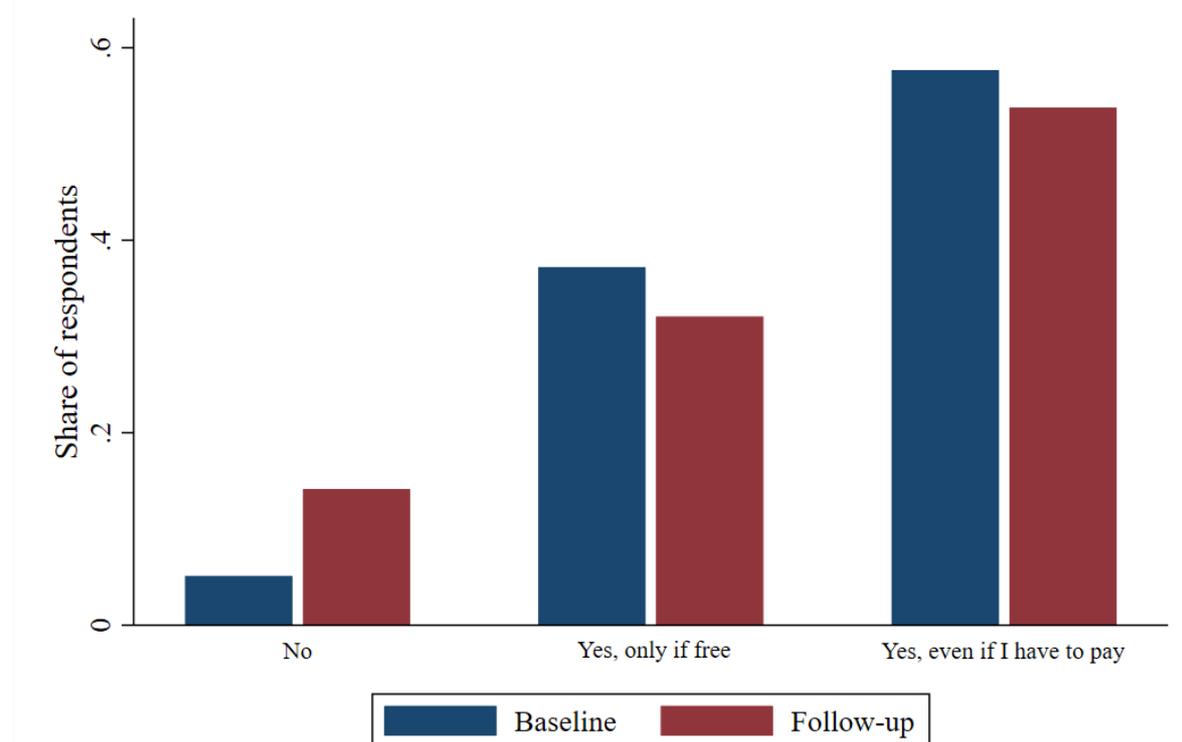
⁷ This is discussed in our blog: <https://www.theigc.org/blog/covid-19-and-the-willingness-to-vaccinate-evidence-from-india/>

(MTA Dialog 2020). In comparison, the willingness to vaccinate in Indian slums remain relatively high as lockdown restrictions come to an end.

It is important to note that willingness to be vaccinated does not mean willingness to pay for the vaccine. We find that 37% of slum dwellers in the baseline survey and 30% in the follow-up survey would only be willing to vaccinate if it were free. We see a similar drop in percentage of slum dwellers willing to pay for the vaccine, as 60% were willing to pay in the baseline survey compared to 52% in the follow-up survey. This is depicted in

Figure 6 below.

Figure 6. Willingness to vaccinate when COVID-19 vaccination becomes available

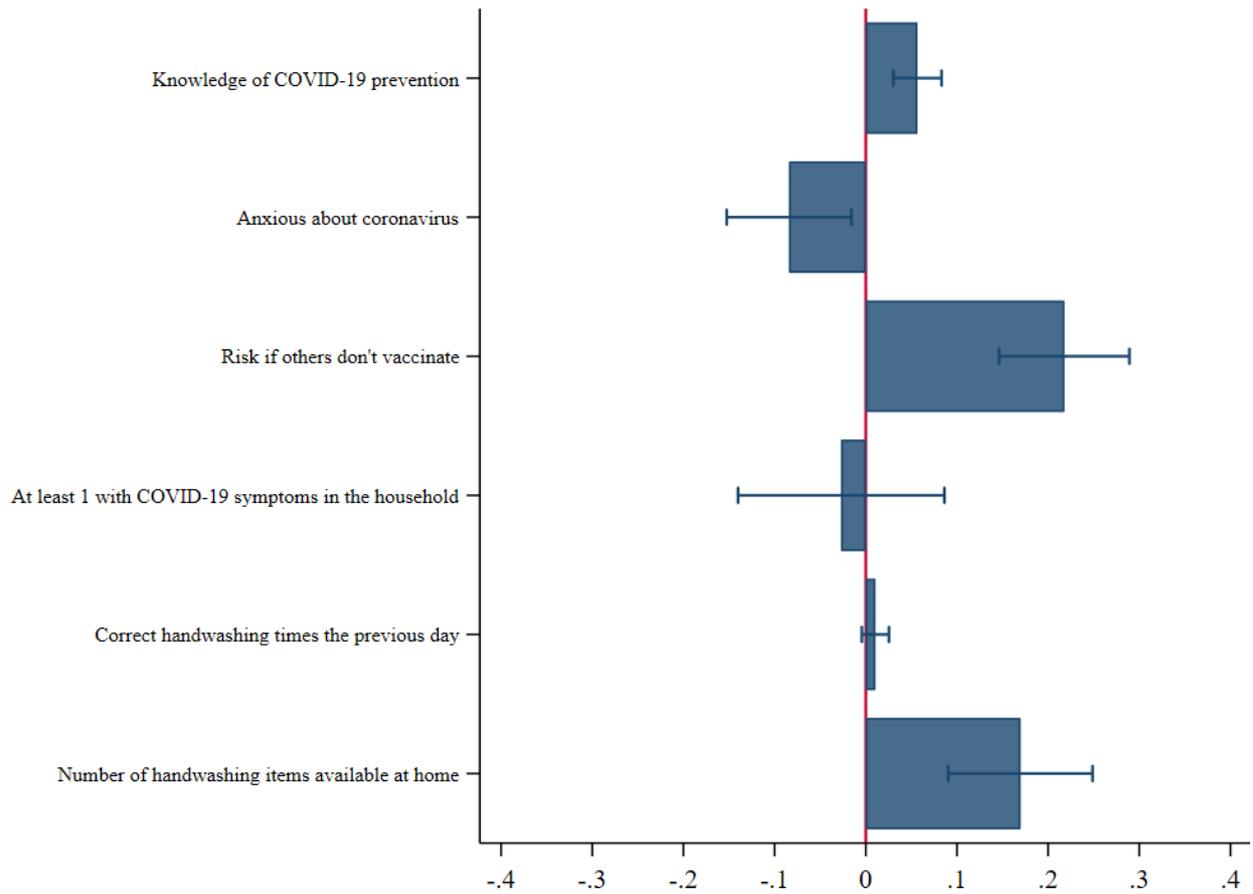


Note: Data collected from 815 households in the baseline survey and 806 households in the follow-up survey.

If payment is required, it is not only those with little means to pay who would not get vaccinated. We find that those who are not willing to pay for vaccinations are also less likely to adhere to COVID-19 guidelines. Even after accounting for poverty status, stated willingness to pay for COVID-19 vaccination is positively associated with better knowledge of COVID-19 prevention behaviour and proper hand-washing hygiene, greater availability of hygienic items at home, and higher awareness of risk if others do not vaccinate. This is highlighted in Figure 7.

We show in the same figure that those more anxious about the virus are less willing to pay for a vaccine. This may be driven by the fear of side effects, which is a factor for resistance to vaccination against COVID-19, as found in a study in the US (Reiter, Pennell and Katz 2020). Extreme anxiety can also result in a loss of hope of the effectiveness of any vaccination to come.

Figure 7. Relationship between willingness to pay and other factors

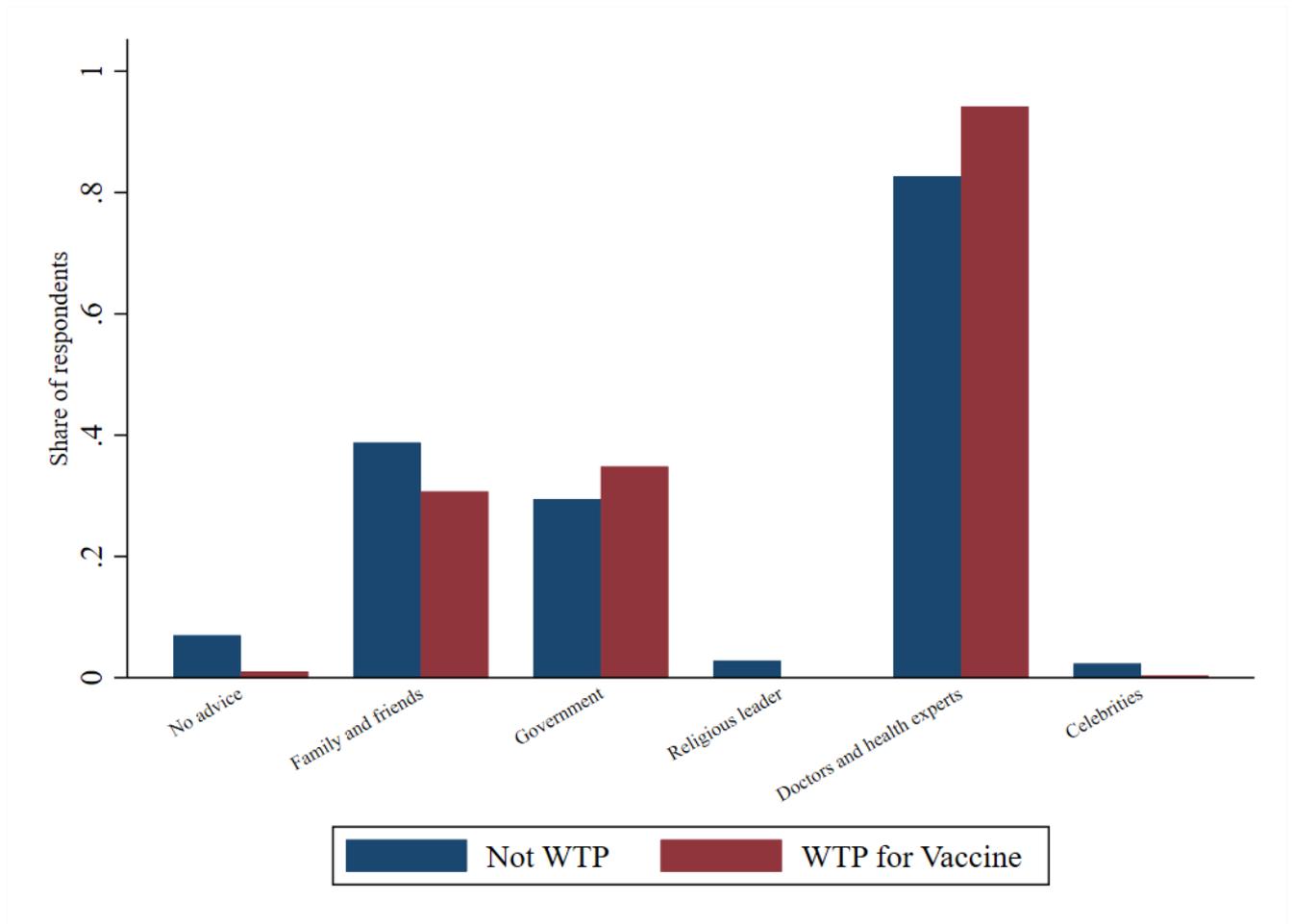


Note: Estimates from a linear regression model with slum fixed effects and controlling for an indicator of dwelling strength (from 2018 census), age, sex, relationship of respondent to household head, and caste.

Our data suggest that doctors and health officials can play an important role in disseminating accurate information related to COVID-19 and its potential vaccination. 90% of slum dwellers in the baseline survey reported that they would turn to these health specialists for advice in case a vaccine against COVID-19 is introduced. This percentage is even higher among those respondents that also report a willingness to pay for any COVID-19 vaccine, as shown in Figure 8.

On the contrary, those who were not willing to pay for the vaccine were also more likely to not seek advice, or to rely on friends and family, religious leaders, or celebrities for advice on the vaccine.

Figure 8. Potential sources of advice for COVID-19 vaccine, by willingness to pay



Note: Data collected from 811 households in the baseline survey.

V. Second component: Debunking Fake News

In this section, we reply to the following research questions.

RQ1: How effective are doctors' messages to counter misinformation about ways to prevent COVID-19?

RQ2: Can higher financial rewards lead to higher uptake of messages and hence be more effective in counteracting misinformation?

This section describes the field experiment aimed at debunking fake news about COVID-19 in slums, making use of mobile phone technology. We next provide evidence in support of the internal validity of our evaluation and next, we present our key results of the experiment.

V.1. Intervention

The key component of the intervention we evaluate are messages from different doctors working in renowned local hospitals in the study area, debunking fake news and reminding

the audience about the proven ways to protect against COVID-19. We refer to this as the “Doctor” intervention.

The messages are sent to households in one of two forms: (i) as short videos (approximately 2 minutes) through a Whatsapp chatbot⁸, (ii) or as an audio version via voice messages. The latter is done given that 50% of the slum households do not have a smartphone with Whastapp⁹. Each message, whether sent by video or audio, starts with a short clip of a citizen from Uttar Pradesh introducing the doctors’ messages.

The control group, rather than receiving no message, is sent a message debunking fake news about Bollywood stars. Doing so, allows us to disentangle the effects of our intervention from receiving a message through mobile phone technologies.

We incentivise households to watch the video and listen to the audio, by giving participants the chance to enter a lottery. Half of the households enter a “high incentive” lottery, where they get the chance to win for Rs. 5,000, the remaining households are subject to the “low incentive” lottery where the price is Rs. 2,500. This cross-randomization allows us to analyse the effect of a high expected payoff on the uptake of messages. There are 2 winners (1 winner per city) out of 500 participants in each lottery round.

V.1. Randomisation

We address the research questions using a field experiment through mobiles phones in 142 slums in the cities of Lucknow and Kanpur, Uttar Pradesh.

We randomly allocate 3,991 households (independent of the number of mobile phones in the household) to receive Doctor messages vs. Control messages, and cross-randomize whether households are allocated to the High incentive vs. Low incentive treatment, providing us with a 2 x 2 cross-randomized design. To randomly¹⁰ allocate households to the treatment arms, we stratify the sample by religion (Hindu or other) and by city of study (Lucknow or Kanpur).

Randomisation into the experimental arms is conducted at the household level given that the intervention is directed one-to-one through mobile phones. Using households as the randomization unit allows us to take advantage of greater variation in response to the intervention within slums.

Table 6. Distribution of households across treatment arms

Households	Treatment arm
2,002	Doctor video
1,989	Control video
Total: 3,991	
2,013	High-incentive
1,978	Low-incentive
Total: 3,991	

⁸ Whatsapp chatbot is a software program that runs on encrypted WhatsApp platform. WhatsApp users can communicate with a chatbot through the chat interface as they would talk to a real person.

⁹ We use a program that allows us to identify which phone numbers are active on Whastapp.

¹⁰ The statistical software Stata, and specifically the random number generator, is used to apply this procedure.

V.2. Estimation strategy

The evaluation design for the comparison of different interventions examines differences in outcomes across households assigned to different treatment groups. Since these households were allocated at random to different treatment groups, they are expected to be identical on average on all their other characteristics, observed or unobserved. A simple comparison of households across groups gives us the impact on household-level outcomes of implementing one versus another intervention.

We start by focusing on the general effect of receiving the “doctor” vs. “control” message, testing differences in mean across the main treatment and control groups. We next evaluate if there are differential effects by varying the incentives to uptake messages.

For household-level outcomes, let $T1_{im}$ be indicator variables that takes value 1 if household is allocated to “doctor-low incentive” intervention and “control-low incentive” otherwise; and $T2_{im}$ takes value 1 if household allocated to the “doctor-high incentive” intervention; and =0 if allocated to “control-high incentive” intervention.

In order to estimate the effect of the interventions on the outcome Y_{imt} at time t , we estimate the following model:

$$Y_{imt} = \alpha + \beta_1 T1_{im} + \beta_2 T2_{im} + \theta_m + \varepsilon_{im} \quad (1)$$

where θ_m are strata dummy variables capturing the dimensions along which the randomization was stratified (i.e. city and religion). ε_{im} is a residual idiosyncratic error term picking up unobserved determinants of the outcome of interest. We cluster standard errors by slum level due to potential intra-cluster correlation, even though the randomization was done at the individual level.

The impact on outcome Y_{imt} of receiving a doctor message, conditional on a higher financial incentive to watch the video is given by β_2 .

During the follow-up survey, to be able to measure outcomes close to the implementation of the intervention, we split the sample equally in 4 batches. Per batch, we first implemented the intervention and then during the following two weeks, we collected the follow-up data round. See Appendix 2 for the distribution of sample households in batches.

V.3. Baseline balance and attrition

Table 7 provides descriptive statistics at baseline, namely respondents’ and households’ characteristics, trust, and attitudes related to the COVID-19 pandemic collected during the baseline survey. Columns (1) and (2) present the means and standard deviations for the whole sample and the control group respectively.

The sample at the baseline were predominantly male (79%) and belonged to the Hindu religion (79%). The average age of the respondents in the sample is 39.5 years. 81% of the households in the sample are headed by a male figure and the average size of the household consists of 5 members. 13% reported to have at least one household member with COVID-19 symptoms, and 67% of them reported to be anxious during the pandemic. Prior to the treatment, an overwhelming majority of the sample (95%) have expressed trust in doctors and health experts.

Columns (3) and (4) show the difference between the control group and those randomly allocated into the treatment arms. The results in general demonstrate that the randomization was successful in creating observationally equivalent groups for the “Doctors’ message” and “High-incentive” treatments. We only find that treatment allocation is associated with being a Muslim, but since this is a stratification variable, we control for it in all our estimated treatment effects.

Table 7. Sample characteristics and balance at baseline

	(1)	(2)	(3)	(4)
	Full Sample	Control	Doctor Treatment	High Incentive Treatment
	Mean	Mean	Diff	Diff
	[sd]	[sd]	(se)	(se)
Respondent is male	0.79	0.79	0.00	0.02
	[0.41]	[0.41]	(0.01)	(0.02)
Respondent is Muslim	0.21	0.19	0.02**	-0.01
	[0.40]	[0.40]	(0.01)	(0.01)
Respondent age	39.46	39.73	-0.52	-0.33
	[11.34]	[11.46]	(0.40)	(0.47)
Household head is male	0.81	0.81	0.00	0.02
	[0.39]	[0.39]	(0.01)	(0.01)
Strong dwelling index	0.84	0.85	0.00	0.01
	[0.31]	[0.31]	(0.01)	(0.01)
Have a ration card	0.38	0.39	-0.01	-0.01
	[0.49]	[0.49]	(0.02)	(0.02)
Total household members	5.18	5.14	0.08	-0.09
	[2.17]	[2.16]	(0.07)	(0.07)
Household has at least one member with COVID-19 symptoms	0.13	0.12	0.01	0.00
	[0.33]	[0.33]	(0.01)	(0.01)
No. of correct answers for identifying COVID-19 symptoms	1.58	1.59	-0.02	0.00
	[0.65]	[0.65]	(0.02)	(0.02)
Trust: Doctors and health experts	0.95	0.95	0.01	0.01
	[0.22]	[0.23]	(0.01)	(0.02)
Not anxious during the coronavirus pandemic	0.33	0.33	0.01	0.00
	[0.47]	[0.47]	(0.01)	(0.02)

Note: This table corresponds to the baseline round and includes all households surveyed during the baseline. Column (1) and (2) reports sample mean and standard deviation in brackets for the whole sample and the control group respectively. Column (3) and (4) reports the difference with the control group for each treatment group. Standard errors clustered at slum level are reported in parentheses. Statistical significance denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The attrition rate between baseline and follow-up is 35%. This may seem like a high attrition rate for a field experiment, but there are a couple of considerations to highlight. First, attrition

rates of phone surveys were as high as 62% during the Ebola crisis and 50% in non-crisis contexts (Himelein, Eckman, Lau and McKenzie, 2020). Second, migration across State borders invalidates mobile phones because of roaming.

Table 8, columns (1) and (2) show that attrition is orthogonal to treatment allocation, though slightly significant when looking at the association with the “Doctor” treatment. Column (3) shows that attrition is positively associated with the respondent being male at baseline and from a Muslim household, while negatively associated with a household having a male head. Attrition is not associated with the respondents’ age, nor household size.

Table 8. Attrition

	No Response		
	(1)	(2)	(3)
<i>Doctor</i>	0.03* (0.02)		
<i>High incentive</i>		0.02 (0.02)	
Respondent is Male			0.06** (0.02)
Respondent is Muslim			0.06** (0.03)
Respondent age			0.00 0.00
Household head is male			-0.05** (0.02)
Household size			-0.01 0.00
Sample	All	All	All
Control Mean	0.35	0.35	0.35
Slums	142	142	142
Households	3,757	3,757	3,757

Notes: The outcome variable is a dummy =1 for no response and =0 otherwise. Statistical significance denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors were clustered by slum and shown in parentheses.

To deal with non-random attrition, which could bias the treatment effects, we follow Molina and Macours’ (2017) approach to weight the treatment effect by the inverse probability of a household being surveyed at follow-up. We construct this probability with baseline characteristics from all sampled households. Appendix 5 shows that results remain robust to this adjustment.

V.4. Treatment effects

In this section we present the results of the experiment we conducted, focusing on the impacts on the primary and secondary outcomes (see Appendix 3 for a detailed definition of each outcome). The estimates of linear regression models are shown for doctor's messages, conditional on the incentives to pay attention to videos. In all estimations we control for the stratification variables: (i) city and (ii) religion.

Table 9 presents the intention-to-treat estimates (ITT) on primary outcomes. The outcome in columns (1) is an index capturing agreement with confirmed ways; columns (2) disagreement with unconfirmed ways of preventing COVID-19; columns (3) an indicator for number of correct answers for identifying COVID-19 symptoms over the reported ones; column (4) whether the respondent answers to the call; and column (5) if the respondent recalls receiving a message regarding COVID-19. The agreement and disagreement with confirmed and unconfirmed ways of preventing COVID-19 is constructed as a latent variable using principal component analysis (keeping the first component). The construction of the index and the items that contributed are presented in Appendix 4.

Table 9. Treatment effects on primary outcomes

	Agree with confirmed ways (1)	Disagree with unconfirmed ways (2)	Knowledge about COVID-19 symptoms (3)	Proportion of message listened (4)	Recalls COVID-19 message (5)
<i>Doctor x Low incentive</i>	0.03 (0.73)	-0.05 (0.44)	-0.02 (0.18)	-0.16*** 0.00	-0.01 (0.52)
<i>Doctor x High incentive</i>	0.02 (0.75)	0.05 (0.42)	0.01 (0.64)	-0.12*** 0.00	0.01 (0.51)
Difference	0.00 (0.97)	0.10 (0.27)	0.03 (0.16)	0.04 (0.17)	0.03 (0.34)
Control Mean (Low incentive)	0.01	-0.02	0.57	0.35	0.21
Control Mean (High incentive)	-0.03	0.02	0.56	0.35	0.21
Slums	142	142	142	142	142
Households	2,455	2,435	2,457	2,458	2,458

Notes: The outcome in column (1) is an index measuring the extent to which the respondent agrees with confirmed ways of preventing COVID-19. Likewise, the outcome in column (2) refer to the extent to which the respondent disagreeing with unconfirmed ways of prevent COVID-19. The items that are used in building the index and also the impacts on the individual items are added in Table 10. Outcome for Column (3) is the ratio of number of correct answers identified by the respondent as symptoms of COVID-19 to the total number of symptoms listed. Column (4) refers to the proportion of the audio message (treatment) listened by the respondent. Outcome in column (5) is if the respondent was able to recall receiving a message about COVID-19. In all specifications we control for stratification variables: city and religion. Statistical significance denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors clustered by slum are shown in parentheses.

We find that the doctor treatment, independent of incentive amount, has no effect on agreeing (disagreeing) with confirmed (unconfirmed) ways of preventing COVID-19. However, we do find, as shown in

Table 10 that the doctor message, conditional on being allocated to the “High incentive” treatment increases by 5 pts the probability of respondents disagreeing with the statement “Indians are protected from COVID-19 because of a stronger immune system” (35% more disagreement than high-incentive control group).

We do not find a statistically significant impact on knowledge of COVID-19 symptoms, which is in line with no information about symptoms having been provided in the messages. Furthermore, respondents allocated to the doctor video, whether it was in the high or low incentive treatment, listened to a lower proportion of the voice message. This could be explained by the fact that the doctor video was longer. We do not find a statistically significant impact on recalling receiving messages about COVID-19 through voice or Whastapp.

Table 10. Treatment effects on knowledge of COVID-19 prevention

	Agree with using mask in crowded places	Agree with keeping physical distance with others	Agree with washing hands more frequently and for longer	Disagree with eating vegetarian as way to prevent COVID-19	Disagree with Indians having stronger immunity to prevent COVID-19	Disagree with coronavirus not surviving warm weathers	Disagree with COVID-19 being a disease of rich people, so poor people are safe
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Doctor x Low incentive</i>	0.01 (0.17)	0.00 (0.81)	0.01 (0.48)	-0.02 (0.33)	-0.03* (0.09)	0.01 (0.73)	-0.01 (0.65)
<i>Doctor x High incentive</i>	0.00 (0.96)	0.00 (0.85)	0.01 (0.36)	0.00 (1.00)	0.02 (0.37)	-0.03 (0.33)	0.02 (0.58)
Difference	-0.01 (0.33)	0.00 (0.97)	0.00 (0.84)	0.02 (0.50)	0.05* (0.07)	-0.04 (0.37)	0.03 (0.49)
Control Mean (Low incentive)	0.96	0.96	0.94	0.34	0.16	0.41	0.59
Control Mean (High incentive)	0.97	0.95	0.92	0.34	0.14	0.46	0.57
Slums	142	142	142	142	142	142	142
Households	2,455	2,457	2,458	2,457	2,457	2,449	2,442

Notes: All the columns refer to different individual questions/statements (as mentioned above) from the survey as outcomes. These questions are used to build the index in Table 9 [columns (1) & (2)]. The responses to the statements are captured using Likert scale with options varying from strongly agree to strongly disagree. The outcomes are built as dummy variables by recoding ‘strongly agree or agree’ as 1 & other responses as 0; and similarly recoding ‘strongly disagree’ or ‘disagree’ as 1 and others as 0 for statements that begin with disagree or capture unconfirmed ways of preventing COVID-19. In all specifications we control for stratification variables: city and religion. Statistical significance denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors were clustered by slum and shown in parentheses.

Table 11 and Table 12 present the ITT on secondary outcomes. The secondary outcomes in

Table 11 are: column (1) an indicator of whether time spend getting informed about COVID-19 is above the median of the distribution; column (2) an indicator capturing if the respondents always or very frequently checks the truthfulness of the news; column (3) an indicator capturing if the respondent is (very confident or) confident in identifying fake news; and column (4) if the respondent has given any information or advice regarding COVID-19 to anyone in the previous two weeks.

Table 11 shows that receiving a doctor message, conditional on a low incentive to pay attention, decreases by 8 percentages points (ppts) the probability of spending a high amount of time (i.e., above the median of time distribution) in getting informed about COVID-19 (or 13% less than low-incentive control mean). Notably, this negative effect is off-set by the high-incentive treatment. Receiving a doctors' message crowds-out the private investment in searching for information, but this is not the case when actually paying attention to the information provided.

We also find that receiving the doctors' message, conditional on a low incentive to pay attention, decreases by 10 ppts the probability of passing on information or advising others about COVID-19 (or 17% less than low-incentive control mean). Again, this negative is reversed for those with higher incentive to pay attention to the message. We find no statistically significant effect on checking truthfulness of the news and confidence identifying fake news.

Table 11. Treatment effects on acquiring and disseminating information

	Time spent on getting informed about COVID-19 greater than median (1)	Always/Freq check truthfulness of the news (2)	Confident in identifying fake news (3)	Given info/advice to anyone about COVID-19 (4)
<i>Doctor x Low incentive</i>	-0.08*** 0.00	0.01 (0.80)	0.02 (0.44)	-0.10*** 0.00
<i>Doctor x High incentive</i>	0.00 (0.84)	-0.03 (0.20)	0.04 (0.11)	0.03 (0.25)
Difference	0.08** (0.03)	-0.04 (0.28)	0.02 (0.54)	0.13*** 0.00
Control Mean (Low incentive)	0.6	0.34	0.45	0.58
Control Mean (High incentive)	0.54	0.32	0.43	0.51
Slums	142	142	142	142
Households	2,458	2,458	2,458	2,332

Notes: The outcome in column (1) refers to a dummy denoting if the respondent has spent more than median amount of time on getting informed about COVID-19. Likewise, the outcome in column (2) signifies if the respondent 'always or very frequently' checks the truthfulness of news s/he shares or discusses with family and friends. Outcomes for Column (3) again refer to a dummy for the confidence (1= confident or very confident, else 0) in identifying fake news related to coronavirus. Column (4) captures the outcome if the respondent has given any information or advice to anyone about COVID-19 in last two weeks. In all specifications we control for stratification variables: city and religion. Statistical significance denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors were clustered by slum and shown in parentheses.

The secondary outcomes in Table 12 refer to complying with governments guidelines of self-isolation and hygienic behaviour, as well as willingness to vaccinate. The outcome in Column (1) is an indicator of whether the respondent had received any visitors in the last week; column (2) if s/he left the slum in the last week; and in column (3) if the respondent always wears a mask when they go out; in column (4) is the number of correct handwashing practices the respondent is engaged in; in column (5) the number of hygiene items available in their homes; and in column (6) an indicator of whether the respondent is willing to get vaccinated when the vaccine is introduced.

Table 12. Treatment effects on complying with government guidelines

	Received visitors last week (1)	Left slum in the last week (2)	Always wear a mask when I go out (3)	Correct hand-washing practices per day (4)	Hygiene items available at home (5)	Willingness to vaccinate (6)
<i>Doctor x Low incentive</i>	-0.06 (0.21)	-0.03 (0.40)	0.01 (0.75)	-0.07 (0.67)	-0.03 (0.56)	-0.02 (0.56)
<i>Doctor x High incentive</i>	0.02 (0.70)	-0.08** (0.01)	-0.02 (0.64)	0.07 (0.70)	-0.01 (0.89)	-0.01 (0.89)
Difference	0.08 (0.27)	-0.06 (0.20)	-0.03 (0.60)	0.14 (0.60)	0.02 (0.75)	0.02 (0.75)
Control Mean (Low incentive)	0.74	0.92	0.74	3.94	1.81	0.84
Control Mean (High incentive)	0.70	0.90	0.74	3.76	1.80	0.80
Slums	141	141	141	142	142	142
Households	825	825	825	806	806	806

Notes: Column (1) refers to a dummy if the respondents have received any visitors in the last week. Similarly, column (2) captures if the respondent has left the slum in the last week. Column (3) signifies if the respondent always wears a mask when s/he steps out of the house. In (4) columns, the outcomes denote the number of correct hand-washing practices as reported by the respondent. Column (5) signifies the outcome on the number of hygiene items (such as soap, sanitizer etc.) available at the respondent's house. Outcome in columns (6) signify if the respondent is willing to get vaccinated for COVID-19 when they are introduced. In all specifications we control for stratification variables: city and religion. Statistical significance denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors were clustered by slum and shown in parentheses.

We find that receiving the doctors' message, conditional on a high incentive to pay attention, decreases by 8 pts (or 8% over high-incentive control mean) the probability of leaving the slum. This effect is statistically significant at the 5 percent level. We find no other statistically significant effects on hygiene behaviour nor willingness to vaccinate against COVID-19.

VI. Conclusions and Policy Recommendations

One of the most, if not the most, at-risk groups of COVID-19 is the urban poor, living in overcrowded conditions with very limited access to public (health) infrastructure. Due to the COVID-19 crisis, conditions worsened significantly. In our study setting, slums of two Indian cities, Lucknow and Kanpur, Uttar Pradesh, slum dwellers lost their livelihoods, experienced reductions in income, and the majority was not able to comply with lockdown measures. The poorest population was hit the hardest, while those with better knowledge about how to prevent COVID-19 were able to protect themselves better.

Misinformation about COVID-19 and how to prevent it is widespread in this population (as elsewhere). To counteract such fake news, we conduct a field experiment. Slum households were randomly assigned to be either receiving a message from a doctor debunking fake news sent via mobile phone or not. In addition, we cross-randomize a low or high financial incentive to pay attention to the message.

Doctors' messages debunking fake news about COVID-19 prevention, conditional on high financial incentives to pay attention compared to low incentives, counter misinformation, increase the probability of sharing advice and information about how to prevent COVID-19 with others and self-isolation within slums.

It is essential to develop policies that release the constraints of the population living in slums to comply with policy guidelines. The results of our analysis so far lead us to provide four key policy recommendations.

First, most of the urban poor rely on casual jobs that forces them to leave the slum frequently. Cash transfers have the potential to off-set economic hardships, while promoting self-isolation. Yet, they have proven to be insufficient given that a large share of slum dwellers experienced a drop in income below subsistence levels. Recent evidence also suggests that cash transfers in the form of universal basic income during the pandemic have achieved positive, but only modest size effects on well-being (Banerjee, Faye, et al. 2020). We propose to target cash transfers to households in slums where heads are lower educated, as these are the ones that were hit the hardest economically.

Second, self-isolation within slums is impossible due to the extent to which this population shares basic facilities. Policy efforts need to be concentrated on incentivising slum dwellers to stay in slums as much as possible. Our study suggests that doctors' messages debunking fake news about ways to prevent COVID-19, accompanied by high incentives to pay attention, can be a useful tool to achieve this goal. It is essential to find the optimal level of financial reward that triggers a positive behavioural response in different contexts, as a less than optimal level can crowd-out private investments in getting informed about prevention and disseminating information.

Third, improved hygienic behaviour is associated with having more hygiene products home. This relationship may seem obvious, but inputs do not always ensure a behavioural response. In light of our finding, we propose distributing hygiene items that can kill COVID-19. An effective behavioural response can be achieved if the distribution of hygiene items is accompanied by low-cost messages through mobile technologies countering misinformation about way to prevent COVID-19.

Fourth, spreading accurate information about how to prevent COVID-19 is key for vaccine compliance. Misperceptions of ways to prevent COVID-19 can generate a false feeling of safety and reduce the willingness to get vaccinated. Doctors and health experts play an important role in distributing accurate information about any potential vaccine. Besides, any future COVID-19 vaccine should not only be sold at cost by the pharmaceutical corporations developing it but also be subsidised or made available for free to the people. When the social benefits are larger than the private willingness, or ability, to pay, there is scope for public intervention to distribute subsidised or even free vaccines. Evidence suggests that one-off subsidies for preventive health goods could boost long-run adoption (even if having to pay in the future), through learning (Dupas et al. 2014). Given the logistical constraints to expand coverage rapidly and the less than universal willingness to pay for the vaccine, governments should consider targeting free vaccines to vulnerable people and those in high-risk jobs.

VII. References

- Afridi, F., Dhillon, A., & Roy, S. (2020, April 23). *How has COVID-19 crisis affected the urban poor? Findings from a phone survey - I*. Retrieved from Ideas for India: <https://www.ideasforindia.in/topics/poverty-inequality/how-has-covid-19-crisis-affected-the-urban-poor-findings-from-a-phone-survey.html>
- Afridi, F., Dhillon, A., & Roy, S. (2020, May 11). *How has COVID-19 crisis affected urban poor? Findings from a phone survey - II*. Retrieved from Ideas for India: <https://www.ideasforindia.in/topics/poverty-inequality/how-has-covid-19-crisis-affected-urban-poor-findings-from-a-phone-survey-ii.html>
- Awasthi, P. (2020, April 8). UP seals off hotspots in 15 districts, including Lucknow, Noida to contain spread. *The Week*. Retrieved from <https://www.theweek.in/news/india/2020/04/08/up-seals-off-hotspots-in-15-districts-including-lucknow-noida-to-contain-spread.html>
- Banerjee, A., Faye, M., Krueger, A., Neihaus, P., & Suri, T. (2020). Effects of a Universal Basic Income during the Pandemic.
- Brown, C., Ravallion, M., & van de Walle, D. (2020). Can the World's Poor Protect Themselves from the New Coronavirus? *National Bureau of Economic Research*.
- Bursztyjn, L., Rao, A., Roth, C. P., Yanagizawa-Drott, D. H., & Alesina, A. e. (2020). Misinformation During A Pandemic. *NBER Working Paper*.
- Callen, M., Isaqzadeh, M., Long, J. D., & Sprenger, C. (2014). Violence and Risk Preference: Experimental Evidence from Afghanistan. *The American Economic Review*, 104(1), 123-148.
- Corburn, J., Vlahov, D., Mberu, B., Riley, L., Caiaffa, W. T., Rashid, S. F., . . . Ayad, H. (2020). Slum Health: Arresting COVID-19 and Improving Well-Being in Urban Informal Settlements. *Journal of Urban Health*, 97, 348-357.
- Deshpande, A., & Ramachandran, R. (2020, July). Is COVID-19 "The Great Leveler"? The Critical Role of Social Identity in Lockdown-induced Job Losses. *Ashoke University Discussion Paper Series in Economics*, 34.
- Dupas, P., Black, S., Chassang, S., Cohen, J., Duflo, E., De Giorgi, G., & Einav, L. (2014). Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence from a Field Experiment. *Econometrica*, 82(1), 197-228.
- Fischer, D. G., & Fick, C. (1993). Measuring Social Desirability: Short Forms of the Marlowe-Crone Social Desirability Scale. *Educational and Psychological Measurement*, 53(2), 417-424.
- Habitat for Humanity. (2018, May 24). *What is a slum?* Retrieved from Habitat for Humanity: <https://www.habitatforhumanity.org.uk/what-we-do/slum-rehabilitation/what-is-a-slum/>
- Himelein, K., Eckman, S., Lau, C., & McKenzie, D. (2020, August 04). Mobile Phone Surveys for Understanding COVID-19 Impacts: Part II Response, Quality, and Questions. *World Bank Development Impact Blog*.
- Kanich, C., Kreibich, C., Levchenko, K., Enright, B., Voelker, G. M., Paxson, V., & Savage, S. (2009). Spamalytics. *Communications of the ACM*, 52(9), 99-107.

- Lazarus, J. V., Ratzan, S. C., Palayew, A., Gostin, L. O., Larson, H. J., Rabin, K., . . . El-Mohandes, A. (2020). A global survey of potential acceptance of a COVID-19 vaccine. *Nature Medicine*.
- Millan, M., Teresa, & Macours, K. (2017). *Attrition in Randomized Control Trials: Using Tracking Information to Correct Bias*. Retrieved from IZA Discussion Paper Series.
- Ministry of Home Affairs India. (2011). *Slum Census*. Retrieved from Slum households by availability of type of latrine facility:
https://www.censusindia.gov.in/2011census/hlo/Slum_table/hl-slum/SHH2808-crc.pdf
- Ministry of Home Affairs India. (2020, April 24). *Continuation of Order No. 40-3/2020-DM-I(A)*. Retrieved from Ministry of Home Affairs:
https://www.mha.gov.in/sites/default/files/MHAopening_24042020.pdf
- Ministry of Home Affairs India. (2020, May 17). *Extension of Lockdown up to May 31, 2020*. Retrieved from MHA Press Releases:
https://www.mha.gov.in/sites/default/files/17052020Lockdown_1.pdf
- Ministry of Home Affairs India. (2020, March 24). *Government of India issues Orders prescribing lockdown for containment of COVID-19 Epidemic in the country*. Retrieved from MHA Press Releases:
https://www.mha.gov.in/sites/default/files/PR_NationalLockdown_26032020.pdf
- Ministry of Home Affairs India. (2020, May 30). *Guideline for Phased Re-opening (Unlock 1)*. Retrieved from Ministry of Home Affairs:
https://www.mha.gov.in/sites/default/files/MHAOrderDt_30052020.pdf
- Ministry of Home Affairs India. (2020, July 29). *Guidelines for Phased Re-opening (Unlock 3)*. Retrieved from Ministry of Home Affairs:
https://www.mha.gov.in/sites/default/files/Unlock3_29072020.pdf
- Ministry of Home Affairs India. (2020, August 29). *Guidelines for Phased Re-opening (Unlock 4)*. Retrieved from Ministry of Home Affairs:
https://www.mha.gov.in/sites/default/files/MHAOrder_Unlock4_29082020.pdf
- Ministry of Home Affairs India. (2020, April 15). *MHA Issues Consolidated Revised Guidelines for the Containment of COVID-19 epidemic in the Country*. Retrieved from MHA Press Releases:
https://www.mha.gov.in/sites/default/files/PR_15042020RevisedConsolidatedGuidelinesfortheContainmentofCOVID19.pdf
- Ministry of Home Affairs India. (2020, July 29). *MHA issues Unlock 3 Guidelines, opens up more activities outside Containment Zones*. Retrieved from MHA Press Releases:
https://www.mha.gov.in/sites/default/files/Unlock3_29072020_0.pdf
- Ministry of Home Affairs India. (2020, September 30). *MHA Order Dt. 30.9.2020 on guidelines for re-opening*. Retrieved from Ministry of Home Affairs:
https://www.mha.gov.in/sites/default/files/MHAOrderDt_30092020.pdf
- Ministry of Home Affairs India. (2020, June 29). *Ministry of Home Affairs (MHA) issues new Guidelines for Unlock 2*. Retrieved from MHA Press Releases:
https://www.mha.gov.in/sites/default/files/MHAUnlock2_29062020.pdf
- MTA Dialog. (2020). *Corona: Die Impfbereitschaft sinkt*. Retrieved from Universität Heidelberg: <https://www.mta-dialog.de/artikel/corona-die-impfbereitschaft-sinkt.html>

- Patel, A. (2020). Preventing COVID-19 Amid Public Health and Urban Planning Failures in Slums of Indian Cities. *World Medical and Health Policy*.
- Reiter, P. L., Pennell, M. L., & Katz, M. L. (2020). Acceptability of a COVID-19 vaccine among adults in the United States: How many people would get vaccinated? *Vaccine*, 38(42), 6500-6507.
- Reserve Bank of India. (2019). *State-wise Poverty Rate*. Delhi: Delhi: National Sample Survey Organisation, NITI Aayog.
- Richardson, M., Dominowska, E., & Ragno, R. (2007). *Predicting Clicks: Estimating the Click-Through Rate for New Ads*. Retrieved from <https://www.microsoft.com/en-us/research/publication/predicting-clicks-estimating-the-click-through-rate-for-new-ads/>
- United Nations. (2018). *World Urbanization Prospects: The 2018 Revision*. New York, US: United Nations Department of Economic and Social Affairs, Population Division.
- Wasdani, K. P., & Prasad, A. (2020). The impossibility of social distancing among the urban poor: the case of an Indian slum in the times of COVID-19. *Local Environment*, 25(5), 414-418.
- World Bank. (2020). World Development Indicators.
- Young Lives. (2020). COVID-19 Phone Survey Headlines Report: Listening to Young Lives at Work in Adhra Pradesh and Telangana.

VIII. Appendix

Appendix 1. Characteristics of slum dwellers in Uttar Pradesh and all India

	(1)	(2)
	India	Uttar Pradesh
Slum census		
% Male	0.52	0.53
% Female	0.48	0.47
Sex ratio	1.08	1.12
% Children 0-6	0.12	0.14
Scheduled Castes	0.20	0.22
Scheduled Tribes	0.03	0.00
Literacy rate	0.78	0.69
Population census		
Owns latrine	0.47	0.66
Drinking water facility: Piped	0.44	0.68
Drinking water facility: Not piped	0.56	0.32
Religion: Hindu	0.80	0.80
Religion: Muslim	0.14	0.19
Religion: Other	0.06	0.01
Dwelling ownership: Own	0.87	0.95
Dwelling ownership: Rented	0.11	0.04
Dwelling ownership: Others	0.02	0.01
Assets: TV	0.47	0.33
Assets: Internet	0.03	0.02
Assets: Computer/laptop	0.09	0.08
Assets: Mobile	0.59	0.64
Assets: 2-wheeler	0.21	0.20
Assets: Car	0.05	0.04

Note: Data from the Indian Census and Indian Slum Census, 2011.

Appendix 2. Random allocation of households to follow-up survey batches

Module	Number of households	Percentage (%)	Survey dates
Batch 1	1,053	26.38	01 Oct - Oct 15
Batch 2	951	23.83	16 Oct – 02 Nov
Batch 3	941	23.58	04 Nov – 13 Nov
Batch 4	1,046	26.21	07 Nov – 18 Nov
Total	3,991	100.00	

Note: the dates of batches 3 and 4 overlap because of recurrent calling to be able to survey non-response households.

Appendix 3. Variable definitions

Variables	Definitions
Demographics	
Age	Age of respondent
Gender	Gender (male/female) of respondent
Religion	Religion of respondent
Caste	Caste of respondent
Relationship to household head	Relationship of respondent to household head
Household head did not complete primary education	Household head did not complete primary education
Dwelling strength	Strong dwelling index
Strong dwelling	Strong dwelling index equal to or greater than median index score
Household asset level	Household asset index
High household asset level	Household asset index equal to or greater than median household asset index score
Slum with low % of Muslims	Household lives in a slum where the percentage of Muslims in the slum is lower than the slum median percentage
Household facilities	
Household owns a latrine	Household owns a latrine
Piped water	Household normally gets water for handwashing from piped water inside dwelling
Social desirability	Social desirability index
Perceptions and experiences of COVID-19	
Agree with confirmed ways	Index measuring the extent to which the respondent agrees with confirmed ways of preventing COVID-19
Agree with using mask in crowded places	Respondent agrees with the statement 'using mask in crowded places prevents COVID-19'
Agree with keeping physical distance with others	Respondent agrees with the statement 'keeping physical distance with others prevents COVID-19'
Agree with washing hands more frequently and for longer	Respondent agrees with the statement 'washing hands more frequently and for longer prevents coronavirus'
Disagree with unconfirmed ways	Index measuring the extent to which the respondent agrees with confirmed ways of preventing COVID-19

Disagree with eating vegetarian as way to prevent COVID-19	Respondent disagrees with the statement 'eating vegetarian as way to prevent COVID-19'
Disagree with Indians having stronger immunity to prevent COVID-19	Respondent disagrees with the statement 'Indians having stronger immunity to prevent COVID-19'
Disagree with coronavirus not surviving warm weathers	Respondent disagrees with the statement 'Living in warm weather protects from COVID-19 because the coronavirus doesn't survive'
Disagree with COVID-19 being a disease of rich people, so poor people are safe	Respondent disagrees with the statement 'Coronavirus is a disease of rich people, so poor people are safe'
% audio listened	Proportion of the audio message listened by the respondent
Recalls COVID-19 message	Respondent was able to recall receiving a message about COVID-19
Always wear a mask when I go out	Respondent always wears a mask when s/he steps out of the house
Knowledge about COVID-19 prevention (only baseline)	Number of correct answers regarding ways to prevent COVID-19
Anxious about coronavirus	Respondent feels very/extremely anxious about the coronavirus
Risk if others don't vaccinate	Agrees/strongly agrees that respondent's health is at risk if neighbours refuse to vaccinate against COVID-19
At least 1 with COVID-19 symptoms in the household	Respondent or someone in the respondent's household developed COVID-19 symptoms since the first lockdown (March 25, 2020)
Information	
Time spent on getting informed about COVID-19 (> median)	Respondent spent more than the median amount of time on getting informed about COVID-19
Always/Freq check truthfulness of the news	Respondent 'always or very frequently' checks the truthfulness of news s/he shares or discusses with family and friends
Confident in identifying fake news	Respondent is confident in identifying fake news related to coronavirus
Given info/advice to anyone about COVID-19	Respondent has given any information or advice to anyone about COVID-19 in last two weeks.
Economic activity	
At least 1 household member lost job	At least 1 household member lost job, income source or livelihood due to the COVID-19 crisis

At least 1 household member still has not regained job	At least 1 household member who lost job, income source or livelihood due to the COVID-19 crisis still has not regained their job
Current household income lower than before pandemic	Current household income (including assistance) is lower than before the COVID-19 crisis
Person who lost job was a salaried worker	Household member who lost job was a salaried/wage labourer (e.g. maids)
Person who lost job was a casual labourer	Household member who lost job was a casual labourer/daily wager (e.g. construction worker)
Person who lost job was self-employed	Household member who lost job was self-employed (e.g. street vendor)
Social distancing	
Reasons for the last time they left the slum	Reasons given by the respondent for leaving the slum the last time
Left the slum within the last week	Respondent left the slum within the last week
Received outside visitors within the last week	Somebody from outside the slum visited the respondent or other members of the respondent's household
Handwashing behaviour	
Correct handwashing times the previous day	The number of appropriate occasions the respondent washed hands the previous day
Number of handwashing items available at home	Number of items used to clean hands available at home (e.g. soap, hand sanitiser)
Willingness to vaccinate	
Willingness to vaccinate when COVID-19 vaccination becomes available	Respondent would like to get the vaccine for coronavirus when it becomes available
Potential sources of advice for COVID-19 vaccine	Sources of advice the respondent would go to for advice in case the vaccine becomes available

Appendix 4. Factor loading of indices

Constructing index for 'Agree with confirmed ways' using PCA

Variable	Sign with which variable enters index	Factor Loading
Agree with 'using mask in crowded places to prevent COVID-19'	+	0.64
Agree with 'keeping physical distance with other people'	+	0.65
Agree with 'washing hands more frequently and for longer with soap'	+	0.42

Constructing index for 'Agree with confirmed ways' and 'Disagree with unconfirmed ways' using PCA

Variable	Sign with which variable enters index	Factor Loading
Disagree with 'eating vegetarian as way to prevent COVID-19'	-	0.54
Disagree with 'being Indian means having stronger immunity to prevent COVID-19'	-	0.47
Disagree with 'coronavirus cannot survive warm weathers'	-	0.50
Disagree with 'COVID-19 being a disease of rich people, so poor people are safe'	-	0.49

Appendix 5. Main impact tables using inverse probability weights to deal with non-random attrition

Primary outcomes

	Agree with confirmed ways (1)	Disagree with unconfirmed ways (2)	Knowledge about COVID-19 symptoms (3)	Proportion of message listened (4)	Recalls COVID-19 message (5)
<i>Doctor x Low incentive</i>	0.02 (0.83)	-0.04 (0.59)	-0.02 (0.14)	-0.16*** 0.00	-0.01 (0.56)
<i>Doctor x High incentive</i>	0.05 (0.53)	0.05 (0.46)	0 (0.83)	-0.12*** 0.00	0.01 (0.56)
Difference	0.03 (0.76)	0.09 (0.39)	0.03 (0.22)	0.05 (0.12)	0.02 (0.40)
Control Mean (Low incentive)	0.01	-0.02	0.57	0.35	0.21
Control Mean (High incentive)	-0.03	0.02	0.56	0.35	0.21
Slums	142	142	142	142	142
Households	2,455	2,435	2,457	2,458	2,458

Notes: This table involves inverse probability weights to deal with non-random attrition. The outcome in column (1) is an index measuring the extent to which the respondent agrees with confirmed ways of preventing COVID-19. Likewise, the outcome in column (2) refer to the extent to which the respondent disagreeing with unconfirmed ways of prevent COVID-19. Outcome for Column (3) is the ratio of number of correct answers identified by the respondent as symptoms of COVID-19 to the total number of symptoms listed. Column (4) refers to the proportion of the audio message (treatment) listened by the respondent. Outcome in column (5) is if the respondent was able to recall receiving a message about COVID-19. In all specifications we control for stratification variables: city and religion. Statistical significance denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors clustered by slum are shown in parentheses.

Knowledge of COVID-19 prevention

	Agree with using mask in crowded places	Agree with keeping physical distance with others	Agree with washing hands more frequently and for longer	Disagree with eating vegetarian as way to prevent COVID-19	Disagree with Indians having stronger immunity to prevent COVID-19	Disagree with coronavirus not surviving warm weathers	Disagree with COVID-19 being a disease of rich people, so poor people are safe
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Doctor x Low incentive</i>	0.01 (0.14)	0 (0.89)	0.01 (0.43)	-0.02 (0.43)	-0.03* (0.09)	0.02 (0.56)	0 (0.87)
<i>Doctor x High incentive</i>	0 (0.71)	0 (0.81)	0.02 (0.23)	0 (0.99)	0.02 (0.48)	-0.02 (0.39)	0.01 (0.62)
Difference	-0.01 (0.43)	0 (0.95)	0.01 (0.74)	0.02 (0.56)	0.05* (0.09)	-0.04 (0.34)	0.02 (0.64)
Control Mean (Low incentive)	0.96	0.96	0.94	0.34	0.16	0.41	0.59
Control Mean (High incentive)	0.97	0.95	0.92	0.34	0.14	0.46	0.57
Slums	142	142	142	142	142	142	142
Households	2,455	2,457	2,458	2,457	2,457	2,449	2,442

Notes: This table involves inverse probability weights to deal with non-random attrition. All the columns refer to different individual questions/statements (as mentioned above) from the survey as outcomes. The responses to the statements are captured using Likert scale with options varying from strongly agree to strongly disagree. The outcomes are built as dummy variables by recoding 'strongly agree or agree' as 1 & other responses as 0; and similarly recoding 'strongly disagree' or 'disagree' as 1 and others as 0 for statements that begin with disagree or capture unconfirmed ways of preventing COVID-19. In all specifications we control for stratification variables: city and religion. Statistical significance denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors were clustered by slum and shown in parentheses.

Acquiring and disseminating information

	Time spent on getting informed about COVID-19 greater than median (1)	Always/Freq check truthfulness of the news (2)	Confident in identifying fake news (3)	Given info/advice to anyone about COVID-19 (4)
<i>Doctor x Low incentive</i>	-0.09*** 0.00	0.01 (0.71)	0.04 (0.24)	-0.10*** 0.00
<i>Doctor x High incentive</i>	0.01 (0.70)	-0.04 (0.14)	0.03 (0.24)	0.04 (0.19)
Difference	0.10** (0.01)	-0.05 (0.20)	0.00 (0.99)	0.14*** 0.00
Control Mean (Low incentive)	0.60	0.34	0.45	0.58
Control Mean (High incentive)	0.54	0.32	0.43	0.51
Slums	142	142	142	142
Households	2,458	2,458	2,458	2,332

Notes: This table involves inverse probability weights to deal with non-random attrition. The outcome in column (1) refers to a dummy denoting if the respondent has spent more than median (of all observations in the sample) amount of time on getting informed about COVID-19. Likewise, the outcome in column (2) signifies if the respondent 'always or very frequently' checks the truthfulness of news s/he shares or discusses with family and friends. Outcomes for Column (3) again refer to a dummy for the confidence (1= confident or very confident, else 0) in identifying fake news related to coronavirus. Column (4) captures the outcome if the respondent has given any information or advice to anyone about COVID-19 in last two weeks. In all specifications we control for stratification variables: city and religion. Statistical significance denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors were clustered by slum and shown in parentheses.

Complying with policy guidelines and willingness to vaccinate

	Received visitors last week	Left slum in the last week	Always wear a mask when I go out	Correct hand-washing practices per day	Hygiene items available at home	Willingness to vaccinate
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Doctor x Low incentive</i>	-0.06 (0.21)	-0.03 (0.40)	0.01 (0.75)	-0.07 (0.67)	-0.03 (0.56)	-0.02 (0.56)
<i>Doctor x High incentive</i>	0.02 (0.70)	-0.08** (0.01)	-0.02 (0.64)	0.07 (0.70)	-0.01 (0.89)	-0.01 (0.89)
Difference	0.08 (0.27)	-0.06 (0.20)	-0.03 (0.60)	0.14 (0.60)	0.02 (0.75)	0.02 (0.75)
Control Mean (Low incentive)	0.74	0.92	0.74	3.94	1.81	0.84
Control Mean (High incentive)	0.70	0.90	0.74	3.76	1.80	0.80
Slums	141	141	141	142	142	142
Households	825	825	825	806	806	806

Notes: This tables involves inverse probability weights to deal with non-random attrition. Column (1) refers to a dummy if the respondents have received any visitors in the last week. Similarly, column (2) captures if the respondent has left the slum in the last week. Column (3) signifies if the respondent always wears a mask when s/he steps out of the house. In (4) columns, the outcomes denote the number of correct hand-washing practices as reported by the respondent. Column (5) signifies the outcome on the number of hygiene items (such as soap, sanitizer etc.) available at the respondent's house. Outcome in columns (6) signify if the respondent is willing to get vaccinated for COVID-19 when they are introduced. In all specifications we control for stratification variables: city and religion. Statistical significance denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors were clustered by slum and shown in parentheses.

The International Growth Centre (IGC) aims to promote sustainable growth in developing countries by providing demand-led policy advice based on frontier research.

Find out more about our work on our website
www.theigc.org

For media or communications enquiries, please contact
mail@theigc.org

Subscribe to our newsletter and topic updates
www.theigc.org/newsletter-signup

Follow us on Twitter
[@the_igc](https://twitter.com/the_igc)

Contact us
International Growth Centre,
London School of Economic and Political Science, Houghton Street, London WC2A 2AE

IGC

**International
Growth Centre**



Designed by soapbox.co.uk