How COVID-19 Risk Information Affects Beliefs and Behaviors: Experimental Evidence from Bangladesh

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Abstract

The local prevalence of infections and the severity of its consequences are among the key determinants of the adoption of preventive behaviors for an infectious disease. As local COVID-19 infection statistics are not easily available in Bangladesh I find that most people either do not know or underestimate the local prevalence of COVID-19 infections. Most of them also overestimate the fatality rate. In a randomized experiment, I give the treatment group information about the coronavirus case number in their districts and the case fatality rate in Bangladesh and worldwide. Immediately after receiving the information, the treatment group perceives higher infection risk. Nine to fifteen days after the intervention, those who received information underestimate the local prevalence less and, consequently, still perceive higher infection risk than the control group. The treatment group also updates their belief about the fatality rate downward. Potentially due to this countervailing update of risk beliefs, the information does not have any effect on the self-reported preventive behaviors.

JEL Codes: I12, I15, I18, O12

Keywords: COVID-19, Risk Beliefs, Risk Information, Health Behavior, Bangladesh

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1 Introduction

How one responds to disease partly depends on both the likelihood of getting infected by the disease and the severity of its consequences. For example, people may not react seriously to a disease like seasonal influenza, the infection risk of which is very high, but the fatality rate is very low. On the other hand, people may not also respond seriously to a disease like Ebola if it is not prevalent in their region even though it has a very high fatality rate. Therefore, both perceived susceptibility to disease (infection risk) and its perceived severity of consequences (e.g., fatality risk) jointly determines people's preventive behaviors (Weinstein, 2000).

However, misperceptions about the health risks of various diseases are prevalent around the world[1]. Such misperceptions about health risks may cause underinvestment or overinvestment in health care (Dupas, 2011a). Information intervention can correct such misperceptions and, thereby, affect health behaviors. For example, after receiving information people in Malawi, who overestimated both HIV prevalence and transmission risk, revised their beliefs downward and changed their behaviors (Kerwin, 2017). However, there are also instances where people underestimate one risk and overestimate another risk of the same disease. For example, also in Malawi, people overestimate infection risk and underestimate mortality risk of HIV (Delavande & Kohler, 2016). To best of my knowledge, there does not exist any experimental study on how people would respond to information in such a situation. An information intervention may change their beliefs about the risks, but it is not clear whether the information will affect behaviors; and even if it does, the direction is ambiguous.

[1] In developed countries: Breast cancer (Waters et al., 2011), obesity risk (Hazzard et al., 2017), diabetes risk (Wilkie et al., 2017) in the US; cardiovascular risk in Switzerland (Desgraz et al., 2017), etc.
In developing countries: Malaria in in Mali (Rhee et al., 2005); arsenic risk in Bangladesh (Madajewicz et al., 2007), etc.
During outbreak of a new disease: Ebola in Germany; H1N1 influenza in Italy(Poletti et al., 2011); HIV/AIDS in Malawi (Anglewicz & Kohler, 2009), in Kenya (Dupas, 2011a), and in Cameroon (Dupas et al., 2018).
About COVID-19: In the US (Lammers et al., 2020), (Abel et al., 2020), and (Pennycook et al., 2020); in Malawi (Banda et al., 2020).

In this paper, I study such a situation in Bangladesh where the participants underestimate the local prevalence of coronavirus infections which is one of the key determinants of the infection risk and overestimate the fatality rate which partly represents the severity of consequences. After receiving the information, the treatment group updates their belief on infection risk upward and the belief on fatality risk downward. The effect on the risk beliefs persists even after nine to fifteen days. Potentially due to this countervailing update of risk beliefs, the information does not have any effect on the self-reported preventive behaviors.

Specifically, in a phone survey of more than two thousand individuals in Bangladesh, I find that people show a substantial lack of awareness about the prevalence of COVID-19 infection in their localities and the fatality rate of the disease. Most of the respondents (90%) do not know and many (44%) even cannot make a guess about the number of coronavirus infection in their districts. Among the respondents who responded to the question on local prevalence, around 65% underestimate (compared to government reported case number) the number of coronavirus infection in their districts. Actual underestimation can be even higher as the government reported case number may also be underestimation of the true prevalence due to inadequate testing. Similarly, the majority (83%) also do not know the fatality rate of COVID-19. However, among the respondents who know or guess the fatality rate, most of them overestimate it (74% believe it is higher than 2%)[2].

To study how this group of people, who underestimate the prevalence of the disease in their communities and overestimate fatality risk of coronavirus, respond to risk information, I conduct a field experiment in Bangladesh when the daily reported number of coronavirus cases peaked in July 2020. Randomly assigned 1,121 people out of 2,302 respondents receive information about the coronavirus case number in their district and the case fatality rate in Bangladesh and worldwide during a phone survey[3]. As expected, the treatment group perceives higher infection risk immediately after receiving the information:

[2] As per WHO, the infection fatality rate of COVID-19 is approximately 0.5% to 1%.
[3] The case fatality rate was 4.88% for the world and 1.27 for Bangladesh at the beginning of the survey in July 2020.

the average person in the treatment group sees 7.7% higher risk of themselves or their family members getting infected by a coronavirus than the control group.

Nine to fifteen days after giving the information, I conduct a follow up survey and observe that the treatment group retains the risk information. Although both treatment group and control group respond to the local prevalence question at around the same proportion, the treatment group's perception about the local prevalence is more accurate. While 63.7% of the control group still underestimate the local prevalence, around 55% of the treatment group underestimate local prevalence of coronavirus infections. Consequently, they perceive 6.2% higher infection risk than the control group.

Although the treatment group perceives higher infection risk than the control group, their preventive behaviors remain the same as the control group. The reason for treatment having no effect on behaviors even after heightening infection risk could be the downward belief update on fatality rate. A higher percentage of the participants from the treatment group responded to the fatality rate question in the follow-up survey than the control group (80.5% for the treatment group vs. 76.8% for the control group, p=0.065). Not only did the treatment group respond more, but they also reported a fatality rate which on average is lower than the fatality rate reported by the control group (p=0.031). While updating perceived infection risk upward would cause adoption of more preventive measures, updating the perceived fatality risk downward would cause adoption of fewer preventive measures. Potentially due to this countervailing update of risk beliefs, the information has had no effect on the behaviors of the treatment group participants.

Some health behavior theories posit that the risk appraisal affects health behavior indirectly, via its impact on intention (Sheeran et al., 2014). During the first round of the survey, after receiving the information the treatment group shows an intention to take slightly higher (statistically significant) precaution in the future: the mean precaution the treatment group intends to take is 1.38% higher than the precaution the control group plans to take. In a meta-analysis of the experimental evidence, Webb & Sheeran (2006) provides empirical evidence that intention has a causal effect on health behavior. Contrary to that literature, I find the intention does not translate into actual behavior.

An intervention that provides only risk information may not be effective when the perceived benefits of adoption of health behavior are less than the perceived cost (Abraham & Sheeran, 2014). This may not be a constraint for this study as my sample consists of international migrant workers who were stuck in Bangladesh due to travel restrictions for whom infection by a coronavirus is very costly (as it would restrict their return to the host countries) but there exist little barriers (as almost none of them are employed in Bangladesh) to adopt preventive health behavior.

This paper makes three contributions to health behavior literature. First, I provide additional experimental evidence that people update their risk beliefs after receiving information which is consistent with existing literature (Dupas, 2011b; Kerwin, 2017). While the participants received information from educational sessions at schools in Dupas et al. (2018), and from the enumerators at the end of an in-person survey in Kerwin (2017), I show evidence that risk information over the phone, which is much less costly, may also be effective in changing people's risk beliefs in developing countries. Not only the participants change their beliefs after receiving the information, but that beliefs update also sustains even after 9 to 15 days since the intervention. In a recent study, Banerjee et al. (2020) found text messages of a video link containing information about better health practices effective to improve self-reported health behaviors in India. My paper shows that phone communication can also be effective for sharing risk information.

The main contribution of this paper is showing that correcting people's misperception about the health risks of a disease may not result in a change in health behavior when people underestimate one risk and overestimate another. This implies that even with misperceptions people may have already been adopting their optimal health behavior. If a social planner has a short-term goal of improving or reducing adoption of certain behaviors, it may provide people with specific risk information instead of giving them all available information. For example, if the social planner wants to improve adoption of a preventive behavior, it needs to share the risk information that heightens the perceived risk.

Finally, this paper documents the existence of misperceptions about health risks of COVID-19 in a developing country like Bangladesh. This is not surprising for two reasons: first, although misperceptions about health risks are prevalent everywhere, people in the developing countries may have a larger lack of awareness about health risks than the people in developed nations due to factors like the lower levels of education, the lower penetration of public health communications, etc. (Dupas, 2011a). Second, during an emerging outbreak, the misperceptions can be even wider due to the lack of scientific evidence at the early stage, the proliferation of misinformation on social media (Pennycook et al., 2020), sensationalization and exaggeration of the disease by mass media (Towers et al., 2015), etc. At this stage, people may not know how the disease spreads[4], the prevalence of infected people in their area[5], the infection risk[6], how infections grow[7], how severe the consequence (e.g., fatality rate) is, etc.

2 Sample Selection and Data Collection

Correcting people's misperceptions alone may not be sufficient to change people's health behavior if perceived benefit does not outweigh the perceived cost/barriers (Abraham & Sheeran, 2014). As I intend to estimate how information that changes people's perception about health risks affect their behavior, I conduct the study on a sample for whom this is not a constraint (their perceived benefit is apparently higher than their perceived cost). Therefore, the international migrant workers who were stuck in their home country due to travel restrictions during the peak of COVID-19 pandemic are an interesting sample for this study.

For this study, I surveyed 2,302 Bangladeshi international migrant workers who were in Bangladesh during the survey mainly due to travel restrictions and lockdown. Their perceived benefit of not getting infected by the coronavirus is much higher than the rest of the population. This is because in addition to avoiding the health consequences, they will be able to return to their host countries only if they do not get infected. If they contract the coronavirus, they may not be able to return to their host countries as many countries require a negative COVID-19 test result for entry. Infection may cost them their jobs or at least delayed return to their host countries, both of which are very costly to them. The perceived private cost of

[4] Misperceptions regarding transmission of Ebola among German people (Rübsamen et al. 2015), and among Americans (SteelFisher et al., 2015).
[5] People in Malawi overestimate the prevalence of HIV infection in their community (Anglewicz & Kohler, 2009).
[6] Italian people misperceive the infection risk of H1N1 influenza (Poletti et al. 2011).
[7] Americans underestimate the actual growth of the virus's over time (Lammers et al., 2020)

preventive measures is also lower for this sample than the cost faced by the rest of the population. Because staying home or avoiding social gatherings, some of the best preventive measures, are not costly for them as almost all of them were not working in Bangladesh while most workers based in Bangladesh had to return to their jobs after the government lifted the nationwide lockdown in late May.

In addition, as infection can be very costly to these people, I expect them to be more aware about the COVID-19 situation than the rest of the population. Lack of awareness or any misperception about COVID-19 among this group of people would indicate even a wider misperception among the rest of the population.

The data for this study come from an individual level phone survey I conducted along with BRAC Institute of Governance and Development (BIGD) of BRAC University Bangladesh.[8] We surveyed 2,302 individuals by phone from July 5, 2020 to July 13, 2020 from a list of migrant workers who landed in Bangladesh from December 2019 to July 2020 with 91% returning between January and March (Figure A3 in Appendix). The respondents of the survey are from a list I compiled by collecting administrative data from BRAC's migration program and some offices of district administration. The enumerators filled out the survey forms on their phones/tablets using SurveyCTO. This round of survey generated a cross-sectional dataset spanning nine days.

3 Context of COVID-19 in Bangladesh and People's Perception on Related Risks

The study took place in Bangladesh which was severely affected by the worldwide pandemic of coronavirus disease 2019 (COVID-19) since the first reporting of coronavirus cases in Bangladesh on March 8, 2020. To slowdown the spread of COVID-19, the government of Bangladesh imposed restrictions on international air travel from mid-March to Mid-June. The government also declared a ten-day national lockdown on March 23 and extended the holiday several times ending on May 30, ordering shutdown of all offices, stay at home and practice of social distancing for the public. However, media reports show that people loosely maintained those measures and the infection number of coronavirus and associated death toll kept rising.

[8] The survey was a part of a study designed to evaluate the impact of COVID-19 on Bangladeshi international migrant workers with a view to provide policy suggestions to relevant stakeholders like government agencies and NGOs.

By the first week of July, at the start of the survey, the number of reported cases of coronavirus exceeded 150,000 with around 2,000 death.

Even though Bangladeshi media heavily publicized the aggregated statistics of reported COVID-19 infections and deaths in Bangladesh, disaggregated data by local area was not easily and accurately available to the public. A news report about a particular district may contain the number of infections and deaths in that district, but one cannot find information about any district they want from the print and electronic media and on their websites, which is the COVID-19 information source for the highest number of the participants in our sample[9]. Facebook, which is the second main source of COVID-19 related information, does not display COVID-19 statistics for Bangladesh on its COVID-19 Information Center page as it does in developed countries such as the United States. A Google search result shows aggregated and division-wise reported COVID-19 infection and death numbers. However, information about a division is still not local enough[10] and those division-wise infection numbers were wrong by a huge margin[11]. The official government COVID-19 tracking website of Bangladesh, http://covid19tracker.gov.bd/, showed the district-wise number of reported cases in Bangladesh in addition to the country-level aggregated statistics of infections and deaths. However, it is difficult to find this website unless the exact address is known.[12]

I find that people are not aware of local prevalence of coronavirus infection and most of them underestimate it. Very few of the participants in our sample (only 9.73%) said they knew the number of COVID-19 infection in their districts. When requested to make a guess, another 44.87% selected a range from given options. The remaining 45.4% of our sample preferred not to even make a guess (Figure 2). For 64.52% of the participants, who said they knew or made a guess, the selected case number/range was smaller than the government-reported number. To be noted, the number of reported cases can be lower than

[9] See Figure A1 in appendix which shows the source of COVID-19 information of these respondents.
[10] On an average 18 million people lives in a division in Bangladesh. Google search result shows county wise COVID-19 statistics in the USA and a county has an average population of around 100 thousand.
[11] The case number of all the divisions shown in google search results add up to 24,425, while itself shows the total case number of the country is 250,000 as on August 6, 2020.
[12] For example, google search of “coronavirus bangladesh”, “coronavirus Bangladesh website” or “coronavirus Bangladesh government” does not show the website on its first page of search results.

the actual number of infections as testing was inadequate[13]. This may explain why 13.21% respondents mentioned a range of infections which was higher than the reported number. Among the participants who underestimated, 75% underestimated by more than a range (see the distribution in Figure 3).

Among the many factors contributing to this lack of awareness of local prevalence of COVID-19, the local level COVID-19 statistics not being easily available is certainly one of those. It is evident from the fact that higher percentage (60.95%) of respondents knew or made a guess about the COVID-19 infection number in their host countries, which is easily available, compare to the percentage (54.6%) of respondents knew or made a guess about the COVID-19 infection number in their districts. Also, their estimation was more accurate; only 42.76% underestimate COVID-19 infection number in their host countries which is much lower than 64.52% underestimation in district case number.

While the majority of respondents underestimated local prevalence of COVID-19, most of them overestimated the fatality rate[14]. Relatively higher percentage (64.31%) of our sample said they knew or made a guess about the fatality rate than the percentage (54.6%) of people said they knew or made a guess about the local case number. Among those who knew or made a guess about they fatality rate, 93.1% believe the fatality rate is higher than 1% and 73.75% think it is more than 2% (Figure 4). One reason for this overestimation can be the media reports of people dying with COVID-19 symptoms. Around 61% of the participants who responded to both case number and fatality rate questions underestimate local prevalence and overestimate fatality rate (Table 1).

While the participants of this study lack awareness about the local prevalence and fatality risk, they seem aware of the COVID-19 symptoms and are taking very high level of precautions. In a subsample of 519 people[15], 95% mentioned fever, 93% mentioned cough, 68% mentioned breathing problems, and 13% mentioned other symptoms when the enumerators asked them to name the symptoms of COVID-19. Most

[13] Both total test per thousand (5.15) and new test per thousand (below 0.1) in Bangladesh were among the lowest in the world (Hasell et al., 2020). Bangladeshi media also reported the shortage of testing in Bangladesh.
[14] As per WHO, the infection fatality rate of COVID-19 is approximately 0.5% to 1%. During the period of survey, the case fatality rate of COVID-19 was 1.3% in Bangladesh and 4.7% worldwide.
[15] Because of the budget constraint and to keep the survey short, we ask this question only to a subsample.

of them are also taking good preventive measures. Around 56% reported they always wear masks and another 38% mentioned they wear masks most of the times. Around 97.5% reported they do not attend any kind of social gathering. Around 46% of this subsample do not go outside of their home at all unless it is an emergency and another 32% went outside only 7 times or less in the previous seven days for non-emergencies.

4 Conceptual Framework

Preventive health behaviors depend on both the perceived susceptibility to disease and its perceived severity of the consequences. In the context of COVID-19, the susceptibility to this infectious disease depends on the local prevalence among other factors. The likelihood of getting infected by a coronavirus is higher where more people are already infected. As the prevalence of coronavirus infections varies by region, people may perceive different levels of susceptibility to this disease. If local prevalence data is not easily available, even people in the same area may perceive different infection risks and adopt different levels of preventive behaviors.

The severity of the consequences of a disease depends partly on fatality rate. For example, the severity of the consequences of seasonal flu is different than the severity of the consequences of Ebola or HIV/AIDS. Due to these differences in the severity, people also behave differently when they face the infection risk of seasonal flu versus Ebola. It takes time and resources to accurately estimate the fatality rate of a new disease, and even the experts may not know the fatality rate accurately during the emerging stage of an outbreak. Therefore, it is plausible that ordinary people may misperceive the fatality rate.

In the setting of this paper, most of the survey respondents underestimate local prevalence and overestimate fatality rate. After receiving information about the number of infections in their districts, the participants in the treatment arm may update their risk beliefs upward and may perceive a higher risk of infection. Heightening perception of a risk usually results in adoption of improved preventive measures. On the other hand, after receiving information about the fatality rate, the participants in the treatment arm may update their risk beliefs downward and may perceive a lower fatality risk. Lowering perception of a risk usually encourages adoption of risky behaviors. Due to these countervailing effects of the information treatment, it is ambiguous how the participants in the treatment group change their behaviors.

5 Information Intervention

In my data, the perceived local case number is positively correlated with the infection risk. I also observe that knowing the local prevalence of infection is positively correlated with knowing the symptoms, precautions, wearing a mask, and the intention of better health behaviors; and negatively correlated with the unnecessary outside visits. However, knowing the local case number is endogenous. Therefore, I implement an experiment to estimate how an intervention that provides information about local case number and fatality rate affects people's health risk beliefs of COVID-19 and their preventive behaviors.

I randomly pre-assigned potential survey participants into treatment or control group. At the start of the survey, the enumerators selected the pre-assigned group for the respondents and then completed the forms as displayed. After the questions on their perception of the number of COVID-19 cases in their districts, host countries, and fatality rate, the enumerators provided the following information only to the respondents in the treatment group:

a) Total number of COVID-19 cases in their district as reported by the government.
b) Total number of COVID-19 cases in their host country[16].
c) Case fatality rate in Bangladesh and worldwide.

My field team collected the number of district-level COVID-19 cases from the official COVID-19 tracker website of the Bangladesh government and sent the updated information to the enumerators daily. Based on that information, the enumerator read the following to the treatment group participant: "As per the government reported number, so far ____ people in your district have been tested positive for coronavirus." Then the enumerators also entered the number on the survey form. Similarly, the enumerators

[16] I provide this information to see whether knowing this affect their decision to return to their host countries. The results of this treatment to be added later in the appendix.

also shared the number of cases in the host countries with the participants in the treatment group. The third piece of information the treatment group respondents received is the global and Bangladesh's case fatality rate (as of July 1, 2020) which is stated as "Out of each hundred people who have been reported to be infected by a coronavirus in the world, 4.88 (slightly below five) people died. And out of each hundred people who have been reported to be infected by coronavirus in Bangladesh, 1.27 (slightly above one) died."

6 Measure of Outcome Variables

One of the key outcome variables of this study is the perception of infection risk. The literature on health behavior provides empirical evidence that risk perception affects people's intentions and health behaviors (Sheeran et al., 2014). Specifically, for the COVID-19, Bruin & Bennett (2020) find that an increase of 1 quartile in perceived infection risk is related to being 1.45 times more likely to report handwashing. To test whether the information treatment can change people's risk perception, I collect participants' subjective risk belief of getting infected by the coronavirus. I ask the participants to assess the likelihood of themselves and their family members being infected by the coronavirus on a scale of 1 to 10 with 10 being the highest risk. This kind of explicit probability scale has advantages over Likert scales or non-cardinal measures (Manski, 2004). There might be some concerns of using this measure in a developing country context due to the overall literacy level. However, Delavande et al. (2011) refutes those concerns showing that people in developing countries understand probabilistic questions and these measures are useful predictors of future behavior and recommended to incorporate more in the surveys in developing countries. The use of subjective probabilities in a developing country has been growing recently.

Here I elicit experiential risk perception as this kind of risk perception predicts health behaviors better (Weinstein et al., 2007; Ferrer & Klein, 2015). In experiential risk perception, people make a rapid judgment of a negative outcome based on their intuition or gut even without consciously processing the information contributing to the formation of judgment (Ferrer & Klein, 2015). This kind of risk perception is a contrast to deliberative risk perception where individuals systematically process information to derive an estimate of a negative outcome.

Another outcome variable is the intention of taking precautions to avoid infection by a coronavirus. Health behavior literature provides both theoretical and empirical grounds to use intention as an outcome variable. Protection Motivation Theory by Rogers (1983) and the Theory of Planned Behavior by Ajzen's (1991) argues that risk perception affects health behaviors indirectly via change of intentions. A meta-analysis by Webb & Sheeran (2006) shows that successful interventions that changed people's intentions subsequently affected their health behavior as well. To test whether information intervention can affect people's intentions of better health behavior, I ask the participants to share the level of precautions they are planning to take in the future to avoid infection by the coronavirus. I ask them to choose from a scale of 1 to 10 with 10 being the highest precaution one can take to prevent coronavirus infection.

Finally, to measure the health behavior I collect self-reported behavioral responses. The participants report the number of outside visit during the last seven days, whether they wear masks or join social gatherings, etc. In addition, they also evaluate their level of overall precaution on a scale of 1 to 10 with 10 being the highest level of precaution. I find the overall precaution is reasonably correlated with the behavioral responses (Table 2).

7 Estimation Strategy and Results

The randomized assignment to treatment provides the source of identification. In expectation, both the treatment group and the control group are similar in characteristics. As shown in Table 3, there are no statistically significant differences in characteristics between the two groups before the intervention. To estimate the causal effect, I use simple reduced form regression specifications. I estimate the treatment effect using the following specifications:

$$y_i = \alpha + \beta T_i + e_i$$

where y_i is the outcome variable (e.g., perceived infection risk, overall precautions, specific health behavior, etc.) and T_i is the treatment indicator. In addition, I use other specifications such as district fixed effect, survey day fixed effect, addition of control variables (e.g., age, education, salary), clustering standard errors by district, etc. for robustness check.

After sharing the information with the treatment group, the enumerators immediately asked the participants what they think about the reported number. 54.6% of the treatment group participants answered that the reported number "seems plausible/believable" to them. Among the subset of the treatment group who underestimated the district case number, 57% found this information believable. Since most of the participants underestimated the case number and most of the treatment group participants believed the information, immediately after the intervention, the treatment group perceived higher infection risk: the average person in the treatment group perceived 7.7% higher risk of themselves or their family members getting infected by the coronavirus than the control group (column 1 in Table 4). This effect is robust to various specifications as shown in Table A1 in the Appendix.

Similarly, the enumerators sought the participants' opinion about the fatality rate immediately after sharing the information. Some of the participants updated their belief about the reduced fatality rate immediately after receiving the information. While around 45% of the treatment group believed that the COVID-19 fatality rate is 5% or higher before the intervention, after receiving the information only 31% of the treatment group believed that the COVID-19 fatality rate is 5% or higher (Figure 5). However, among those who used to believe the fatality rate is below 1%, some of them updated their beliefs upward.

During the first round of the survey, the enumerator also asked what level of precautions they intend to adopt in the coming days. The treatment group shows the intention to take slightly higher (statistically significant) precaution in the future: the mean precaution the treatment group intends to take is 1.38% higher than the precaution the control group plans to take (column 2 in Table 4). As shown in Table A2 in the Appendix, this effect is also robust to various specifications. This result is interesting because while the treatment group now perceived more infection risk, the majority of them updated their fatality rate belief downward.

All these results are based on the responses within a minute after the intervention. It may happen that people have not been able to fully process the information within that short period of time. It is also possible that they would gather more information after the intervention and update their belief accordingly. Therefore, I conducted a follow-up survey, nine to fifteen days after the intervention, to see how they update their beliefs once they get time to process the information. Also, I am interested to see whether the intention translates into actions.

8 Follow-up Survey and Its Results

From July 20, 2020 to July 22, 2020, I conducted the follow-up survey, once again over the phone. In the follow-up survey, 71.2% of the baseline respondents participated. I do not observe any evidence of differential attrition, i.e., participation in the follow-up survey is not significantly correlated with the treatment status.

I find that a higher percentage of respondents both in the control and treatment group now respond to the questions on local COVID-19 cases and fatality than they responded in the baseline survey. In the follow-up survey, around 65% of the participants responded to the question on local prevalence compared to around 55% in the baseline. Surprisingly, the response rate is not correlated with treatment status. Although both the treatment group and the control group responded to the local prevalence question at around the same proportion, the treatment group's perception about the local prevalence is more accurate. While 63.7% of the control group still underestimate the local prevalence, around 55% of the treatment group underestimate the local prevalence of coronavirus infections.

At the follow-up survey, both treatment and control groups perceive higher infection risk than before. As the treatment group underestimates local prevalence less than the control group, they perceive a 6.2% higher infection risk than the control group (Table 6). Although the treatment group perceives higher infection risk than the control group, they do not take higher overall precautions than the control group (Table 5). Self-reported overall precautions of the treatment group (mean: 8.96 and 90% confidence interval: 8.9- 9.02) are not statistically different than the control group (mean: 9.01 and 90% confidence interval: 8.94- 9.07). This result is robust to different specifications as shown in Table A3 in the Appendix. I also do not find any effect on specific preventive behaviors such as wearing masks, joining social gatherings, etc. However, the estimates may be biased as treatment may cause differential social desirability[17]. To address this issue, I collected some additional information like their support for various policies to prevent the spread of the coronavirus (e.g., requiring a mask, restricting social gatherings, etc.) which might be less susceptible to desirability bias. I also do not find any effect of the risk information on the support for a policy on requiring a mask. However, I find very small negative effect on the support for a policy on restricting social gathering (around 1% less likely to support the policy than the control group).

While treatment heightens infection risk, it does not affect health behavior, possibly due to the downward belief update on the fatality rate. Relatively higher percentage of the participants from the treatment group (80.5%) responded to the question on the fatality rate in the follow-up survey than the participants from the control group (76.8%). The treatment group also reported a fatality rate which on average is lower than the fatality rate reported by the control group (p=0.031). Due to the risk compensation, while updating perceived infection risk upward would cause more preventive measures, updating the perceived fatality risk downward would cause fewer preventive measures. Potentially due to this countervailing update of risk beliefs, the participants in the treatment group has not changed their behaviors differently than the control group.

Although the treatment group reported intention to adopt higher precautions at the baseline, their behaviors remain the same as the control group at the follow-up survey which contrasts the existing literature in health behavior (Webb & Sheeran, 2006). One possible explanation for this could be that the treatment group shared the intention to adopt higher precautions immediately after receiving the information without carefully processing the information. If they got more time, they would have intended to plan the adoption of precautions consistent with their change of risk beliefs and behaviors reported at the end line survey.

[17] Due to social desirability, the self-reported preventive behaviors may cause bias in the estimate. Although I did not recommend any health behavior, it is possible that the treatment group overreports health behavior due to social desirability. If that, in fact, is the case, the estimates I calculated is biased upward, indicating that the intervention may have a negative effect on health behaviors.

I do not find any heterogeneous effect based on baseline risk beliefs. Since the majority of the participants underestimate the local prevalence and overestimate the fatality rate, there are very few who just overestimate the fatality rate or just underestimate the local prevalence leaving little statistical power to detect any heterogeneous effect.

One explanation for the zero effect on health behaviors could be the “question-behavior effect”, i.e., just asking questions may influence the control group to change behavior (Dholakia, 2010). However, this may not be the reason for the information intervention having no effect because the control group did not change their intentions on future precautions and risk perceptions at the baseline even after facing the same questions. It is possible that they may have learned the risk information after participating in the survey. But if that were the case, they would have been more accurate about local prevalence and fatality rate. The percentage of the participants from the control group underestimates the local prevalence is the same at the baseline and end line. Their perceived fatality rate remained higher than the treatment group at the end line survey.

Even after changing risk beliefs, people may not change health behaviors if the perceived benefit of the adoption of a recommended behavior is less than the perceived cost (Abraham & Sheeran, 2014). This may not be a constraint for this sample since infection could be very costly for them. If they contracted the coronavirus, they may not be able to return to their host countries as many countries require a negative COVID-19 test result for entry. Infection may cost their jobs or at least delayed return to the host countries, both of which are very costly to them. Therefore, in addition to health benefits, they have huge economic benefits of adopting healthy behaviors to prevent contraction of the coronavirus. The perceived cost of preventive measures is also relatively lower for this sample because staying home, which is one of the best preventive measures, is not costly for them as most of them were not working in Bangladesh.

Information campaigns may not be effective if the information or the source of information is not credible (Dupas, 2011b). In this study, the credibility of information seems not the reason as most participants believed the information given to them and they updated their belief accordingly, and even after nine to fifteen days, many retained the information. Also, this sample has a very high level of trust in government and NGO sources for COVID-19 information (Figure 2 in appendix). Another constraint that may make the information intervention ineffective can be credit constraints. In many settings where the required health investment is relatively high credit can be a constraint. But in this case, preventive behaviors require little investment. There may be a high opportunity cost of not going to work or joining a social gathering, but it is not a problem for this sample.

The zero effect of the information intervention on behavior is also not due to the study being underpowered. The sample size is big enough to detect an effect of around 1% change in behaviors with a power of 0.80. As a comparison, Dupas (2011a) finds a treatment effect of a 28% decrease in childbearing.

The participants in this survey had already been taking a very high level of precautions (median level of precautions is 9 out of 10), leaving very limited room for an increase in precautions. This could be a reason for the zero effect if the theoretical prediction of the effect of the intervention was positive. But for this study, theoretical prediction is ambiguous, the information could have a positive, negative, or zero result. Adoption of an already high level of precautions is not a constraint for not having negative or zero results. Therefore, I cannot say that the reason for people not changing their behavior is their preintervention adoption of high-level precautions.

9 Conclusion

Similar to many other settings in both developed and developing countries around the world, I document another case of misperceptions of health risks. As information is not easily available, people in Bangladesh underestimate the local prevalence of COVID-19 infections and overestimate the fatality rate. How people would change their health behaviors after receiving information in this setting is theoretically ambiguous. Although similar situations (i.e., underestimation of one risk and overestimation of another) exist in other settings (Delavande & Kohler, 2016), to the best of my knowledge, there does not exist any experimental/causal evidence of how people would respond after receiving information about both health risks. This paper provides causal evidence from a randomized experiment in Bangladesh during the peak of the COVID-19 pandemic.

Like Dupas et al. (2018) and Kerwin (2017), I find that information intervention can improve people's knowledge of health risks. While the participants received information from educational sessions at schools in Dupas et al. (2018), and from the enumerators at the end of an in-person survey in Kerwin (2017), I show evidence that information over the phone, which is much less costly, may also be effective in changing people's risk beliefs in developing countries. Not only the participants change their beliefs after receiving the information, but that belief update also sustained even after 9 to 15 days since the intervention.

Since misperceptions about health risks may cause underinvestment or overinvestment in health care (Dupas, 2011a), changing those misperceptions usually causes changes in behavior (Dupas et al., 2018; Kerwin, 2017). However, in this study the participants changed two risk beliefs, offsetting the effect of each other. Potentially due to this reason, the information does not change the behaviors of the treatment group participants. This result indicates the even with misperceptions people may adopt optimal health behavior when they misperceive multiple risks in opposite directions (i.e., one risk is underestimated, and another is overestimated).

During an emerging outbreak of infectious disease, people may have misperceptions about the associated risks. One implication of this study is that correcting all those misperceptions may not change people's behavior. Therefore, instead of giving people all available information, the social planner may give people specific risk information to improve or reduce the adoption of certain behaviors in the short run. For example, by sharing only the information that heightens risk perception, the social planner may improve the adoption of preventive behaviors.

However, limiting information or not sharing complete risk information may have long-run consequences as people may lose trust in the social planner. But not adopting socially optimal preventive behavior during a pandemic may be even costlier since people may underinvest in preventive behaviors if they do not internalize the externalities of their health behavior. This can be costlier because at the early stage of an epidemic/pandemic, when vaccinations for such new diseases are not readily available, the adoption of healthy preventive behavior is key to control the spread of the disease; otherwise, the pandemic may have severe consequences on lives and economy.

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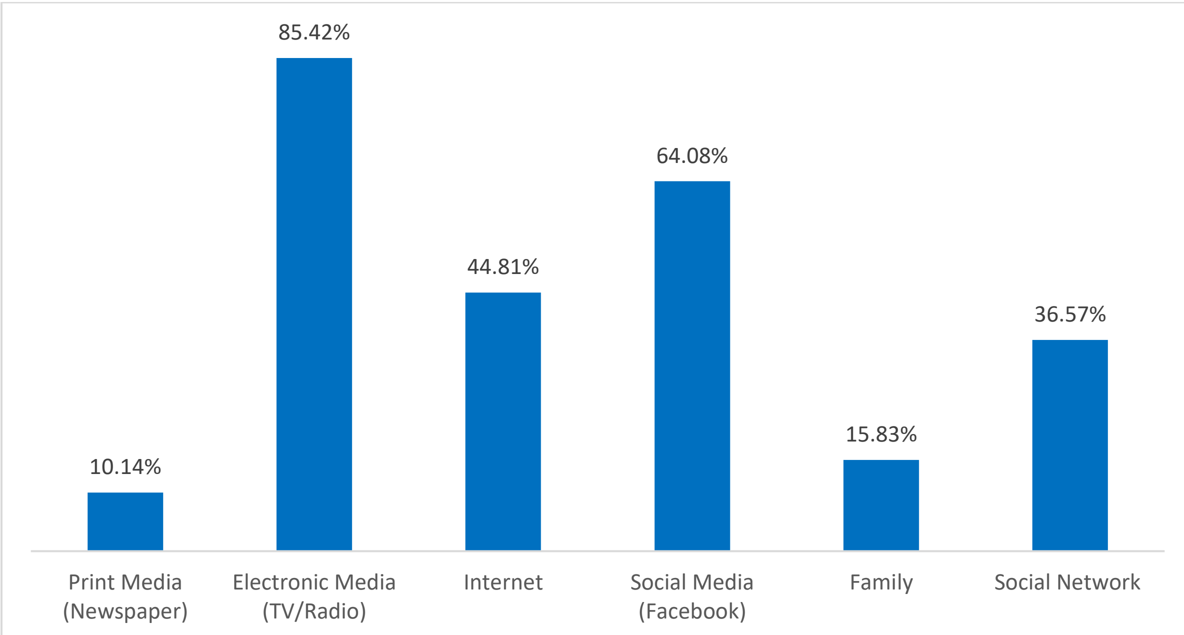
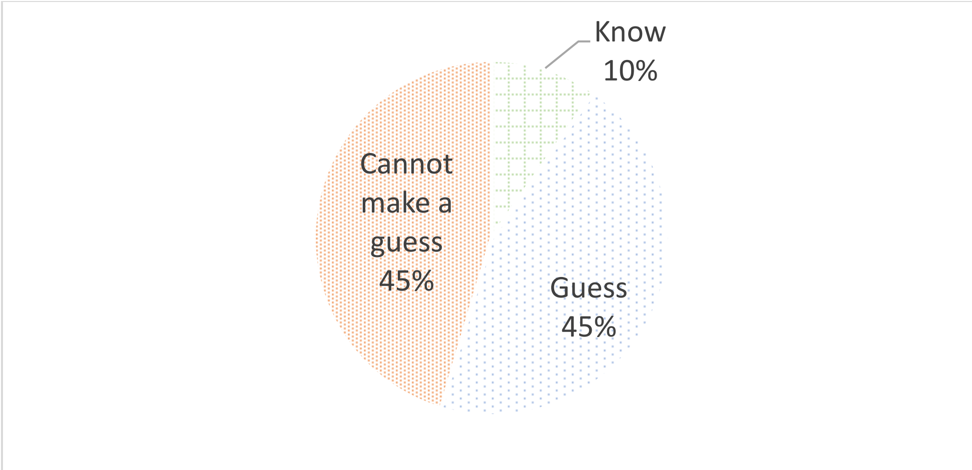
10 Figures

Figure 1: Source of COVID-19 Information

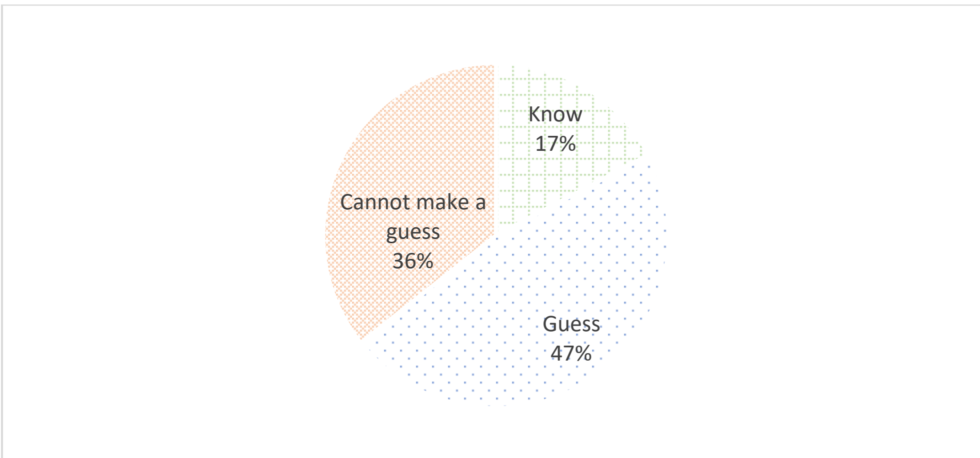


Note: This bar graph plots the sources from where the participants receive COVID-19 related information.

Figure 2: Response to questions on local prevalence and fatality rate



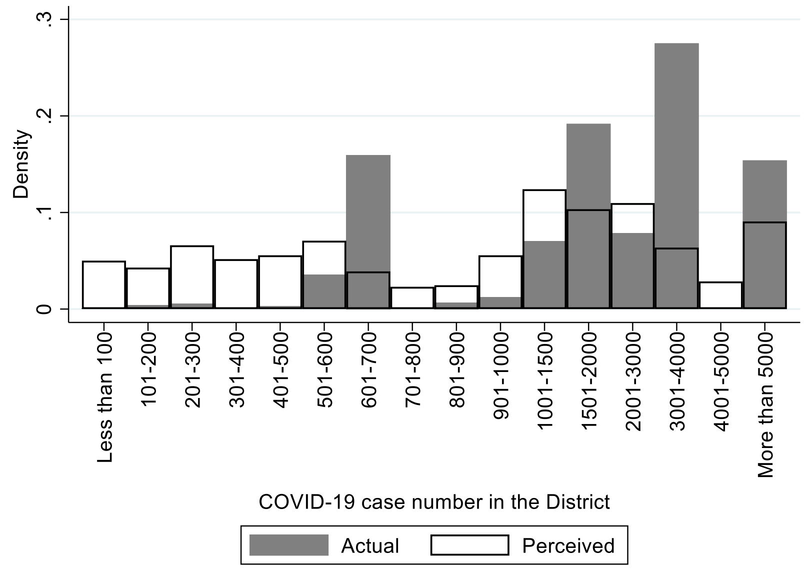
Panel A: Response to the question on local case number



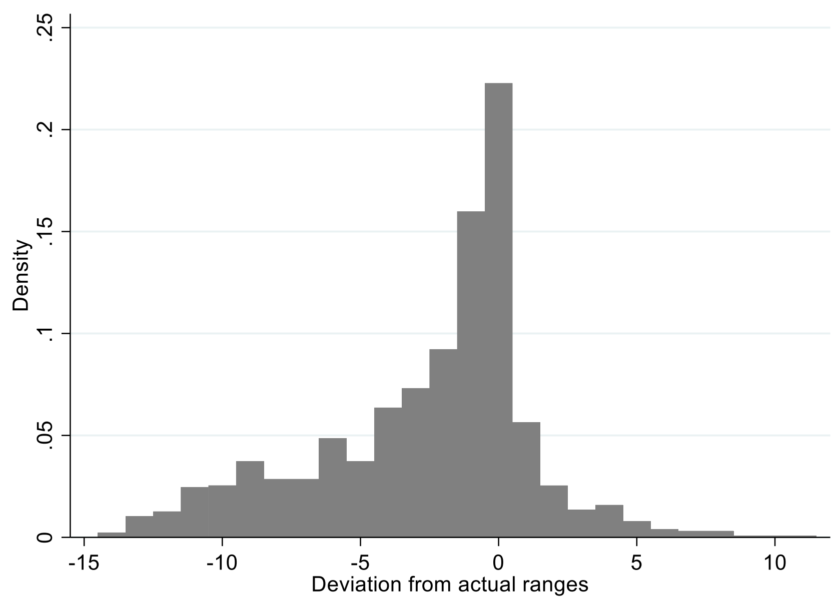
Panel B: Response to the question on fatality rate

Note: The two pie charts show the distribution of the responses of questions on local case number of COVID-19 infection (Panel A) and on fatality rate (Panel B). In both questions, the participants first responded whether they know it. If they answered "yes", they mentioned the number/rate they knew. If they responded "no", the enumerators requested them to make a guess from choices mentioned to them. I allowed the participants not to make a guess too.

Figure 3: Distribution of district case number and deviation from actual case number



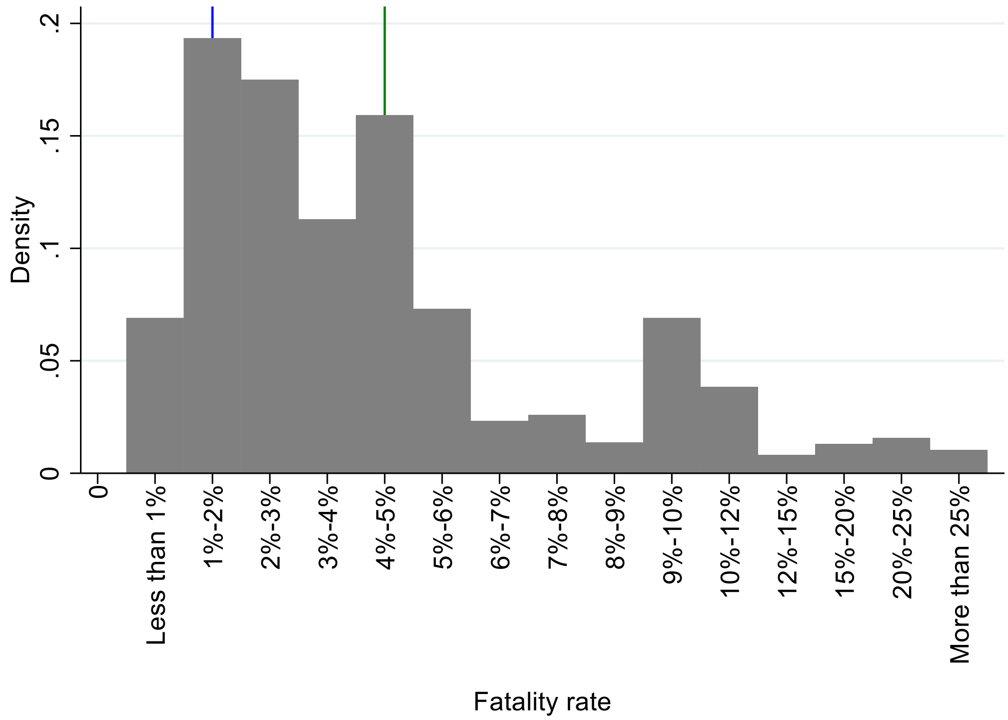
Panel A: Distribution of actual case number and perceived case number



Panel B: Distribution of deviation of perceived case number from actual case number

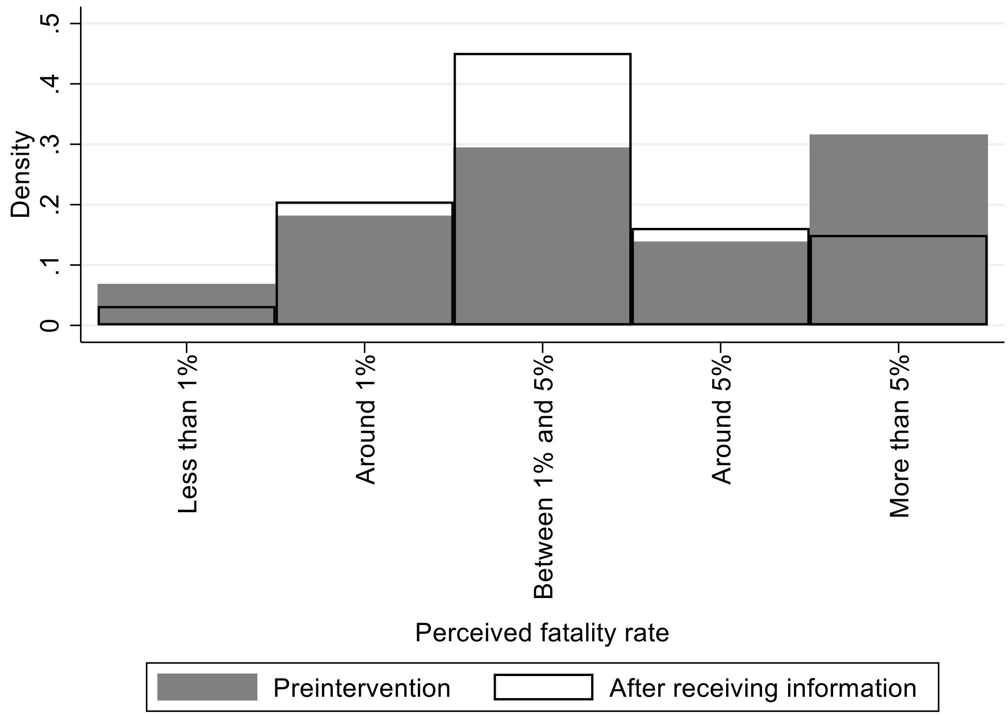
Note: The histogram in Panel A compares the distribution of actual (government reported) district coronavirus case numbers with perceived (participants' reported) numbers. The histogram in Panel B plots the distribution of number of ranges by which perceived case numbers deviated from actual case numbers. For example, -5 indicates that the participant reported a range that is five range lower than the actual range (government reported).

Figure 4: Distribution of reported fatality rate



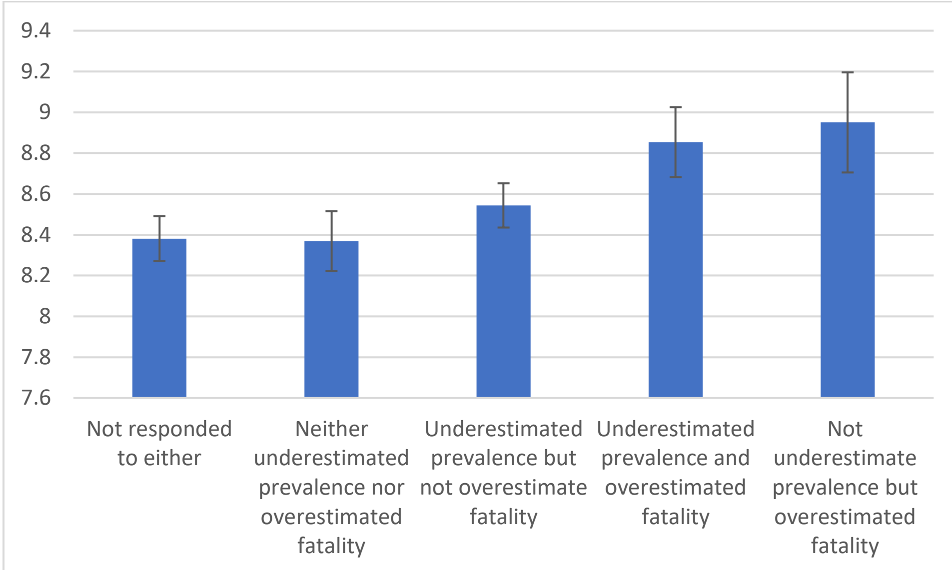
Note: The histogram plots the distribution of the perceived fatality rate of COVID-19. The blue line indicates the case fatality rate of Bangladesh (1.27%) and the green line indicate worldwide case fatality rate (4.88%) as of July 1, 2020. As per WHO, infection fatality rate of COVID-19 is approximately 0.5% to 1%.

Figure 5: Distribution of perceived fatality rate before and after intervention



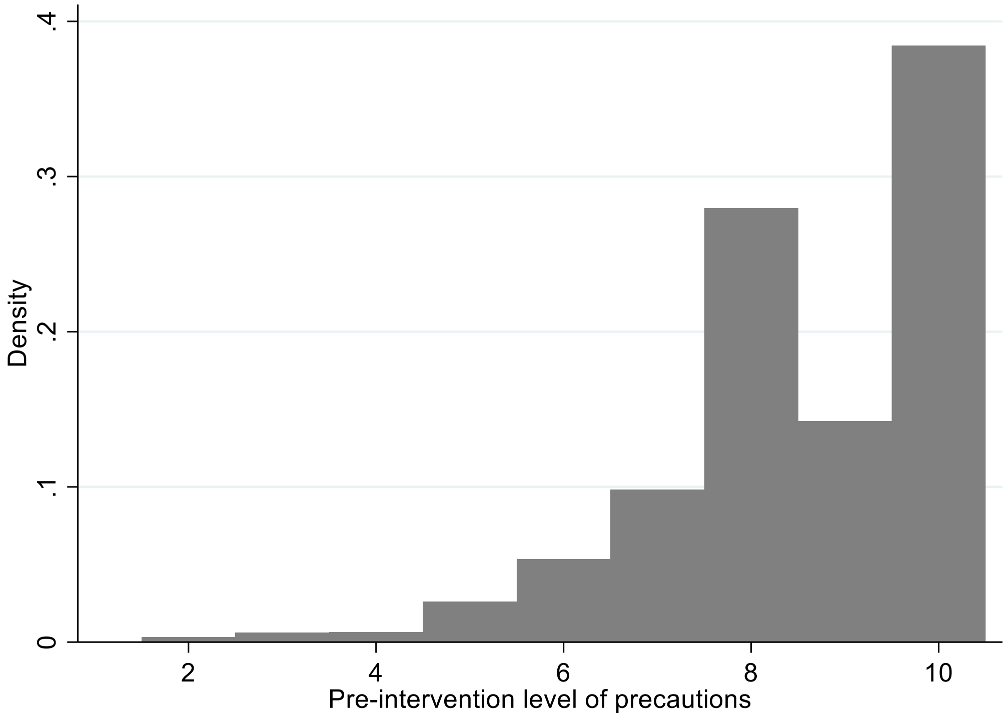
Note: The figure shows the distribution of perceived fatality rate of the treatment group immediately before and after the information treatment.

Figure 6: Pre-intervention precautions by perceptions of local prevalence and fatality rate



Note: The figure presents point estimates of pre-intervention precautions by perceptions of local prevalence and fatality rate. The whiskers show 90% confidence intervals. The first column is for those who responded neither to local prevalence nor the fatality rate questions. The right four columns are for those who responded to both questions. Since the majority underestimate the local prevalence, I created a dummy variable with 1 for underestimation of local prevalence. I also created another dummy variable for overestimation of fatality rate with 1 for overestimation (if perceived fatality rate is higher than 5%). So, there can be a combination of four groups based on their perception of local prevalence and fatality rate.

Figure 7: Distribution of pre-intervention precautions



Note: The figure shows the distribution of pre-intervention precautions. It is a self-reported measure of a 10-point likert scale with 10 being the highest.

11 Tables

Table 1: Cross distribution of misperceptions of local prevalence and fatality rate

	Do not overestimate fatality rate	Overestimate fatality rate	Total
Do not underestimate district case number	24	351	375
	(2.3%)	(33.5%)	(35.8%)
Underestimate district case number	38	635	673
	(3.6%)	(60.6%)	(64.2%)
Total	62	986	1048
	(5.9%)	(94.1%)	(100.0%)

Note: The table shows cross distribution of misperceptions of local prevalence and fatality rate based on the sample that responded to both local prevalence and fatality rate questions during the survey. Here the overestimate of fatality is defined as fatality rate over than 1%.

Table 2: Pairwise correlation of precaution measure with specific health behavior

Correlation of precaution with	
Outside visit	-0.1603*
Emergency outside visit	-0.0583
Unnecessary outside visit	-0.1225*
Wear mask	0.4178*
Join social gathering	-0.1926*

Note: The table shows how various preventive behaviors correlate with an overall precaution measure. These pairwise correlations are based on the responses collected before the intervention. I asked the behavioral questions to only a subset of (519) of my sample (2302) to validate the overall precaution measure. Star (*) marks indicate the coefficients are significant at 10%.

Table 3: Balance of pre-intervention characteristics

	Control Mean & SE	Treatment Mean & SE	T-test p-value
Age	35.48	35.73	0.46
	(0.24)	(0.25)	
Family size	6.14	5.97	0.14
	(0.08)	(0.08)	
Education	7.60	7.46	0.318
	(0.09)	(0.10)	
Monthly salary	46188.83	44574.95	0.298
	(1082.54)	(1111.14)	
Family income	57458.98	55570.93	0.37
	(1469.73)	(1508.55)	
Healthy	0.92	0.93	0.969
	(0.01)	(0.01)	
Tested	0.15**	0.12**	0.011
	(0.01)	(0.01)	
Infected	0.02	0.02	0.744
	(0.00)	(0.00)	
Infection in social network	0.16	0.17	0.827
	(0.01)	(0.01)	
Death in social network	0.05	0.05	0.701
	(0.01)	(0.01)	
Underestimate local prevalence	0.66	0.63	0.347
	(0.02)	(0.02)	
Known fatality rate	5.35	5.98	0.41
	(0.53)	(0.55)	
Precaution	8.54	8.57	0.552
	(0.04)	(0.05)	
Unnecessary outside visit	0.31	0.26	0.107
	(0.02)	(0.02)	
Face mask	3.46	3.52	0.35
	(0.04)	(0.04)	
Social gathering	0.02	0.03	0.983
	(0.01)	(0.01)	
Know symptom	2.57	2.55	0.891
	(0.06)	(0.06)	

Note: The table compares statistics of preintervention characteristics. p<0.1; ** p<0.05; *** p<0.01

Table 4: Treatment effect on perceived infection risk and intention

VARIABLES	(1) Perceived infection risk	(2) Intention of precaution
Treatment	0.178*	0.116**
	(0.100)	(0.048)
Control Mean	2.322***	8.709***
	(0.053)	(0.046)
Observations	2,302	2,302
R-squared	0.002	0.002

Note: The table shows average treatment effect of intervention on risk perception and intention. The outcome variable in column 1 measures the subjective risk perception of being infected by coronavirus on a scale of 1 to 10 with 10 being the highest risk. The intention of precaution variable in column 2 is the intention of level of precautions one plan to take for the future on a scale of 1 to 10 with 10 being the highest precaution one can take to prevent coronavirus infection. Robust standard errors, clustered by district, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Treatment effect on behavior

VARIABLES	(1) Overall precaution	(2) Non-emergency outside visit	(3) Wearing masks	(4) Joining social gathering	(5) Support for a policy requiring a mask	(6) Support for restriction on social gathering
Treatment	-0.042	0.007	-0.026	0.002	0.003	-0.048**
	(0.050)	(0.016)	(0.025)	(0.006)	(0.013)	(0.021)
Control Mean	9.006***	0.378***	3.767***	0.023***	4.950***	4.837***
	(0.043)	(0.018)	(0.011)	(0.007)	(0.011)	(0.025)
Observations	1,638	1,567	1,638	1,638	1,638	1,638
R-squared	0.000	0.000	0.001	0.000	0.000	0.002

Note: The outcome variable in column 1 is the level of overall precaution taken in previous one week. The outcome variable in column 2 is the percentage of total outside visit that were due to non-emergency. Wearing mask is a 4-point likert scale question with 4 indicating wearing mask always when outside. Joining social gathering is a Yes/No question with 1 for Yes and 0 for No. Column 5 and column 6 is based on 5-point likert scale questions with 5 being full support on how much they would support those policies. Robust standard errors, clustered by district, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

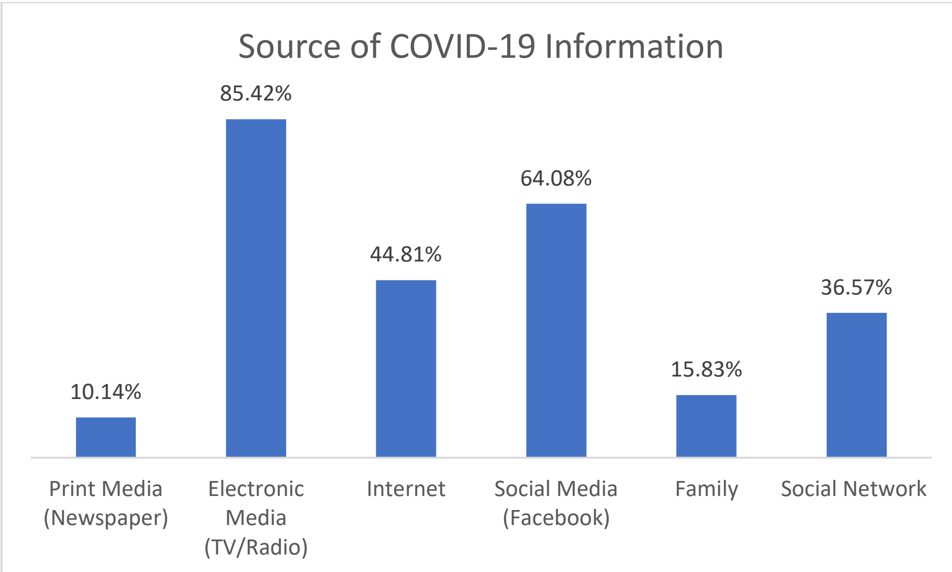
Table 6: Treatment effect on perceived risks during the follow up survey

VARIABLES	(1) Underestimation of district case number	(2) Perceived infection risk
Treatment	-0.088***	0.152**
	(0.025)	(0.071)
Control Mean	0.637***	2.470***
	(0.061)	(0.053)
Observations	1,067	1,638
R-squared	0.008	0.001

Note: The outcome variable in column 1 is a binary variable with 1 for underestimating the district case number during the follow up survey. The outcome variable in column 2 measures the subjective risk perception of being infected by coronavirus on a scale of 1 to 10 with 10 being the highest risk. Robust standard errors, clustered by district, in parentheses.
The number of observations in column 1 is 1,067 because the rest did not respond to the local prevalence question. However, the response is not correlated with treatment.
*** p<0.01, ** p<0.05, * p<0.1.

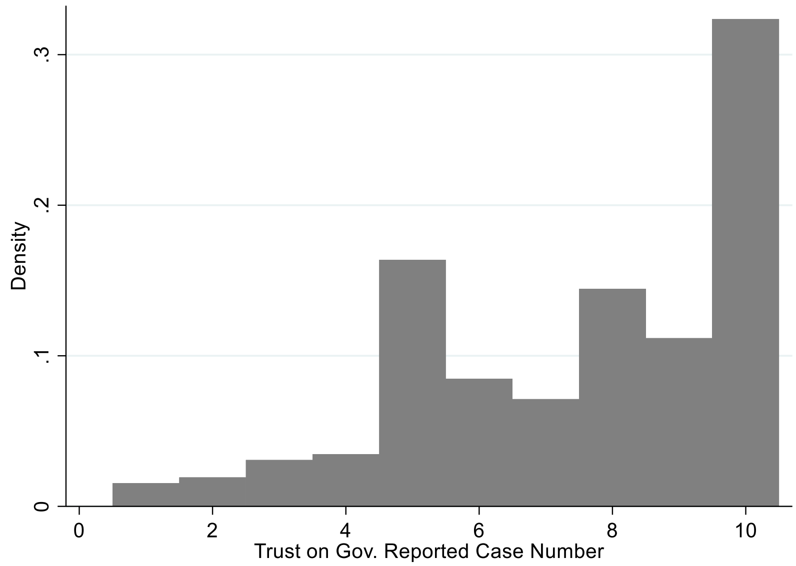
12 Appendix

Figure A1: Source of COVID-19 information

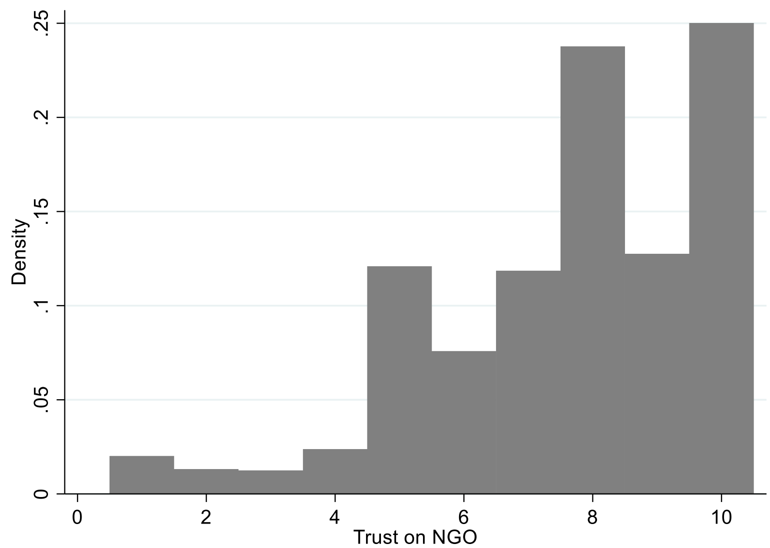


Note: This is based on a question where participants mention the sources from where they receive COVID-19 information.

Figure A2: Trust on various sources of COVID-19 information



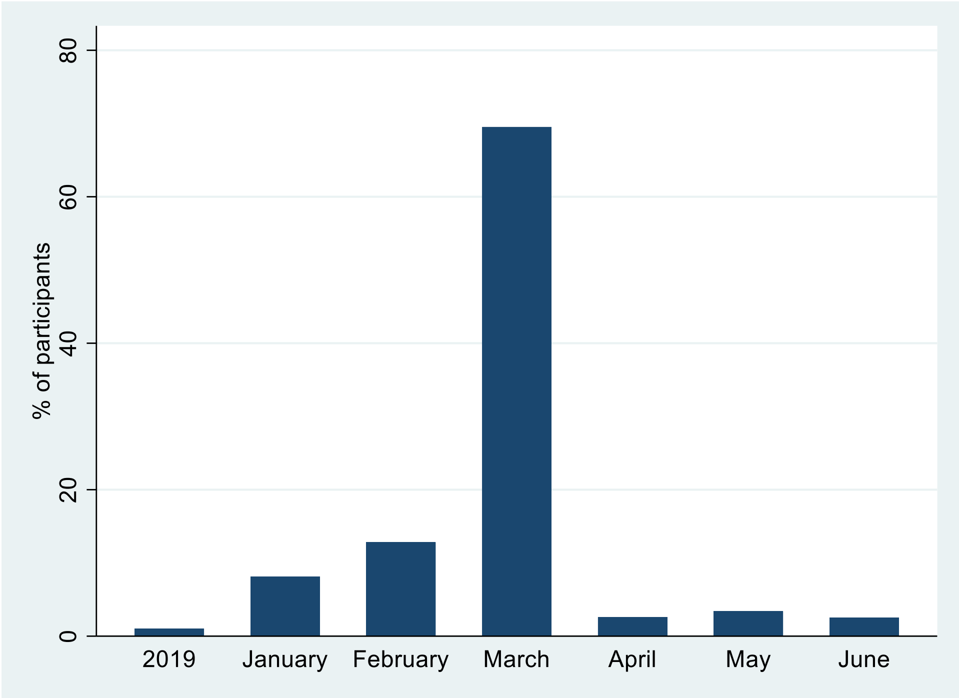
Panel A: Trust on Government reported case number



Panel B: Trust on NGO as a medium of COVID-19 information

Note: Panel A shows the distribution of how much trust the participants have on government reported case number on a scale of 1 to 10. The histogram in Panel B shows the distribution how much trust participants have on NGO as a medium of COVID-19 information on a scale of 10. In both cases, 10 is the highest level of trust.

Figure A3: Return Month of the Respondents



Note: The figure shows the distribution of the respondents by the month of their return from the host countries

Table A1: Immediate effect of treatment on risk perception

	(1)	(2)	(3)	(4)	(5)
VARIABLES			Perceived infection risk		
Treatment	0.178**	0.166*	0.169**	0.180**	0.180*
	(0.086)	(0.086)	(0.085)	(0.086)	(0.106)
Age				0.004	0.004
				(0.005)	(0.004)
Education				0.050***	0.050***
				(0.013)	(0.011)
Salary				-0.002	-0.002
				(0.001)	(0.001)
Constant	2.322***	3.834***	2.640***	1.883***	1.883***
	(0.060)	(1.028)	(0.159)	(0.228)	(0.216)
Fixed effect	None	District	Survey day	None	None
Observations	2,302	2,302	2,302	2,286	2,286
R-squared	0.002	0.026	0.011	0.009	0.009

Note: The table shows the treatment effect of intervention on risk perception. The outcome variable measures the subjective risk perception of being infected by coronavirus on a scale of 1 to 10 with 10 being the highest risk. Column 1 shows average treatment effect. The model in column 2 and 3 includes district and survey day fixed effect, respectively. The model in column 4 adds control variables. And in column 5, standard errors are clustered by district. Standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Immediate effect of treatment on intentions

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			Intentions			
Treatment	0.116*	0.110*	0.122**	0.123**	0.123**	0.091**
	(0.060)	(0.060)	(0.060)	(0.060)	(0.048)	(0.038)
Age				-0.000	-0.000	-0.003
				(0.004)	(0.003)	(0.003)
Education				0.045***	0.045***	0.003
				(0.009)	(0.008)	(0.005)
Salary				0.002**	0.002***	0.001*
				(0.001)	(0.001)	(0.000)
Preintervention level of precautions						0.742***
						(0.013)
Constant	8.709***	9.640***	8.251***	8.282***	8.282***	2.422***
	(0.042)	(0.721)	(0.112)	(0.160)	(0.134)	(0.165)
Fixed effect	None	District	Survey day	None	None	None
Observations	2,302	2,302	2,302	2,286	2,286	2,286
R-squared	0.002	0.036	0.014	0.018	0.018	0.605

Note: The table shows the treatment effect of intervention on intention of future precautions. The outcome variable is the intention of level of precautions one plan to take for the future on a scale of 1 to 10 with 10 being the highest precaution one can take to prevent coronavirus infection. Column 1 shows average treatment effect. The model in column 2 and 3 includes district and survey day fixed effect, respectively. The model in column 4 adds control variables. Preintervention level of precautions is included in column 6. In column 5 and 6, standard errors are clustered by district. Standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Effect of treatment on level of precautions

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			Level of precautions			
Treatment	-0.042	-0.048	-0.039	-0.039	-0.039	-0.042
	(0.057)	(0.058)	(0.058)	(0.058)	(0.050)	(0.051)
Age				0.006*	0.006*	0.006*
				(0.004)	(0.003)	(0.003)
Education				0.005	0.005	0.002
				(0.009)	(0.011)	(0.011)
Salary				0.000	0.000	0.000
				(0.001)	(0.001)	(0.001)
Preintervention level of precautions						0.056***
						(0.014)
Constant	9.006***	9.548***	9.004***	8.736***	8.736***	8.284***
	(0.040)	(0.818)	(0.105)	(0.154)	(0.187)	(0.152)
Fixed effect	None	District	Survey day	None	None	None
Observations	1,638	1,638	1,638	1,628	1,628	1,628
R-squared	0.000	0.043	0.004	0.002	0.002	0.008

Note: The table shows the treatment effect of intervention on self-reported level of precaution. The outcome variable measures the self-reported level of precaution in last one week on a scale of 1 to 10 with 10 being the highest level. Column 1 shows average treatment effect. The model in column 2 and 3 includes district and survey day fixed effect, respectively. The model in column 4 adds control variables. Preintervention level of precautions is included in column 6. In column 5 and 6, standard errors are clustered by district. Standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.