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COVID-19 information and demand for protective gear in the UK*

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Abstract

Amid the COVID-19 crisis in the UK, we study the demand and willingness to pay for hand sanitiser gel, disposable face masks and disposable gloves, and the role of information on tested people and COVID-19 deaths in explaining the demand and willingness to pay (WTP) for these products. The specific hypotheses to test and concrete questions to study were pre-registered in AsPredicted (#38962) on 10 April 2020, and an online survey was launched in Prolific on a sample of the UK general population representative by age, sex and ethnicity on 11 April 2020. We find that there is a demand for these products, estimate the average WTP for them, and show that the provision of information affected the demand (and WTP) for disposable face masks. Giving information on the numbers of COVID-19 cumulative tested people and COVID-19 cumulative deaths increases the stated demand for disposable face masks by about 8 percentage points [95% CI: 0.8, 15.1] and 11 percentage points [95% CI: 3.7, 18.2], respectively. We also investigate whether the provision of information affects donations to UK charities focusing on groups more vulnerable to the COVID-19 pandemic (Age UK, British Lung Foundation, Samaritans, and Women's Aid), but find no evidence of any relevant effect. We do not find differences by sex in the average WTP, or in the effects of information on demands and donations.

Key words: coronavirus, demand, donations, hand sanitiser gel, face masks, gloves.

JEL codes: C99, D12, I12, I18.

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1. Introduction

In the midst of the COVID-19 pandemic, we investigate whether there is a demand for 'protective gear' –hand sanitiser, disposable face masks, or disposable gloves– in the UK, and whether this demand is affected by providing *generic* information on COVID-19 –information on the cumulative numbers of tested people and COVID-19 deaths. Providing an answer to these two questions is a fundamental empirical matter that will help us to understand ways of decreasing the spread of the virus and finding effective ways (i.e. wearing protective gear) to return to our daily routines –once lockdown measures are lifted– while minimising a new wave of COVID-19 infections.

From a microeconomic point of view, the demand for protective gear depends on the utility that individuals derive from it and the costs of acquiring and using it. Consider for instance the decision of buying medical (disposable) face masks. An individual will decide whether her demand for masks is positive (or zero) after comparing the costs of buying and wearing a mask –including the monetary (price) and non-monetary costs (e.g. stigma associated to wearing masks, see Joachim and Acorn, 2000; Li and Abdelkader, 2020)– with the utility gains of using a mask –including the increased perception of security and the reduced transmission probability per contact (see Howard et al. 2020).

We also investigate whether the provision of information affects donations to Age UK, British Lung Foundation, Samaritans, and Women's Aid. These UK charities focus on elderly people, people suffering from lung/respiratory diseases, people struggling with mental health, and women who are victims of domestic violence. These are four vulnerable groups affected directly (e.g. via a weaker immune system) and/or indirectly (e.g. via lockdown measures) by the COVID-19 pandemic.

We collected primary data from a sample of the UK general population representative by age, sex and ethnicity with an online survey and an informational experiment in Prolific on 11 April 2020. We gathered information from our participants on several socio-demographic dimensions, health, concerns and beliefs about the COVID-19 spread, and also ran an experiment providing information.

Our main findings are twofold. First, there is a demand for protective gear in the UK. In our sample, 57% report having *disposable gloves* at home, and 26% report having *disposable face masks*.[1] When asked whether they would buy these items, at an average price of £14.90 per pack of 100 disposable gloves and £11.65 per pack of 10 disposable face masks, around 33% of respondents answered affirmatively. The average WTP for a pack of 100 disposable gloves is estimated at £9.24 [95% CI: 7.84, 10.64] using a linear probability model or at £5.90 [95% CI: 3.65, 8.14] using a logit model, while for a pack of 10 face masks it is £5.99 [95% CI: 4.87, 7.13] or £1.95 [95% CI: –1.37, 5.27], respectively. This evidence is noteworthy given that the UK government has been adamant and persistent in not recommending any disposable gloves or masks at all. Second, providing basic information about the COVID-19 spread is relevant for the stated demand of a particular type of protective gear: disposable face masks. Giving information on the cumulative cases of people tested for COVID-19 and COVID-19 cumulative deaths increases the stated demand for disposable face masks by about 8 percentage points [95% CI: 0.9, 15.1] and 11 percentage points [95% CI: 3.7, 18.2], respectively. Also, the average WTP for disposable face masks increases significantly from the control to the group that receives the information on COVID-19 deaths.

Our investigation on whether the provision of information affects donations to UK charities focusing on COVID-19 vulnerable groups (Age UK, British Lung Foundation, Samaritans, and Women's Aid) reveals no statistically significant effect. However, we acknowledge that the estimated effects on donations are not precisely estimated.

Our study shows that a very simple message on cumulative number of COVID-19 tested people or deaths, based on the information contained in the daily tweet from the Department of Health and Social Care (@DHSCgovuk), affects the stated demand for disposable face masks. If this effect carries over to the actual demand for disposable face masks, this opens the door to informational campaigns that might reduce the spread of the virus. It is worth emphasizing that our treatment consists of very general information that is already present in the internet, and that corresponds verbatim to the daily

[1] These percentages come from Oreffice and Quintana-Domeque (2020) who present the descriptive facts about our survey and its respondents.

tweets by the government. That is, we report already available information with no additional detail or twist or highlights. Therefore, health campaigns based on providing detailed facts on COVID-19 (for instance about its spread under massive adoption of protective gear) may have a widespread impact on the demand and usage of protective gear. Our findings are particularly important at present: it has now become clear that the UK government is reluctant to recommend the widespread usage of disposable masks, or even less so to make it mandatory, in stark contrast to the policies implemented in many other countries affected by COVID-19.[2]

Of course, in making a recommendation to implement informational campaigns that might increase the demand for disposable face masks, one needs to make sure that this does not leave healthcare workers without the adequate protective gear (Abaluck et al., 2020, Howard et al., 2020). This problem seems to be the official reason why the UK government does not to promote the use of protective gear. However, if the supply is limited, at least in the short run, one recommendation would be to incentivise the demand for cloth masks, as done in the US (Centers for Disease Control and Prevention, 2020), while rapidly increasing production of masks (Abaluck et al., 2020, Howard et al., 2020).

Although we are aware that perfectly enforced social distancing can be very effective, protective gear is important in slowing the spread of the virus from customers to key workers, and from key workers to customers, in grocery shops, pharmacies and other essential services. Thus, face masks might play an important role in slowing down the spread of the virus, even in the presence of enforced social distancing. It goes without saying that any attempt to stimulate the demand for face masks needs to be accompanied with accurate messaging that combines different preventative measures (e.g. washing hands, social distancing) so that any form of risk compensation is minimised (Howard et al., 2020).

Our study has two main limitations: one about external validity, and the other about internal validity. With regards *external* validity, and as with previous research using Prolific data (Geldsetzer,

[2] "If everyone is wearing masks to decrease the chance that they themselves are unknowingly infecting someone, everyone ends up being more protected" (p.2., Howard et al., 2020).

2020a; 2020b), our sample of participants is representative of the UK general population by age, sex, and ethnicity, but our respondents may differ from the general population along other characteristics. With regards *internal* validity, one potential concern is whether extrapolating our findings based on “stated” demands to “actual” demands is a sensible thing to do. Our stated demands are based on *hypothetical* questions about buying a product for a given price randomly allocated across respondents, and this may generate hypothetical bias.[3] While much has been written about the main problems of using these hypothetical behavioural questions to learn about actual behaviour, it is important to emphasise two distinctive aspects of our setting: first, our contingent valuation exercise is based on well-known products by our respondents, as judged by their actual demands (73% has hand sanitiser gel at home, 57% has disposable gloves at home, and 26% has disposable face masks at home); second, the stated demands at the random prices are *lower* than the actual demands (24% would buy hand sanitiser gel, 33% would buy disposable gloves, and 33% would buy disposable face masks). Hence, given that respondents seem familiar with the product at stake and the stated demands are, if anything, lower than the actual ones, hypothetical biases are unlikely to distort our WTP estimates. Moreover, even if a distortion occurs, and as long as this is independent of any treatment effect, our experimental design should not be affected by hypothetical bias.

With the previous two limitations in mind, it is interesting to document sizable effects on stated demands obtained with a basic treatment of *generic* information on number of people tested and deaths. One could anticipate that *specific* information about protection from face masks (e.g. relative benefits of medical masks vs. homemade cloth masks vs. no masks at all, specific figures on how much a high take-up rate of masks decreases the spread of COVID-19) or about protection from disposable gloves would have even larger effects. This is important when thinking about the design of effective public health policies, even more so in the UK when the government has repeatedly decided not to promote any widespread use of protective gear, with an emphasis on washing hands in the early stages of the COVID-19 spread. In fact, we would not expect any major increase in the demand for hand sanitiser gel resulting from further information campaigns or any need for these measures: 24% of our

[3] Zweifel et al. (2009) discuss different types of bias in Chapter 2.

respondents would buy hand sanitiser gel, while 73% already report having hand sanitiser at home; one may also effectively wash their hands with soap at home when they stay home during the lockdown.

The next section provides a brief summary of the data used to measure the main outcomes in our study and test our particular hypotheses. Section 3 focuses on the demand and willingness to pay for protective gear. Section 4 estimates the causal effect of information on the demand and willingness to pay for protective gear. Section 5 estimates the causal effect of information on donations to four different UK charities whose goal is on phenomena that are more or less visibly related to the COVID-19 crisis. Section 6 provides a summary of our main findings.

2. Data and measurement

The data used in this paper were collected via an online survey in Prolific on 11 April 2020. We obtained a representative sample of UK respondents by cross-stratifying on sex (male or female), age (18-27, 28-37, 38-47, 48-57, or 58+) and ethnicity (Asian, Black, Mixed, Other, or White).

The size of the working sample of our survey, 949 respondents, and their sociodemographic description are documented in great detail in the report by Oreffice and Quintana-Domeque (2020). Here we highlight the following facts: 51% of them are women, their average age is 46.7, 85% of them are white, 53% of them have attended University, and their median annual income (before tax) in 2019 is £20,000-£24,999.

The survey (https://uebs.eu.qualtrics.com/jfe/form/SV_eCYLWSz1SbEM1Gl)[4] contains two types of questions: questions asked *before* the experiment, and questions asked *after* the experiment. The main sections of the questionnaire are the following:

1. Section on pre-experimental questions (e.g. whether respondents have {hand sanitiser gel, disposable face masks, disposable gloves} at home).
2. Random allocated message (information): control, treatment 1, treatment 2.
3. Section on (**pre-registered**) post-experimental outcomes:

[4] If you want to check the survey, when prompted to enter your Prolific ID, please enter “anonymous”.

- Stated demands for {hand sanitiser gel, face masks, gloves}
- Donations to UK charities

The main purpose of this paper is to analyse the questions asked after the experiment that were pre-registered in AsPredicted (#38962) as post-experimental outcomes.

2.1. Stated demands for protective gear

The individual stated demands for hand sanitiser gel, disposable face masks and disposable gloves were measured as the answers {Yes, No} to the following questions:

Stated demand for hand sanitiser gel: **"Would you buy a 100ml bottle of hand sanitiser gel at a price of £ {2, 4, 10, 24}?"**

Stated demand for disposable face masks: **"Would you buy a pack of 10 disposable face masks at a price of £ {3, 6, 12, 26}?"**

Stated demand for disposable gloves: **"Would you buy a pack of 100 disposable gloves at a price of £ {4, 8, 16, 32}?"**

For each question, individuals were randomly assigned (and evenly split) to one price, so that the demand curve is identified *across* individuals facing *different* prices for the *same* product. The ranges of prices for these three different products were based on a pilot implemented on 7 April 2020 and a search of prices for these products on Amazon. Table A1 in the Online Appendix shows that the average of the randomly assigned price for a 100ml bottle of hand sanitiser is £10.6 (SD = £8.8), for a pack of 10 disposable face masks is £11.7 (SD = £8.8), and for a pack of 100 disposable gloves is £14.9 (SD = £10.8). The fractions of respondents stating that they would buy these goods are: 24% for hand sanitiser gel, 33% for disposable face masks, and 33% for disposable gloves.

2.2. Donations to UK charities

At the end of the survey, participants were given the option to ask us to donate up to 50p to a UK charity. Participants might donate the whole 50p, part of it, or none to any of four UK charities: AGE UK, British Lung Foundation (BLF), Samaritans and Women's Aid.[5]

We decided to select these four charities to measure the strength of the (revealed) relative preference for "helping elderly people" (as captured by the donation to AGE UK), for "helping people suffering from lung/respiratory diseases" (donation to BLF), for "helping people struggling with mental health issues" (donation to Samaritans), and for "helping women who are victims of domestic violence" (donation to Women's Aid). Nothing donated to any of them would represent no preference for supporting any of these charities.

Elderly people, people suffering from lung/respiratory diseases, people struggling with mental health, and women who are victims of domestic violence are four vulnerable groups affected directly (e.g. via a weaker immune system) and/or indirectly (e.g. via lockdown measures) by the COVID-19 pandemic. Stronger or weaker preferences for supporting these charities (and ultimately their targeted groups) might vary for different reasons. One of the potential reasons is that, ceteris paribus, the problems these charities try to address may vary on how visibly-related to the COVID-19 pandemic they are (see the VOX video on the politics of visibility by Ray (2020)).

Table A1 in the Online Appendix shows that the charity with the *highest* average donation per participant is Age UK (12.15 p) and the one with the *smallest* average donation per participant is Women's Aid (8.51 p).[6] Donations to the UK charities were implemented on 20 April 2020.[7]

[5] Participants were asked to allocate the 50p among these four charities and "Amount not to be donated".
[6] The average "no donation" is 8.95 p.
[7] £115 were donated to Age UK, £104 were donated to the British Lung Foundation, £90 were donated to Samaritans, and £81 were donated to Women's Aid.

3. Demand and willingness to pay for protective gear

We start our analysis by focusing on the actual and stated demands for hand sanitiser, disposable face masks and gloves. As explained in the previous section, the actual (revealed) demands were measured at the beginning of the survey by asking individuals whether they had hand sanitiser gel, disposable face masks and disposable gloves at home. The stated demands were measured *after* the experiment. In order to estimate the demand and willingness to pay for protective gear, *regardless* of any informational treatment effect, this section studies the placebo (control) group, as pre-registered in AsPredicted (#38962).

3.1. Main analysis on demand and willingness to pay without treatments

Linear and non-linear regressions. We consider the following demand equations for each individual i and product j ={a 100ml bottle of hand sanitiser gel, a pack of 10 disposable face masks, a pack of 100 disposable gloves}:

$$Y_{ij} = a_j + b_j P_{ij} + \eta_{ij}, \tag{1}$$

and

$$Y_{ij} = F\left(a'_j + b'_j P_{ij}\right) + \eta'_{ij}, \tag{2}$$

where P_{ij} is the price randomly assigned to individual i for product j, and η_{ij} is an unobservable demand shifter. Equation (1) is a linear demand model, and we estimate its parameters a_j and b_j using linear regression (Linear Probability Model). Equation (2) is a non-linear demand model, and we estimate its parameters a'_j and b'_j using non-linear regression (Logit Probability Model).[8]

Estimated WTP. In the linear probability model (LPM), the WTP is defined as the triangle formed by the regression line (e.g. Zweifel et al., 2009; Whitehead, 2017). Hence, in the linear probability model the WTP for product j is estimated as:

$$\widehat{WTP}_j^{LPM} = \frac{1}{2}\hat{a}_j\left(-\frac{\hat{a}_j}{\hat{b}_j}\right). \tag{3}$$

[8] We assume that F is the logistic cumulative distribution function.

In the Logit probability model the WTP is estimated as:

$$\widehat{WTP}_j^{Logit} = -\frac{\widehat{a'}_j}{\widehat{b'}_j}. \tag{4}$$

As stated in our pre-registration plan, we also estimate *conditional* WTP estimates for the Logit model. In particular we estimate the conditional WTP as:

$$\widehat{WTP}_{j,+}^{Logit} = -\frac{\ln\left(1+\exp\left(\widehat{a'}_j\right)\right)}{\widehat{b'}_j}. \tag{5}$$

As recently emphasized by Whitehead (2017), the derivation of and rationale for (5) is provided by Hanemann (1989), who shows how focusing over the positive portion of the probability distribution may overcome one of the main limitations of the Logit model. In the Logit model, the WTP is given by the ratio of the constant over the parameter on the price, hence, a negative constant will lead to a negative WTP estimate when evaluated over the entire range of prices and probabilities (Hanemann, 1984).

Standard errors. The coefficients in the LPM are estimated using robust standard errors to heteroskedasticity, while the standard errors for the WTP estimates are obtained via *bootstrapping* (with 1,000 replications).[9]

Findings. Table 1 reports the estimates of the coefficients in equations (1) and (2), and the estimated WTP according to equations (3), (4) and (5). The average WTP for a 100 ml bottle of hand sanitiser is £5.10 [95% CI: 4.21, 5.99] using a linear probability model, or £2.97 [95% CI: 2.29, 3.65] using a logit probability model. As pre-registered, for the logit model, we also estimate the conditional average WTP, which we estimate at £3.41 [95% CI: 2.81, 4.03]. For protective gear we find that the average WTP for a pack of 10 face masks is £5.99 [95% CI: 4.87, 7.13] using a linear probability model, or £1.95 [95% CI: –1.37, 5.27] using a logit probability model. However, the conditional average WTP is £5.73 [95% CI: 4.36, 7.10]. Finally, the average WTP for a pack of 100 disposable gloves is estimated at £9.24 [95% CI: 7.84, 10.64] using a linear probability model and at £5.90 [95% CI: 3.65, 8.14] using

[9] For the logit model we do not use robust standard errors. The rationale for not using robust standard errors for nonlinear models is clearly discussed by Giles (2013).

a logit model. The conditional average WTP for gloves is estimated at £8.45 [95% CI: 6.83, 10.07]. Table A2 in the Online Appendix reports estimated demand curves after adding a vector of control variables.

Table 1. Estimated Demands and Willingness to Pay.

	Linear Probability Model			Logit Model		
	Hand sanitiser	Face masks	Gloves	Hand Sanitiser	Face masks	Gloves
Price	–0.024***	–0.018***	–0.019***	–0.481***	–0.148***	–0.141***
	(0.002)	(0.002)	(0.002)	(0.082)	(0.028)	(0.022)
Constant	0.490***	0.466***	0.593***	1.429***	0.288	0.833***
	(0.040)	(0.043)	(0.044)	(0.331)	(0.241)	(0.233)
WTP	5.10***	5.99***	9.24***	2.97***	1.95	5.90***
	(0.45)	(0.58)	(0.72)	(0.35)	(1.69)	(1.14)
	[4.21, 5.99]	[4.87, 7.13]	[7.84, 10.64]	[2.29, 3.65]	[–1.37, 5.27]	[3.65, 8.14]
Conditional WTP	--	--	--	3.41***	5.73***	8.45***
				(0.31)	(0.700)	(0.824)
				[2.81, 4.03]	[4.36, 7.10]	[6.83, 10.07]
Observations	316	316	316	316	316	316
R-squared	0.227	0.119	0.196	--	--	--

Note: In parentheses we report robust standard errors for the coefficients of the LPM and standard errors for the Logit coefficients. Standard errors for WTP estimates (LPM and Logit) are bootstrapped (1,000 replications). 95% confidence intervals are reported in brackets. *** p<0.01, ** p<0.05.

3.2. Secondary analysis on WTP without treatments: analysis by sex

Table A3 in the Online Appendix displays the estimates of the WTP by sex. While the point estimates of the WTP for hand sanitiser are very similar by sex, a few differences can be observed when looking at face masks and gloves. Perhaps, the most striking difference is found for the WTP for disposable face masks when using the logit model: –£0.750 [95% CI: –10.87, 9.37] among men versus £3.57 [95% CI: 0.622, 6.53] among women. However, none of these differences is statistically significant.[10]

[10] If we look at the conditional average WTP the point estimates [95% confidence intervals] are: £5.55 [2.97, 8.12] among men and £5.99 [4.24, 7.75] among women.

4. The causal effect of COVID-19 information on the demand and WTP for protective gear

We conducted a *between-subject* experiment to infer the causal effect of information about the prevalence of coronavirus in the UK (as measured by either number of cumulative cases or number of cumulative deaths) on the (stated) demands for hand sanitiser gel, disposable face masks, and disposable gloves in the UK.

4.1. Informational treatments

Participants were randomly assigned (and evenly split) to one of three arms: information treatment 1 (T1), information treatment 2 (T2), or control.[11]

T1 arm. Participants were informed on the number of people tested for coronavirus in the UK, as reported in the daily tweet of the Department of Health and Social Care (@DHSCgovuk): **"In the UK, as of 9am on 10 April, a total of 256,605 people have been tested for Coronavirus."**

T2 arm. Participants were informed on the number of coronavirus deaths in the UK among those hospitalised who tested positive for Coronavirus, as reported in the daily tweet of the Department of Health and Social Care (@DHSCgovuk): **"In the UK, as of 5pm on 9 April, of those hospitalised who tested positive for Coronavirus, 8,958 have sadly died."**

Control arm. Participants were not given any information.

Table A4 in the Online Appendix provides a randomisation check to assess whether the randomization was successful in balancing observable pre-treatment characteristics across treatment arms. While a few individual statistical differences can be observed, we cannot reject the hypothesis that pre-treatment individual characteristics do not predict participation in any particular arm ($\chi^2(48)$ = 50.95, p-value = 0.3585).[12]

[11] All participants were given the same information at the end of the survey, as described in Figure A1 in the Online Appendix.

[12] Technically speaking, the randomly allocated price is not a *pre*-treatment characteristic, since prices are randomly allocated after the allocation to the arm. Excluding the comparisons of prices from the omnibus test we obtain $\chi^2(42)$ = 43.98 with p-value = 0.3877.

4.2. Main hypothesis: the effect of information on demands

The main hypothesis is that the provision of generic information on either coronavirus tested people or coronavirus deaths increases the (stated) demands for {hand sanitiser gel, disposable face masks, disposable gloves}, but that the informational treatments have different effects. As is well-known (e.g. Kuziemko et al. 2015, Haaland and Roth, 2017), these effects may emerge as pure informational effects, as salience effects, or as a combination of both. Here we are interested in testing whether the delivery of this information changes demand, which is a first order concern.

4.2.1. Parametric analysis

Identification. This hypothesis is investigated and tested by estimating the following linear equation for each product $j =${a 100ml bottle of hand sanitiser gel, a pack of 10 disposable face masks, a pack of 100 disposable gloves} by OLS:

$$Y_{ij} = \alpha_j + \beta_{1j}T_{1i} + \beta_{2j}T_{2i} + u_{ij}, \tag{6}$$

where $Y_{ij} = 1$ if individual i answers "Yes" to the question about the demand for product j (**"Would you buy j at a price of** […] **?"**), $= 0$ if individual i answers "No"; $T_{1i} = 1$ if individual i is assigned to T1 arm, $= 0$ else; $T_{2i} = 1$ if individual i is assigned to T2 arm, $= 0$ else; u_{ij} is an error term capturing any other relevant factor of the individual $i's$ demand for product j. The parameters of interest are β_{1j}, which is the causal effect of T1 on Y_{ij}, and β_{2j}, which is the causal effect of T2 on Y_{ij}. Of course, if some individuals did not pay attention to the informational treatment, what we are identifying are *intent-to-treat* effects.

Testing. We estimate standard errors robust to heteroskedasticity and test the following hypotheses:

- $\beta_{1j} = 0$ against $\beta_{1j} \neq 0$;
- $\beta_{2j} = 0$ against $\beta_{2j} \neq 0$;
- $\beta_{1j} = 0$, $\beta_{2j} = 0$ against at least one $\beta_{kj} \neq 0$ for $k = \{1,2\}$;
- $\beta_{1j} = \beta_{2j}$ against $\beta_{1j} \neq \beta_{2j}$.

The minimum detectable effect (MDE) was estimated at 0.07 (see section A in the Online Appendix).

Findings. The estimates and tests of (6) are reported in Table 2. We find that the provision of information has no statistically significant effects on either the demand for hand sanitiser gel or disposable gloves. For hand sanitiser gel, the point estimates [95% confidence intervals] for the average causal effects of giving information on number of tested people and on number of deaths are –0.032 [–0.09, 0.03] and 0.006 [–0.06, 0.07], respectively. For disposable gloves, the point estimates [95% confidence intervals] for the average causal effect of giving information on number of tested people and on number of deaths are –0.041 [–0.11, 0.03] and 0.059 [–0.015, 0.133], respectively, although we reject the hypotheses that both effects are zero (F = 3.63, p-value = 0.0268) and that the effects are the same (F = 7.24, p-value = 0.0072).

However, we find statistically significant and sizable effects on the demand for disposable face masks: giving information on the numbers of cumulative tested people and COVID-19 cumulative deaths increases the stated demand for disposable face masks by about 8 percentage points [0.8, 15.1] and 11 percentage points [3.7, 18.2], respectively. We cannot reject that the average effects of providing these two types of information on the stated demand for disposable face masks are the same, and we reject that all the treatment effects are simultaneously zero ($\chi^2(6) = 18.25$, p-value = 0.0056). Figures A2-A4 in the Online Appendix summarise graphically these findings.[13]

[13] For completeness, in Table A5 in the Online Appendix, we estimate the average treatment effects of information on the demand for hand sanitiser gel, disposable face masks and disposable gloves using a Logit model. Not surprisingly, we obtain virtually the same estimates and very similar standard errors.

Table 2. OLS regressions of hand sanitiser, face masks or gloves on T1 and T2.

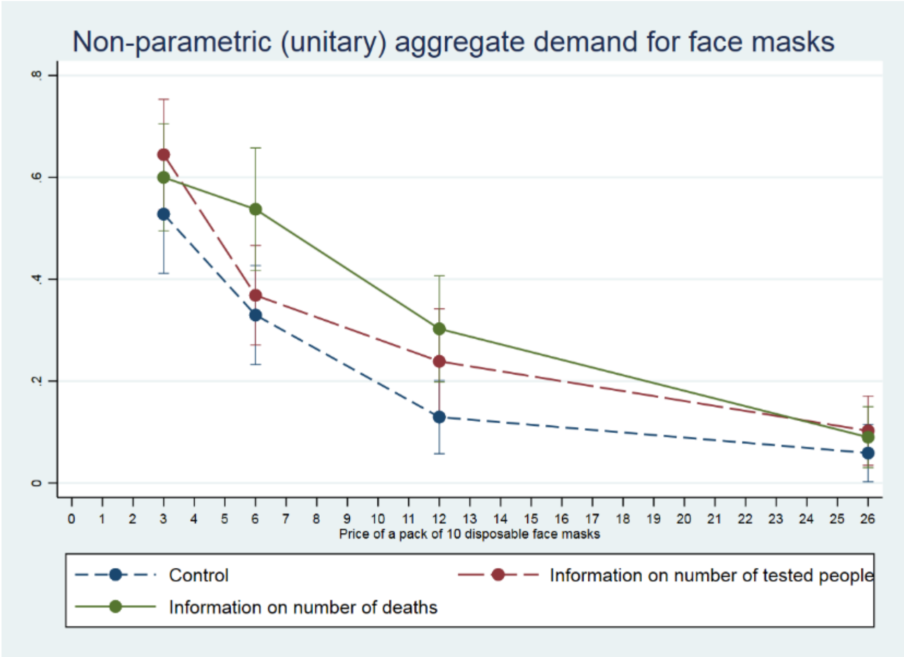
	Hand Sanitiser	Face Mask	Gloves
T1	–0.032	0.079**	–0.041
	(0.034)	(0.036)	(0.036)
	[–0.09, 0.03]	[0.008, 0.151]	[–0.11, 0.03]
T2	0.006	0.110***	0.059
	(0.034)	(0.037)	(0.038)
	[–0.06, 0.07]	[0.037, 0.182]	[–0.015, 0.133]
Mean Control	0.247***	0.263***	0.320***
	(0.024)	(0.025)	(0.026)
	[0.20, 0.29]	[0.21, 0.31]	[0.27, 0.37]
F tests: F-statistic {p-values}			
No treatment effect	0.72	4.84	3.63
	{0.4856}	{0.0081}	{0.0268}
Same treatment effect	1.22	0.64	7.24
	{0.2697}	{0.4244}	{0.0072}
Observations	949	949	949

Note: Robust standard errors in parentheses. Each column displays a regression of an indicator of whether the individual would buy a 100ml bottle of hand sanitiser, a pack of 10 disposable face masks, or a pack of 100 disposable gloves on a constant, and the two informational treatment indicators (T1 and T2). 95% confidence intervals are reported in brackets. *** p<0.01, ** p<0.05.

4.2.2. Non-parametric analysis

We also conduct a non-parametric analysis of the effects of information on the demand for hand sanitiser, face masks and gloves. To that end, we plot the (aggregate) demand curve for each product j ={a 100ml bottle of hand sanitiser gel, a pack of 10 disposable face masks, a pack of 100 disposable gloves} by arm {T1, T2, control}. Each curve is based on four points: the average demand (fraction of Yes-answers) for each product j for a given randomly assigned price. Figures A5-A6 in the Online Appendix display the estimated demand curves for hand sanitiser gel and disposable gloves, and Figure 1 below displays the corresponding one for disposable face masks. All figures contain 95% confidence intervals for each point estimate of the (aggregate) demand curve.

Figure 1. Non-parametric stated demand for disposable face masks by treatment arm.



Note: Each point estimate is accompanied with its 95% CI.

Non-parametric analyses are more demanding than parametric ones, and while they can be noisier, they might offer insights that go beyond the mean. The two main takeaways from Figure 1 (and Figures A5 and A6) are: (1) *the law of demand* (i.e. for each good, there is a negative relationship between the fraction of individuals "willing to buy" it and its price); (2) *information matters, at least for masks* (more specifically, the demand for disposable face masks is higher at each price among those who were given the information on deaths than among those who were not given any information). This evidence is consistent with our parametric analysis, and with the suggestion that public health campaigns may play an important role in the UK at present.

4.3. Main hypothesis: the effect of information on WTP

In this subsection we investigate whether the WTP differs by treatment arm. Table 3 suggests that, if anything, the average WTP for disposable face masks, as measured in the linear probability model, increases from £5.99 [95% CI: 4.87, 7.13] in the control group to £9.35 [7.90, 10.71] in the group that receives the information on COVID-19 deaths. There is also evidence that the average conditional WTP for disposable face masks, after fitting a Logit probability model, increases from £5.73 [95% CI: 4.36, 7.10] to £9.43 [95% CI: 7.58, 11.27].

Table 3. Willingness to Pay by Treatment Arm.

	Linear Probability Model			Logit Model		
	Hand sanitiser	Face masks	Gloves	Hand Sanitiser	Face masks	Gloves
WTP (control)	5.10***	5.99***	9.24***	2.97***	1.95	5.90***
	[4.21, 5.99]	[4.87, 7.13]	[7.84, 10.64]	[2.29, 3.65]	[−1.37, 5.27]	[3.65, 8.14]
WTP (T1)	4.85***	8.21***	8.70***	2.16***	4.16***	4.37***
	[3.96, 5.73]	[6.86, 9.55]	[7.27, 10.12]	[0.98, 3.33]	[1.47, 6.85]	[1.36, 7.38]
WTP (T2)	5.20***	9.35***	11.32***	2.91***	6.35***	8.61***
	[4.34, 6.07]	[7.90, 10.71]	[9.79, 12.85]	[1.97, 3.85]	[4.11, 8.59]	[6.53, 10.69]
Conditional WTP (control)	--	--	--	3.41***	5.73***	8.45***
				[2.81, 4.03]	[4.36, 7.10]	[6.83, 10.07]
Conditional WTP (T1)	--	--	--	3.60****	8.31***	8.44***
				[2.85, 4.35]	[6.40, 10.22]	[6.80, 10.07]
Conditional WTP (T2)	--	--	--	3.70***	9.43***	11.09***
				[2.94, 4.45]	[7.58, 11.27]	[9.01, 13.16]

Note: Standard errors for WTP estimates (LPM and Logit) are bootstrapped (1,000 replications). 95% confidence intervals are reported in brackets. *** p<0.01, ** p<0.05.

4.4. Secondary hypothesis: the effect of information on demands by sex

We have also investigated whether the effects of delivering information on demands vary by sex, but failed to find evidence that this is the case. Table A6 and Figures A7-A9, which contain our parametric and non-parametric analyses by sex, can be found in the Online Appendix.

5. The causal effect of COVID-19 information on donations

5.1. Main hypothesis: the causal effect of information on donations

The main hypothesis is that the provision of information on either coronavirus tested people or coronavirus deaths increases the donations for {AGE UK, the British Lung Foundation, Samaritans, Women's Aid}, but that the informational treatments have different effects. These charities all focus on issues that are more or less visibly related to the COVID-19 crisis.

We follow the same identification and testing approach as in Section 5. In Table 4 we estimate the same type of regression as in (6) but replacing the dependent variable Y_{ij} with D_{ij}, which is the fraction (0-1) out of 50p donated to the UK charity j, where j ={AGE UK, the British Lung Foundation, Samaritans, Women's Aid}.[14] None of the point estimates is statistically significant at the 5% level, and their magnitudes fluctuate between –0.05 and 0.04. These can be interpreted as differences in percentage points over the mean in the control group, and can be quite large. For example, the point estimate of the average causal effect of T2 on donations to Samaritans suggests an effect of 23% of the mean. However, none of the estimates is precisely estimated, with quite wide confidence intervals (e.g. [–0.072, 0.031]). Moreover, we cannot reject that all the treatment effects are simultaneously zero ($\chi^2(8)$ = 8.58, p-value = 0.3787).[15]

Table 4. OLS regressions of fraction donated to Age UK, BLF, Samaritans, Women's Aid or None on T1 and T2.

	Age UK	BLF	Samaritans	Women's Aid	None
T1	0.016	–0.021	0.018	0.029	–0.043
	(0.027)	(0.026)	(0.023)	(0.023)	(0.029)
	[–0.037, 0.068]	[–0.072, 0.031]	[–0.027, 0.064]	[–0.015, 0.074]	[–0.100, 0.015]
T2	0.016	–0.049	0.039	0.023	–0.029
	(0.027)	(0.026)	(0.024)	(0.023)	(0.030)
	[–0.037, 0.068]	[–0.099, 0.001]	[–0.008, 0.085]	[–0.021, 0.068]	[–0.087, 0.030]
Mean control	0.233***	0.242***	0.170***	0.153***	0.203***
	(0.019)	(0.020)	(0.016)	(0.015)	(0.022)
	[0.196, 0.269]	[0.204, 0.281]	[0.139, 0.200]	[0.123, 0.182]	[0.160, 0.246]
F tests: F-statistic {p-values}					
No treatment effect	0.23	1.88	1.34	0.97	1.07
	{0.7960}	{0.1528}	{0.2621}	{0.3786}	{0.3438}
Same treatment effect	0.00	1.36	0.68	0.06	0.24
	{0.9996}	{0.2439}	{0.4104}	{0.7992}	{0.6213}
Observations	945	945	945	945	945

Note: Robust standard errors in parentheses. Each column displays a regression of fraction donated on a constant, and the two informational treatment indicators (T1 and T2). 95% confidence intervals are reported in brackets. *** p<0.01, ** p<0.05.

[14] Note that the sum of D_{ij} over j needs not be equal 1, since any individual i might decide to leave any "Amount not to be donated."

[15] For completeness, in Table A7 in the Online Appendix, we estimate the average treatment effects of information on the fraction donated to the UK charities using a fractional Logit model. Not surprisingly, we obtain virtually the same estimates and very similar standard errors.

5.2. Secondary hypothesis: the effect of information on donations by sex

We have also investigated whether the effects of delivering information on donations vary by sex, but failed to find evidence that this is the case. The estimates are reported in Table A8, located in the Online Appendix.

6. Discussion

Our main findings are five:

First, there is a (stated) demand for protective gear in the UK, including disposable face masks. The fractions of respondents *stating* that they would buy 'protective gear' are: 24% for hand sanitiser gel, 33% for disposable face masks, and 33% for disposable gloves; these can be compared with the fraction of respondents *having them at home*: 73% for hand sanitiser gel, 26% for disposable face masks, and 57% for disposable gloves.

Second, the average WTP (based on a linear model and without delivering information) for a 100ml bottle of hand sanitiser gel is about £5 [95% CI: 4.2, 6], for a pack of 10 disposable face masks is about £6 [95% CI: 4.9, 7.1] and for a pack of 100 disposable gloves is about £9 [95% CI: 7.8, 10.6].

Third, the (stated) demand for disposable face masks is increased by providing *generic* information on COVID-19: delivering information on COVID-19 deaths increases the stated demand of disposable face masks by about 11 percentage points [95% CI: 3.7, 18.2].

Fourth, the average WTP for disposable face masks is increased by providing information on COVID-19 deaths: the average WTP increases from about £6 [95% CI: 4.9, 7.1] in the control group to almost £9.5 [95% CI: 7.9, 10.7] in the group receiving the information on COVID-19 deaths, which is consistent with the increase in the stated demand.

Five, donations to four UK charities (Age UK, British Lung Foundation, Samaritans and Women's Aid) are not affected by the provision of information on either the number of tested people for COVID-19 or COVID-19 deaths.

It has now become clear that the UK government is reluctant to recommend the widespread usage of disposable masks, or even less so to make it mandatory, in stark contrast with the policies adopted in many other countries affected by COVID-19. In these circumstances, we see our results as a relevant step forward to understand spread containment channels in addition to social distancing; our evidence also supports the use of health campaigns to encourage the adoption of mask wearing, and potentially of other protective gear as well. Our treatment consisted of very general information that is already present in the internet, and that corresponds verbatim to the daily tweets by the government. We believe that targeted informational campaigns based on detailed facts on COVID-19 (e.g. about its spread rate under massive adoption of protective gear) may have a widespread impact on the demand and usage of protective gear, and ultimately on the further spread of the virus.

We hope that our findings will help to understand and devise ways to decrease the spread of the virus, and encourage effective actions (i.e. wearing protective gear) to return to our daily routines –once lockdown measures are lifted– while minimising a new wave of COVID-19 infections.

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COVID-19 information and demand for protective gear in the UK

[ONLINE APPENDIX (not for publication)]

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Section A. Statistical Inference and Sample Size

Our main focus when designing our study was on the causal effect of information on the demand for hand sanitiser gel, disposable face masks and disposable gloves. For this reason, our sample size was based on minimum detectable effects for β_{1j} and β_{2j}. For a test with power of 80% this was computed following (Kondylis and Loeser, 2020):

$$MDE_{0.8} = 2.8\sigma\sqrt{\frac{1}{N_C} + \frac{1}{N_T}},$$

where N_C is the number of observations in the control group, N_T is the number of observations in the treatment group, and σ is the standard deviation of the main binary outcome of interest. In our pilot, the minimum standard deviation among the three main binary outcomes of interest (e.g. "Would you buy …?") was ~ 0.3. We expected to interview ~ 1,000 respondents, split equally in each arm –T1 and T2 (treatment arms) and placebo (control arm)– and with a minimum number of 300 observations in each arm. This implies a minimum detectable effect (MDE) of

$$MDE_{0.8} \approx 0.07.$$

This was deemed as a reasonable MDE, since in the pilot the point estimates of the effects (T2 against T1) for the three relevant outcomes ranged from 0.11 to 0.18.[1]

[1] In the pilot we compared *different* treatments without a pure placebo.

Section B. Summary statistics

Table A1. Summary statistics.

	Mean	SD	Min	Max
Price of hand sanitiser (£)	10.63	8.80	2	24
Price of face masks (£)	11.66	8.83	3	26
Price of gloves (£)	14.90	10.77	4	32
Stated demand for hand sanitiser	0.238	0.426	0	1
Stated demand for face masks	0.326	0.469	0	1
Stated demand for gloves	0.326	0.469	0	1
Donation to Age UK (p)	12.15	16.79	0	50
Fraction donated to Age UK	0.243	0.336	0	1
Donation to British Lung Foundation (p)	10.95	15.99	0	50
Fraction donated to British Lung Foundation	0.219	0.320	0	1
Donation to Samaritans (p)	9.43	14.97	0	50
Fraction donated to Samaritans	0.189	0.299	0	1
Donation to Women's Aid (p)	8.51	14.41	0	50
Fraction donated to Women's Aid	0.170	0.288	0	1

Note: Number of observations is 949 for prices and stated demands, and 945 for donations (amount and fraction). Four respondents could not complete the donation question for logistic issues.

Section C. Estimated Demands with control variables.

Table A2 reports estimated demand curves after adding a vector of control variables: *standard socioeconomic characteristics* (sex (female = 1 if female, = 0 if male), age (2020 – year of birth), ethnicity (white = 1 if white, white = 0 else), 11 regional dummies,[2] marital status (partnered = 1 if married or cohabiting, = 0 else), household size, education (university = 1 if university, = 0 else), and income (= log of income)[3]), and an indicator of whether the individual has at home the product being demanded {hand sanitiser gel, disposable face masks, disposable gloves}.

[2] East Midlands, East of England, London, North East, North West, Northern Ireland, Scotland, South East, South West, Wales, and West Midlands

[3] As described in Oreffice and Quintana-Domeque (2020), income is reported in intervals. Here we construct our (discrete) income measure by assigning the midpoint value of each interval for intervals other than the top and the bottom. For the bottom and the top intervals, we take the maximum value (of the bottom interval) and the minimum value (of the top interval).

Table A2. Estimated Demands with control variables.

	Linear Probability Model			Logit Model		
	Hand sanitiser	Face masks	Gloves	Hand Sanitiser	Face masks	Gloves
Price	–0.023***	–0.018***	–0.018***	–0.521***	–0.156***	–0.153***
	(0.002)	(0.002)	(0.002)	(0.088)	(0.029)	(0.024)
Control variables	YES	YES	YES	YES	YES	YES
Test of all controls = 0	0.69	2.21	2.80	14.68	23.91	29.49
{p-value}	{0.8334}	{0.0030}	{0.0001}	{0.6837}	{0.1997}	{0.0427}
Observations	316	316	316	313	316	313

Note: Linear probability model (LPM) is estimated with robust standard errors. Test of all controls = 0: it reports the value of the F-statistic that all coefficients on the control variables in the LPM are zero (F(19,295)); it reports the value of the χ^2-statistic that all coefficients on the control variables in the Logit model are zero ($\chi^2(18)$ in columns 1 and 3, and χ^2 (19) in column 2). *** p<0.01, ** p<0.05.

Section D. Estimated WTP by sex.

Table A3. Estimated Willingness to Pay by sex.

	Linear Probability Model		Logit Model	
	Men	Women	Men	Women
Hand sanitiser	5.02***	5.17***	2.96***	2.98***
	[3.74, 6.29]	[3.94, 6.40]	[2.01, 3.91]	[1.98, 3.98]
Face masks	5.44***	6.62***	–0.750	3.57***
	[3.64, 7.24]	[5.05, 8.19]	[–10.87, 9.37]	[0.622, 6.53]
Gloves	9.44***	9.04***	5.25***	6.42***
	[7.33, 11.55]	[7.18, 10.90]	[1.22, 9.29]	[3.94, 8.89]

Note: Standard errors for WTP estimates (LPM and Logit) are bootstrapped (1,000 replications). 95% confidence intervals are reported in brackets. *** p<0.01, ** p<0.05.

Section E. Last screen of the survey.

Figure A1. Last screen of the survey

UNIVERSITY OF EXETER

Thank you for your participation!

To prove that you have completed our survey, please follow this link: https://app.prolific.co/submissions/complete?cc=128C3B33

Spread of Coronavirus in the UK

As of 9am on 10 April:

- A total of 256,605 people have been tested for Coronavirus.

As of 5pm on 9 April:

- Of those hospitalised who tested positive for Coronavirus, 8,958 have sadly died.

Advice for everyone: stay at home

For advice RE Coronavirus, visit the NHS webpage: https://www.nhs.uk

Struggling with stress, anxiety or depression?

If you're struggling with stress, anxiety or depression, it's best to speak to someone:

You can call Samaritans free on 116 123 if you want to talk to someone now.

Section F. Randomization check.

Table A4 display the average characteristics of our respondents across arms, individual tests for differences across arms, and an omnibus test based on a multinomial logit where we test whether pre-treatment individual characteristics predict participation in any particular arm (control, T1, and T2).

Table A4. Means of pre-treatment characteristics by treatment arm.

Individual tests	**Means**			**Test of equality of means**		
	C	**T1**	**T2**	**C = T1** *p-value*	**C = T2** *p-value*	**C = T1 = T2** *p-value*
Actual demands						
Hand sanitiser gel	0.73	0.71	0.75	*0.596*	*0.512*	*0.492*
Disposable face masks	0.28	0.24	0.27	*0.275*	*0.981*	*0.454*
Disposable gloves	0.62	0.54	0.54	*0.044*	*0.032*	*0.054*
Demographics						
Female	0.52	0.52	0.49	*1.000*	*0.551*	*0.789*
Age	47.02	46.45	46.59	*0.649*	*0.729*	*0.893*
White	0.86	0.84	0.84	*0.317*	*0.442*	*0.572*
Region or nation						
East Midlands	0.07	0.06	0.07	*0.629*	*0.886*	*0.802*
East of England	0.06	0.05	0.07	*0.592*	*0.628*	*0.592*
London	0.14	0.13	0.15	*0.643*	*0.923*	*0.834*
North East	0.03	0.06	0.02	*0.030*	*0.398*	*0.014*
North West	0.16	0.12	0.12	*0.134*	*0.164*	*0.260*
Northern Ireland	0.01	0.01	0.01	*0.704*	*0.707*	*0.905*
Scotland	0.09	0.09	0.04	*0.783*	*0.004*	*0.003*
South East	0.13	0.16	0.18	*0.363*	*0.065*	*0.182*
South West	0.10	0.09	0.11	*0.593*	*0.908*	*0.783*
Wales	0.03	0.04	0.06	*0.678*	*0.137*	*0.323*
West Midlands	0.10	0.09	0.11	*0.789*	*0.806*	*0.876*
Living with a partner	0.63	0.61	0.63	*0.567*	*0.910*	*0.764*
Household size	2.77	2.72	2.67	*0.598*	*0.338*	*0.632*
University	0.52	0.54	0.52	*0.577*	*0.967*	*0.799*
Log(income)	10.05	10.06	10.08	*0.784*	*0.291*	*0.547*
Prices						
Price of hand sanitiser	10.33	11.25	11.30	*0.190*	*0.962*	*0.307*
Price of face masks	11.23	11.49	12.25	*0.713*	*0.147*	*0.330*
Price of gloves	14.37	15.58	14.76	*0.161*	*0.641*	*0.360*
Observations	316	316	317			
Omnibus test			$\chi^2(48) = 50.95$ p-value = 0.3585			

Note: Test of equality of means is obtained from an OLS regression on the corresponding variable on a constant, T1 and T2, with robust standard errors. The column for "test for C = T1" displays the p-value of the t-test that the coefficient on T1 is zero; the column for "test for C = T2" displays the p-value of the t-test that the coefficient on T2 is zero; the column for "test for C = T1 = T2" displays the p-value of the F-test that the coefficients on T1 and T2 are both zero. The Omnibus test: test that all the coefficients of a multinomial logit of participation in an arm (probability of participating in each arm) on the pre-treatment characteristics are zero.

Section G. Visual representation of treatment effects on demands.

Figure A2. Stated demand for hand sanitiser gel. Mean and 95% CI by treatment arm.

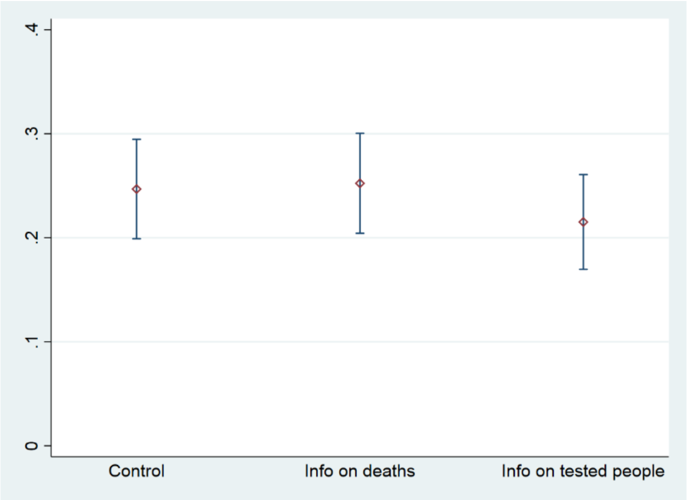


Figure A3. Stated demand for disposable face masks. Mean and 95% CI by treatment arm.

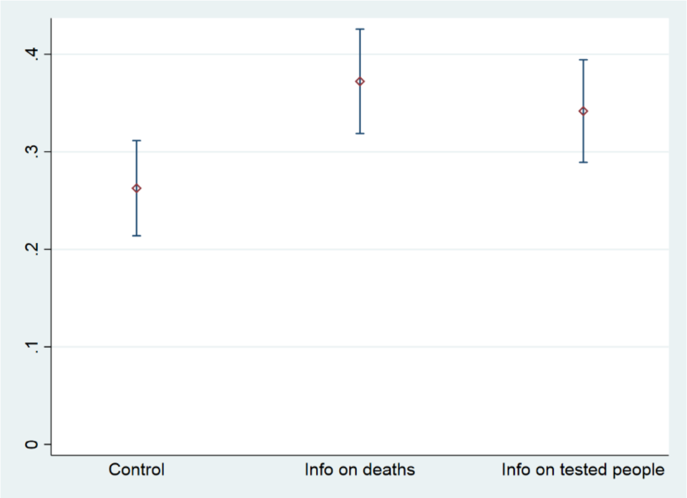
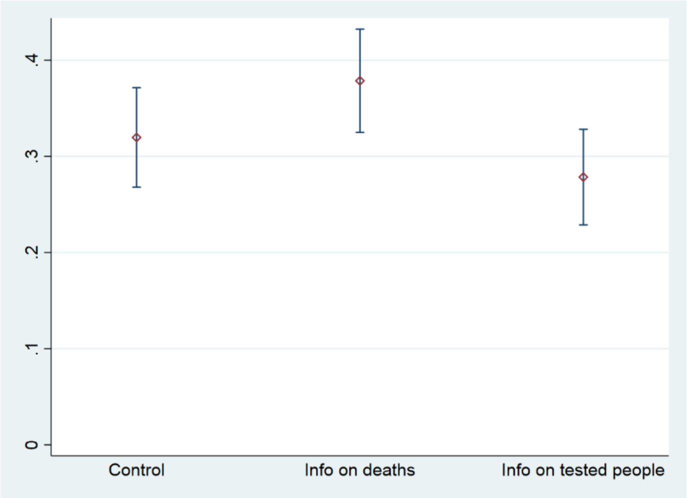


Figure A4. Stated demand for disposable gloves. Mean and 95% CI by treatment arm.



Section H. Robustness check: estimating treatment effects with a Logit model.

Table A5. Average treatment effects of information using a Logit probability model.

	Hand Sanitiser	Face Mask	Gloves
T1	–0.032	0.082**	–0.043
	(0.034)	(0.038)	(0.038)
	[–0.099, 0.035]	[0.008, 0.156]	[–0.117, 0.031]
T2	0.005	0.111***	0.057
	(0.033)	(0.037)	(0.036)
	[–0.060, 0.071]	[0.038, 0.183]	[–0.014, 0.128]
Observations	949	949	949

Note: Delta-method standard errors in parentheses. 95% CI in brackets. *** p<0.01, ** p<0.05.

Section I. Non-parametric analysis of treatment effects.

Figure A5. Non-parametric stated demand for hand sanitiser gel by treatment arm.

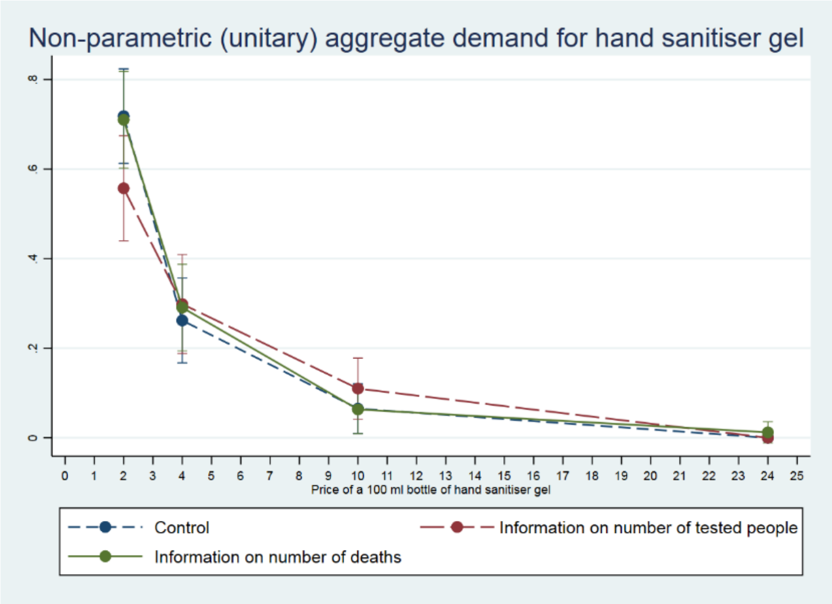
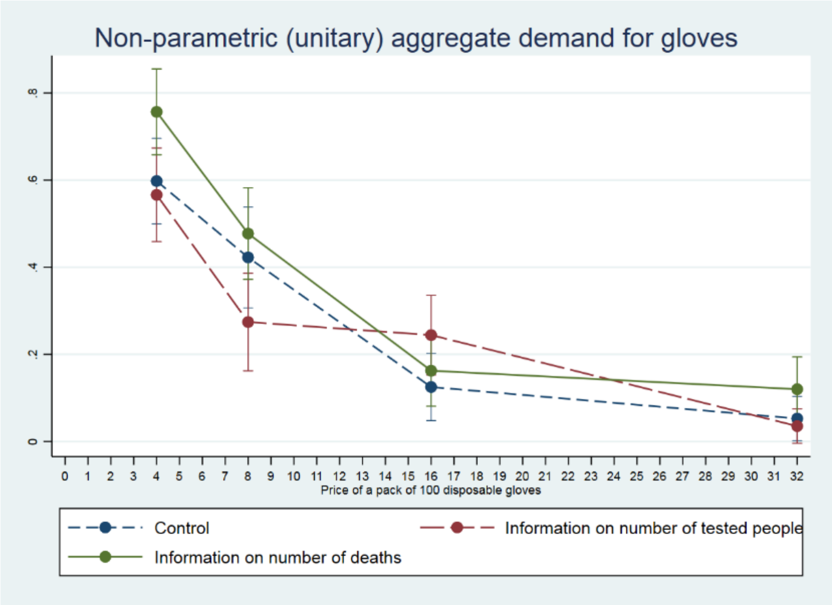


Figure A6. Non-parametric stated demand for disposable gloves by treatment arm.



Section J. Secondary hypothesis: the effect of information on demands by sex.

J.1. Parametric analysis.

Identification. We proceed by adding an indicator variable for female, F_i, and the interactions of the treatment indicators with F_i to equation (5):

$$Y_{ij} = \alpha_j + \beta_{1j}T_{1i} + \beta_{2j}T_{2i} + \gamma_j F_i + \delta_{1j}T_{1i}F_i + \delta_{2j}T_{2i}F_i + v_{ij}, \tag{J1}$$

where $F_i = 1$ if individual i is a female, $= 0$ if individual i is a male. The parameter δ_{1j} (resp. δ_{2j}) measures whether the causal effect of T1 (resp. T2) on Y_{ij} differs by sex.

Testing. We estimate standard errors robust to heteroskedasticity and test the following hypotheses:

- $\delta_{1j} = 0$ against $\delta_{1j} \neq 0$;
- $\delta_{2j} = 0$ against $\delta_{2j} \neq 0$.

Findings. The estimates and tests of (J1) are reported in Table A6. We do not find evidence of heterogeneous effects by sex.

Table A6. OLS regressions of hand sanitiser, face masks or gloves on T1, T2, female and interactions.

	Hand Sanitiser	Face Mask	Gloves
T1	–0.046	0.026	–0.026
	(0.047)	(0.050)	(0.053)
T2	0.032	0.106**	0.059
	(0.049)	(0.051)	(0.054)
Female	0.022	0.040	0.011
	(0.049)	(0.050)	(0.053)
T1 × Female	0.027	0.103	–0.029
	(0.067)	(0.072)	(0.073)
T2 × Female	–0.052	0.009	0.001
	(0.069)	(0.074)	(0.076)
Mean Control	0.235***	0.242***	0.314***
	(0.034)	(0.035)	(0.038)
Observations	949	949	949

Note: Robust standard errors in parentheses. Each column displays a regression of an indicator of whether the individual would buy a 100ml bottle of hand sanitiser, a pack of 10 disposable face masks, or a pack of 100 disposable gloves on a constant, two treatment indicators (T1 and T2), a female indicator, and the interactions of the previous indicators. *** p<0.01, ** p<0.05.

J.2. Non-parametric analysis.

Figure A7. Non-parametric stated demand for hand sanitiser gel by treatment arm and sex.

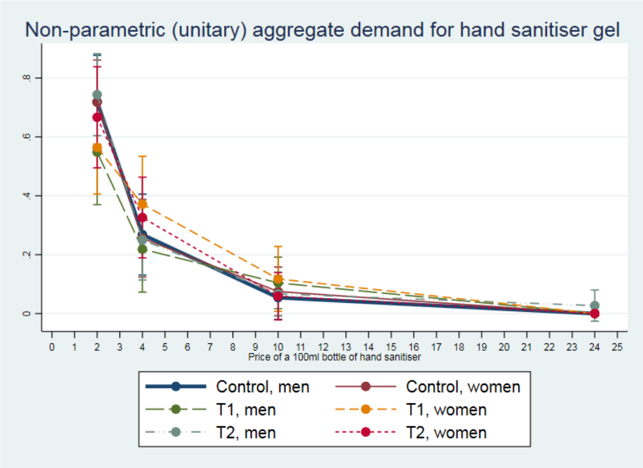


Figure A8. Non-parametric stated demand for disposable face masks by treatment arm and sex.

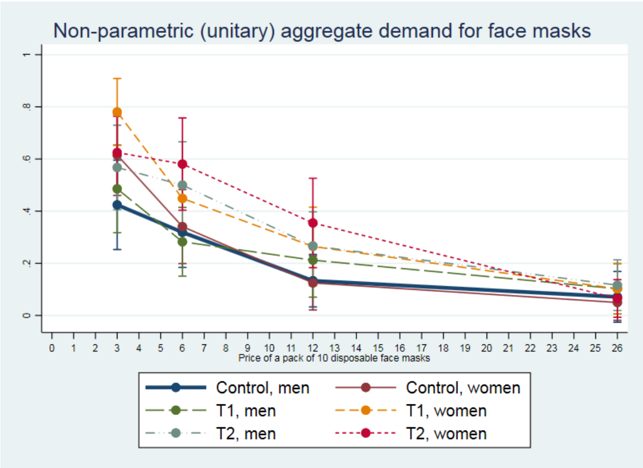
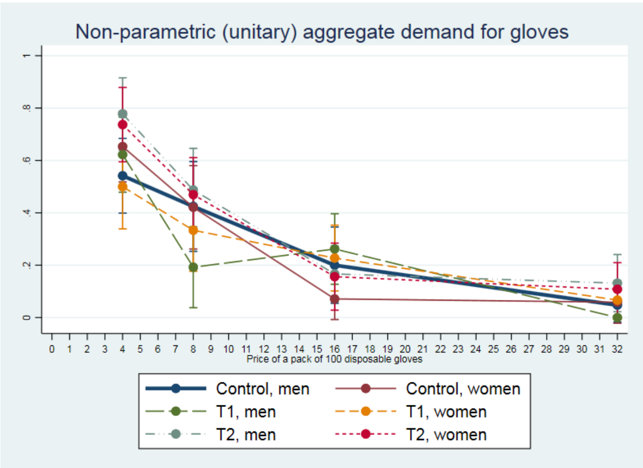


Figure A9. Non-parametric stated demand for disposable gloves by treatment arm and sex.



Section K. Robustness check: estimating treatment effects with a Fractional Logit model.

Table A7. Average treatment effects of information using a Fractional Logit model.

	Age UK	BLF	Samaritans	Women's Aid	None
T1	0.016	–0.020	0.019	0.030	–0.042
	(0.027)	(0.025)	(0.024)	(0.023)	(0.029)
	[–0.037, 0.068]	[–0.069, 0.030]	[–0.028, 0.066]	[–0.015, 0.075]	[–0.099, 0.015]
T2	0.016	–0.049	0.039	0.024	–0.027
	(0.027)	(0.026)	(0.024)	(0.023)	(0.029)
	[–0.037, 0.068]	[–0.100, 0.001]	[–0.008, 0.085]	[–0.021, 0.070]	[–0.084, 0.029]
Observations	945	945	945	945	945

Note: Delta-method standard errors in parentheses. 95% CI in brackets. *** p<0.01, ** p<0.05.

Section L. Secondary hypothesis: the effect of information on donations by sex

We follow the same approach as in Section J.1 but replacing Y_{ij} with D_{ij}.

Table A8. OLS regressions of fraction donated to Age UK, BLF, Samaritans, Women's Aid or None on T1, T2, female and interactions.

	Age UK	BLF	Samaritans	Women's Aid	None
T1	0.026	–0.009	0.050	0.013	–0.081*
	(0.038)	(0.039)	(0.035)	(0.024)	(0.042)
T2	0.025	–0.063*	0.049	0.003	–0.014
	(0.038)	(0.037)	(0.035)	(0.022)	(0.045)
Female	–0.001	–0.025	–0.015	0.098***	–0.057
	(0.037)	(0.039)	(0.031)	(0.030)	(0.044)
T1 × Female	–0.021	–0.023	–0.062	0.032	0.074
	(0.053)	(0.053)	(0.047)	(0.044)	(0.059)
T2 × Female	–0.019	0.028	–0.023	0.046	–0.032
	(0.054)	(0.051)	(0.047)	(0.044)	(0.059)
Mean control	0.233***	0.255***	0.177***	0.102***	0.232***
	(0.027)	(0.028)	(0.023)	(0.016)	(0.032)
Observations	945	945	945	945	945

Note: Robust standard errors in parentheses. Each column displays a regression of the fraction donated on a constant, two treatment indicators (T1 and T2), a female indicator, and the interactions of the previous indicators. *** p<0.01, ** p<0.05.

References

Kondylis, F. and J. Loeser. (2020) "Back-of-the-envelope power calcs." *Development Impact World Bank Blog*: https://blogs.worldbank.org/impactevaluations/back-envelope-power-calcs