Online Appendix
Estimating the Distaste for Price Gouging with Incentivized Consumer Reports

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A   Theoretical Framework

In this section we derive the willingness to pay to report and solve for the equilibrium of the model. The payoff that consumers get for buying the product minus the payoff from not buying it is $u - p$, disregarding whether they report and whether they are the first ones to meet with the seller. Define $q(p) \equiv 1 - G_u(p)$ as the probability that individuals buy the product (expected demand). When individuals are the second ones to match with the seller, their report does not make a difference, so the value of reporting vs not reporting is just $-c_r$.

When they match first with the seller, the value of reporting relative to not reporting is:

$$\underbrace{\mathbb{E}(e(p)q(p))}_{\text{External payoff from a random meeting}} - \left(\underbrace{\frac{M-1}{M}\mathbb{E}(e(p)q(p))}_{\text{Random meeting}} + \underbrace{\frac{1}{M}e(p)q(p)}_{\text{The other Seller } p} \right) - c_r.$$

Intuitively, when the consumer does not report, the other consumer might meet the seller with $1/M$ chance and meets a random seller with the remaining $(M-1)/M$ chance. This past expression simplifies to:

$$\frac{1}{M}\left[\mathbb{E}(e(p)q(p)) - e(p)q(p) \right] - c_r$$

Because consumers match first with the seller with $1/2$ probability, the expected willingness to pay to report is given by Equation 1.

To find the equilibrium price distribution we need to find the sellers' optimal pricing strategy given consumers' reporting and buying strategies. Call $\sigma(p)$ the probability that a consumer reports price offer p after meeting. The expected profits of sellers that make price

offer p are:

$$\pi(p) = \frac{1}{M}\left[q(p)p - \sigma(p)\kappa + \underbrace{(1-\sigma(p))\frac{1}{M}q(p)p}_{\text{Meets with second consumer}}\right] +$$

$$\underbrace{\frac{M-1}{M}\left(\frac{\mathbb{E}(\sigma(p))}{M-1} + \frac{1-\mathbb{E}(\sigma(p))}{M}\right)}_{}\underbrace{[q(p)p - \sigma(p)\kappa]}_{\text{Seller meets the second consumer}}$$

(with the brace "Seller meets one consumer first" under the first bracketed term)

We can rewrite profits as $\pi(p) = \pi^0(p)(1-\sigma(p)) + \pi^1(p)\sigma(p)$; that is, as a linear combination between profits under a zero probability of reporting, $\pi^0(p)$, and profits when the probability of reporting is one, $\pi^1(p)$. These two functions are:

$$\pi^0(p) = \frac{q(p)p}{M}\left(2 + \frac{\mathbb{E}(\sigma(p))}{M}\right)$$

$$\pi^1(p) = \pi^0(p) - \frac{1}{M}\left(\frac{q(p)p}{M} + \kappa\left(2 - \frac{1}{M}[1 - \mathbb{E}(\sigma(p))]\right)\right),$$

where $\pi^0 \geq \pi^1$. When there is no reporting, profits are $2q(p)p/M$. Assume that second order conditions hold and let p^m be the monopolist price that maximizes this profit function. Notice that $\pi^0(p)$ and $\pi^1(p)$ are also maximized at p^m and hence $\pi^{0'}(p^m) = \pi^{1'}(p^m) = 0$. Then, it is easy to check that $\pi'(p^m) = -\sigma'(p)(\pi^0(p^m) - \pi^1(p^m)) < 0$, so profits are maximized with prices smaller than p^m.

Finally, we highlight the importance of understanding the mechanisms driving the external payoff. Consider a policy that—costlessly—fixes prices at level $\bar{p}$ and an alternative policy in which the government subsidizes purchases of the product for an amount $s(\bar{p})$ per unit, financed with a lump-sum tax to consumers. The government sets the subsidy such that the quantity in both cases is the same; that is, at a level equal to the monopoly price (with the subsidized demand) minus the controlled price $\bar{p}$. In the absence of externalities, both policies result in the same social surplus because they achieve the same equilibrium outcome. In this case, with both policies, the expected direct payoff of consumers is equal to the average utility among those who purchase the product, $2\int_{\bar{p}} u \, dG_u$.

Up until now we have assumed that consumers get an external payoff $e(p)$ that is decreasing in the price of the third-party transaction. We now generalize this payoff to a new function $e(p^c, p^p)$ that captures the possibility of having two different prices; the price paid by the other consumer p^c and the price received by the producer, p^p.

Besides the expected direct payoff, then, consumers now get an aggregate external payoff equal to $2q(\bar{p})e(\bar{p},\bar{p})$ with the price control, but $2q(\bar{p})e(\bar{p},\bar{p}+s(\bar{p}))$ with the subsidy. Because the subsidy is positive, the external payoff is lower with the subsidy if it is decreasing in

the price that the seller receives. In other words, the welfare implications of both policies differ, even if they achieve the same equilibrium quantities, due to the presence of distaste for profits or markups. Intuitively, the presence of external payoffs implies that the distribution of surplus between consumers and producers will now matter for welfare.

B Product Tracking Algorithm

To track goods and prices for our survey respondents we used the Rainforest API. It allowed us to get real-time data on availability, prices and comments on all products that are listed in the queries to "hand sanitizer" and "face mask".

The steps of the algorithm were:

1. Get the list of products that appear in the search results for the Hand Sanitizer and Face mask categories.[1]

2. Get information for each product: price, image, description, shipping date, etc.

3. Run an image classification algorithm to select which products were actually hand sanitizers and face masks

4. Process the text in the title, product description and product dimensions with regular expressions to extract and parse the number of units (fl oz, count, etc.)

We collected search results on 8 dates, covering the 2 days that our survey lasted and 2 weeks before and after our experiment. We collect prices, listing titles and product images for all searches. The output from these queries included some "false positive" results, that is, not everything was truly one of the products we cared about. Because many products are advertised in multiple search categories (e.g., soaps in the hand sanitizer section), to avoid tracking and reporting incorrect items we classified 1200 results for "face mask" and 500 results for "hand sanitizer" with the help of Amazon MTurk workers to identify surgical face masks and alcohol based hand sanitizer gel. We used 3 labels to classify face masks: surgical masks, N-95 and not a mask. We used a binary label for hand sanitizer. These examples were then used to train a neural network classifier on PyTorch that used product images and text features from the product title as input to identify items of interest.

We used the pre-trained resnet50 model available in Torchvision to extract features from product images (see He et al. (2016)). To this convolutional model, we added two extra linear layers that allowed us to incorporate a vector of zeros and ones that identified the presence

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[1]Hand sanitizers can be found in product category 2265897011; see `https://www.amazon.com/handsanitizers/b?ie=UTF8&node=2265897011`. Likewise, face masks correspond to product catecories 6125377011, 8404646011 and 17864516011.

Table A1: Extracted title features

Face Mask	'cloth', 'Surgical', 'Dust', 'respirator', 'dust', 'reusable'
Hand Sanitizer	'hand', 'gel', 'Purell', 'WIPES', 'TISSUES', 'paper', 'glo', 'GERM', 'lamp', 'uv', 'ULTRAVIOLET', 'IODINE', 'cotton', 'lotion', 'spray', 'air', 'holder', 'dispenser', 'soap'

of particular words in the product title, obtained by visual inspection. The word-features used for each product model can be found in Table A1. During the learning step, only the last linear layer of the resnet50 model and the two extra layers had their weights updated to fully take advantage of knowledge already incorporated in the pre-trained model. The trained model had an out-of-sample accuracy of 0.95 and cross-entropy loss of 0.23 for Hand Sanitizers while the respective quantities were 0.97 and 0.0957 for Masks.

Afterwards, we collected more detailed product characteristics from the filtered results, such as shipping dates, stock availability, product description and dimensions. As detailed on step 4 above, we used this information to convert prices into common units.

C Supplemental evidence

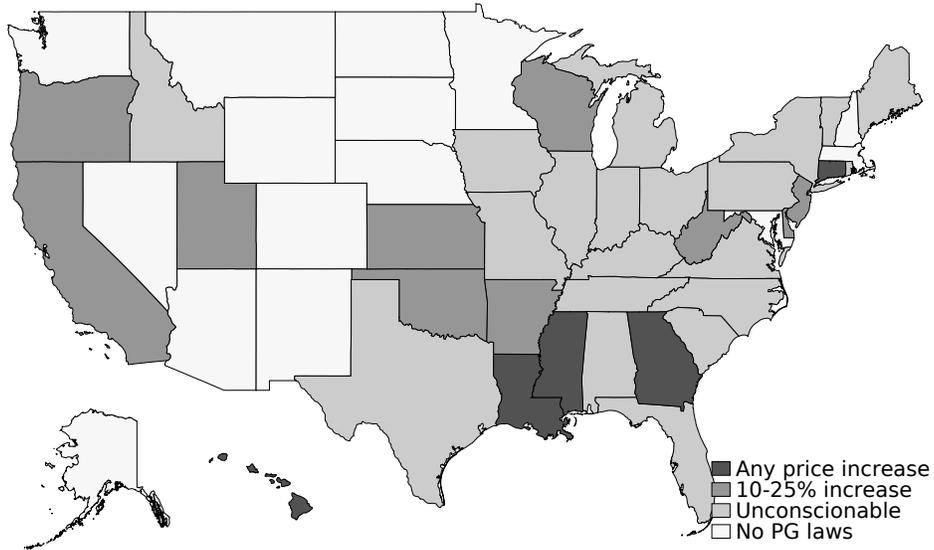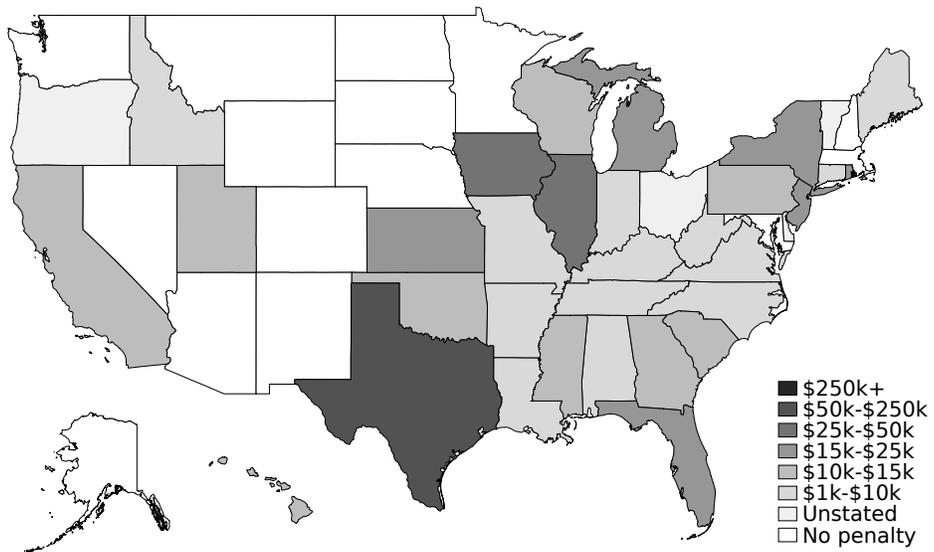**Figure A1:** Map of Price Gouging Laws

**Figure A2:** Map of Civil Penalties for Price Gouging

Figure A3: Map of Criminal Penalties for Price Gouging

No prison
Prison

Table A2: Most frequent unigrams and bigrams in actual price gouging reports

Unigrams		Bigrams	
Description	Solution	Description	Solution
price	price	price gouge	price gouge
sell	gouge	toilet paper	stop price
gouge	fine	hand sanitizer	hold accountable
item	stop	normal price	toilet paper
paper	store	grind beef	fair price
store	people	dozen egg	gas price
egg	refund	grocery store	normal price
toilet	business	gas station	reasonable price
charge	time	oz bottle	regular price
pack	charge	paper towel	raise price
buy	low	gas price	fix income
purchase	sell	previously price	low price
mask	advantage	week ago	price increase
roll	item	lb bag	essential item
time	investigate	charmin toilet	grocery store
normal	product	mega roll	stop sell
hand	feel	raise price	gouge consumer
sanitizer	normal	regular price	gouge law
pay	crisis	covid pandemic	hand sanitizer
people	pandemic	price increase	hard time

Notes: The table includes the most frequent words that appear in price gouging reports filed to the AGs of Idaho, Illinois, Missouri and Wisconsin. There are 1890 complaints in our sample (68 from ID, 102 from IL, 1271 from MO and 449 from WI). "Description" is the field where consumers detail the reason why they are submitting the complaint. "Solution" is the field where consumers express any relief/solution that they are requesting. We have solutions for 488 complaints. Missouri did not include a field to detail the requested solution. We exclude from the analysis common English stop words and lemmatize the words using the Hunspell dictionary. Unigrams denote single words and Bigrams denote sequences of two adjacent words. Frequency is calculated counting occurrence across complaints.

Figure A4: Distribution of sentiment in price gouging complaints
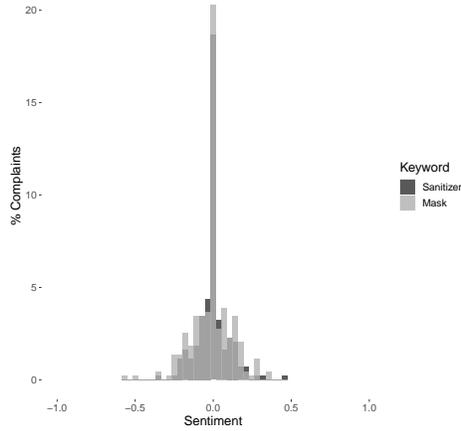
**(a)** Description
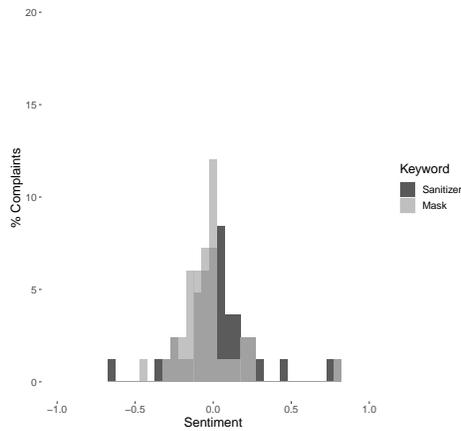
(b) Suggested solution

Notes: We calculate sentiment scores using the sentimentR package; see Naldi (2019) for a description and comparison with other sentiment lexicons. Sentiment ranges from -1 (negative) to 1 (positive). Mask/sanitizer complaints correspond to those that include the words 'mask' or 'sanitizer', respectively. We cannot reject the null of equality of distributions of description sentiments (Kolmogorov-Smirnov (KS) using Abadie (2002) bootstrap procedure with 10,000 resamples), with a p-value of 0.4015. Instead, we reject the null of equality of distributions of suggested solution sentiments, with a KS p-value of 0.0314. Moreover, we cannot reject the nulls of first and second order stochastic dominance (of sanitizer dominating masks) with p-values of 0.7540 and 0.6074, respectively.

Table A3: Willingness to Pay to Report is at least $5

|	(1) WTP ≥ 5	(2) WTP ≥ 5	(3) WTP ≥ 5	(4) WTP ≥ 5	(5) WTP ≥ 5
Seller Charges 27.50 to 30	0.13	0.13	0.13	0.12	0.12
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Face Masks		-0.04	-0.04	-0.05	-0.05
		(0.03)	(0.03)	(0.04)	(0.04)
Seller Charges 27.50 to 30 $\times$ Face Masks				0.02	0.02
				(0.05)	(0.05)
Constant	0.49	0.51	0.70	0.52	0.70
	(0.02)	(0.02)	(0.09)	(0.03)	(0.09)
Semi-Elasticity Estimate	.15	.15	.15	.14	.14
Controls	NO	NO	YES	NO	YES
R2	0.017	0.018	0.041	0.018	0.041
Observations	1391	1391	1391	1391	1391

 Notes: Table displays the effect of treatments on the probability of having a willingness to pay to report greater than or equal to five. Omitted category is hand sanitizer sold for $7.50 to $10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. Heteroskedasticity robust standard errors in parentheses.

Figure A5: Probability of Choosing to Report Seller at Any Price
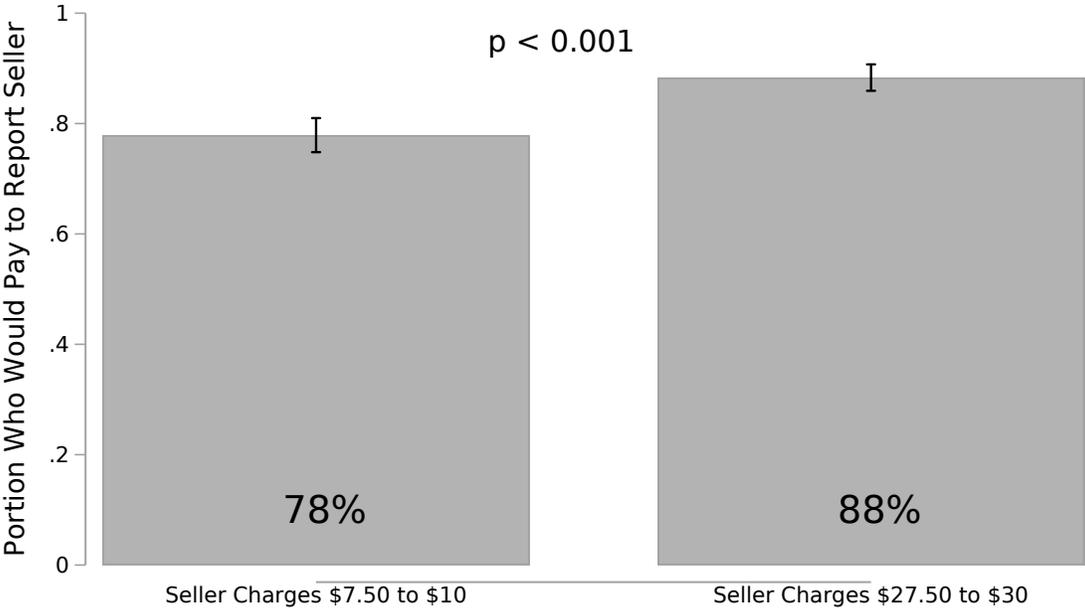
Notes: Figure displays the effect of treatments on the probability of choosing to report the seller at any price with 95% confidence intervals.

Figure A6: Relationship between Willingness to Report and Propensity to Donate
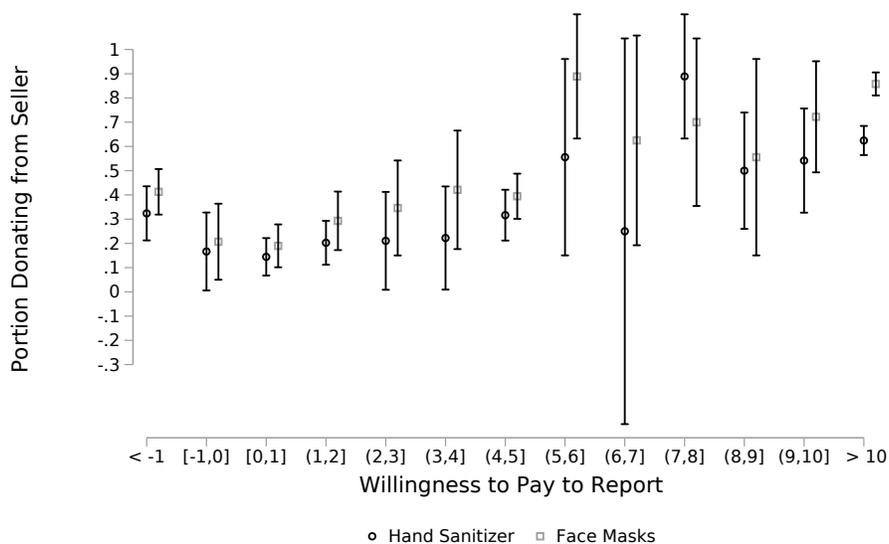
(a) Type of Good
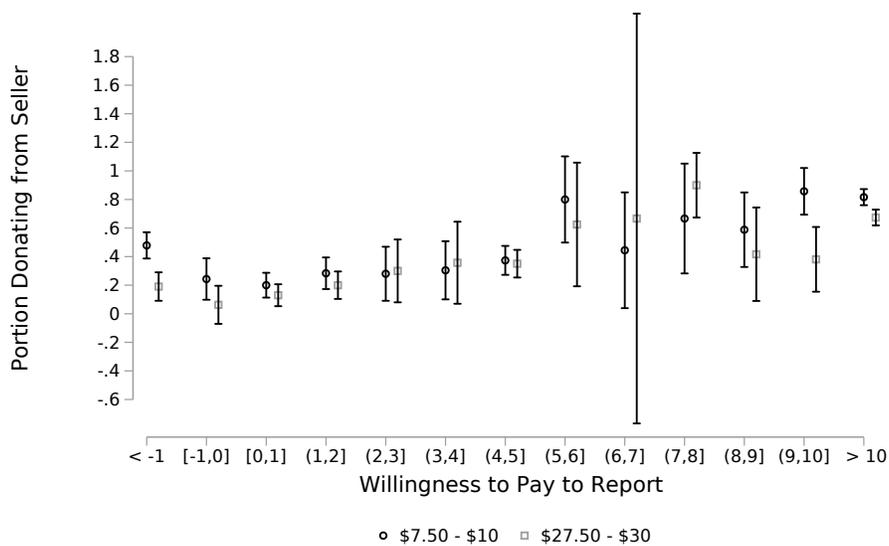
(b) Seller Price

Notes: Panel (a) plots the average portion of subjects choosing to donate PPE within every willingness to report bin, by good. Panel (b) plots the average portion of subjects choosing to donate PPE within every willingness to report bin, by price.

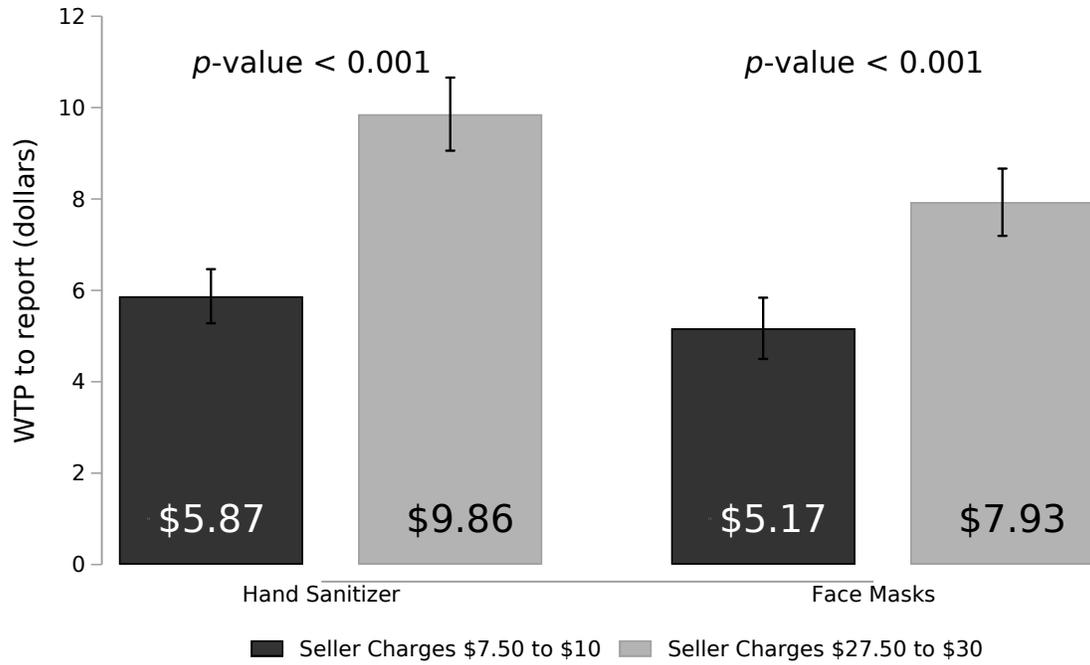**Figure A7:** Willingness to Pay to Report Using a Triangular Distribution

Notes: This figure displays the average willingness to report sellers for price gouging at different prices separately by PPE type with 95% confidence intervals. We use the procedure in Allcott and Kessler (2019) to impute WTP from the results of the multiple price list. For each interior range, we assign the value of the midpoint. For the exterior unbounded ranges we assume a triangular distribution.

Table A4: Willingness to Pay to Report Using a Triangular Distribution

	(1) WTP	(2) WTP	(3) WTP	(4) WTP
Seller Charges 27.50 to 30	3.369	3.372	3.371	4.048
	(0.428)	(0.427)	(0.433)	(0.614)
Face Masks		-1.314	-1.364	-0.688
		(0.427)	(0.431)	(0.550)
Seller Charges 27.50 to 30 $\times$ Face Masks				-1.360
				(0.869)
Constant	5.521	6.177	9.857	9.552
	(0.271)	(0.332)	(1.391)	(1.386)
Elasticity Estimate	.36	.36	.36	.43
Controls	NO	NO	YES	YES
R2	0.043	0.049	0.067	0.069
Observations	1391	1391	1391	1391

Notes: This table shows regressions of individual willingness to pay to report on treatment dummies. We use the procedure in Allcott and Kessler (2019) to impute WTP from the results of the multiple price list. For each interior range, we assign the value of the midpoint. For the exterior unbounded ranges we assume a triangular distribution. Heteroskedasticity robust standard errors in parentheses. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. Elasticity estimate calculated using the midpoint of seller price range.

Table A5: Propensity to Donate by WTP Report

	(1) Donate	(2) Donate	(3) Donate	(4) Donate
WTPR $\geq$ 5	0.36	0.38	0.35	0.35
	(0.02)	(0.02)	(0.04)	(0.04)
Seller Charges 27.50 to 30		-0.11	-0.18	-0.19
		(0.02)	(0.04)	(0.04)
Face Masks		0.13	0.08	0.08
		(0.02)	(0.04)	(0.04)
Seller Charges 27.50 to 30 $\times$ Face Masks			0.09	0.09
			(0.05)	(0.05)
Seller Charges 27.50 to 30 $\times$ WTPR $\geq$ 5			0.05	0.06
			(0.05)	(0.05)
Constant	0.27	0.25	0.28	0.18
	(0.02)	(0.02)	(0.03)	(0.08)
Controls	NO	NO	NO	YES
R-squared	0.128	0.157	0.159	0.173
Observations	1,386	1,386	1,386	1,386

Notes: Table displays the effect of treatments on the propensity to donate along with the correlation between having a WTP to report exceeding \$5 and donating. Omitted category is hand sanitizer sold for \$7.50 to \$10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. State laws is an indicator equal to 1 if the subject's state has laws against price gouging. Heteroskedasticity robust standard errors in parentheses.

Table A6: Treatment Effect on Attention

	(1) Attention	(2) Attention	(3) Attention	(4) Attention
Seller Charges 27.50 to 30	-0.20	-0.20	-0.19	-0.17
	(0.02)	(0.02)	(0.02)	(0.03)
Face Masks		0.00	-0.00	0.02
		(0.02)	(0.02)	(0.02)
Seller Charges 27.50 to 30 × Face Masks				-0.04
				(0.04)
Constant	0.94	0.94	0.80	0.79
	(0.01)	(0.01)	(0.06)	(0.06)
Controls	NO	NO	YES	YES
R-squared	0.076	0.076	0.109	0.110
Observations	1,391	1,391	1,391	1,391

Notes: Table displays the effect of treatments on the propensity correctly answer the attention question. Omitted category is hand sanitizer sold for $7.50 to $10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. State laws is an indicator equal to 1 if the subject's state has laws against price gouging. Heteroskedasticity robust standard errors in parentheses.

Table A7: Treatment Effects on Attentive Subjects

	(1) WTPR	(2) WTPR	(3) Donate	(4) Donate
Seller Charges 27.50 to 30	-1.28	1.79	-0.09	-0.11
	(0.93)	(0.38)	(0.11)	(0.04)
Face Masks	0.29	-0.95	0.12	0.06
	(1.28)	(0.36)	(0.17)	(0.04)
Seller Charges 27.50 to 30 × Face Masks	-0.42	0.35	-0.01	0.12
	(1.44)	(0.54)	(0.18)	(0.06)
Constant	6.21	5.16	0.42	0.47
	(0.79)	(0.26)	(0.10)	(0.03)
Attentive	NO	YES	NO	YES
Elastcity Estimate	-0.798	1.117		
R-squared	0.017	0.051	0.017	0.019
Observations	219	1,172	214	1,172

Notes: Table displays the effect of treatments on the WTP to report and propensity to donate. Omitted category is hand sanitizer sold for $7.50 to $10.00. Odd Columns include the full sample of subjects. Even columns drop subjects who answered the attention question incorrectly. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. State laws is an indicator equal to 1 if the subject's state has laws against price gouging. Heteroskedasticity robust standard errors in parentheses.

Table A8: Treatment Effect on Higher Quality Belief

	(1) Higher Quality	(2) Higher Quality	(3) Higher Quality	(4) Higher Quality
Seller Charges 27.50 to 30	-0.03	-0.03	-0.04	-0.06
	(0.02)	(0.02)	(0.02)	(0.03)
Face Masks		0.02	0.02	0.00
		(0.02)	(0.02)	(0.03)
Seller Charges 27.50 to 30 × Face Masks				0.04
				(0.04)
Constant	0.23	0.22	0.32	0.33
	(0.02)	(0.02)	(0.07)	(0.07)
Controls	NO	NO	YES	YES
R-Squared	0.002	0.002	0.123	0.123
Observations	1,391	1,391	1,391	1,391

Notes: Table displays the effect of treatments on the propensity to claim that higher priced PPE is higher quality. Omitted category is hand sanitizer sold for \$7.50 to \$10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. State laws is an indicator equal to 1 if the subject's state has laws against price gouging. Heteroskedasticity robust standard errors in parentheses.

Table A9: Treatment Effects on Subjects who Think Quality Increases with Price

	(1) WTPR	(2) WTPR	(3) Donate	(4) Donate
Seller Charges 27.50 to 30	1.730	-0.960	-0.106	-0.115
	(0.394)	(0.748)	(0.0415)	(0.0847)
Face Masks	-0.835	-1.195	0.0990	-0.0435
	(0.404)	(0.680)	(0.0431)	(0.0793)
Seller Charges 27.50 to 30 × Face Masks	0.134	1.737	0.0587	0.199
	(0.559)	(1.037)	(0.0599)	(0.117)
Constant	5.059	5.812	0.446	0.525
	(0.289)	(0.477)	(0.0304)	(0.0562)
Higher Quality	NO	YES	NO	YES
Elastcity Estimate	4.41	-2.44		
R2	0.043	0.012	0.024	0.012
Observations	1,093	298	1,088	298

Notes: Table displays the effect of treatments on the WTP to report and propensity to donate. Omitted category is hand sanitizer sold for \$7.50 to \$10.00. Odd columns include the full sample of subjects. Even columns drop subjects who answered the attention question incorrectly. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. State laws is an indicator equal to 1 if the subject's state has laws against price gouging. Heteroskedasticity robust standard errors in parentheses.

Table A10: Treatment Effect by Whether the Subject Found the Price Excessive

	(1) WTPR	(2) WTPR	(3) Donate	(4) Donate
Seller Charges 27.50 to 30	1.97	0.58	-0.08	-0.14
	(0.53)	(0.46)	(0.06)	(0.05)
Face Masks	-1.51	-0.86	0.00	0.08
	(0.62)	(0.43)	(0.07)	(0.05)
Seller Charges 27.50 to 30 × Face Masks	-0.56	1.12	0.10	0.11
	(0.86)	(0.61)	(0.09)	(0.07)
Constant	4.97	5.46	0.45	0.48
	(0.38)	(0.33)	(0.04)	(0.04)
Elastcity Estimate	0.260	0.068	-0.011	-0.016
R2	0.066	0.023	0.007	0.026
Observations	496	895	492	894

Notes: Heteroskedasticity robust standard errors in parentheses. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. Elasticity estimate calculated using the midpoint of seller price range.

Table A11: Willingness to Pay to Report by Deaths (Above Median)

	(1) WTPR	(2) WTPR	(3) WTPR	(4) WTPR	(5) WTPR
Seller Charges 27.50 to 30	1.59	1.62	1.55	1.86	1.86
	(0.34)	(0.34)	(0.34)	(0.38)	(0.39)
High Deaths	0.13	0.16	0.16	0.13	0.16
	(0.35)	(0.35)	(0.36)	(0.35)	(0.36)
Seller Charges 27.50 to 30 × High Deaths	-0.36	-0.41	-0.31	-0.38	-0.34
	(0.49)	(0.49)	(0.50)	(0.49)	(0.50)
Seller Charges 27.50 to 30 × Face Masks				-0.52	-0.59
				(0.35)	(0.36)
Constant	4.71	5.06	6.72	4.71	6.71
	(0.24)	(0.27)	(0.81)	(0.24)	(0.81)
Elasticity Estimate	0.20	0.20	0.19	0.23	0.23
Controls	NO	NO	YES	NO	YES
R-Squared	0.024	0.030	0.041	0.025	0.043
Observations	1,391	1,391	1,391	1,391	1,391

Notes: Table displays the effect of treatments on the willingness to pay to report. Omitted category is hand sanitizer sold for $7.50 to $10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. The outcome is the number of deaths due to covid in the subject's state by the date of the experiment. Heteroskedasticity robust standard errors in parentheses.

Table A12: Willingness to Pay to Report by Deaths

	(1) WTPR	(2) WTPR	(3) WTPR	(4) WTPR	(5) WTPR
Seller Charges 27.50 to 30	1.34 (0.31)	1.36 (0.31)	1.28 (0.31)	1.58 (0.36)	1.56 (0.37)
Deaths per Thousand	-0.13 (0.67)	-0.12 (0.68)	-0.12 (0.69)	-0.13 (0.67)	-0.13 (0.69)
Seller Charges 27.50 to 30 X Deaths per Thousand	0.11 (0.92)	0.01 (0.92)	0.26 (0.93)	0.05 (0.92)	0.19 (0.93)
Seller Charges 27.50 to 30 × Face Masks				-0.44 (0.35)	-0.53 (0.36)
Constant	4.81 (0.22)	5.14 (0.25)	6.93 (0.82)	4.81 (0.22)	6.93 (0.82)
Elasticity Estimate	0.17	0.17	0.16	0.19	0.19
Controls	NO	NO	YES	NO	YES
R-Squared	0.022	0.027	0.040	0.023	0.042
Observations	1,370	1,370	1,370	1,370	1,370

Notes: Table displays the effect of treatments on the willingness to pay to report. Omitted category is hand sanitizer sold for $7.50 to $10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. Deaths per 1000 is the number of deaths due to covid in the subject's state by the date of the experiment per 1000 people in the state. Heteroskedasticity robust standard errors in parentheses.

Table A13: Willingness to Pay to Report by State Law

	(1) WTPR	(2) WTPR	(3) WTPR	(4) WTPR	(5) WTPR
Seller Charges 27.50 to 30	1.07	1.00	0.90	1.27	1.15
	(0.69)	(0.69)	(0.71)	(0.71)	(0.73)
Price-Gouging is Illegal	-0.31	-0.36	-0.47	-0.31	-0.47
	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)
Seller Charges 27.50 to 30 X Price-Gouging is Illegal	0.35	0.44	0.52	0.37	0.54
	(0.74)	(0.74)	(0.76)	(0.74)	(0.76)
Seller Charges 27.50 to 30 $\times$ Face Masks				-0.44	-0.54
				(0.35)	(0.36)
Constant	5.04	5.42	7.32	5.04	7.32
	(0.46)	(0.48)	(0.93)	(0.46)	(0.93)
Elasticity Estimate	0.13	0.12	0.11	0.16	0.14
Controls	NO	NO	YES	NO	YES
R-Squared	0.022	0.027	0.042	0.023	0.044
Observations	1,367	1,367	1,367	1,367	1,367

Notes: Table displays the effect of treatments on the willingness to pay to report. Omitted category is hand sanitizer sold for $7.50 to $10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. State laws is an indicator equal to 1 if the subject's state has laws against price gouging. Heteroskedasticity robust standard errors in parentheses.

Table A14: Propensity to Donate by Deaths

	(1) Donation	(2) Donation	(3) Donation	(4) Donation	(5) Donation
Seller Charges 27.50 to 30	-0.07	-0.07	-0.07	-0.16	-0.16
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Deaths per Thousand	0.05	0.05	0.04	0.05	0.04
	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)
Seller Charges 27.50 to 30 X Deaths per Thousand	0.00	0.02	0.02	0.02	0.05
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Seller Charges 27.50 to 30 × Face Masks				0.17	0.16
				(0.04)	(0.04)
Constant	0.49	0.43	0.45	0.49	0.45
	(0.02)	(0.03)	(0.09)	(0.02)	(0.09)
Semi-Elasticity Estimate	-0.08	-0.08	-0.08	-0.18	-0.19
Controls	NO	NO	YES	NO	YES
R-Squared	0.005	0.019	0.023	0.019	0.036
Observations	1,365	1,365	1,365	1,365	1,365

Notes: Table displays the effect of treatments on the propensity to donate. Omitted category is hand sanitizer sold for $7.50 to $10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. Deaths per 1000 is the number of deaths due to covid in the subject's state by the date of the experiment per 1000 people in the state. Heteroskedasticity robust standard errors in parentheses.

Table A15: Propensity to Donate by Deaths (Above Median)

	(1) Donate	(2) Donate	(3) Donate	(4) Donate	(5) Donate
Seller Charges 27.50 to 30	-0.04 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.13 (0.04)	-0.13 (0.04)
High Deaths	0.07 (0.04)	0.07 (0.04)	0.07 (0.04)	0.07 (0.04)	0.07 (0.04)
Seller Charges 27.50 to 30 × High Deaths	-0.04 (0.05)	-0.04 (0.05)	-0.03 (0.05)	-0.04 (0.05)	-0.03 (0.05)
Seller Charges 27.50 to 30 × Face Masks				0.16 (0.04)	0.16 (0.04)
Constant	0.46 (0.03)	0.41 (0.03)	0.42 (0.09)	0.46 (0.03)	0.42 (0.09)
Semi-Elasticity Estimate	-0.05	-0.06	-0.06	-0.15	-0.15
Controls	NO	NO	YES	NO	YES
R-Squared	0.007	0.019	0.024	0.020	0.036
Observations	1,386	1,386	1,386	1,386	1,386

Notes: Table displays the effect of treatments on the propensity to donate. Omitted category is hand sanitizer sold for $7.50 to $10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. High deaths is an indicator equal to one if the number of deaths due to covid in the subject's state by the date of the experiment per 1000 people in the state is above the median for the whole country. Heteroskedasticity robust standard errors in parentheses.

Table A16: Propensity to Donate by State Law

	(1) Donation	(2) Donation	(3) Donation	(4) Donation	(5) Donation
Seller Charges 27.50 to 30	-0.05	-0.03	-0.04	-0.12	-0.12
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Price-Gouging is Illegal	-0.06	-0.05	-0.06	-0.06	-0.06
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Seller Charges 27.50 to 30 X Price-Gouging is Illegal	-0.02	-0.04	-0.02	-0.03	-0.03
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Seller Charges 27.50 to 30 $\times$ Face Masks				0.17	0.16
				(0.04)	(0.04)
Constant	0.55	0.48	0.51	0.55	0.51
	(0.05)	(0.05)	(0.10)	(0.05)	(0.10)
Semi-Elasticity Estimate	-0.06	-0.04	-0.05	-0.15	-0.14
Controls	NO	NO	YES	NO	YES
R-Squared	0.006	0.020	0.024	0.020	0.037
Observations	1,362	1,362	1,362	1,362	1,362

Notes: Table displays the effect of treatments on the propensity to donate. Omitted category is hand sanitizer sold for $7.50 to $10.00. Controls include race indicators, gender indicator, age, income, education, and whether they chose to track either product, has purchased either item on Amazon in the past and whether they have Amazon Prime. State laws is an indicator equal to 1 if the subject's state has laws against price gouging. Heteroskedasticity robust standard errors in parentheses.

Table A17: Main Results for Calibrated Sample to Match U.S. Adults Bounds

	WTP to report				Donation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Seller Charges 27.50 to 30	1.35	1.16			-0.08	-0.05		
	(0.443)	(0.433)			(0.046)	(0.047)		
Would buy at treatment price			-0.89					
			(0.433)					
Considers treatment price excessive				1.63				
				(0.310)				
$\mathbb{1}\{WTR > 0\}$							0.31	
							(0.061)	
$\mathbb{1}\{WTR < 0\}$							0.17	
							(0.073)	
$\mathbb{1}\{WTR = -1\}$								0.17
								(0.073)
$\mathbb{1}\{WTR = 1\}$								-0.01
								(0.071)
$\mathbb{1}\{WTR = 2\}$								0.03
								(0.069)
$\mathbb{1}\{WTR = 3\}$								0.14
								(0.098)
$\mathbb{1}\{WTR = 4\}$								0.20
								(0.109)
$\mathbb{1}\{WTR = 5\}$								0.17
								(0.072)
$\mathbb{1}\{WTR = 6\}$								0.59
								(0.119)
$\mathbb{1}\{WTR = 7\}$								0.32
								(0.173)
$\mathbb{1}\{WTR = 8\}$								0.65
								(0.101)
$\mathbb{1}\{WTR = 9\}$								0.32
								(0.116)
$\mathbb{1}\{WTR = 10\}$								0.46
								(0.106)
$\mathbb{1}\{WTR = 11\}$								0.54
								(0.064)
Observations	695	696	732	1,391	692	694	1,386	1,386
Product	HS	FM	Both	Both	HS	FM	Both	Both

Notes: This table replicates the main results from the paper after re-weighting observations to match the marginal distribution of gender, age, ethnic affinity, and education from Table 3. Robust standard errors in parentheses.

Table A18: Treatment Effect Bounds

Panel: A (Manski-Horowitz Bounds)

	Willingness to pay to report								Donation					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Seller Charges 27.50 to 30	0.563 (0.3455)	1.862 (0.3449)	1.484 (0.3466)	1.723 (0.3449)					-0.053 (0.0361)	-0.169 (0.0360)	-0.004 (0.0377)	-0.030 (0.0377)		
Would buy at treatment price					-0.831 (0.3800)	-0.965 (0.3796)								
Considers treatment price excessive							1.493 (0.2461)	1.581 (0.2454)						
WTR>0													0.273 (0.0567)	0.302 (0.0549)
WTR<0													0.213 (0.0654)	0.296 (0.0628)

Panel: B (Lee Bounds)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Seller Charges 27.50 to 30	0.845 (0.374)	1.820 (0.380)	1.575 (0.350)	1.678 (0.351)	-0.924 (0.383)	-0.888 (0.383)	1.544 (0.249)	1.571 (0.249)	-0.158 (0.041)	-0.086 (0.039)	-0.022 (0.038)	-0.013 (0.038)		
Observations	736	736	703	703	738	738	1408	1408	736	736	703	703	1439	1439
Product	HS	HS	FM	FM	Both	Both	Both	Both	HS	HS	FM	FM	Both	Both

Note: This table estimates bounds for the treatment effect to control for attrition. Robust errors in parentheses.

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D Survey

D.0.1 Demographic questions

1. What is your U.S. ZIP code?

2. What is your year of birth?

3. What is the highest level of school you have completed or the highest degree you have received?

   - Less than high school degree
   - High school graduate (high school diploma or equivalent including GED)
   - Some college but no degree
   - Associate degree in college (2 year)
   - Bachelor's degree in college (4 year)
   - Master's degree
   - Doctoral degree
   - Professional degree (JD, MD)

4. Choose one or more races/ethnicities that you consider yourself to be:

   - White or European American
   - Black or African American
   - Hispanic or Latino
   - Asian or Asian American
   - Other:

5. What is your approximate household annual income? Please indicate the answer that includes your entire household income in 2019 before taxes

   - Less than $10,000
   - $10,000 to $19,999
   - $20,000 to $29,999
   - $30,000 to $39,999
   - $40,000 to $49,999
   - $50,000 to $59,999
   - $60,000 to $69,999

- $70,000 to $79,999
- $80,000 to $89,999
- $90,000 to $99,999
- $100,000 to $149,999
- $150,000 or more

6. What is your sex? Male/Female

7. Have you purchased anything on Amazon in the last month? Yes/No

8. Do you have Amazon Prime? Yes/No

9. Have you bought online or in stores any of the following in 2020? Please select all that apply:

   - Hand sanitizer
   - Face masks
   - None of the above

D.0.2 Quality/attention check questions

1. At which prices did we say we will buy and donate the product?

   - Between $7.50 and $10
   - Between $27.50 and $30

2. Do you think that $50 face masks or hand sanitizers have a higher quality than $5 ones? Yes/No

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Figure A8: Willingness to track the items

Figure A9: Excessive prices

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Excessive prices

For each product, please report the lowest price you consider to be **excessive**, if any

	Is there any price you consider **excessive**?		**Excessive price** Not including shipping or taxes
	Yes	No	USD $
Hand sanitizer 12 FL OZ / 355 mL $5.90 in December 2019	○	○	[ ]
Face masks 50 count $6.70 in December 2019	○	○	[ ]

Figure A10: Elicitation of willingness to pay to report

(a) Instructions

(b) Main question

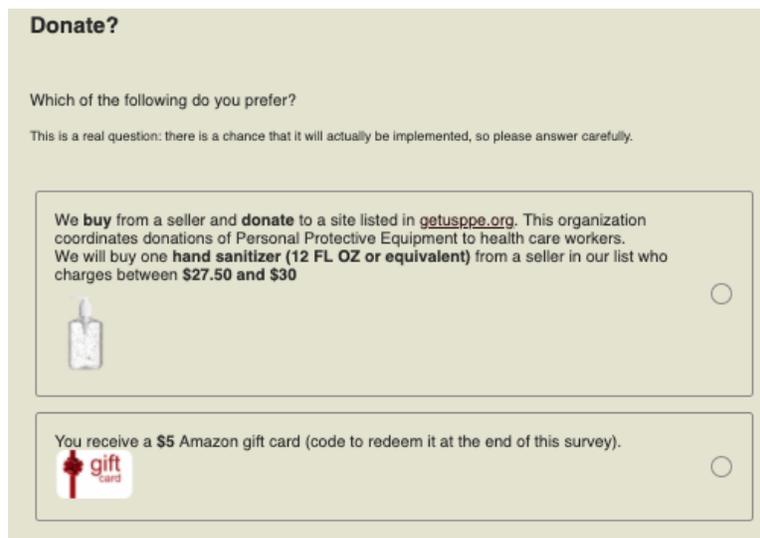**Figure A11:** Donation decision

(a) Instructions

(b) Main question