# Quantifying repugnance to price gouging with an incentivized reporting experiment

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**Abstract**

Anti-price gouging laws are ubiquitous and people take costly actions to report violators to law-enforcement agencies, which suggests that they value punishing price increases during emergencies. We argue with a model that consumer reports contain information about repugnance to price gouging, or willingness to prevent third-party transactions (Roth, 2007). We conduct a field experiment during the first wave of COVID-19 to measure individuals' willingness to pay to report sellers who increase prices of personal protective equipment. The willingness to pay to report is non-negligible, polarized, and responsive to the seller's price. We also find that repugnance is partly due to distaste for seller profits, depending on the product.

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## 1. Introduction

Emergencies like natural disasters or pandemics create ideal conditions for prices of essential products to increase. There is typically an increased demand for certain products paired with an inelastic short-run supply or even supply disruptions (Cavallo et al., 2014). The first wave of the COVID-19 pandemic was no exception: there was a surge in demand for personal protective equipment (PPE) exceeding short-run production capacity. Ninety-percent of U.S. mayors reported PPE shortages and one-third of medical facilities urged donations of personal masks to make up for the insufficient supply (Kamerow, 2020). The sharp increase in demand led to dramatic price increases in online marketplaces (Cabral and Xu, 2020). In response, national and state-level emergency declarations triggered price controls on PPE and other essential goods. Thirty-three attorneys general urged companies to help preventing price-gouging (Selyukh, 2020).

Anti-price gouging laws are ubiquitous; thirty-four states prohibit either increases above pre-crisis prices, 10-20% price increases, or "unconscionable" price increases. In spite of their wide adoption, these laws remain controversial among economists.[1] Basic economics suggest that, under perfect competition, keeping prices artificially low creates shortages and causes markets to clear through other margins such as queues or search efforts (Becker, 1965; Barzel, 1974; Weitzman, 1991). However, these policies can also improve allocative efficiency under imperfect competition (e.g., it is well known since at least Pigou (1920) that price controls can restore efficiency with monopolies (Bronfenbrenner, 1947)). An additional factor that complicates welfare evaluations about these laws is that individuals might regard price-gouging as a repugnant transaction as Roth (2007) argues. In other words, individuals could get negative utility from others trading essential goods at high prices.

This paper proposes a new measure of individuals' repugnance towards price-gouging and provides evidence on its mechanisms. We conduct what we call an Incentivized Reporting Experiment (IRE) in which we measure individuals' willing-

[1] See, for instance, the Economic Experts Panel from the Initiative on Global Markets on price gouging, https://www.igmchicago.org/surveys/price-gouging and prices of medical supplies, https://www.igmchicago.org/surveys/prices-of-medical-supplies.

ness to pay to report price gouging. This method takes advantage of the fact that authorities rely on reports from customers to enforce anti-price gouging regulations, as with many crimes (Akerlof and Yellen, 1994). Through the lens of a model, we argue that reporting decisions reflect how much individuals expect to change repugnance with their report and how much they value punishing sellers. Thus, this method can potentially be used to measure externalities or repugnance in other settings that also rely on reports to enforce laws or regulations.[2] Intuitively, there are two markets: the market for goods, which has an externality (in our case, repugnance), and the "market" for reporting sellers. We argue that the consumer surplus in the reporting market contains information about the externality in the goods market.

We operationalize the (pre-registered) framed field experiment as a nationally representative survey distributed by a survey company, CloudResearch. We develop an algorithm that combines text analysis and image recognition to make a list of PPE products (face-masks or hand-sanitizers) that are listed on Amazon. We randomize subjects into treatments where they make incentive-compatible choices between gift cards of different amounts and reporting a seller from our list who charges either a low or a high price amount to the Department of Justice. Both price ranges ($7.50 - $10) or ($27.50 - $30) represent increases from pre-crisis levels (12-70% and 310-400% , respectively).

We choose the seller at random from the pool of listed sellers and we do not give individuals the seller's information. Hence, reporting decisions reflect only repugnance to price gouging and not other confounders such as the possibility of getting compensation from the seller or reducing own search costs in the future. We use the responses to estimate the subjects' Willingness to Pay to Report (WTPR) sellers.

Subjects also engage in a donation experiment to tease-out the mechanisms underlying the repugnance to price-gouging. There are two main reasons why individuals might report an unknown seller which they are unlikely to meet: 1) distaste

[2]For example, Ba (2018) studies the willingness to pay to report police malfeasance in Chicago. Our method offers an alternative to Ba's that does not depend on the existence of naturally occurring exogenous variation in the costs of reporting.

for seller profits and 2) desire to help other individuals to purchase the product at lower prices or reduced search costs.[3] To tease out between the two, we ask subjects to choose between a $5 gift card and having us donate PPE we purchase from a seller to a hospital. As before, we randomize whether we buy from a high or low-price seller. Since we hold the quantity of PPE donated fixed, donation rates that decrease with higher ask-prices are consistent with a distaste for firm profits, as we argue with our theoretical framework. We also elicit the subjects' willingness to pay for face masks and hand sanitizer, leveraging the fact that our algorithm produces a list of available sellers and that searching is costly.

We provide five main sets of results. First, individuals take costly actions to enforce price-ceilings. Eighty-percent of them forgo money to report sellers in the lower-price range. On average, the willingness to pay to report sellers who charge the lower-price range was $4.78.[4] According to our estimates of the willingness to pay for the product, 50% of subjects are willing to purchase products in this range, which is an essential component of repugnance.[5]

Second, there is a fraction of individuals who are willing to pay to *prevent* us from reporting sellers, so the distribution of WTPR is bimodal. This polarization is consistent with the findings of Elías et al. (2019) in the context of payments for kidney transplants: some individuals strongly oppose the transactions (kidney transplants or price gouging) while others are in favor of them.

Third, the WTPR is increasing in the price that the seller charges, as indicated by our theoretical framework. A one-percent increase in the ask-price increases the WTPR by 0.17%. This increase does not only reflect a change in the average, but a shift in the whole distribution. This contrasts with the findings of Elías et al. (2019),

[3] Another reason for reporting a seller would be simply a direct taste for punishing deviations from a social norm of unfairness, as in Kahneman et al. (1986). This does not threaten our interpretation, as long as the taste does not depend on the seller's price. A model in which this taste depends on the seller's price would be hard to be empirically tested against a model in which people care directly about seller profits. For instance, we would need to have the seller burn their profits after charging a high price. Thus, to be more precise, in this paper we group distaste for firm profits with any tastes to punish violations from the social norm of not raising prices in emergencies that vary with the price level.

[4] Consider that the compensation per participant in these survey companies is around $1.25 for a 10-minute survey.

[5] For repugnance to occur, there needs to be individuals and sellers willing to transact.

where the amount of compensation for kidney transplants had no effect on support for these transactions.

Fourth, we provide some evidence of the underlying mechanism behind reporting. Donation rates decrease by 30% when we buy the PPE from higher-priced sellers, but only for hand-sanitizers; face masks donations are unaffected by seller price. This suggests that there is distaste for profits in hand-sanitizer transactions, but not in masks transactions. Thus, while the reporting behavior is similar for both products, the underlying mechanism is likely different. The reporting behavior we observe for face-masks could be due to a concern for helping others obtain masks at a low price.

Indeed, reporting and donating are positively associated and over 46% of participants are willing to forgo $5 to have us donate the PPE. Half of subjects who are willing to pay to report sellers are also willing to forgo the $5 gift card to have us donate PPE from a price-gouging seller. This result suggests that individuals simultaneously internalize the desire to complete transactions and prevent them from occurring. They are against the transaction when it is other consumers who pay for it but in favor when it is us who pay for it on behalf of a hospital. Hence, one cannot simply partition the population into those who want to transact and those who find the transaction repugnant.[6] This finding is along the lines of Elías et al. (2019), where support for compensation for kidney donations increases when payments come from a public agency.

Our experiment captures a natural setting. Using observational data from actual price gouging consumer reports filed with different attorney generals, we document that complaints were on the rise during our period of study and that the products we chose were prevalent in these complaints. The complaints contain wording that is associated with repugnance, such as “take advantage of people”. Moreover, our results are robust to experimenter demand concerns and other confounders such as quality and attention differences.

This paper contributes to three strands of literature. First, we contribute to the literature on repugnance, a concept pioneered by Roth (2007). Identifying repug-

[6]We thank Al Roth for pointing out this insight.

nance with a non-hypothetical exercise requires a setting where individuals willingly engage in repugnant transactions and third-parties can restrict the choice set of the potential transactors. This is challenging since many repugnant transactions are prohibited by law. For this reason previous studies primarily use hypothetical vignettes to study repugnance (see Ambuehl et al. (2015) and Elías et al. (2019)).[7] This paper introduces a non-hypothetical method of measuring repugnance, which can be used in other settings that rely on reports for enforcement. Additionally, we formally define and micro-found repugnance . The only other paper that we are aware of that formally defines and models repugnance is Ambuehl et al. (2015).[8]

We also contribute to the literature of price-gouging and anti-price gouging laws. Cavallo et al. (2014) document lower product availability but sticky prices following natural disasters, consistent with a model of "consumer anger" against price increases. In the context of COVID-19, Cabral and Xu (2020) argue that seller reputation might explain why larger and older sellers engage less in price gouging. Chakraborti and Roberts (2020a) and Chakraborti and Roberts (2020b) document increased consumer search following anti-price gouging regulations. [9] Our results suggest that price gouging generates an externality, which should be incorporated in welfare calculations when discussing the efficiency of anti-price gouging regulations (Rotemberg, 2008). For example, it might be possible to implement the same allocations in imperfect competition with price controls and subsidies. However, price ceilings might have higher welfare if there is distaste for firm profits, since subsidies increase them. Moreover, our results suggest that this depends on the type of product, so one-size-fits-all policy might not be appropriate in response to emergencies.

Third, we contribute to the literature on fairness and third-party punishment. Kahneman et al. (1986) argue that community standards of fairness restrict profits attainable by firms; consumers judge firm prices relative to reference levels. Rotem-

[7]Clemens (2018) uses exogenous variation in migration of guest workers, a job commonly regarded as repugnant, and analyzes the impact of migration of different outcomes (e.g., debt) as loose conditions to test for repugnance.

[8]This model, however, relies on an observer misjudging the welfare of a third-party transaction. In contrast, our model does not rely on consumer misperceptions to generate repugnance.

[9]Beatty et al. (2020) provide similar evidence.

berg (2005) and Rotemberg (2011) develop models of consumer anger and firm altruism, where consumers want their sellers to feel altruism towards them. Individuals also judge firms with respect to a reference level. Anderson and Simester (2010) provide experimental evidence of consumer anger along these lines. In our model, the reference level of repugnance is endogenous and depends on the distribution of prices in the market. Finally, (Fehr and Fischbacher, 2004) and many others afterward provide lab evidence of third-party punishment of norm violations. Our study provides evidence of third-party punishment of norm deviations (rice increases during emergencies) in the field.

The remainder of our paper proceeds as follows. Section 2 describes the setting and institutional context. Section 3 introduces our theoretical framework. Section 4 describes the subjects and experimental design. Section 5 describes the empirical results and Section 6 argues for their external validity. Section 7 concludes.

# 2. Setting

## 2.1 Observational Data Sources

In addition to the data generated by our experiment (which we describe on Section 4), we use data from two other sources. First, we obtain information about search results and individual product characteristics from surgical face masks and hand sanitizer listings on Amazon, using the application programming interface (API) of Rainforest API. Each search reviews roughly 10,000 results for face masks and 1,800 for hand sanitizers. We combine an image recognition machine-learning algorithm and text analysis to filter unrelated products from the search results and to convert prices from different presentations to common units (12 fl oz. for sanitizer, 50 pack for masks). According to our algorithm, only 6.3% of face mask search results were surgical face masks and 52% of sanitizer search results were hand sanitizer products.[10] Details of the data construction process can be found in Appendix B. Our

[10]Many results in the face mask category were cloth masks, which we distinguish from surgical masks, since the medical community has pointed out differences in their effectiveness (MacIntyre et al., 2015). Many results in the hand-sanitizer search were e.g., soaps.

algorithm, while precise, introduces measurement error relative to selecting products by hand, so the prices that we obtain should be taken with caution.[11]

We also have a database of actual price gouging complaints that consumers filed with Attorney Generals from 6 different states, which we obtained with Freedom-Of-Information-Act (FOIA) requests.[12] Most states required individuals to fill a form that had at least two sections. In the description of the complaint, individuals included information about the seller, product and price. There was also a section that asked individuals what was their suggested solution for the complaint (e.g., whether they wanted compensation, refund or something else). We machine-read and parsed the text from these two sections and obtained close to 1,900 observations.

## 2.2 Context

The experiment occurred on April 30th and May 1st, three months after the first confirmed COVID-19 case in the United States (Holshue et al., 2020). At this time, the demand for PPE outpaced production capacity. Ninety-percent of U.S. mayors reported PPE shortages and one-third of medical facilities urged donations of personal masks to make up for the insufficient supply (Kamerow, 2020). The sharp increase in demand led to dramatic price increases. Cabral and Xu (2020) document that, between January and March 2020, mask and sanitizer prices were equal to 2.72 and 1.8 times the 2019 prices, respectively. Within our sample, we observe an average price ratio of 6 for face masks and 5.3 for hand sanitizers, as compared to December 2019 prices (see Table 1).[13] Figure 1a shows that the price distribution

[11]Our product classification algorithm has an accuracy of over 0.95. We rely on a large-scale algorithm since we needed to detect sellers that are not easily detectable by manual search (e.g., Cabral and Xu (2020) use a sample of 14-17 hand sanitizers and masks) and we needed results in real time since many products were quickly removed by Amazon and new versions were continuously appearing.

[12]Utah, South Carolina, Wisconsin, Idaho, Missouri and Illinois. We filed FOIA requests with every state and with the DOJ, but we only received information from these states.

[13]The difference between our price ratios and those in Cabral and Xu (2020) could be due to the different sample periods covered; they cover dates between January 15th and March 15th, while we cover April and May. Anecdotally, there was a substantial increase in demand between those dates. Moreover, our sample does not include historical price data; the API only provides real-time data. Our pre-crisis prices come from camelcamelcamel.com and correspond to December prices of 5 sanitizers

remained stable throughout our sample period, before and after our experiment, and exhibits large dispersion.

In response to these price increases, Amazon removed over half a million items with excessive prices (Amazon, 2020). State-level emergency declarations triggered price controls on goods "necessary for survival" in thirty-four of these states (see the maps in Figures 7-9 in the Appendix for more information). These laws prevented either any increases above pre-crisis prices, 10-20% price increases or *unconscionable* price increases. Although there is no federal law against price-gouging, Executive Order 13910 issued on March 23rd prohibited the resale of PPE "at prices in excess of prevailing market prices."

Following the Executive Order, the Department of Justice (DOJ) announced a task force to combat hoarding and price gouging of different products, including sanitizing products and PPE. Individuals could report price-gouging practices to their attorney general or to the Department of Justice's National Center for Disaster Fraud (NCDF).[14] The NCDF requests complainants identify themselves along with the accused, and provide as much information as possible about the transactions. At this point, the complaint is filed and investigated. Individuals found guilty of price gouging face steep fines, and up to ten years in prison.

While there is no information about the total number of price gouging complaints received by the DOJ, the states in our sample of complaints had received roughly 1,000 complaints each by the time of our experiment, and they continued to rise afterward. Figure 1b plots the evolution of complaints filed in 6 different states. 13% of complaints in our sample include the word "mask" and 10% of them include the word "sanitizer". We summarize the text in our sample of complaints using an unsupervised machine-learning algorithm (latent Dirichlet allocation, LDA) that detects topics automatically from a document.[15] On Table 2 we can see that complaint descriptions mostly concern products (e.g., eggs, meat, PPE and toilet paper). On the other hand, consumers refer to "lowering prices", "take advantage of

and 2 face masks that we collected by hand.

[14]See https://www.justice.gov/disaster-fraud/webform/ncdf-disaster-complaint-form.

[15]See Gentzkow et al. (2019) for an overview of LDA topic models and some applications to economics. See Table 8 in the Appendix for unigrams and bigrams used in complaints.

people" and "fair prices" in the section of the forms that asks about their suggested solution to the complaint. For example, a (selected) complaint filed with the Idaho AG explains that a fair resolution for the complaint is:

> "I think they should be fined. I don't want a refund. I want justice."

# 3. Theoretical Framework

## 3.1 Setup

We present a simple model to motivate our experimental design and to argue why price gouging complaints contain information about repugnance. The model contains elements from search models (notation and assumptions from Stahl (1989)) and from the volunteer's dilemma of Diekmann (1985). $M > 2$ producers with constant marginal cost $c > 0$ attempt to sell PPE to one of two consumers.[16] Each consumer has a continuous and weakly decreasing demand for the product, $D(p)$.

First, producers choose prices simultaneously from the equilibrium distribution of prices $F$ over $[\underline{p}, \overline{p}]$. We assume $\underline{p} \geq c$ and take $F$ as given to focus on the equilibrium of the second stage, conditional on $F$. Each consumer meets a random producer and observes the ask-price. She then decides whether to accept the offer or keep searching and whether to report the producer for price gouging. Consumers who continue searching match a random unreported producer one more time. Searching costs $c_s \geq 0$ while reporting costs $c_r \in \mathbb{R}$. Reported producers must pay a fine $\kappa \geq 0$. Only one consumer needs to file a report for the seller to be sanctioned and sellers can only be sanctioned once. Reporting is thus a public good; it is useful for removing a producer from the pool of sellers from which people search.[17]

Consumers get utility from their own consumption, consumption of other users and potentially disutility from the profits of the sellers. Given final price offers $p_i$

[16]The constant marginal cost is not essential for our results, but it simplifies the exposition. Indeed, in the short run marginal costs can be steep.

[17]Intrinsic motivations for reporting a seller can be captured in the cost $c_r$. Beyond this, this version of the model does not capture additional private motivations for reporting, such as the possibility of a refund if the seller is punished. The model can be adapted without much loss to account for this. However, this matches closely our design, since participants are matched with a random seller and thus are unlikely to be motivated by obtaining a refund.

and $p_{-i}$, consumer $i$ receives the following payoff:

$$U_i(p_i, p_{-i}) = CS(p_i) + s(D(p_{-i})) - \beta\Pi(p_i, p_{-i}) - C_s - C_r.$$

Demand $D$ includes consumers' internalization that each unit they consume contributes to firm profits.[18] Consumer surplus is: $CS(p_i) = \int_{p_i}^{\infty} D(p)dp.$ and assumed to be finite for all $p \geq c$. The function $s$ is weakly increasing to capture positive externalities or social preferences. This form is general enough to account for the other's surplus, consumption or both. Unlike the model in Ambuehl et al. (2015), we allow individuals to derive direct benefit from the consumption of others via $s(D(p))$. Costs $C_s$ and $C_r$ denote realized searching and reporting costs, respectively.

The realized aggregate profits of producers are: $\Pi(p_i, p_{-i}) = D(p_i)(p_i - c) + D(p_{-i})(p_{-i} - c) - K$, where $K$ is the total amount of fees that sellers pay for price-gouging violations. $K$ is equal to $\kappa$ if consumers report one seller and equal to $2\kappa$ if they report two. We assume that revenue $D(p)(p - c)$ has a unique maximum at the monopoly price, $p^m$, and that for all $p < p^m$ it is strictly increasing.[19]

It will be useful to define "net" consumer surplus, $\widetilde{CS}(p)$, as:

$$\widetilde{CS}(p) \equiv CS(p) - \beta D(p)(p - c)$$

which is the consumer surplus net of the distaste from firm profits accrued from own-consumption. Likewise, we define repugnance as:

**Definition 1.** The repugnance that consumer $i$ derives from the transaction between the other consumer $-i$ and the matched seller is given by the surplus:

$$R(p_{-i}) \equiv -\underbrace{\left(\underbrace{s(D(p_{-i}))}_{\text{External benefits}} - \beta\underbrace{D(p_{-i})(p_{-i} - c)}_{\text{Distaste for profits}}\right)}_{\text{Surplus from other's transaction}} \tag{1}$$

[18] In particular, demand would also be a function of $\beta$; $D(p; \beta)$.

[19] As we show in Appendix A, the probability of reporting is increasing in price, so if we solved the full equilibrium price distribution, sellers would never choose a price above the monopoly price, hence $\overline{p} < p^m$.

The goal of this paper is to provide an approximate measure of $R(p)$ and to tease out whether it is mostly driven by distaste for seller profits or external benefits. Note that this repugnance can be positive, in which case the transaction is repugnant in the usual sense of Roth (2007). In particular, (Roth, 2015, p. 195) calls a transaction repugnant "if some people want to engage in it and other people don't want them to". If $R(p) > 0$, the consumer would be willing to pay to prevent that transaction from happening. However, if $R(p) < 0$ the transaction would be desirable (negative repugnance), so the consumer would be willing to pay to make that transaction happen.[20] Note also that since profits are increasing below the monopoly price, net consumer surplus is decreasing and repugnance is increasing in price.

We can rewrite the realized payoff of consumer $i$ as:

$$U_i(p_i, p_{-i}) = \underbrace{\widetilde{CS}(p_i)}_{\text{Net consumer surplus}} - \underbrace{R(p_{-i})}_{\text{Repugnance}} + \underbrace{\beta K}_{\text{Seller punishment}} - \underbrace{(C_s + C_r)}_{\text{Search and reporting costs}}$$

Thus, a repugnance component emerges from a micro-foundation in which consumers derive utility from others' consumption and firm profits.

We are interested in Bayesian Nash equilibria (BNE), conditional on $F$. Consumers choose behavioral strategies $\sigma^r(z)$ and $\sigma^a(z) \in [0,1]$, that denote the probabilities of reporting and accepting price offer $z$, respectively. The expected value of reporting versus not reporting (see Appendix A) is:

$$v^r(z) - v^n(z) = \underbrace{\beta\kappa\left(1 - \frac{\sigma^r(z)}{M}\right)}_{\text{Expected value of punishment}} + \underbrace{\left(\frac{R(z) - \mathbb{E}R}{M}\right)(1 - \mathbb{E}\sigma^a)}_{\text{Expected change in repugnance}} - c_r \tag{2}$$

where the operator $\mathbb{E}x$ denotes expected value of $x$, $\mathbb{E}x = \int_{\underline{p}}^{\overline{p}} x(p)dF(p)$. Equation 2 shows that the value of reporting depends on the expected value of punishing the seller, the expected change in repugnance and the cost of reporting. The value of accepting an offer versus searching is:

$$v^a(z) - v^s(z) = c_s + \widetilde{CS}(z) - \mathbb{E}\widetilde{CS} + \frac{\mathrm{Cov}(\sigma^r, \widetilde{CS})}{M} \tag{3}$$

[20] An example of a transaction with negative repugnance would be the movement to "buy local".

where $\text{Cov}(x,y) = \int_{\underline{p}}^{\overline{p}} (x(p) - \mathbb{E}x)(y(p) - \mathbb{E}y) dF(p)$. In Appendix A, we prove the existence of a BNE.

In equilibrium, there exists a reservation price $r^*$ such that consumers accept all offers with price smaller than $r^*$, and search when they receive more expensive offers. The equilibrium probability of reporting satisfies:

$$\sigma^r(z) = \max\{\min\{\sigma^*(z), 1\}, 0\}$$

where:

$$\sigma^*(z) = \frac{M}{\beta\kappa}\left[\beta\kappa + \left(\frac{R(z) - \mathbb{E}R}{M}\right)(1 - F(r^*)) - c_r\right] \tag{4}$$

The probability of reporting is thus (weakly) increasing in the producer's ask-price, $z$, and decreasing in the cost of reporting, $c_r$.

## 3.2 Claims

We make four claims regarding the key outcomes of our experiment: reporting and donating.

**Claim 1.** *There exists a monetary compensation such that an individual is indifferent between reporting and not reporting a seller, when the other individual plays an equilibrium strategy. We will call this compensation the willingness to pay to report (WTPR). This quantity depends on the expected change in repugnance.*

The closed-form expression of the WTPR is:

$$WTPR(z) = \begin{cases} \beta\kappa + \left(\frac{R(z) - \mathbb{E}R}{M}\right)(1 - F(r^*)) - c_r & \text{if } \sigma^*(z) < 0 \\ 0 & \text{if } \sigma^*(z) \in [0,1] \\ \beta\kappa(1 - 1/M) + \left(\frac{R(z) - \mathbb{E}R}{M}\right)(1 - F(r^*)) - c_r & \text{otherwise} \end{cases}$$

The WTPR depends on the expected value of punishing a seller and on the expected change in repugnance due to the individual report, minus reporting costs. This claim relies heavily on the assumption that a reported seller is removed from the pool of available sellers next period—and thus is unable to match with the other consumer, if she chooses to keep searching. Note that this WTPR might be positive or negative, depending on punishment values, reporting costs, and how far is $R(z)$ from its average. Also, note that the WTPR does not depend on the individual's own consumer surplus, ruling out direct benefits from reporting. This result is due to the fact that reporting does not change the distribution of sellers that the individual can meet in case she decides to search (since there is no way of matching again with the same seller). Our experiment will also rule out any direct benefit from reporting, since we don't give subjects information about the seller other than their price.

Furthermore, the WTPR does not depend on repugnance $R(z)$ directly, but relative to the average "market" repugnance, $\mathbb{E}R$. Hence, we obtain an endogenous reference price that depends on the price distribution and is used to evaluate the repugnance of a transaction for the purposes of reporting it. This is consistent with the literature on fairness, in which community standards of fairness depend on comparisons with respect to a reference price (Kahneman et al., 1986). Indeed, in our sample of actual complaints it is common that consumers request prices to go back to normal (see Table 2).

**Claim 2.** *The willingness to pay to report a seller is increasing in price.*

As the seller's ask-price increases, consumption of the other consumer decreases and firm profits increase, since prices are below the monopoly price. Both of these forces place upward pressure on the subject's value of reporting. There is also an opposite force, since the probability that the other consumer reports is also higher, and thus the incentives to free-ride on the other report are also higher, but this effect does not dominate in a symmetric equilibrium.

In the next two claims, we use the model to motivate experimental variation that can separate different mechanisms for reporting.

**Claim 3.** *If individuals derive utility from external consumption and demand for the product has positive income effects, individuals should be willing to pay for a donation of the product to the other consumer*

The claim suggests that we can use variation in an incentivized donation experiment to understand whether internal or external consumption concerns drive the decision to report price-gougers. A consumer who gets no utility from the consumption of third-parties or firm profits would always prefer to have money for consumption. However, those with other-regarding preferences may be willing to pay to increase the other's consumption.

Note that demand is a function of the consumer's income $I$. When we donate an amount $\varepsilon > 0$ of PPE to a hospital (as we detail in the experimental design section below), their utility maximization problem changes to: $\max_{\{x,y\}} u(x+\varepsilon, y)$ s.t. $p_x x + p_y y = I$, where $x$ is the amount of PPE they purchase. This problem is equivalent to solving $\max_{\{x,y\}} u(x, y)$ s.t. $p_x x + p_y y = I + p_x \varepsilon$, so demand of $x$ becomes $D(p; I + p_x \varepsilon)$. If $s$ is increasing and PPE is a normal good, then $s(D(p; I + p_x \varepsilon)) > s(D(p; I))$, so individuals are willing to pay for donations.

**Claim 4.** *Under the assumptions of Claim 3, if individuals have distaste for firm profits, their willingness to pay for a donation of the product decreases as the price at which the product is purchased increases.*

When we donate a product that we buy from any seller, external consumption is fixed at $D(p; M + p_x \varepsilon)$ and does not depend on the seller's price. When we buy from a more expensive seller who charges $z' > z$, profits increase by $(z' - z)D(p; M + p_x \varepsilon)$.[21] Thus, only subjects with $\beta \neq 0$ should respond to variation in $z$. Note that one key assumption, embedded in our model, is that supply is not perfectly inelastic, so purchasing from a producer increases its profits.[22] Moreover, our model also assumes that individuals are not altruistic towards us; that is, they don't incorporate the experimenter's budget into their welfare. We discuss experimenter demand effects on Section 6.

[21]We assume that we increase the demand for the products of both sellers so they don't hit their capacity constraints or modify their subsequent pricing decisions. We are also assuming that the subject does not get utility from the experimenter's payoff. This is a standard assumption present in the reporting experiment and experimental elicitations and MPLs.

[22]We thank John List for pointing this out to us. If that producer would sell out its stock disregarding whether we buy or not, our treatment would not have any impact on profits.

## 4. The Experiment

A survey company, CloudResearch, recruited 1,418 participants from the United States for the experiment. The company selected these participants to match the U.S. census on race, Hispanic origin, age, and gender.[23] Panel (a) of Figure 2 illustrates the flow of the experiment, and an exact copy of the survey appears in the Appendix. The experiment begins with questions related to purchasing behavior. We then elicit the willingness to pay for PPE and ask subjects to report the lowest PPE price they consider excessive.

After the surveys, we assigned subjects into treatments using a $2 \times 2$ completely randomized between-subjects design. The treatments varied the type of PPE subjects would consider independently with a seller's ask-price. Half of the subjects considered a lower price range ($7.50 to $10) and a higher price range ($27.50 to $30). Both price-ranges constitute illegal price-increases under many price-gouging regulations. We induce this variation to test Claims 2 and 4 which rely on comparative statics over the seller's price. Within each price-range we evenly split subjects into treatments that consider 2 FL OZ / 355 ML hand sanitizer or 50 count disposable face masks. We use two different types of PPE to investigate good-specific heterogeneity in the willingness to pay to report or the mechanisms. We revealed pre-crisis prices (December 2019) were $5.90 for hand sanitizer and $6.70 for face masks of equivalent presentations, to homogenize the points of reference. We also provided a picture of the goods to prevent subjects from confusing disposable face masks with the more expensive N95 face masks.[24] Following Kuziemko et al. (2015), we undertook several steps to ensure the sample's validity. First, we only allowed participants with U.S. IP addresses and launched our survey on a workday morning. Second, we included a CAPTCHA to exclude potential robots. Third, we told respondents that payment was contingent on survey completion. Finally, we in-

[23]We pre-registered 1,200 observations. CloudResearch automatically added 218 observations to match the target characteristics we requested prior to the experiment. The characteristics of our subjects is shown in Table 3. Treatment balance is shown in 3. There is some imbalance in education, but controlling for education dummies does not change the coefficients in our regression models, suggesting that this chance imbalance did not affect our results.

[24]On April 2nd, 2020, Amazon prohibited the sale of N95 face masks on their platform (Rey, 2020).

cluded attention checks.

### 4.1 Willingness to Pay for Personal Protective Equipment

The survey told subjects about an algorithm we created to track PPE on Amazon. We offered to notify them if the delivery of a similar product was available in two weeks or less. If they wanted to be notified, they could select the maximum price that they were willing to pay for each of the products. At the end of the survey, we provided subjects with a link to a randomly chosen product from our list at or below their maximum willingness to pay. Following our pre-registration plan, we winsorized the data at the 99th percentile.

This procedure is similar to a first-price auction. Subjects have no incentive to quote a maximum that exceeds their valuation of the good—doing so may result in the algorithm showing them a good at a price they are not willing to pay. However, subjects have incentives to report a smaller valuation, trading off higher chances of smaller prices for higher chances of not being informed about a product they are willing to purchase.[25] Throughout the paper we refer to this quantity as willingness to pay for the PPE, with the caveat that it is estimated downwards.

### 4.2 Excessive Prices for Personal Protective Equipment

To compare our incentivized measure of willingness to pay to report with stated measures about repugnance, we asked subjects to tell us the lowest price they considered to be excessive for both goods. Individuals use numerous adjectives to describe prices in the gouging context, e.g. abusive, unfair, exorbitant or excessive. While all these terms have some normative content and could trigger differentiated concepts in subjects' minds, we chose to use '*excessive*" as it is commonly used in laws and describes a situation in which the price is unexpectedly high without placing undue emphasis on potential ill intention of the seller.

[25]Even if this procedure is not incentive-compatible, it still gives some information about valuations and beliefs about the price distribution. So we opted for it, versus a more contrived, but incentive-compatible exercise.

### 4.3 Eliciting willingness to pay to report

We elicited the subject's willingness to pay to have us report a randomly chosen seller for price gouging to the Department of Justice using an interactive multiple price list (iMPL)[26]. The procedure confronts subjects with an array of paired options and asks them to make a single choice within each pair. At each step, the program asks subjects which of the following two options they prefer:

We **report** an Amazon seller to the **Department of Justice National Center for Disaster Fraud**. This Department is in charge of preventing price gouging for critical supplies. We will report one seller in our list who charges between *[$7.50 - $10.00,$27.50 - $30.00]* for one *[2 FL OZ / 355 ML hand sanitizer, 50 count disposable face masks]*.

You receive a $*[Value]* Amazon Gift card.

The respondents first decide between reporting a seller to the DoJ and a $5 Amazon gift card. If the subject chooses to report, her next decision is between an $8 gift card and reporting the seller. If instead, she selects the money, her next decision is between a $2 gift card and reporting the seller. When the differences in values between the last choice and refined choice dropped below $1, the program stopped. We randomly implement one in every ten of the subjects' decisions.[27]

Variation in the gift card amount maps into variation in $c_r$ and in combination with Equation 4, allows us to measure each subject's willingness to pay to report (WTPR). The WTPR can fall into one of thirteen intervals: $(-\infty, -1]$, $(-1, 0]$, $(0, 1]$, $(1, 2]$, ..., $(9, 10]$, and $(10, \infty)$. Following our pre-registration, we either present the portion of subjects falling within a WTPR interval or set the WTPR value to be the maximum of the interval, 11 in the case of the $(10, \infty)$ interval.

[26] Panel (b) of Figure 2 displays the iMPL's decision tree.

[27] The iMPL imposes strict monotonicity and enforces transitivity (Gonzalez and Wu, 1999). The method's main advantages are transparency to subjects and avoiding framing effects. However, it provides interval responses rather than an exact WTPR. We elected not to use a method providing exact WTPR's due to concerns of a flat payoff problem (Harrison, 1992).

To ensure consequentiality, we chose goods subject to price-gouging legislation. Furthermore, we informed our subjects that our algorithm detected sellers who charged prices between five and fifty dollars in the months before the experiment, so both treatments had the same support. Whenever our algorithm identified sellers charging in a price range at which a subject chose to report, we reported the seller to the NCDF. Thus, report decisions exposed sellers to the threat of steep fines or incarceration.

We do not give participants any information about the seller other than the price. By doing this, we restrict the possibility that they might obtain some direct benefit of reporting, such as reducing their own search costs in the future or obtaining a refund from the seller (as many consumers in our sample of complaints look for).[28] Additionally, this prevents participants from reporting the seller by themselves and still get the gift card, especially since we are saving them the costs of filling out the report form.[29]

### 4.4 Donation Experiment

After the reporting experiment, subjects decided between a \$5 Amazon gift card and Donating PPE to a hospital listed in getusppe.org, an organization that allocates PPE donations to health care workers. Under Claim 3, the choices in this stage of the experiment allow us to understand whether individuals derive utility from external consumption. Moreover, we tell subjects that we purchase the PPE from a randomly chosen seller at the price range. The item considered in this step of the experiment matches the iMPL in the type and seller price range. Our treatment thus keeps constant the quantity of PPE donated and varies only the price at which we buy the product. This way, we test our Claim 4 from the theoretical framework. In particular, an individual that receives price offer $z \in \{z_L, z_H\} = \{[\$7.5 - 10, \$27.50, 30]\}$

[28]Since there are thousands of search results, the possibility of reducing their own search cost by reporting a random seller is insignificant. However, many other consumers might still match with that seller, so they can still reduce others' search costs, as in our model.

[29]Participants could still search for a seller by themselves and report it, but this is true across our treatments and gift-card amounts. Moreover, since there are thousands of noisy search results (see Section 2.1), searching is costly

donates if:

$$\mathbb{E}s(D'_{-i}) - \beta z > \mathbb{E}s(D_{-i}) + \$5$$

where $D'_{-i}$ and $D_{-i}$ denote the hospital's demands with and without donation, respectively. Let $\Delta\mathbb{E}s(D_{-i}) \equiv \mathbb{E}s(D'_{-i}) - \mathbb{E}s(D_{-i})$ be the expected change in social preferences. Suppose that each individual in our sample has their own $\Delta\mathbb{E}s(D_{-i})$ and parameter of distaste for profits, $\beta_i$. Our test for distaste for firm profits is the difference between the fraction of individuals donating with the low price versus the fraction of individuals donating with the high price. In particular, we hypothesize that, with distaste for firm profits ($\beta_i \geq 0$):

$$\underbrace{\Pr\left(\Delta\mathbb{E}s(D_{-i}) - \beta_i z_L > \$5\right)}_{\text{Fraction donating with low price}} \geq \underbrace{\Pr\left(\Delta\mathbb{E}s(D_{-i}) - \beta_i z_H > \$5\right)}_{\text{Fraction donating with high price}}$$

Again, we implemented the choice of one in ten respondents. We presented the question to respondents as

We **buy** from a seller and **donate** to a site listed in getusppe.org. This organization coordinates donation of Personal Protective Equipment to health care workers. We will buy one *[2 FL OZ / 355 ML hand sanitizer, 50 count disposable face masks]* from a seller in our list who charges between *[$7.50 - $10.00,$27.50 - $30.00]*.

You will receive a **$5** Amazon gift card (code to redeem it at the end of this survey).

We ensured consequentiality by verifying that getusppe.org had a demand for both types of PPE. Whenever a subject in our sample was randomly selected to have their donation decision implemented, we purchased the items and donated them to a hospital listed in getusppe.org.

In the final part of the experiment, we asked subjects questions that checked their comprehension of the experiment and their beliefs about quality differences between differently priced goods.

# 5. Results

## 5.1 Repugnance Toward Price Gouging

Our first goal was to test whether consumers take costly actions to oppose price gouging. Under Claim 1, this willingness to pay to report can be interpreted as the level of monetary compensation under which an individual is indifferent between reporting and not reporting a seller. We find that 78% of them are willing to forgo compensation to sellers who charge in the low-price range. On average, respondents forgo over four dollars to report sellers. Consistent with claim 2, the WTPR is increasing in the ask-price. Figure 3a and table 5 show that increasing the price range from $7.50-10.00 to $27.50-30.00 increases the WTPR by $1.22 and $1.60 for hand sanitizer and mask, respectively. The economic significance of the treatment effect is substantial as it amounts to slightly over 20% of the pre-pandemic prices of both categories and implies an elasticity of WTPR to the ask-price of 0.17.[30]

The average effect underlies a more dramatic shift in the WTPR distribution. Exhibit 3b shows an increase of subjects willing to forgo the maximum potential gift card and a substantial reduction in individuals expressing indifference or a desire to pay to prevent reporting. The distributions of WTPR for both prices are statistically different (Kolmogorov-Smirnov p-value of 0.00003 for face masks and 0.0009 for hand sanitizer). Moreover, we cannot reject that the distribution of WTPTR under the high prices first and second-order stochastically dominates the distribution under the low prices (p-values of 0.8224, 0.9989 for face masks and 0.8521, 0.9986 for hand sanitizer).[31] Figure 10 in the Appendix contains the CDF of WTPR by price range, where the stochastic dominance is more evident.

Exhibit 3b also shows the distribution of WTPR to be bimodal for the low-price range treatment arms; subjects have polarized preferences towards moderate price-gouging. 17% of subjects are willing to forgo one dollar or more to *avoid* punishing these sellers. Negative willingness to pay to report is perfectly consistent with our theoretical framework; it could be driven either by deriving negative utility from

[30] Elasticity estimate calculated using the midpoint of the seller's price range.
[31] We use the Bootstrap tests from Abadie (2002) with 100,000 bootstrap samples.

punishing sellers or by considering the repugnance of a given price to be much lower than the market average. We found such respondents in both price ranges, but higher-priced sellers are substantially less likely to be protected by our subjects. The bimodal shape of the distribution of the WTPR reflects a polarization that is similar to what Elías et al. (2019) find in the context of kidney donations; some people strongly opposing the transaction and some strongly in favor of it.

Since 50% of subjects are willing to purchase PPE at prices in the lower price range, the decision to punish sellers implies that subjects find these transactions repugnant (Roth, 2007).[32] That is, subjects prevent voluntary transactions between third-parties. Exhibit 4a shows the portion of subjects willing to pay for either type of PPE at different percent changes from the December price. Almost half of the subjects are willing to buy the goods from "low-price" sellers, while at least five percent are still willing to buy from "high-price" sellers.[33] Exhibit 4b displays the CDF of self-reported excessive prices for either type of PPE at different % changes from pre-crisis prices. Only 40% of respondents would consider prices in the lower price range excessive while more than 70% deem prices in the higher -price range excessive.

### 5.2 Underlying Motives

Under Claim 3 of our model, individuals that derive external benefits from PPE consumption derive positive surplus from donations of the product. Consistent with this, over 43% of participants are willing to forgo the five dollars to have us donate the PPE (see Table 6).

Since all subjects completed both tasks, we can use the within-person relationship between these choices to check for consistency between donation and reporting decisions. Nearly 50% of subjects who were willing to pay positive amounts to

[32] As we argued above, it is unlikely that individuals receive any direct benefit (other than moral benefit) from reporting sellers, since we match them with a random seller chosen from a large pool. This means that they cannot claim any refund or expect to face lower prices or search costs in the future because of this decision.

[33] With the caveat, as we argued above, that our measure of WTP for the PPE is biased downwards, since we elicit it with a procedure similar to a first-price auction.

report sellers were also willing to donate. Figure 5b reports a generally positive association between WTPR and donations. This positive correlation is expected from our model, since individuals who derive a high benefit from others' consumption should both be more willing to donate and have a higher repugnance; which would manifest as a higher willingness to pay to report. A notable exception is that subjects who are willing to pay to *avoid* reporting sellers have donation rates twice as large as those who express a WTPR of zero ($p < 0.001$). Their donation rate is less than the average of all subjects who are willing to pay to report price-gouging, and comparable to subjects willing to pay $2 to $5 to report sellers.

Using variation of the seller price in the donation experiment, we find that the mechanism driving the repugnance towards price-gouging is good specific. The donation rates for subjects considering hand-sanitizer decrease by 30% when we purchase the good from a higher priced seller. Conversely, the subjects consider face masks are uninfluenced by seller price (see panel (a) of Figure 5b). In other words, we find evidence of distaste for firm profits in the case of sanitizer, but not face masks. This result is striking, since the willingness to pay to report face masks was at least as responsive to seller price as the one of hand sanitizers (see Figure 3a and Table 5). This finding suggests that a one-size-fits-all policy might not be appropriate for price-gouging. Instead, policymakers should set policy on a good-by-good basis.

While there are many explanations for the difference in mechanisms between products, we see a similar pattern in the observational data of price gouging complaints. We computed the sentiment scores of the text used in complaints.[34] As Exhibit 11 shows, the description field of both mask and sanitizer complaints contains a similar sentiment: we cannot reject the hypothesis that the sentiment distributions are equal. This is reasonable, since complaint descriptions typically include factual information about the seller and the circumstances of the report (e.g., price, location, presentation). However, the language used in the suggested solution fields seems to be quite different: we reject equality of distributions between masks and sanitizers (p-value of 0.314) and we cannot reject first and second-order stochastic

[34] See Gentzkow et al. (2019) for an overview of the use of sentiment analysis in Economics.

dominance (of mask sentiment being more negative, with p-values of 0.7540 and 0.6074, respectively). As we mentioned in Section 2, the suggested solution field of complaints tends to contain more normative views of what should be done to the seller. Our sentiment analysis shows that people use more negative language when suggesting solutions about mask complaints versus sanitizer complaints. Even if we cannot point a specific reason for the different mechanisms, heterogeneity by product seems to be also present in actual complaints.

### 5.3 Heterogeneity

The heterogeneity in WTPR across individuals' willingness to buy the goods at the posted price or the perception of "excessiveness" is reported in panels (c) and (d) of Exhibit 4. The WTPR are higher when the ask-price exceeds individuals' willingness to pay as well as when the price range is considered to be excessive ex-ante.

In our pre-registered study, we also posited that the salience and prevalence of the emergency as measured by the number of reported deaths in the state as well as whether or not price gouging was locally forbidden could affect our results. We found no evidence that the number of deaths affected WTPR but the propensity to donate did increase. Regarding local legislation, tests for respondents in states without any anti-gouging laws lost statistical significance due to the reduced sample size but the results remain qualitatively unchanged. We report these results in the Appendix due to their small informational content.

## 6. Generalizability and Robustness

We use List (2020)'s SANS conditions to understand the experiment's generalizability to the entire United States. We selected our subjects to match the U.S. on race, Hispanic origin, age, and gender. However, the survey over samples subjects with high-school education and under samples subjects with less than high school or more than a four-year degree. We reweight our data to match U.S. population moments (Hotz et al., 2005). Reweighting does not materially change the results (see

Appendix). However, we cannot evaluate unobservable differences between our subjects and those who would never participate.

The compliance rate after randomization is 98%. There are also no motivational or incentive differences across treatments that materially affect attrition. Nevertheless, we use the non-parametric approach in Manski (1989) to derive treatment effect bounds with our data. Our results persist, with less precision, when using the bounding approach (see Appendix).

Regarding the naturalness of the experiment, we use a framed field experiment (see Harrison and List (2004)). Price-gouging legislation activates during declared states of emergency. While atypical, we are operating in precisely the setting to which we wish to generalize. The text analysis of our sample of actual price gouging complaints (Section 2) shows that complaints about face masks and hand sanitizers were common. The iMPL may be unnatural to subjects, but we are comparing choices made in the iMPL to consequential choices made by thousands of individuals outside of the experiment. Moreover, Berry et al. (2020) shows that choices made using within-person elicitations are congruent with decisions in more natural take-it-or-leave-it offers. Since the experiment takes place online at the subject's own pace, subjects are free to seek information that would aid in their decision-making. The donation experiment closely mimics actions taken by Uber during other natural disasters (Uber, 2016). We view our WTPR and mechanism insights as WAVE 1 insights. Further work should attempt to understand the WTPR for goods that do not have positive externalities and focus on trying to understand what drives the differences in mechanisms across goods.

Regarding internal validity, there are four main confounders to our results. First, there might be experimenter demand effects that incentivize individuals to align their responses to what they perceive to be our desired results. We reduce this possibility by providing full anonymity to our participants (de Quidt et al., 2019). We coded the survey to embed bonus payments so as to not require any participant information (whereas many field experiments compensate participants sending gift cards to their email address). Moreover, the heterogeneity observed in Panel (a) of Figure 5 suggests that any experimenter demand effect would need to be good-specific, which is not likely. Second, the treatment might be too subtle for individuals to notice. We asked individuals an attention question at the end of the survey, in which they had to report the price range that they were assigned. Table 18 shows that individuals in the high price range tend to misremember the price range that they were given; that is, they report incorrectly that they were assigned the lower price range. This means that our results, if anything, are biased downwards, since some people in the upper price range believe that they were assigned the lower prices.

Third, individuals might perceive that products of higher prices differ in other ways as well from products with lower prices (e.g., differences in quality, shipping dates, etc.). We tell individuals that our algorithm has found products in the previous weeks with prices from $5 to $50 with similar shipping dates. Moreover, we ask them at the end of the survey whether they agree with the statement that products in the upper price range have a higher quality than products in the lower price range. Table 19 shows that treatment status has mostly insignificant impact on quality beliefs.

Lastly, individuals might also be repugnant to accepting money in exchange for reporting a seller. For instance, Roth (2007) argues that some exchanges become repugnant when money is added. While we cannot rule this out, there is at least a partial rate of substitution between cash payments and reporting or donating, since WTPR and donation rates are responsive to our treatment. Moreover, this would only bias our estimates downwards, since higher cash payments would also entail a higher 'cash repugnance'. Individuals valuation from reporting sellers would thus be higher than what they reveal through cash incentives.

## 7. Conclusions

In this paper we propose an incentivized reporting experiment (IRE) to quantify the repugnance to price-gouging and unpack its mechanisms. This method can be used to study repugnance towards activities that rely on reporting for enforcement, or the willingness to pay to report malfeasance. We argue, with the help of a theoretical model, that reporting a seller for price-gouging contains information about repugnance to this transaction. We conducted the experiment during the first wave of the COVID-19 pandemic, and randomized participants to lower ($7.50 - $10) or higher ($27.50- $30) priced sellers above pre-crisis average prices and asked them to choose between reporting the seller and receiving different amounts of money. The IRE allows us to show that most individuals value reporting price increases, although there is some polarization. Individuals also respond to the price of the seller and increase their willingness to pay to report when facing more expensive sellers. The documented measure implies opposition to transactions that some participants would find beneficial—would be willing to pay for—and thus presents a consequential example of repugnant transactions in the field.

A choice between a $5 gift card and having us donate an item of PPE purchased from a price-gouger clarifies the underlying motivation behind the opposition to large price increases during emergencies. We find evidence for distaste for seller profits in the case of hand sanitizers but a higher priority for others' consumption when it comes to face masks.

The experiment shows that the sale of goods at excessive prices has economically significant negative externalities on third-parties. While this is not an argument for or against anti-price gouging laws, his complicates any welfare evaluation of these policies. As previous repugnance studies have found, consumers might be willing to tolerate inefficiencies (longer waiting times for kidney transplants, as in Elías et al. (2019) or excess PPE demand as in the COVID-19 pandemic) in order to reduce repugnance. Moreover, the fact that individuals may obtain negative externalities from profits suggests an additional welfare cost of policies such as subsidies—that potentially increase profits—versus price controls. Our experiment suggests policymakers should set policy on a good-by-good basis. Noticeably, anti-price gouging regulations cover only a subset of products; further research should understand what drives the heterogeneity across products.

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# 8. Tables

Table 1: Personal Protective Equipment Prices in April and May

| | Product | N | Price Ratio | Price | Lowest Price | Highest Price |
|---|---|---|---|---|---|---|
| April | Face Masks | 1,862 | 5.63 | 37.74 | 5.40 | 349.25 |
| | | | (4.80) | (32.13) | | |
| | Hand Sanitizer | 2,251 | 5.33 | 31.46 | 3.49 | 210.00 |
| | | | (4.52) | (26.68) | | |
| May | Face Masks | 1,122 | 6.35 | 42.56 | 5.99 | 349.50 |
| | | | (5.41) | (36.24) | | |
| | Hand Sanitizer | 986 | 5.32 | 31.38 | 3.49 | 220.15 |
| | | | (5.03) | (29.69) | | |

Note: Table displays summary statistics for the prices of PPE sold on Amazon between April 5th and May 12th. Prices normalized to the units of the goods considered in the experiment. The price ratio column displays the average price of the PPE relative to the December price, which was calculated using the data of 4 products obtained from the price-tracking website *camelcamelcamel.com*. This is $6.70 for face masks and $5.90 for hand sanitizer. Standard deviations appear below the means in parentheses. Data scraped from Amazon on April 5th, April 15th, April 28th, April 30th, May 1st, May 4th, and May 12th 2020.

Table 2: Topics from latent Dirichlet allocation model

| Topic | Prevalence | Top terms |
|---|---|---|
| Description | | |
| 1 | 41.4% | egg, dozen, lb, pound, meat, beef, grocery, grind beef, hamburger, dozen egg |
| 2 | 31.3% | mask, sanitizer, hand, hand sanitizer, bottle, amazon, wipe, lysol, oz bottle, seller |
| 3 | 27.3% | paper, toilet, toilet paper, gas, station, gas station, towel, charmin, paper towel, gas price |
| Solution | | |
| 1 | 36.0% | normal, low price, paper, price normal, toilet, toilet paper, difference, desist, bring, cease |
| 2 | 33.8% | company, gas, raise, complaint, raise price, fix, gas price, report, seller, control |
| 3 | 30.2% | advantage people, community, accountable, food, hold accountable, fair price, grocery, check, change, issue |

Note: The table includes topics from 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 only 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. Top terms are calculated by sorting words according to the $\Pr(topic|word)$. We decided on 3 topics for parsimony.

Table 3: U.S. Adult Sample Description

| | Demographics | Non-attriters | US Pop |
|---|---|---|---|
| Female | 52.95 | 52.91 | 51.00 |
| Age 18-34 | 27.94 | 27.82 | 32.10 |
| Age 35-54 | 36.07 | 36.59 | 31.30 |
| Age 55+ | 36.00 | 35.59 | 36.60 |
| White (non-Hispanic) | 63.72 | 63.84 | 62.30 |
| Black | 12.09 | 12.15 | 12.96 |
| Hispanic | 16.61 | 16.53 | 16.41 |
| Asian | 5.77 | 5.61 | 5.96 |
| Other race/ethnicity | 2.36 | 2.44 | 2.37 |
| Less than HS | 2.08 | 1.94 | 10.60 |
| HS/GED | 15.36 | 15.31 | 28.32 |
| Some college/Associate degree | 31.97 | 31.70 | 27.77 |
| Bachelor's Degree | 30.79 | 30.77 | 21.28 |
| Graduate Degree | 19.81 | 20.27 | 12.04 |
| Income $<$ \$50,000 | 37.53 | 37.38 | 43.70 |
| \$50,000 $\leq$ Income $<$ \$100,000 | 37.46 | 37.10 | 30.00 |
| \$100,000 $\leq$ Income | 25.02 | 25.52 | 26.20 |
| Sample Size | 1439 | 1391 | |

Note: The table describes the demographic characteristics of the respondent sample and compares them to the Vintage 2019 national population estimates from the Census Bureau https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-detail.html. The survey company selected participants to match the U.S. census on race, hispanic origin, age and gender. Sample seems to over-represent high-education and median income subpopulations based on self-reported information.

Table 4: Treatment Balance

| | Hand Sanitizer | | Face masks | | |
|---|---|---|---|---|---|
| | \$7.50-\$10.00 | \$27.50-\$30.00 | \$7.50-\$10.00 | \$27.50-\$30.00 | p-value |
| Age | 46.15 | 45.48 | 47.32 | 47.44 | |
| | (17.02) | (16.6) | (17.5) | (16.59) | 0.35 |
| Female | 0.52 | 0.55 | 0.51 | 0.54 | |
| | (0.5) | (0.5) | (0.5) | (0.5) | 0.69 |
| White | 0.63 | 0.66 | 0.64 | 0.63 | |
| | (0.48) | (0.47) | (0.48) | (0.48) | 0.81 |
| Black | 0.12 | 0.11 | 0.13 | 0.12 | |
| | (0.33) | (0.32) | (0.33) | (0.33) | 0.95 |
| Hispanic | 0.19 | 0.16 | 0.16 | 0.16 | |
| | (0.39) | (0.37) | (0.36) | (0.37) | 0.70 |
| Asian | 0.05 | 0.03 | 0.05 | 0.07 | |
| | (0.21) | (0.18) | (0.22) | (0.25) | 0.21 |
| Other race/ethnicity | 0.04 | 0.05 | 0.04 | 0.03 | |
| | (0.19) | (0.22) | (0.2) | (0.18) | 0.70 |
| Less than high school | 0.02 | 0.02 | 0.02 | 0.01 | |
| | (0.15) | (0.13) | (0.15) | (0.12) | 0.79 |
| High school or GED | 0.13 | 0.2 | 0.18 | 0.11 | |
| | (0.34) | (0.4) | (0.38) | (0.31) | 0.00 |
| Some college/associate degree | 0.32 | 0.34 | 0.27 | 0.34 | |
| | (0.47) | (0.48) | (0.44) | (0.47) | 0.11 |
| Bachelor's degree | 0.34 | 0.27 | 0.3 | 0.33 | |
| | (0.47) | (0.44) | (0.46) | (0.47) | 0.16 |
| Graduate degree | 0.19 | 0.18 | 0.23 | 0.21 | |
| | (0.39) | (0.38) | (0.42) | (0.41) | 0.26 |
| Income $<$ \$50,000 | 0.38 | 0.38 | 0.35 | 0.38 | |
| | (0.48) | (0.49) | (0.48) | (0.49) | 0.83 |
| \$50,000 $\leq$ Income $<$\$100,000 | 0.46 | 0.48 | 0.49 | 0.45 | |
| | (0.5) | (0.5) | (0.5) | (0.5) | 0.69 |
| \$100,000 $\leq$ Income | 0.26 | 0.24 | 0.25 | 0.27 | |
| | (0.44) | (0.43) | (0.43) | (0.44) | 0.82 |
| Sample Size | 349 | 346 | 348 | 348 | |

Note: Table shows the mean and standard deviations in parentheses. P-value is from an F-test testing for the equality of all means.

Table 5: Willingness to Pay to Report

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | WTP | WTP | WTP | WTP |
| Seller Charges $27.50 to $30 | 1.408*** | 1.409*** | 1.390*** | 1.553*** |
| | (0.247) | (0.246) | (0.250) | (0.352) |
| Face Masks | | -0.705*** | -0.744*** | -0.904** |
| | | (0.246) | (0.249) | (0.351) |
| Seller Charges $27.50 to $30 × Face Masks | | | | -0.324 |
| | | | | (0.501) |
| Constant | 4.784*** | 5.136*** | 7.118*** | 7.191*** |
| | (0.175) | (0.214) | (0.793) | (0.804) |
| Elasticity Estimate | 0.17 | 0.17 | 0.17 | 0.19 |
| Demographics Controls | NO | NO | YES | YES |
| $R^2$ | 0.023 | 0.029 | 0.046 | 0.047 |
| Observations | 1,392 | 1,392 | 1,392 | 1392 |

*Note:* Heteroskedasticity robust standard errors in parentheses. Elasticity estimate calculated using the mid-point of seller price range. $^{*}p < 0.10$,$^{**}$ $p < 0.05$,$^{***}$ $p < 0.01$.

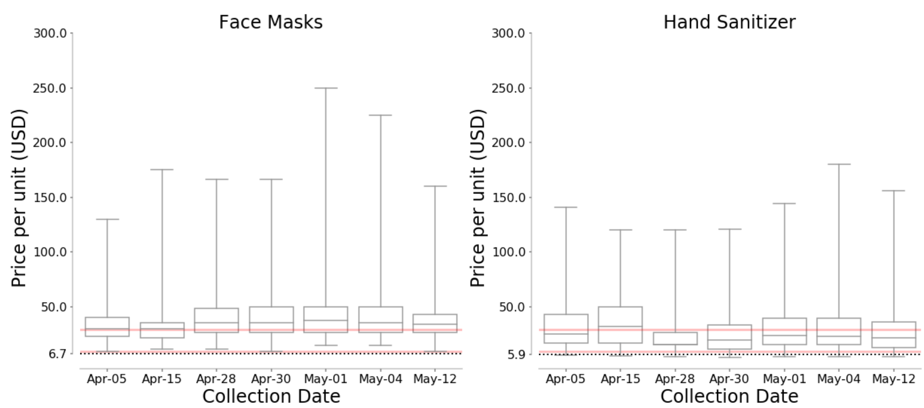
Table 6: Propensity to Donate

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Donate | Donate | Donate | Donate |
| Seller Charges $27.50 to $30 | -0.0645** | -0.0649** | -0.0640** | -0.0183 |
| | (0.0268) | (0.0266) | (0.0269) | (0.0385) |
| Face Masks | | 0.114*** | 0.110*** | 0.0649* |
| | | (0.0266) | (0.0269) | (0.0382) |
| Seller Charges $27.50 to $30 × Face Masks | | | | -0.0912* |
| | | | | (0.0540) |
| Constant | 0.498*** | 0.441*** | 0.405*** | 0.425*** |
| | (0.0190) | (0.0231) | (0.0860) | (0.0871) |
| Semi-Elasticity Estimate | -0.08 | -0.08 | -0.08 | -0.02 |
| Controls | NO | NO | YES | YES |
| $R^2$ | 0.004 | 0.017 | 0.033 | 0.035 |
| Observations | 1,387 | 1,387 | 1,387 | 1,387 |

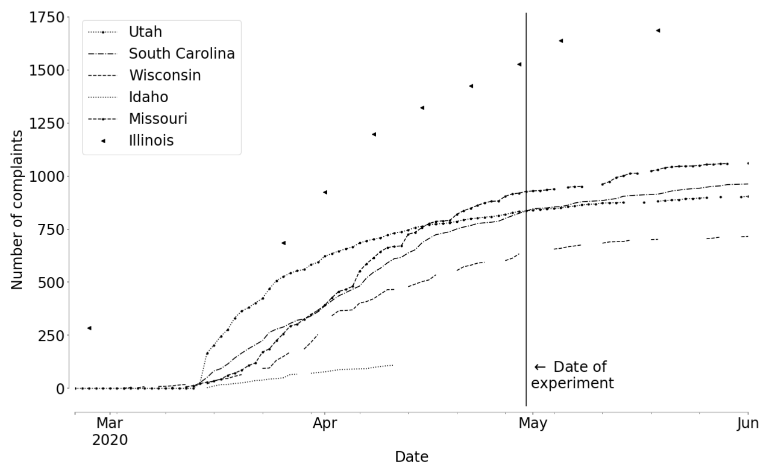
*Note:* Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

# 9. Figures

Figure 1: Observational Price-Gouging and Complaint Data



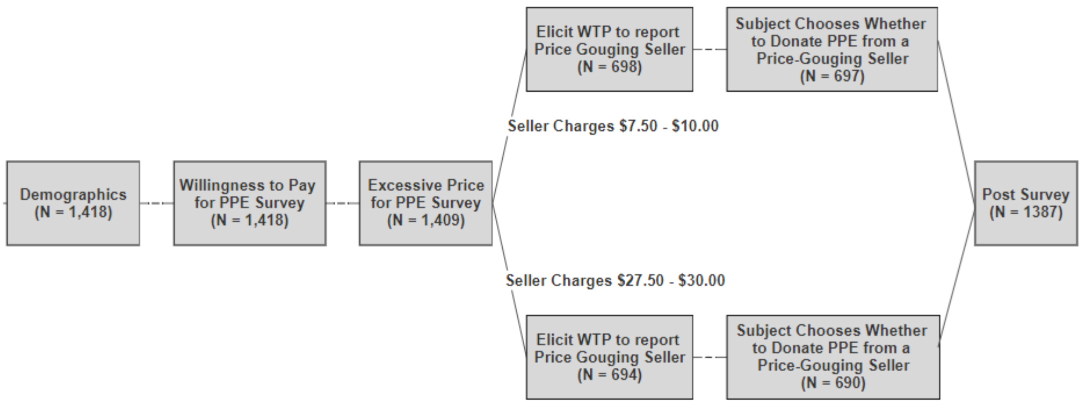

(a) Price distributions on Amazon on dates close to the experiment



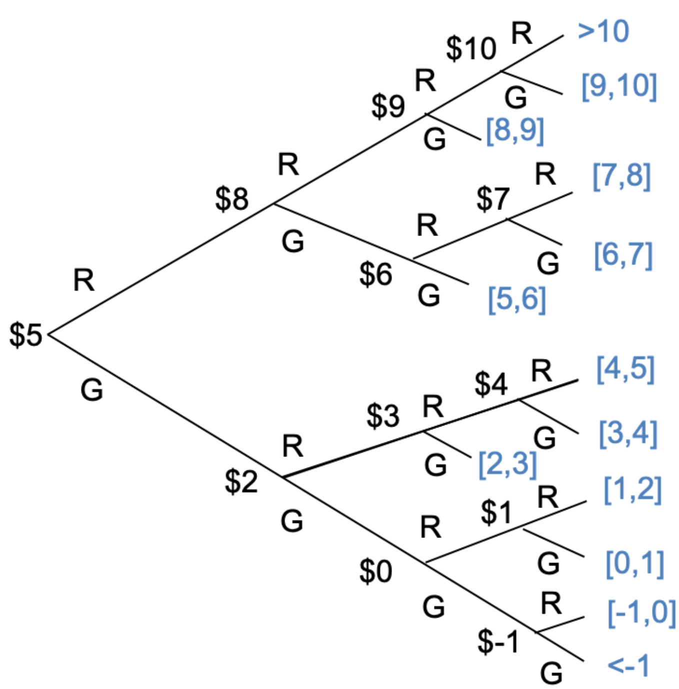

(b) Cumulative Price Gouging Complaints to State Attorney Generals

Note: Panel (a) displays the price distributions on Amazon on dates around our experiment. Boxes contain quartiles of the distributions and the whiskers represent the 1st and 99th percentiles. The pink lines correspond to the price range in our experiment and the dashed lines correspond to the December prices..

Figure 2: Experimental Design



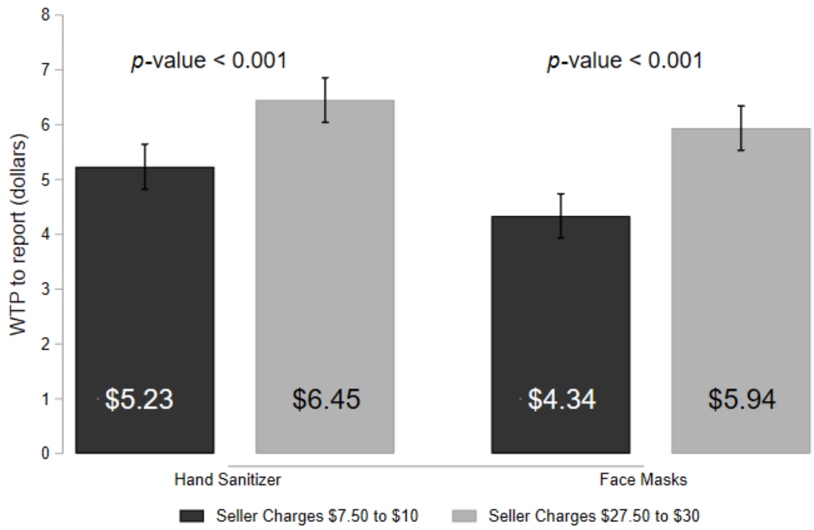

(a) The Structure and Flow of the Experiment



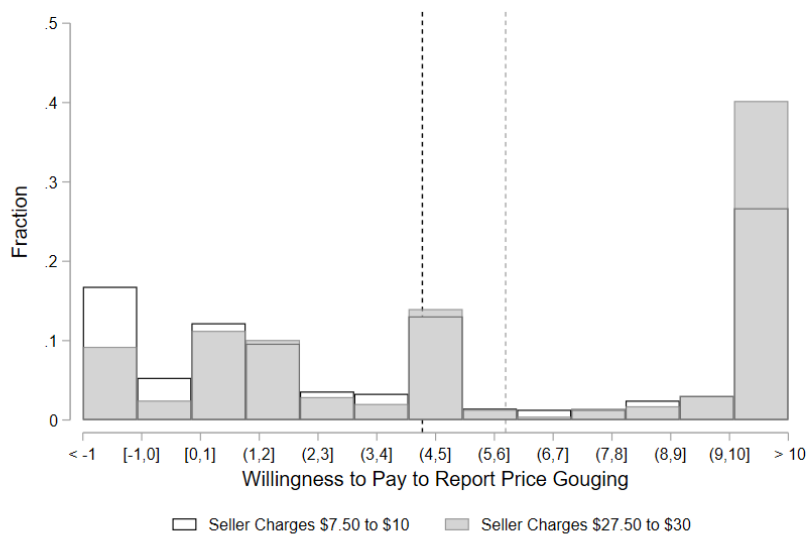

(b) Willingness to Pay to Report Decision Tree

Note: Panel A reports the flow of the experiment. Randomization occurs after the excessive price survey. Within each of the seller price treatments, subjects are randomly split into considering either hand-sanitizer or face masks. Numbers in parentheses represent sample sizes at that stage of the experiment. Panel B displays the decision tree subject's faced during the willingness to pay to report the experiment. All subjects began with the decision between a $5.00 gift card and reporting a seller. Subsequent decisions depend on the subject's choice.

Figure 3: Willingess to Pay to Report



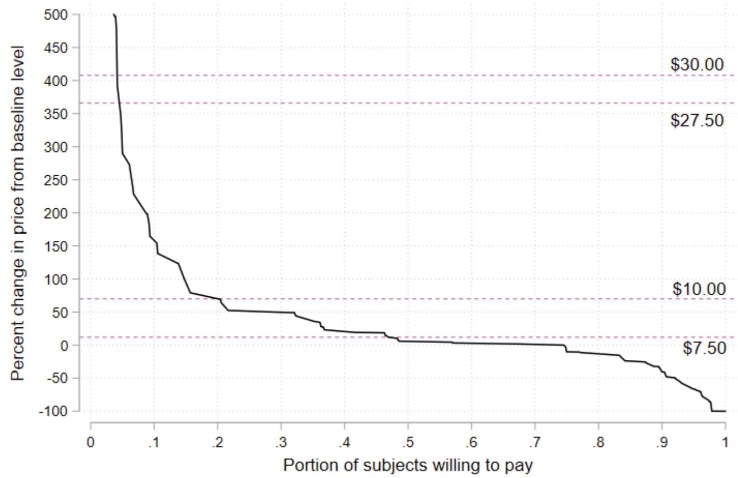

(a) Average Willingness to Pay to Report by Seller Price



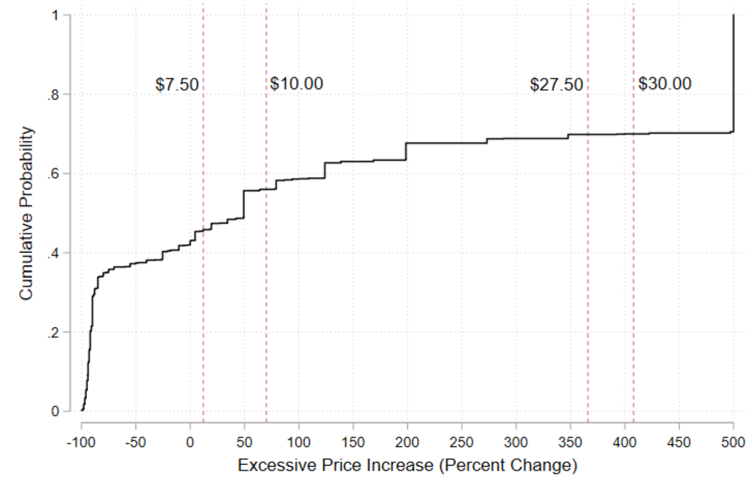

(b) Distributions of Willingness to Pay to Report by Seller Price

Note: Panel (a) displays the average willingness to report sellers force price-gouging at different prices separately by PPE type with 95% confidence intervals. Panel (b) presents the histogram of willingness-to-report price gouging of either good by seller price. The vertical lines represent the average WTPR at each seller price. Kolmogorov-Smirnov p-value of 0.00003 for face masks and 0.0009 for hand sanitizer. p-values of 0.8224, 0.9989 for face masks and 0.8521, 0.9986 for hand sanitizer, for the H0 that the distribution of WTPR under high prices first and second-order stochastically dominates the distribution with low prices, using the Bootstrap tests from Abadie (2002).

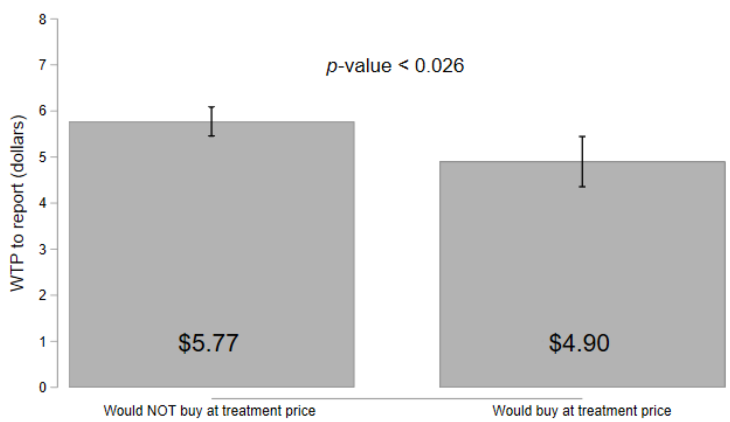
Figure 4: Heterogeneity in Willingness to Report by Survey Responses



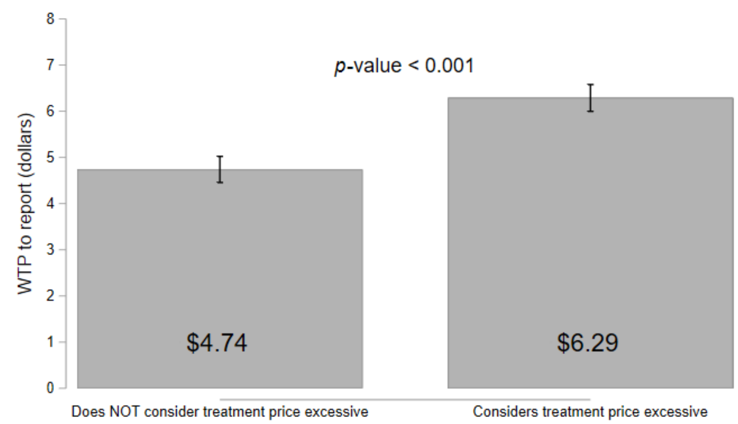

(a) Willingness to Pay for Personal Protective Equipment




(b) Excessive Price of Personal Protective Equipment



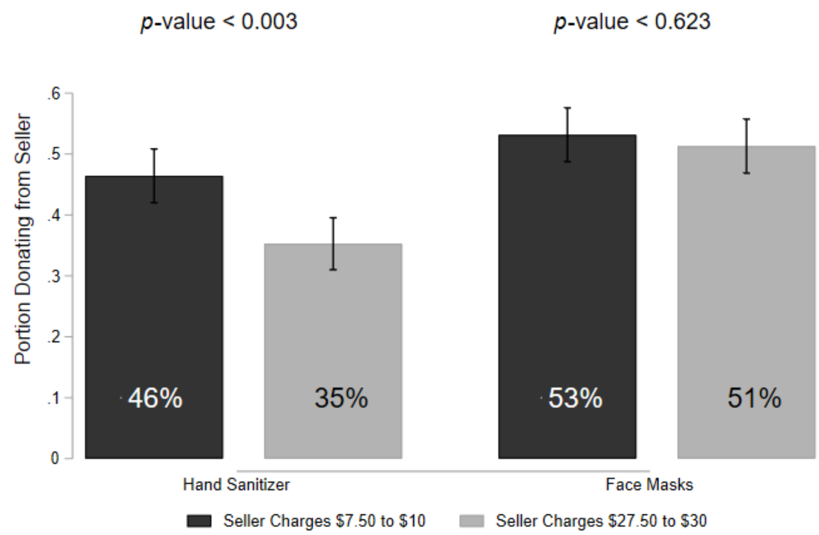

(c) WTPR by willingness to Buy PPE at Seller Price



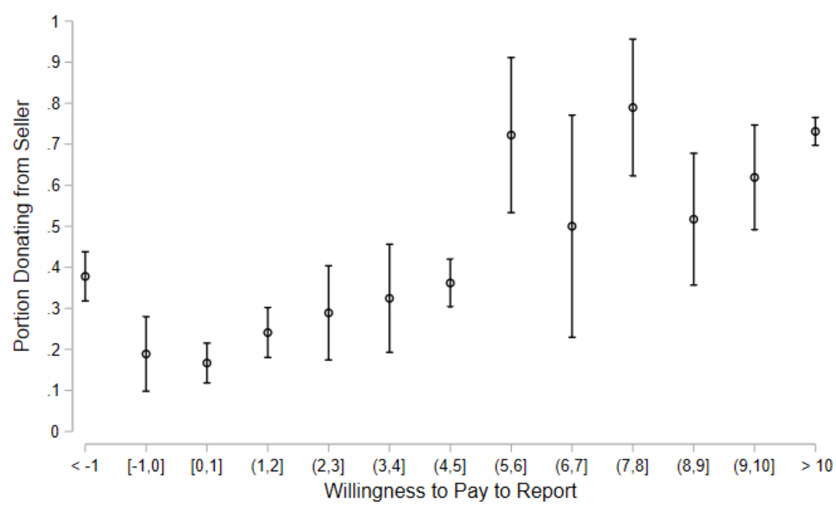

(d) WTPR by whether Subjects Found Seller Price Excessive

Note: Panel (a) shows the portion willing to pay for either type of PPE at% changes from pre-crisis prices. Horizontal lines denote the treatment price ranges. Panel (b) displays the CDF of self-reported excessive prices for either type of PPE at% changes from pre-crisis prices. Vertical lines denote the potential seller price ranges. Data in Panels (a) and (b) are winsorized at the 99th%ile. Panel (c) shows the average WTPR split by whether the subject reported a WTP exceeding the minimum seller price they consider and 95% confidence intervals. Panel (d) displays the average WTPR split by whether the subject reported that they found values in the seller's price range excessive and 95% confidence intervals. Estimates pool subjects across all treatments and exclude subjects who did not report a WTP or excessive price for the PPE considered in their treatment.

Figure 5: Propensity to Donate PPE from Price-Gougers




(a) Propensity to Donate by Seller Price and PPE




(b) Relationship between Willingness to Report and Propensity to Donate

Note: Panel (a) displays the average willingness to report sellers force price-gouging at different prices separately by PPE type with 95% confidence intervals. Panel (b) plots the average portion of subjects choosing to donate PPE within every willingness to reportbin. This figure pools both seller prices and types of PPE.

# A. Theoretical Framework

The expected value of both accepting and reporting an offer $z$ is:

$$v^{r,a}(z) = \beta\kappa - c_r + \widetilde{CS}(z) + \underbrace{\frac{1}{M}\left[ - \underbrace{\sigma^a(z)R(z)}_{\text{The other consumer accepts}} - \underbrace{(1-\sigma^a(z))\mathbb{E}R}_{\text{The other consumer searches}} \right]}_{\text{Consumers matched to the same seller}}$$

$$+ \underbrace{\frac{M-1}{M}\int_{\underline{p}}^{\overline{p}} \left[ - \underbrace{\sigma^a(p)R(p)}_{\text{Accepts}} - \underbrace{(1-\sigma^a(p))\mathbb{E}R}_{\text{Searches}} + \underbrace{\sigma^r(p)\beta\kappa}_{\text{Reports}} \right]}_{\text{Consumers matched to different sellers}} dF(p)$$

The value of reporting the offer and not accepting it (i.e., searching for other offers) is:

$$v^{r,s}(z) = \beta\kappa - c_r - c_s + \underbrace{\frac{1}{M}\left[ \mathbb{E}\widetilde{CS} - \underbrace{\sigma^a(z)R(z)}_{\text{The other consumer accepts}} - \underbrace{(1-\sigma^a(z))\mathbb{E}R}_{\text{The other consumer searches}} \right]}_{\text{Consumers matched to the same seller}}$$

$$+ \underbrace{\frac{M-1}{M}\int_{\underline{p}}^{\overline{p}} \left[ - \underbrace{\sigma^a(p)R(p)}_{\text{Accepts}} - \underbrace{(1-\sigma^a(p))\mathbb{E}R}_{\text{Searches}} \right.}_{\text{Consumers matched to different sellers}}$$

$$\underbrace{\left. + \underbrace{\sigma^r(p)(\beta\kappa + \mathbb{E}\widetilde{CS})}_{\text{Reports}} + \underbrace{(1-\sigma^r(p))\left(\frac{M-2}{M-1}\mathbb{E}\widetilde{CS} + \frac{1}{M-1}\widetilde{CS}(p)\right)}_{\text{Does not report}} \right]}_{\text{Consumers matched to different sellers}} dF(p)$$

The value of accepting an offer and not reporting it is:

$$v^{n,a}(z) = \widetilde{CS}(z) + \underbrace{\frac{1}{M}\left[ - \underbrace{\sigma^a(z)R(z)}_{\text{The other consumer accepts}} - \underbrace{(1-\sigma^a(z))\mathbb{E}R}_{\text{Searches}} + \underbrace{\sigma^r(z)\beta\kappa}_{\text{Reports}} \right]}_{\text{Consumers matched to the same seller}} +$$

$$\underbrace{\frac{M-1}{M}\int_{\underline{p}}^{\overline{p}} \left[ - \underbrace{\sigma^a(p)R(p)}_{\text{Accepts}} - \underbrace{(1-\sigma^a(p))\left( \frac{M-2}{M-1}\mathbb{E}R + \underbrace{\frac{1}{M-1}R(z)}_{\text{Might match } z} \right)}_{\text{Searches}} + \underbrace{\sigma^r(p)\beta\kappa}_{\text{Reports}} \right]}_{\text{Consumers matched to different sellers}} dF(p)$$

Finally, the value of neither accepting nor reporting an offer is:

$$v^{n,s}(z) = -c_s + \frac{1}{M}\underbrace{\left[\mathbb{E}\widetilde{CS} - \underbrace{\sigma^a(z)R(z)}_{\text{The other consumer accepts}} - \underbrace{(1-\sigma^a(z))\mathbb{E}R}_{\text{Searches}} + \underbrace{\sigma^r(z)\beta\kappa}_{\text{Reports}}\right]}_{\text{Consumers matched to the same seller}}$$

$$+ \frac{M-1}{M}\int_{\underline{p}}^{\overline{p}} \left[\underbrace{-\underbrace{\sigma^a(p)R(p)}_{\text{Accepts}} - \underbrace{(1-\sigma^a(p))\left(\frac{M-2}{M-1}\mathbb{E}R + \underbrace{\frac{1}{M-1}R(z)}_{\text{Might match } z}\right)}_{\text{Searches}}}_{\text{Consumers matched to different sellers}}\right.$$

$$\left.\underbrace{+\underbrace{\sigma^r(p)(\beta\kappa + \mathbb{E}\widetilde{CS})}_{\text{Reports}} + \underbrace{(1-\sigma^r(p))\left(\frac{M-2}{M-1}\mathbb{E}\widetilde{CS} + \frac{1}{M-1}\widetilde{CS}(p)\right)}_{\text{Does not report}}\right] dF(p)}_{\text{Consumers matched to different sellers}}$$

Then, the value of reporting versus not reporting satisfies:

$$\begin{aligned} v^r(z) - v^n(z) &= v^{r,a}(z) - v^{n,a}(z) = v^{r,s}(z) - v^{n,s}(z) \\ &= \beta\kappa\left(1 - \frac{\sigma^r(z)}{M}\right) - c_r + \left(\frac{R(z) - \mathbb{E}R}{M}\right)(1 - \mathbb{E}\sigma^a) \end{aligned} \tag{5}$$

And the value of accepting an offer versus searching:

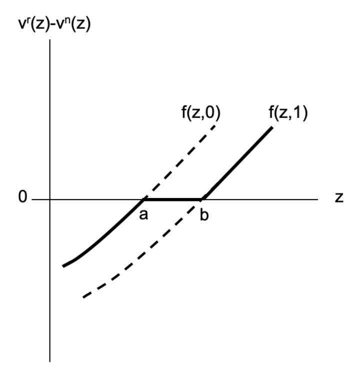
$$\begin{aligned} v^a(z) - v^s(z) &= v^{r,a}(z) - v^{r,s}(z) = v^{n,a}(z) - v^{n,s}(z) \\ &= c_s + \widetilde{CS}(z) - \mathbb{E}\widetilde{CS} + \frac{\text{Cov}(\sigma^r, \widetilde{CS})}{M} \end{aligned} \tag{6}$$

An equilibrium is given by functions $\sigma^a$ and $\sigma^r$ with range in $[0,1]$ such that $\sigma^r(z) = 0$ implies $v^r(z) - v^n(z) \leq 0$, $\sigma^r(z) = 1$ implies $v^r(z) - v^n(z) \geq 0$ and $\sigma^r(z) \in (0,1)$ implies $v^r(z) - v^n(z) = 0$. $\sigma^a$ has to be consistent in a similar way with $v^a(z) - v^s(z)$ and they both have to be consistent with $\text{Cov}(\sigma^r, \widetilde{CS})$ and $\mathbb{E}\sigma^a$. In other words, we proceed by first finding conditional $\sigma^r(z; \mathbb{E}\sigma^a)$ and $\sigma^a(z; \text{Cov}(\sigma^r, \widetilde{CS}))$ and then showing that there exist equilibrium values $A^*$ and $B^*$ such that
$\text{Cov}(\sigma^r(z; A^*), \widetilde{CS}(z)) = B^*$ and $\mathbb{E}[\sigma^a(z; B^*)] = A^*$.

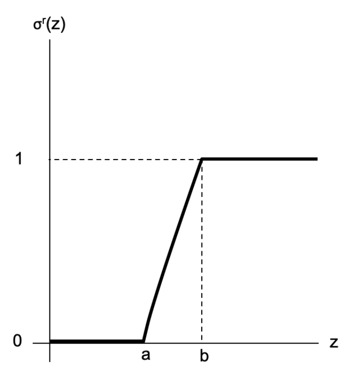
We first find the conditional equilibrium probability of reporting, $\sigma^r(z; \mathbb{E}\sigma^a)$. Fix $\mathbb{E}\sigma^a$. Define $f(z,s) = \beta\kappa(1 - s/M) - c_r + \left(\frac{R(z)-\mathbb{E}R}{M}\right)(1 - \mathbb{E}\sigma^a)$. Note that $f(z,s)$ is increasing in $z$ (strictly if $\mathbb{E}\sigma^a < 1$) and strictly decreasing and continuous in $s$. The functions $f(z,0)$ and $f(z,1)$ bound $v^r(z) - v^n(z)$ since $v^r(z) - v^n(z) = f(z, \sigma^r(z)) \in [f(z,1), f(z,0)]$. For any $z$ such that $f(z,0) \leq 0$ (if any such $z$ exists), any equilibrium $\sigma^r(z)$ has to be zero, since otherwise $\sigma^r(z) = s^* > 0$ would imply $v^r(z) - v^n(z) = f(z,s^*) < f(z,0) \leq 0$, which contradicts the equilibrium conditions above. For any $z$ such that $f(z,1) < 0 < f(z,0)$, any equilibrium has to satisfy $\sigma^r(z) \in (0,1)$, so $\sigma^r(z) = s^*$ for an $s^*$ such that $f(z,s^*) = 0$. A unique $s^*$ exists since $f$ is strictly decreasing and continuous in $s$. Lastly, for any $z$ such that $f(z,1) \geq 0$, any equilibrium $\sigma^r(z)$ has to be one, since $\sigma^r(z) = s^* < 1$ would imply $v^r(z) - v^n(z) = f(z,s^*) > f(z,1) \geq 0$. This can be seen graphically in Exhibit 6. Hence, the unique equilibrium (conditional) probability of reporting is $\sigma^r(z) = \max\{\min\{\sigma^*(z),1\},0\}$, where:

$$\sigma^*(z) = \frac{M}{\beta\kappa}\left[\beta\kappa - c_r + \left(\frac{R(z) - \mathbb{E}R}{M}\right)(1 - \mathbb{E}\sigma^a)\right] \tag{7}$$

Figure 6: Value of reporting and (conditional) probability of reporting




(a) Value of reporting in excess of not reporting




(b) Conditional probability of reporting

Now we find the equilibrium (conditional) probability of accepting, $\sigma^a(z;\mathrm{Cov}(\sigma^r,\widetilde{CS}))$. If there exists a reservation price $r \in [\underline{p},\overline{p}]$ such that $v^a(r) - v^s(r) = 0$, then it is unique, since $\widetilde{CS}(z)$ is strictly decreasing. Define the reservation price $r$ to be equal to this unique root of $v^a(r) - v^s(r)$, if it exists, and let $r = \overline{p}$ if $v^a(\overline{p}) - v^s(\overline{p}) > 0$ and $r = \underline{p}$ if $v^a(\underline{p}) - v^s(\underline{p}) < 0$. Note that $v^a(z) - v^s(z) \gtreqqless 0 \iff z \lesseqqgtr r$, so $\sigma^a(z;\mathrm{Cov}(\sigma^r,\widetilde{CS}))$ is $1$ for $z \leq r$ and 0 for $z \geq r$.

Note that $\mathbb{E}[\sigma^a(z)] = \Pr(z \leq r) = F(r)$, so consistency of $\mathbb{E}\sigma^a$ and $\mathrm{Cov}(\sigma^r, \widetilde{CS})$ reduces to finding consistency of $F(r)$ and $\mathrm{Cov}(\sigma^r, \widetilde{CS})$. Equations (6) and (7) pin down the equilibrium. The reservation price $r$ is a weakly increasing function of $\mathrm{Cov}(\sigma^r, \widetilde{CS})$; more negative values of this covariance (which is negative since $\widetilde{CS}$ is decreasing and $\sigma^r$ is increasing) make the right-hand side of Equation (6) lower. Hence, $F(r(\mathrm{Cov}(\sigma^r, \widetilde{CS})))$ is also an increasing function of $\mathrm{Cov}(\sigma^r, \widetilde{CS})$. Call this function $\gamma(\mathrm{Cov}(\sigma^r, \widetilde{CS}))$, which is between 0 and 1. If $\mathrm{Cov}(\sigma^r, \widetilde{CS}) \leq \mathbb{E}\widetilde{CS} - \widetilde{CS}(\underline{p}) - c_s \leq 0$ then $\gamma = 0$. If $\mathrm{Cov}(\sigma^r, \widetilde{CS}) \geq \mathbb{E}\widetilde{CS} - \widetilde{CS}(\overline{p}) - c_s$ (if this number is negative) then $\gamma = 1$. When $\mathrm{Cov}(\sigma^r, \widetilde{CS})$ is in between these bounds, $\gamma$ is strictly increasing.

Plugging in $\mathbb{E}\sigma^a = F(r)$ in Equation (7) we can see that higher $F(r)$ reduces $\sigma^*(z)$ for $z$ bigger than $z^e$, where $R(z^e) = \mathbb{E}R$, and increases $\sigma^*(z)$ for $z < z^e$, so $\sigma^r(z)$ becomes flatter. Hence, higher $F(r)$ increases the covariance $\mathrm{Cov}(\sigma^r, \widetilde{CS})$ (makes it less negative).[35] Call this function $\delta(F(r))$, which takes non-positive values. Note that $\delta(1) = 0$ and $\delta(F(r)) \leq 0$ for any $F(r) < 1$. An equilibrium is thus a value $F^*$ such that both curves intersect; $\gamma(\delta(F^*)) = F^*$. We have two cases. If $\delta(0) < \mathbb{E}\widetilde{CS} - \widetilde{CS}(\underline{p}) - c_s$, then $F^* = 0$ is an equilibrium, since $\gamma(\delta(0)) = 0$. There could be additional equilibria if $\gamma(0) = 1$. In the second case, if $\delta(0) > \mathbb{E}\widetilde{CS} - \widetilde{CS}(\underline{p}) - c_s$, then there exists a single equilibrium since $\delta \in [0, 1]$ and $\gamma$ has to cross $\delta$ at some point to the right of $\delta(0)$.

# 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.[36]
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 7 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. Since 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

[35] To see why, let $F(r') > F(r)$. We just argued that $\sigma^r(z; F(r)) - \sigma^r(z; F(r'))$ is an increasing function of $z$. To show that $\mathrm{Cov}(\sigma^r(z; F(r)), \widetilde{CS}(z)) < \mathrm{Cov}(\sigma^r(z; F(r')), \widetilde{CS}(z))$, note that $\mathrm{Cov}(\sigma^r(z; F(r)), \widetilde{CS}(z)) - \mathrm{Cov}(\sigma^r(z; F(r')), \widetilde{CS}(z)) = \mathrm{Cov}(\sigma^r(z; F(r)) - \sigma^r(z; F(r')), \widetilde{CS}(z)) < 0$. This is negative since it's the covariance between an increasing and a decreasing function of $z$.

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

| | |
|---|---|
| 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' |

Table 7: Extracted title features

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 of particular words in the product title. The word-features used for each product model can be found in Table 7. 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 7: Map of Price Gouging Laws

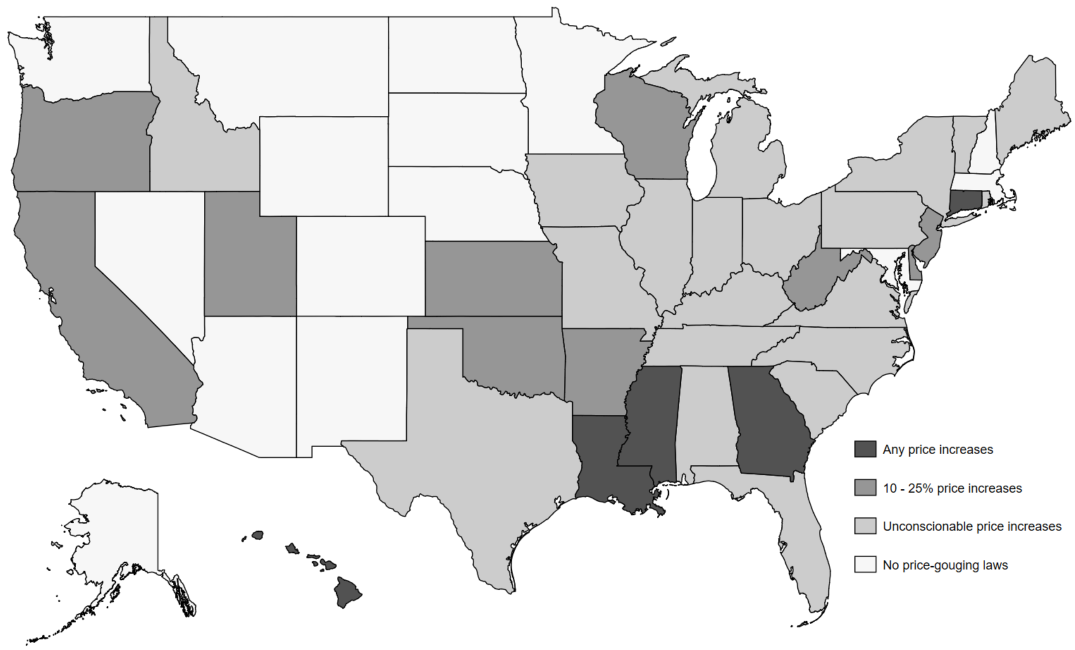


Figure 8: Map of Civil Penalties for Price Gouging

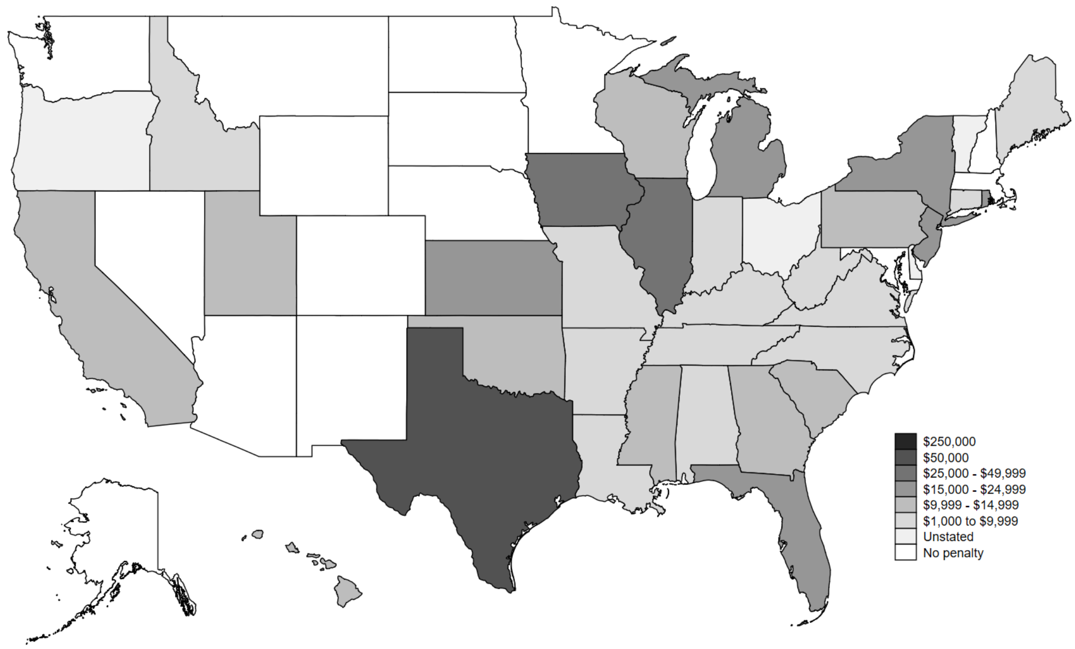


Figure 9: Map of Criminal Penalties for Price Gouging

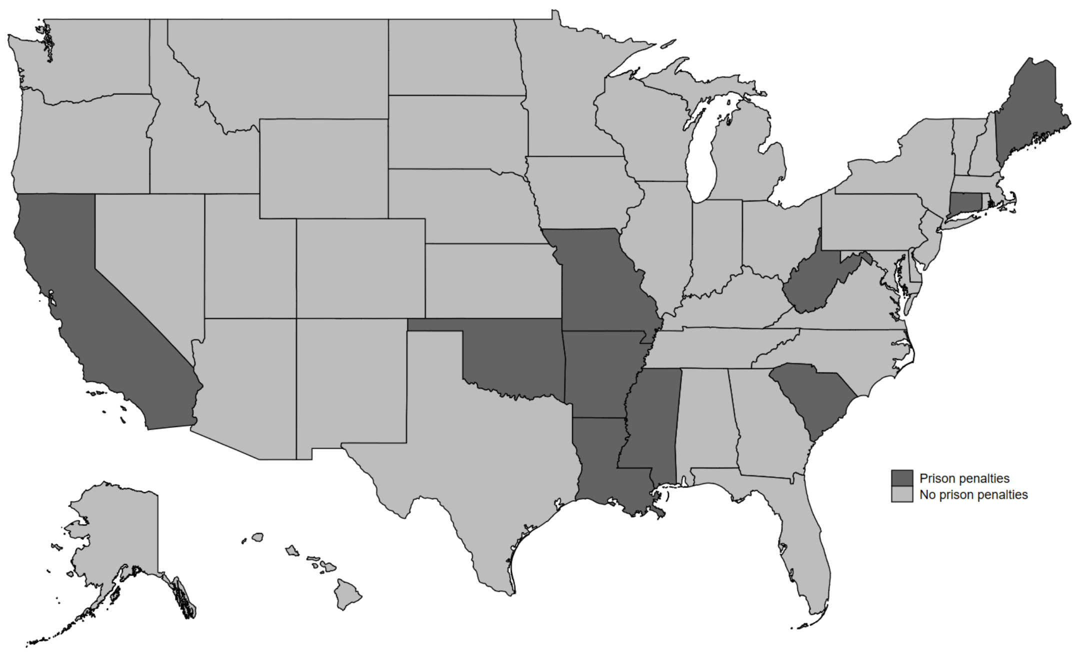


Figure 10: CDF of WTPR by price range

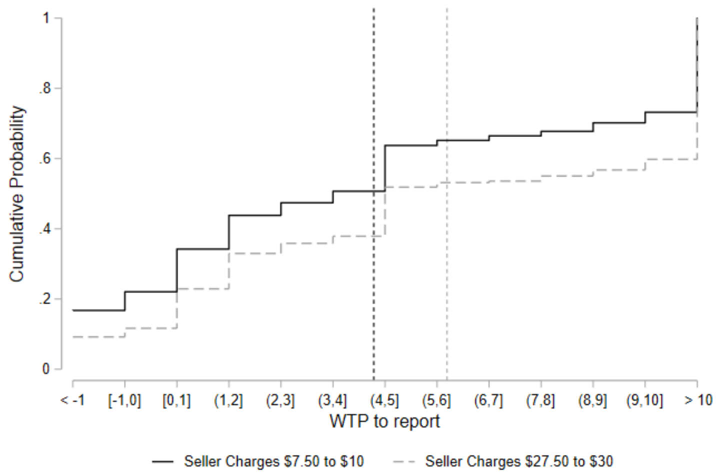
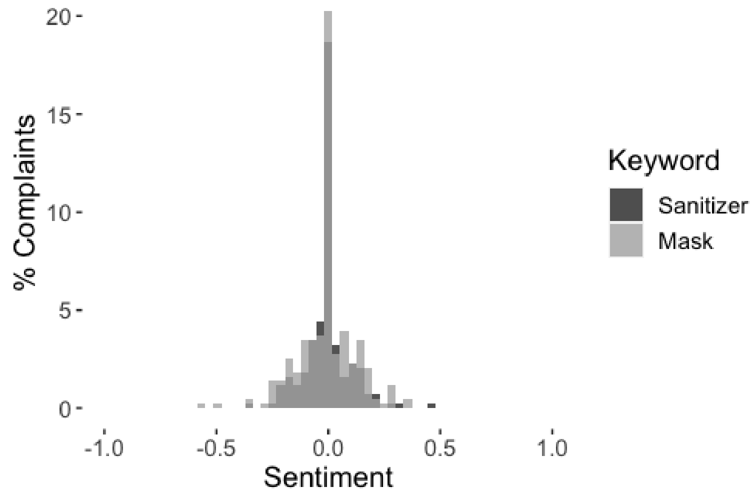
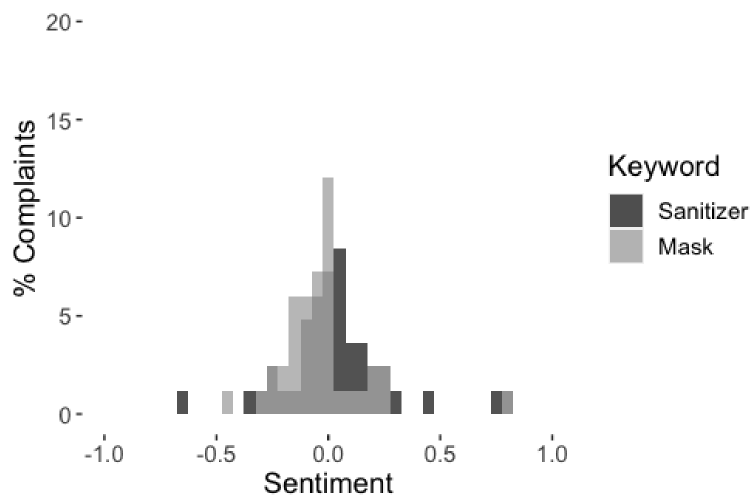


Figure 11: Distribution of sentiment in price gouging complaints




(a) Description




(b) Suggested solution

Note: 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.

Figure 12: Propensity to Pay to Report by Local Covid-19 Deaths

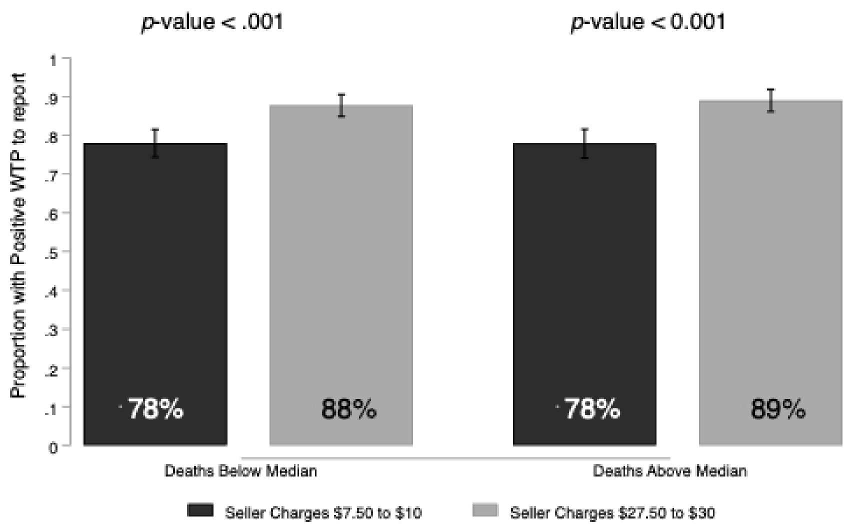



Figure 13: Willingness to Report by Local Covid-19 Deaths

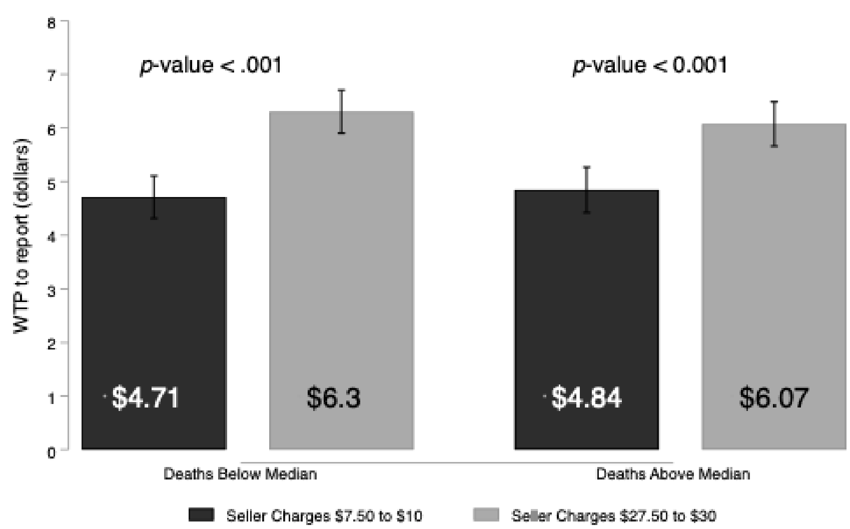


Figure 14: Willingness to Report by Local Laws against Price-Gouging

Figure 15: Donation by Local Covid-19 Deaths

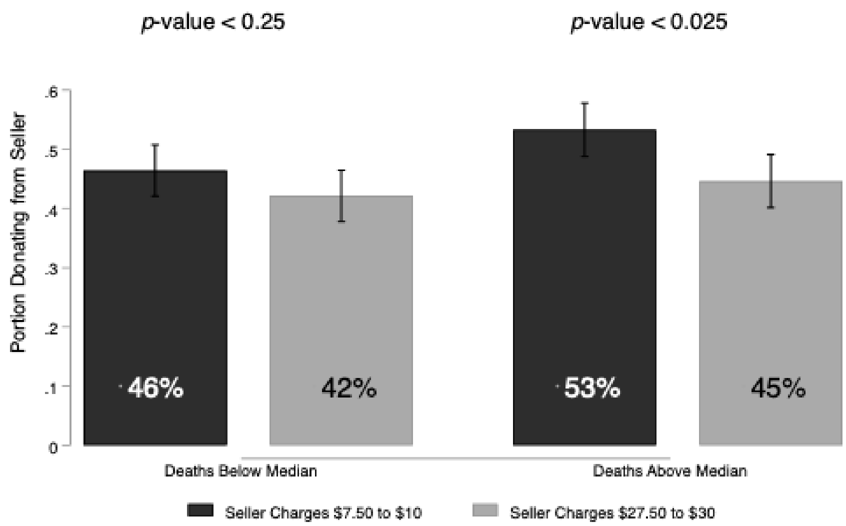



Figure 16: Donation by Laws

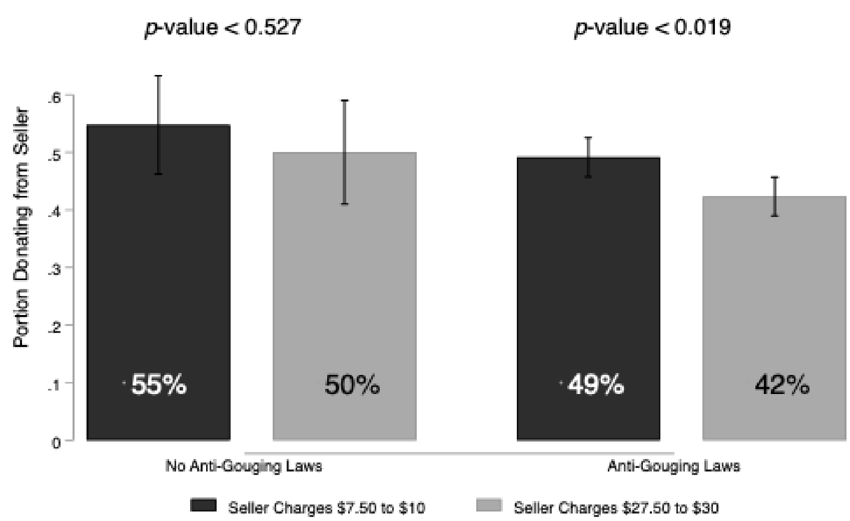


Figure 17: Propensity to Pay to Report by Local Covid-19 Deaths

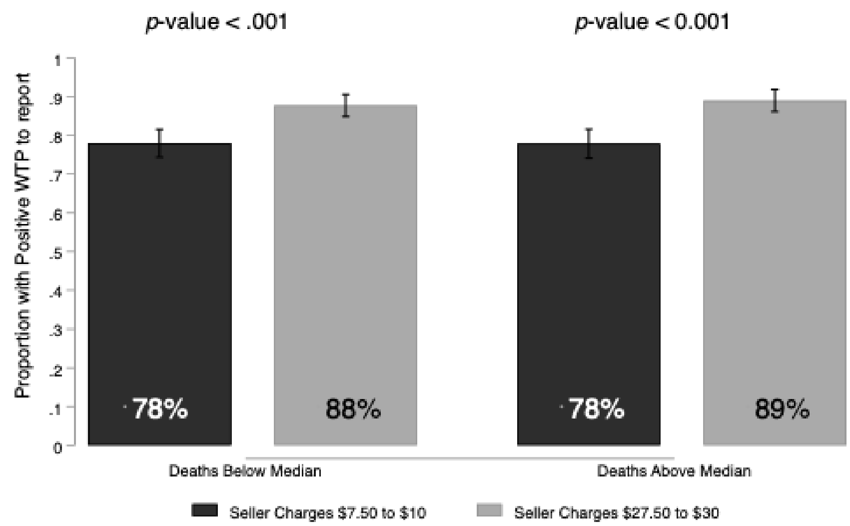
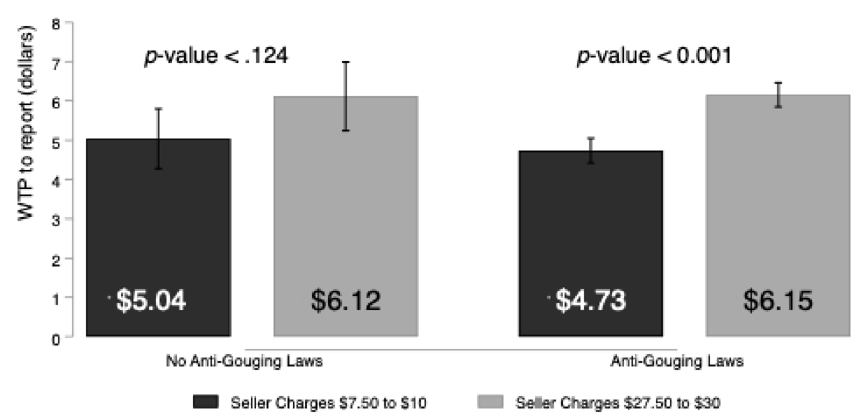



Figure 18: Willingness to Report by Local Laws Against Price Gouging



## D. Tables

Table 8: 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 |

Note: 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.

Table 9: Willingness to Pay to Report equals 5 dollars dummy

| | (1) WTP | (2) WTP | (3) WTP | (4) WTP |
|---|---|---|---|---|
| Seller Charges \$27.50 to \$30 | 0.00921 | 0.00912 | 0.00853 | 0.0194 |
| | (0.0183) | (0.0183) | (0.0181) | (0.0277) |
| Face Masks | | 0.0429** | 0.0422** | 0.0314 |
| | | (0.0183) | (0.0182) | (0.0257) |
| Seller Charges \$27.50 to \$30 × Face Masks | | | | -0.0217 |
| | | | | (0.0374) |
| Constant | 0.131*** | 0.109*** | 0.0851 | 0.0900 |
| | (0.0128) | (0.0151) | (0.0613) | (0.0620) |
| Elasticity Estimate | .04 | .04 | .04 | .09 |
| Controls | NO | NO | YES | YES |
| R2 | 0.000 | 0.004 | 0.024 | 0.025 |
| Observations | 1391 | 1391 | 1391 | 1391 |

Note: Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 10: Willingness to Pay to Report by Deaths (Above Median)

| | (1) WTP | (2) WTP | (3) WTP | (4) WTP |
|---|---|---|---|---|
| Seller Charges \$27.50 to \$30 | 1.591*** | 1.616*** | 1.575*** | 1.744*** |
| | (0.340) | (0.338) | (0.343) | (0.419) |
| Deaths Above Median | 0.134 | 0.155 | 0.178 | 0.182 |
| | (0.350) | (0.349) | (0.353) | (0.352) |
| Seller Charges \$27.50 to \$30 × High Deaths | -0.361 | -0.410 | -0.366 | -0.364 |
| | (0.494) | (0.493) | (0.498) | (0.498) |
| Face Masks | | -0.721*** | -0.758*** | -0.926*** |
| | | (0.246) | (0.249) | (0.351) |
| Seller Charges \$27.50 to \$30 × Face Masks | | | | -0.339 |
| | | | | (0.501) |
| Constant | 4.711*** | 5.060*** | 7.032*** | 7.106*** |
| | (0.238) | (0.269) | (0.814) | (0.825) |
| Elasticity Estimate | 0.200 | 0.200 | 0.190 | 0.210 |
| Controls | NO | NO | YES | YES |
| R2 | 0.024 | 0.030 | 0.047 | 0.047 |
| Observations | 1391 | 1391 | 1391 | 1391 |

Note: Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 11: Willingness to Pay to Report by Deaths

| | (1) WTP | (2) WTP | (3) WTP | (4) WTP |
|---|---|---|---|---|
| Seller Charges \$27.50 to \$30 | 1.345*** | 1.363*** | 1.302*** | 1.485*** |
| | (0.310) | (0.308) | (0.313) | (0.394) |
| Deaths per 1000 | -0.125 | -0.120 | -0.130 | -0.128 |
| | (0.672) | (0.677) | (0.698) | (0.700) |
| Seller Charges \$27.50 to \$30 × Deaths per 1000 | 0.107 | 0.0139 | 0.160 | 0.183 |
| | (0.915) | (0.918) | (0.936) | (0.939) |
| Face Masks | | -0.664*** | -0.711*** | -0.897** |
| | | (0.249) | (0.252) | (0.355) |
| Seller Charges \$27.50 to \$30 × Face Masks | | | | -0.376 |
| | | | | (0.506) |
| Constant | 4.808*** | 5.142*** | 7.255*** | 7.344*** |
| | (0.219) | (0.254) | (0.820) | (0.832) |
| Elasticity Estimate | .17 | .17 | .16 | .18 |
| Controls | NO | NO | YES | YES |
| R2 | 0.022 | 0.027 | 0.046 | 0.047 |
| Observations | 1370 | 1370 | 1370 | 1370 |

*Note:* Heteroskedasticity robust standard errors in parentheses. Elasticity estimate calculated using the mid-point of seller price range. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 12: Extensive-Margin Willingness to Pay to Report by Deaths (Above Median)

| | (1) WTP | (2) WTP | (3) WTP | (4) WTP |
|---|---|---|---|---|
| Seller Charges \$27.50 to \$30 | 0.0975*** | 0.0996*** | 0.0986*** | 0.122*** |
| | (0.0279) | (0.0278) | (0.0279) | (0.0358) |
| Deaths Above Median | -0.00117 | 0.000685 | 0.000343 | 0.000937 |
| | (0.0315) | (0.0314) | (0.0315) | (0.0315) |
| Seller Charges \$27.50 to \$30 × High Deaths | 0.0140 | 0.00980 | 0.00279 | 0.00305 |
| | (0.0398) | (0.0397) | (0.0401) | (0.0401) |
| Face Masks | | -0.0616*** | -0.0637*** | -0.0869*** |
| | | (0.0199) | (0.0200) | (0.0314) |
| Seller Charges \$27.50 to \$30 × Face Masks | | | | -0.0469 |
| | | | | (0.0406) |
| Constant | 0.780*** | 0.809*** | 0.935*** | 0.945*** |
| | (0.0218) | (0.0231) | (0.0633) | (0.0638) |
| Elasticity Estimate | 0.070 | 0.080 | 0.070 | 0.090 |
| Controls | NO | NO | YES | YES |
| R2 | 0.019 | 0.026 | 0.057 | 0.058 |
| Observations | 1391 | 1391 | 1391 | 1391 |

Note: Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 13: Willingness to Pay to Report by State Law

| | (1) WTP | (2) WTP | (3) WTP | (4) WTP |
|---|---|---|---|---|
| Seller Charges \$27.50 to \$30 | 1.074 | 0.997 | 0.815 | 1.005 |
| | (0.695) | (0.695) | (0.714) | (0.751) |
| State Laws | -0.310 | -0.361 | -0.530 | -0.546 |
| | (0.496) | (0.495) | (0.503) | (0.504) |
| Seller Charges \$27.50 to \$30 $\times$ State Laws | 0.348 | 0.436 | 0.616 | 0.622 |
| | (0.744) | (0.745) | (0.763) | (0.763) |
| Face Masks | | -0.668*** | -0.726*** | -0.921*** |
| | | (0.249) | (0.251) | (0.355) |
| Seller Charges \$27.50 to \$30 $\times$ Face Masks | | | | -0.391 |
| | | | | (0.507) |
| Constant | 5.042*** | 5.422*** | 7.709*** | 7.818*** |
| | (0.458) | (0.481) | (0.929) | (0.944) |
| Elasticity Estimate | .13 | .12 | .1 | .12 |
| Controls | NO | NO | YES | YES |
| R2 | 0.022 | 0.027 | 0.048 | 0.048 |
| Observations | 1367 | 1367 | 1367 | 1367 |

Note: Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14: Propensity to Donate for 5-dollar reporters

| | (1) Donate | (2) Donate | (3) Donate | (4) Donate |
|---|---|---|---|---|
| WTPTR=$5 | -0.120*** | -0.129*** | -0.150*** | -0.147*** |
| | (0.0379) | (0.0379) | (0.0554) | (0.0554) |
| Seller Charges $27.50 to $30 | | -0.0630** | -0.0673** | -0.0190 |
| | | (0.0265) | (0.0289) | (0.0401) |
| Face Masks | | 0.118*** | 0.115*** | 0.0682* |
| | | (0.0265) | (0.0268) | (0.0381) |
| Seller Charges $27.50 to $30 × WTPTR=$5 | | | 0.0395 | 0.0316 |
| | | | (0.0768) | (0.0771) |
| Seller Charges $27.50 to $30 × Face Masks | | | | -0.0941* |
| | | | | (0.0539) |
| Constant | 0.482*** | 0.455*** | 0.420*** | 0.440*** |
| | (0.0144) | (0.0234) | (0.0866) | (0.0877) |
| Elasticity Estimate | | -.07 | -.08 | -.02 |
| Controls | NO | NO | YES | YES |
| R2 | 0.007 | 0.025 | 0.041 | 0.043 |
| Observations | 1386 | 1386 | 1386 | 1386 |

Note: Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 15: Propensity to Donate by Deaths

| | (1) Donate | (2) Donate | (3) Donate | (4) Donate |
|---|---|---|---|---|
| Seller Charges \$27.50 to \$30 | -0.0664** | -0.0700** | -0.0743** | -0.0283 |
| | (0.0334) | (0.0333) | (0.0337) | (0.0431) |
| Deaths per 1000 | 0.0547 | 0.0536 | 0.0425 | 0.0432 |
| | (0.0747) | (0.0745) | (0.0761) | (0.0760) |
| Seller Charges \$27.50 to \$30 × State Laws | 0.000817 | 0.0180 | 0.0414 | 0.0475 |
| | (0.102) | (0.101) | (0.103) | (0.103) |
| Face Masks | | 0.118*** | 0.116*** | 0.0693* |
| | | (0.0268) | (0.0271) | (0.0386) |
| Seller Charges \$27.50 to \$30 × Face Masks | | | | -0.0948* |
| | | | | (0.0546) |
| Constant | 0.488*** | 0.429*** | 0.396*** | 0.418*** |
| | (0.0237) | (0.0273) | (0.0881) | (0.0894) |
| Elasticity Estimate | -.08 | -.08 | -.09 | -.03 |
| Controls | NO | NO | YES | YES |
| R2 | 0.005 | 0.019 | 0.036 | 0.038 |
| Observations | 1365 | 1365 | 1365 | 1365 |

*Note:* Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 16: Propensity to Donate by Deaths (Above Median)

| | (1) Donate | (2) Donate | (3) Donate | (4) Donate |
|---|---|---|---|---|
| Seller Charges $27.50 to $30 | -0.0427 | -0.0471 | -0.0514 | -0.00361 |
| | (0.0371) | (0.0369) | (0.0373) | (0.0463) |
| Deaths Above Median | 0.0688* | 0.0653* | 0.0634* | 0.0647* |
| | (0.0379) | (0.0379) | (0.0385) | (0.0385) |
| Seller Charges $27.50 to $30 × High Deaths | -0.0441 | -0.0360 | -0.0251 | -0.0244 |
| | (0.0535) | (0.0532) | (0.0539) | (0.0539) |
| Face Masks | | 0.112*** | 0.110*** | 0.0622 |
| | | (0.0266) | (0.0269) | (0.0382) |
| Seller Charges $27.50 to $30 × Face Masks | | | | -0.0959* |
| | | | | (0.0541) |
| Constant | 0.464*** | 0.410*** | 0.374*** | 0.395*** |
| | (0.0262) | (0.0291) | (0.0876) | (0.0887) |
| Elasticity Estimate | -.05 | -.06 | -.06 | 0 |
| Controls | NO | NO | YES | YES |
| R2 | 0.007 | 0.019 | 0.036 | 0.038 |
| Observations | 1386 | 1386 | 1386 | 1386 |

*Note:* Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$.

Table 17: Propensity to Donate by State Law

| | (1) Donate | (2) Donate | (3) Donate | (4) Donate |
|---|---|---|---|---|
| Seller Charges $27.50 to $30 | -0.0474 | -0.0340 | -0.0304 | 0.0167 |
| | (0.0744) | (0.0743) | (0.0757) | (0.0799) |
| State Laws | -0.0559 | -0.0469 | -0.0500 | -0.0541 |
| | (0.0552) | (0.0559) | (0.0572) | (0.0569) |
| Seller Charges $27.50 to $30 × State Laws | -0.0209 | -0.0365 | -0.0398 | -0.0383 |
| | (0.0798) | (0.0796) | (0.0811) | (0.0809) |
| Face Masks | | 0.117*** | 0.113*** | 0.0653* |
| | | (0.0268) | (0.0271) | (0.0387) |
| Seller Charges $27.50 to $30 × Face Masks | | | | -0.0968* |
| | | | | (0.0545) |
| Constant | 0.547*** | 0.481*** | 0.452*** | 0.479*** |
| | (0.0511) | (0.0541) | (0.103) | (0.104) |
| Elasticity Estimate | -.06 | -.04 | -.04 | .02 |
| Controls | NO | NO | YES | YES |
| R2 | 0.006 | 0.020 | 0.037 | 0.039 |
| Observations | 1362 | 1362 | 1362 | 1362 |

*Note:* Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 18: Treatment Effect on Attention

| | (1) Attention | (2) Attention | (3) Attention | (4) Attention |
|---|---|---|---|---|
| Seller Charges $27.50 to $30 | -0.197*** | -0.197*** | -0.188*** | -0.212*** |
| | (0.0181) | (0.0181) | (0.0185) | (0.0262) |
| Face Masks | | -0.00388 | -0.00294 | 0.0210 |
| | | (0.0177) | (0.0182) | (0.0176) |
| Seller Charges $27.50 to $30 × Face Masks | | | | 0.0482 |
| | | | | (0.0368) |
| Constant | 0.949*** | 0.950*** | 0.797*** | 0.787*** |
| | (0.00801) | (0.0118) | (0.0617) | (0.0617) |
| Elasticity Estimate | | | | |
| Controls | NO | NO | YES | YES |
| R2 | 0.078 | 0.078 | 0.109 | 0.110 |
| Observations | 1465 | 1465 | 1417 | 1417 |

*Note:* Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 19: Treatment Effect on Higher Quality Belief

| | (1) Quality | (2) Quality | (3) Quality | (4) Quality |
|---|---|---|---|---|
| Seller Charges \$27.50 to \$30 | -0.0175 | -0.0191 | -0.0368* | -0.0161 |
| | (0.0210) | (0.0210) | (0.0207) | (0.0302) |
| Face Masks | | 0.0391* | 0.0265 | 0.00619 |
| | | (0.0211) | (0.0208) | (0.0300) |
| Seller Charges \$27.50 to \$30 × Face Masks | | | | -0.0410 |
| | | | | (0.0411) |
| Constant | 0.212*** | 0.194*** | 0.311*** | 0.320*** |
| | (0.0148) | (0.0174) | (0.0643) | (0.0645) |
| Elasticity Estimate | | | | |
| Controls | NO | NO | YES | YES |
| R2 | 0.000 | 0.003 | 0.123 | 0.124 |
| Observations | 1465 | 1465 | 1417 | 1417 |

*Note:* Heteroskedasticity robust standard errors in parentheses. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 20: Main Results for Calibrated Sample to Match U.S. Adults Bounds

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | WTR | WTR | WTR | WTR | Donation | Donation | Donation | Donation |
| Seller Charges $27.50 to $30 | 1.246** | 1.142* | | | -0.0776 | -0.0448 | | |
| | (0.461) | (0.449) | | | (0.0480) | (0.0487) | | |
| Would buy at treatment price | | | -1.072* | | | | | |
| | | | (0.455) | | | | | |
| Considers treatment price excessive | | | | 1.646*** | | | | |
| | | | | (0.321) | | | | |
| WTR>0 | | | | | | | 0.324*** | |
| | | | | | | | (0.0617) | |
| WTR<0 | | | | | | | 0.191* | |
| | | | | | | | (0.0752) | |
| WTR -1 | | | | | | | | 0.191* |
| | | | | | | | | (0.0752) |
| WTR 1 | | | | | | | | 0.00590 |
| | | | | | | | | (0.0712) |
| WTR 2 | | | | | | | | 0.0491 |
| | | | | | | | | (0.0704) |
| WTR 3 | | | | | | | | 0.172 |
| | | | | | | | | (0.103) |
| WTR 4 | | | | | | | | 0.226* |
| | | | | | | | | (0.112) |
| WTR 5 | | | | | | | | 0.173* |
| | | | | | | | | (0.0730) |
| WTR 6 | | | | | | | | 0.616*** |
| | | | | | | | | (0.122) |
| WTR 7 | | | | | | | | 0.352 |
| | | | | | | | | (0.182) |
| WTR 8 | | | | | | | | 0.663*** |
| | | | | | | | | (0.103) |
| WTR 9 | | | | | | | | 0.353** |
| | | | | | | | | (0.121) |
| WTR 10 | | | | | | | | 0.477*** |
| | | | | | | | | (0.110) |
| WTR 11 | | | | | | | | 0.557*** |
| | | | | | | | | (0.0650) |
| Cionstant | 5.297*** | 4.443*** | 5.833*** | 4.688*** | 0.442*** | 0.540*** | 0.166** | 0.166** |
| | (0.333) | (0.320) | (0.248) | (0.226) | (0.0343) | (0.0349) | (0.0588) | (0.0588) |
| $N$ | 695 | 696 | 732 | 1391 | 692 | 694 | 1386 | 1386 |

*Note:* This table replicates the main results from the paper after re-weighting observations to match the marginal distribution of gender, age, ethnic affinity, education and income. Robust standard errors in parentheses. ${}^{*}p < 0.10, {}^{**}p < 0.05, {}^{***}p < 0.01$.

## Table 21: Treatment Effect Bounds

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Hand Sanitizer | | Face Mask | | | | | | Hand Sanitizer | | Face Mask | | | |
| | WTR [LB] | WTR [UB] | WTR [LB] | WTR [UB] | WTR [LB] | WTR [UB] | WTR [LB] | WTR [UB] | Donation [LB] | Donation [UB] | Donation [LB] | Donation [UB] | Donation [LB] | Donation [UB] |
| *Panel: A (Manski-Horowitz Bounds)* | | | | | | | | | | | | | | |
| Seller Charges $27.50 to $30 | 0.563 | 1.862*** | 1.484*** | 1.723*** | | | | | -0.0526 | -0.169*** | -0.00447 | -0.0300 | | |
| | (0.346) | (0.345) | (0.347) | (0.345) | | | | | (0.0361) | (0.0360) | (0.0377) | (0.0377) | | |
| Would buy at treatment price | | | | | -0.831* | -0.965* | | | | | | | | |
| | | | | | (0.380) | (0.380) | | | | | | | | |
| Considers treatment price excessive | | | | | | | 1.493*** | 1.581*** | | | | | | |
| | | | | | | | (0.246) | (0.245) | | | | | | |
| WTR>0 | | | | | | | | | | | | | 0.273*** | 0.302*** |
| | | | | | | | | | | | | | (0.0567) | (0.0549) |
| WTR<0 b | | | | | | | | | | | | | 0.213** | 0.296*** |
| | | | | | | | | | | | | | (0.0654) | (0.0628) |
| Constant | 5.758*** | 4.664*** | 4.354*** | 4.286*** | 5.732*** | 5.795*** | 4.734*** | 4.734*** | 0.422*** | 0.513*** | 0.526*** | 0.534*** | 0.204*** | 0.185*** |
| | (0.241) | (0.244) | (0.244) | (0.243) | (0.190) | (0.190) | (0.172) | (0.172) | (0.0252) | (0.0255) | (0.0267) | (0.0267) | (0.0549) | (0.0529) |
| $N$ | 736 | 736 | 703 | 703 | 738 | 738 | 1408 | 1408 | 736 | 736 | 703 | 703 | 1439 | 1439 |
| *Panel: B (Lee Bounds)* | | | | | | | | | | | | | | |
| lower | 0.845* | | 1.575*** | | -0.924* | | 1.544*** | | -0.158*** | | -0.0218 | | | |
| | (0.374) | | (0.350) | | (0.383) | | (0.249) | | (0.0405) | | (0.0384) | | | |
| upper | 1.820*** | | 1.678*** | | -0.888* | | 1.571*** | | -0.0860* | | -0.0133 | | | |
| | (0.380) | | (0.351) | | (0.383) | | (0.249) | | (0.0391) | | (0.0383) | | | |
| $N$ | 736 | | 703 | | 738 | | 1408 | | 736 | | 703 | | | |

*Note:* This table estimates bounds for the treatment effect to control for attrition. Robust errors in parentheses. $^{*}p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$.

## D.1 Survey

### D.1.1 Demographic questions

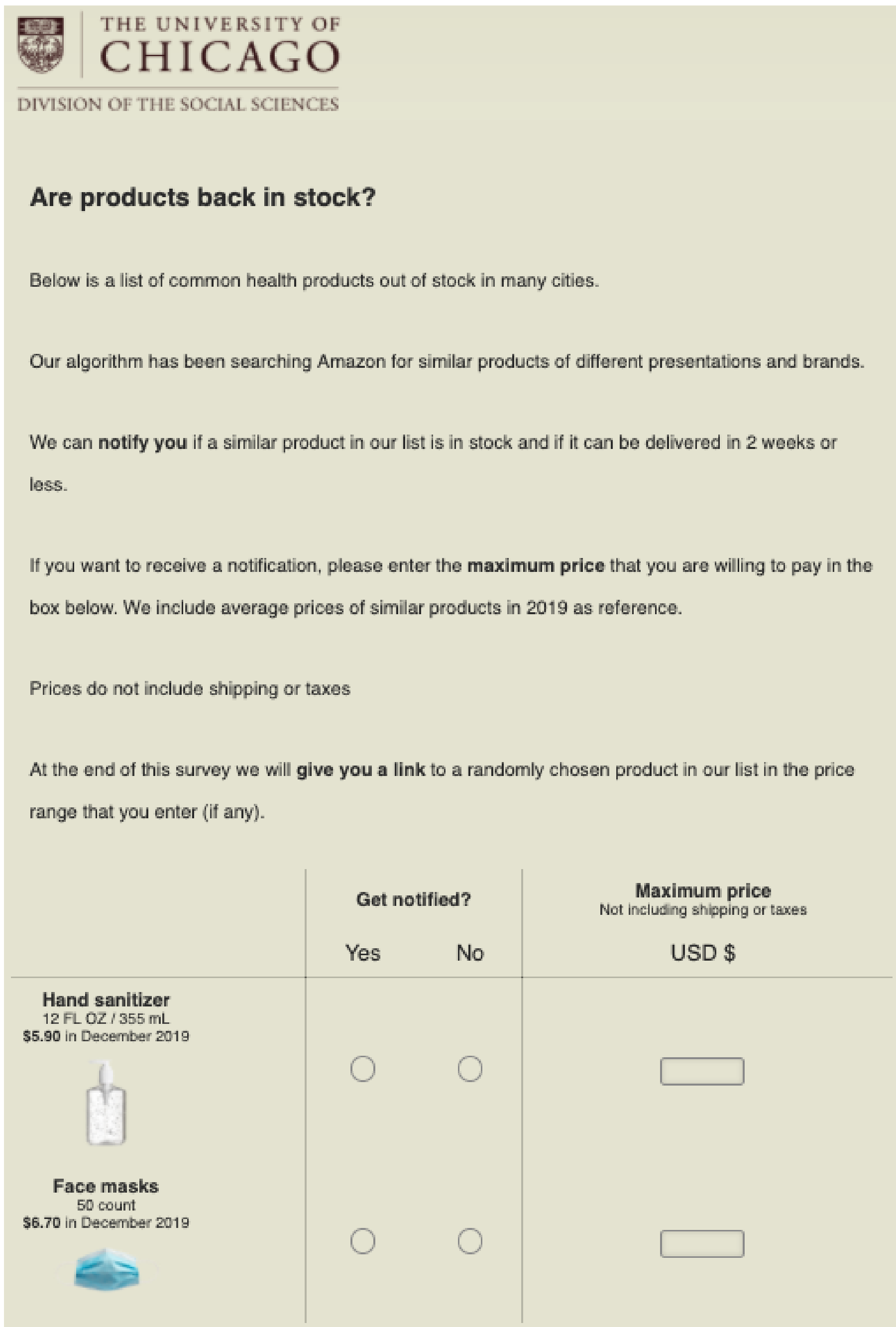
1. What is your U.S. ZIP code?
2. What is your year of birth?
3. What is the highest level of school you have completed or the highest degree you have received?
    - Less than high school degree
    - High school graduate (high school diploma or equivalent including GED)
    - Some college but no degree
    - 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.1.2 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

Figure 19: Willingness to track the items



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## Are products back in stock?

Below is a list of common health products out of stock in many cities.

Our algorithm has been searching Amazon for similar products of different presentations and brands.

We can **notify you** if a similar product in our list is in stock and if it can be delivered in 2 weeks or less.

If you want to receive a notification, please enter the **maximum price** that you are willing to pay in the box below. We include average prices of similar products in 2019 as reference.

Prices do not include shipping or taxes

At the end of this survey we will **give you a link** to a randomly chosen product in our list in the price range that you enter (if any).

| | **Get notified?** | | **Maximum 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 20: Excessive prices

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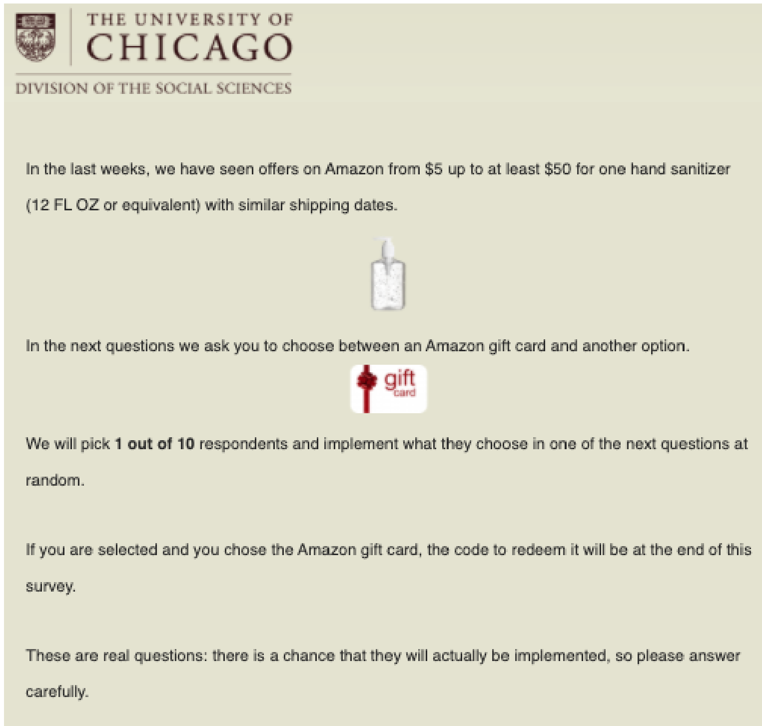
**Excessive prices**

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 21: Elicitation of willingness to pay to report



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In the last weeks, we have seen offers on Amazon from $5 up to at least $50 for one hand sanitizer (12 FL OZ or equivalent) with similar shipping dates.

In the next questions we ask you to choose between an Amazon gift card and another option.

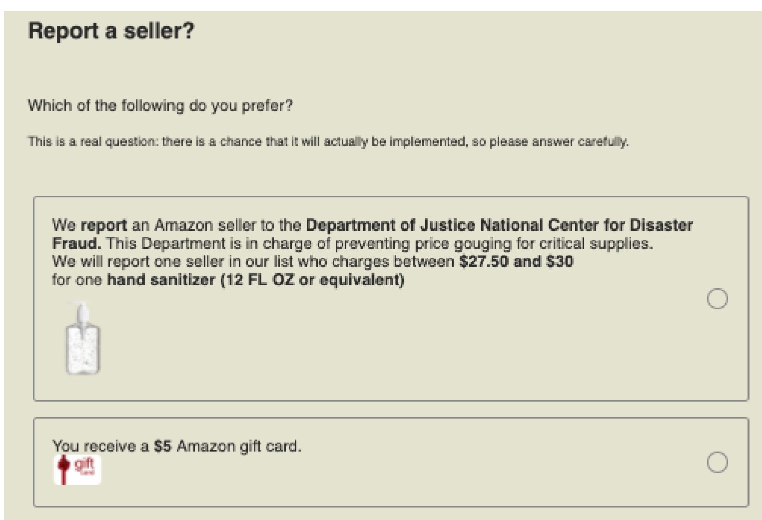
gift card

We will pick **1 out of 10** respondents and implement what they choose in one of the next questions at random.

If you are selected and you chose the Amazon gift card, the code to redeem it will be at the end of this survey.

These are real questions: there is a chance that they will actually be implemented, so please answer carefully.

(a) Instructions



**Report a seller?**

Which of the following do you prefer?

This is a real question: there is a chance that it will actually be implemented, so please answer carefully.

We **report** an Amazon seller to the **Department of Justice National Center for Disaster Fraud.** This Department is in charge of preventing price gouging for critical supplies.
We will report one seller in our list who charges between **$27.50 and $30** for one **hand sanitizer (12 FL OZ or equivalent)**

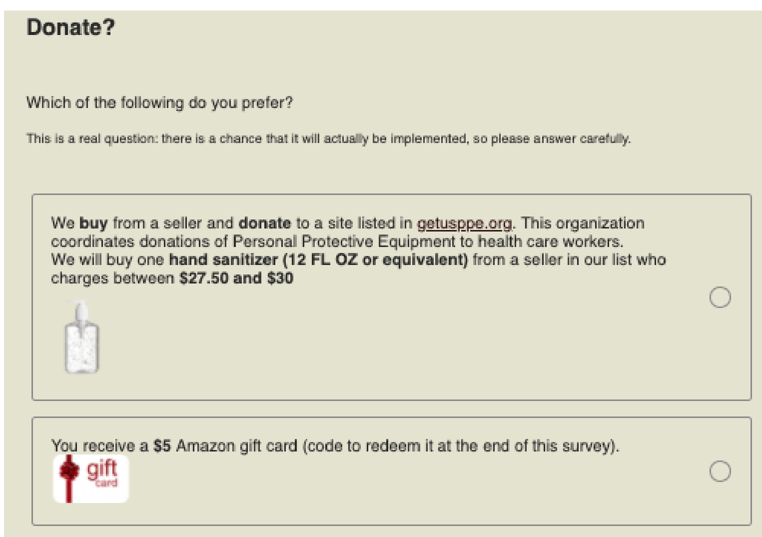
You receive a **$5** Amazon gift card.

gift card

(b) Main question

Figure 22: Donation decision


(a) Instructions




(b) Main question