Seller Reputation and Price Gouging: Evidence from the COVID-19 Pandemic

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April 2020

Abstract. We test the theory that seller reputation moderates the effect of demand shocks on a seller's propensity to price gouge. From mid January to mid March 2020, 3M masks were priced 2.72 times higher than Amazon sold them in 2019. However, the difference (in price ratios) between a post-COVID-19 entrant and an established seller is estimated to be about 1.6 at times of maximum scarcity, that is, post-COVID-19 entrants price at approximately twice the level of established sellers. Similar results are obtained for Purell hand sanitizer. We also consider cumulative reviews as a measure of what a seller has to lose from damaging its reputation and, again, obtain similar results. Finally, we explore policy implications of our results.

Keywords: price gouging, COVID-19, Amazon.
JEL codes: D01.

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Views presented in this paper are those of the authors, and do not necessarily represent the Bank of Canada's views.

1. Introduction

In the wake of unexpected negative supply shocks — or positive demand shocks — prices tend to surge. Many economists — most? — find such price hikes normal and in fact efficient: it's the law of supply and demand at work. By contrast, most of the world accuses sellers of price gouging and clamors for laws protecting buyers from unfair pricing. For example, in the aftermath of Hurricane Sandy, which struck the US in October 2012, New Jersey authorities filed civil suits accusing seven gas stations and one hotel of price gouging. Meanwhile, Libertarian TV personality John Stossel was inviting his readers to "hug a price gouger" today.

The tension between efficiency and fairness has existed for as long as economic relations have existed. It is not our goal to resolve this tension — nor would we have the ability to do so. Instead, we are interested in a third possibility, a third way between the efficiency-only and the fairness-only extremes, namely the possibility that the *seller reputation* may act as a moderator of the "price gouging" forces.

This is by no means a novel idea. For example, Akerlof (1980) addresses the issue of what we might call out-of-equilibrium customs, that is, customs from which there is a privately profitable deviation. If deviating from a custom is profitable and if the cost of deviation is lower when more agents deviate, then one might expect the custom eventually to disappear. Akerlof's (1980) point is that reputation — and the threat of its loss — provides the "binding force" that keeps in place a custom that's hard to keep, in the sense that it's costly to keep.

As an application, Akerlof (1980) considers the puzzle of involuntary unemployment. Suppose there is a social code barring employers from paying less than a certain threshold. Then the outcome may be excess demand in the labor market, unemployment. Clearly, there is a profitable deviation from this equilibrium, namely hiring unemployed workers at a lower wage, but such deviation does not take place due to the prevailing custom. One possible reason is that, by hiring workers at a wage below the prescribed minimum, the employer loses its reputation of being a "fair" employer, whereby existing workers "punish" the employer by not cooperating, for example, in the training of new workers.

Although Akerlof's (1980) analysis does not directly address the issue of price gauging, one might think of fair pricing as a generally accepted principle and custom (except possibly by a number of economists). As in Akerlof (1980), we observe that attitudes toward fair pricing remain remarkably stable even tough there is a strong incentive to deviate, especially in times of large demand or supply shocks. One reason why sellers to not deviate is the law, as the Hurricane Sandy example illustrates. A second reason, proposed by Akerlof (1980) as a general principle and studied by us in the context of price gouging, is seller reputation. Similarly to Akerlof (1980), we posit that a seller who violates the fair-pricing custom and price gouges is likely to lose its reputation as a "fair" seller, which in turn may hurt it in the future. Specifically, a natural punishment for a badly behaved seller is subsequent boycott by buyers.

The goal of this paper is to develop this idea in the context of the recent COVID-19 pandemic and the multiple cases of price gouging that followed. We propose a test of Akerlof's (1980) theory in the context of online sales of a specific set of products, namely masks and hand sanitizers. Theory predicts that, during a time of excess demand, sellers with a reputation at stake are less like to hike their prices than sellers with no reputation to defend. In the wake of the Hurricane Sandy crisis, Cowen (2017) argued that

> The reluctance to raise prices is especially strong for nationally branded stores. A local merchant may not care much if people in Iowa are upset at his prices, but major companies will fear damage to their national reputations. The short-term return from selling the water at a higher price is dwarfed by the risk to their business prospects.

In the example considered by Cowen (2017), high reputation is associated with being a national brand (as opposed to a local brand). We consider two online equivalents of the distinction between sellers who have a lot to lose and sellers who don't. First, we would expect that, all else equal, incumbent sellers — that is, continuing sellers — have more to lose than entrants, where the latter are defined as sellers who only start selling after the demand shock takes place. Second, we would expect that large sellers, which we define as sellers with a greater number of consumer reviews, have more to lose than small sellers.

■ **The 2019-2010 COVID-19 pandemic.** The first known COVID-19 case can be traced back to December 1st, 2019, in Wuhan, Hubei, China. The local health authorities released a public notice announcing the new virus on December 31st. Throughout the next month, the virus spread to other Chinese provinces as well as to other countries. The first known US case was confirmed on January 20, 2020, a 35-year-old who had returned from Wuhan five days earlier. On January 29, the White House Coronavirus Task Force was established, and two days later the Trump administration declared a public health emergency. By March 26 the United States had overtaken China and Italy with the highest number of confirmed cases in the world.

As the number of cases increased and media coverage widened, American consumers rushed to stores and online sites in search of personal protective products such as face masks and hand sanitizer. Reports of price gouging soon appeared in the media. For example, a two liter bottle of Purell sold for as much as $250.

As a result, on March 25th a coalition of 34 attorneys general sent letters to Amazon, Facebook, Ebay, Walmart, and Craiglist advising them that, "as the American community faces an unprecedented health crisis," they need to do more to prevent price gouging on their platforms. Two days earlier Amazon had already itself published a statement to the effect that "price gouging has no place in our stores" and further reporting that

> Amazon has already removed well over half a million of offers from our stores due to coronavirus-based price gouging. We have suspended more than 3,900 selling accounts in our U.S. store alone for violating our fair pricing policies. We began taking these enforcement actions promptly upon discovering this kind of misconduct, and we've been partnering directly with law enforcement agencies to combat price gougers and hold them accountable.[1]

Notwithstanding Amazon's assurance that they operate "dynamic automated systems" that "locate and remove unfairly priced items," we observe significant price hikes on Amazon from mid January till mid March.[2] One explanation is that the actual implementation of

1. https://blog.aboutamazon.com/company-news/price-gouging-has-no-place-in-our-stores, visited on March 26, 2020.
2. Throughout the paper, we refer to prices of items actually on sale, that is, we exclude prices of stocked-out items.

these mechanisms took place not long before the statement was published. Accordingly, our analysis focuses on the period from the US onset of the COVID-19 pandemic to middle March, when we believe Amazon changed its de facto policy.

■ **Summary of results.** We construct a dataset of prices, measures of seller reputation, and indicators of excess demand. To account for endogeneity issues we use time series of number of COVID-19 cases and number of COVID-19-related deaths as instruments of demand and number of competitors.

We then test that the price coefficient on the excess demand variable is decreasing on seller reputation, as implicitly predicted by Akerlof (1980). The results conform with theory: Higher-reputation firms are less likely to take advantage of shortages of supply. The effect is statistically and economically significant. For example, during our sample period the 2020 price of 3M masks was 2.72 times higher than the average 2019 price. However, the difference (in price ratios) between an entrant and an incumbent is estimated to be about 1.6 at times of maximum scarcity (or about 0.8 at times of average scarcity). In other words, at times of maximum scarcity entrants price-gouge at a level that is approximately twice as large as incumbent sellers.

We consider various measures of seller reputation — that is, estimates of the seller's stakes — and various measures of scarcity.[3] We always find economically and statistically significant moderating effects of seller reputation. That said, our analysis also suggests that these reputation effects are insufficient to completely limit the extent of price hikes.

■ **Related literature.** In addition to Akerlof (1980), Kahneman, Knetsch, and Thaler (1986) is very germane to our paper. They study whether community standards of fairness matter when it comes to price setting. Based on telephone surveys, they argue in the affirmative. In particular, buyers would be less willing to repeat purchase from a seller who price gouged. A seller who places a large weight on future sales effectively corresponds to a seller for whom reputation is important. In this sense, our setting matches naturally that of Kahneman, Knetsch, and Thaler (1986). One important difference is that, whereas they use telephone surveys, our source of evidence is actual price setting.

Our paper is also related to some literature on Corporate Social Responsibility (CSR). In particular, Bénabou and Tirole (2010) present a vision of CSR which essentially corresponds to long-term corporate decision making. For example, they argue that

> a firm could economize on safety or pollution control; this also increases short-run profits, but creates contingent liabilities down the road: risk of future lawsuits, consumer boycotts and environmental clean-up costs.

Along these lines, we may think of price gouging as a type of (lack of) CSR, where the corresponding dynamic link is subsequent consumer boycott.

■ **Roadmap.** The next section lays out the two basic econometric models we propose as a test of the Akerlof (1980) hypothesis. Next, Section 3 describes our data. Our results are included in Section 4. Section 5 concludes the paper.

3. The above results correspond to our second (of three) measures of scarcity. See Section 2 for details.

2. Model

We wish to test the basic Akerlof (1980) hypothesis that seller reputation moderates the immediate incentive to price gouge. Specifically, we posit that sellers with less to lose in terms of reputation are more likely to price gouge than sellers who have more to lose in terms of reputation. Consistent with this hypothesis, we propose two models, each corresponding to a different way of measuring seller reputation.

■ **Incumbents and entrants.** In the first model, we compare Amazon.com with third-party sellers, and further distinguish between incumbent and entrant sellers. Amazon is a platform where an item can be sold either by Amazon.com or by a third-party seller. Amazon.com is the largest seller on Amazon, accounting for roughly 40% of the total sales as of 2019. Though having no clear reputation measures, Amazon.com is widely known to be more reliable than third-party sellers. Also, for many buyers Amazon.com is effectively a "focal" or "default" seller, a reference point, namely in terms of price.

We separate third-party sellers into two categories: incumbents and entrants. Incumbent sellers of an item are those who were selling that item from January 1 to January 15, 2020 (that is, before the COVID-19 US outbreak). By contrast, entrant sellers are those who started selling the item in question after January 16, 2020. Our hypothesis suggests that continuing sellers — who have more at stake than incoming sellers — are less likely to increase prices, or do so by less. Accordingly, our first baseline model takes the form:

$$\mathrm{PriceR}_{ijt} = \alpha_s + \alpha_j + \beta_A \, \mathrm{A}_i \cdot \mathrm{Scar}_{jt} + \beta_I \, \mathrm{I}_i \cdot \mathrm{Scar}_{jt} + \beta_E \, \mathrm{E}_i \cdot \mathrm{Scar}_{jt} + \mathrm{Controls} + \epsilon \qquad (1)$$

where i denotes the seller, j the item on sale, and t the day the item is on sale. α_s and α_j control for seller type and item fixed effects, respectively. The value of PriceR_{ijt} is defined as

$$\mathrm{PriceR}_{ijt} = \mathrm{Price}_{ijt}/\mathrm{Amazon19}_j$$

where $\mathrm{Amazon19}_j$ is item j's average price in 2019 when sold by Amazon.com. In other words, PriceR measures the price ratio between the price at time t and the 2019 price. In a steady state situation, we would expect PriceR to be approximately equal to 1 (except possibly for inflation, which during the period of analysis is minimal, or other exogenous factors). A_i I_i and E_i are indicator variables equal to 1 if seller i is Amazon.com, an incumbent seller, or an entrant seller, respectively.

The main independent variable is Scar_{jt}, a measure of scarcity of item j in day t. We consider three different scarcity measures, that is, Scar $\in$ {S1, S2, S3}. The first measure, S1, is a dummy variable that turns one if Amazon is out of stock of that item on that day:

$$\mathrm{S1} \equiv \begin{cases} 1 & \text{if Amazon is out of stock} \\ 0 & \text{otherwise} \end{cases}$$

The idea is that Amazon is generally believed and observed not to price gouge. Moreover, many American buyers use Amazon.com as their primary source. For these reasons, when there is a run on a given product Amazon.com is typically the first target and one of the first sellers to run out of stock. Note that the first measure applies to third-party sellers only, because once Amazon.com runs out of stock, there is no pricing data available.

The second measure of scarcity, S2, is defined as

$$\text{S2} \equiv \text{percentage of incumbent sellers out of stock}_{jt}$$

In other words, S2 measures the percentage of item j's sellers during the January 1-15 period who are out of stock at day t. If all sellers active at the beginning of 2020 — before the COVID-19 crisis developed — are stocked at time t, then we say there is no scarcity, that is, S2 equals 0. If none of them is stocked, then we say S2 equals 1, the maximum value. The idea underlying this measure is that, when a large supply or demand shock takes place that results in significant excess demand, speculators get in the scene and price gouge. This results in a high seller turnover rate — entry of speculators, exit of stocked-out sellers — which in turn results in a high value of S2.

A third possible measure of scarcity, S3, is the cumulative intensity of Google searches, as measured by Google Trends.

$$\text{S3} \equiv \text{cumulative intensity of Google search for word } j$$

where word j relates to the product in question. To maintain consistency across three measures, our Google Trends measure is normalized to the [0,1] interval.

In order to account for possible endogeneity of prices and scarcity measures, we consider a variety of instruments. Specifically, we consider the logarithm of the number of confirmed COVID-19 cases and deaths due to COVID-19 in three different regions: US, China and the rest of the world (ROW). One concern of using this set of instruments is the potential impact on prices through competition. To address this issue and to control for competition effects, we include the number of sellers in the regression, which is also instrumented using the same set of instruments.

■ **Seller history.** The distinction between entrant and incumbent provides a first approach at measuring what a seller has to lose from squandering its reputation. However, this is clearly not the only approach. Another possibility is the length of a seller's history. Specifically, we propose the following alternative model:

$$\text{PriceR}_{ijt} = \alpha_j + \beta_1 \log(\text{RC}_i) + \beta_2 \text{Scar}_{jt} + \beta_3 \log(\text{RC}_i) \cdot \text{Scar}_{jt} + \text{Controls} + \epsilon \qquad (2)$$

where the main independent variable is $\log(\text{RC}_i)$, the logarithm of seller i's review count. Cabral and Hortaçsu (2010) show that, on eBay, the length of a seller's customer feedback record is a good proxy for the seller's previous sales. In this sense, RC_i can be thought of as a proxy of the seller's past experience. The idea is that, the longer a seller's history and/or a seller's size is, the more the seller has to lose from a reputation breakdown, and thus the less the seller is likely to price gouge. Specifically, Akerlof's (1980) hypothesis implies a negative β_3 coefficient: the greater a seller's reputation, the less likely the seller is to increase price as the result of an increase in scarcity.[4]

3. Data

In this section we describe our data. First, we justify our choice of a sample period. Next we describe the product categories under consideration. Finally, we briefly review some basic descriptive statistics.

4. Note that Amazon.com is excluded in this analysis because the review count is only available for third-party sellers.

■ **Sample period.** As mentioned in the introduction, the first known COVID-19 case in the US can be traced back to January 15, 2020. By mid March, under pressure from both media and the law, Amazon implemented a series of measures to fight price gougers on its platform. Since we want to study the role of market reputations, we restrict to the period from January 15 to March 15. Our analysis is robust to changing the precise beginning and end dates.

■ **Product categories.** We focus on two categories of consumer goods that are heavily affected by the outbreak of COVID-19: face masks and hand sanitizers. There are countless items and brands being sold on the market in each of these categories. We focus on the two best known brands: 3M and Purell. We search for 3M face masks and Purell hand sanitizers on Amazon. To exclude illegitimate items and to calculate price margins, we further select items based on the following criteria: First, we restrict to items sold by Amazon.com for at least seven months during 2019. Second, we also restrict to items with more than 3 product reviews.[5] Applying these filters, we obtain 31 items, including 14 3M different face masks and 17 different Purell hand sanitizers. Tables 1 and 2 list the various 3M and Purell products included in our sample. As can be seen, the differences across products (within the same category) correspond primarily to differences in package size.

We collect price history data and seller characteristics from Keepa, a website that tracks prices of products sold on Amazon. In addition to price, we obtain information on each seller's cumulative number of consumer reviews.

■ **Descriptive statistics.** Table 3 provides basic descriptive statistics of our data. An immediately striking feature is the enormous range in price ratios. For example, 3M masks price ratios vary from .74 (lower price in 2020 than in 2019) to a whopping 43.88, a range that would be unusual during normal times. Second, we observe considerable variation in seller size, with an average of about 10,000 reviews but a standard deviation of about 50,000. Our measures of scarcity also vary significantly, in fact S1 and S2 vary from 0 to 1 (S3 varies from 0 to 1 by construction).

In order to get a better idea of the evolution of scarcity, Figure 1 plots our three measures of scarcity over the first three months of 2020.[6] As can be seen, S1 and S2 are highly correlated, with a sharp increase during the last weeks of January. The third measure, by contrast, is less correlated and also more volatile. For example, there is a significant spike in Google searches for masks in end of February, whereas searches for hand sanitizers peaked in mid-March.

4. Results

We finally come to our results. We structure this section as follows. First, we present some preliminary aggregate analysis of the change in prices by type of seller. This preliminary analysis suggests that there are significant differences between low-reputation and high-reputation sellers. We then turn to formal regression analysis, including IV regression (to

5. Other selection criteria are used as a robustness test. Our main results do not change significantly.
6. Our first measure, the dummy variable which turns 1 when Amazon is out of stock, only takes two values. The time series in Figure 1 corresponds to the fraction of products — within a given category — for which Amazon is out of stock.

account for endogeneity of scarcity as well as the number of sellers) and quantify the extent to which reputation acts as a moderator of the effect of scarcity on price. Finally, we consider various robustness tests and extensions of our basic results.

■ **Preliminary summary statistical analysis.** As a preliminary stage in our analysis, Table 4 shows some basic descriptive statistics of our price data. Price ratios are defined with respect to Amazon's 2019 prices. For this reason, the values in the third are equal to 1 by construction. The remaining columns show that, in 2019, third-party sellers were selling for about 60% higher prices than Amazon. In 2020, Amazon set prices slightly higher than in the previous year (about 3 to 4%). By contrast, third-party sellers' markup with respect to Amazon increased from about 60% to about 141% (masks) and 72% (hand sanitizer).

To further decompose the price changes, we divide 2020 into two time periods: before and after the US outbreak of COVID-19, which we place at January 16, 2020. Table 5 largely confirms our prior from Akerlof's (1980) theory: incumbent sellers set a price close to twice the Amazon 2019 price, whereas entrants set a price that was on average between three to four times higher than Amazon's 2019 price.

Figures 2 and 3 further extend the analysis by plotting price ratios over time by type of seller. We only plot price data when an item is in stock. Since Amazon's items moved frequently between in and out of stock, we plot Amazon's data as a scatter plot. As for third-party sellers, we observe that there is a clearly defined date when they become out of stock. Accordingly, we plot a continuous price ratio line until that date. For example, 3M mask incumbent sellers (left panel in Figures 2) run out of stock on March 12, about the same time as Amazon, whereas entrant sellers run out of stock on March 25.

In Figure 2 we distinguish between incumbents and entrants. (Recall that entrants are sellers who begin to sell after the first US COVID-19 case.) Both for masks and for hand sanitizer the data clearly shows that (a) on average third-party sellers charge a higher price than Amazon; and, more important, (b) within third-party sellers, entrants are particularly prone to charge higher prices. For masks, our rough estimate is that entrants charge approximately twice as much as incumbents. For hand sanitizer, the difference varies a lot over time, but generally speaking — and with the exception of early February — entrants charge higher prices than incumbents.

While it makes sense to think of incumbents as having more to lose than entrants, presumably some of the entrants could by very large sellers who, not having a specific history in selling masks or purifiers, have a long history of selling on Amazon. To account for this possibility, we consider a second measure of seller reputation, customer review count. In Figure 3, we distinguish between high-RC sellers (RC greater than 1,000) and low-RC sellers (RC less than 1,000). Similar to the incumbent/entrant split, we see that, for masks, on average low-RC sellers set considerably higher prices than high-RC sellers. Regarding hand sanitizer, while the difference is not as clearcut as in the case of masks, the pattern of higher prices by low-RC sellers persists.

■ **Regression analysis results.** Our systematic regression analysis is guided by a series of choices. First, we consider two possible measures of seller "reputation", that is, measures of what sellers have to lose from consumer boycott. These measures are (a) whether the seller is an incumbent or an entrant (all else equal, incumbents have more to lose); and (b) a seller's cumulative number of reviews (all else equal, a seller with a larger number of reviews — a proxy for seller size — has more to lose).

Second, we consider three measures of scarcity: (a) a dummy variable indicating whether Amazon is stocked out, (b) the fraction of incumbent sellers who are out of stock, and (c) the intensity of Google searches for the relevant term.

Finally, in order to account for possible endogeneity, we consider both OLS and IV regressions, where the instruments correspond to COVID-19-related cases and deaths in the US, China and the rest of the world.

All in all, this corresponds to a large number of regressions. In all of them, the dependent variable is a seller's price for a given product at a given date (measured as a price ratio with respect to Amazon's 2019 price). We organize the regressions as follows. Table 6 explores the contrast between Amazon.com, incumbent and entrant sellers, whereas Table 7 focuses on a seller's size as measured by its prior review count. In each case, we consider six different regression models, corresponding to three scarcity variables times two regression methods (OLS and IV).

Consider first the coefficient estimates displayed in Table 6, where we focus on the distinction between incumbent sellers and entrant sellers. As predicted by theory, the impact of scarcity on prices is greater for third-party sellers than for Amazon. And, more important, within third-party sellers, the effect is greater for entrants than for incumbents. Consider for example the IV regression using the S1 scarcity measure (Amazon is stocked out). When Amazon stocks out, entrants increase price by the equivalent of 100% of 2019's price, whereas the incumbents' increase corresponds to 60%. This is consistent with the idea that entrants have less to lose from ruining their reputation than incumbents have. Consider next the S2 IV regression (fourth model).

An alternative way of measuring the desired effect is to consider a one-standard deviation change in the independent variable. From Table 3, we see that the standard deviation of S1 is given by .47. This implies that a one-standard deviation in S1 is associated with a change in an entrant's price equal to 47% of Amazon's 2019 price, whereas for an incumbent the number is 28%. The standard deviation of S2 is given by .39. We thus estimate that a one-standard deviation increase in S2 leads entrants to increase in price by $2.479 \times 0.39 = .97$, or about 97% of the 2019 price. By contrast, incumbents increase price by $0.914 \times 0.39 = .36$, or 36% of the 2019 price. The corresponding values for S3 are and 119% and 76% for entrants and incumbents, respectively.

In sum, we estimate that a one-standard deviation increase in scarcity leads incumbents to increase price by 47 to 119%, whereas entrants increase price by 28 to 76%. Although the numbers do vary a bit according to the scarcity measure we use, we note that they are broadly speaking of the same order of magnitude and, more important, the estimate is economically and statistically greater for entrants than it is for incumbents.

Consider now the coefficient estimates displayed in Table 7, where we focus on a seller's reputation count. Our hypothesis predicts that sellers with higher reputation counts have more to lose and are thus less likely to increase prices. In terms of regression coefficients, we predict a negative coefficient on the interaction of scarcity and review counts.

The regression results confirm this expectation: all estimation coefficients of the interaction review count times scarcity are negative. Moreover, the coefficients are significant from both a statistical and an economic perspective. From Table 3, the mean value of the scarcity measures is given by 0.64, 0.51 and 0.23. Moreover, the standard deviation of log(RC) is 3.32. Restricting to IV regressions, we see that a one-standard deviation increase in log(RC) leads to a decrease of 8.3% in the price increase with respect to 2019 when considering the S1 scarcity measure. In other words, reputation — as measured by log(RC) — acts as a moderator of the effect of scarcity on prices. The corresponding values for S2 and S3 are 9.7 and 15.1%. Again, the fact these estimates fall within a reasonably tight range gives us confidence regarding our measurement of scarcity.

■ **Extensions and robustness tests.** We performed a series of robustness tests in terms of variable definitions and sample period. We found that our results are fairly robust, specifically concerning the sign and statistical significance of the key parameter estimates.

One particularly interesting extension consists in combining our two approaches to measuring seller reputation: the distinction between incumbent and entrant; and the cumulative number of buyer reviews. Specifically, we consider the following model, which basically combines (1) and (2)

$$\begin{aligned}\mathrm{PriceR}_{ijt} = \alpha_j + \alpha_{type} + \beta_1 \log(\mathrm{RC}_i) + \beta_2 \log(\mathrm{RC}_i) \cdot \mathrm{E}_i + \beta_3 \,\mathrm{Scar}_{jt} + \beta_4 \,\mathrm{Scar}_{jt} \cdot \mathrm{E}_i \\ + \beta_5 \log(\mathrm{RC}_i) \cdot \mathrm{Scar}_{jt} \cdot \mathrm{E}_i + \mathrm{Controls} + \epsilon \end{aligned} \tag{3}$$

The question of interest now is whether β_5 positive or negative, that is, whether the moderating factor of seller history, log(RC), differs from incumbent and entrant sellers.

Table 8 displays the estimates corresponding to (3). As before, we consider three different measures of scarcity (S1, S2 and S3) and two regression types (OLS and IV). Restricting to the set of IV regressions, we see that, except for the first scarcity variable (Amazon is stocked out), the coefficient estimate is statistically significant. In all three cases, the coefficient is negative, indicating that the moderating factor of log(RC) is greater for entrants than for incumbents. This suggests that being an incumbent or being a large/old seller are substitute factors in terms of moderating the incentives for price gouging.

5. Conclusion

The COVID-19 pandemic has resulted in emergency declarations in most US states. These declarations have the effect of triggering anti-price gouging statutes. These statutes suffer from several limitations. First, as many economists point out, they may defeat the incentive effect of prices, in particular the incentive to increase supply. Second, they can be rather vague (to the extent that they refer, for example, to terms such as "reasonable" price increases or "necessary" goods and services).

Free-market proponents suggest that seller reputation may substitute for regulation when it comes to preventing price gouging, possibly to the point of rendering anti-price gouging unnecessary. Our evidence suggests that seller reputation does act as a limit on how much sellers price-gouge: Higher-reputation sellers are less likely to take advantage of shortages of supply. The effect is statistically significant. However, our analysis also suggests that these reputation effects are far from sufficient to limit the extent of price gouging.

In their letter to Amazon and other sellers, a group of 34 attorneys general (AG) recommended that the platform

> Set policies and enforce restrictions on unconscionable price gouging during emergencies: Online retail platforms should prevent unconscionable price increases from occurring by creating and enforcing strong policies that prevent

> sellers from deviating in any significant way from the product's price before an emergency. Such policies should examine historical seller prices, and the price offered by other sellers of the same or similar products, to identify and eliminate price gouging.

Our results suggest one specific way cross-seller price comparison can be made, namely with respect to incumbent sellers. In other words, a possible implementation of the AG recommendation is that, once an emergency period is triggered, new sellers be prevented from selling at a higher price than incumbent sellers. While this would not eliminate price increases, we suggest that it might significantly reduce their extent.

Admittedly, one weakness of this argument is that the price set by incumbent sellers is an equilibrium price, and running a counterfactual without a model is a dangerous exercise. It's possible that, absent the high prices set by entering firms, incumbents would themselves price higher than otherwise. This would defeat the purpose of the proposed rule.

Moreover, there is nothing in the AG argument or in our proposal that shows consumers would be better off by preventing price gouging. As mentioned in the introduction, it is not our purpose to provide a welfare analysis of price gouging or the efforts to prevent it. Such analysis would require considerably more and better data, at the very least data on sales and seller characteristics.

Figure 1

Scarcity measures over the first months of 2020
(S1: % items Amazon is out of stock, S2: % continuing sellers, S3: Google searches)

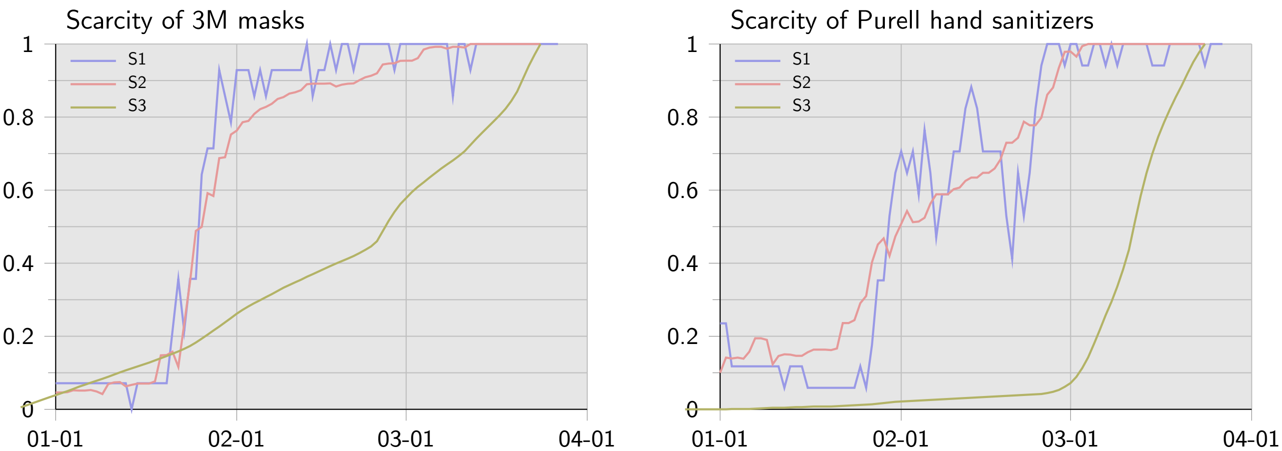

Figure 2
Price ratio by type of seller
(Amazon data as scatter plot to reveal stockouts)

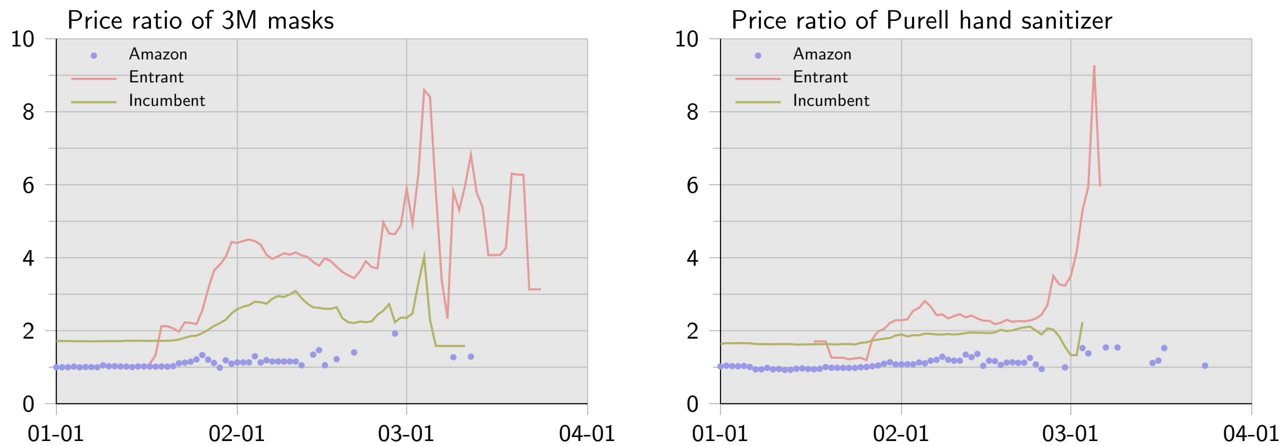

Figure 3
Price ratio by type of seller
(Amazon data as scatter plot to reveal stockouts)

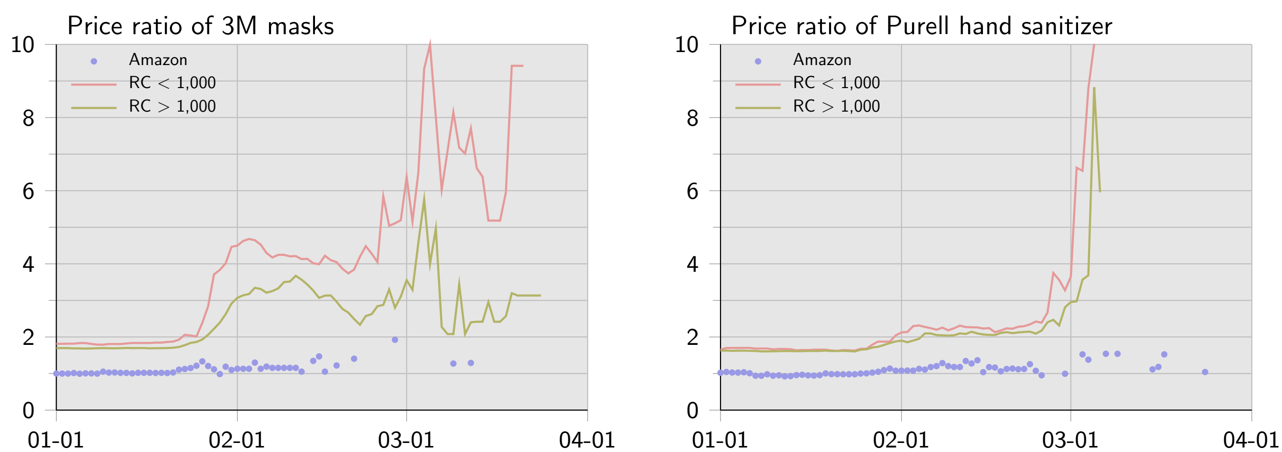

Table 1
List of 3M products in sample

3M 50051138543438 Particulate Respirator 8511, N95 (Pack of 10)
3M 8210V Particulate Respirator with Cool Flow Valve, Grinding, Sanding, Sawing, Sweeping, Woodworking, Dust, 10/Box
3M 8233PA1-A Lead Paint Removal Valved Respirator
3M 8293 P100 Disposable Particulate Cup Respirator with Cool Flow Exhalation Valve, Standard
3M 8511 Respirator, N95, Cool Flow Valve (10-Pack)
3M 8577CA1-C-PS Chemical Odor Valved Respirator, 2-Pack
3M 8661PC1-A Home Dust Mask, 5-Pack
3M Air Pollution & Pollen Particulate Respirator, N95, Designed for Smoke and Smog Particles, 2 Pack, Adult
3M Particulate Respirator 8210PlusPro, N95, Smoke, Dust, Grinding, Sanding, Sawing, Sweeping, 10/Pack
3M Particulate Respirator 8211, N95
3M Particulate Respirator 8247, R95, with Nuisance Level Organic Vapor Relief, 20/Box
3M Particulate Respirator 8514, N95, with Nuisance Level Organic Vapor Relief
3M Particulate Respirator 8577, P95, with Nuisance Level Organic Vapor Relief
3M Particulate Respirator, 8110S, N95, Smoke, Dust, Grinding, Sanding, Sawing, Sweeping, Smaller Size, 20/Pack

Table 2
List of Purell products in sample

PURELL Advanced Green Certified Hand Sanitizer, Gentle & Free Foam, 535 mL EcoLogo Certified Sanitizer Table Top Pump Bottles (Case of 4)
PURELL Advanced Hand Sanitizer Green Certified Refreshing Gel, Fragrance Free, 12 fl oz Pump Bottle (Pack of 12)
PURELL Advanced Hand Sanitizer Naturals with Plant Based Alcohol, Citrus Scent, 12 fl oz Pump Bottle (Pack of 2)
PURELL Advanced Hand Sanitizer Naturals with Plant Based Alcohol, Citrus scent, 2 fl oz Pump Bottle (Pack of 24)
PURELL Advanced Hand Sanitizer Naturals with Plant Based Alcohol, Citrus scent, 2 fl oz pump bottle (Pack of 6)
PURELL Advanced Hand Sanitizer Naturals with Plant Based Alcohol, Citrus Scent, 28 fl oz Pump Bottle (Pack of 4)
PURELL Advanced Hand Sanitizer Naturals with Plant Based Alcohol, Citrus Scent, 8 fl oz Pump Bottle (Pack of 12)
Purell Advanced Hand Sanitizer Refreshing Gel 8 oz
PURELL Advanced Hand Sanitizer Refreshing Gel, Clean Scent, 2 fl oz Portable Flip Cap Bottle (Pack of 24)
PURELL Advanced Hand Sanitizer Soothing Gel for the workplace, Fresh scent, with Aloe and Vitamin E - 8 fl oz pump bottle (Pack of 4)
PURELL Advanced Hand Sanitizer Variety Pack, Naturals and Refreshing Gel, 1 fl oz Portable Flip Cap Bottle with JELLY WRAP Carrier (Pack of 36)
PURELL Advanced Hand Sanitizer, Refreshing Gel, 2 fl oz Portable, Travel sized Flip Cap Bottles (Pack of 24)
PURELL Advanced Hand Sanitizer, Refreshing Gel, 36 - 1 fl oz Portable, Travel Sized Flip Cap Bottles with Display Bowl
PURELL Advanced Hand Sanitizer, Refreshing Gel, 8 fl oz Sanitizer Table Top Pump Bottles (Pack of 2)
PURELL Healthcare Advanced Hand Sanitizer Foam, Clean Scent, 18 fl oz Pump Bottle (Pack of 4)
PURELL Naturals Advanced Hand Sanitizer Gel, with Skin Conditioners and Essential Oils, 12 fl oz Counter Top Pump Bottle (Case of 12)
PURELL SF607 Advanced Hand Sanitizer Foam, Fragrance Free, 535 mL Sanitizer Counter Top Pump Bottles (Pack of 4)

Table 3
Descriptive statistics

Variable	# obs.	Mean	St. Dev.	Min	Max
Price (3M)	13773	45.51	29.07	6.21	349.99
Price (Purell)	9239	51.45	35.27	2.99	199.99
PriceR (3M)	13773	2.72	1.77	0.74	43.88
PriceR (Purell)	9239	1.82	1.02	0.49	17.50
RC	961	10,600	51,558	0	954,539
log(RC)	961	5.42	3.22	0	13.76
S1	2697	0.64	0.47	0	1
S2	1956	0.51	0.39	0	1
S3	180	0.23	0.24	0	1
Instruments					
Cases (China)	88	44,785	36,282	0	81,999
Deaths (China)	88	1,544	1,382	0	3,299
Cases (US)	88	6,774	21,357	0	121,478
Deaths (US)	88	101	327	0	2,026
Cases (ROW)	88	42,138	95,986	0	457,229
Deaths (ROW)	88	1,996	5,068	0	25,327

Table 4
Average price ratio descriptive statistics

	#	2019		2020	
Brand	Items	Amazon	Third-Party	Amazon	Third-Party
3M	14	1.00	1.60	1.04	2.41
Purell	17	1.00	1.57	1.03	1.72

Table 5
Price ratio by seller type

	Before outbreak			After outbreak		
	Mean	Min	Max	Mean	Min	Max
Amazon.com	0.99	0.54	1.6	1.08	0.54	1.92
Third-Party (incumbent sellers)	1.68	0.67	6.03	1.95	0.49	14.71
Third-Party (entrant sellers)	-	-	-	3.69	0.66	43.88

Table 6
Price gouging across different seller types: Amazon vs. incumbents vs. entrants
Dependent variable: price ratio. *p* levels: 0.01, 0.05, 0.1

	Scarcity Measure 1		Scarcity Measure 2		Scarcity Measure 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Scarcity $\times$ Amazon			0.550***	0.432***	1.508***	1.468***
			(0.11)	(0.12)	(0.41)	(0.42)
Scarcity $\times$ Incumbent	0.541***	0.605***	0.902***	0.914***	3.185***	3.186***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.10)	(0.10)
Scarcity $\times$ Entrant	0.780***	1.008***	2.665***	2.479***	4.939***	4.954***
	(0.05)	(0.05)	(0.07)	(0.07)	(0.10)	(0.10)
N. of Sellers	0.002***	-0.007***	0.006***	-0.001	0.004***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	2.268***	2.384***	2.752***	2.873***	2.833***	2.860***
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Item & Seller Type FE	×	×	×	×	×	×
Model	OLS	IV	OLS	IV	OLS	IV
N	22986	22986	22986	22986	22986	22986
R^2	0.560	0.546	0.584	0.577	0.595	0.595

Table 7
Effects of reputation on price gouging
Dependent variable: price ratio. *p* levels: 0.01, 0.05, 0.1

	Scarcity Measure 1		Scarcity Measure 2		Scarcity Measure 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Review Count	-0.011***	0.004	0.006	0.027***	0.008**	0.066***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Scarcity	2.023***	2.724***	2.875***	3.355***	8.235***	11.213***
	(0.04)	(0.07)	(0.05)	(0.08)	(0.12)	(0.20)
Review Count × Scarcity	-0.118***	-0.130***	-0.140***	-0.191***	-0.358***	-0.656***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
N. of Sellers	0.003***	-0.014***	0.007***	-0.002**	0.006***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	2.622***	2.243***	2.975***	2.945***	3.248***	2.722***
	(0.05)	(0.06)	(0.05)	(0.06)	(0.04)	(0.06)
Item FE	×	×	×	×	×	×
Model	OLS	IV	OLS	IV	OLS	IV
N	22044	22044	22044	22044	22044	22044
R^2	0.524	0.462	0.564	0.551	0.576	0.565

Table 8
Effects of reputation on price gouging - incumbents vs. entrants
Dependent variable: price ratio. *p* levels: 0.01, 0.05, 0.1

	Scarcity Measure 1		Scarcity Measure 2		Scarcity Measure 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Review Count	0.001	0.013***	-0.000	0.019***	0.013***	0.044***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Review Count × Entrant	-0.044***	0.141*	0.006	0.311***	0.015	0.212***
	(0.01)	(0.08)	(0.02)	(0.04)	(0.01)	(0.02)
Scarcity	1.238***	2.095***	1.791***	2.603***	6.147***	9.189***
	(0.07)	(0.15)	(0.10)	(0.19)	(0.28)	(0.66)
Scarcity × Entrant	-0.261**	2.052***	1.360***	3.046***	0.506	3.665***
	(0.12)	(0.59)	(0.17)	(0.40)	(0.33)	(0.82)
Review Count × Scarcity	-0.080***	-0.137***	-0.102***	-0.179***	-0.326***	-0.659***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.07)
Review Count × Scarcity × Entrant	0.044***	-0.114	0.015	-0.335***	0.030	-0.425***
	(0.02)	(0.09)	(0.02)	(0.05)	(0.04)	(0.10)
Num of Sellers	0.002***	-0.008***	0.006***	0.001	0.004***	0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	2.724***	1.131**	3.144***	0.881***	3.119***	1.815***
	(0.05)	(0.52)	(0.05)	(0.28)	(0.05)	(0.15)
Item & Seller Type FE	×	×	×	×	×	×
Model	OLS	IV	OLS	IV	OLS	IV
N	22044	22044	22044	22044	22044	22044
R^2	0.562	0.513	0.584	0.569	0.595	0.571

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