Do price gouging laws cause shortages? Evidence from Google Searches during the COVID-19 pandemic.

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Abstract

I investigate the effect of price gouging laws on shortages for goods affected by the COVID-19 pandemic. Utilizing Google Shopping search data for hand sanitizer, toilet paper, and masks, I compare product searches in US states with and without price gouging laws. I hypothesize that states with price gouging laws had more shortages in 2020, which caused them to have more Google Shopping searches than states without price gouging laws. I estimate the effect of price gouging laws on Google Shopping searches, and find no significant difference between Google Shopping search index values of states with and without price gouging laws.

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1 Introduction

Price gouging has become a topic of national interest in the wake of the COVID-19 pandemic. Public and media figures have accused stores of unfairly raising prices on desperate consumers. Several states have anti-price gouging laws which prevent vendors from raising prices above a certain level during disaster periods. The language of these laws differs by state; some give a specific percentage by which prices are not allowed to increase, while others forbid raising prices by an unspecified amount which the law deems to be excessive. Many economists oppose anti-price gouging laws, which they believe function as a price ceiling and create shortages.

Several states responded to public outcry at price gouging during the pandemic by passing new price gouging legislation, while others claimed to have authority to prevent price gouging under existing legislation. In addition, several private companies, including Amazon, have implemented internal policies to prevent price gouging (King & Spalding, 2021).

While many state attorneys general claim to have the authority to enforce price gouging laws, 36 states have specific price gouging statutes (King & Spalding, 2021). Through my empirical work, I try to infer whether shortages of key goods occurred more often in 2020 for states with specific price gouging statutes. In this paper, I will investigate the effect of anti-price gouging laws on markets for necessities during the COVID-19 pandemic.

To examine the effect of price gouging laws, I examine Google Shopping Trends data for toilet paper, hand sanitizer, masks, and shoes in 2020. My empirical strategy is similar to that used in "Anti-Gouging Laws, Shortages, and COVID-19: Insights from Consumer Searches," in which the authors examine Google Shopping Trends Data for February and March 2020 and find significantly higher Google Shopping searches for hand sanitizer and toilet paper in states with price gouging laws (Chakraborti and Roberts, 2020). For my empirical strategy, I analyze data for all of 2020, and find no significant difference between states with and without price gouging laws. My results challenge Chakraborti and Roberts' findings. They claimed that their results imply a connection between price gouging laws and shortages (Chakraborti and Roberts, 2020). My results suggest that the connection between price gouging laws and in store shortages in 2020 is not clear from Google Shopping Trends data.

2 Literature Review

The debate over price gouging laws has stretched across disciplines. Many politicians, philosophers, and citizens judge price gouging to be immoral. Outcry over price gouging laws increased in 2020, as price gouging has come under attack by journalists and politicians (Chakraborti and Roberts, 2020). Political support for price gouging laws in the United States is strong and increasing, with 36 states currently possessing specific price gouging legislation. Two states, Colorado and Alaska, introduced price gouging legislation in 2020 as a result of the pandemic (King & Spalding, 2021). Most states without specific price gouging legislation have claimed to be able to prosecute price gouging under existing laws. In states both with and without price gouging legislation, complaints about price gouging have reached a high. For example, the New York Attorney General's office received over 5,500 complaints of price gouging in Spring 2020 (King & Spalding, 2021).

Raising a price during a period when people are most in need seems unconscionable to many. However, economists who study the issue from an empirical perspective are divided on the effects of price gouging laws. Many see prices as a mechanism to efficiently distribute resources, and believe price gouging laws prevent efficient distribution.

Economists have studied price ceilings from a theoretical and empirical perspective in a variety of scenarios, but the research on anti-price gouging laws is limited. Under classical economic theory, a price ceiling below the market equilibrium price will produce a shortage of the good in question. Many economists interpret anti-gouging laws as similar to other price ceilings, and believe the market should be left to operate freely, even in natural disasters (Lee 2015). Generally, academic economists tend to be more critical of anti-gouging laws than the public. Recently, more than 150 economists signed a petition to ban anti-gouging laws (Niles 2015).

However, not all theoretical economists agree that anti-gouging laws are harmful and the market should be left to operate freely in natural disasters. In "Can Prohibitions on 'Price Gouging' Reduce Deadweight Losses?," Robert K. Fleck wrote that anti-gouging laws can reduce deadweight loss under certain situations when rational consumers increase their consumption in anticipation of a shortage (Fleck 2014). By being prepared for a shortage and stocking up on goods in advance, many consumers will be better off (Fleck 2014). However, consumers anticipating a shortage may exacerbate the shortage issue by buying up the supplies in advance. Whether a theoretical economist believes anti-gouging laws to be harmful or beneficial often depends on their assumptions about the market in question. Assuming a competitive, efficiently operating market, price gouging laws prevent the market from allocating resources efficiently and cause shortages. However, real world markets rarely resemble this perfectly competitive ideal. Measuring the nature and competitiveness of markets is a difficult task. Thus, to study anti-gouging laws, I will analyze their effects on consumer demand rather than the nature of the market.

Few empirical papers have been published on the effect of anti-gouging laws on shortages during disaster periods. In "The Impact of Regulatory Change on Retail Pricing: The New York State Milk Price Gouging Law," Adam N. Rabinowitz and Yizao Liu found that a change to more stringent administration of anti-gouging laws led to lower prices and greater consumer welfare. They argued that the change in price gouging law administration reduced previously possible collusion between players with market power in the milk market (Rabinowitz and Liu 2014).

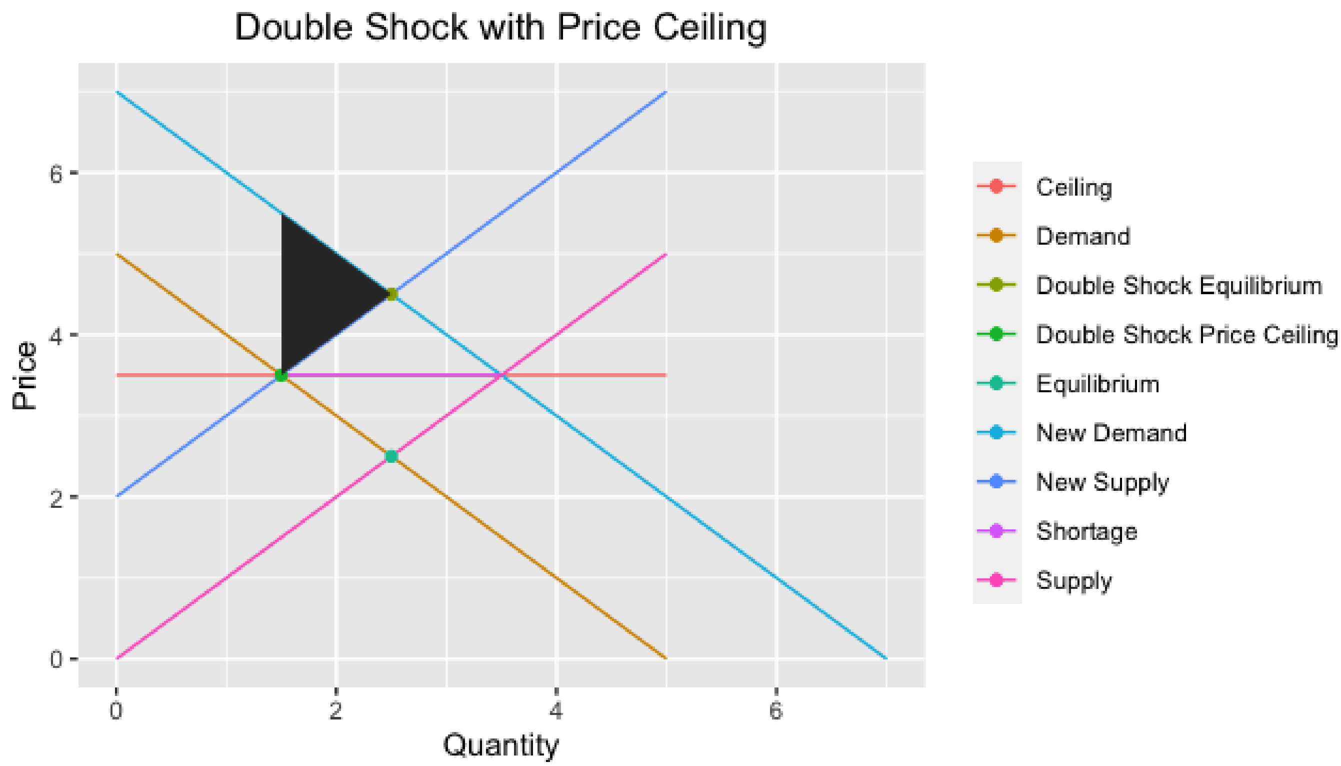
Very little work has been done on anti-gouging laws during the coronavirus pandemic since there is little available published data. A paper by Chakraborti and Roberts is most similar to my own, as the authors used empirical techniques to investigate the effect of anti-gouging laws on markets for necessities during the COVID-19 pandemic. Chakraborti and Roberts used Google Trends data to assess the impact of anti-price gouging laws on searches for toilet paper and hand sanitizer during February and March 2020. They found empirical evidence that states with anti-gouging laws had more consumer searches for hand sanitizer and toilet paper in early 2020 than states without price gouging laws (Chakaraborti and Roberts 2020).

The goal of my paper is to extend Chakraborti and Roberts' work to include more data. Rather than analyzing Google Trends data for only February and March 2020, I will use data for all of 2020. One good that was conspicuously missing from Chakraborti and Roberts' paper was COVID-19 face masks. I will add COVID-19 masks to my study to understand the effect of anti-gouging laws on online demand for face masks. The addition of Google Trends data for all of 2020 and face masks to Chakraborti and Roberts' initial work provides a more complete view of the effect of anti-gouging laws during the coronavirus pandemic in 2020.

3 Economic Model for Price Gouging Laws

Price gouging often occurs due to shocks in supply and demand following a natural disaster. More consumers wanting to buy face masks in the wake of increasing COVID-19 cases is a demand shock, while toilet paper production being slowed is a supply shock. Negative supply shocks and positive demand shocks raise the price of the good in question if the market is unregulated, which often leads to accusations of price gouging. When both a negative supply shock and positive demand shock occur simultaneously, the two shocks combine to create a large price increase.

The below graph shows the effect of a price ceiling after a negative supply shock and positive demand shock. The deadweight loss is filled in with black.



The deadweight loss above shows the loss of efficiency from a price gouging law. Economists who oppose price gouging laws cite this loss of efficiency caused by a price ceiling. However, proponents of anti-price gouging laws argue that these laws rebalance the transfer of surplus from consumers to producers. The argument to implement anti-gouging laws is stronger when a greater transfer from consumer to producer surplus occurs without the law, and the deadweight loss from the price gouging law is less.

The extent to which an unregulated demand shock transfers surplus from consumers to producers depends on the nature of the market. The more elastic the supply curve, the less price will rise following a positive demand shock, and the more quantity will increase. Thus, the transfer from consumer to producer surplus will be greater the more inelastic the supply curve. The more elastic the demand curve, the more consumer demand decreases in response to a price increase, and the less surplus will be transferred following a demand shock.

Another factor which effects the market after a disaster is the competitiveness of the market. In perfectly competitive markets, sellers have no price power and set a price where supply equals demand. In less competitive markets resembling oligopoly, sellers have price power and can collude to raise prices above competitive levels. When sellers with market power collude, the transfer from consumers to producers following a demand shock will be more extreme than in a competitive market. The relationships between elasticity, competitiveness of the market, and the size of the transfer between consumers and producers are summarized in the table below.

Table 1: Effects of Market Characteristics on Transfers Following Demand Shocks

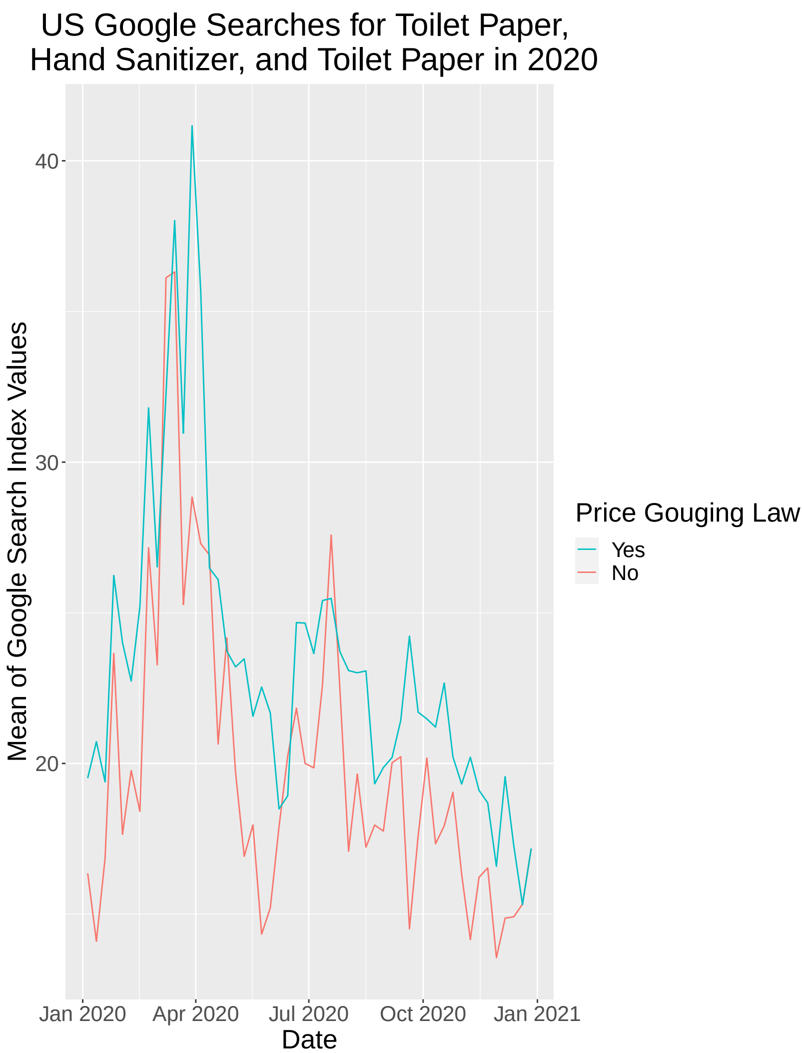
Market Characteristic	Association with Transfer from Consumers to Producers
Competitiveness of Market	Negative
Elasticity of Supply	Negative
Elasticty of Demand	Negative

The size of the deadweight loss from a price gouging law is related to the elasticity of supply. The higher the elasticity of supply, the greater the size of the deadweight loss from the price gouging law. In markets with elastic supply curves, producers will reduce quantity more in response to the price gouging law, which will increase the size of the shortage and deadweight loss from the price gouging law.

Choosing whether to implement a price gouging law is often a choice between efficiency and equity, assuming one believes the rebalance of surplus from producers to consumers to be equitable. How much efficiency needs to be exchanged for how much equity depends on the nature of the market. The size of the transfer from consumers to producers from a demand shock decreases when the elasticity of either supply or demand increases. The volume of this transfer increases when markets are more concentrated. The deadweight loss and size of the shortage from the law increases with elasticity of supply. To understand the efficiency versus equity trade-off of a price gouging law, one needs to understand the nature of the market.

4 Methods

4.1 Data



The above graph shows the mean Google Shopping index for hand sanitizer, toilet paper, and masks over 2020. The blue line shows the mean for states with price gouging laws, and the red line shows the mean for states without price gouging laws. The mean level was consistently higher for states with price gouging laws. In my empirical strategy, I attempt to discern whether this difference was due to the price gouging laws or other factors which vary between states.

The mean index for these searches spiked in March 2020 to over twice the level from January 2020. The level of searches has declined over 2020, but was above the level from January throughout most of the year (Google Trends Data, 2020). Google Shopping searches for these items are clearly related to the coronavirus pandemic and its influence on demand for COVID-19 necessities.

Google Trends is the main data source for this paper. Google Shopping Trends shows trends in searches made using the Google Shopping feature. Searches entered on Google Shopping return products from sellers who have decided to advertise on Google Shopping. Thus, Google Shopping Trends are a good proxy for how many people are searching online to buy products.

The central question of my thesis is whether anti-price gouging laws have contributed to shortages during the COVID-19 pandemic. Since I cannot measure shortages directly, I am using Google Shopping search indices as a probabilistic implication of shortage. I am assuming that customers are more likely to search online for the products in question when there are shortages at brick and mortar stores. The probabilistic connection between in-person shortages and online searches is a strong assumption, and the merit of my analysis depends on this relationship. My hypothesis is that states with anti-price gouging laws had more searches for toilet paper, hand sanitizer, and masks in 2020 than states without anti-gouging laws, ceteris paribus. My empirical strategy is similar to that used by Chakraborti and Roberts in their 2020 paper. They looked at Google Shopping searches for hand sanitizer and toilet paper as well. I decided to add masks as a search term because demand for masks skyrocketed due to the COVID-19 pandemic. Hand sanitizer, masks, and toilet paper all experienced large positive demand shocks due to the COVID-19 pandemic. The combination of large positive demand shocks due to the COVID-19 pandemic combined with possible negative supply shocks made these goods prime candidates for price increases and thus allegations of price gouging. These goods are also easily purchased online, which makes them appropriate product choices for my study using Google Shopping searches.

I downloaded panel data spanning January 1st to December 31st 2020 from Google Shopping Trends for searches on "hand sanitizer", "toilet paper", "masks" and "shoes." I included "shoes" as a search term to be used as a control variable, since the market for shoes should not have experienced a strong demand shock due to the COVID-19 pandemic and was likely unaffected by price gouging legislation. I also downloaded panel data for searches on "price gouging." The data for "price gouging" searches included all Google searches for price gouging, not just Google Shopping searches. I included this variable to see if interest in price gouging as a topic varied significantly between states. My dataset consists of $2,703$ observations for each search term.

Google Shopping Trends standardizes data by indexing search volumes on a scale from 0 to 100. I downloaded data for all of 2020 indexed by state. A higher index for a product means that searches are relatively more popular in that state, not that there are absolutely more searches. For example, a state with 10 searches for hand sanitizer out of 20 total searches will get a higher indexed score than a state with 20 searches for hand sanitizer out of 100 total searches.

Table 2 gives an overview of my Google searches data. Searches for toilet paper, hand

Table 2: Summary of Google Search Data

Search Term	Mean	Median	Min	Max	Std. Dev
Toilet Paper	21.64	19.00	0.00	100.00	18.76
Hand Sanitizer	3.16	0.00	0.00	100.00	9.65
Masks	42.02	42.00	0.00	100.00	23.04
Shoes	3.11	0.00	0.00	92.00	8.36
Price Gouging	9.14	0.00	0.00	100.00	19.83

sanitizer, masks, and shoes were all indexed together, so search index values not only reflect trends over time for these four key goods, but the relative popularity of searches between these items. For example, the mean index value for toilet paper, 21.64, was significantly higher than the mean index value for hand sanitizer, 3.16, which shows that Google Shopping searches for toilet paper were significantly more popular on average than searches for hand sanitizer in 2020. Price gouging was indexed separately, so the price gouging index does not show its relative popularity compared to other search terms in the table.

While processing the Google Shopping Trends data, I encountered several issues. There were several data points listed as $< 1\%$ in the dataset, meaning the Google search index value was less than 1%. I decided to replace these data points with 0% since there was no way of knowing these values' exact size and the values were presumably very small. Additionally, the Google dataset contained several missing values in cases when there was not enough search data available.

By studying data for all of 2020, I aim to get a comprehensive picture of the effect of anti-price gouging laws over the course of 2020. Online shopping data for hand sanitizer, toilet paper, masks, and shoes are the variables of interest in my study.

To isolate the effect of anti-price gouging laws on consumer searches, I downloaded several datasets containing information on control variables for my study. Information on anti-price gouging laws and emergency declaration dates in each state was found in the survey "COVID-19 Survey of Federal and State Price Gouging Laws" (King & Spalding, 2020). It is worth noting that anti-price gouging statutes are not uniform across states, as there is no uniform definition of price gouging. Most states understand price gouging as a price being raised too far above the baseline level during some disaster period. However, how high of a price raise constitutes price gouging differs across states, with some states using a qualitative definition of price gouging (i.e an unreasonably high price increase) while others use a quantitative definition (i.e an increase of over 10%).

I use data from the US Census Bureau on total population in each state to control for differences in state population (United States Census Bureau, 2017). I use Google Mobility data as a control variable for the level of social distancing. Google publishes a mobility index for grocery stores which measures the frequency at which people are going shopping in person. Google Mobility data spans the entire year and was endorsed as a measure of social distancing by the World Bank (Sampi and Jooste 2020). Measures of social mobility are an important control variable since consumers who are able to go to stores are less likely to purchase goods online. Additionally, I include case rate data to control for COVID-19 incidence in each state (New York Times, 2020). The COVID-19 case rate (number of cases per 100,000) is a key indicator of the status of the pandemic in each state.

4.2 Empirical Strategy

I use a differences-in-differences regression to account for variation over time and states for Google Shopping searches. My independent variables of interest are anti-price gouging laws in each state, the dates emergencies were declared, and the interaction between the two variables. The coefficient of interest in my study is on the interaction term between anti-price gouging laws and state emergency declarations. Anti-price gouging laws come into effect once state emergencies have been declared, so the coefficient on this term represents the effect of anti-price gouging laws once they come into effect.

I run three regressions each on Google Shopping searches for hand sanitizer, masks, toilet paper, shoes, and price gouging. I use a differences-in-differences model to estimate the effect of price gouging laws on searches for hand sanitizer, toilet paper, masks, and shoes.

$$searchindex_{i,t} = \beta_0 + \beta_1 \cdot Law_{i,t} + \beta_2 \cdot Declared_{i,t} + \beta_3 \cdot Law_{i,t} \cdot Declared_{i,t} + \beta_4 \cdot Mobility_{i,t} + \beta_5 \cdot Cases_{i,t} + \beta_6 \cdot Population_i + \alpha_i + \theta_t + \varepsilon$$

In my first regression, I add state and time fixed effects to capture differences between states i and over time t unrelated to the COVID-19 pandemic. The time variable t ranges from 1 to 53 depending on the week in 2020. The dependent variable *searchindex* represents the Google Search Index for the product in question, scaled from 0 to 100. $Law = 1$ for states with price gouging laws and 0 otherwise. The legal definitions of price gouging are often complicated in each state, so encoding price gouging laws as a 1 or 0 is an oversimplification of reality, but necessary for my empirical analysis. It is worth noting that my *Law* variable varies over both state and time, since Colorado and Alaska both introduced an anti-price gouging statute in 2020. $Declared = 1$

for states in a state of emergency and 0 otherwise. States of emergency in states with price gouging laws typically lasted from the declaration date to at least the end of 2020 (King & Spalding, 2021). β_1 gives the average difference in Google Shopping Search Index between states with and without price gouging laws, and β_2 gives the effect of a state emergency being declared. Since price gouging laws only come into effect once a state of emergency has been declared, my desired difference-in-differences estimate is β_3, which gives the effect of price gouging laws once those laws have come into effect.

Mobility is a control variable which represents the Google Mobility Index for grocery stores on a specific week in each state. A higher Google Mobility Index means more people are going grocery shopping in person. *Cases* represents the number of COVID-19 cases per $100,000$ people in each state, and *Population* represents the total population in each state. I also added time and state fixed effects to my model, where α_i represents state fixed effects and θ_t represents time fixed effects.

The most likely issue with this regression is the potential collinearity between fixed effects and other variables. Adding time fixed effects may absorb the effects of time dependent variables, while adding state fixed effects may absorb the effects of state dependent variables. Thus, my desired differences in differences estimate, β_3, could be biased by including time and state fixed effects. Another possible issue with this regression is that it relies on the assumption that Google search trends before COVID-19 emergencies were declared would have continued without the pandemic and emergency declarations. Otherwise, the coefficient on β_3 would be picking up information unrelated to price gouging laws and emergency declarations.

To combat possible issues with including time fixed effects, my second regression only includes state fixed effects and is represented by the equation below:

$searchindex_{i,t} = \beta_0 + \beta_1 \cdot Law_{i,t} + \beta_2 \cdot Declared_{i,t} + \beta_3 \cdot Law_{i,t} \cdot Declared_{i,t} + \beta_4 \cdot Mobility_{i,t} + \beta_5 \cdot Cases_{i,t} + \beta_6 \cdot Population_i + \alpha_i + \varepsilon_{i,t}$

Since state fixed effects are still included, there may be collinearity issues between state fixed effects and all the other variables. State fixed effects may absorb some of the effect of my variable of interest *Law* x *Declared*, since state fixed effects will include the effect of the *Law* variable. Without time fixed effects, it is possible that my estimate on β_3 will capture differences over time that are not connected to price gouging laws or emergency declarations. The lack of time fixed effects may also bias the coefficient β_2 on state emergency declarations.

In my third regression, I did not include time or state fixed effects:

$searchindex_{i,t} = \beta_0 + \beta_1 \cdot Law_{i,t} + \beta_2 \cdot Declared_{i,t} + \beta_3 \cdot Law_{i,t} \cdot Declared_{i,t} + \beta_4 \cdot Mobility_{i,t} + \beta_5 \cdot Cases_{i,t} + \beta_6 \cdot Population_i + \varepsilon_{i,t}$.

Not including state fixed effects could lead to bias on β_3. Since state fixed effects are not included in this regression, the estimate on my interaction term may capture differences arising between states but unrelated to price gouging laws. Since time fixed effects are again not included, β_3 could capture differences over time that are not connected to price gouging laws or emergency declarations. Additionally, the coefficients β_1 on *Law* and β_2 on *Declared* may be biased due to the lack of fixed effects.

5 Results

Table 3: Searches for Hand Sanitizer

Predictors	State and Time Fixed Effects *Estimates*	State Fixed Effects *Estimates*	No Fixed Effects *Estimates*
Intercept	-1.67 (1.38)	-1.30 (1.53)	2.95 *** (0.75)
State Anti Price Gouging Law	0.23 (1.37)	-3.64 (1.88)	0.82 (0.91)
State Emergency Declared	-0.81 (1.72)	1.73 * (0.77)	1.11 (0.85)
Google Mobility Index for Grocery Stores	0.31 (0.21)	0.43 ** (0.16)	-0.55 *** (0.15)
Case Rate	0.14 (0.17)	-0.92 *** (0.10)	-0.91 *** (0.11)
State Anti Price Gouging Law & State Emergency Declared	0.83 (0.66)	0.44 (0.91)	0.25 (1.00)
Observations	2704	2704	2704
R^2 / R^2 adjusted	0.607 / 0.591	0.238 / 0.222	0.031 / 0.029

* *p<0.05*   ** *p<0.01*   *** *p<0.001*

Table 4: Searches for Toilet Paper

Predictors	State and Time Fixed Effects *Estimates*	State Fixed Effects *Estimates*	No Fixed Effects *Estimates*
Intercept	-3.54 (3.12)	6.18 * (2.94)	11.26 *** (1.33)
State Anti Price Gouging Law	-7.25 * (3.11)	-11.55 ** (3.62)	0.81 (1.61)
State Emergency Declared	-1.11 (3.89)	16.53 *** (1.49)	15.76 *** (1.51)
Google Mobility Index for Grocery Stores	1.48 ** (0.48)	-3.07 *** (0.31)	-2.54 *** (0.27)
Case Rate	0.64 (0.39)	-3.85 *** (0.20)	-3.53 *** (0.19)
State Anti Price Gouging Law & State Emergency Declared	0.83 (1.49)	-0.78 (1.75)	-0.48 (1.79)
Observations	2704	2704	2704
R^2 / R^2 adjusted	0.469 / 0.447	0.253 / 0.238	0.187 / 0.185

* *p<0.05*   ** *p<0.01*   *** *p<0.001*

Table 5: Searches for Masks

Predictors	State and Time Fixed Effects *Estimates*	State Fixed Effects *Estimates*	No Fixed Effects *Estimates*
Intercept	22.28 *** (3.93)	26.45 *** (3.19)	45.36 *** (1.69)
State Anti Price Gouging Law	6.83 (3.91)	6.28 (3.93)	6.81 *** (2.04)
State Emergency Declared	8.64 (4.90)	-14.99 *** (1.61)	-14.42 *** (1.91)
Google Mobility Index for Grocery Stores	-0.51 (0.60)	1.16 *** (0.34)	1.81 *** (0.34)
Case Rate	1.16 * (0.48)	0.32 (0.21)	0.82 *** (0.24)
State Anti Price Gouging Law & State Emergency Declared	-1.21 (1.88)	-0.65 (1.90)	-2.07 (2.26)
Observations	2704	2704	2704
R^2 / R^2 adjusted	0.442 / 0.419	0.416 / 0.404	0.136 / 0.134

** p<0.05   ** p<0.01   *** p<0.001*

Table 6: Searches for Shoes

Predictors	State and Time Fixed Effects *Estimates*	State Fixed Effects *Estimates*	No Fixed Effects *Estimates*
Intercept	-1.27 (1.25)	1.85 (1.46)	3.56 *** (0.64)
State Anti Price Gouging Law	2.80 * (1.25)	-0.77 (1.80)	0.71 (0.78)
State Emergency Declared	6.58 *** (1.57)	0.69 (0.74)	0.49 (0.73)
Google Mobility Index for Grocery Stores	0.35 (0.19)	0.30 (0.16)	0.09 (0.13)
Case Rate	0.14 (0.15)	-1.05 *** (0.10)	-1.00 *** (0.09)
State Anti Price Gouging Law & State Emergency Declared	-0.50 (0.60)	-0.68 (0.87)	-0.76 (0.86)
Observations	2704	2704	2704
R^2 / R^2 adjusted	0.567 / 0.550	0.071 / 0.052	0.053 / 0.051

** p<0.05   ** p<0.01   *** p<0.001*

Table 7: Searches for Price Gouging

	State and Time Fixed Effects	State Fixed Effects	No Fixed Effects
Predictors	*Estimates*	*Estimates*	*Estimates*
Intercept	3.64 (2.93)	6.33 (3.44)	5.67 *** (1.51)
State Anti Price Gouging Law	7.72 ** (2.92)	-2.56 (4.25)	0.62 (1.83)
State Emergency Declared	4.60 (3.66)	7.79 *** (1.74)	7.55 *** (1.72)
Google Mobility Index for Grocery Stores	0.10 (0.45)	-1.25 *** (0.37)	-0.85 ** (0.31)
Case Rate	0.76 * (0.36)	-2.98 *** (0.23)	-2.71 *** (0.22)
State Anti Price Gouging Law & State Emergency Declared	1.43 (1.40)	-0.05 (2.05)	-0.18 (2.03)
Observations	2704	2704	2704
R^2 / R^2 adjusted	0.580 / 0.563	0.079 / 0.060	0.060 / 0.058

* *p<0.05* ** *p<0.01* *** *p<0.001*

In my regressions for hand sanitizer, toilet paper, masks, shoes and price gouging, the coefficient on my interaction term *Law* x *Declared* was insignificant. In the state fixed effects model, the estimate of my desired differences-in-differences coefficient was positive for hand sanitizer and toilet paper, but negative for masks. My hypothesis was that price gouging laws would increase online searches once they came into effect. The effect of price gouging laws coming into effect on searches for shoes also appears to be insignificant, as expected. Price gouging laws likely did not affect searches for shoes in 2020. There is no obvious reason why price gouging would have occurred for shoes during the COVID-19 pandemic.

The coefficients on state anti price gouging law, case rate, and Google Mobility Index varied widely between regressions. The coefficients on these variables yielded several positive and negative results depending on the regression, yielding no consistent pattern. It is possible that the coefficients were greatly effected by the inclusion of time and state fixed effects, which caused the large variation.

The coefficient on total population was positive across the majority of regressions. The positive effect of total population on search indices for COVID-19 necessities indicates that states with higher populations had more Google Shopping searches for COVID-19 related products relative to all searches than states with lower populations. The reason for this positive effect might be due to some omitted variable correlated with both total population and Google Shopping searches for necessities. It might be that states with higher total population have more urban, educated populations which are more likely to order COVID-19 necessities online. State emergency declarations yielded a positive coefficient across most regressions, with a notable exception for significant, negative coefficients in the masks regressions with no fixed effects and state fixed effects. This positive effect could be due to state emergency declarations making citizens more aware of the pandemic.

The insignificant coefficients for the variables of interest on my initial regressions differed from the significant effects of price gouging laws found by Chakraborti and Roberts (2020). To investigate whether the difference in results was due to different time periods for our data sets, I also ran regressions with the same time period as Chakraborti and Roberts: February 15, 2020 to March 15, 2020.

Table 8: Searches for Hand Sanitizer, February 15, 2020 to March 15, 2020

	State and Time Fixed Effects	State Fixed Effects	No Fixed Effects
Predictors	*Estimates*	*Estimates*	*Estimates*
Intercept	-8.12 (7.73)	-3.51 (8.92)	6.17 ** (2.21)
State Anti Price Gouging Law	-27.57 (43.36)	-6.82 (50.11)	0.35 (2.22)
State Emergency Declared	-6.49 (7.97)	1.26 (9.27)	-3.05 (7.17)
Google Mobility Index for Grocery Stores	-2.80 (3.54)	4.06 (2.41)	0.40 (1.74)
Case Rate	412.67 (6857.69)	16947.75 * (7627.29)	16797.97 * (6671.10)
State Anti Price Gouging Law & State Emergency Declared	7.20 (8.97)	10.68 (10.49)	12.58 (8.43)
Observations	208	208	208
R^2 / R^2 adjusted	0.541 / 0.367	0.352 / 0.123	0.061 / 0.033

* *p<0.05* ** *p<0.01* *** *p<0.001*

Table 9: Searches for Toilet Paper, February 15, 2020 to March 15, 2020

	State and Time Fixed Effects	State Fixed Effects	No Fixed Effects
Predictors	*Estimates*	*Estimates*	*Estimates*
Intercept	11.67 (10.22)	20.36 (11.74)	15.62 *** (2.64)
State Anti Price Gouging Law	14.21 (57.32)	10.55 (65.93)	-0.81 (2.65)
State Emergency Declared	5.74 (10.54)	11.84 (12.20)	20.76 * (8.54)
Google Mobility Index for Grocery Stores	7.79 (4.68)	6.31 * (3.18)	1.43 (2.08)
Case Rate	-13240.75 (9066.74)	-6659.72 (10035.42)	-1383.09 (7952.42)
State Anti Price Gouging Law & State Emergency Declared	-8.79 (11.86)	-9.93 (13.81)	-16.64 (10.05)
Observations	208	208	208
R^2 / R^2 adjusted	0.437 / 0.223	0.212 / -0.066	0.063 / 0.035

* *p<0.05* ** *p<0.01* *** *p<0.001*

Table 10: Searches for Masks, February 15, 2020 to March 15, 2020

Predictors	State and Time Fixed Effects *Estimates*	State Fixed Effects *Estimates*	No Fixed Effects *Estimates*
Intercept	37.07 ** (13.91)	33.90 * (13.61)	46.67 *** (4.02)
State Anti Price Gouging Law	18.62 (78.00)	-0.13 (76.44)	8.05 * (4.03)
State Emergency Declared	16.25 (14.34)	12.78 (14.14)	22.98 (13.02)
Google Mobility Index for Grocery Stores	8.94 (6.36)	2.49 (3.68)	3.26 (3.16)
Case Rate	2674.72 (12336.92)	-3476.32 (11634.42)	-4378.70 (12115.46)
State Anti Price Gouging Law & State Emergency Declared	-15.27 (16.14)	-14.99 (16.01)	-27.99 (15.31)
Observations	208	208	208
R^2 / R^2 adjusted	0.558 / 0.390	0.550 / 0.392	0.077 / 0.050

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 11: Searches for Shoes, February 15, 2020 to March 15, 2020

Predictors	State and Time Fixed Effects *Estimates*	State Fixed Effects *Estimates*	No Fixed Effects *Estimates*
Intercept	-18.43 * (7.90)	-11.17 (10.00)	3.29 (2.58)
State Anti Price Gouging Law	-44.52 (44.32)	5.20 (56.14)	3.33 (2.59)
State Emergency Declared	1.27 (8.15)	12.44 (10.38)	11.28 (8.37)
Google Mobility Index for Grocery Stores	2.13 (3.61)	19.03 *** (2.70)	5.88 ** (2.03)
Case Rate	17412.93 * (7009.57)	40733.35 *** (8544.70)	36216.19 *** (7789.47)
State Anti Price Gouging Law & State Emergency Declared	2.66 (9.17)	5.63 (11.76)	8.53 (9.84)
Observations	208	208	208
R^2 / R^2 adjusted	0.719 / 0.613	0.524 / 0.355	0.250 / 0.228

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 12: Searches for Price Gouging, February 15, 2020 to March 15, 2020

	State and Time Fixed Effects	State Fixed Effects	No Fixed Effects
Predictors	*Estimates*	*Estimates*	*Estimates*
Intercept	-4.48 (13.48)	3.01 (14.42)	7.42 * (3.64)
State Anti Price Gouging Law	-55.51 (75.61)	2.53 (80.98)	2.64 (3.66)
State Emergency Declared	13.44 (13.90)	24.07 (14.98)	14.30 (11.81)
Google Mobility Index for Grocery Stores	-1.31 (6.17)	18.58 *** (3.90)	6.05 * (2.87)
Case Rate	32037.61 ** (11958.53)	53630.60 *** (12325.64)	39303.00 *** (10988.43)
State Anti Price Gouging Law & State Emergency Declared	-7.90 (15.65)	-6.46 (16.96)	2.46 (13.89)
Observations	208	208	208
R^2 / R^2 adjusted	0.533 / 0.355	0.433 / 0.232	0.146 / 0.121

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Even though these regressions use the same time period as Chakraborti and Roberts, there is no significant impact of price gouging laws once they come into effect on searches for hand sanitizer, masks, toilet paper, shoes, and price gouging. None of the coefficients on price gouging law, state emergency declared, or their interaction term is significant. Many of the coefficients had large standard errors, which is partially due to the shorter time period and smaller number of observations than in the regressions for all of 2020.

There are several differences between the regressions used by Chakraborti and Roberts and my regressions. For one, they ran regressions on searches for toilet paper and hand sanitizer, but not on searches for masks, shoes, and price gouging. However, I do not find a significant effect of price gouging laws on my regressions for toilet paper and hand sanitizer. They used a logged searches variable, even though searches were already scaled 0-100 (Chakaborti and Roberts, 2020). I did not log my searches variable, which might cause some differences in coefficients. Instead of Google Mobility Data, Chakraborti and Roberts used New York Times Interstate travel data.

Interstate travel data measures mobility but can only attain 5 discrete values, while the Google Mobility Index specifically focuses on grocery stores and has a continuous range of possible values (Chakraborti and Roberts, 2020). The key variable missing from Chakraborti and Roberts' regressions is case rate. Not including case rate makes their key regression coefficients susceptible to picking up effects from the COVID-19 pandemic unrelated to price gouging laws. Rather than use total population in their regression formula, Chakraborti and Roberts use a nearest neighbor propensity matching strategy for population density, racial demographics, household size, and other time invariant variables (Chakraborti and Roberts, 2020). It is possible that this nearest neighbor propensity matching strategy can account for part of the difference in our results. The differences between my results from early 2020 and those published by Chakraborti and Roberts likely stem from their omission of case rate as a control variable, their use of a nearest neighbor propensity matching strategy, and their omission of total population as a control variable.

6 Discussion

My results suggest that when accounting for state and time fixed effects, the effect of price gouging laws once they came into effect was insignificant on Google Shopping searches for COVID-19 related goods in 2020. Classical economic theory predicts that states with price gouging laws would have shortages for many goods where demand spiked due to the COVID-19 pandemic. I theorized that states with shortages would have more online product searches for COVID-19 related goods. There are several possible explanations for the insignificant coefficients on my variables of interest.

It is possible that states without price gouging laws had higher prices and customers in those states turned to online searches because of higher prices. Thus, shortages in states with price gouging laws did not lead to significantly more searches than in states without price gouging laws, where high prices also pushed consumers to online product searches.

Another explanation for my results is that states with specific price gouging laws did not actually enforce price gouging more than states without price gouging laws. Many attorneys general in states without price gouging laws made statements during the pandemic that they could prosecute price gouging under existing legislation, even though the legislation did not specifically prohibit price gouging laws (King & Spalding, 2021). Thus, the difference in price gouging enforcement for states with and without specific price gouging laws may have been negligible.

People may have decided not to participate in price gouging for reasons not relating to state laws. For example, social pressure and societal ideas of morality might prevent a business from raising prices during a pandemic. Some companies, such as Amazon, made internal price gouging rules to prevent vendors from price gouging. My dataset does not include information on whether price gouging actually occurred more in states without price gouging laws. It is possible that price gouging laws are simply not an accurate predictor of how much price gouging occurs in each state.

As discussed in Section 3, the size of the shortage and deadweight loss from a price ceiling is positively associated with the elasticity of the market's supply curve. It is possible that my insignificant results are a result of inelastic supply curves in the production of COVID-19 necessities. In other words, the effect of price gouging laws on causing lower supply quantities for these necessities was small. Supply's lack of response to price gouging laws could be due to either the inherently inelastic nature of market supply curves or societal pressure to not lower production of necessities during a public health crisis.

My results shows no significant evidence of an impact of price gouging laws on searches for COVID-19 related goods in 2020. It is possible that price gouging laws did not cause shortages as many economists predicted, or that price gouging laws caused shortages but did not lead to an increase in Google Shopping searches.

7 Conclusion

While basic economics predicts price gouging laws cause shortages, a large number of US states have price gouging laws which restrict price levels during disaster periods. My results suggest that when accounting for time and state fixed effects, price gouging laws did not account for a significant increase in Google Shopping searches for toilet paper, hand sanitizer, and masks in 2020. My empirical findings differ from a similar study which found a significant, positive impact of price gouging laws on consumer searches in early 2020 (Chakraborti and Roberts 2020). My work calls into question the robustness of these previous empirical findings.

While my results show no significant impact of price gouging laws on consumer searches, it is still unclear whether price gouging laws cause shortages. It is possible that price gouging laws do cause shortages, but these shortages do not lead to an increase in Google Shopping searches. Basic economic logic on price gouging laws is founded in competitive markets with elastic supply curves, which may not apply during disaster periods.

Many economists hold the view that price gouging laws are inefficient and cause shortages, and the market should just be left to operate. Previous economists have used Google Shopping Data to argue that price gouging laws have a positive effect on Google Shopping searches (Chakraborti and Roberts 2020). My paper suggests that the effect of price gouging laws once they come into effect on Google Shopping searches is insignificant. While many economists predict price gouging laws cause shortages, my results suggest that reality may be messier than basic economics predicts.

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