MISSING PRICE INFORMATION AND ITS IMPACT ON EQUILIBRIUM PRICE DISPERSION: EVIDENCE FROM GASOLINE SIGNBOARDS

MICHAEL D. NOEL* and HONGJIE QIANG†

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Abstract

This article seeks to quantify the importance of price information in reducing consumer search costs and equilibrium price dispersion in a competitive setting. It exploits a natural experiment in the retail gasoline industry in which stations post the prices of only certain grades of gasoline on large street-side signboards, and not others, except where required by law. Differential-by-grade signboard information predicts a specific curvature in price dispersion across grades, and differentiates itself from other non-informational factors such as income and cost. The impact of readily-available price information on search and price dispersion is found to be exceptionally large.

JEL Classification Codes: L11, L15, L81, L91, Q31

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I INTRODUCTION

THE 'LAW OF ONE EQUILIBRIUM PRICE' states that sellers of homogeneous goods will charge the same uniform price in a competitive equilibrium, but this law rarely holds in practice (Sorensen [2000]). Price dispersion is the norm in relatively homogeneous goods industries, and it is well known that both high-price and low-price sellers regularly make positive sales at different prices. Early studies examining this phenomenon (Stigler [1961] and Diamond [1971]) highlight the importance of consumer search in generating price dispersion, and later game-theoretic models (Varian [1980],

*Texas Tech University, Lubbock, Texas. michael.noel@ttu.edu.

†Central South University, hongjie.qiang@csu.edu.cn; research funding by the 'Basic Science Center Project: the theory and application of resource and environment management in the digital economy era (72088101)', from the National Natural Science Foundation of China.

Stahl [1987], Janssen et al. [2011]) show that search and price-dispersion are interdependent. The key insight is that consumers are not homogeneous even if the products are. When consumers differ in their personal costs of searching for the best price, they are not equally informed. Some sellers will offer lower prices to attract more informed consumers, and some will charge higher prices in hopes of snagging less informed ones. Chandra and Tappata [2011] show that the search-price dispersion relationship is non-monotonic in general, but tends to be negative in competitive markets, i.e. lower search costs work to increase consumer search and decrease equilibrium price dispersion.

In this article, we examine the relationship between search costs and price dispersion empirically. We focus on an important source of search costs – the ease of gathering price information. We take the retail gasoline industry as our application and consider one of the most recognizable physical features of gasoline stations in the U.S. – the large often-twenty-foot-tall street-side signboards advertising at least *some* of the prices of gasoline. They make gasoline prices among the most visible of any prices on the street, at least for those grades of gasoline whose prices are not normally excluded from the signboard. We take a closer look at the content of signboard information itself and ask whether the practice of displaying gasoline prices on signboards translates into meaningfully lower consumer search costs and lower price dispersion on those specific gasoline products whose prices are displayed, compared with those gasoline products whose prices are not. We find that it does, and conclude that signboard information, via its impact on consumer search, is empirically important in reducing price dispersion and compressing the price distribution for gasoline.

Gasoline signboards standing in the forecourt of gasoline stations are so ubiquitous and visible, it is surprising so little research has been done to examine their content and impact. Few studies have examined the effects of increased price transparency on gasoline prices in general (e.g. Rossi and Chintagunta [2016] on highway signs in Italy, Luco [2019] on internet-posted prices in Chile), and fewer still on the effects of price transparency in the United States.[1] Those that do generally do not address the impact of forecourt signboard information on gasoline prices, which is surprising given that forecourt signboard information is the primary source of gasoline price information for

[1] Maurizi [1972] considered laws that *prohibited* gasoline price advertising (a sign of the changing times) but with limited data not matched to jurisdictional boundaries, results were inconclusive.

U.S. consumers. It is also interesting that researchers often cite the large gasoline signboards in front of gasoline stations as evidence that gasoline prices are highly transparent and that search frictions cannot be an issue in their studies when, empirically speaking, complete signboard information is actually very rare.[2] Some U.S. jurisdictions have even imposed laws requiring firms to display more complete signboard information, yet we know very little about whether the signboards are important to consumers and whether these laws are ultimately useful.

The only study we are aware of that examines the content of U.S. gasoline price signboards on price dispersion specifically is Noel and Qiang [2019], which looks at the effect of signboards on price dispersion for a small Texas city. Their results are consistent with a signboard price information story, but carries a necessary limitation. The limitation, and the challenge in estimating the impact of signboard price information generally, is with the identification of effects. Signboards in a given area almost always contain the same sets of information, with little or no variation in what is and is not posted from one station to the next, and over time, and that is also true of the city they study. Their innovation was to examine cross-*grade* variation, exploiting the historical artifact in the gasoline industry that stations in most areas display only the price of regular grade gasoline on signboards, and not the price of midgrade or premium grade gasoline, unless laws dictate otherwise.

The artifact causes an obvious and discrete divide in consumers' ease of collecting price information, with regular grade gasoline on one side of the divide and both midgrade and premium grade gasoline on the other. They argue that if signboard information is important, one should see an equally obvious divide in price dispersion along that same divide, and thus a concave pattern in the price dispersion across the three ordered grades. They acknowledge that other factors affecting price dispersion differentially across grades – differences in the incomes of buyers for example – can pull on the curvature of the grade-price dispersion relationship as well and obscure the overall effect. Their study is essentially a horserace between competing effects, and a net overall effect is estimated. In short, it is difficult to isolate the independent effect of signboard information without the benefit of an explicit control group.

[2] For example, in the important paper by Chandra and Tappata [2011], they state that 'the phenomenon of gas stations prominently displaying their prices [...] controls for imperfect information'. However, only one of the four states in their dataset requires stations to post complete price information on signboards. Taking all grades of gasoline into account, only about half of the gasoline prices were actually posted on signboards at the stations in their study.

In this study, we have that explicit control group. We examine several large metropolitan areas that includes markets subject to complete signboard information laws and markets not subject to complete signboard information laws, enabling us to control for confounding effects and isolate the effect of signboard price information on price dispersion directly. We do this in a controlled natural experiment setting. Without such laws, the historical artifact is that signboards generally display only the price of regular grade gasoline. With such laws, stations are required to display the prices of all three major grades, i.e. midgrade and premium grade gasoline as well as regular grade gasoline. If signboard information is important, we should expect to find higher degrees of price dispersion in the incomplete-information area (the treatment area) relative to the complete-information area (the control area), but only on those higher grades of gasoline (treatment grades) that the law meaningfully affects. In contrast, regular grade gasoline (the control grade) is virtually always posted, and controls for city-specific differences in price dispersion. In other words, for the first time, we can estimate the underlying cross-grade pattern of price dispersion in the complete-signboard-information world, where all grades are prominently displayed and signboard information cannot be the cause of differential-by-grade price dispersion patterns, and subtract away that pattern from the price dispersion pattern we find in the incomplete-signboard-information world, to reveal the direct effect of signboard information on price dispersion.

The natural experiment is an advance upon previous work for this reason alone, but we can improve identification further because we actually have two distinct treatment groups – namely midgrade gasoline and premium grade gasoline – that are receiving the exact same treatment of 'no posting' in incomplete-signboard-information areas. Since each grade receives the identical treatment, we should expect to see very similar treatment effects for each. So more than just the usual comparison between a scalar control and a scalar treatment, we are actually performing a difference-in-differences estimation on entire coefficient patterns – comparing the concavity of coefficients in the incomplete-signboard-information world and the concavity of coefficients in the complete-signboard-information world. The empirical framework can be described as a multiple-equal-treatment difference-in-differences analysis, and is an advance over previous work.

Our analysis proceeds in three steps. First, we test whether the concavity results of Noel and Qiang [2019] carry over to multiple large metropolitan areas beyond their small sample city of

Lubbock, Texas. We find that it does. Second, we test the power of their concavity methodology by applying their test to a large metropolitan area where signboard information is complete as required by law, and cannot be responsible for differential price dispersion across grades. It is essentially a falsification exercise where the concavity test should fail and we find that it does fail. Third, and most importantly, we expand the analysis to include both incomplete signboard information (treatment) and complete signboard information (control) areas in a multiple-equal-treatment difference-in-differences framework and estimate the direct effect of signboard information on price dispersion. To preview the final takeaway, we find that signboard price information is far and away the dominant factor behind the different degrees of price dispersion across the three grades of gasoline. Income has surprisingly little independent effect, contrary to the usual (though ex ante reasonable) presumption in the literature (Chandra and Tappata [2011]).

The results are highly significant and we interpret them through the lens of a consumer search model. However, we also consider an alternate search story in which signboards reduce price dispersion not by increasing consumer search but primarily by increasing firm search. After all, more complete information can enable anyone to make more informed decisions, whether it be consumers who can now search for low prices more effectively, or competing firms who can now compete more effectively. If firms were instead attempting to coordinate prices, the more complete signboard information could similarly enable coordinating firms to coordinate more effectively.[3]

The remainder of the study is organized as follows. Section II discusses the previous literature, and Section III presents the relevant curvature theory. Section IV describes the data and methodology, and Section V presents results. Section VI concludes.

II LITERATURE

The theoretical search literature emphasizes the interdependence of consumer search and price dispersion. In an early article, Diamond [1971] shows that if all consumers have positive search costs, no matter how small, prices of homogeneous goods necessarily rise to monopoly levels, price dispersion falls to zero, and consumer search falls to zero – the so-called 'Diamond Paradox'. At

[3]We thank an anonymous referee for suggesting we include this alternate story.

the other extreme, if all consumers have zero search costs, prices fall to competitive levels and consumer search is again zero. Varian [1980], Stahl [1989], Janssen et al. [2011] and others solve the paradox by showing that, as long as some consumers have zero or negative search costs and some consumers have positive search costs, consumer search and price dispersion are both present in equilibrium. Chandra and Tappata [2011] show that the relationship between consumer search and price dispersion is non-monotonic – higher search tends to reduce price dispersion in competitive markets but tends to increase price dispersion in largely monopolistic ones.

Empirical studies tend to find a negative relationship, consistent with competitive markets. Since search can be difficult to measure, most studies use a proxy for search costs, or sometimes search benefits, which is expected to impact consumer search in the obvious way. Brynjofsson and Smith [2000] examine on-line stores and brick-and-mortar stores, and argue that price dispersion should be lower in the former, since the costs of searching on a computer are presumably lower than traveling from store to store. Sorensen [2000] examines pharmaceuticals used to treat acute and chronic conditions, and argues that price dispersion should be smaller in the latter case, since the benefits of searching are presumably higher for drugs that are purchased repeatedly. Other studies examining price dispersion with proxies for search costs or benefits include Dahlby and West [1986] on the auto insurance industry, Brown and Goolsbee [2002] on life insurance, Walsh and Whelan [1999], Zhao [2006], Dubois and Perrone [2018] and Sherman and Weiss [2017] on groceries, Baye et al. [2003] and Tang et al. [2010] on shopbots, Hortacsu and Syverson [2004] on stock market investors, Milyo and Waldfogel [1999] on liquor, and Orlov [2011] on airlines.

Specific to the retail gasoline industry, Barron et al. [2004] show that price dispersion falls when competing gasoline stations are more densely situated. Lewis [2008] shows that price dispersion is lower still when nearby gasoline stations are of the same brand type and Chandra and Tappata [2011] show that price dispersion is lowest when stations share an intersection. Lewis and Marvel [2011] show that price dispersion is higher when prices are falling, as opposed to rising, since consumers tend to be less concerned and less motivated to search when prices fall.[4] Pennerstorfer

[4] This is related to the very large 'rockets and feathers' literature, which shows that gasoline prices tend to rise quickly after a cost increase and fall slowly after a cost decrease. These include Bacon [1991], Borenstein et al. [1997], Peltzman [2000], Godby et al. [2000], Bachmeier and Griffin [2003], Galeotti et al. [2003], Radchenko [2005], Deltas [2008], Verlinda [2008], Noel [2009], Kristoufek and Lunachova [2015], Li and Stock [2019], and Eleftheriou et al. [2018]. See Eckert [2013] and Noel [2016] for surveys. Yang and Ye [2008], Tappata [2009], Lewis [2011], and

et al. [2020] show that gasoline price dispersion depends on the fraction of commuters in the area who are presumably more informed. Byrne et al. [2015], Byrne and de Roos [2015] and Noel [2018a] all exploit retail gasoline price cycles (Noel [2007]) to examine how shocks to price dispersion, for reasons other than search, affect consumer search itself.

While there has been much interest in how increased gasoline price information in the hands of consumers affects gasoline price dispersion, the bulk of the literature focuses on the effects of station and consumer proximity, taking the existence of highly visible price boards for granted. There is much less work on gasoline price visibility itself, and the often-twenty-foot-tall streetside signboards with one-to-two-foot-tall numbers have largely been overlooked.

The only study to our knowledge that examines the impact of price visibility stemming from the large signboards located in gasoline station forecourts is Noel and Qiang [2019]. That study exploits the fact that virtually all stations in their sample city of Lubbock, Texas, display the price of regular grade gasoline but virtually none display the price of midgrade or premium grade gasoline, causing significant differences in the ease of gathering price information across different grades. The authors develop a model that predicts a concave pattern in price dispersion across the three ordered grades of gasoline if signboard information were the dominant cause, and a convex pattern if income or various other causes were dominant. They ultimately find a concave pattern on balance and conclude that signboard information is a factor.

There are several other studies that examine gasoline price transparency but that do not consider forecourt signboards. Perhaps the closest is that of Rossi and Chintagunta [2016]) who examine highway signs placed by the Italian government along major Italian highways, displaying the prices of a few selected nearby gasoline stations located off an upcoming exit. The authors find that when the new signs were erected, price competition intensified and retail gasoline margins fell, as expected. Counterintuitively, they find no impact of the highway signs on price dispersion.

A few others examine the effects of gasoline price transparency in the form of newly-passed laws that require stations to post gasoline prices on the internet. Byrne et al. [2014] find that competition intensified and gasoline prices responded more quickly to wholesale price decreases with

Cabral and Fishman [2012] all develop dynamic models of consumer search that produce asymmetric passthrough in equilibrium.

the 2001 introduction of the 'FuelWatch' program in Western Australia, a program that required online posting of gasoline prices. Luco [2019] find an opposite result in Chile, that gasoline margins actually increased after the 2012 introduction of a Chilean law that required online posting of gasoline prices. The author argues that the law primarily benefited firms and enabled them to collude with one another on a mass scale across the entire country of Chile. We will address and ultimately dismiss such a story in our data.

III THEORETICAL BACKGROUND

As background for our empirical analysis, we extend the consumer search model of Janssen et al. [2011]. Consider a market with $N \geq 2$ firms providing homogeneous goods at an identical marginal cost c. There are two types of consumers – a proportion $\mu \in (0, 1)$ who are shoppers and have zero search costs, and the remainder $1 - \mu$ who are non-shoppers and have a positive search cost $s > 0$. Consumers search prices sequentially and can always come back to previously searched firms at zero cost. Janssen et al. [2011] show that the cumulative distribution function of Nash equilibrium prices in this situation is given by:

$$F(p) = 1 - \left(\frac{1}{N} \frac{1 - \mu}{\mu} \frac{\overline{p} - p}{p - c} \right)^{\frac{1}{N-1}} \tag{1}$$

where $\overline{p}$ is the upper bound of the price distribution equal to:

$$\overline{p}(c, s) = c + s/(1 - \alpha) \tag{2}$$

and s is the search cost. The constant α is given by:

$$\alpha = \int_0^1 \frac{dz}{1 + \frac{\mu}{1-\mu} N z^{N-1}} \tag{3}$$

The lower bound of the price distribution $\underline{p}$ is a weighted average of marginal cost and the upper bound price and is equal to:

$$\underline{p}(c,s) = \frac{\mu N}{\mu N + (1-\mu)} c + \frac{(1-\mu)}{\mu N + (1-\mu)} \overline{p}(c,s) \tag{4}$$

One measure of price dispersion is the difference in these two bounds, $r(c,s) = \overline{p}(c,s) - \underline{p}(c,s)$, which we call the max-min range and denote r.

In our study, we are interested in two things – how r depends on search cost s, and how search cost s correlates with the three ordered grades of gasoline g. First, it is easy to show that r is linear in the search cost s. We have:

$$\begin{aligned} r(s) &= \overline{p}(c,s) - \underline{p}(c,s) \\ &= c + \frac{s}{(1-\alpha)} - \frac{\mu N}{\mu N + (1-\mu)} c - \frac{(1-\mu)}{\mu N + (1-\mu)} \left(c + \frac{s}{(1-\alpha)} \right) \\ &= \frac{s}{(1-\alpha)} \cdot \frac{\mu N}{\mu N + (1-\mu)} = \lambda s \end{aligned} \tag{5}$$

where

$$\lambda = \frac{1}{(1-\alpha)} \cdot \frac{\mu N}{\mu N + (1-\mu)} \tag{6}$$

showing that r and s are linearly related. The same linear relationship holds if we use standard deviations instead of max-min ranges, as shown in the appendix.

Now we turn to how s correlates with g. The key insight is that search cost s is not linear in g but rather takes on either a convex or concave curvature, depending on the net effect of at least three factors.

The first factor is the native visibility of prices. The historical practice in the U.S. has been to post the price of regular grade gasoline on large streetside signboards but not the prices of midgrade and premium grade gasolines, unless otherwise required by law. This creates a non-linear divide in search costs across the three grades, with regular grade gasoline on one side of the divide and both midgrade and premium grade gasolines on the other. Considering this price information effect alone, we expect to see equal degrees of price dispersion on midgrade and premium grade gasoline, that are both substantially higher than that of regular grade gasoline. Denoting regular grade gasoline as R, midgrade as M, and premium grade as P, we have:

$$\begin{aligned} s_R &< s_M = s_P \\ \lambda s_R &< \lambda s_M = \lambda s_P \\ r_R &< r_M = r_P \end{aligned} \tag{7}$$

in the absence of confounding factors. This creates an extreme form of concavity in our price dispersion measure r across the three ordered grades (regular, midgrade, premium). We call this perfect Γ concavity because, in a plot of price dispersion on the vertical axis and the three ordered grades of gasoline on the horizontal axis, the curve approaches a slanted Γ shape. Of course, we may not expect to observe such an extreme concavity in practice even when price information were a dominant effect (absent controls), since other factors are likely to be pulling on the curvature at the same time.

The second factor, and the one generally discussed in the literature, is income. Buyers of the different grades of gasoline tend to have different incomes and different search costs. Since search cost s itself is linear in income (the primary cost of searching being the opportunity cost of time, i.e. hours searched multiplied by the hourly wage), the question is whether the buyers of the three grades of gasoline are distributed linearly or non-linearly across the terciles of the income distribution. The relationship turns out not to be linear, and the resulting pattern in r turns out to be convex.

To understand why, note that there is a fundamental physical identity across the three grades of gasoline. Midgrade gasoline (with an octane of 89) is nothing more than a 50-50 mix of regular grade gasoline (octane 87) and premium grade gasoline (octane 91), generally mixed on the fly in the hose at the pump, by drawing equally from regular and premium grade underground gasoline tanks. A gallon of midgrade gasoline is a perfect physical substitute to half a gallon of regular grade and half a gallon of premium grade combined. This means a consumer's type can be represented as a single probability number p, where $p = 1$ corresponds to a consumer who always purchases premium grade, $p = 0$ corresponds to a consumer who always purchases regular grade, and $p = 0.5$ corresponds to a consumer who always purchases midgrade, or alternatively who buys the other two grades in equal proportions over time. Now imagine an Engel curve with income Y on the vertical axis and probability p on the horizontal. Coats et al. [2005] estimates income elasticities across the three grades and their results imply that the Engel curve is convex when drawn in this way. A convex Engel curve is also shown empirically by Noel and Qiang [2019]. The convexity in the Engel curve in turn means that r takes on a convex pattern across the three ordered grades of gasoline, since Y, s, and r are all interchangeable up to scaling factor:

$$\frac{\partial^2 r}{\partial p^2} = \frac{\partial^2 \lambda s}{\partial p^2} = \frac{\lambda \partial^2 \tau \omega}{\partial p^2} = \lambda \tau \varphi \frac{\partial^2 Y}{\partial p^2} > 0 \tag{8}$$

where τ is the time required to conduct a search, ω is the hourly wage, φ is a scaling factor, and λ is as above. Therefore, the income effect in isolation should produce relatively similar degrees of price dispersion on regular grade and midgrade gasoline, that are both substantially lower than that of premium grade gasoline:

$$\begin{aligned} s_R &\approx s_M < s_P \\ \lambda s_R &\approx \lambda s_M < \lambda s_P \\ r_R &\approx r_M < r_P \end{aligned} \tag{9}$$

in the absence of confounding effects. Intuitively, the incomes of midgrade buyers are empirically 'closer' to those of regular grade buyers than to those of premium grade buyers, so the largest divide in search costs now falls between midgrade and premium grade gasoline, with regular grade and midgrade gasoline on one side of the divide and premium grade gasoline on the other. This means that income leads to a convexity in r.

There is a practical reality underlying the convexity. The vast majority of vehicles are designed to run only on regular grade gasoline, and higher grades of gasoline are neither necessary nor helpful for these vehicles. Only certain luxury vehicles and high performance vehicles require premium grade gasoline, and these are generally owned by the wealthiest individuals. There are almost no vehicles that require a minimum of midgrade gasoline, so midgrade is neither appropriate for high performance vehicles nor necessary for the rest. Those who buy midgrade gasoline anyway tend to own the same types of vehicles as those who exclusively buy regular grade gasoline, and come from a more similar range in the income distribution.[5] This leads to the convexity.

A third factor that has received little attention but can generate price dispersion is cost dispersion. Stations have different suppliers with different contract terms, and their product acquisition costs can vary. While we see no reason for cost dispersion to vary differentially by grade of gasoline (and there is evidence that it does not),[6] a cost dispersion effect would work towards a convex price dispersion pattern across the three grades as well. The reason is that the aforementioned physical identity necessarily means that a station's selling cost of midgrade gasoline is the simple average of the selling cost of the other two grades:

$$c_M = (c_R + c_P)/2 \tag{10}$$

Simple calculations show:

$$\begin{gathered} \max(c_M) \leq (\max(c_R) + \max(c_P))/2 \text{ and } \min(c_M) \geq (\min(c_R) + \min(c_P))/2 \\ \max(c_M) - \min(c_M) \leq (\max(c_R) - \min(c_R))/2 + (\max(c_P) - \min(c_P))/2 \end{gathered} \tag{11}$$

which in a competitive market with proportional margins implies that:

$$r_M \leq (r_R + r_P))/2 \tag{12}$$

[5] Midgrade is (infrequently) purchased by two general types of consumers. The first type consists of consumers who think higher octane means 'better' gas even though in general it is not. These are likely to be a little wealthier than the typical regular purchaser. The second type consists of consumers with very old vehicles and declining engine performance that experience 'engine knock'. The higher octane in midgrade is actually useful for older engines near the end of their usable lives that experience engine knock. These consumers are likely to be a little less wealthy than the typical regular purchaser. Overall, midgrade buyers tend to be similar to regular grade buyers on average. Midgrade is the least purchased of any fuel, with a 2% market share, compared to an 82% market share for regular and a 16% market share for premium. Midgrade is generally priced at or a little above the midpoint of the regular grade price and the premium grade price.

[6] Noel and Qiang [2021] show that wholesale price differentials between regular grade and midgrade and between regular grade and premium grade are virtually constant over time. Any cost-based price dispersion in regular grade gasoline should then carry over equally strongly into higher grades.

in the absence of other factors. In words, cost dispersion generates a convex pattern in r. The left hand side is equal to the right hand side (and the pattern of price dispersion is linear) if the maximum prices of all three grades always occur at the same station and the minimum prices of all three grades also occur at the same station (the max-min equivalent of perfect correlation). The inequality is strict and the pattern is strictly convex otherwise.

In summary, there are competing effects pulling on the curvature of the (s, g) relationship. Differential-by-grade signboard information works towards a perfectly concave pattern in price dispersion across the three grades, whereas income and cost dispersion effects both work towards a convex one. Without controls, we would only see the combined impact of all these effects. If signboard information is dominant, we would expect to see concavity on net, and if income and/or cost-dispersion were dominant, we would expect convexity on net.

However, with a suitable control area where signboard information is complete and where differential-by-grade price dispersion cannot be due to signboards, we can go further. We can extract the natural underlying pattern of convexity (if any) caused by these convex-leaning effects, and subtract that pattern from our treatment area pattern to isolate the underlying pattern of price dispersion generated solely by signboard information itself. We do that here for the first time.

IV DATA AND METHODOLOGY

As noted, we proceed in three steps. First, we perform the concavity test on the large metropolitan areas in our dataset that have incomplete signboard information. Second, we perform a falsification exercise in which we perform the concavity test on a large metropolitan area where signboard information is complete. Third and finally, we incorporate both our incomplete (treatment) and complete (control) signboard information metropolitan areas into a single model to estimate the effect of signboard price information directly.

< insert Table I about here >

We collect daily station-level retail gasoline prices for each of the three common grades of gasoline – regular, midgrade, and premium – in three U.S. metropolitan areas, Houston, Los Angeles, and Phoenix. The data consists of 27,089 individual prices across 1,721 stations which were reported to the GasBuddy.com website each Thursday between September 17, 2020 and November 5, 2020, a total of eight weeks. GasBuddy.com is a crowdsharing website where interested drivers can report recently observed gasoline prices for use by other drivers who also use the site.[7] GasBuddy price data has been widely used in academic research (e.g. Lewis and Marvel [2011], Atkinson et al. [2014], Noel [2018a]) and is shown to give a good representation of the distribution of gasoline prices at a point in time (Atkinson [2009]).[8] Summary statistics on prices from the complete dataset are given in Table I.

We test for concavity in a single metropolitan area using:

$$
\begin{aligned}
PDISP_{gmrct} &= \alpha_{0c} + \alpha_{1c} MIDGRADE_g + \alpha_{2c} PREMIUM_g \\
&\quad + \sum_{t=2}^{\overline{T}} \phi_{tc}^{T} T_t + \sum_{m=2}^{\overline{M}} \phi_{tc}^{M} M_m + \alpha_{3c} SCOUNT_{mrct} + \eta_{gmrct}
\end{aligned}
\tag{13}
$$

where $PDISP_{gmrct}$ is price dispersion measured either as the standard deviation of prices or the difference between maximum and minimum prices (the 'max-min range'), for gasoline grade g across all stations s within a market area m of a larger region r of a Metropolitan Statistical Area (MSA) c at time t. The unit of observation is a grade-market-time triplet. Each market is defined as having one of the sample stations at its center and includes all competing stations within a two mile radius of that central station.[9] Since markets centered on nearby stations can overlap, price dispersion measures across neighboring markets are not independent. We adjust standard errors to account for the non-independence by dividing each MSA into equally sized large regions and cluster standard errors at this larger regional level.[10] Summary statistics for our price dispersion measures are in Table II.

[7] Drivers may collect prices from station signboards or directly from pump displays. The latter requires the driver to enter the gas station (e.g. when going to fill up), and this can explain why higher-grade gasoline prices are more thoroughly covered in Los Angeles than in Houston. However, there is not a selection concern, since we see that the distribution of regular grade prices in Houston when only regular is reported is very similar to the distribution of regular grade prices in Houston when all three are reported.

[8] The site is popular enough with reporters to ensure near complete coverage of gasoline stations, but not so popular as to replace the need for signboard information.

[9] We use the term 'market' here for convenience, and in no way mean that these areas constitute markets in an antitrust sense. Using other reasonable radii has no meaningful effect on our results or conclusions.

[10] There are between 35 and 47 regions in each MSA. We experimented with other regional breakdowns and our results do not meaningfully change.

< *insert Table II about here* >

The two variables of interest are dichotomous variables $MIDGRADE_g$, equal to one if the price is for midgrade gasoline and zero otherwise, and $PREMIUM_g$, equal to one if the price is for premium grade gasoline and zero otherwise. The omitted grade is regular grade gasoline. We include daily fixed effects T_t and market fixed effects M_m. We define $SCOUNT$ to be the number of stations within a market, to control for possible competitive effects.[11] The η_{gst} are normally distributed error terms, potentially correlated within regions.

While virtually all stations sell all three grades of gasoline (noting that midgrade is costlessly mixed on the fly at the pump), we do not observe all three prices on a given day if not all three are reported. We handle this by discarding all prices for a given station on a given day unless we have all three prices for that station that day. This prevents our grade-specific measures of price dispersion from being based on different subsets of stations, which would create an obvious composition bias. Note that we drop individual station-days, not stations, so that stations without complete information on one day are generally represented in the dataset on the other days, so we would not expect any composition bias to be meaningfully large.[12]

A possible concern with the above framework is that we assume that a price that is not posted is also not widely known (or easily predictable) without additional search. While reasonable, a consumer could potentially infer the non-posted price of higher grades of gasoline from regular grade alone if stations are known to apply constant price differentials across grades. To account for this, we estimate a price *residuals* version of Equation 13 as well, using station-specific and grade-specific price residuals on the left hand side instead of prices, which removes this potential predictability. The residuals-based analysis keeps only unpredictable surprise deviations from a station's average price differentials across grades. We acquire the residuals by regressing prices on

[11] $SCOUNT$ is included for completeness only. The effects of competitive density have been well studied elsewhere (e.g. Lewis [2008], Deltas [2008]) and we do not wish to rehash that literature here. We refrain from a causal interpretation on $SCOUNT$ as well, given endogenous entry and essentially no market structure variation over our short (eight-week) and largely cross-sectional sample. The theoretical effect of competitive density on price dispersion is ambiguous in general (Borenstein and Rose [1994], Barron et al. [2004], Dai et al. [2004]). Variants of the competition control variable or no competition control variable at all does not affect our results of interest.

[12] The summary statistics shown in Tables I are based on the original raw data, before dropping any station-days due to this issue. We find the same patterns in prices and price dispersion with the reduced dataset as well, the only notable difference being that the number of observations are now the same for each grade, i.e. it is now balanced. This is seen in Table II which shows price dispersion measures based on the final dataset. Our regression results are similar whether we use the entire dataset (accepting the composition bias) or the final balanced dataset.

a set of station-specific indicator variables I_s, grade-specific indicator variables $MIDGRADE$ and $PREMIUM$, and all interactions of the two:

$$\begin{aligned} PRICE_{gsmrct} &= \zeta_1 + \zeta^{MID} MIDGRADE_g + \zeta^{PRE} PREMIUM_g + \sum_{s=2}^{\overline{S}} \zeta_s I_s \\ &\quad + \sum_{s=2}^{\overline{S}} \zeta_s^{MID} I_s \cdot MIDGRADE_g + \sum_{s=2}^{\overline{S}} \zeta_s^{PRE} I_s \cdot PREMIUM_g + \nu_{gsmrct} \end{aligned} \tag{14}$$

where $PRICE_{grsct}$ is the price of gasoline grade g at station s in market m of region r of metropolitan area c at time t. We then use price residuals instead of prices themselves to calculate price dispersion on the left hand side of Equation 13.

We quickly establish that there are significant differences in price dispersion across grades in incomplete-signboard-information areas, and the next step is to understand why. The price information hypothesis works toward a concave shape in the grade-specific price dispersion coefficients, i.e. in the ordered triplet $\{0, \alpha_1, \alpha_2\}$, taking the omitted regular grade price dispersion coefficient to be zero, and where α_1 and α_2 are the MSA-specific coefficients of $MIDGRADE$ and $PREMIUM$ from 13 respectively. The income-based and cost-based hypotheses work towards a convex pattern instead. Concavity requires $0 - 2\alpha_1 + \alpha_2 < 0$, or $2\alpha_1 > \alpha_2$, yielding our Concavity Test:

$$\begin{aligned} H_0 &: 2\alpha_1 = \alpha_2 \\ H_A &: 2\alpha_1 \neq \alpha_2 \end{aligned}$$

The null hypothesis is that there is no concavity on net, i.e. linearity. A statistically significant negative test statistic rejects linearity in favor of concavity, and a statistically significant positive test statistic rejects linearity in favor of convexity.[13]

If the price information hypothesis dominates to the near exclusion of other effects, we would not only expect a concave pattern, but something approaching perfect Γ concavity, $\alpha_1 = \alpha_2 \gg 0$. In other words, we would expect the two treatment effects – on midgrade gasoline and premium grade gasoline – to be approximately equal since they both received the same treatment of not

[13] As written, the test allows for net convexity, but our language reflects the fact that our test statistics will be negative and the question will come down to significant versus insignificant concavity.

being posted with no confounding effects are present. We test this with our Perfect Concavity Test:

$$H_0 \ : \ \alpha_1 = \alpha_2$$
$$H_A \ : \ \alpha_1 < \alpha_2$$

The Perfect Concavity Test statistic is only meaningful when the Concavity Test statistic is significant and negative.[14] The interpretation of it is also different. In the Concavity Test, a rejection of linearity in favor of concavity provides support for a concave relationship among the coefficients, i.e. the price information hypothesis. In the Perfect Concavity Test, a rejection of equality in the coefficients rejects that there is a perfectly concave relationship among the coefficients and provides support for a less perfect concave relationship. If we have both concavity and perfect Γ concavity, we should reject the first and not reject the second.

The above analysis has the advantage that it requires only variation in the content of signboard information across *grades* and not variation in the content of signboard information across *stations.* However, and new to this study, we have exogenous variation in the content of signboards across stations and exploit it here. We use data from the Los Angeles metropolitan area, an MSA that has been subject to a complete signboard information law for over fifty years. Los Angeles serves as a control for the pattern of price dispersion across grades that we would expect in a city such as Houston in the absence of incomplete signboard information.

After performing a single-MSA falsification exercise using Los Angeles, we pool the Houston and Los Angeles data together and estimate a multiple-equal-treatment difference-in-differences model – comparing differences in price dispersion across the three grades of gasoline in Houston where signboard information is incomplete, to differences in price dispersion across the three grades of gasoline in Los Angeles where signboard information is complete. The estimating equation is given

[14] Perfect concavity is obviously rejected if the coefficients are convex, so the case $\alpha_1 > \alpha_2$ is irrelevant.

by:

$$
\begin{aligned}
PDISP_{gmrct} \quad = \quad & \beta_0 + \beta_1 MIDGRADE_g + \beta_2 PREMIUM_g \\
& + \beta_3 MIDGRADE \cdot INCOMPLETE_c + \beta_4 PREMIUM_g \cdot INCOMPLETE_c \\
& + \sum_{t=2}^{\overline{T}} \theta_t^T T_t + \sum_{m=2}^{\overline{M}} \theta_m^M M_m + \beta_5 SCOUNT_{gmrct} + \eta_{gmrst} \qquad (15)
\end{aligned}
$$

where $INCOMPLETE_c$ is an indicator variable equal to one if MSA c does not have a law requiring complete posting of gasoline prices for all three grades, and zero otherwise. The coefficients of interest are on the interaction terms. They measure the excess price dispersion on midgrade and premium grade gasoline up and above that of regular, in the treatment MSA up and above that of the control MSA.[15] We conduct our concavity tests on the interactions.

Houston and Los Angeles are different gasoline markets, but this is not an issue in and of itself. We never compare Houston prices to Los Angeles prices directly or Houston price dispersion to Los Angeles price dispersion directly. We only compare the difference in price dispersion across the three different grades of gasoline in Houston on one hand, to the difference in price dispersion across the three different grades of gasoline in Los Angeles on the other. The identifying assumption is that the pattern of price dispersion across grades of gasoline in Los Angeles reflects what the pattern of price dispersion would be in Houston if not for incomplete signboard information. There is no reason to suspect that the patterns would meaningfully differ.

Finally, given that the station-specific price data is collected on the same day of the week each week, a concern might arise if there were day-of-the-week pricing patterns such as Edgeworth price cycles that might make Thursdays unusual in some way. Edgeworth price cycles have been found in numerous markets in the U.S. Midwest over the past twenty years and often follow a day-of-the-week pricing pattern (e.g. Lewis and Noel [2009], Noel [2018b]). However, Edgeworth price cycles are not present in any grade in any of the sample cities. An examination of GasBuddy price

[15] In particular, we are estimating the total effect of a shock to consumer search on equilibrium price dispersion, taking into account all rebound and feedback effects. This is standard in the literature and is more interesting than estimating just a partial 'first round' effect. See Noel [2018a] for a good discussion of feedback effects. In this setting, an initial shock to consumer search cost in the form of differential signboard information impacts search, which in turn impacts price dispersion, which in turn impacts the benefits of searching and search, which in turn impacts price dispersion, and so on, until a new steady state is reached. It is the total effect from the original to the final steady state equilibrium that is of interest.

data at the city level and on a daily basis over the relevant time period confirms that there are no day-of-the-week price effects from cycles or otherwise.

V RESULTS

We begin with the Houston metropolitan area. Virtually all gasoline stations in Houston post the price of regular grade gasoline on streetside signboards but only a very small percentage post the prices of midgrade and premium grade gasolines as well.[16] Prices of higher grades are genreally only visible at a station by driving up to the gas pump and checking a roughly one-inch tall digital price display.

< insert Table III about here >

Price dispersion results for Houston are shown in Table III. Specifications (1) and (2) use standard deviations as the measure of price dispersion and Specifications (3) and (4) use max-min ranges. Odd-numbered specifications use price levels on the left hand side of Equation 13 and even-numbered ones use price residuals. We are interested in the coefficients on the grade indicator variables (including the omitted regular grade gasoline 'coefficient' of zero), and any non-linearity across them. Test statistics for the Concavity Test and the Perfect Concavity Test are presented near the center of each column. A significant negative Concavity Test statistic implies that the price information hypothesis is dominant (concavity) and a significant positive test statistic implies that income- and/or cost-based hypotheses are dominant (convexity). Conditional on concavity, an insignificant Perfect Concavity Test means that we cannot reject complete dominance of the price information hypothesis to the near exclusion of other effects, i.e. we cannot reject that the treatment effects on our two treatment grades are the same.

Specification (1) uses the standard deviation of price levels on the left hand side of Equation 13. The $MIDGRADE$ coefficient is estimated at 9.900 and the $PREMIUM$ coefficient is estimated at 10.790, both large and statistically significantly different from zero. The Concavity Test easily rejects linearity in favor of concavity (the coefficient triplet being $(0.00, 9.90, 10.79)$) and the Perfect

[16] In our review of Google Street View images, less than one in ten stations in Houston displayed all three prices.

Concavity Test cannot reject that the pattern is also perfectly Γ concave. The two coefficients are extremely close economically, and statistically indistinguishable from one another even with tight standard errors. The Concavity Test supports the hypothesis that signboard price information is an important source of differential-by-grade price dispersion. The Perfect Concavity Test supports the hypothesis that signboard price information is the dominant source of differential-by-grade price dispersion to the near exclusion of other effects.

Other specifications in Table III confirm this. Specification (2) uses the standard deviation of price residuals on the left hand side instead of the standard deviation of prices themselves, and yields a $MIDGRADE$ coefficient of 0.702 and a $PREMIUM$ coefficient of 0.694, both large and statistically significantly different from zero.[17] The Concavity Test rejects linearity in favor of concavity and the Perfect Concavity Test cannot reject that the pattern is perfectly Γ concave. The coefficients are statistically indistinguishable from one another with a tiny difference of 0.008.

Specification (3) uses the max-min range of prices on the left hand side instead of the standard deviation of prices. It yields a $MIDGRADE$ coefficient of 28.585 and a $PREMIUM$ coefficient of 30.222, easily rejecting linearity in favor of concavity $(0.00, 28.59, 30.22)$. It is also consistent with perfect Γ concavity, with the latter two coefficients being only a cent and a half per gallon apart, yet being approximately thirty cents per gallon higher than that of regular grade. Specification (4) uses the max-min range of price residuals instead of prices themselves, and shows a $MIDGRADE$ coefficient of 2.132 and a $PREMIUM$ coefficient of 2.115, significantly concave and again consistent with perfect Γ concavity.

The above analysis points to the importance – and dominance – of the price information hypothesis. But the analysis also assumes that the price information hypothesis is the only hypothesis that can predict a concave relationship. Indeed, this is the identifying assumption used by Noel and Qiang [2019]. While we are not aware of other reasonable concave-inducing hypotheses, we can test the assumption just the same by performing a falsification exercise using the Los Angeles metropolitan area. Los Angeles has complete signboard information and any differential-by-grade price dispersion there cannot be caused by differential-by-grade signboard information. The con-

[17] Since these are based on price residuals rather than price levels, the point estimates are not directly comparable with those of the previous specification.

cavity test should fail in this case and we find that it does fail.

< *insert Table IV about here* >

We report results in Table IV. Specification (5) uses the standard deviation of prices as the measure of price dispersion on the left hand side of Equation 13. We find a $MIDGRADE$ coefficient of -0.128 and a $PREMIUM$ coefficient of 0.311, both vastly smaller than the corresponding coefficients for Houston from Specification (1) of Table III. The $MIDGRADE$ coefficient is just $1/77^{th}$ as much (in absolute value) and the $PREMIUM$ coefficient is just $1/35^{th}$ as much. Only the $PREMIUM$ coefficient is statistically significant and then only at the 10% level. Economically speaking, the estimates are very small, fractions of a penny, and price dispersion across all three grades are meaningfully the same. The Concavity Test rejects linearity in favor of convexity this time, noting that the convexity is very weak.

Specification (6) uses the standard deviation of price residuals on the left hand side instead of prices themselves, and yields a similar result. The $MIDGRADE$ coefficient is estimated at -0.028 and the $PREMIUM$ coefficient is estimated at 0.008, economically very small, neither one statistically significantly different from zero, and not statistically significantly different from each other. The Concavity Test can no longer reject linearity. In fact, we cannot reject that price dispersion is exactly the same for every grade. Specifications (7) and (8) use the max-min ranges of prices and price residuals instead of the standard deviations of prices and price residuals, and produce coefficients that are again economically very small. We find a statistically significant but weak convex relationship in the coefficients in Specification (7), which disappears when using price residuals in Specification (8).

In summary, there is no evidence of concavity in any specification in the complete information setting, and in fact, no evidence of economically meaningful differences in price dispersion across the three grades at all. The falsification exercise performs exceptionally well – when signboard information is complete and cannot be the cause of differential-by-grade price dispersion in a concave pattern, we find no hint of a concave pattern, and little hint of anything else.

We can also check for differences in *within-station* price dispersion over time. Search models not only predict price dispersion across stations, but also price dispersion within a given station over time as stations mix over the price distribution. We preface by saying that this is largely handled already by our price residuals analysis, which removes any stable station-specific and grade-specific price component over time, and looks only at a station's price surprises, or randomizations, around its mean. That analysis shows significant degrees of price dispersion and concavity. Had there been no within-station price dispersion, we would have seen uniformly zero coefficients on our grade-specific variables instead.

One can also check the degree of within-station price variation directly. If we look at within-station price variation over the eight weeks in Houston, we can see the tell-tale concave pattern on a station-specific basis. The mean within-station standard deviation in Houston is 2.83, 2.93 and 2.92 across the three grades respectively, showing the expected divide between regular grade gasoline on one hand and midgrade and premium grade gasolines on the other. Noting that these means include many zeros (for those stations that did not change prices over our short eight-week data window), we can look in particular at the stations in the upper tail of the standard deviation distribution where prices did change during our short window. For these stations, the concavity becomes even more apparent. We find that the standard deviation *of* the standard deviation in Houston is 2.65 for regular, but 3.33 for midgrade and 3.43 for premium. In other words, there is significantly more within-station price dispersion on the higher grades for those stations whose prices did change. Contrast this to Los Angeles where the corresponding figures are 3.70, 3.67, and 3.70 across the three grades. There is no meaningful within-station price dispersion concavity at all in Los Angeles.

The within-station results for Houston are especially notable given that our data period is relatively short, only eight weeks and during a time of relatively flat wholesale prices. We would not expect to see very many within-station price changes within such a short window, given that consumers purchase fuel only every few weeks and it can take months for consumers to gather relatively complete local information on prices. In other words, we would expect that the period of a station's randomization process would exceed the eight-week period of our sample. Even still, we observe significant concavity in just eight weeks and would expect further concavity as more stations re-randomize over time (and the 'zeros' noted above are no longer 'zeros').[18]

The above analyses are all single-MSA analyses, but to isolate the direct effect of signboard price information distinct from confounding factors, we incorporate both incomplete and complete signboard information areas into a single analysis. We pool together price data from both Houston and Los Angeles and use the combined dataset to estimate the direct effect of signboard price information in a multiple-equal-treatment difference-in-differences model. Houston is our treatment city (with the incomplete information treatment) and Los Angeles is our control city (with the complete information control). Midgrade and premium grade gasolines are our treatment grades and regular grade is our control grade. Essentially, we are using the complete-signboard-information environment of Los Angeles as a benchmark for what the pattern of price dispersion would otherwise look like in Houston if signboard information were not a factor. Both midgrade and premium grade gasoline receive the identical treatment in Houston of not being posted so we would expect to find large and very similar treatment effects on these two grades.

< insert Table V about here >

We report results in Specifications (9) through (12) of Table V. The variables of interest are the interaction terms $MIDGRADE \cdot INCOMPLETE$ and $PREMIUM \cdot INCOMPLETE$, which reflect the excess price dispersion on higher grades of gasoline vis-a-vis regular grade gasoline in Houston, all relative to any excess price dispersion in the higher grades of gasoline vis-a-vis regular grade gasoline in Los Angeles.

Specification (9) uses the standard deviation of prices as the measure of price dispersion on the left hand side of Equation 15. We find that the midgrade interaction coefficient is 10.028 and the premium interaction coefficient is 10.479, both economically large, statistically significantly different from zero, and statistically indistinguishable from each other. They are more than ten cents per gallon higher than the regular grade 'coefficient' of zero, yet the difference between them is less than half of one cent per gallon. We strongly reject linearity in favor of concavity, and cannot reject perfect Γ concavity as well $(0.00, 10.03, 10.48)$, even with tight standard errors. In

[18] In our experience, stations generally use cost shocks as a trigger for simultaneous randomization – i.e. when price changes are forced, they can adjust each price a little more or a little less than the cost increase on each adjustment, creating margin dispersion and differential-by-grade price dispersion.

other words, the two treatment effects are expected to be the same and they are the same. They are expected to be large and they are large. The results support the hypothesis that price information is singularly the dominant cause of the differences in price dispersion across the three grades of gasoline. Specification (10) uses the standard deviation of price residuals on the left hand side instead of the standard deviation of prices themselves, and we again easily reject linearity in favor of concavity. We again cannot reject perfect Γ concavity in the coefficients.

Specification (11) uses the max-min range of prices instead of the standard deviation of prices and shows that the max-min ranges of both midgrade and premium grade are approximately 28 cents per gallon higher than that of regular grade, yet the difference between them is just $1/6^{th}$ of one cent per gallon. We find essentially perfect Γ concavity again in this case. Specification (12) uses the max-min range of price residuals instead of the max-min of prices themselves and shows a similarly strong concavity in the coefficients.

In summary, our main analysis supports the price information hypothesis almost exclusively – that the differential-by-grade price dispersion we observe in areas with incomplete information is almost entirely due to the relative ease with which consumers can collect price information from price signboards. Our results are consistent with consumer search theory – in that lower search costs lead to more consumer search and ultimately lower price dispersion – but inconsistent with the general presumption in the gasoline literature that the differential-by-grade price dispersion we observe is likely due to differences in the incomes of the buyers of the different grades. We find that incomes of buyers have little to do with differential-by-grade price dispersion and that signboard price information matters a great deal.

< insert Table VI about here >

We now perform a battery of robustness tests to check the strength of the above results. First, since it is well known that Los Angeles prices tend to be higher than Houston prices, one possible concern with the above analysis is that higher prices in Los Angeles may leak into our price dispersion estimates and, conceivably, into our price dispersion difference estimates. We address this concern by normalizing the average price of gasoline in each metropolitan area to be equal to one ($\widehat{p}_{gsmrct} = p_{gsmrct}/p_c$), and using these standardized prices, instead of actual prices, to calculate the price dispersion measures on the left hand side of Equation 15. If there were a mechanical link between absolute price levels and price dispersion levels, it would be removed here by standardizing. We present results using standardized prices instead of raw price levels in Table VI. In short, none of our results meaningfully change and all conclusions carry through. The Concavity Test rejects linearity in favor of concavity in all four specifications and the Perfect Concavity Test does not reject perfect Γ concavity in any.

< insert Table VII about here >

Second, we re-perform our analysis under a wide range of different assumptions about local market size (the unit of observation over which price dispersion is calculated). We reestimate the model with circle markets of different radii, from one to six miles instead of two, and with rectangular disjoint markets where each station is assigned to exactly one market in a complete grid, and in each case find very similar results. We also reestimate the model using a more sophisticated network model, a hierarchical clustering model similar to that used by Lemus and Luco [2021], which creates multiple levels of clusters based on stations' geographic proximity to one another. At the bottom level, stations are paired into small local clusters, and at the next higher level those clusters are themselves grouped into larger clusters (i.e. clusters of clusters) based on the relative proximity of the centerpoints of the clusters below it. At each higher level larger clusters are grouped together into even larger clusters until there is a single top-level cluster including all stations. The hierarchical nesting tree formed by these clusters is then 'pruned' at its bottom-most levels to form a single, disjoint set of mid-level clusters, i.e. markets, based on the relative closeness of the lower-level clusters under them and the greater distance to the mid-level clusters beside them.[19] We then reestimate the model using geographic markets derived from this algorithm and, in this case as well, find very similar results. We show the results in Table VII. We reject linearity in favor of concavity in all four specifications and cannot reject the extreme case of perfect Γ concavity in any. All of our conclusions carry through.

[19] The procedure is described under the 'Hierarchical Clustering' entry in the MATLAB R2021b software documentation by MathWorks Inc. Each station is assigned to exactly one market under this method. In our setting, we have 35 markets in Houston, 46 in Los Angeles and (later) 38 in Phoenix.

Third, we address possible concerns relating to the fact that Houston stations, while not required, are also not prohibited from displaying complete signboard information. We perform a manual, site-by-site visual examination of every station in Houston using Google Street View technology and found that less than one out of every ten stations in Houston displayed complete signboard information even though not required to. (In contrast, we found no stations in Los Angeles that did not display complete signboard information which they are required to). We reestimate our model excluding these stations and the markets centered around them, and again find very similar results as before (results not shown to preserve space).[20] Coefficients (measured in cents per gallon) are generally within a few tenths of a cent of their previous counterparts, and all our conclusions carry through.

Fourth, we address possible concerns relating to the fact that there are more observed prices in Los Angeles than in Houston generally. Part of this is simply because the Los Angeles MSA is larger, and part of this is because Los Angeles has greater coverage (itself due to the ease in collecting prices with complete signboard information). This is not a problem in and of itself since it is well known that GasBuddy data does a good job representing the true price distribution in a given market even with incomplete coverage (Atkinson [2009]). Even if that were not true, the stations covered in the data would be those most frequently patronized by consumers and of primary interest anyway. Nonetheless, we can control for the uneven sample sizes by performing a covariate matching exercise, in which we match like for like local markets within Houston and Los Angeles based on similar covariates. Our covariates include the number of stations in a market, the average distance of a station from market center, and the distance of a market center to the city center (the latter being the most notable since rural area stations around an MSA's perimeter are likely to have less coverage). Under covariate matching, we again find very similar results (not shown for space). We reject linearity in favor of concavity in all four specifications and cannot reject the extreme case of perfect Γ concavity in any.

Fifth, we address possible concerns relating to the fact that the price data was collected in late 2020 during Covid-19 (albeit at a time when the U.S. was open for business and gasoline demand and prices were back to pre-pandemic levels). While there is no reason to suspect that the difference

[20] Results from this and other robustness checks are available from the corresponding author upon request.

in the price dispersion patterns we find in Houston and Los Angeles would be pandemic-caused and not carry over to other periods, we can nonetheless check this empirically, by reference, in two parts. First, it is easy to see that the late 2020 Houston result is not anomalous because the concavity pattern in Houston from late 2020 closely matches the concavity pattern that Noel and Qiang [2019] found for the city of Lubbock, Texas, in both shape and magnitude. Data for the latter was collected back in 2016 and was unaffected by the then-unknown pandemic. Second, it is easy to check that the flat price-dispersion pattern in Los Angeles from late 2020 was also not anomalous. We use a small sample of station-specific and grade-specific gasoline prices for approximately one hundred stations in the city of San Diego, California, that we collected weekly between November 2017 and January 2018 for other purposes. San Diego is close to Los Angeles and subject to the same complete-signboard regulation as Los Angeles. We perform the equivalent of our 2020 Los Angeles falsification exercise with our pre-Covid-19 San Diego sample and find no significant concavity in San Diego at that time either (p-values in excess of 0.9). The sample is small but indicates that there was nothing anomalous going on in price dispersion patterns in Southern California in late 2020 because of Covid-19.

Sixth, we address possible concerns relating to the potential for policy endogeneity. Regulations are not randomly assigned across jurisdictions, so if the California signboard law was a response to, rather than a cause of, changes in our left-hand-side variables, causality is reversed and our interpretation would be incorrect. In general, policy endogeneity is of most concern when evaluating the response to a new law (e.g. as with policies studied by Rossi and Chintagunta [2016] or Luco [2019]), but is implausible in our setting given the specific comparisons we are making, the nature of our left-hand-side variable, and the fact that the law has been in place for over fifty years. The reverse causality argument would go like this – fifty years ago, legislators felt that price dispersion on the higher grades of gasoline was too low and too similar to regular grade gasoline, so they passed a signboard law to require higher grade prices be posted as well, with the goal of raising price dispersion on higher grades to the much higher levels seen on higher grades in other cities (a goal which incidentally the law failed to achieve even today, fifty years later). The line of logic obviously makes little policy sense, but it is the only way in which our result (relatively low price dispersion on higher grades in LA) could have caused the law, instead of the other way around. The reality is that California is a regulation-heavy state when it comes to fuels, and the stated purpose of the law was to enable consumers to price shop more easily (i.e. to lower consumer search costs), which it did. The causal direction is clear and policy endogeneity is not the concern here as it would be for a new law or for a typical natural experiment framework with a before-and-after time dimension (noting that our natural experiement does not have a time dimension – our dimensions are locations and grades).

Seventh, and finally, we address possible concerns that Houston might be anomalous in some way. While we have no reason to suspect this to be the case, we can check it by expanding our dataset to include prices from a third metropolitan area, Phoenix. On one hand, Phoenix is more similar to Los Angeles geographically and culturally and prices there are closer to those in Los Angeles than those in Houston. On the other hand, Phoenix is more similar to Houston informationally, since stations are not required to provide complete signboard information and very rarely do. Under the price information hypothesis, we should see a concave shape in the grade specific coefficients in Phoenix, just as we did for Houston.

We report results for this new set of robustness checks in the tables appendix. Our single-MSA results for Phoenix are in Table VIII. In short, we find similar results for Phoenix as we did for Houston. The Concavity Test rejects linearity in favor of concavity at better than the 1% level of significance in every specification. We cannot rule out the extreme form of perfect Γ concavity as well in the two specifications using price residuals to remove potentially predictable standard cross-grade price differentials at a given station.

Next, we pool Phoenix and Los Angeles prices together and perform a difference-in-differences estimation, and present results in Table IX. We again find very similar results to the earlier difference-in-differences estimates for Houston and Los Angeles. The coefficient patterns continue to be exceptionally concave, and similar to the corresponding Table V results involving Houston. We reject linearity in favor of concavity in all specifications and do not reject the most extreme form of concavity in three out of four specifications, including both specifications that use price residuals.

We then pool the data from all three metropolitan areas together and perform a difference-in-differences specification using them all. We report results in Table X. The coefficient patterns are again exceptionally concave and all our conclusions carry through as strongly. We reject linearity in all specifications and cannot reject that the coefficients are perfectly Γ concave at the 5% level in any. The degree of concavity is strong, both statistically and economically speaking.

Finally, we repeat the analysis of Table VI (using standardized prices instead of price levels in our measures of price dispersion) and Table VII (using markets based on hierarchical clustering rather than fixed radii) but for all three metropolitan areas pooled together, and report the results in Tables XI and XII. In short, the results again show exceptional concavity. We reject linearity in favor of concavity in every specification in both tables, and cannot reject perfect Γ concavity in three of four specifications in each table, including all specifications that using price residuals.

Our interpretation of the above results is straightforward. Gasoline signboard information, by lowering consumer search costs, increases consumer search and compresses the price distribution on those gasoline products whose prices are posted (all three grades in Los Angeles but only regular grade gasoline in Houston and Phoenix), compared with those that are not (midgrade and premium grade in Houston and Phoenix only). Our interpretation is consistent with the vast majority of studies in the gasoline literature examining other types of shocks to consumers' search costs (e.g. Barron et al. [2004], Lewis [2008], Chandra and Tappata [2011]), which all generally find benefits to increased price visibility on competition.

A notable exception to these studies is Luco [2019], who argues that increased price transparency actually caused gasoline margins to increase in Chile at the same time when price dispersion fell, following the required online price posting law there. That study argues that the law primarily benefited Chilean firms who used the information to coordinate prices and tacitly collude on a mass scale. While our study is very different than that one (different price transparency policies in different countries and using different identification techniques, for example), we address the possibility of a similar price coordination story here.[21]

The potential for retail gasoline price coordination continues to be a concern to regulators (and a favorite talking point of politicians) even though the FTC has conducted dozens of investigations into the industry over the years without finding any evidence of widespread wrongdoing. There are isolated cases from time to time though. Clark and Houde [2014] document a price fixing

[21] We thank an anonymous referee for suggesting we address this alternate story.

conspiracy in four small cities in Quebec, Canada, where station operators were alleged to have explicitly colluded by communicating with each other by telephone. While that study has little to do with signboards (communication was by telephone and signboards display only regular grade prices in Quebec), such isolated cases perpetuate interest among researchers in looking for signs of more widespread coordination in gasoline markets.

Price transparency laws have been cited as one possible way that coordination could become easier. OECD Secretariat [2001] notes that 'although enhanced price transparency will generally increase competition to the benefit of consumers, it can have the opposite effect in some special situations'. It goes on to discuss a case that was brought before Swedish courts about retailers sharing sales volume information with one another (though dismissed by the court) and an investigation into Brazilian retailers allegedly using shared price information to monitor a cartel agreement. Price transparency laws of some form are actually fairly common in OECD countries, and as the OECD notes, the effects could in principle go either way.

In essence, more information enables anyone to make more informed decisions, whether it be consumers who can search more effectively, competing firms who can compete more effectively, or coordinating firms who can coordinate more effectively. The effects of signboard transparency laws should thus depend on 1) whose information is most improved by the law and 2) if it is firms' information that is most improved, what it is to be done with that information, i.e. if it is being used by competing firms to compete better or coordinating firms to coordinate better.

In our setting, we expect that consumers' information would be most improved by more complete signboard information, which would result in lower search costs and prices, and make the second question moot. The reason is that signboards are primarily sources of price information for consumers and not for retailers. The vast majority of retailers in these large cities are large themselves, operating a network of retail stations, and generally getting competitor price information in real time from a price subscription service such as the Oil Price Information Service Retail Radius Report ('RRR'). The RRR is a service that electronically collects and then distributes real-time gasoline price information to its subscribers to stay abreast of competitor price changes in their local areas. No major retailers in Houston or Los Angeles drive around looking at signboards anymore, as in decades past. Pricing decisions are more commonly made by off-site managers or management teams who relay gasoline price changes to in-store personnel or simply change them remotely via computer. In contrast, consumers *do* look at signboards and signboards are the primary source of consumer price information. Given these differences in how consumers and retailers collect gasoline price information today, we would expect consumers' information to be more improved by more complete signboards and consumers to primarily benefit from them.[22]

If this is correct, we should expect to see lower prices on gasoline grades that are posted vis-a-vis gasoline grades that are not posted, controlling for grade and city differences. We test this and find it to be true. While prices in Los Angeles are high in general (due to higher taxes and higher environmental fuel standards), we also find that the prices on the posted higher grades of gasoline in Los Angeles are relatively good deals. Posted premium grade prices in Los Angeles are only 27 cents per gallon higher than regular grade prices there, whereas unposted Houston premium grade prices are 63 cents per gallon higher (and unposted Phoenix premium grade prices are 55 cents per gallon higher), in addition to being more variable. The midgrade-regular price differentials tell a similar story. In short, the price transparency law in Los Angeles leads to lower prices on posted grades compared to what they would have been if unposted.[23] This is consistent with a consumer search story and inconsistent with a coordination story. It is also consistent with the simple fact that U.S. retailers generally already have complete information on the prices of different grades via subscription, and the primary effect of complete signboards is to provide that information locally to consumers as well.

In summary, we conclude that differential-by-grade signboard information, through its effects on consumer search costs, is singularly the most dominant factor in explaining differential-by-grade price dispersion on gasoline. When signboard information is incomplete, we observe a precise divide in price dispersion across the three grades of gasoline exactly where the divide in signboard information occurs – with regular grade gasoline on one side of the divide and midgrade and premium grade gasolines on the other. Where signboard information is complete, there is no such

[22] Even for a small mom and pop retailer who might still use signboards for market information, it makes little sense to drive to each relevant station to collect the information on the (incomplete) signboard and not bother to drive up to the pump to collect the other prices, given the cost-benefit tradeoff of doing so.

[23] One could argue that the prices of all three grades would naturally be closer together in Los Angeles if stations there were coordinating on the price of all three, but the same logic would predict that Houston and Phoenix stations would more easily coordinate on regular grade gasoline, and regular grade gasoline only, meaning that the price differentials in Houston and Phoenix should still be smaller, and they are not.

divide there or anywhere. The concavity we find is essentially perfect in that we find almost identical treatment effects across our two distinct treatment grades – midgrade and premium grade. Since these two grades both receive the identical treatment of no signboard information in Phoenix and Houston, we should expect to find a very similar treatment effect for each, and this is exactly what we find. We find the effects to be large.

Our results provide evidence that more easily-accessible information in the hands of consumers has important effects on consumer search and, through consumer search, on price dispersion. Greater information in the hands of consumers enables them to search more effectively, at lower cost, and ultimately make more informed decisions on how to best distribute their limited resources.

VI CONCLUSION

This study seeks to quantify the importance of visible and readily-accessible price information for consumer search and equilibrium price dispersion. We examine the information-search-price dispersion mechanism empirically in an important setting that is familiar to almost all of us, but that has received surprisingly little attention to date – the effect of the often twenty-foot-tall gasoline price signboards located in the forecourts of gasoline stations.

The long-standing practice of stations in most areas has been to post the price of regular grade gasoline on large streetside signboards but not the prices of midgrade and premium grade gasoline. The practice creates a natural divide in consumers' ease of collecting price information across the three grades of gasoline – with regular grade gasoline on one side of the divide and higher grades of gasoline on the other. If displaying price information prominently in front of consumers matters for search, this should lead to lower degrees of price dispersion on regular grade gasoline whose price is easily observed and higher degrees of price dispersion on the higher grades whose prices are not as easily observed. This is what we find.

The result is especially interesting given the default assumption in the literature that higher price dispersion on higher grades is likely income related. We find that income matters relatively little. When consumers are presented with complete signboard information, there is little difference in price dispersion across all three grades of gasoline, even though premium grade gasoline is disproportionately bought by higher income consumers. Only when price information is missing from streetside signboards does price dispersion on the higher grades shoot up dramatically.

Our study adds to the growing body of evidence that search and search costs matter for prices, price dispersion, and market outcomes. Ours is among only a handful of studies that examine the causes of gasoline price dispersion in general, and one of very few to examine the impact of highly visible signboard price information in particular. It is also one of the few studies that explicitly examine midgrade and premium grade gasoline prices in their own right. We would argue there is much to learn from a broader analysis of gasoline products beyond just regular grade gasoline, as our results show, and we postulate that it may be worth revisiting some older studies with this in mind.

Our study also helps us better quantify the potential benefit of so-called 'gasoline price transparency regulations'. Gasoline price transparency regulations have been implemented in numerous jurisdictions around the world, and seek to make gasoline prices even more transparent than they already are. Some jurisdictions require stations to post complete sets of prices on price signboards, while others require them to post their prices on a government run website, and some even require retailers to provide advance online notice of future price increases, something largely unheard of with other consumer products.

We recognize that our results may be interpreted as a call for more regulation in the retail gasoline industry, but we would advise not to jump so quickly, and for three reasons. First, the gasoline industry would be an unusual place to focus efforts on increasing price transparency. Regular grade gasoline already has the most visible price of virtually any consumer product on the street, and prices of higher grades are less transparent only in juxtaposition with the price of regular. While this sets up an excellent natural experiment to identify the effects of information on price dispersion, which is our goal here, it is important to keep in mind that the prices of gasoline, generally speaking, are among the most transparent in the universe of consumer product prices. They are also fully tax-inclusive, unlike most other brick-and-mortar consumer products.

Second, it is important to remember that transparency regulations are not costless. They come with a not-insignificant compliance cost which must be weighed against any potential benefits in a complete cost-benefit analysis, which is beyond the scope of the study here.

Third, and related to the above, increased price transparency could actually have an unexpected negative effect on lower income consumers because of the unique nature of the gasoline price structure. Gasoline retailing is competitive, and higher margins on premium grade and midgrade gasoline are often used to subsidize lower margins on regular grade gasoline (as a loss leader), while still allowing stations to cover fixed costs and break even. A regulation that would require complete signboard information could potentially force down margins on higher grades of gasoline bought by higher income consumers, but at the expense of lower income consumers whose regular grade gasoline prices would have to rise in the rebalancing. While these issues are beyond the scope of this study, they should give the reader pause before interpreting our results as necessarily a call for more regulation in this particular industry.

Having said this, there are some obvious situations of outright price obfuscation outside the gasoline industry where the cost-benefit analysis of a new transparency regulation is likely be more favorable. Two obvious such situations are 'drip pricing' practices and 'ex post pricing' practices. Well-known examples of 'drip pricing' include hotel resort fees and rental car add-on fees, where the actual price of a service is substantially higher than the advertised price, and the actual price is not revealed until later in the buying process when the buyer is more behaviorally committed to buy. Examples of 'ex post pricing' include medical billing in general, and surprise medical billing in its most extreme form, where the actual price of a service is not known with any certainty until after the service is consumed, even with meaningful effort by the consumer to inquire about prices. In these cases, prices are difficult or impossible for consumers to obtain before committing, literally or behaviorally, to buy. Since markets do not appear to fix the issue, discussions about improved price transparency in such cases would surely be appropriate.

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APPENDIX

Price dispersion is also linear in search cost s when price dispersion is measured as standard deviations instead of max-min ranges. Let $\sigma^2(p)$ be the variance of the price distribution. Then

$$\begin{aligned}\sigma^2(p) &= E(p^2) - [E(p)]^2 \\ &= \int_0^1 p^2 \cdot dF(p) - \left[\int_0^1 p \cdot dF(p)\right]^2\end{aligned} \tag{16}$$

where F is defined in the text. Taking

$$z = 1 - F(p) = \left(\frac{1}{N}\frac{1-\mu}{\mu}\frac{\overline{p}-p}{p-c}\right)^{\frac{1}{N-1}} \tag{17}$$

we have

$$\begin{aligned}\sigma^2(p) &= \int_0^1 \left[\frac{\overline{p}-c}{1+\frac{\mu}{1-\mu}Nz^{N-1}}+c\right]^2 dz - \left[\left(\int_0^1 \frac{\overline{p}-c}{1+\frac{\mu}{1-\mu}Nz^{N-1}}+c\right)dz\right]^2 \\ &= (\overline{p}-c)^2 \cdot \left(\int_0^1 \left[\frac{1}{1+\frac{\mu}{1-\mu}Nz^{N-1}}\right]^2 dz - \alpha^2\right)\end{aligned} \tag{18}$$

where α is defined in the text. Taking

$$\beta = \int_0^1 \left(\frac{1}{1+\frac{\mu}{1-\mu}Nz^{N-1}}\right)^2 dz \tag{19}$$

we have

$$\begin{aligned}\sigma &= \sqrt{\beta-\alpha^2}\,(\overline{p}-c) \\ &= \sqrt{\beta-\alpha^2}\frac{s}{1-\alpha} = \kappa s\end{aligned} \tag{20}$$

so σ and s are linear.

TABLES APPENDIX

< *insert Table VIII here* >

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Table I
Summary Statistics - Prices

	Num. Obs.	Mean	Std. Dev.	Minimum	Maximum
Houston	6131	200.67	31.94	148.00	319.00
Regular Grade Price	3505	179.57	13.62	148.00	249.00
Midgrade Price	1282	214.44	22.44	174.00	294.00
Premium Grade Price	1344	242.56	24.35	180.00	319.00
Los Angeles	14496	332.34	26.50	249.00	439.00
Regular Grade Price	5410	318.52	24.05	249.00	409.00
Midgrade Price	4450	335.13	23.09	269.00	409.00
Premium Grade Price	4636	345.78	24.46	279.00	439.00
Phoenix	6462	252.91	27.02	194.00	354.00
Regular Grade Price	3093	230.01	11.15	194.00	309.00
Midgrade Price	1572	261.25	12.52	229.00	334.00
Premium Grade Price	1797	285.03	16.68	228.00	354.00

All prices in cents per gallon.

Table II

Summary Statistics - Market Area Price Dispersion Measures

	Num. Obs.	Mean	Std. Dev.	Minimum	Maximum
Houston					
Standard Deviation of Prices in Market Area					
Regular Grade	1,574	4.51	1.99	0.00	11.74
Midgrade	1,574	9.44	4.04	1.51	21.60
Premium Grade	1,574	9.89	3.35	1.14	20.22
Max-Min Range of Prices in Market Area					
Regular Grade	1,574	11.75	5.06	0.00	24.93
Midgrade	1,574	26.00	11.42	3.49	53.84
Premium Grade	1,574	26.81	9.61	2.49	46.86
Los Angeles					
Standard Deviation of Prices in Market Area					
Regular Grade	7,662	6.30	1.66	0.00	13.36
Midgrade	7,662	6.27	1.69	0.00	13.36
Premium Grade	7,662	6.40	1.74	0.66	13.60
Max-Min Range of Prices in Market Area					
Regular Grade	7,662	18.92	5.61	0.00	39.11
Midgrade	7,662	19.07	5.68	0.00	39.11
Premium Grade	7,662	19.60	5.89	1.20	39.11
Phoenix					
Standard Deviation of Prices in Market Area					
Regular Grade	2,004	2.72	1.65	0.00	9.23
Midgrade	2,004	3.79	1.92	0.00	12.58
Premium Grade	2,004	4.31	2.13	0.00	13.87
Max-Min Range of Prices in Market Area					
Regular Grade	2,004	7.66	4.88	0.00	24.12
Midgrade	2,004	10.55	5.53	0.00	31.63
Premium Grade	2,004	12.01	6.23	0.00	32.42

All price dispersion measures in cents per gallon.

Table III
Price Dispersion Across Stations by Grade of Gasoline, Houston

Dep. Var.: PDISP	(1)	(2)	(3)	(4)
	Standard Deviation	Standard Deviation	Max-Min Range	Max-Min Range
MIDGRADE	9.900***	0.702**	28.585***	2.132**
	(1.764)	(0.278)	(5.070)	(0.781)
PREMIUM	10.790***	0.694**	30.222***	2.115**
	(1.665)	(0.335)	(4.503)	(0.998)
SCOUNT	-0.070	0.072**	1.374**	0.477**
	(0.111)	(0.031)	(0.279)	(0.112)
Concavity Test	-9.010***	-0.711***	-26.947***	-2.148***
H_0: *2*MIDGRADE=PREMIUM*	(2.020)	(0.305)	(6.188)	(0.858)
Perfect Concavity Test	0.890	-0.009	1.637	-0.016
H_0: *MIDGRADE=PREMIUM*	(0.561)	(0.160)	(1.892)	(0.505)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	N	N	N	N
Daily Indicator Variables	Y	Y	Y	Y
Market Indicator Variables	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.686	0.428	0.691	0.383
Num. Obs.	4722	4722	4722	4722

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.

Table IV
Price Dispersion Across Stations by Grade of Gasoline, Los Angeles

Dep. Var.: PDISP	(5) Standard Deviation	(6) Standard Deviation	(7) Max-Min Range	(8) Max-Min Range
MIDGRADE	-0.128	-0.028	0.487	-0.104
	(0.136)	(0.068)	(0.532)	(0.263)
PREMIUM	0.311*	0.008	2.278***	0.002
	(0.168)	(0.070)	(0.682)	(0.285)
SCOUNT	0.044	0.077**	1.589**	0.623**
	(0.039)	(0.017)	(0.205)	(0.067)
Concavity Test	0.568***	0.064	1.303***	0.211
H_0: *2*MIDGRADE=PREMIUM*	(0.162)	(0.077)	(0.575)	(0.295)
Perfect Concavity Test	0.440***	0.036	1.791***	0.106
H_0: *MIDGRADE=PREMIUM*	(0.094)	(0.029)	(0.338)	(0.123)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	N	N	N	N
Daily Indicator Variables	Y	Y	Y	Y
Market Indicator Variables	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.626	0.535	0.602	0.541
Num. Obs.	22986	22986	22986	22986

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.

Table V

Price Dispersion by Grade, Houston v. Los Angeles Difference-in-Differences

Dep. Var.: PDISP	(9)	(10)	(11)	(12)
	Standard Deviation	Standard Deviation	Max-Min Range	Max-Min Range
MIDGRADE	-0.128	-0.028	0.487	-0.104
	(0.136)	(0.068)	(0.532)	(0.263)
PREMIUM	0.311*	0.008	2.278***	0.002
	(0.167)	(0.070)	(0.682)	(0.285)
INCOMPLETE	-15.393**	-0.465**	-44.655**	-1.928**
	(1.252)	(0.209)	(3.563)	(0.647)
MIDGRADE*INCOMPLETE	10.028**	0.731**	28.097**	2.236**
	(1.716)	(0.278)	(4.946)	(0.802)
PREMIUM*INCOMPLETE	10.479**	0.686**	27.944**	2.113**
	(1.624)	(0.332)	(4.420)	(1.009)
SCOUNT	0.041	0.079**	1.576**	0.621**
	(0.037)	(0.016)	(0.187)	(0.063)
Concavity Test	-9.578***	-0.776***	-28.250***	-2.359***
H_0: *2*MIDGRADE=PREMIUM*	(1.966)	(0.306)	(6.029)	(0.883)
Perfect Concavity Test	0.450	-0.045	-0.153	-0.123
H_0: *MIDGRADE=PREMIUM*	(0.552)	(0.158)	(1.866)	(0.505)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	N	N	N	N
Daily Indicator Variables	Y	Y	Y	Y
Market Indicator Variables	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.675	0.520	0.672	0.536
Num. Obs.	27708	27708	27708	27708

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.

Table VI

Standardized Price Dispersion by Grade, Difference-in-Differences Houston v. Los Angeles

Dep. Var.: PDISP	(13)	(14)	(15)	(16)
	Standard Deviation	Standard Deviation	Max-Min Range	Max-Min Range
MIDGRADE	-0.039	-0.009	0.147	-0.031
	(0.041)	(0.020)	(0.160)	(0.079)
PREMIUM	0.094*	0.002	0.685***	0.001
	(0.050)	(0.021)	(0.205)	(0.086)
INCOMPLETE	-3.797**	0.337**	-11.900**	0.653**
	(0.612)	(0.101)	(1.679)	(0.296)
MIDGRADE*INCOMPLETE	4.974**	0.359**	14.103**	1.094**
	(0.854)	(0.136)	(2.457)	(0.386)
PREMIUM*INCOMPLETE	5.285**	0.343**	14.381**	1.054**
	(0.807)	(0.163)	(2.187)	(0.490)
SCOUNT	0.013	0.024**	0.497**	0.192**
	(0.012)	(0.005)	(0.058)	(0.019)
Concavity Test	-4.662***	-0.374***	-13.826***	-1.134***
H_0: *2*MIDGRADE=PREMIUM*	(0.978)	(0.149)	(2.997)	(0.424)
Perfect Concavity Test	0.311	-0.015	0.277	-0.040
H_0: *MIDGRADE=PREMIUM*	(0.272)	(0.078)	(0.921)	(0.247)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	Y	Y	Y	Y
Daily Indicator Variables	Y	Y	Y	Y
Market Indicator Variables	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.682	0.503	0.648	0.494
Num. Obs.	27708	27708	27708	27708

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.

Table VII

Price Dispersion by Grade, Diff-in-Diff Houston v. Los Angeles, Hierarchical Clustering

Dep. Var.: PDISP	(17)	(18)	(19)	(20)
	Standard Deviation	Standard Deviation	Max-Min Range	Max-Min Range
MIDGRADE	-0.214	-0.047	-0.415	-0.231
	(0.202)	(0.079)	(0.719)	(0.302)
PREMIUM	0.178	-0.006	1.438*	-0.110
	(0.230)	(0.079)	(0.838)	(0.336)
INCOMPLETE	-14.746**	-2.175**	-32.953**	-6.891**
	(1.417)	(0.399)	(5.070)	(1.637)
MIDGRADE*INCOMPLETE	9.534**	0.869**	27.827**	2.868**
	(1.350)	(0.385)	(3.663)	(1.229)
PREMIUM*INCOMPLETE	10.491**	0.900**	28.398**	2.811*
	(1.311)	(0.445)	(3.465)	(1.498)
SCOUNT	0.105	0.047*	1.552**	0.531**
	(0.078)	(0.027)	(0.325)	(0.125)
Concavity Test	-8.577***	-0.839***	-27.257***	-2.926***
H_0: 2*MIDGRADE=PREMIUM	(1.817)	(0.416)	(4.986)	(1.342)
Perfect Concavity Test	0.957	0.030	0.570	-0.057
H_0: MIDGRADE=PREMIUM	(0.829)	(0.193)	(2.239)	(0.714)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	N	N	N	N
Daily Indicator Variables	Y	Y	Y	Y
Hierarchical Clustering Methoc	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.693	0.495	0.686	0.506
Num. Obs.	1194	1194	1194	1194

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.

Table VIII
Price Dispersion Across Stations by Grade of Gasoline, Phoenix

Dep. Var.: PDISP	(21)	(22)	(23)	(24)
	Standard Deviation	Standard Deviation	Max-Min Range	Max-Min Range
MIDGRADE	2.705***	0.571***	7.304***	1.634***
	(0.401)	(0.108)	(1.166)	(0.304)
PREMIUM	4.008***	0.727***	11.003***	2.025***
	(0.613)	(0.147)	(1.591)	(0.414)
SCOUNT	-0.074	0.038	1.168**	0.476**
	(0.124)	(0.039)	(0.346)	(0.132)
Concavity Test	-1.402***	-0.414***	-3.605***	-1.243***
H_0: *2*MIDGRADE=PREMIUM*	(0.515)	(0.139)	(1.660)	(0.401)
Perfect Concavity Test	1.303***	0.157	3.699***	0.391
H_0: *MIDGRADE=PREMIUM*	(0.400)	(0.093)	(1.133)	(0.271)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	N	N	N	N
Daily Indicator Variables	Y	Y	Y	Y
Market Indicator Variables	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.561	0.322	0.551	0.346
Num. Obs.	6012	6012	6012	6012

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.

Table IX
Price Dispersion by Grade, Difference-in-Differences Phoenix v. Los Angeles

Dep. Var.: PDISP	(25) Standard Deviation	(26) Standard Deviation	(27) Max-Min Range	(28) Max-Min Range
MIDGRADE	-0.128	-0.028	0.487	-0.104
	(0.136)	(0.068)	(0.531)	(0.262)
PREMIUM	0.311*	0.008	2.278***	0.002
	(0.167)	(0.070)	(0.680)	(0.284)
INCOMPLETE	-13.315**	-1.598**	-43.854**	-4.983**
	(0.479)	(0.158)	(2.133)	(0.558)
MIDGRADE*INCOMPLETE	2.833**	0.599**	6.817**	1.739**
	(0.416)	(0.126)	(1.262)	(0.397)
PREMIUM*INCOMPLETE	3.697**	0.720**	8.725**	2.023**
	(0.625)	(0.160)	(1.703)	(0.496)
SCOUNT	0.019	0.077**	1.503**	0.619**
	(0.039)	(0.016)	(0.196)	(0.063)
Concavity Test	-1.970***	-0.478***	-4.908***	-1.454***
H_0: *2*MIDGRADE=PREMIUM*	(0.530)	(0.157)	(1.727)	(0.491)
Perfect Concavity Test	0.864***	0.121	1.908	0.284
H_0: *MIDGRADE=PREMIUM*	(0.403)	(0.096)	(1.162)	(0.293)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	N	N	N	N
Daily Indicator Variables	Y	Y	Y	Y
Market Indicator Variables	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.779	0.492	0.762	0.528
Num. Obs.	28998	28998	28998	28998

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.

Table X
Price Dispersion by Grade, Difference-in-Differences All Cities

Dep. Var.: PDISP	(29)	(30)	(31)	(32)
	Standard Deviation	Standard Deviation	Max-Min Range	Max-Min Range
MIDGRADE	-0.128	-0.028	0.487	-0.104
	(0.136)	(0.068)	(0.532)	(0.263)
PREMIUM	0.311*	0.008	2.278***	0.002
	(0.167)	(0.070)	(0.681)	(0.285)
INCOMPLETE	-12.904**	-0.493**	-37.537**	-1.942**
	(0.894)	(0.121)	(2.615)	(0.416)
MIDGRADE*INCOMPLETE	5.998**	0.657**	16.178**	1.957**
	(1.211)	(0.148)	(3.574)	(0.453)
PREMIUM*INCOMPLETE	6.680**	0.705**	17.180**	2.063**
	(1.157)	(0.179)	(3.257)	(0.559)
SCOUNT	0.018	0.077**	1.498**	0.615**
	(0.037)	(0.015)	(0.181)	(0.060)
Concavity Test	-5.317***	-0.609***	-15.177***	-1.852***
H_0: *2*MIDGRADE=PREMIUM*	(1.354)	(0.170)	(4.178)	(0.520)
Perfect Concavity Test	0.682*	0.048	1.001	0.105
H_0: *MIDGRADE=PREMIUM*	(0.346)	(0.093)	(1.123)	(0.294)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	N	N	N	N
Daily Indicator Variables	Y	Y	Y	Y
Market Indicator Variables	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.750	0.485	0.748	0.521
Num. Obs.	33720	33720	33720	33720

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.

Table XI
Standardized Price Dispersion by Grade, Difference-in-Differences All Cities

Dep. Var.: PDISP	(33)	(34)	(35)	(36)
	Standard Deviation	Standard Deviation	Max-Min Range	Max-Min Range
MIDGRADE	-0.039	-0.009	0.147	-0.031
	(0.041)	(0.020)	(0.160)	(0.079)
PREMIUM	0.094*	0.002	0.685***	0.001
	(0.050)	(0.021)	(0.205)	(0.086)
INCOMPLETE	-2.408**	0.361**	-7.933**	0.753**
	(0.446)	(0.051)	(1.243)	(0.160)
MIDGRADE*INCOMPLETE	2.809**	0.289**	7.740**	0.861**
	(0.618)	(0.066)	(1.813)	(0.194)
PREMIUM*INCOMPLETE	3.160**	0.311**	8.379**	0.912**
	(0.593)	(0.080)	(1.662)	(0.244)
SCOUNT	0.004	0.024**	0.474**	0.193**
	(0.012)	(0.005)	(0.057)	(0.018)
Concavity Test	-2.457***	-0.267***	-7.100***	-0.810***
H_0: *2*MIDGRADE=PREMIUM*	(0.676)	(0.076)	(2.076)	(0.223)
Perfect Concavity Test	0.351***	0.022	0.639	0.051
H_0: *MIDGRADE=PREMIUM*	(0.152)	(0.042)	(0.497)	(0.130)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	Y	Y	Y	Y
Daily Indicator Variables	Y	Y	Y	Y
Market Indicator Variables	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.688	0.458	0.675	0.467
Num. Obs.	33720	33720	33720	33720

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.

Table XII

Price Dispersion by Grade, Difference-in-Differences All Cities, Hierarchical Clustering

Dep. Var.: PDISP	(37)	(38)	(39)	(40)
	Standard Deviation	Standard Deviation	Max-Min Range	Max-Min Range
MIDGRADE	-0.214	-0.047	-0.415	-0.231
	(0.202)	(0.079)	(0.718)	(0.301)
PREMIUM	0.178	-0.006	1.438*	-0.110
	(0.230)	(0.079)	(0.836)	(0.336)
INCOMPLETE	-12.031**	-2.255**	-24.845**	-7.231**
	(1.133)	(0.327)	(4.380)	(1.373)
MIDGRADE*INCOMPLETE	5.534**	0.760**	16.041**	2.425**
	(0.768)	(0.195)	(2.256)	(0.626)
PREMIUM*INCOMPLETE	6.417**	0.900**	16.852**	2.706**
	(0.833)	(0.219)	(2.345)	(0.717)
SCOUNT	0.107	0.040	1.576**	0.497**
	(0.072)	(0.024)	(0.296)	(0.107)
Concavity Test	-4.651***	-0.620***	-15.230***	-2.144***
H_0: 2*MIDGRADE=PREMIUM	(0.930)	(0.218)	(2.760)	(0.718)
Perfect Concavity Test	0.883***	0.140	0.811	0.281
H_0: MIDGRADE=PREMIUM	(0.435)	(0.099)	(1.213)	(0.352)
Using Price Residuals	N	Y	N	Y
Using Standardized Prices	N	N	N	N
Daily Indicator Variables	Y	Y	Y	Y
Hierarchical Clustering Methoc	Y	Y	Y	Y
Only with All Grades Reported	Y	Y	Y	Y
R-Squared	0.774	0.439	0.768	0.489
Num. Obs.	1644	1644	1644	1644

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Robust standard errors in parentheses.