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PRICE DISPERSION AND COMPETITION WITH DIFFERENTIATED SELLERS*

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I measure price dispersion among differentiated retail gasoline sellers and study the relationship between dispersion and the local competitive environment. Significant price dispersion exists even after controlling for differences in station characteristics, and price differences between sellers change frequently. The extent of price dispersion is related to the density of local competition, but this relationship varies significantly depending on the type of seller and the composition of its competitors. These findings are consistent with interactions between seller and consumer heterogeneity that are not well understood in the existing price dispersion literature.

I. INTRODUCTION

The term *price dispersion* normally describes firms in the same market selling identical goods for different prices (at the same time). Casual observation reveals that gas stations within the same local area often charge different prices for gasoline. Is this evidence of price dispersion? The most straightforward explanation for these price differences may be that gas stations (and the gasoline they sell) are not homogeneous. Stations differ in convenience and amenities, and some consumers may be willing to pay a premium for a brand of gasoline that they perceive to be of higher quality. One would only consider price dispersion to be present in a differentiated product market if price variation remained even after controlling for these differences in consumers' willingness to pay for one product over another.

Unfortunately, the theoretical literature on price dispersion does not extend to differentiated product markets. While consumer search models and spatial competition models help illustrate the potential underlying motivation for price dispersion, their direct

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predictions do not necessarily apply in this case.[1] I discuss a number of theoretical and empirical issues that arise when examining price dispersion in a differentiated product setting, and apply these ideas to the retail gasoline market. The empirical results reveal that substantial gasoline price variation remains even after product differentiation is controlled for, and that the extent of the remaining price dispersion is related to the local density of competing stations. However, this relationship varies significantly across types of sellers. The findings suggest an important interaction between the extent of price dispersion and presence of seller or product differentiation that is not captured in existing theoretical models of homogeneous product price dispersion.

To empirically identify price dispersion in this setting it must be isolated from the price variation caused by product or seller heterogeneity. One approach is to control for price variation of this type using observed seller and product characteristics. Barron, Taylor & Umbeck [2004] adopt this strategy in their study of retail gasoline price dispersion. The potential problem with this approach is that unobserved station differences may be responsible for some of the remaining price variation, resulting in an overestimate of price dispersion.

The alternative approach adopted here takes advantage of panel data by using seller fixed effects control for any price differences resulting from observed or unobserved seller heterogeneity. This measure of dispersion excludes any constant price differences between sellers that result from variation in consumers' tastes or variation in seller costs or demand conditions. As a result, some sources of price dispersion are absent from this measure. For example, price dispersion resulting from homogeneous products being sold by spatially differentiated sellers with different costs will be picked up by seller fixed effects to the extent that these cost differences are constant over time. Therefore, the fixed effects measure can be seen as a relatively conservative estimate of price dispersion.

Once seller fixed effects are removed, the remaining price dispersion captures the intensity of relative price movements between sellers. While theoretical models of price dispersion are predominantly static in nature, they imply certain situations in which we might expect price differences to change over time. Sellers may change their relative prices to prevent consumers from learning the equilibrium price distribution whenever searching consumers repeatedly purchase a particular product in the same market. Alternatively, spatially differentiated sellers will change relative prices over time when they experience idiosyncratic cost or demand shocks.

[1] Spatially differentiated firms selling homogeneous products will exhibit price dispersion whenever the firms have different costs or face different demand intensities. See Carlson & McAfee [1983].

My empirical analysis of gas station prices reveals significant price dispersion even after using station fixed effects to control for seller heterogeneity. Moreover, individual stations' prices move frequently and significantly relative to each other over time. After controlling for individual station fixed effects, 33% of sellers in the highest or lowest quartiles of their local price distribution move to the opposite half of the price distribution within 4 weeks. Regardless of the cause of dispersion, frequent relative price movements suggest that consumers are more likely to have imperfect price information because it is more difficult for consumers to learn over time which stations have relatively high or low prices (after controlling for station heterogeneity).

After establishing the presence of price dispersion, I examine how the extent of dispersion relates to local market or seller characteristics. I focus specifically on how the number (or density) of nearby competitors influences price dispersion. Theories of dispersion often differ in their predictions on how the extent of competition influences equilibrium price dispersion, suggesting that empirical examination may be particularly valuable.

I determine the relationship between retail gasoline price dispersion and seller density to be more complex than has been previously considered. My initial results are consistent with a similar study by Barron et al. [2004], who find a negative relationship between dispersion and seller density. However, I show that this relationship varies significantly across different types of stations. To separate station types I create a *high-brand* group made up of premium branded stations and a *low-brand* group consisting of discount brands and independent (unbranded) stations.[2] When the relationship between seller density and dispersion is identified for each of these groups separately, the estimates suggest a strong negative relationship for low-brand sellers and an insignificant, and in some cases, weakly positive relationship for high-brand sellers.

Interestingly, using a more localized measure of dispersion also affects the implied relationship between seller density and dispersion. When price dispersion is measured relative to nearby stations rather than relative to the city as a whole (as in Barron et al. [2004]), the relationship with station density becomes predominantly positive. The results indicate a strong positive relationship for high-brand sellers and an insignificant or weakly positive relationship for low-brand sellers. For both measures of dispersion, an increase in density leads to an increase in dispersion for high-brand sellers relative to that of low-brand sellers. Dispersion among high-brand stations increases even more strongly

[2] High-brands tend to have more stations and command greater brand recognition and brand loyalty from consumers. See Section III for details.

when there is an increase number of low-brand stations specifically.

These empirical findings suggest that seller differentiation continues to affect the extent of price variation across stations even after controlling for persistent differences in station price levels. Though the theoretical literature on consumer search focuses exclusively on models of homogeneous product markets, my results imply that relationships between seller characteristics and consumer heterogeneity (in search costs for example) can result in different patterns of price dispersion among different types of sellers. To illustrate why these differences might arise, suppose consumers that are more willing to purchase low-brand gasoline are also more likely to search and have better price information. In markets with more low-brand stations, these consumers may find it even more convenient to locate and purchase low-brand gasoline rather than buy from a high-brand station. As a result, the consumers left buying gas from high-brand stations in the area may be even less likely to search and less well informed about prices. In this case, differences in consumers' propensity to search interact with station differences. Different types of stations may face different demand elasticities and may be differentially affected by additional competitors of a particular type. The empirical results presented in this paper are consistent with such interactions, and highlight a need for more theoretical research examining markets with price dispersion and seller heterogeneity.

II. MEASURING PRICE DISPERSION

II(i). *Data*

I measure gasoline price dispersion using station price data collected by The Utility Consumer Action Network (UCAN), a consumer advocacy group located in San Diego, California, who reported the information on their website to help consumers find the lowest gas prices. The price data are posted retail prices for 327 stations in the San Diego area recorded on each Monday morning during the years 2000 and 2001. During this time period, prices were collected by a handful of *spotters* who drove around a designated area to record prices from each gas station's sign. The reported prices are for regular grade (87 octane) unleaded gasoline. Observing prices at a given time each week gives a series of *snapshots* of the current price distribution. Price changes within the week are not observed in the data. However, this study focuses on the nature of price dispersion at a given point in time and exploits the weekly observations to better understand the extent to which this price distribution can change over time.

Unfortunately, many of the stations in the sample are missing price observations for one or more weeks during the period. During the 91 weeks used in the analysis, the average station has 3.8 weeks in which the price observation is missing. However, the selection does not appear to be systematic in any way. It appears that, on fairly isolated occasions, the data collectors simply failed to record prices for individual stations or small clusters of stations for that particular week. Linear probability regressions of the occurrence of a missing price on observable station characteristics do reveal small differences across brands and station sizes. Fortunately, the probability of a missing value is not systematically correlated with measures that might be of particular concern for my analysis, such as the type of station (high-brand or low-brand) or the general direction that prices are moving. Given that there are relatively few missing values and that they appear to have no significant patterns, the missing observations are dropped from the empirical analysis.

The price data are matched with other station information using a census of all gas stations in the San Diego area (over 700 stations) collected by Whitney Leigh Corporation. This census reports the location and various characteristics of each station. Street address locations from the station census are converted to geographic coordinates using TeleAtlas geocoding software, and distances between each station are calculated. The combined data reveal both the pricing behavior and the nature and location of all competitors for a significant subsample of the city's gas stations. The panel nature of these data is crucial for examining the dynamic evolution of the station price distribution over time.[3] The level of retail gasoline prices generally fluctuates significantly over time due to wholesale price volatility. However, this study focuses on *differences* in retail prices between stations at a given point in time and examines how these price differences change over time. Therefore, I abstract from movements in the overall price level by studying station prices relative to the citywide average. One could alternatively study differences in stations' retail-wholesale margins. Commodity prices for wholesale gasoline, such as the Los Angeles Harbor Spot Gasoline prices, are available from the Energy Information Agency and represent a good measure of the marginal cost for all retail gasoline operations in the area. However, wholesale-retail margins fluctuate over time due to the lagged response of retail prices to wholesale price changes and would add another source of variation that is not of interest for this study. As a result, I use week fixed effects to control for movements in the general price level rather than incorporating wholesale price information.

[3]Price dynamics are not discussed by Barron et al. [2004] because their analysis was limited to cross-sectional data.

II(ii). *Seller Heterogeneity and Market Definition*

The most important step in measuring price dispersion is to control for price differences resulting from station heterogeneity. I avoid using observed characteristics to control for seller differences because this can potentially overestimate price dispersion by failing to account for unobserved product differentiation.[4] In contrast, seller fixed effects can control for both observed and unobserved price differences resulting from seller differentiation as long as station characteristics do not change over time and the effects of station characteristics on the station's profit function do not fluctuate over time. Fortunately, the most common sources of perceived product heterogeneity in this market are all attributes that rarely change over the short sample period (For example: station brand, location, station quality, gasoline quality, etc.). In addition, observing prices on the Monday morning of every week eliminates any changes in consumer preferences that vary systematically within the week.[5]

Several other empirical studies of price dispersion rely on a similar approach. Lach [2002] uses seller fixed effects to measure price dispersion for five different consumer products in Israel. Sorensen [2000] uses a similar method to measure prescription drug price dispersion among local pharmacies, though he relies on multiple drugs sold at the same pharmacy (rather than multiple time periods) to identify seller fixed effects. Hosken, McMillan & Taylor [2007] examine gas prices in the Washington, DC metropolitan area using station fixed effects to control for differences in prices and margins. However, Hosken et al. [2007] focus on changes in station margins over time and on the theories of retail pricing that can potentially explain such changes, while my analysis focuses directly on isolating and studying price dispersion and relating it to theories of consumer search.

To estimate gasoline price dispersion I begin with a basic fixed effects regression model of retial prices:

$$p_{it} = \alpha + \sum_{i=1}^{I} \beta_i \mathit{Station}_i + \sum_{t=1}^{T} \phi_t \mathit{Week}_t + u_{it}.$$

Week fixed effects capture changes in average price level over time that mostly result from regional wholesale price movements. The station fixed effects identify any persistent price differences between stations due to differences in product characteristics, seller characteristics, costs, or demand conditions. Each station fixed effect reveals the average difference

[4]In fact, most of the observed characteristics in my data do not significantly explain price differences. Brand dummies are the only significant explanatory variables in a regression of price on station characteristics.

[5]For example, one might expect that demand for gasoline might be higher and/or more inelastic during the weekend at a gas station that is located next to a shopping mall.

between the price at station i and the city average price. Estimates of these station fixed effects can be used to create an *adjusted price* measure, $\tilde{p}_{it} \equiv p_{it} - \hat{\beta}_i$, representing a station's price series net of any price differences resulting from variation in station characteristics. Each residual, $\hat{u}_{it}$, simply reveals whether the price of station i was above or below its expected level relative to the city average price during week t. Therefore, the estimated variance of u_{it} can be interpreted as a measure of price dispersion.

Due to the significant movements in wholesale prices over the sample period, week fixed effects account for roughly 90% of overall retail price variation. Of the remaining (within-week) price variation, station fixed effects account for roughly 66% of observed variation. However, the remaining unexplained price variation is not trivial. The residuals from the price regression have a standard error of 3.7 cents/gallon.

It should be noted that the estimated variance of u_{it} represents a *city-wide* measure of true price dispersion. Yet competition in the retail gasoline market is often considered to be fairly localized. Therefore, a localized measure of price dispersion may be more relevant. For example, suppose all stations in a particular area have large positive residuals in week t. This would represent a high level of dispersion from the city average price level, but dispersion between the local stations may actually be quite low.

Measuring localized dispersion requires one to define the local market. One common approach is to define the relevant market for a station as all competing stations that are less than *x* miles away. To be consistent with earlier studies, including Barron et al. [2004], competitors in this analysis are defined as those stations within a 1.5 mile radius.[6]

Using this local market definition, an alternative measure of price dispersion is constructed as the variance of the difference between the a station's residual and the average of the residuals of stations within 1.5 miles. A station's local deviation becomes:

$$\hat{\delta}_{it} \equiv \left(\hat{u}_{it} - (\sum_{j \in J} \hat{u}_{jt})/N_J \right) \equiv \left(\tilde{p}_{it} - (\sum_{j \in J} \tilde{p}_{jt})/N_J \right)$$

where J is the set of stations within 1.5 miles of station i and $\tilde{p}_{it} \equiv \hat{p}_{it} - \beta_i$ is the adjusted price for station i. The variance of $\hat{\delta}_{it}$ measures the average level of price dispersion relative to nearby stations. Interestingly, the extent of local price dispersion is nearly identical to the city-wide level of dispersion. The standard deviation of the estimated local deviations, $\hat{\delta}_{it}$, is also 3.7 cents/gallon. This suggests that there is as much unexplained price variation within local markets as there is across the city.

[6] Changing the size of the relevant market to include a 1 mile radius or 2 mile radius turns out not to significantly change the results or conclusions.

II(iii). *Changes in Relative Price Differences*

Since there appears to be a significant amount of price dispersion in this market (even after controlling for station differences), it is important to better understand how stations' prices change over time relative to one another. For example, controlling for the average price level of a particular station, how often or how quickly does this station go from having an unusually high price to an unusually low price.[7] This is particularly important when considering the possibility that price dispersion results from imperfect information and consumer search. In most search models price dispersion results from a mixed strategy equilibrium, and frequent relative price changes may be necessary to prevent consumers who purchase repeatedly from learning the price distribution.

Examining the week to week price dynamics of both the city-wide price deviation, $\hat{u}_{it}$, and the local price deviation, $\hat{\delta}_{it}$, requires quantifying how each station's adjusted prices move around the distribution over time. To do this I divide the citywide and local distributions of adjusted prices for each week into quartiles and study how particular stations' adjusted prices move between quartiles over time. Comparing station prices to their local price distributions is attractive given that competition is likely to be localized. However, quartiles of local price distributions must be interpreted carefully given the small number of prices used to define each quartile. Local quartiles are also constructed to specifically ensure that missing price observations do not generate artificial movements in another station's quartile location from week to week. Prices for several competing stations are graphed in Figure 1 to illustrate the types of price movements typically observed in the sample. I discuss how these stations' prices move relative to one another, and relative to other stations within their local area and throughout the city. I then present statistics from the entire sample describing the frequency with which prices move between quartiles.

Figure 1 reports price movements over several months from an arbitrarily selected station and its two nearest neighbors as well as the percentiles of prices from a larger group of stations. A map of the selected station (operating under the Union 76 brand) and its nearby competitors is displayed in Figure 2. The selected station has two competitors within a half mile (a Mobil branded station and a 7-Eleven station) and a total of 11 competitors within 1.5 miles (the stations within the circle). Price information is observed for 8 of the 11 competing stations, and these prices are used to construct local price quartiles. In this case the prices of these 9 stations (the 76 station and 8 competitors) were observed in all of the 20 weeks displayed in the graph, so quartile movements are

[7] Here unusually high or low refers to the price being higher or lower than the station's average price.

Figure 1: Selected Station Prices Relative to Citywide and Local Price Quartiles

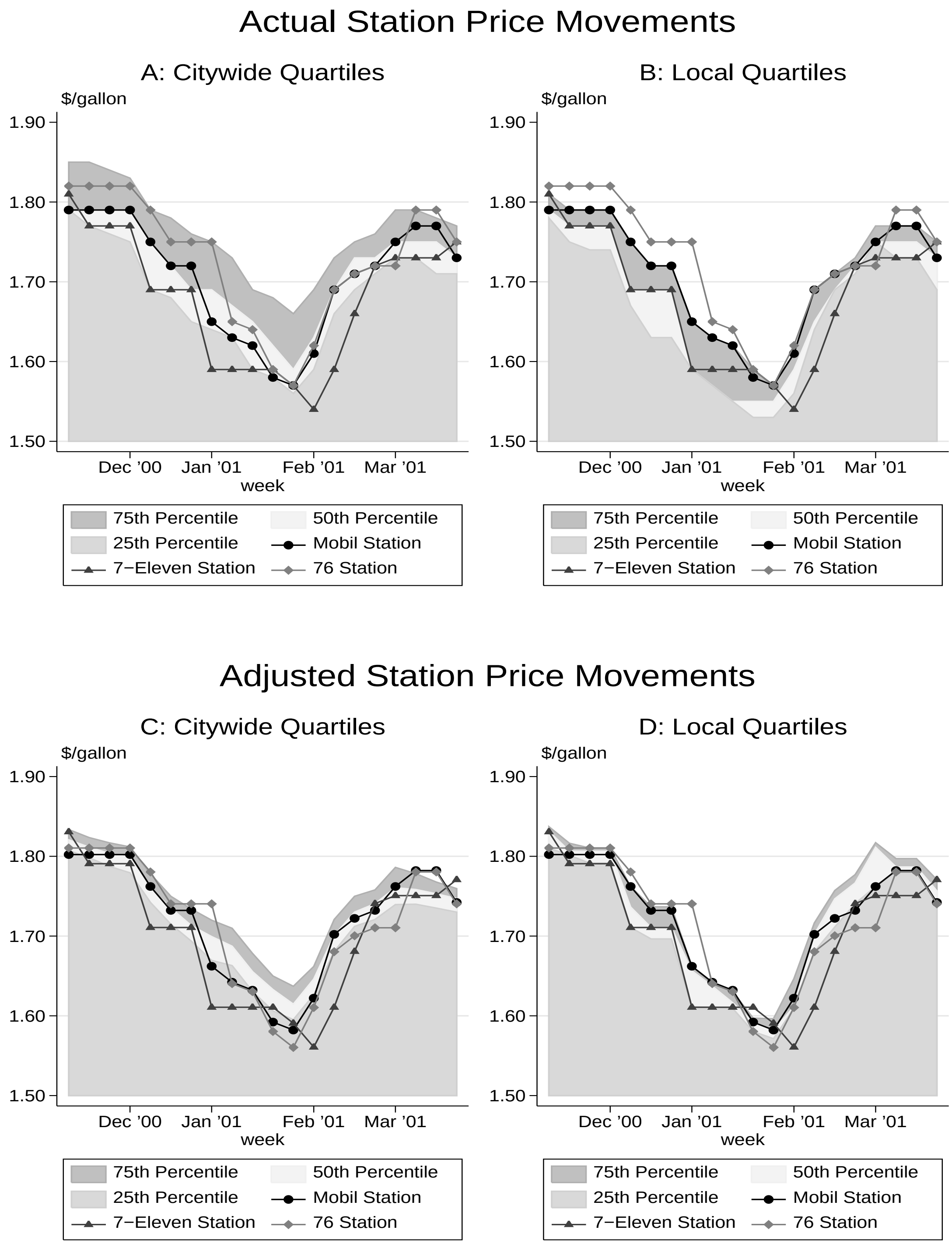

Figure 2: Example of a Typical Station and the Locations of Surrounding Competitors

Note: Circle represents 1.5 mile radius around the highlighted Union 76 station.

not affected by missing price observations.[8] To illustrate the effects of controlling for station differences, Figure 1 Panels A and B show the actual prices from the stations while Panels C and D show the adjusted prices after subtracting out station fixed effects. Using adjusted prices helps to highlight the large changes from week to week in the relative price differences between stations. The shaded quartiles in each figure show how other stations' prices are moving relative to these three competitors. The citywide quartiles in Figure 1 Panels A and C show the quartiles of prices throughout the city, and local quartiles in Panels B and D show the quartiles of prices from stations within a 1.5 mile radius.

The prices of the three competitors move together to some extent but are not perfectly correlated. Notice in Figure 1 Panel A that (unadjusted) prices at the 7-Eleven station tend to be below its competitors. One possible reason for this is that Mobil and 76 both have more established gasoline brands and maintain a reputation for having higher quality gasoline. However, the difference in price between this 7-Eleven and its com-

[8]When constructing quartiles with a small number of prices, the number of prices in each quartile will not necessarily be the same. Prices are allocated to quartiles from lowest to highest, so with 9 prices, the first quartile will contain 3 prices, while the 2nd, 3rd and 4th will only contain 2 prices. For this reason, I also restrict analysis of local quartiles to stations with 4 or more local competitors, which leaves 76.5% of the original sample remaining.

petitors fluctuates, causing its adjusted price (in Figure 1 Panel C) to be higher than its competitors in some weeks and lower in others. If consumers' preferences for one station or another are fairly stable from week to week, these relative price changes could significantly affect some consumers' purchase decisions.[9]

Changes in relative prices from week to week are also evident when comparing the prices of these three competitors with the price quartiles of surrounding stations. For example, in Figure 1 Panel C the adjusted prices of these three stations remain in the lowest price quartile when compared to other prices throughout the city during the month of January 2001, but at other times their prices were commonly in the upper three quartiles of the citywide price distribution. Large movements within the price distribution from one week to the next are not uncommon. The prices of both Mobil and 76 moved from the upper half of the citywide distribution to the lowest quartile during the first few weeks of January 2001. Figure 1 Panel D shows similar week to week fluctuations in the prices at these three stations relative to the prices of other competitors within 1.5 miles. Together Panels A through D illustrate that relative price differences change frequently and significantly over time across neighboring stations, across stations within the same local area, and even across stations in different areas of the city.

To determine whether the relative price movements highlighted in the example above resemble those observed in the full sample, I measure the frequency with which each station's price moves between quartiles from week to week. Missing price observations must be handled appropriately in this analysis. Within a local price distribution, a missing price for one station could cause several competitors to be reclassified into different quartiles even when no stations have changed their actual price ordering. Therefore, I calculate quartile movements from one week to the next by defining both the current and previous week's quartiles using only stations whose prices are observed in both weeks.

As in the example above, adjusted station prices frequently move around within citywide and local relative price distributions from week to week. Table I shows the quartile transition probability matrices for a representative station. These matrices describe the share of weeks in which a station's adjusted price lies in Quartile X in week t and Quartile Y in week $t+1$. Panels A & B show the transitions from one week to the next for citywide and local quartiles respectively. A station observed in the 2nd or 3rd citywide or local price quartile is more likely to be in a different quartile the following week than it is to remain in the same quartile.

[9]Of course, the effect on purchasing behavior is dependant on the extent to which consumers observe these prices.

Table I: Adjusted Station Price Quartile Transition Matrices

One Week Transition Matrices*
(# of observations = 26,423)

A. Citywide Quartiles	q_1	q_2	q_3	q_4	B. Local Quartiles (1.5 Mile Radius)	q_1	q_2	q_3	q_4
q_1	65.9%	19.6%	9.3%	5.9%	q_1	66.1%	17.4%	10.5%	6.0%
q_2	22.8%	45.3%	22.3%	9.7%	q_2	23.6%	45.5%	22.7%	8.2%
q_3	7.7%	26.3%	44.5%	21.0%	q_3	11.1%	22.5%	50.0%	16.4%
q_4	3.6%	8.8%	23.8%	63.4%	q_4	6.4%	9.0%	24.9%	59.8%

Four Week Transition Matrices
(# of observations = 24,552)

C. Citywide Quartiles	q_1	q_2	q_3	q_4	D. Local Quartiles (1.5 Mile Radius)	q_1	q_2	q_3	q_4
q_1	42.4%	22.6%	18.2%	17.8%	q_1	46.8%	20.8%	18.9%	13.5%
q_2	26.0%	30.7%	24.7%	18.8%	q_2	28.1%	29.8%	27.7%	14.4%
q_3	17.4%	27.5%	30.2%	24.1%	q_3	20.1%	25.9%	34.2%	19.8%
q_4	14.1%	19.3%	26.9%	39.3%	q_4	17.9%	17.0%	27.5%	37.6%

*Rows = Week t price quartiles, Columns = Week $t + j$ price quartiles
Percentages in columns add to 100%

Movements within the relative price distribution are even more pronounced over a slightly longer time frame. Table I Panels C & D relate the adjusted price quartile a station is currently in with its quartile four weeks later. The observed transition probabilities suggest that a station is always more likely to be in a different quartile than in the same quartile four weeks later. More than 26% of the time stations move at least two quartiles away from the citywide quartile they were in four weeks earlier, and for local quartiles this occurs more than 28% of the time.[10] Clearly, it is common for stations in the sample to change prices relative to their competitors. Hosken et al. [2007] report similar evidence of frequent relative price movements for gas stations around Washington, DC.

The analysis of relative price dynamics shows that a large portion of observed gasoline price dispersion cannot be explained by long-term cost or demand differences across stations. Frequent relative price movements clearly resemble the theoretical mixed strategy equilibrium of a typical consumer search model. They could also result from frequent

[10]The four week transition matrices in Table I reveal only slightly less movement around the price distribution than would be implied by four weeks of Markovian transitions based on the one week matrix. This is an interesting property to note when comparing observed behavior to that of a mixed strategy equilibrium in which stations are randomizing their pricing behavior.

and significant station specific cost and/or demand changes from week to week.[11] In either case, the observed price volatility does suggest that imperfect price information and consumer search may be important in this market since consumers would find it difficult to learn prices over time.

III. PRICE DISPERSION AND SELLER DENSITY

Given that true price dispersion (beyond that explained by seller heterogeneity) appears to be present and significant in this market, the remainder of this study examines how dispersion is related to the number of nearby competitors (and other local market characteristics). This is partially motivated by the fact that existing theoretical models of price dispersion do not tend to agree in their predictions. In some cases, the implied relationship between the number of competing firms and the level of price dispersion differs between search models and spatial competition models. Barron, Taylor & Umbeck [2004] highlight these conflicting results by noting that an increase in the density of stations in a spatial model implies less price dispersion, while the search models of Varian [1980] and Carlson & McAfee [1983] find that price dispersion rises with the number of firms. However, the results of the Varian [1980] and Carlson & McAfee [1983] are somewhat unique within the consumer search literature. Many search models, including Reinganum [1979] and MacMinn [1980], assume a continuum of firms and are unable to make predictions about the relationship between the number of firms and the equilibrium price distribution.[12]

[11] Cost and/or demand changes could cause relative price movements even in a purely spatial model of competition (without imperfect information).

[12] The number of stations could also have an indirect effect on equilibrium price dispersion. A higher density of stations reduces price dispersion in a spatial model by reducing consumers' travel costs and, therefore, increasing the elasticity of demand faced by the firms. Similarly, in a search model one might expect an increase in the number of firms to reduce consumers' search costs. The level of search costs often impacts the extent of price dispersion in consumer search models, but this relationship is subtle and its predicted sign varies across models. A decrease in search costs implies an increase in price dispersion in the MacMinn [1980] model, a decrease in dispersion in the Reinganum [1979] model, and does not affect dispersion in the Carlson & McAfee [1983] model. The predicted relationship in models by Varian [1980] and Stahl [1989] changes sign depending on other parameters. In their survey, Baye, Morgan & Scholten

A number of empirical studies specifically address the relationship between market concentration and price dispersion. Baye, Morgan & Scholten [2004] use data from a price comparison web site to study dispersion in the prices of consumer electronics sold by internet retailers. They show that product markets with more retailers tend to display less price dispersion. Alternatively, Borenstein & Rose [1994] show that dispersion in airline fares on a route is higher when more competitors serve the route. However, some of this price variation results from differences in fare restrictions. In the context of retail gasoline markets, Marvel [1976] finds weak evidence that markets with more competitors (lower HHI) exhibit a smaller range of prices. Barron et al. [2004] also find that price dispersion among gas stations is negatively related to the number of sellers in a local market and conclude that observed patterns of price dispersion are consistent with models of spatial competition rather than models of imperfect information and consumer search. However, Barron et al. [2004] use observed station characteristics to control for seller heterogeneity, leaving the possibility that unobserved station differences are responsible for some of the remaining price dispersion.

Similar to Barron et al. [2004], I empirically model dispersion as a function of the density of local competition and other seller or market characteristics. As in Section II, price dispersion is measured as the variance in the error term from a regression of prices on station and week fixed effects. Therefore, the following analysis is based on the assumption that the error term in this equation is heteroskedastic and that the variance of the error term may be a function of the local density of competition.

Consider the following heteroskedastic regression model of station prices:

$$\begin{aligned}
&(1) & p_{it} &= \alpha + \sum_{i=1}^{I} \beta_i \mathit{Station}_i + \sum_{t=1}^{T} \phi_t \mathit{Week}_t + u_{it} \\
&(2) & E(u_{it}) &= 0 \\
&(3) & Var(u_{it}) &= e^{\gamma + \zeta ln(\mathit{Density})_i + \eta X_i + \sum_{t=1}^{T} \xi_t \mathit{Week}_t}
\end{aligned}$$

where X_i contains the station characteristics and brand indicators listed in Table II, and

[2005] discuss the various aspects of existing search models in more detail and highlight the range of predictions regarding search costs and price dispersion.

Table II: Station Characteristic Variables

(Number of Stations Observed = 327)

Variable	Description	Mean	S.D
p	Retail Station Price[a]	118.2	(16.6)
Station Competition:			
Density	Number of stations within a 1.5 mile radius	12.6	(7.03)
ln(Density)	Log of Density	2.36	(.660)
Same Brand Share	Share of stations within a 1.5 mile radius with the same brand as station *i*	.092	(.112)
Station Characteristics[b] *(X_i):*			
Full Service	Station sells full-serve gas	.077	(.267)
Garage	Station has service bay	.303	(.460)
C-store	Station has convenience store	.445	(.498)
Pumps	Number of fueling positions	7.94	(2.79)
7-11	Station brand: 7-11	.097	(.298)
76	Station brand: Union 76	.107	(.309)
ARCO	Station brand: ARCO	.234	(.424)
Chevron	Station brand: Chevron	.110	(.313)
Exxon	Station brand: Exxon	.039	(.193)
Mobil	Station brand: Mobil	.104	(.306)
Shell	Station brand: Shell	.116	(.320)
Texaco	Station brand: Texaco	.083	(.276)
Economic Census Variables (X_i):			
Retail Establishments	Number of retail establishments within the same census tract	172	(105)

[a] Prices observed for 91 weeks
[b] Omitted brand category = unbranded

$ln($*Density*$)$ is the log of the number of competitors within 1.5 miles. The omitted brand category is unbranded stations that are not affiliated with a major refining company or gasoline brand.

Equation 3 implies a multiplicative heteroskedasticity model which is both commonly used and attractive because it ensures that estimates of the variance of u_{it} are positive.[13] The main coefficient of interest is that on $ln($*Density*$)$ in Equation 3, which describes how the unexplained variation of station prices varies with the density of nearby competitors. Week fixed effects in Equation 3 control for changes over time in the market-wide average level of price dispersion.[14]

Since *Density*$_i$ measures the number of nearby stations, it is possible that some of these stations might be owned by the same firm as station i. This could influence how

[13] The model and estimation techniques are of the forms discussed by Harvey [1976].

[14] Lewis [2005] presents some empirical evidence that price dispersion increases during periods of high retail margins and declining retail prices.

the price of station i tends to vary relative to its neighbors. I do not have direct information on ownership, and station brand is not a perfect measure because many brand name stations are leased or owned and operated by a local dealer rather than being operated by the parent company. Nonetheless, I include a measure, *Same Brand Share*$_i$, of the share of stations within 1.5 miles that have the same brand name as station i. The other station characteristics and local demographic variables, X_i, included in Equation 3 act as controls to help isolate the effect of competitor density and provide a check on the robustness of this relationship. These variables can also reveal whether other aspects of the market help to predict price dispersion. Stations with a convenience store or stations with more fueling pumps might have different pricing strategies that affect the levels of price dispersion at these stations. In addition, local demographics could capture differences in consumers' purchasing behavior that affect dispersion. Census tract level demographic variables from both the 2000 U.S. Census and the 2002 Economic Census (such as median income, number of drivers, average commute time and employment) were included in some specifications but were insignificant in all cases. The only variable that was significant and highly consistent across specifications was the number of retail establishments in the area. As a result, the log number of retail establishments is included in Equation 3 along with the station characteristics listed in Table II.

The coefficients of Equation 3 are recovered using a two-step procedure. Equation 1 is estimated by OLS, and the residuals from that regression are used to estimate Equation 3. The second-step regression is:

$$ln(\hat{u}_{it}^2) = \gamma + \zeta ln(\mathit{Density})_i + \eta X_i + \sum_{t=1}^{T} \xi_t \mathit{Week}_t + w_{it} \tag{4}$$

where $\hat{u}_{it}$ is the it^{th} residual from the estimation of Equation 1. The second step regression here is akin to estimating the covariance structure in an Feasible Generalized Least Squares procedure. However, in this case the coefficients of interest are in the variance equation rather than the price equation.[15]

[15]With the additional assumption that the u_{it} is distributed normally with the mean and variance specified

Since retail gasoline prices exhibit a certain amount of persistence from week to week, u_{it} may be serially correlated even after allowing for week fixed effects. In addition, within a week, the prices of stations competing with each other are likely to be correlated. As a result, w_{it} in Equation 4 may also be correlated, both over time and across stations. To control for this I allow w_{it} to follow an AR(1) process over time and estimate standard errors that are robust to arbitrary correlation across stations within a particular week t. More specifically:

$$w_{it} = \rho w_{i,t-1} + \nu_{it} \quad \text{and} \quad E(\mathrm{w}_t \mathrm{w}_t') \equiv \Omega_t \tag{5}$$

where $E(\nu_{it}) = 0$.

Estimates of the parameters in Equation 4 are presented in Column 1 of Table III. Recall that the dependant variable represents the unexplained variation in station prices after controlling for fixed station differences. The negative and significant coefficient estimate on the number of competitors suggests that prices among similar stations with a high number of competitors tend to be less disperse than prices among similar stations with a low number of competitors. Given the log-log form of Equation 4, the estimates in Column 1 imply that a station with 50% more competing stations (within 1.5 miles) would have a 7.5% lower measure of price dispersion. However, all indications are that this relatively small negative relationship is sensitive to the overly restrictive assumption that increased density of competition affects unexplained price variation at all stations in the same way. If consumer heterogeneity interacts with seller heterogeneity so that stations with different characteristics tend to sell to different types of consumers, then the effect of competitor density is likely to vary across station types.

One natural way to identify sellers of different types is to classify them by their brand affiliation. I take an approach similar to that of Hastings [2004] and split stations up into *high-brand* and *low-brand* categories. As Hastings [2004] suggests, it is likely that the perceived quality of a brand, and potentially the level of consumer loyalty to a

in Equations 2 & 3, the model can also be estimated using maximum likelihood estimation. However, since the results using maximum likelihood estimation are very similar to those of the two-step procedure, they are not reported in the paper.

Table III: Price Dispersion Specifications

Dependant Variable:	Citywide Variation: $ln(\hat{u}_{it}^2)$			Local Variation: $ln(\hat{v}_{it}^2)$		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Density)	-0.149**	-0.324**	-0.077	0.263**	0.077	0.256**
	(0.046)	(0.058)	(0.049)	(0.041)	(0.050)	(0.042)
ln(Density)* High-Brand		0.401**			0.474**	
		(0.074)			(0.063)	
Ave. Price Level of Station[a]			-0.037*			0.001
			(0.021)			(0.025)
ln(Density)*Ave. Price Level of Station			0.041**			0.032**
			(0.008)			(0.009)
Same Brand Share	-0.324	-0.203	-0.024	-1.593**	-1.959**	-2.182**
	(0.279)	(0.373)	(0.368)	(0.251)	(0.326)	(0.317)
Same Brand Share* High-Brand		-0.123	-0.772		1.689**	1.634**
		(0.504)	(0.521)		(0.448)	(0.442)
ln(Retail Establishments)	0.119**	0.118**	0.088**	0.134**	0.128**	0.129**
	(0.028)	(0.028)	(0.028)	(0.030)	(0.030)	(0.030)
C-store	-0.200**	-0.169**	-0.128**	-0.220**	-0.176**	-0.139**
	(0.059)	(0.059)	(0.060)	(0.060)	(0.060)	(0.059)
ln(Pumps)	-0.379**	-0.371**	-0.354**	-0.404**	-0.398**	-0.329**
	(0.057)	(0.059)	(0.058)	(0.065)	(0.064)	(0.063)
7-11	-0.261**	-0.286**	-0.414**	-0.165	-0.162	-0.256**
	(0.116)	(0.114)	(0.113)	(0.113)	(0.116)	(0.115)
76	0.119	-0.876**	-0.267**	0.363**	-0.879**	-0.173
	(0.122)	(0.215)	(0.124)	(0.108)	(0.175)	(0.116)
ARCO	-0.679**	-0.734**	-0.689**	0.368**	-0.333**	-0.210**
	(0.117)	(0.123)	(0.125)	(0.108)	(0.103)	(0.102)
Chevron	-0.412**	-1.407**	-0.768**	-0.249**	-1.482**	-0.729**
	(0.109)	(0.216)	(0.110)	(0.094)	(0.167)	(0.099)
Exxon	0.123	-0.178	-0.306	0.159	0.108	-0.049
	(0.188)	(0.187)	(0.190)	(0.151)	(0.149)	(0.152)
Mobil	-0.439**	-1.428**	-0.693**	-0.318**	-1.565**	-0.703**
	(0.110)	(0.212)	(0.112)	(0.090)	(0.164)	(0.094)
Shell	-0.201	-1.214**	-0.609**	-0.010	-1.338**	-0.538**
	(0.124)	(0.226)	(0.121)	(0.113)	(0.184)	(0.122)
Texaco	-0.193	-0.254	-0.484**	0.105	0.063	-0.209**
	(0.121)	(0.122)	(0.118)	(0.106)	(0.107)	(0.106)
constant	0.957**	1.390**	1.072**	-0.133	0.355*	-0.088
	(0.207)	(0.216)	(0.208)	(0.185)	(0.212)	(0.182)
# of obs	28697	28697	28697	28697	28697	28697
Mean of Dep. Var.	.785	.785	.785	.366	.366	.366
S.D. of Dep. Var.	2.38	2.38	2.38	2.43	2.43	2.43

Coefficients of week fixed effects have been omitted.
Coefficients of *Garage* and *Full Service* are insignificant in every specification and have been omitted.
* Denotes significance at the 10% level, ** at the 5% level
[a] In columns 1-3 *Average Price Level of Station*$_i$ is the station fixed effect (β_i) from Equation 1.
In columns 4-6 *Average Price Level of Station*$_i$ is a difference relative to other stations within 1.5 miles: $(\beta_i - (\sum_{j \in J} \beta_j)/N_J)$.

brand, may be correlated with the brand's market share and its average price level. While most evidence regarding consumers' gasoline buying patterns and station preferences is anecdotal, some consumers do perceive certain brands of gasoline to be superior and become loyal to stations of that brand. A recent survey found that 36% of adults are loyal to one brand of gasoline and that the extent of this brand loyalty varies across brands.[16] Following this logic, Shell, Chevron, Union 76, and Mobil sellers are designated as *high-brand* stations likely to have higher brand loyalty and perceived quality. These four brands have the highest market share in San Diego, excluding Arco which is widely thought of as an ultra-competitive brand with lower prices and limited service (such as not accepting credit cards). In addition, these four *high-brands* tend to have higher prices in my sample.[17] It does appear that these brands do behave significantly differently in this market.

I separate high-brand and low-brand stations because they are likely to face different residual demand elasticities. Consumers that have higher brand-loyalty or are more sensitive to perceived quality may also have lower price sensitivity and higher search/travel costs causing them to be more inelastic with regard to price differences across stations. These consumers are more willing to pay a brand/quality premium and are more likely to purchase from well established brands. Price premiums for well established (or high quality) brands are one source of the differentiation based price variation identified by station fixed effects. However, even after controlling for these average price differences, stations still differ in the types of consumers they serve. If consumers at low-brand stations have less brand loyalty and a greater propensity to search, a change in the number of local competitors may affect the extent of price dispersion at these stations differently than at high-brand stations.

To investigate whether seller type has any influence on the relationship between competitor density and price dispersion, the price dispersion equation (Equation 3) is

[16] This survey was performed by the consulting group Brand Keys and described in a New York Times article by Blumberg [2002].

[17] These high-brands are very similar to those identified by Hastings [2004] in her study of vertical relationships in the San Diego gasoline market.

altered so that station density is interacted with an indicator for being a high-brand station. Table III, Column 2 reports coefficient estimates of this new specification. The results reveal that an increase in the number of local competitors significantly decreases price dispersion for low-brand stations, but weakly increases dispersion at high-brand stations. The coefficient estimates imply that a low-brand station with 50% more competing stations (within 1.5 miles) would have a 16% lower measure of price dispersion. Alternatively, a high-brand station with 50% more competitors would have 4% more price dispersion.[18] Clearly a station's brand and the nature of its consumers have an important impact on how local competition affects price dispersion.

Station differentiation does not need to be identified at the brand level. It is likely that lower priced stations in general tend to be those that sell to more price sensitive (and possibly better informed) consumers. Under this hypothesis we might also expect to see that lower priced stations exhibit less price dispersion in markets with more competitors nearby, whereas higher price stations exhibit higher price dispersion in markets with more competitors.

The average price level of a station relative to each week's city average price is simply the value of the station fixed effect identified in the estimation of Equation 1. This price difference will be positive for stations whose price is typically above the city average and negative for those with prices typically below the city average. As an alternative specification of station differentiation, the price dispersion equation is re-estimated interacting average price level with competitor density. The resulting coefficients (Table III, Column 3) reveal that a higher number of nearby competitors is associated with less price dispersion for stations that have lower prices and more price dispersion for stations that have higher prices. According to the estimates in Column 3, a station that has an average price level one standard deviation (or 5.0 cents/gallon) above the city mean will effectively have a coefficient on $ln(\textit{Density})$ of around .13, while a station who generally prices one standard deviation below the city mean has a coefficient of -.28. This implies that a low

[18]This 4% estimate is not statistically different from zero, but is statistically different (at the 95% level) from the low-brand estimate of -16%.

price station with 50% more competing stations (within 1.5 miles) would have a roughly 14% less price dispersion while a higher price station with 50% more competing stations would exhibit 6.5% greater price dispersion. These effects are similar to those estimated using the high-brand/low-brand classification.

Coefficient estimates for several station characteristics variables are also significant and consistent across specifications. All else equal, stations with convenience stores have up to 20% lower price dispersion, and a doubling of the number of fuel pumps at a station is associated with 37% lower dispersion on average. In contrast, a doubling of the number of retail establishments in the census tract is associated with 9% to 12% greater price dispersion. This could be because consumers buying gasoline at stations near shopping areas may be less familiar with the area (or less well informed about gas prices) than consumers buying gas near their home or along their commuting route.

III(i). *Local Price Dispersion*

The results above are based on a citywide measure of dispersion that describes stations' unexplained price variation relative to the average price in the city. Since retail gasoline competition is highly localized, it is useful to also consider a measure of unexplained price variation relative to the prices of local competitors. If unexplained price movements are correlated within local submarkets, these two measures of dispersion may differ significantly. Therefore, as in Section II(ii), I construct a measure of price variation conditional on the average prices of all nearby stations. For a set J of stations within 1.5 miles of station i, the variance of u_{it} conditional on $(\sum_{j\in J} u_{jt})/N_J$ can be estimated using the residuals of the regression:

$$\hat{u}_{it} = \lambda(\sum_{j\in J} \hat{u}_{jt})/N_J + \upsilon_{it}.$$

Using the same approach as in Equation 4, local unexplained price variation can be modeled as a function of competitor density and other station characteristics:

$$ln(\hat{\upsilon}_{it}^2) = \gamma + \zeta ln(\textit{Density})_i + \eta X_i + \sum_{t=1}^{T} \xi_t \textit{Week}_t + \omega_{it}. \tag{6}$$

The model in Equation 6 is estimated as well as two more general specifications interacting station type variables with competitor density. The results are reported in Table III, Columns 4 through 6, with each specification being comparable to the corresponding citywide regression in Columns 1 through 3. In contrast with the citywide regression, the coefficient on $ln(\textit{Density})$ in Column 4 is positive and statistically significant. This suggests that increases in $ln(\textit{Density})$ are associated with greater dispersion within local submarkets, but less dispersion across submarkets. When $ln(\textit{Density})$ is interacted with the high-brand indicator (in Column 5) the coefficient differs significantly by station type, with an insignificant (positive) effect for low-brands and a large positive value for high-brands. The relationship between local price dispersion and density remains positive (as in Column 4), but, just as in the citywide regression, the coefficient is significantly more positive for high-brand stations than for low-brand stations. In contrast to the citywide regressions, the coefficient on the share of nearby stations with the same brand is now negative and statistically significant for low-brand stations. While difficult to interpret, this may be because low-brands such as 7-Eleven and Arco are more likely to have company owned and operated stations that potentially determine prices jointly.[19]

As a final specification, the average price level of the station is interacted with $ln(\textit{Density})$. Since this is a model of local price dispersion the price level measure is redefined slightly to be the average difference between the station's price and the prices of stations within 1.5 miles. The estimates from this specification are reported in Column 6 of Table III. The conclusions are similar to those in Column 5. These coefficients imply that a station with an average price level one standard deviation (or 3.9 cents/gallon) above the local area mean price will effectively have a coefficient on $ln(\textit{Density})$ of around .38, while a station who generally prices one standard deviation below the local mean has a coefficient of .13. This implies that a low price station with 50% more competing stations (within 1.5 miles) would have a roughly 6.5% more price dispersion while a higher price

[19]Though the coefficient on *Same Brand Share*$_i$ is highly significant in the local price dispersion regressions, its presence does not greatly effect the coefficients on *ln(Density)*. For example, when estimating the model in Column 4 without *Same Brand Share*, the coefficient on *ln(Density)* is only slightly lower at .213.

station with 50% more competing stations would exhibit 14% more price dispersion.

Comparing across all specifications in Table III several clear patterns arise regarding the relationship between price dispersion and local competition. When using a city-wide measure of dispersion (unexplained deviations from the city average price) more competitors are generally associated with somewhat lower price dispersion. However, when dispersion is measured locally (unexplained deviations from the local average price) more competitors are associated with somewhat higher dispersion. In other words, stations with higher competitor density seem to exhibit more across submarket dispersion but less within submarket dispersion. Secondly, for either measure of dispersion, high-brand stations or higher priced stations have a significantly greater coefficient on $ln(\textit{Density})$. This implies that the relationship between the number of competitors and price dispersion is generally either more positive or less negative for high-brand or higher priced sellers than for low-brand or low priced sellers.

III(ii). *Relative Effects of Different Types of Competitors*

Competitor density clearly relates to price dispersion differently for different types of stations. This pattern could result from heterogenous stations selling to consumers with different tastes and possibly different search/travel costs or propensities to search. In that case it is also possible that the effect of a new competitor on prices and price dispersion might vary based on that competitor's type. For example, a higher concentration of low-price/low-brand stations in an area is likely to increase competition among such stations. But, it may also increase the likelihood that more price sensitive consumers will find a low-price station. This has the effect of raising the average elasticity of consumers purchasing from high-price/high-brand stations, and possibly increasing price dispersion among high-price stations.[20]

[20]Alternatively, in a model with spatial competition in both the geographic and product space, one might expect a similar effect. A high density of low-brand/low-price firms is likely to lower price dispersion among their own firms even more than among high-brand/high-price firms. In addition, if consumers with more brand loyalty also tend to have higher travel costs, then the average travel costs of consumers left buying from high-price/high-brand stations may increase.

To test how the existence of different types of competitors affect price dispersion, two measures of competition density are created, $ln(\textit{Density}_H)$ and $ln(\textit{Density}_L)$, representing the log of the number of high-brand and low-brand stations respectively within 1.5 miles. Incorporating these two measures into the model of price dispersion identifies how competition of each type relates to price dispersion. The $ln(\textit{Density})$ measure in Equation 3 is replaced by these two separate type-specific competitor density measures, and each of these measures is also interacted with a dummy variable indicating whether station i is a high-brand station. The interactions allow the density of a particular competitor type to have different effects on the level of price variation for different types of stations. The following specification is estimated:

$$
\begin{aligned}
(7) \qquad ln(\hat{u}_{it}^2) \quad = \quad & \gamma + \zeta_1 ln(\textit{Density}_L)_i + \zeta_2 ln(\textit{Density}_L)_i * \textit{High-Brand}_i + \\
& \zeta_3 ln(\textit{Density}_H)_i + \zeta_4 ln(\textit{Density}_H)_i * \textit{High-Brand}_i + \\
& \eta X_i + \sum_{t=1}^{T} \xi_t \textit{Week}_t + \omega_{it}.
\end{aligned}
$$

Due to the log-log specification, the coefficients of $ln(\textit{Density}_H)$ and $ln(\textit{Density}_L)$ do not sum up to the coefficient on $ln(\textit{Density}_L)$ in Equation 3. However, the new coefficients do isolate the relationships between density and price dispersion for different station types, and altering the functional form has little effect on the general implications of these results.

The estimation results from the model in Equation 7 are reported in Table IV. For both the citywide and local measures of price dispersion, the largest and most statistically significant effect is the coefficient on $ln(\textit{Density}_L)$ for high-brand stations. In other words, among high-brand stations, those with a higher density of low-brand competitors nearby have significantly more price dispersion. A 50% increase in low-brand density is associated with a 10% increase in citywide dispersion and a 35% increase in local dispersion for high-brand stations. These large positive effects suggest that low-brand station density (rather than high-brand density) is responsible for generating larger coefficient estimates on overall $ln(\textit{Density})$ for high-brand stations in Table III.

Table IV: Price Dispersion and Density by Brand Type

(Coefficients of station characteristics and week fixed effects are omitted)

Dependant Variable:	(1) Citywide Variation: $ln(\hat{u}^2)$ from Eq. 1	(2) Local Variation: $ln(\hat{v}^2)$ from Eq. 6
ln(Density$_L$)	-0.193**	-0.057
	(0.050)	(0.052)
ln(Density$_L$)$*$ High-Brand	0.389**	0.757**
	(0.069)	(0.071)
ln(Density$_H$)	-0.137**	0.163**
	(0.052)	(0.069)
ln(Density$_H$)$*$ High-Brand	-0.052	-0.419**
	(0.076)	(0.087)
ln(Same Brand Share)	-0.204	-1.786**
	(0.363)	(0.348)
ln(Same Brand Share)$*$ High-Brand	0.719	2.879**
	(0.495)	(0.497)
# of obs	28697	28697
Mean of Dep. Var.	.776	.366
S.D. of Dep. Var.	2.34	2.43

* Denotes significance at the 10% level, ** at the 5% level

For the citywide measure of dispersion, low brand station density is positively related to dispersion at high-brand stations, but all other station density effects are negative and significant. Perhaps higher density tends to reduce unexplained deviations from the city average price in general, but for high-brand stations there is an overriding market composition effect that interacts with consumer heterogeneities to cause unexplained price deviations to increase when more low-brand competitors are present.

For local price dispersion, a greater density of high-brand stations appears to have a different effect. More high-brand competitors are associated with less dispersion at high-brand stations but more dispersion at low-brand stations.[21] Overall, the results suggest that stations of a particular type experience less local price dispersion when there is a greater density of nearby stations of the same type but that market composition effects may lead to greater dispersion among stations of the opposite type. It would not

[21] One explanation for this result could be that areas with a greater density of high-brand stations (conditional on low-brand density) tend to have consumers with higher search or travel costs, leading low-brand stations to have slightly higher price dispersion.

be surprising to see larger market composition effects when price dispersion is measured locally. Changes in the types of stations in a local market could affect how the average local market price moves as well as how a particular station's price moves relative to the local market average. Regardless of the mechanism, price dispersion varies significantly depending on the local composition of station types and one's own station type.

III(iii). *Alternative Explanations*

The previous discussion highlights the possible interactions between seller and consumer heterogeneities. However, there are other potential explanations as to why high-brand and low-brand stations have such contrasting relationships between dispersion and density. One possibility is that seller heterogeneity and competition affect price dispersion because the relative wholesale costs faced by different sellers vary systematically over time.

As discussed in Section II, unobserved idiosyncratic cost differences between stations are capable of generating price dispersion when search costs or travel costs are present. For any retail station, distribution level market prices for generic wholesale gasoline are the best measure of the replacement cost of selling another gallon of gasoline to consumers. In the San Diego area, the Los Angeles Harbor spot gasoline prices (or, if available, the unbranded gasoline prices from the San Diego distribution terminal) accurately represent this replacement cost. However, one might suggest that differences in vertical contract structure between refiners and retailers could effect the way this marginal cost is incorporated into the final pricing decision. Brand name refiners each resell gas to their branded stations at different prices. Usually these branded wholesale prices are very similar across brands but often differ from the unbranded wholesale prices paid by independent stations. Unbranded wholesale prices are generally lower than branded prices, but when prices are increasing rapidly unbranded wholesale prices can temporarily approach or exceed branded prices. If these prices truly reflect the opportunity costs with which station pricing decisions are made, then changes over time in relative difference between wholesale prices to branded and unbranded stations could lead to different patterns of price dispersion depending on station type.

Suppose the price dispersion identified in the sample is predominantly generated by fluctuations in the relative wholesale costs of unbranded and branded stations. Since unbranded stations make up less than 20% of the market, one might expect that unbranded station retail prices would vary more relative to the citywide average retail price causing the measure of price dispersion to be larger for unbranded stations. There is some evidence of this, as price dispersion is measured to be 40% higher on average for unbranded stations than for branded stations. In addition, one might expect prices at branded stations with more nearby unbranded competitors to be more sensitive to the fluctuations of unbranded wholesale costs and possibly to have higher price dispersion as well. The evidence in Table IV appears to be consistent with this prediction. Unbranded stations are classified in the low-brand group, and the coefficient estimates indicate that high-brand stations with more low-brand competitors nearby tend to have higher price dispersion. However, a more detailed investigation shows that relative cost variation between branded and unbranded stations may not be responsible for the identified relationships between dispersion and density. When the analysis in Table IV is altered to define stations types as branded and unbranded rather than high-brand and low-brand, branded stations are not estimated to have significantly higher dispersion when more unbranded competitors are nearby. In other words, for branded stations the coefficient on the log density of unbranded stations nearby is very small and negative. Therefore, the significant differences in the coefficients on low-brand station density between low-brand and high-brand stations in Table IV do not appear to be driven by differences between branded and unbranded stations.

IV. CONCLUSIONS

Price dispersion is prevalent in retail gasoline markets even after controlling for differences in stations' average price levels. In addition, station prices move frequently relative to each other over time. These findings imply that consumers may have imperfect price information and that consumer search could be an important aspect of competition in these markets. The level of price dispersion that is observed is sensitive to both the number of local competitors and the nature of local competitors. Price dispersion is larger for high-brand stations when they have a higher number of competing low-brand stations nearby. In contrast, price dispersion is lower for both high-brand and low-brand stations when there are more competitors of their own type in the local market. These findings contrast with those of earlier studies which generally do not account for differences among sellers when examining the effects of competitor density on price dispersion. The results suggest that price dispersion is sensitive to to composition of station types in the local market. Such compositional effects could arise if consumers with different search/travel costs segment themselves among different types of sellers. Though virtually all theoretical models of price dispersion concentrate on homogeneous sellers, these findings suggest that models incorporating seller differentiation would have important applications.

Using a more localized measure of price dispersion also seems to affect the general relationship between seller density and dispersion. Barron et al. [2004] use a citywide average price as a benchmark for calculating gasoline price dispersion and find a negative relationship between seller density and dispersion (similar to my citywide dispersion results). However, when dispersion is measured within localized submarkets, this relationship becomes positive and significant. Since consumers often observe prices and purchase from a small set of stations in their area, localized price variation may more accurately reflect the price dispersion consumers encounter. Therefore, results describing the extent of local price dispersion and its relationship to seller density help to improve the current understanding price dispersion in retail gasoline and other differentiated product markets.

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