Consumer and competitor reactions: Evidence from a retail-gasoline field experiment

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Abstract

The standard differentiated-product model with Nash-equilibrium price setting suggests that the density of sellers in a market can affect both a seller's price elasticity of demand and a competitor's reaction to a price change. Using field experiment data collected around a series of exogenously imposed price changes, we are able to demonstrate that a gasoline retailer's price elasticity of demand is directly related to seller density, where density is measured by the number of sellers within a given geographical area. This finding appears to be one potential source for observed persistent price differences. The data also allow us to examine the reaction of rivals to exogenous price changes. Consistent with the theory, we find that competitors' price reactions are in the same direction, with the magnitude of the competitors' reactions being inversely related to the market's density of sellers.

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This paper draws upon a field experiment that was conducted in three urban areas of California. We were provided limited ability to fix retail prices at 54 company-operated gasoline stations of a major retailer over a three month period in early 1999. In particular, at the start of each week we were allowed to set prices at a subset of stations and then hold the prices constant for the week's remaining days. The result was to create exogenous deviations in prices at "control" stations away from what they otherwise would have been. During this period, we collected information on the daily volumes of each grade of gasoline sold at control stations, as well as the daily prices at every competitor-station within two miles of any of the 54 control stations.[1]

The motivation for this field experiment arose out of events that began in 1995, when surveys in California revealed significant geographic differences in retail gasoline prices. The average retail price of a gallon of regular grade, self-serve gasoline in the Los Angeles area was higher than either the San Francisco (Bay) or the San Diego areas, and the difference substantially exceeded the cost of shipping gasoline from one area to another. Legislative hearings were held at both the state and local levels and the price differences were initially written off as merely market aberrations: short term deviations from text book equilibrium where geographic price differences for a homogeneous product would eventually equal the cost of transporting the product between markets.

However, the observed price differences did not go away and by early 1999 the California attorney general, as well as the Federal Trade Commission, began investigations. The "short-run

[1] The actual procedure, discussed in more detail in the text, involved increasing or decreasing the prices at a subset of the stations (typically by 2 cents) from the price on the prior day and then fixing this new price for one week. We thank the owner of these stations for recently giving us permission to use these data.

aberration" theory no longer seemed plausible and many legislators suggested that there was something wrong. New hearings were held and remedial legislation, including divorcement, open supply and outright price controls were proposed.

Standard differentiated-product models with Nash-equilibrium price setting suggest differences in the number of sellers in a market as one reason for price differences, with an increase in the number of sellers in a market resulting in lower prices as each seller faces a more elastic demand. Given that the density of gasoline stations in the LA area is greater than that in either San Diego or the Bay areas, this offers one potential explanation for persistent geographic price differences. A major petroleum retailer, interested in this possibility, provided us limited control of retail prices for a small number of stations stratified by the number of rival gasoline retailers each station had within two miles.

Although individual sellers' price elasticities of demand are critical in determining pricing strategy and price-cost mark-ups in many economic models, including standard differentiated-product models, estimates of such elasticities are not common. What is common are estimates of market demand elasticities for a variety of products, including gasoline.[2] While not directly applicable to the questions addressed in this paper, these estimates do highlight a common issue in estimating elasticities, namely the importance of identifying price changes that are exogenous to changes in consumers' demand behavior. Although our sample size of control stations is small (54) and the time period over which price movements were tracked is short (79 days), the field experiment creates such exogenous price changes, and thus provides the rare opportunity to test for differences in sellers' price elasticities across markets with different numbers of sellers.

[2] For recent examples of such studies of the market price elasticity of demand for gasoline, see Kayser (2000), Graham and Glaister (2002), Nicole (2003), and Oladosu (2003) as well as the references cited in these papers.

As prices at every competing station within two miles of each control station were also surveyed, these data allow us to perform a second test. Namely, to the extent we were successful in posting prices at control stations that differed from what relevant competitors expected prices to be at these stations, we can test for reactions to a rival's exogenous price change, as well as for differences in the extent of the reaction based on the direction of the price change, the number of rivals in the market (seller density), the station's type of ownership, distance from the rival station and brand type.

A great deal of empirical work has focused on retail gasoline markets as a suitable proving ground for theories of price wars, dynamic pricing patterns and collusive behavior. For example, building on the earlier price-war studies of Porter (1983) and Bresnahan (1987), Slade (1992) collects price-war data on ten competing service stations in Vancouver over an apparent punishment phase to assess firm's responses to exogenous shocks "of an unusual magnitude."[3] Also analyzing dynamic pricing behavior, Noel (2001) considers a panel of 22 competing stations in Toronto, identifying Edgeworth Cycles similar to those of Maskin and Tirole (1988), where, in a dynamic Bertrand duopoly model, focal prices and cyclical prices are both Markov perfect Nash equilibria. Eckert (2003) also provides evidence of retail price cycles across many Canadian markets.[4]

One clear difference between our approach and this earlier work is that any variation in price or reaction of a competing station to price changes is necessarily endogenous to the pricing behaviors of the collective stations in the sample. In contrast, our dataset incorporates truly

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[3] Slade (1992) also finds that firms respond asymmetrically to rival-price increases and decreases – sellers responding more quickly to price increases by "major" firms than to price decreases. This asymmetry is in the opposite direction for responses to independent firms' price changes.

exogenous price shocks imposed as we arbitrarily changed prices charged by stations located in a number of different markets. Previous studies have not had this luxury of identifying exogenous price changes at specific stations.[5]

The paper is divided into four sections. Section 1 introduces a well-known monopolistic competition model of price determination in order to motivate a fundamental claim, namely that an increase in the number of sellers in a market reduces market prices by raising individual sellers' price elasticities of demand. Section 2 presents an empirical test regarding the link between seller density and a seller's price elasticity of demand using the field experiment data. A key finding is that, as predicted by theory, in markets where consumers have a higher number of alternative sellers, individual sellers face a higher price elasticity of demand. We illustrate how this finding can explain price differences between the LA, San Diego, and Bay areas.[6]

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[4] Among other topics considered in the literature concerning gasoline markets are the wholesale-price response to crude-price fluctuation (e.g. Borenstein and Shepard, (2002), Bachmeier and Griffin (2002)) and vertical relationships (e.g. Hastings (2002)).

[5] There are a number of laboratory experiments that have empirically examined strategic behavior. Recent examples of experiments adopting a Cournot framework are Rassenti, Reynolds, Smith and Szidarovszky (2000) and Cox and Walker (1998). Other experiments have focused more on pricing behavior, such as those examining the implications of the Bertrand-Edgeworth model (e.g., Kruse, Rassenti, Reynolds and Smith (1994)) and the use of a posted-offer pricing mechanism (e.g. Ketcham, Smith and Williams (1984)).

[6] Note that our focus here is on explaining price differences across markets, not price differences at different sellers in the same market. A number of studies have considered price dispersion within particular markets. For instance, using city-level data, Marvel (1976) finds support for increased frequency of search (proxied by a larger volume of purchases) and lower search costs (measured by greater correlation of successive prices in the price distribution) reducing prices and price dispersion. Png and Reitman (1994), using station-level data from Massachusetts, find evidence that stations differentiate themselves on the basis of consumers' willingness to wait in line to buy gasoline. Contrary to Marvel's results, however, they find that prices are more dispersed in markets with a greater number of competitors, supporting their service-time differentiation hypothesis. Adams (1997), using a sample of 20 convenience stores that sell gasoline, finds that grocery items sold in the convenience stores have a higher degree of price dispersion than gasoline. Adams attributes this difference to the higher search costs associated with purchasing convenience store items relative to those search costs incurred when shopping for gasoline. Barron, Taylor, and Umbeck (2003) contrast the predictions of search theoretic models concerning price dispersion with variants of the monopolistic competition model adopted in this paper and find support for the monopolistic competition approach. For empirical studies of other industries that have investigated the link between search costs or market structure and the resulting price distribution consult Sorensen (2000), Walsh and Whelan (1999), Giulietti and Waterson (1997), Borenstein and Rose (1994), Dahlby and West (1986).

Section 3 retains the simple monopolistic competition view of retail gasoline markets, and in that context identifies the role of seller density in determining the extent of the reaction of competitors to an exogenous price change by one seller. We then develop measures of unexpected price changes by the control station and examine the relationship between competitor reaction to these changes and seller density. Empirical tests indicate that, as predicted by theory, the reactions of stations to a price change at another station are partial and the extent of the reaction is greater in lower-density markets. Section 4 explores further issues, including additional evidence of differences between the Los Angeles area and the San Diego and Bay areas.

1. A Simple Model of Monopolistic Competition

To provide a simple theoretical framework for considering the effect of station density on prices and competitor reactions, we postulate a market for a good that involves *L* consumers, each purchasing one unit of the good. Let *N* be the total number of sellers in the market ($N \geq 2$), such that sales of the representative seller equal *L*/*N*. For seller *i*, the production of q_i units of output has a common fixed cost component, *K*, and a constant marginal cost component, α. That is,

$$C\left(q_i\right) = K + \alpha q_i , \tag{1}$$

where $K > 0$ and $\alpha > 0$.

In general, the demand function faced by seller *i* will depend on the number of consumers and sellers in the market (*L* and *N*, respectively), the price charged by seller *i*, p_i, and the vector of prices charged by the other sellers, p_{-i}. In addition, the demand function depends on consumers' common consumption value of the good, *r*, and consumers' costs to visiting sellers. Let *v* denote the cost to a consumer of visiting a seller. By assumption, a consumer's cost to visiting a particular seller is the realization of a random variable drawn from the continuous distribution $F(v)$ with lower and upper bounds *a* and *b*, respectively.[7]

We assume that each consumer knows the prices and visiting costs of all sellers at the time of their decision to purchase. As such, a consumer with realized visiting costs v_i , $i = 1,\ldots,N$ purchases from seller *i* only if $p_i + v_i \leq \min_{k \neq i}[p_k + v_k]$ and $r \geq p_i + v_i$. Thus, given the second condition holds, the probability that consumer *j* buys from seller *i* is given by

$$q_i^j = \int_a^b \prod_{k \neq i}[1 - F(p_i + v - p_k)] \; dF(v) \,. \tag{2}$$

Summing across *L* consumers who each purchase one unit of the good, the expected demand for seller *i* becomes

$$q_i = \sum_{j=1}^{L} q_i^j \,. \tag{3}$$

Each period, each seller chooses a pricing strategy that maximizes expected profit taking as given the pricing strategies of other sellers. Specifically, each seller sets a unique price that maximizes profits given the resulting level of expected demand. Such a pure-strategy equilibrium means that for seller *i*, the maximization problem is:

$$\max_{p_i} \; \pi_i = p_i \, q_i - C(q_i), \tag{4}$$

where (1) and (3) define the cost and demand functions, respectively. Seller *i*'s profit-maximizing price satisfies the standard first-order condition:

$$p_i = m_i \alpha \,, \tag{5}$$

[7] This leads to realized product differentiation, the key assumption that provides a rationale for a finite price elasticity of demand, as illustrated by Perloff and Salop (1985) and Anderson and Renault (1999), among others.

where $m_i = e_i / (e_i - 1) > 1$, and $e_i = -(\partial q_i / \partial p_i)(p_i / q_i)$ is firm *i*'s price elasticity of demand. Eq. (5) is the familiar expression stating that the optimal price equals the firm's marginal cost multiplied by a markup factor, m_i, which, in turn, is decreasing in the firm's price elasticity of demand, e_i. That is, where consumers are more responsive to adjustments in p_i, firm *i* will optimally choose a smaller markup over marginal cost.

As Perloff and Salop (1985) have shown, given identical marginal costs and demands for each seller, the market equilibrium has all firms charging the same price, with expected sales by each seller equal to *L*/*N*. This common price in the market is simply

(6) $$p = m\alpha \ .$$

The zero-return condition then determines the number of sellers, with the resulting equilibrium characterized by a price set by all sellers that is equal to the common marginal cost α plus average fixed cost *K*/(*L*/*N*). We assume in equilibrium that the consumption value of the good, *r*, exceeds the upper bound of the distribution of visiting costs plus equilibrium price, such that all consumers purchase from one of the *N* sellers.

As we will develop more fully below, the model suggests that the increase in the number of sellers (*N*) that would accompany either an increase in the market size (*L*) or reduction in the fixed costs (*K*) affects not only the price elasticity of demand faced by an individual seller, and thus the optimal price level, but also the reaction of other sellers to a price change by one seller in the market. To test these implications for gasoline stations requires a measure of the number of other sellers in a station's market.

To create such a measure, we adopt the convention of identifying other sellers in a station's market by their proximity to the station. In particular, we count as other sellers those stations within a two-mile radius of each station. The density of competitors faced by a particular seller is then simply the number of such stations that meets this proximity requirement. The choice of two-mile circular "markets" is, in part, due to the sample data available. However, we note that two-mile radii markets are often assumed in the literature even in the absence of data availability issues and that the results reported in Table 1 are generally robust to permutations of this two-mile radius. An alternative measure of density that includes information on the average distance to a control station's competitor is discussed following our presentation of empirical results and the results using this alternative measure are provided in Appendix B.[8]

To determine the density of sellers for stations located in our three geographic areas in California (Los Angeles, San Diego, and the San Francisco areas), three data sources are used. From Lundberg, Inc., we obtained a census of stations in San Diego and the Los Angeles areas taken in 1996. Lundberg also provided 1997 census data for the San Francisco and San Diego areas. From Whitney-Leigh, we obtained an annual census of stations for the San Diego, Los Angeles, and San Francisco areas for the years 1995 to 1998. A third company, MPSI, provided a census of specific areas in the Los Angeles and San Diego areas taken in 1999.[9]

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[8] Our goal is to define each station's market in such a way as to include most of the station's competitors. While a two-mile-radius circle around a station likely defines the station's rivals in most cases, we note that even where two stations are across the street from each other, traffic patterns may impede effective competition. For example, a consumer's access to both stations may depend on which side of the road the consumer is traveling on. Alternatively, one might argue that driving *time* between stations, as opposed to the *distance* is a more appropriate measure. Unfortunately, such data are unavailable for our sample of stations and we rely on our two measures of density, acknowledging their imperfections.

[9] The stations recorded in each census from these three companies were matched to each other and to a list of proprietary station data provided to us by a large gasoline retailer using a variety of matching algorithms based on street address, intersection, city, and brand. Substantial care was taken in the matching process to make sure that the same station identified by two different sources would not be counted as two separate stations. The time-consuming process of matching stations across the three censuses was done for a variety of reasons. First, all three censuses contain some stations in areas not included in the other two censuses, so each census provides additional observations. Second, while the Lundberg census provides key information on location (latitude and longitude) not contained in the Whitney-Leigh census, the 1998 Whitney-Leigh census provides more current information on existing stations than the Lundberg 1996 census. Finally, matching stations from different censuses allows us to check the validity of key data, in particular the latitude and longitude data provided in the MPSI and Lundberg censuses. Additional data checks were also made as described in Appendix A. The resulting merged dataset

We use this information in two ways. First, it allows us to determine the average density of sellers for the San Francisco, San Diego, and Los Angeles areas. The average for LA, 22.2 stations within a two-mile radius, is above both the average of 17.5 stations for the San Diego area and 18.2 stations for the San Francisco area. Second, it allowed us to stratify the sample of stations chosen as control stations to assure differences in seller density.

2. Seller Density and the Responsiveness of Consumers

We now explore the link between seller density and a seller's price elasticity demand. For the monopolistically competitive model presented in Section 1, Perloff and Salop (1985) show that either a larger market size or lower fixed costs can explain why one market has a higher number of sellers. The theory predicts that accompanying this increase in the number of sellers will be an increase in the price elasticity of demand for individual sellers, and thus, according to (6), a lower equilibrium price.[10] Intuitively, the higher price elasticity of demand arises as an increase in the number of sellers in the market, or what we term the density of sellers, introduces more "close substitutes" for buyers. We thus have the following two predictions:

> **Hypothesis 1:** A seller's price elasticity of demand will be higher where the density of sellers is higher.
>
> **Hypothesis 2:** The market equilibrium price will be lower where the density of sellers is higher.

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provides a simple way to calculate the number of alternative stations within a two-mile radius of each station in the Los Angeles, San Diego, and San Francisco areas in early 1999.

[10] Note that in the limiting case price approaches marginal cost. Of course, the reason for the larger number of sellers has implications for the ratio of buyers to sellers. If the increase in number of sellers is due to an increase in market size, then the zero-return constraint suggests that there will not only be a lower equilibrium price but also an increase in the number of consumers per seller. On the other hand, if the increase in the number of sellers is due to lower fixed costs, then the number of consumers per seller will fall.

One focus of this paper is to directly test Hypothesis 1. We then combine the estimated price elasticity results and information on station density across different areas to predict differences in price levels across areas and compare these predictions to actual price differences across areas.

A. Field experiment data

It is well known in the econometric literature that obtaining estimates of the price elasticity of demand is a difficult task. The reason for this is that to estimate the price elasticity of demand, we must isolate the effect of changes in prices on sales holding constant other factors that can influence the level of demand. But often a price change occurs precisely because of a change in one of the factors affecting the level of demand, and it is thus difficult to be sure that observed price changes occurred independently.

The above discussion highlights the unique and valuable character of our field experiment. In particular, a large gasoline retailer allowed us to randomly change the prices charged at some of its company-operated stations. The company permitted us to control and survey prices at 54 stations of our choosing over a three-month period from February 8, 1999 to April 27, 1999. The 54 stations chosen for this field experiment consisted of 9 stations from the San Francisco area, 25 stations from the Los Angeles area, and 20 stations from the San Diego area. In choosing stations, an attempt was made to stratify these 54 stations by the number rival sellers.

Once the sample of stations was chosen, a procedure for instituting price changes at the individual stations was devised. The sample of 54 stations was divided into two groups. At the start of each week, the prices at stations in one of these two groups were increased or decreased by two cents from their respective prices on the prior day. To assure that company personnel would not know ahead of time the direction of a price change, the exact identity of the stations in terms of the direction of its price change was known only to us until the price change was implemented. This new price was then maintained for one week, after which control of the price at the station would revert to the company for a week and standard company procedures determined the price. The process would then be repeated. Thus, for each station, a week of price control would be followed by a week of "normalizing."[11]

During the three-month period of the experiment, daily volumes sold at each of the 54 stations were collected. In addition, the company sent out surveyors each weekday to record the prices charged by other stations within a two-mile radius of the station.[12] We thus have a dataset that includes daily prices and quantities of 54 control stations as well as the prices at stations surrounding each control station over a period of 79 days. An important feature of this dataset is that one can be reasonably confident that the price changes are largely the result of exogenous "supply-side" factors rather than due to changes in factors affecting demand.[13] We refer to this dataset as the 1999 Proprietary Price Survey.

B. Estimating seller price elasticity of demand

To estimate the price elasticity of demand at a station for a given grade of gasoline, we specify a log-linear form for the demand equation of a particular station in a market of density *d* such that

(7) $$\ln(S_{it}) = \delta - \beta_d \ln(P_{it}) + \gamma_d \ln(\bar{P}_{it}) + \lambda \ln(X_{it}) + \upsilon_i + \varepsilon_{it} \quad ,$$

[11] There was one exception to this pattern. A major explosion at a San Francisco area refinery (Tosco's Avon refinery, 23 February, 1999), followed by lesser problems at other refineries resulted in a substantial supply disruption in the middle of the experiment period. Control of stations was suspended for approximately three weeks after this event although we continued to collect the relevant market data from our survey. In our subsequent analysis of competitor reaction to our imposed changes, concern for the potential asymmetry in how this affected the three geographic areas of concern is addressed by interacting day and county in the first-stage estimation.

[12] Prices during weekends at competitor stations were interpolated linearly from the prices charged on Friday and Monday.

[13] Even the refinery explosions noted in footnote 10 turned out to be fortuitous for our study because the large relative price increases were attributable to supply changes.

where S_{it} denotes the sales of gasoline of a particular grade by control station *i* during the period (day) *t*, P_{it} denotes the price of the i^{th} control station, $\overline{P}_{it}$ denotes the average price of the other sellers in the market of control station *i,* and X_{it} denotes a vector of station characteristics.[14] The parameters β_d and γ_d denote the own and cross-price elasticities of demand respectively for a station in a market of density *d*, υ_i is a station-specific residual representing the extent to which the intercept of the i^{th} control station differs from the overall intercept and ε_{it} is the error term. As such, Eq. (7) implicitly allows a unique intercept term for each control station to account for differences in average sales across stations independent of price differences.

In the initial empirical treatment, we divide stations in our sample into three approximately equally sized groups, those with a low density (strictly fewer than 19 other stations within a two-mile radius, $d = l$), those with a mid-level density of stations (at least 19 and less than 27 other stations within a two-mile radius, $d = m$), and stations with a high density of other sellers (27 or more other stations within a two-mile radius, $d = h$). Our discussion of the role of density as directly influencing the price elasticity of demand leads to the predictions that in estimating separate price coefficients for each group, we expect $\hat{\beta}_h > \hat{\beta}_m > \hat{\beta}_l$ and $\hat{\gamma}_h > \hat{\gamma}_m > \hat{\gamma}_l$. That is, we expect these estimated elasticities to be greater at stations in markets where consumers face a higher density of alternative sellers.[15]

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[14] As we have defined markets as two-mile circles around each control station, in ten instances control stations are within two miles of each other and appear in each other's market. We do not use these stations in the calculation of average market prices. However, estimates are robust to their inclusion.

[15] With respect to the potential endogeneity of station density, any bias is likely to be against finding evidence in support of Hypothesis 1. That is, we would expect to see the highest station densities in markets where demand is least elastic, suggestion that any bias would be toward finding low elasticities in high-density markets.

Eq. (7) is estimated using a random-effects model controlling for a first-order autoregressive disturbance term. First-order autocorrelation can be detected through calculation of the Durbin-Watson statistic as generalized for use with panel data in Bhargava, Franzini, and Narendranathan (1982), which provides tables for testing the significance of the null hypothesis that no autocorrelation exists. For the models fit in this study, first-order autocorrelation does exist.[16]

The estimation results for the three grades of gasoline are reported in columns 1, 4 and 7 of Table 1.[17] To control for potential within-station substitution between grades of gasoline, we also include controls for the relative price(s) of neighboring grade(s) at the control station. We expect the estimated elasticities to fall with the inclusion of controls for the relative prices of other grades since changes in sales volumes should, in part, be due to changes in the relative prices of these substitute grades. The results of estimating seller-level price elasticity across the three grades of gasoline with the addition of the relative prices of other grades at the control station are reported in columns 2, 5 and 8 of Table 1.[18] Finally, columns 3, 6, and 9 provide a continuous estimate of the effect of seller density on elasticity by including price and price interacted with the log of the number of sellers in the market. As with earlier specifications, results provide support for the influence of station density on a seller's price elasticity of demand.

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[16] As our panel is unbalanced, we adopt the procedure of Baltagi and Wu (1999).

[17] Note that β_l corresponds to the coefficient on the price variable alone, β_m corresponds to this coefficient plus the coefficient on the price variable interacted with the mid-level density indicator, and β_h corresponds to the sum of the coefficient of the price variable and the price variable interacted with the high density indicator.

[18] Controlling for own-grade prices, as the ratio of mid-grade price to regular-grade price rises, sales of mid-grade gasoline decrease. Further, as the ratio of premium-grade price to mid-grade price rises, sales of mid-grade grade gasoline increase. Also of note is that the point estimates of elasticity or regular and mid-grade do generally fall with the inclusion of such controls for within-station substitution.

*** Insert Table 1 here. ***

Our tests provide strong support for the hypothesis that the density of sellers in a market directly affects the price elasticity of demand faced by individual sellers. For instance, according to Column 2 of Table 1, a one percent increase in a station's regular-grade price, other things equal, reduces sales of regular-grade gasoline by 1.4 percent at stations with low density of rivals (i.e. small number of other sellers in the market), 2.1 percent at stations with mid-level density and 4.4 percent at stations with a high density. Results are comparable for mid-grade and premium-grade gasoline. From Column 5, a one percent increase in a station's mid-grade price, other things equal, reduces sales of mid-grade gasoline by 1.5 percent at stations with low density of rivals, 2.0 percent at stations with mid-level density, and 3.8 percent at stations with a high density. The corresponding elasticities for premium-grade gasoline, from Column 8, are $\hat{\beta}_l$ = -2.8, $\hat{\beta}_m$ =-3.5 and $\hat{\beta}_h$ =-4.9, respectively. Note that, unlike our finding for regular-grade gasoline, the estimates for low and mid-level density markets are not significantly different for mid- and premium-grade gasoline.

While theory suggests that the number of rivals a particular station faces is an appropriate measure of what we call "station density," it may well be argued that such a measure allows for the miss-classification of markets according to their true "competitiveness." For example, consider two stations, one with a single competitor located immediately across the street and the other with two competitors, each located one mile down the street. A simple station-count would suggest that the second station (the one with more competitors) is in a more competitive market. Yet this may not be the case. As such, we adopt an alternative representation of density to that reported in Table 1 which goes beyond this simple station-count to include information on the distance of each competitor from the control station. Results indicate the robustness of our findings to this alternative specification.[19]

It is important to recognize that the estimated price elasticities of demand derive from customers' responses to a price change over relatively short periods of time. Thus, while suggestive, these estimated magnitudes probably are below the true levels of sellers' price elasticities of demand.[20] However, for our purposes, it is not so much the levels of the price elasticities of demand as it is the differences in the price elasticities of demand across stations of different types that is important for the analysis to follow. In this regard, any influence of the limited time period over which we consider customers' responses is of less concern.

C. Seller density and prices

As reported in the introduction, a substantial price difference emerged between retail gasoline prices in the Los Angeles area compared to prices in the San Diego and San Francisco areas during the latter part of the 1990s. Using Lundberg, Inc. bi-monthly price surveys, Figure 1 plots monthly Los Angeles self-serve regular prices for the period 1995 to 1999.[21] Also plotted in Figure 1 are differences between the prices in the San Diego and San Francisco areas and the average price in the Los Angeles area.

*** Insert Figure 1 here. ***

We can combine our estimates of the sellers' price elasticities in markets that vary in the number of sellers as reported in Table 1 with the average number of sellers per station for the three areas to obtain a rough measure of the average seller price elasticity of demand by area.

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[19] Specifically, Table B2 of Appendix B reports the results of an estimation of Eq. (7) using an index of competition for each control station defined as the ratio of the number of stations within two miles of the respective control station to the average distance to stations within two miles of the respective control station.

The first column in Table 2 reports this predicted average price elasticity of demand for the typical station in each of the three areas. Immediately one notes that this average price elasticity of demand is higher in LA than in San Diego or the San Francisco areas.

Given these average prices elasticities, Eq. (6) provides us with the predicted ratios of price to marginal cost for each area. The second column in Table 2 reports this calculation. From these predicted price-marginal cost ratios, the third column in Table 2 shows the predicted prices in the San Francisco and San Diego areas relative to the Los Angeles area under the assumption of common marginal costs. These predictions support the notion that differences in demand conditions arising from differences in the density of stations and thus the price elasticity of demand may be one source of the observed higher prices of regular-grade gasoline in San Diego and the San Francisco areas relative to the Los Angeles area. Note however that the predicted differences for regular-grade gasoline are significantly above the actual price differences, while the predicted differences in premium-grade gasoline are significantly less than the actual price differences.[22]

*** Insert Table 2 here. ***

One caveat should be noted at this point regarding our discussion of the source of price differences. Eq. (6) reveals two types of asymmetry across markets that can result in differences in prices between markets. The one we have focused on is heterogeneity across markets in price

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[20] Of course, these estimates are not comparable to the standard *market* demand elasticities that are common in the literature, which are typically below one.

[21] The 1999 data are through the end of May 1999.

[22] One reason for the too large predicted differences for regular-grade gasoline could be that our short-run estimates of price elasticity of demand vary systematically with density from the true long run price elasticity of demand. For instance, if one postulated that consumers respond more quickly to price changes in markets with higher seller density, then this would imply less of a difference in long-run price elasticities between L.A. and San Diego than is implied by our elasticity estimates, and thus a lower predicted price difference.

elasticities of demand and thus mark-ups, a heterogeneity that can arise from differences in the number of sellers in a market. But heterogeneity across markets in the marginal production cost can also lead to differences, although probably not of the magnitudes observed.[23]

3. Seller Density and Competitor Reactions to Exogenous Price Changes

The unique character of the data set, with the price of one seller in each of a number of markets being exogenously changed, has allowed us to examine how seller density can affect the reaction of consumers to a price change by a seller as summarized by a seller's price elasticity of demand. However, these data also allow us to examine the reaction of sellers to an exogenous change in price by one of its competitors. In this regard, to provide a framework for our analysis, let us return to the simple Bertrand differentiated product model of Section 1, but now with the focus on the reaction of other competitors in a market to an exogenous price change by one seller.

A. Competitor reaction

Denote p^c as the price at the control station. For non-control station *i*, we obtain from (2) and (3) the following expected market demand across the *L* consumers given the common price p^* for the other *N*-2 sellers:

$$q_i = (L/N)\int_a^b N(1 - F(p_i + v - p^*))^{N-2}(1 - F(p_i + v - p^c))\, dF(v)\,. \tag{8}$$

Rewriting (5), the resulting optimal price at non-control station *i* will satisfy:

[23] As there are no refineries in the San Diego area, San Diego County receives about 92 percent of its gasoline from a pipeline that runs from the Los Angeles refining center to distribution terminals located in the Mission Valley and San Diego Harbor. The rest of the gasoline (about 8 percent) is delivered to the area by tanker trucks. The shipping cost by pipeline from the Los Angeles refineries to the San Diego terminals is about 1 cent more per gallon than the cost to ship to the Los Angeles area terminals from the same refineries. Shipping gasoline to the San Diego region by tanker truck costs 2 to 4 cents per gallon (Rohy, (1996)).

(9) $$p_i = \alpha - q_i /(\partial q_i / \partial p_i),$$

where (8) determines the magnitude of the term $q_i /(\partial q_i / \partial p_i)$.

Assume initially that all sellers including seller *i* and the control station *c* set the common price p^*, with p^* set such that (9) is satisfied for all sellers. At these equilibrium prices, let $((q_i /(\partial q_i / \partial p_i))^*$ denote the corresponding ratio of seller *i*'s output to the derivative of output with respect to a change in seller *i*'s price, *i* = 1, … , *N*. We now consider station *i*'s reaction to a change in the price at the control station. To examine this issue, let the control station's price be $p^c = p^* + x$ with $x > 0$, such that control station *c* sets its price above the original market price p^*.

There are two types of reactions for seller *i* that one might consider theoretically. One is a deviation in seller *i*'s price from p^* that satisfies (9) given the deviation *x* in the control station's price and the belief that the other *N*-2 sellers will maintain their prices at the original equilibrium level, p^*. However, except in the case when there are only two sellers, this reaction is based on an incorrect belief of inaction on the part of the other *N*-2 sellers. Thus, we focus instead on the reaction in terms of the deviation in seller *i*'s price from p^* that satisfies (9) given the deviation *x* in the control station's price *and* the correct anticipation of the reactions of the other *N*-2 sellers. In other words, we focus on the equilibrium deviation from the original price p^* such that Eq. (9) remains satisfied for the other *N*-1 sellers at the new exogenous price for the control station.

Not surprisingly, at the original price p^* for the *N*-1 sellers, an increase (decrease) in the price at the control station alone induces each of the other sellers to change their prices in the same direction.[24] However, these price changes will be less than the amount of the imposed deviation, *x*. The reason for this is that, at the original price, the increase (decrease) in demand at the *N*-1 non-control stations reduces (increases) the price elasticity of demand, leading to a higher (lower) price satisfying Eq. (9). However, were the non-control stations to match the increase (decrease) in the price of the control station, then demand would be identical to before, but the price elasticity would be higher (lower). Of course, Eq. (9) would not be satisfied if the prices at the *N*-1 non-control stations were to increase (decrease) by *x*. Thus we have:

> **Hypothesis 3:** An exogenous deviation in price from the equilibrium price by one of *N* sellers in a market will result in a deviation in the prices of the other *N*-1 sellers from the equilibrium price in the same direction, but by a lesser absolute amount.

A natural question that arises is whether the price increase of competitors in response to an exogenous increase in the price of a single seller in the market will be affected by seller density. While the general form of demand makes analytical results difficult to calculate, Table 3 presents simulations of the analysis under the assumption of a uniform distribution for visiting costs, *F*(*v*). For illustrative purposes, we consider markets with 2, 4, and 6 sellers, with the number of sellers

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[24] Note that for the case when $p_i = p^c = p^*, -\left(\frac{-q_i}{\partial q_i / \partial p_i}\right)^* = \frac{\int (1-F(v))^{N-1} dF(v)}{\int (N-1)(1-F(v))^{N-2} f(v) dF(v)}$. On the other hand, if $p_i = p^*$ but $p^c - p^* = x > 0$, we have:

$$-\left(\frac{-q_i}{\partial q_i / \partial p_i}\right)' = \frac{\int (1-F(v))^{N-2}(1-F(v-x))dF(v)}{\int (N-2)(1-F(v))^{N-3}(1-F(v-x))f(v) + (1-F(v))^{N-2} f(v-x)dF(v)}.$$

Comparing these two equations, it follows that $-q_i /(\partial q_i / \partial p_i)' > -(q_i /(\partial q_i / \partial p_i))^*$, and thus the reacting station's optimal price increases with an increase in the control station price.

reflecting either differences in market size (Panel A) or differences in the fixed costs of entry (Panel B). Note that, consistent with Hypothesis 2, the equilibrium price is lower in markets with higher seller density. More relevant for the current discussion, however, are the final two columns of the table which indicate that for an identical price deviation by the control station, the magnitude of the reaction of the *N*-1 sellers falls with an increase in seller density.

*** Insert Table 3 here. ***

For instance, for the 4-seller case, if one of the four sellers, the control station, increases its price by two cents, the deviation in the equilibrium price for the other three sellers is 0.15 cents. Note that the same deviation from the initial equilibrium price by the control station leads to larger deviation in the price at the other sellers where the total number of sellers is reduced to two, but a smaller deviation where the total number of sellers is increased to six. Such results are robust to a variety of parameter values and are similar in magnitude for a price decrease by the control station.

Our simulation results thus lead to the following hypothesis:

> **Hypothesis 4:** An exogenous deviation in price from the equilibrium price by one of *N* sellers in a market will result in a deviation in the prices of the other *N*-1 sellers from the equilibrium price that is decreasing in seller density.

The intuition behind Hypothesis 4 is straightforward. As the number of sellers in a market increases, the effect of an exogenous change in price by any one seller on the other sellers' demands is less. As such, their reactions to exogenous price changes by rivals are muted as seller density increases.

B. A test of competitor reactions

The simplest measure of the reaction of a competing station to an exogenous price change at a corresponding control station would consider the change in price at the reacting station in the period subsequent to the imposed change. Of course, one could also consider more complete responses to a price shock introduced in one period by following changes in the prices of competitors over multiple periods. Unfortunately, we are limited to analyzing only the single-period reaction due to data restrictions that result in substantial reductions in sample sizes if we were to consider lengthier reaction periods.[25]

With this in mind, we adopt a two-stage procedure to test the reaction of competing stations to an exogenous price change by the control station, as suggested by hypotheses 3 and 4.[26] The first stage estimates a model of prices that enables one to predict what equilibrium prices would have been for individual stations in the absence of exogenous deviations from equilibrium-prices by the control stations. Recall that as part of the experimental design, we staggered periods of control across market areas and time such that, for any day within the entire sample period, approximately one half of all stations were not within two miles of a control station at which price was being controlled. Using only this sub-sample of prices at stations in markets during the time periods when all stations in the market (and the control station in particular) were freely able to set their prices allows us to estimate a model of prices in the absence of exogenously

[25] Later we discuss in more detail these data limitations that preclude us from fully testing for such rates of response.

[26] Recall that our data consists of all stations within two linear miles of 54 control stations. Thus, each non-control station in our sample has a corresponding station within two linear miles at which we are changing prices. It is to the closest control station that we will measure each non-control station's reaction.

imposed changes and therefore predict what prices *would have been* for periods when a market's control station was, in fact, being controlled.[27]

For the periods when a market had no station with a controlled price, we regress gasoline prices (separately by grade) of the various stations in the market on the log-number of competing stations within two miles, the average distance to these competitors, the minimum distance to these competitors, brand indicators, indicator variables corresponding to each day within our sample period alone and interacted with county indicators, controls for city and station characteristics such as hours of operation, car washes, convenience stores and number of nozzles, as well as an indicator to capture whether the station is company operated. In order to exploit both time-series and cross-sectional variation, this first stage adopts a random-effects model. Given the nature of our price data, we again account for first-order autocorrelation.

The second stage focuses on the sample of prices at stations in markets during periods when the price at the control station was set exogenously. For a non-control station *i*, Hypotheses 3 and 4 suggest the following price equation, where η_{it} is an error term:

(10) $$p_{it} = p_{it}^{*} + \beta_d (p_{ct} - p_{ct}^{*}) + \eta_{it}$$

with Hypothesis 3 predicting $0 < \beta_d < 1$ and Hypothesis 4 predicting that β_d be decreasing in seller density. This empirical categorization of markets mirrors that of columns 3, 6 and 9 of Table 1. However, to estimate (10) requires knowledge of what the equilibrium prices (p_{it}^{*} and p_{ct}^{*}) would have been during these periods when a market's control station's price was fixed.

[27] Note that while the first-stage does not include stations on days during which the corresponding market's control station was being controlled, our experimental design ensures that we have a control group for every day and each geographic of the three geographic areas during our entire sample period.

For this we rely on the first-stage regression. That is, as the observed control-period prices do not contribute to the first-stage estimation procedure, we use the first-stage regression to make out-of-sample predictions of prices during control periods.[28]

Note that it is, in fact, possible for spurious correlation to exist between a control-station's deviation from predicted prices and reactions of a non-control-station in the second stage because the two stations are in the same market. However, any such correlation will only occur if there is some unobserved factor that influences prices specifically in this market and not in other markets, and in a way that is specific only to periods of control. Further, this factor must influence prices commonly across stations within this market. Finally, for this to matter with respect to our key interest in the role of density in affecting reactions, this factor must also be correlated with density. Assuming this is not the case, the predicted out-of-sample prices for the non-control and control stations, $\hat{p}_{it}^{*}$ and $\hat{p}_{ct}^{*}$, provide measures of the prices that would have existed in the absence of price setting at the control station. That is, we assume:

(11) $$\hat{p}_{it}^{*} = p_{it}^{*} + v_i + \varepsilon_{it}$$

(12) $$\hat{p}_{ct}^{*} = p_{ct}^{*} + v_c + \varepsilon_{ct}$$

where v_i and v_c are station-specific residuals in predicting each sellers' equilibrium price in the absence of market intervention and ε_{it} and ε_{ct} are i.i.d. error terms.

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[28] Note that as long as the influence of the above regressors is not systematically different across control and non-control periods, deviations from these predicted prices should also be independent of the above station and market characteristics. If we regress deviations of actual prices from these out-of-sample predictions (i.e. if we regress "out-of-sample errors" of sorts) on the same set of first-stage regressors (where R^2 was .95), we find little predictive power remaining (R^2 = .06), suggesting that our model provides reasonable out-of-sample predictions on average and that the effect of these regressors has been netted out reasonably well.

Equations (10) through (12) link deviations in the control station price from its projected market equilibrium to deviations in a reacting station's price from its projected market equilibrium. To see how this is accomplished, we substitute (11) and (12) into (10) and rearrange to obtain:

$$(13) \qquad \Delta_{it} = \alpha_{ic} + \beta_d \Delta_{ct} + \upsilon_{it} .$$

where $\Delta_{it} = p_{it} - \hat{p}^*_{it}$, $\Delta_{ct} = p_{ct} - \hat{p}^*_{ct}$, $\alpha_{ic} = \beta_d v_c - v_i$ and $\upsilon_{it} = \eta_{it} - \varepsilon_{it} + \beta_d \varepsilon_{ct}$.[29]

Given the form of Eq. (13), it is natural to estimate a fixed-effects model on the underlying variables, Δ_{it} and Δ_{ct}. Recall that these variables reflect the differences between actual and predicted prices for non-control and control stations, respectively. To ensure that the deviation in an actual price from that predicted at one station can be legitimately interpreted as a "reaction" to a deviation at a second station, we lag the deviation for the control-station by one day.[30] Motivated by Hypothesis 4, we allow reactions to differ across station density by including the interaction of seller density with the differences between actual and predicted prices for control stations.

C. Empirical results

The results reported in columns 1, 4 and 7 of Table 4 clearly support our discussion of hypotheses 3 and 4 above. First, we find that sellers do respond to the exogenously imposed

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[29] Note that Eq. (13) is an example of the classic problem of measurement error as the regressor is correlated with the disturbance. Recall that our approach is to generate a proxy for unobservable equilibrium prices, that is prices that would have existed had the price at one station in the market not been fixed. As such, coefficient estimates are inconsistent, with a bias toward zero. This measurement error is more severe where the true coefficient is higher. Thus, the bias makes it more difficult to find a clear relationship between market density and the price reaction of a competing seller to an exogenous change in the price of another seller in the market.

[30] While our price changes were typically imposed at 10:00am, the survey of a particular competitor's price *may* have been made as early as 9:00am in some cases. Thus, by lagging the control station deviations from expected prices by one day, we ensure that the imposed price change was strictly before surveyed prices at competitors. As such, we implicitly allow competing stations one day to react before observing their prices.

changes by changing their own prices, and by amounts less than the imposed changes across all grades. Second, we find that in markets with higher seller density, sellers respond less to the imposed change in the control station's price, again across all grades. From the estimated coefficients in Column 1 of Table 4, the mean reaction of non-control station regular-grade prices is 18.7 percent of the deviation imposed at corresponding control stations.[31] Consistent with the prediction of Hypothesis 4, regular-grade reactions are, on average, 23.6 percent of the imposed shocks in a low-density market and only 11.7 percent of the imposed shocks in a high-density market. These figures define low and high density markets as seller density equal to the 25th or 75th percentile of station density, respectively, for our sample. We also find that average reactions to control-station price changes are monotonically decreasing in grade of gasoline. Finally, the pattern of stations in high-density markets reacting less is also found in mid- and premium-grade gasoline prices.[32]

*** Insert Table 4 here. ***

Columns 2, 4, and 6 of Table 4 introduce two interaction terms to investigate the possibility that reactions differ depending on the direction of the imposed shock to control-station prices. While alone, the point estimate on the interaction term for positive deviations (in Column 2) suggests that the reaction of a station to a positive price shock is less than the reaction to a

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[31] Results reported in the text are statistically significant unless otherwise noted. This figure is the net of the predicted effect of a price shock at the control station that takes into account both the direct effect (coefficient on the lagged control-station price difference) as well as the indirect effects of this difference interacted with the density of sellers surrounding the non-control station. Recall the earlier discussion of the bias (toward zero) in estimating the reaction coefficient. While this is of little concern for our analysis of the potential difference across markets of different seller density, the average estimated reactions may be properly thought of as lower bounds on the true reactions of stations to exogenously imposed changes at our control stations.

[32] The mean reactions of non-control station mid- and premium-grade prices are 14.0 percent of the deviation imposed at corresponding control stations and 11.7 percent of the deviation imposed at corresponding control stations, respectively. Comparing again the upper and lower quartiles of station density suggests that the corresponding reactions in mid- and premium-grade markets are 7.7 percent and 18.4 percent for mid-grade and 7.2 percent and 15.0 percent for premium-grade markets.

negative shock, this does not take into account the additional interaction term that includes the effect of seller density. Doing so, we find that, in fact, stations react more to positive shocks, matching positive shocks to control stations' regular-grade-prices by increasing prices by 25.5 percent of the imposed shock, on average, while matching negative shocks by decreasing prices by only 12.2 percent of the imposed shock. This pattern for regular grade gasoline also appears to hold for mid-grade and premium grade gasoline. Further, note that due to the significance of seller density on competitor reactions, our results suggest that this asymmetry in reactions is more extreme in high density markets.[33]

Columns 3, 6 and 9 in Table 4 introduce five additional interaction terms to investigate whether station characteristics affect the extent of reaction to imposed deviations. Recall that the theory has characterized differences across markets solely in terms of the number of competitors in the market, which implies that the reaction to a price change by one of the *N*-1 other sellers in the market is the same regardless of which of the other sellers changes price. However, if "higher density" merely signifies a higher proportion of stations that are "close, but not close enough to react to our imposed changes," reactions might be less, on *average*, where reacting stations are in more densely competitive markets. Therefore, the first interaction is the distance the station is from the corresponding control station where the shock was introduced. In addition, as the response of the "reacting station" may differ if the reacting station is the same brand as the control station we introduce controls for same-brandedness. Further, as Noel (2001)

[33] Allowing for asymmetric reactions, at the upper quartile of station density, the average reactions to positive and negative shocks are, on average, 24.2 percent and 4.9 percent of imposed shocks, respectively. At the lower quartile of station density, the average reactions to positive and negative shocks are, on average, 29.2 percent and 20.0 percent of imposed shocks, respectively. Recall that our simulation does not suggest an asymmetry in the response of seller-price to an exogenous change in a rival's price. This suggests that further investigation may be warranted. In separate estimations (not reported) we allow for non-linear responses to our imposed deviations. We cannot reject the null of linear responses.

finds some evidence of differences in response rates across station types, we include a measure of the stations' ownership and a control for whether the station is a major brand.[34] In all cases, we allow the influence of these characteristics to differ for positive and negative shocks.

Interestingly, while one might suppose that the distance from the particular seller that changes price may affect the magnitude of the reaction, this appears not to be the case. Another interesting finding from the inclusion of additional interaction terms with respect to regular-grade gasoline is that company-operated stations are more responsive to negative shocks than are stations of other ownership types. Major-branded stations are also different in their responsiveness to positive shocks than are independent stations, their regular-grade prices being 58.8 percent less responsive to positive shocks than non-major retailers, on average.[35]

As noted above, extending the above analysis to consider reactions over time, rather than our simple one-day reaction, would be interesting. Unfortunately, the nature of the field-experiment as well as limitations in data collection vitiates the usefulness of such an exercise. In particular, our week-on, week-off rule for imposing price changes ultimately yields a fairly short time-series over which one can analyze reactions. Combined with data on competing stations being collected on weekdays only, the potential number of reacting days is further reduced. Specifically, note that even with only one additional lag included, the sample size is cut by 43 percent. If we include a third lag, the sample size is cut by 83 percent from our original sample.

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[34] Noel (2001) follows endogenous price changes and station "responses" for a sample of 22 retail stations as opposed to our method of measuring deviations from predicted prices during periods when we set control station prices exogenously. Our sample includes nine major brands: 76, ARCO, BP, Chevron, Exxon, Mobil, Shell, Texaco and Unocal. All other sellers are considered independent, or non-major, retailers.

[35] Major retailers respond by 22.6 percent of the positive shock, on average, while non-major retailers respond by 54.9 percent of the imposed shock.

As such, results of estimating equations similar in form to Eq. (13), but with the addition of multiple lagged terms for the underlying variable, Δ_{it}, are not instructive.

4. Conclusion and Further Remarks

A substantial literature developed following Maskin and Tirole's 1988 article that presented a dynamic Bertrand duopoly model where two firms alternate in the setting of prices. Notably, the model demonstrates that both rigid prices and cyclical prices can exist in equilibrium. A number of papers have adopted this approach in empirical work, including analyses of retail-gasoline markets.[36] For our empirical analysis, we adopt instead the theoretical framework of the standard differentiated-product model that considers simultaneous pricing equilibria for *N* firms, and then consider the implications of a single deviant seller. One reason for adopting this view of pricing is to focus on the effect of the number of sellers on buyer behavior, as this has important implications for equilibrium prices. A second reason is to isolate how the number of sellers affects reactions by competitors to exogenous deviations by a single station in the market. This focus is possible given our access to a unique data set. Rarely can economists obtain field data with known, self-imposed exogenous price changes. A key feature of this paper is a dataset that collected prices and volumes over a period of time for a sample of retail gasoline stations stratified by the number of rivals within two miles, plus prices at these rival stations when prices at a sub-sample of the "control" stations were intermittently determined exogenously.

Although there are limitations – a small number of control stations, a short period of time for price collection, restricted data collection during weekends, the existence of other shocks in the retail gasoline market during this period – the dataset still presents the ability to test two key

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[36] Recent examples include Castanias and Johnson (1993), Noel (2001) and Eckert (2003).

implications of the differentiated-product model, namely that an increase in the number of rivals increases the price elasticity of demand of an individual seller and that the reaction of rivals to an exogenous price change by one seller in the market will decrease with an increase in the number of rivals.

Our findings confirm both implications. With respect to the elasticity findings, the direct link we find between the number of sellers in a market and the individual seller's price elasticity of demand supports the premise for a key folk theorem, namely that an increase in the number of competitors in a market will reduce prices. With respect to our reaction findings, our empirical findings are also important, as they indicate that station responses are partial. This finding of only a partial response to a price deviation by one seller contrasts with the simple two-firm sequential pricing model of Maskin and Tirole, a model that suggests a rival firm would "over-react" to an exogenous price decrease, leading to a price war.[37] Our finding that rival-responses depend inversely on the number of sellers in the rival's market reinforces the importance of considering the role of the number of sellers in price-setting behavior. Finally, as our control stations were all "major" sellers, the evidence of asymmetry in the responses of other sellers to exogenous deviations from the equilibrium price by one station provides support for an earlier finding by Slade (1992) which finds firms more responsive to "major" firm price increases than to decreases.

The preceding analysis suggests that the higher prices in San Diego and the San Francisco area relative to the Los Angeles area reflect to some extent lower price elasticities of demand

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[37] A word of caution is in order, as the Maskin and Tirole analysis presumes a homogeneous good and our elasticity results argue in favor of a differentiated-product environment for retail gasoline markets.

arising from lower station density. Other things equal, such price differences should translate into a lower return to stations in the Los Angeles area relative to the other two areas. Economic theory suggests that in the long run these differences in returns will be dissipated. There are several potential avenues through which this could occur. One way would be a decrease in the number of stations in the Los Angeles area relative to the San Francisco and San Diego areas. Figure 2 indicates that this in fact did occur. Using Whitney-Leigh annual censuses of the three areas, evidence indicates a decrease in the number of stations in the Los Angeles area between 1995 and 1998 relative to the number in both the San Francisco or San Diego areas.

Further, there also exists evidence of entry restrictions in the San Diego and San Francisco areas. Note that if entry into these two areas were restricted we would expect to see the existing stations being utilized more intensively than stations in the LA area. From the Whitney-Leigh census data we can construct a measure of the capacity utilization of gasoline stations. This capacity measure uses information on hours of operation, monthly gasoline volume and number of fueling position to calculate the capacity utilization of a station in terms of the quantity of gasoline pumped per hour per fueling position.

*** Insert Table 5 here. ***

Table 5 indicates the average capacity utilization of stations across the three areas. As the numbers reported in Table 5 make clear, stations in the San Diego and San Francisco areas were more heavily utilized relative to stations in Los Angeles during the 1995 to 1998 period. This observation is consistent with there being factors in the San Diego and San Francisco areas that limit the entry of new stations relative to the Los Angeles area. If there are such restrictions to entry in the San Francisco and San Diego areas, then competition for the relatively restricted number of prime service station locations in the San Diego and San Francisco areas will result in higher utilization rates and higher "fixed" costs for the station operators.

Table 1: Gasoline Sales at Stations with Different Seller Density.

All equations are random-effects models with first-order autoregressive disturbance terms. Absolute values of *z*-statistics are in parentheses. Coefficients are not reported for six day-of-week indicator variables that were included in the estimation of all equations. Mid-level density corresponds to markets of at least 19 and less than 27 stations, while high density corresponds to markets of 27 or more stations. Sample means are reported in Table B1 of Appendix B.

	Log of sales volume (self-serve gasoline) at control station								
Independent variable		Regular-Grade			Mid-Grade			Premium-Grade	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of self-serve price	-1.465	-1.445	3.436	-1.750	-1.485	1.425	-2.749	-2.763	-0.398
	(5.94)***	(5.69)***	(4.14)***	(5.56)***	(4.60)***	(1.32)	(8.70)***	(8.68)***	(0.38)
Log of self-serve price interacted with:									
Mid-level density indicator	-0.659	-0.665		-0.380	-0.496		-0.716	-0.703	
	(1.91)*	(1.93)*		(0.82)	(1.07)		(1.50)	(1.47)	
High density indicator	-2.920	-2.930		-2.253	-2.357		-2.175	-2.176	
	(8.31)***	(8.33)***		(5.13)***	(5.39)***		(4.89)***	(4.89)***	
Log of number of stations within 2 miles			-2.032			-1.313			-1.132
			(7.44)***			(3.69)***			(3.25)***
Log of market-average self-serve price	1.612	1.593	-3.028	0.863	0.598	-2.485	1.083	1.109	-1.418
	(6.14)***	(5.93)***	(3.47)***	(2.41)**	(1.63)	(2.06)**	(2.97)***	(2.98)***	(1.20)
Log market-average price interacted with:									
Mid-level density indicator	0.701	0.709		0.444	0.568		0.826	0.814	
	(1.90)*	(1.92)*		(0.85)	(1.09)		(1.52)	(1.49)	
High density indicator	2.841	2.853		2.466	2.569		2.370	2.374	
	(7.48)***	(7.49)***		(4.90)***	(5.12)***		(4.60)***	(4.61)***	
Log of number of stations within 2 miles			1.938			1.403			1.221
			(6.71)***			(3.53)***			(3.10)***
Mid-level density indicator	-0.205	-0.206		-0.067	-0.069		-0.260	-0.260	
	(2.33)**	(2.35)**		(0.56)	(0.59)		(1.77)*	(1.78)*	
High-level density indicator	-0.425	-0.426		-0.449	-0.449		-0.626	-0.627	
	(4.95)***	(4.98)***		(3.85)***	(3.90)***		(4.37)***	(4.40)***	
Log of number of stations within 2 miles			-0.344			-0.259			-0.431
			(5.07)***			(2.66)***			(3.68)***
San Diego area indicator	0.065	0.065	0.082	-0.065	-0.065	-0.052	0.136	0.135	0.159
	(0.90)	(0.90)	(1.15)	(0.68)	(0.69)	(0.52)	(1.14)	(1.14)	(1.30)
San Francisco indicator	0.228	0.230	0.247	0.252	0.242	0.240	0.442	0.441	0.448
	(2.39)**	(2.41)**	(2.62)***	(2.00)**	(1.95)*	(1.79)*	(2.82)***	(2.84)***	(2.79)***
Log of Mid-to-Regular price ratio		0.085	0.066		-0.866	-0.830			
		(0.34)	(0.26)		(2.91)***	(2.76)***			
Log of Premium-to-Mid price ratio					1.007	0.921		0.178	0.130
					(1.95)*	(1.78)*		(0.34)	(0.25)
Constant	8.491	8.484	9.295	7.159	7.174	7.767	7.057	7.039	8.019
	(118.59)***	(114.20)***	(44.69)***	(74.14)***	(65.83)***	(25.72)***	(59.24)***	(54.49)***	(22.20)***
Observations / number of control stations	4,073 / 54	4,073 / 54	4,073 / 54	4,073 / 54	4,073 / 54	4,073 / 54	4,073 / 54	4,073 / 54	4,073 / 54
	Wald $\chi^2(17)$ = 1,365.6	Wald $\chi^2(18)$ = 1,365.9	Wald $\chi^2(18)$ = 1,334.1	Wald $\chi^2(17)$ = 2,021.3	Wald $\chi^2(19)$ = 2,060.8	Wald $\chi^2(19)$ = 2,002.1	Wald $\chi^2(17)$ = 5,312.5	Wald $\chi^2(18)$ = 5,311.9	Wald $\chi^2(18)$ = 5,229.8
Mean of dependent variable	8.380	8.380	8.380	6.718	6.718	6.718	6.207	6.207	6.207

Results are robust to dropping all observations corresponding to Saturday and Sunday. * significant at 10% level. ** significant at 5% level. *** significant at 1% level.

Table 2: Differences in Price Elasticity, Predicted Prices, and Actual Prices Across Areas

Regular-Grade Gasoline

Area	Predicted average price elasticity of demand [a]	Predicted price/marginal cost ratio (*m*)	Predicted percentage difference from LA area price	Actual percentage difference from LA area price (Lundberg 1995-99)
San Francisco	2.46	1.69	9.8% higher	7.7% higher
San Diego	2.37	1.73	12.5% higher	6.3% higher
Los Angeles	2.86	1.54	---	---

Mid-Grade Gasoline

Area	Predicted average price elasticity of demand [a]	Predicted price/marginal cost ratio (*m*)	Predicted percentage difference from LA area price	Actual percentage difference from LA area price (Lundberg 1995-99)
San Francisco	2.38	1.72	7.2% higher	6.6% higher
San Diego	2.33	1.75	9.0% higher	6.2% higher
Los Angeles	2.65	1.61	---	---

Premium-Grade Gasoline

Area	Predicted average price elasticity of demand [a]	Predicted price/marginal cost ratio (*m*)	Predicted percentage difference from LA area price	Actual percentage difference from LA area price (Lundberg 1995-99)
San Francisco	3.68	1.37	2.2% higher	6.7% higher
San Diego	3.63	1.38	2.7% higher	6.0% higher
Los Angeles	3.90	1.34	---	---

[a] Calculated from the own-price coefficients estimated in Table 1, columns 3, 6, and 9, and the average number of stations in each market area (22.2 in LA; 17.5 in the San Diego area and 18.2 in the San Francisco area).

Table 3: Simulations of Reaction Deviation to Control Station Deviation, by Station Density

Panel A: Differences in Market Size

Number of sellers (N)	Parameter Values (zero profits, markets differ by number of buyers): Number of buyers (L)	Fixed costs (K)	Marginal cost (α)	Lower bound on uniform distribution of visiting costs	Upper bound on uniform distribution of visiting costs	Initial Equilibrium price	Control station's deviation (increase) from initial equilibrium price	Reacting sellers' (N-1) deviation in price from initial equilibrium price
2	5,000	50,000	100	0	40	120.0	2.0	1.0
4	20,000	50,000	100	0	40	110.0	2.0	.15
6	45,000	50,000	100	0	40	106.7	2.0	.06

Panel B: Differences in Fixed Entry Costs

Number of sellers (N)	Parameter Values (zero profits, markets differ by size of fixed cost): Number of buyers (L)	Fixed costs (K)	Marginal cost (α)	Lower bound on uniform distribution of visiting costs	Upper bound on uniform distribution of visiting costs	Initial Equilibrium price	Control station's deviation (increase) from initial equilibrium price	Reacting sellers' (N-1) deviation in price from initial equilibrium price
2	20,000	2,000,000	100	0	40	120.0	2.0	1.0
4	20,000	50,000	100	0	40	110.0	2.0	.15
6	20,000	22,222	100	0	40	106.7	2.0	.06

Table 4: Reactions to Exogenous Changes in Control-Station Gasoline Prices.

All equations are fixed-effects models with first-order autoregressive disturbance terms. Absolute value of *t*-statistic is in parentheses.

Independent variable	Non-control station self-serve price: (Actual – predicted)								
	Regular-Grade			Mid-Grade			Premium-Grade		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged control-station price deviation:									
(Actual – predicted)	0.908	1.065	0.991	0.791	0.706	0.659	0.586	0.568	0.606
	(3.88)***	(3.07)**	(2.78)***	(3.54)**	(2.17)**	(1.95)*	(2.87)***	(1.87)*	(1.89)*
(Actual - predicted); positive deviations only		-0.454	-0.123		0.127	0.511		0.060	0.201
		(0.88)	(0.23)		(0.22)	(0.87)		(0.12)	(0.40)
Lagged control-station price deviation interacted with:									
Log of number of stations within 2 miles	-0.233	-0.301	-0.296	-0.210	-0.195	-0.169	-0.151	-0.169	-0.148
	(3.10)***	(2.75)**	(2.66)***	(2.88)**	(1.86)*	(1.58)	(2.29)**	(1.69)*	(1.45)
Distance from control station			0.041			-0.046			-0.001
			(0.44)			(0.45)			(0.01)
Same (major) brand as control station			0.125			0.178			0.174
			(0.95)			(1.22)			(1.22)
Ownership indicator (Company			0.298			0.206			0.242
operated = 1)			(1.87)*			(1.21)			(1.43)
Major-brand indicator (Major			-0.055			-0.063			-0.207
brand = 1) [a]			(0.48)			(0.51)			(1.63)
Lagged control-station price deviation: (positive deviations only)									
Log of number of stations within 2 miles		0.185	0.198		-0.015	-0.051		0.022	0.062
		(1.11)	(1.15)		(0.08)	(0.26)		(0.14)	(0.37)
Distance from control station			-0.085			0.162			-0.076
			(0.59)			(0.98)			(0.49)
Same (major) brand as control station			0.037			0.170			0.076
			(0.18)			(0.75)			(0.34)
Ownership indicator (Company			-0.294			-0.174			-0.340
operated = 1)			(1.17)[b]			(0.64)			(1.35)
Major-brand indicator (Major			-0.269			-0.492			-0.143
brand = 1) [a]			(1.45)[c]			(2.40)**			(0.73)
Constant	0.005	0.002	0.002	0.006	0.003	0.004	0.004	-0.001	-0.000
	(17.76)***	(5.28)**	(5.00)***	(17.56)*	(6.93)**	(7.13)***	(12.13)**	(1.12)	(0.71)
Observations / number of unique control stations		3,090 / 566			3,063 / 561			3,077 / 563	
	F(2,2522) = 24.67	F(4,2520) = 13.31	F(12,2512) = 5.61	F(2,2500) = 15.96	F(4,2498) = 8.26	F(12,2490) = 5.07	F(2,2512) = 11.46	F(4,2510) = 6.50	F(12,2502) = 3.79
Mean of dependent variable		0.000			0.001			0.001	

[a] Our sample includes nine major brands: 76, ARCO, BP, Chevron, Exxon, Mobil, Shell, Texaco and Unocal. All other sellers are considered independent, or non-major, retailers.
[b] The net effect of company ownership on reactions to positive shocks is statistically insignificant (i.e. company operated stations react more only to negative shocks).
[c] The net effect of major-brandedness on reactions to positive shocks is statistically significant (i.e. major branded stations react less only to positive shocks).
* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 5: Capacity Utilization by Area

Year	San Francisco Area average gasoline sales per fueling position per hour	Los Angeles Area average gasoline sales per fueling position per hour	San Diego Area average gasoline sales per fueling position per hour
1995	29.4	24.6	28.3
1996	29.1	26.7	25.5
1997	30.0	26.4	27.5
1998	31.4	26.8	30.8

Source: Whitney-Leigh census

Figure 1
Los Angeles Self-Serve Regular Price and Difference Between Prices in the San Diego and Bay Areas and the Los Angeles Area

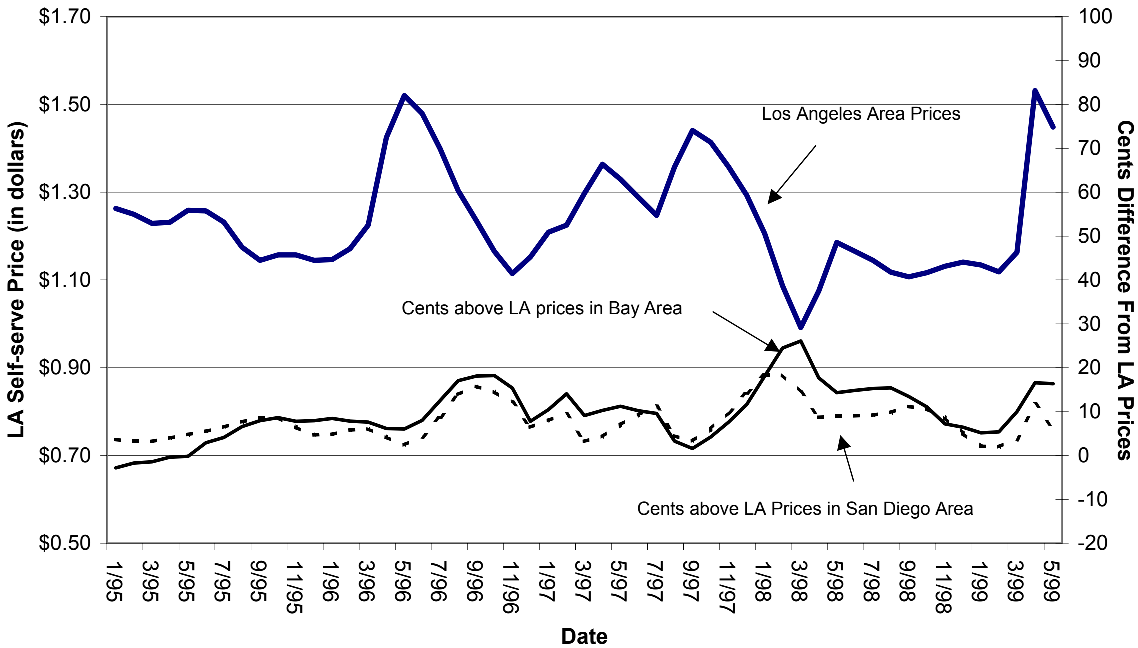
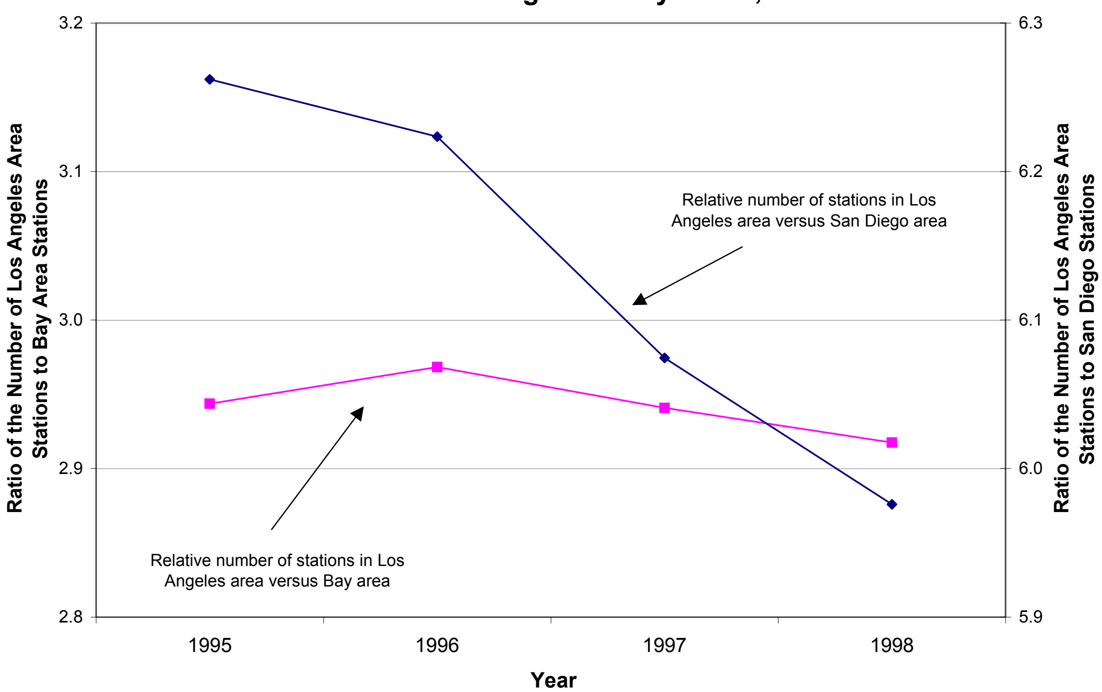


Figure 2
Ratios of the Number of Stations in the Los Angeles Area to the Number in the San Diego and Bay Areas, 1995-1998



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Appendix A: Census Data and Station Density

This Appendix provides further detail on the merging of the Census data and other data sources to generate a dataset used to calculate station densities for the San Francisco, Los Angeles, and San Diego areas. Once the census data were matched as described in the text, the data were then matched to the 721 stations contained in the 1999 Proprietary Price Surveys as well as to a listing of California company-operated stations provided by the large, major brand gasoline retailer.[38] Table A1 reports the various types of matches of the census data with each other and with the Proprietary Price Survey. The source of the 1999 Proprietary Price Survey is discussed in Section 2 of the text.

Table A1: Identification of Stations From Various Censuses

Source or Sources of Station Information	Stations not in 1999 Proprietary Price Survey	Stations in 1999 Proprietary Price Survey	Total number of stations
Lundberg, MPSI, and Whitney-Leigh census	3,312	501	3,813
Lundberg and MPSI census only	35	1	36
Lundberg and Whitney-Leigh census only	2,384	212	2,596
MPSI and Whitney-Leigh census only	113	1	114
Whitney-Leigh and company stations only	1		1
Lundberg census only	676	5	681
MPSI census only	131	1	132
Whitney-Leigh census only	142		142
Company-operated stations only	4		4
Total Number of Stations	6,798	721	7,519

[38] As mentioned above, the researchers controlled the retail prices at 54 control stations. To measure the impact of these price changes, we surveyed each day of the week all of the other stations within a two-mile radius around the control station. We call this survey of 721 stations the Proprietary Price Survey.

Our next step was to delete stations in our combined dataset that appear not to have been in operation during the period of our price survey (Spring, 1999). First, we deleted 36 stations only found in the Whitney-Leigh census that were reported in that census as "not in operation." Next, we deleted 10 stations in the various Lundberg censuses that could not be matched with any other census and that the 1999 Proprietary Price Survey specifically identified as "not in operation" at the time of the survey. Third, we deleted 125 stations in the Lundberg census that could not be matched with either of the other two censuses and that the Lundberg census cited as "not in operation." Fourth, we deleted 148 stations that were in both the Lundberg and Whitney-Leigh census and were cited as stations "not in operation" at the time of the census.

Next, we dropped 20 stations that were in both the Whitney-Leigh census and Lundberg, but for whom the match to the Whitney-Leigh census was not to the most recent (1998) Whitney-Leigh census. The presumption was that these stations were missing from the most recent Whitney-Leigh census because they had gone out of operation. We also dropped 44 stations with the brand CFN that only appeared in the Lundberg census. Apparently stations selling this brand closed down subsequent to Lundberg's 1996 census, and thus did not appear in either the Whitney-Leigh or the MPSI census. Finally, we dropped 4 company-operated stations of the gasoline retailer that were not in any of the areas covered by the census and 20 Whitney-Leigh stations that were in counties outside those covered by the Lundberg and MPSI surveys.

Among the stations left, a number were in both the Lundberg census and the MPSI census. We thus had two sets of latitudes and longitudes for these stations, and could check the accuracy of these location data. If the two censuses indicated locations that differed by more than one fifth of a mile, an independent assessment of location was made using the most recent mapping programs and address information taken from the matched data in order to determine the correct latitude and longitude data. This mapping process was also used to fill in missing latitude and longitude data, especially for the Whitney-Leigh stations that did not match with either the Lundberg or MPSI census stations. There remained, however, 67 stations for which a latitude and longitude could not be computed. These were typically stations in rural areas with addresses that provided neither a street number nor a crossing street. Without such exact location data, these stations had to be excluded from the calculations of the density of other sellers.

The outcome of the above elimination of stations not in operation as of 1999 or without location data is the identification of 7,045 stations across the three areas (Los Angeles, San Diego, and the San Francisco areas). Table A2 reports the various types of matches for these stations. One important item to note is that all 721 stations in the 1999 Proprietary Price Survey are contained in the census data analyzed.

Table A2: Stations in Operation in 1999 From Various Censuses

Source or Sources of Station Information	Stations not in 1999 Proprietary Price Survey	Stations In 1999 Proprietary Price Survey	Total number of stations
Lundberg, MPSI, and Whitney-Leigh census	3,312	501	3,813
Lundberg and MPSI census only	35	1	36
Lundberg and Whitney-Leigh census only	2,185	212	2,397
MPSI and Whitney-Leigh census only	113	1	114
Whitney-Leigh and company stations only	1		1
Lundberg census only	479	5	484
MPSI census only	131	1	132
Whitney-Leigh census only	68		68
Total Number of Stations	6,324	721	7,045

Table A3 reports the results of an estimation of Eq. (7) using an alternative representation of density to that reported in the paper which goes beyond the simple number of competitors suggested by the theory. Specifically, the index of competition for each control station is defined as the ratio of the number of stations within two miles of the respective control station to the average distance to stations within two miles of the respective control station.

Appendix B: Supplementary Tables

Below we provide two supplementary tables. The first, Table B1, provides sample means for Table 1. The second, Table B2, replicates Table 1, but uses the alternative measure of density that incorporates an adjustment for the average distance to competitors.

Table B1: Descriptive Statistics

Numbers represent mean values of variables in Table 1. Standard errors are in parenthesis.

Independent variable	Regular-Grade	Mid-Grade	Premium-Grade
Log of sales volume (self-serve gasoline) at control station	8.38 (.344)	6.718 (.451)	6.207 (.593)
Log of self-serve price	.230 (.168)	.320 (.162)	.391 (.154)
Price interacted with:			
Mid-level density indicator	.076 (.145)	.106 (.178)	.128 (.205)
High density indicator	.079 (.147)	.112 (.178)	.138 (.205)
Log of the number of stations within two miles	.694 (.525)	.967 (.519)	1.181 (.506)
Log of market-average self-serve price	.265 (.157)	.355 (.144)	.421 (.136)
Log of market-average price interacted with:			
Mid-level density indicator	.087 (.154)	.116 (.187)	.136 (.213)
High density indicator	.092 (.155)	.125 (.187)	.149 (.214)
Log of number of stations within 2 miles	.799 (.493)	1.072 (.468)	1.270 (.458)
Mid-level density indicator (index)	.319 (.466)	.319 (.466)	.319 (.466)
High density indicator (index)	.362 (.481)	.362 (.481)	.362 (.481)
Log of (number of stations within 2 miles) / (average distance from control)	3.015 (.502)	3.015 (.502)	3.015 (.502)
San Diego area indicator	.370 (.483)	.370 (.483)	.370 (.483)
San Francisco area indicator	.165 (.371)	.165 (.371)	.165 (.371)
Log of Mid-to-Regular price ratio	.090 (.019)	.090 (.019)	
Log of Premium-to-Mid price ratio		.071 (.012)	.071 (.012)
Observations / number of unique control stations	4,073 / 54	4,073 / 54	4,073 / 54

Table B2: Gasoline Sales at Stations with Different Seller Density using Average Distance to Competitors.

This table reports estimated elasticities across market densities using an index of competitiveness for each control station, defined as the ratio of the number of stations within two miles of the control station to the average distance to a station within two miles of the control station. Like Table 1, markets are designated low, mid and high-density according to whether the market's index falls below the 33rd percentile in the sample, between the 33rd and 67th percentiles, or above the 67th, respectively. All equations assume that the disturbance term is first-order autoregressive. Absolute values of *z*-statistic are in parentheses. Coefficients for six day-of-week indicator variables are included in the estimation of all columns. Further, note that where one includes a separate measure of average distance to competitors within 2.0 miles, the estimated coefficient is insignificant.

	Log of sales volume (self-serve gasoline) at control station								
Independent variable	Regular-Grade			Mid-Grade			Premium-Grade		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of self-serve price	-1.935 (8.26)***	-1.937 (7.98)***	4.558 (4.20)***	-1.991 (6.34)***	-1.759 (5.48)***	2.710 (1.96)*	-3.173 (10.05)***	-3.187 (10.03)***	-0.323 (0.24)
Log of self-serve price interacted with:									
Mid-level density indicator (index)	0.094 (0.27)	0.095 (0.28)		-0.246 (0.55)	-0.335 (0.75)		0.054 (0.12)	0.061 (0.13)	
High density indicator (index)	-2.318 (6.70)***	-2.318 (6.68)***		-1.873 (4.14)***	-1.929 (4.28)***		-1.824 (3.96)***	-1.825 (3.96)***	
Log of (number of stations within 2 miles) / (average distance from control)			-2.513 (6.68)***			-1.816 (3.80)***			-1.204 (2.58)***
Log of market-average self-serve price	2.079 (8.34)***	2.082 (8.11)***	-4.059 (3.53)***	1.078 (3.04)***	0.854 (2.37)**	-3.821 (2.46)**	1.558 (4.32)***	1.585 (4.31)***	-1.429 (0.93)
Log of market-average price interacted with:									
Mid-level density indicator (index)	-0.032 (0.09)	-0.033 (0.09)		0.433 (0.86)	0.525 (1.04)		-0.033 (0.06)	-0.040 (0.08)	
High density indicator (index)	2.189 (5.83)***	2.189 (5.82)***		2.060 (3.98)***	2.108 (4.09)***		1.980 (3.72)***	1.983 (3.73)***	
Log of (number of stations within 2 miles) / (average distance from control)			2.381 (5.95)***			1.927 (3.57)***			1.272 (2.38)**
Mid-level density indicator (index)	-0.157 (1.79)*	-0.157 (1.79)*		0.018 (0.16)	0.016 (0.13)		-0.064 (0.43)	-0.065 (0.43)	
High density indicator (index)	-0.338 (3.82)***	-0.338 (3.83)***		-0.351 (2.92)***	-0.348 (2.94)***		-0.492 (3.26)***	-0.493 (3.29)***	
Log of (number of stations within 2 miles) / (average distance from control)			-0.350 (3.70)***			-0.283 (2.16)**			-0.487 (3.07)***
San Diego area indicator	0.073 (0.97)	0.073 (0.97)	0.064 (0.84)	-0.048 (0.48)	-0.048 (0.49)	-0.063 (0.61)	0.156 (1.23)	0.155 (1.23)	0.129 (1.03)
San Francisco area indicator	0.192 (1.95)*	0.191 (1.95)*	0.212 (2.14)**	0.223 (1.72)*	0.215 (1.69)*	0.218 (1.63)	0.388 (2.35)**	0.387 (2.37)**	0.416 (2.55)**
Log of Mid-to-Regular price ratio		-0.009 (0.04)	0.035 (0.14)		-0.798 (2.68)***	-0.864 (2.88)***			
Log of Premium-to-Mid price ratio					0.995 (1.93)*	0.956 (1.84)*		0.193 (0.37)	0.077 (0.15)
Constant	8.444 (115.49)***	8.444 (111.37)***	9.281 (33.51)***	7.081 (72.22)***	7.089 (64.41)***	7.808 (20.28)***	6.931 (55.93)***	6.911 (51.82)***	8.141 (17.48)***
Observations / number of unique control	4,073 / Wald $\chi^2(17)$ = 1,365.6	4,073 / Wald $\chi^2(18)$ = 1,365.9	4,073 / Wald $\chi^2(18)$ = 1,334.1	4,073 / Wald $\chi^2(17)$ = 2,021.3	4,073 / Wald $\chi^2(19)$ = 2,060.8	4,073 / Wald $\chi^2(19)$ = 2,002.1	4,073 / Wald $\chi^2(17)$ = 5,312.5	4,073 / Wald $\chi^2(18)$ = 5,311.9	4,073 / Wald $\chi^2(18)$ = 5,229.8
Mean of dependent variable	8.380	8.380	8.380	6.718	6.718	6.718	6.207	6.207	6.207

Results are robust to dropping all observations corresponding to Saturday and Sunday and to the inclusion of controls for number of nozzles, hours of operation and C-store existence.
* significant at 10% level. ** significant at 5% level. *** significant at 1% level.