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Consumer and competitor reactions: Evidence from a field experiment ☆

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Abstract

In response to a price change by a single seller, it is common for the density of sellers in the market to influence both the quantity response of consumers and the price response of other sellers. Using field experiment data collected around a series of exogenously imposed price changes we find that an individual retailer with a larger number of competitors faces a more-responsive demand. This finding is fundamental to a predicted inverse relationship between market prices and the number of competitors. We also examine the reaction of rival stations to exogenous price changes, and find that the magnitude of a competitor's response is inversely related to the density of stations in the market.

JEL classification: D43; L13; D83

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In changing a price, a seller must confront two key questions: What will be the reaction of consumers to a price change and what will be the reaction of competitors? A common feature of many models that consider price-setting is that answers to both questions depend on the number of competitors in the market. This paper draws on a field experiment that was conducted in three urban areas of California to see whether the number of competitors does indeed determine the extent of the reaction by a seller's potential customers as well as the extent of the reaction by competitors. The experiment set for short time intervals retail prices at 54 company-operated gasoline stations of a major retailer. In particular, prices at two alternating subsets of stations were changed and then fixed at these new levels for one-week periods over a three-month period. The result was to create exogenous deviations in the prices at "treatment" stations from what they otherwise would have been. During this period, information on the daily volumes of gasoline sold at the treatment stations was collected, as well as the daily prices at competitor stations within two miles of each of the 54 treatment stations.[1]

Barron et al. (2004) considered the effect of the number of sellers ("seller density") on aggregate price levels and on price dispersion across markets using single-day

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[1] We thank the owner of these stations for recently granting permission to use these data.

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comparisons of prices across stations. The current paper is distinguished from this paper and related literature in its use of unique firm-level data on volume and prices over time in conjunction with exogenous variations in prices over time to provide evidence concerning the effect of the number of sellers on the responsiveness of both consumers and competitors to a price change by a single seller.[2] Although the number of treatment stations is somewhat small (54) and the time period over which price movements were tracked is short (80 days), our experimental field data created exogenous price changes that provides an opportunity to identify the effect of the number of alternative sellers in a market on an individual seller's price elasticity.[3] As prices at competing stations within two miles of each treatment station were also surveyed, analysis of competitor reactions to exogenous price changes is also possible with these data. Namely, to the extent instituted prices at treatment stations differ from what relevant competitors expect prices to be at these stations, we can quantify rivals' reactions to an exogenous price change, including potential differences in the extent of reaction based on the direction of the price change and the number of rivals in the market.

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 price-shocks "of an unusual magnitude."[4] Also analyzing dynamic pricing behavior, Noel (2007) 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.[5] Our analysis adds to this literature by providing new evidence on empirical regularities in responses to exogenously imposed price shocks at individual stations.[6]

The paper is divided into four sections. Section 1 provides an example of the potential role that the number of sellers can have on an individual seller's price elasticity of demand. We do this in the context of the well-known Salop–Perloff monopolistic competition model, a model that predicts an inverse relationship between the number of sellers in a market and an individual seller's price elasticity of demand. While one might expect such a result, and a resulting inverse relationship between prices and the number of sellers, there are models that suggest the opposite. For instance, Varian (1980, 1981) considers a symmetric randomized-pricing equilibrium in a market where some consumers are captive buyers and others purchase from the seller with the lowest price. In Varian's setting, sellers in markets with a higher number of sellers, due to either a larger number of consumers or lower fixed costs, can face the same price elasticity of demand. A second example is Stiglitz (1987). One of the cases Stiglitz considers assumes convex search costs and search without replacement. In this setting, he finds that an increase in the number of sellers does not change a sellers' price elasticity of demand for a price increase, but reduces the price elasticity of demand for a price-decrease, suggesting, on average, a decrease in a seller's price elasticity of demand in markets with a higher number of sellers.[7]

Section 2 presents the results of an empirical analysis that links seller density to individual sellers' price elasticity of demand based on the field experiment data, with identification achieved through the use of our treatments as

[2] Such evidence could not be provided in Barron et al. (2004) since it was based on single-day census data of gasoline station prices across different markets that varied in the number of sellers.

[3] Our analysis of the price elasticities of individual sellers is distinct from the more common estimates of market demand elasticities (e.g., Kayser, 2000; Graham and Glaister, 2002; Nicol, 2003; Oladosu, 2003). While not directly applicable to the questions addressed in this paper, these estimates do highlight a common issue in estimating responses of consumer to price changes, specifically the importance of identifying exogenous price changes.

[4] 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.

[5] Eckert (2003) also provides evidence of retail price cycles across many Canadian markets. 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, 2003) and vertical relationships (e.g. Hastings, 2002).

[6] There are a number of laboratory experiments that have empirically examined strategic behavior. Recent examples of experiments adopting a Cournot framework are Rassenti et al. (2000), Cox and Walker (1998), and Deck and Wilson (2003). Other experiments have focused more on pricing behavior, such as those examining the implications of the Bertrand–Edgeworth model (e.g., Kruse et al., 1982) and the use of a posted-offer pricing mechanism (e.g., Ketcham et al., 1984).

[7] The key factor behind the Varian result is the proposed mixed strategy equilibrium in prices, an equilibrium that requires that all prices within the set of admissible prices generate the same expected profits, such that the change in profits arising from a price change is zero. Given a constant marginal cost, this implies that the price elasticity of demand equals the ratio of price to the markup of price over marginal cost. Thus, the price elasticity of demand at a specific price is predicted to be identical across markets that differ in the number of sellers, with differences in the number of sellers arising due to either differences in fixed costs or differences in the aggregate number of consumers. The key factor behind the Stiglitz result is that consumers know the price distribution, but not the location of individual prices. The location of prices can only be ascertained through costly sequential search. In this setting, an increase in the number of sellers reduces the elasticity of demand for a price-decrease because, with a larger number of sellers, consumers face a higher cost to finding a low-price store, and this limits consumers' response to a price decrease by a single seller.

instrumental variables. We find consistent evidence that individual sellers face a higher price elasticity of demand in markets where consumers have a higher number of alternative sellers. We then illustrate how our results could be extrapolated to explain, in part, price differences across locations that have different seller densities.[8]

Section 3 examines how seller density can also affect the extent of the reaction of competitors to an exogenous price change by one seller. Here, we again exploit our treatments as the foundation for instrumental variables in a two-stage specification of retail prices. Our analysis indicates that the reactions of stations to a competitor's price change are partial, and larger in magnitude in lower-density markets. Section 4 contains concluding remarks.

1. A simple theoretical framework

This section reviews the theoretical framework of monopolistic competition models to provide an example of a case where seller density can be linked to consumer and competitor reactions. To do so, consider 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 units of output q_i has a common fixed cost component, K, and a constant marginal cost component, α. That is,

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

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 particular seller, the realization of a random variable drawn from the continuous distribution $F(v)$ with lower and upper bounds a and b, respectively.[9]

If a consumer knows the prices and visiting costs of all sellers at the time of their decision to purchase, then the 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 $r \geq p_i+v_i$. In such a case, given the second condition holds, the probability that consumer j buys from seller i is given by

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

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:

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

where $m_i = e_i/(e_i - 1) > 1$ and $e_i = -(\partial q_i/\partial p_i)(p_i/q_i)$. 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.

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

$$p = m\alpha. \tag{6}$$

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 $K/(L/N)$.[10]

For the above model of price-setting, either a larger market size (L) or lower fixed costs (K) can lead to a

[8] Note that our focus here is on 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, for gasoline and related markets, see Marvel (1976), Png and Reitman (1994), Borenstein and Shepard (1996), Adams (1997), and Coloma (1999). 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).

[9] 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.

[10] 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.

market with a higher number of sellers (N). From (3) and (6), it can be shown that accompanying this increase in the number of sellers in the market will be an increase in the price elasticity of demand for each individual seller and a lower equilibrium price.[11] This effect of the number of sellers, or what we term seller density, on an individual seller's price elasticity of demand arises because an increase in the number of sellers introduces more "close substitutes" for buyers. As we discuss later in Section 3, the model also can be used to illustrate a potential link between the reaction of other sellers to a price change by one seller in the market and the number of sellers in the market.

2. Seller density and the responsiveness of consumers to price changes

The focus in this section is an examination of the relationship between a seller's price elasticity of demand and the density of sellers. We then illustrate one potential implication of the analysis by showing how the combine the estimated price elasticity results and information on station density across different areas could be used to make out-of-sample predicted differences in price levels across areas.

Our empirical analysis 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 surrounding stations that meet this proximity requirement. In a densely populated urban area, some researchers have used a one mile radii market, however, because the data were available, we chose to go out two miles. We note that one to two-mile radii markets are often assumed in the literature even in the absence of data availability issues and that the results reported are generally robust to permutations of this two-mile radius. An alternative measure of density that also includes information on the average distance to a treatment station's competitor is discussed following our presentation of empirical results and the results are robust to using this alternative measure.[12]

To determine the density of sellers for stations located in the three geographic areas in California containing treatment stations (the Los Angeles, San Diego, and San Francisco areas), three data sources were 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.[13] This information allowed us to stratify the sample of stations chosen as treatment stations in these three areas to assure differences in seller density across the treatment stations.

2.1. The field data

Our field experiment involved a large gasoline retailer, who allowed us to change the price, and then hold it constant for a week, 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

[11] 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.

[12] 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. Unfortunately, such data on traffic patterns are unavailable for our sample of stations and we rely on our two simple measures of density, acknowledging their potential imperfections.

[13] The stations recorded in each census from these three companies were matched 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 a supplement available on request. The resulting merged dataset 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.

stations involved in 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. The stations in the sample were stratified, for each geographic area, by volume and by the number of competitors.

Once the sample of stations was identified, 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."[14]

There was one important exception to the above pattern. A major explosion at a San Francisco area refinery, followed by lesser problems at other refineries, resulted in a substantial supply disruption in the middle of the experiment period. When this occurred, the company requested that control of station prices be suspended, and this suspension lasted for approximately three weeks. We continued to collect the relevant market data from our survey during this period. Thus, there are in our sample four potential sources of exogenous variation in relative prices, variation that is required to estimate changes in purchases by consumers. These four potential sources are: a) at the start of the treatment period when prices at the treated stations were increased or decreased by two cents; b) during the treatment period when prices at the treated stations were held fixed (assumes changes in other stations' prices); c) at the end of the treatment period, when the treated stations' prices were allowed to vary; and, d) relative price changes induced by potential differences in the timing of marginal cost changes across stations following the refinery explosion.

During the three-month period of the experiment, daily volumes sold at each of the 54 stations were collected as well as prices. To obtain prices of competitor stations, we use two sources. First, from Oil Price Information Service (OPIS) we obtained daily retail prices for many of the stations within a two-mile radius of the treatment stations. OPIS retail price data are derived from actual credit card usage associated with retail sales of gasoline, but they were only collected for days when sales using a specific set of credit cards occurred at a particular station. To supplement the OPIS retail price data on competitors, we also obtained company-generated surveys of prices charged by stations within a two-mile radius of any treatment station each weekday.[15]

We thus have a dataset that includes daily prices and quantities of 54 treatment stations as well as the prices at stations surrounding each treatment station over a period of 80 days. After dropping observations with missing values, the dataset consists of 4188 observations for regular-grade gasoline.

2.2. A raw-variation approach

An important feature of this dataset is that the price changes at treatment stations are largely the result of exogenous "supply-side" factors rather than due to changes in factors affecting demand. While we ultimately focus on the results of an instrumental variable approach to estimating elasticities, we begin our analysis by providing the results of a simple model of volume — estimating the price elasticity of demand at a station by specifying a log-linear form for the demand equation of a particular station in a market of density d, such that

$$\ln(S_{it}) = \delta - \beta_d \ln(P_{it}) + \gamma_d \ln(\overline{P}_{it}) + \lambda X_{it} + v_i + \varepsilon_{it}. \quad (7)$$

In (7), S_{it} denotes the volume of gasoline sold at treatment station i during the period (day) t, P_{it} denotes the price of the ith treatment station, and $\overline{P}_{it}$ denotes an average of the prices of the other sellers in the market of treatment station i.[16] The parameters β_d and γ_d are therefore the own-

[14] This random assignment of price change direction, as well as the alternating pattern of a week of fixed prices and a week of prices being freely chosen by the station, makes it less likely for competing stations to recognize intervals when prices at the station were fixed. As the experiment only lasted three months, and as noted below was interrupted by a period when all stations were free to set prices following a refinery accident, it is reasonable to assume that other stations were unlikely to be aware of the restrictions the experiment placed on the pricing behavior of the station at certain times.

[15] Note that prices at competitor stations were often missing during weekends. For our elasticity analysis only, missing prices during weekends at competitor stations were interpolated linearly from the prices charged on Friday and Monday.

[16] This paper suggests that geographic proximity may influence the extent to which customers will switch to other stations given a change in the relative price. In particular, changes in prices at the closer competitors may have a greater effect. Accepting that more weight should be placed on prices of sellers closer to the treatment stations and assuming the importance of the price change is approximated by a linear function of distance, one can weight the price of each competitor by a variable equal to two minus the distance in miles the competitor is from the treatment station. We then sum these weighted prices and divide by the sum of the weights to obtain the alternative index of the prices of competitors.

and cross-price elasticities of demand respectively for a station in a market of density d. Note that we are unable to measure cross-price elasticities at a similar level of analysis. That is, these estimated cross-price elasticities are with respect to changes in the mean price of competitors and not with respect to changes in the price of a single competitor (as is the case with our estimates of own-price elasticities). While we report our results using a simple average of prices at other sellers, the results reported are robust to the specification of a weighted average of prices of competitor stations constructed along the lines suggested by Pinkse et al. (2002).[17] In (7), X_{it} denotes a set of controls for day-of-week and a time trend variable and v_i are station-specific residuals representing the extent to which the intercept of the ith cross-sectional unit differs from the overall intercept, and ε_{it} is the traditional error term, unique to each observation.

The fixed effects estimation results representing this initial methodology are reported in the first three columns of Table 1. In Column (1), we show the results of a specification that restricts elasticities to be common across market densities, which reveals an estimate of the average price-elasticity for our sample of treatment stations. Likewise, we restrict cross-price elasticities to be common across market densities. Here we see own- and cross-price elasticity estimates in the neighborhood of −3.3 and 2.9, respectively.[18] In allowing for seller density, we take two approaches — one discrete classification and the other exploiting the underlying continuous measure of station density. These results are reported in Columns (2) and (3), respectively.

In the discrete classification of density, we divide stations in our sample into three equally sized groups, those with low station density (less than 18 other stations within a two-mile radius, $d=l$), those with mid-level density (at least 18 and less than 27 other stations within a two-mile radius, $d=m$), and stations with high density (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, (in absolute value) 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 with a higher density of alternative sellers.

Column (3) provides an estimate of the general effect of seller density on elasticity by including log-price and log-price interacted with the log of the number of sellers in the market. While results are comparable across specification, we report three specifications to aid in interpretation, especially given the potential for the positive point estimate on own-price variable alone in Column (3) to be misleading. All specifications clearly support the empirical regularity that the density of sellers in a market affects the price elasticity of demand faced by individual sellers, with differentials implying elasticities of $\hat{\beta}_l = -1.6$, $\hat{\beta}_m = -3.2$ and $\hat{\beta}_h = -4.5$, respectively.

2.3. An IV approach

While suggestive, these initial results should be considered with some caution. Specifically, while our experimental design introduced known exogenous variation in prices in treated weeks, this does not mean that prices are exogenous in all weeks. In fact, the experiment design adjusted price only every other week, on average, and allowed pricing decisions to revert back to being market driven (i.e., endogenous) between the treated weeks. Fortunately, our experimental design affords an alternative to the specifications of Columns (1) through (3). In the remaining columns of Table 1, we exploit this design by using our known treatments as instruments in an instrumental variable approach. These columns report the same series of three specifications, but derive coefficient estimates from an instrumental procedure that exploits our own treatments as instruments for endogenous prices in the first-stage regression. Specifically, Columns (4) through (6) employ indicator variables for "price increased at treatment station" and "price decreased at treatment station" as instruments for P_{it} and $\overline{P}_{it}$. Employing our experimental treatments as instruments yields somewhat larger own- and cross-price elasticity estimates — in the neighborhood of −5.5 and 7.1, respectively.

While the Tosco refinery explosion that occurred within our sample period also affords a convenient instrument for prices, note that the length of time over which we might allow the explosion to speak to variation in prices is

[17] Note that it is important to control for average market prices, as our subsequent analysis of price reactions suggests that a given change in price by the treatment station will result in less of a change in its price relative to competitors in markets with lower seller density, as competitors react more in such markets. A key point, however, is that these reactions are partial, so that our analysis can still capture the change in purchases by consumers in response to changes in relative prices initiated by exogenous price changes (from the consumer's perspective) at the treatment stations. In fact, even the refinery explosions noted earlier turned out to be fortuitous for our study because the resulting large relative price increases are attributable to individual stations' different reactions to supply shocks. Having defined markets as two-mile circles around each treatment station, treatment stations are within two miles of each other in ten instances and therefore 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.

[18] Although, recall that cross-price elasticities have the interpretation of quantity responses to changes in the market-average price, not to changes in the price of a single competitor's price.

subjective. That is, while our own periods of experimental treatment are well defined (i.e., we know exactly when down- and up-treated weeks begin and end), we are somewhat less confident in the timing of the Tosco refinery explosion — with the end of this episode, in particular. The explosion itself (occurring on 23 February) can certainly be justified as an instrumental variable. Only in our third series of results (Columns (7) through (9) of Table 1) do we encompass the full set of available instruments, including the refinery explosion.[19]

Overall, these tests provide 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 (5) of Table 1, a one percent increase in a station's regular-grade price, other things equal, reduces the volume of sales by 2.4% at stations with low density of rivals (i.e., small number of other sellers in the market), 6.3% at stations with mid-level density and 8.4% at stations with a high density. Considering the continuous density measure, we see an inner-quartile range in the estimated elasticity of 3.5 (14 stations within two miles) to 7.5 (30 stations within two miles). Employing the refinery explosion as additional instruments does little to change these comparative-static results, yielding only a slightly larger an inner-quartile range of 3.3 to 7.5. Similarly, cross-price elasticities also vary systematically across market density. As cross-price elasticities are with respect to changes in the average price at competitor stations, the quantity response to such changes, not to changes in the price of a single competitor's price, are larger in markets with higher seller density.

2.4. Sensitivity tests and discussion

While theory suggests that the number of rivals is an appropriate measure of the extent of substitutability among differentiated-products in the market, it may be argued that such a measure could result in a miss-classification of markets according to their true extent of product differentiation. 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 market with less product differentiation. Yet this may not be the case. As such, we adopt an alternative representation of density to that reported in Table 1, going beyond this simple station-count to include information on the distance of each competitor from the treatment station. Results indicate the robustness of our findings to this alternative specification.[20]

In specifying our stratified sample of treatment stations by seller density, an effort was made to obtain a similar set of treatment stations across markets that differed in seller density. However, some differences remain for our sample of treatment stores. In particular, treatment stations in markets with high seller density tend to sell lower volume and are less likely to have non-gasoline sales. To see if these differences in treatment stations affect our results, we created two new variables, the first identifying large treatment stations in terms of gasoline volume and the second identifying those treatment stations by their non-gasoline sales. Results (not reported) that include interactions of these variables with prices indicate similar price elasticity across stations that differ in sales volume. With respect to non-gasoline sales, we find no significant difference in elasticity for stations that also operate a convenience store. While point estimates would suggest a tendency toward less-elastic demand at stations that have non-gasoline sales, even when we take into account the extent to which sales events include a non-gasoline sale, we find no significant evidence of differentials in elasticity. In all cases, the inclusion of these additional variables does not alter our key finding of higher individual seller price elasticity of demand in markets with greater seller density.[21]

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 are likely to reflect less of a reaction than would be exhibited were reactions measured over lengthier intervals.[22] However, for our purposes, it is not so much the levels of individual

[19] In particular, in this third set, the first-stage price models include a control for the day of the explosion itself (i.e., 23 February), and, separately, controls for 24 February, 25 February and 26 February. We thus restrict the instruments to be the four-day period following the explosion but refrain from restricting any price response (to the explosion, that is) to be common across these four days. In alternative specifications, the inclusion of any additional days (e.g., 27 February, 28 February, etc.) yields no significant predictive power in the first-stage.

[20] Specifically, we used an index of competition for each treatment station defined as the ratio of the number of stations within two miles of the respective treatment station to the average distance to stations within two miles of the respective treatment station.

[21] Note also that for the three categories of markets distinguished by seller density, there is no statistically significant difference in the likelihood a competitor station sells either a major brand of gasoline in general, or sells the specific major brand of the treatment station in particular. Thus, our characterization of product differentiation based on the number of competitors is not correlated with product differentiation arising from the brand identification of the competitors.

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

Table 1
Station-level elasticity estimates of gasoline sales across seller densities

Independent variable	FE			FE-IV (instruments from experimental design) [a]			FE-IV (instruments from experimental design and Tosco Refinery explosion) [b]		
		Discrete densities	Continuous density		Discrete densities	Continuous density		Discrete densities	Continuous density
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of self-serve price	−3.313***	−1.628***	3.511***	−5.559***	−2.424***	10.229***	−5.444***	−2.055**	10.943***
	[0.122]	[0.212]	[0.621]	[0.450]	[0.820]	[2.981]	[0.439]	[0.798]	[2.927]
Log of self-serve price interacted with: [c]									
Mid-level density indicator		−1.618***			−3.907***			−4.092***	
		[0.299]			[1.140]			[1.115]	
High-level density indicator		−2.909***			−6.093***			−6.482***	
		[0.292]			[1.052]			[1.026]	
Log of number of stations within two miles			−2.282***			−5.217***			−5.414***
			[0.206]			[0.973]			[0.956]
Log of market-mean self-serve price	2.935***	1.261***	−3.806***	7.136***	3.761***	−9.967***	6.895***	3.292***	−10.846***
	[0.137]	[0.226]	[0.663]	[0.629]	[0.931]	[3.511]	[0.608]	[0.902]	[3.446]
Log market-mean price interacted with: [c]									
Mid-level density indicator		1.791***			4.506***			4.638***	
		[0.321]			[1.307]			[1.278]	
High-level density indicator		2.852***			6.560***			6.928***	
		[0.317]			[1.147]			[1.120]	
Log of number of stations within two miles			2.274***			5.666***			5.880***
			[0.222]			[1.148]			[1.128]
Trend (day)	0.004***	0.004***	0.004***	−0.007***	−0.008***	−0.007***	−0.006***	−0.007***	−0.006***
	[0.000]	[0.000]	[0.000]	[0.002]	[0.002]	[0.002]	[0.001]	[0.002]	[0.001]
Individual-station fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8.308***	8.313***	8.306***	8.141***	8.122***	8.147***	8.151***	8.134***	8.156***
	[0.010]	[0.010]	[0.010]	[0.029]	[0.032]	[0.029]	[0.029]	[0.031]	[0.028]
Observations/treatment stations	4188/54	4188/54	4188/54	4188/54	4188/54	4188/54	4188/54	4188/54	4188/54
R-squared	0.24	0.27	0.26						

* significant at 10% level. ** significant at 5% level. *** significant at 1% level.

All equations are fixed effects models that absorb unobserved heterogeneity specific to individual treatment stations. Standard errors are in brackets. Coefficients are not reported for six day-of-week indicator variables that were included in the estimation of all equations. The mean value of the dependent variable is 8.383, which is roughly equivalent to $4372. Other summary statistics are reported in a supplement available on request.

[a] Instruments for own self-serve price and market prices include indicators for "price increased at treatment station" and "price decreased at treatment station." Where appropriate, these treatment variables interacted with density are also included as instruments in the first-stage.

[b] Instruments for own self-serve price and market prices include indicators for "price increased at treatment station," "price decreased at treatment station", and separate indicators for February 23, February 24, February 25, and February 26. Again, these treatment variables interacted with density are also included as instruments in the first-stage, where appropriate.

[c] Mid-level density corresponds to markets of at least 18 and less than 27 stations, while high-level density corresponds to markets of 27 or more stations.

sellers' price elasticities of demand as it is the differences in the price elasticities of demand across stations in different market settings that are important for the analysis to follow.

2.5. An example of the potential effect of seller density on prices

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. 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 competitors per station for the three areas to provide an example of how our analysis can provide insight on one potential source of these price differences. In particular, Table 2 reports the predicted price elasticity of demand for the typical station in each of the three areas based on our

Table 2
Differences in price elasticity, predicted prices, and actual prices across areas (regular unleaded)

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	5.06	1.25	4.3% higher	7.7% higher
San Diego	4.84	1.26	4.1% higher	6.3% higher
Los Angeles	6.11	1.20	–	–

[a] Calculated from the own-price coefficients estimated in Table 1, Column 6, and the average number of stations within 2 miles of stations in each of the three geographic areas based on census data. The average number of stations within a 2-mile radius is 22.4 for stations in the LA area; 17.4 for stations in the San Diego area, and 18.2 for stations in the San Francisco area.

elasticity results. Note that the predicted average price elasticity of demand is higher in Los Angeles than in San Diego or San Francisco areas due to higher station density.

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 illustrate that differences in demand conditions arising from differences in the density of stations, and thus predicted differences in individual sellers' price elasticities 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 are below the actual price differences.[23]

Eq. (6) identifies two types of asymmetry across markets that can result in differences in prices between markets. Our discussion has focused on heterogeneity across markets in markups arising from differences in price elasticities of demand due to differences in the average number of competitors in local gasoline markets. The second type of asymmetry across markets that can result in differences in prices arises from differences in marginal production costs. Given actual price differences in excess of our simple projections based on different demand conditions, higher marginal costs of gasoline in the San Diego or San Francisco areas relative to the Los Angeles area could also contribute to the observed price differences.[24]

To the extent higher prices in San Diego and the San Francisco areas relative to the Los Angeles area reflect lower price elasticities of demand arising from lower station density, then such price differences should translate into a lower return to stations in the Los Angeles area relative to the other two areas, other things equal. 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. Fig. 1 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.

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 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.

[23] The actual prices are taken from Lundberg, Inc. bi-monthly price surveys (through the end of May 1999). One reason for the large predicted differences 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.

[24] Note that there were no refineries in the San Diego area; San Diego County received about 92% 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%) was delivered to the area by tanker trucks. The shipping cost by pipeline from the Los Angeles refineries to the San Diego terminals was 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 cost 2 to 4 cents per gallon (Rohy, 1996).

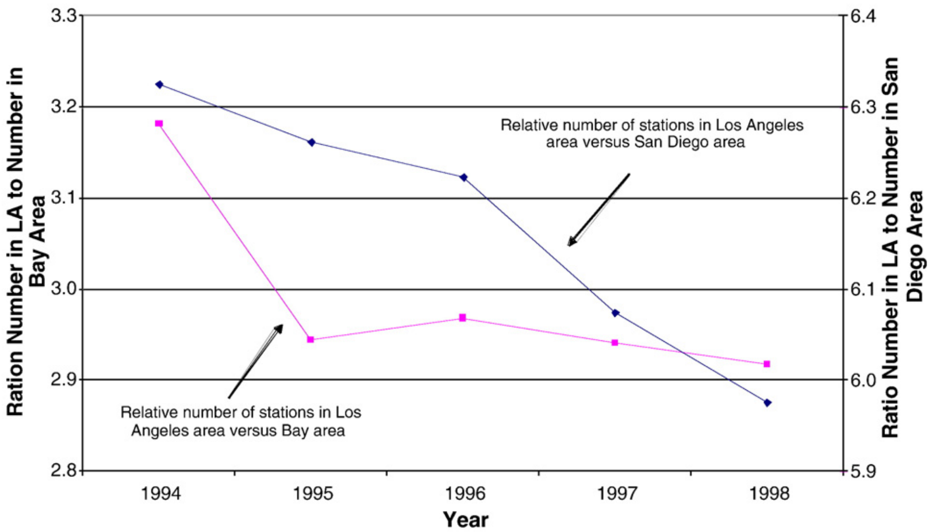

Fig. 1. Relative number of station in Los Angeles relative to San Diego and Bay Areas, 1994–1998.

Table 3 indicates the average capacity utilization of stations across the three areas. As the numbers reported in Table 3 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. Zero profits occur at a higher equilibrium price and a reduced number of sellers in the market.

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, allows us not only to examine how seller density can affect the reaction of consumers to a price change by a seller, but also to examine the reaction of sellers to an exogenous change in price by one of its competitors. In the following discussion, we motivate our empirics by first reconsidering the simple differentiated-product model of ''Section 1 which suggests factors that could be important in considering the reaction of other competitors in a market to an exogenous price change by one seller. We then present our instrumental variables approach to empirically identifying reactions.

3.1. Competitor reaction

Denote p_T as the price at the treatment station. For a competitor station i, we obtain from (2) and (3) the following expected market demand across the L consumers given the treatment station's price p_T and the common price p^* for the other $N-2$ sellers:

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

Rewriting (5), the resulting optimal price at competitor station i will satisfy:

$$p_i^* = \alpha - q_i/(\partial q_i/\partial p_i), \tag{9}$$

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

Assume initially that all sellers (including seller i and the treatment station) set the common price p^*, with p^* set such that (9) is satisfied for all sellers. Now consider station i's reaction to a change in the price at the treatment station. In particular, let the new treatment station price be, instead, $p_T=p^*+x$ with $x>0$, such that treatment station T sets its price above the original market price.

To provide some structure to our discussion of the reaction of seller i, consider the change in its price from p^* that satisfies (9) given the deviation in the treatment station's price and the correct anticipation of similar

Table 3
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.

reactions by the other $N-2$ sellers. In other words, consider the change from the original price p^* such that (9) remains satisfied for the other $N-1$ sellers at the new exogenous price for the treatment station. In this setting, at the original price p^* for the $N-1$ sellers, a change in the price at the treatment station induces each of the other sellers to change their prices in the same direction.[25]

Were the untreated stations to match the increase (decrease) in the price of the treatment station, then demand would be identical to before the price changes, but the price elasticity would be higher (lower).[26] However, (9) would not be satisfied if the prices at the $N-1$ untreated stations were to increase (decrease) by x. This implies that while an exogenous deviation in price by one of N sellers in a market may result in a deviation in the prices of the other $N-1$ sellers in the same direction, it would be 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. Table 4 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 reflecting either differences in market size (Panel A) or differences in the fixed costs of entry (Panel B). Note that, consistent with the above intuition, 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 treatment station, the magnitude of the reaction of the $N-1$ sellers falls with an increase in seller density.

For instance, for the 4-seller case, if one of the four sellers increases its price by two cents, the deviation in price for the other three sellers is 0.15 cents. Note that the same deviation from the initial equilibrium price by the treatment station leads to a larger deviation in other sellers' prices when the total number of sellers is two, but a smaller deviation when the total number of sellers is six. Such results are robust to a variety of parameter values and are similar in magnitude for a price-decrease by the treatment station. In short, 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 increasingly muted as seller density increases.

3.2. Empirical specification of competitor reactions

The prior discussion provides insight into the direction and extent of price adjustment by a station to an exogenous price deviation by another station in its market (in our case, this is the treatment station). However, the analysis is not dynamic, and so provides no explicit guidance as to the timing of this adjustment to a price deviation. Assuming gasoline stations react quickly to price changes of competitors, we focus our analysis on the reaction one day later. One advantage of doing so is that it allows us to work with a more extensive data set by limiting the number of consecutive periods required to consider reactions. In addition, because stations tend to move prices across different grades in lockstep, we focus only on reactions for regular-grade gasoline prices. Note that our data for regular-grade gasoline combines competitor prices from OPIS-collected retail prices supplemented with company price surveys.[27]

[25] Note that for the case when $p_i = p_T = p^*, -\left(\frac{-q_i}{\partial q_i/\partial p_i}\right)^* = \frac{\int (1-F(v))^{N-1} dF(v)}{\int (N-1)(1-F(v))^{N-2} f(v) dF(v)}$. On the other hand, if $p_i = p^*$ but $p_T - p^* = x > 0$, 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 treatment station's price.

[26] The identical demand follows from our assumptions of unit demands by consumers and sufficiently high reservation value for gasoline such that the number of consumers in the market remains constant.

[27] Of course, one could consider more complex dynamic reactions in which the responses to a price shock introduced in one period are spread out over multiple periods. While we would not rule such patterns in responses, our data set is best suited to analyzing the single-period reaction, in that there are substantial reductions in the sample if we were to consider lengthier reaction periods.

Table 4
Simulations of reaction deviation to treatment 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	Treatment station's deviation (increase) from initial equilibrium price	Reacting sellers' ($N-1$) deviation in price from initial equilibrium price
2	5000	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	Treatment 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

In Table 5, we report results that reveal systematic patterns by which competitors react to exogenously imposed changes to treatment station prices. In terms of empirical methodology, we regress the competing stations' price on the price of the treated stations while exploiting the experimental design for instruments. Specifically, then, we employ an instrumental procedure that exploits our own treatments as instruments for endogenous prices in a first-stage regression using indicator variables for "price increased at treatment station" and "price decreased at treatment station." In all specifications, we also control for station-specific time-invariant factors by fixed effects which addresses the endogeneity problem that may arise from any unobserved time-varying demand factors within each market.

3.3. Empirical results

Estimated coefficients from the second-stage regressions are provided in Column 1 of Table 5, where we see that the regularities in the data support our anticipated patterns. First, we find that sellers do respond to the exogenously imposed changes by changing their own-prices, and by amounts less than the imposed changes. Second, we find that in markets with higher seller density, sellers respond less to the imposed change in the treatment station's price.

Column 2 of Table 5 introduces an interaction term to investigate the possibility that reactions differ at major brand stations. Slade (1992), for example, finds that rivals can respond differently in a period of price war based on major brandedness. As our analysis considers only reactions of rivals to price changes by one type of station (treatment stations are all major brand and company-operated), we include an indicator variable equal to one if the competitor is a major brand. The point estimate suggests that observed reactions at major brand retailers are indeed dampened.

Column 3 in Table 5 introduces two additional interaction terms to investigate whether station ownership type or distance from the treatment station 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. Including the interaction of lagged treatment station price and the distance the station is from the corresponding treatment station where the shock was

Table 5
Competitor station reactions to changes in treatment station prices

Independent variable	Regular-grade, self-serve price		
	(1)	(2)	(3)
Lagged treatment station price	1.049***	1.103***	1.106***
	[0.056]	[0.056]	[0.057]
Lagged treatment station price interacted with:			
Log of number of stations within two miles	−0.083***	−0.067***	−0.064***
	[0.017]	[0.017]	[0.017]
Major brand indicator [a]		−0.132***	−0.130***
		[0.016]	[0.017]
Distance from treatment station			−0.013
			[0.012]
Ownership indicator (Company-operated=1)			−0.018
			[0.024]
Day-of-week indicators	Yes	Yes	Yes
Trend (day)	0.001***	0.002***	0.002***
	[0.000]	[0.000]	[0.000]
Constant	0.272***	0.281***	0.282***
	[0.012]	[0.012]	[0.012]
Wald	ψ^2 (6)=2.95e+07	ψ^2 (7)=2.93e+07	ψ^2 (6)=2.92e+07
Observations/treatment stations	28,917/724	28,917/724	28,917/724

* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

In all specifications, we exploit our own treatments as instruments for endogenous prices (i.e., for lagged treatment station price) in a first-stage regression using indicator variables for "price increased at treatment station" and "price decreased at treatment station." As interaction terms are added to the model in Columns (2) and (3), corresponding instrumental variables are also included in the first-stage regression. All specifications include station fixed effects. Standard errors in brackets.

[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.

introduced reveals no such patterns of response. As Noel (2007) finds some evidence of differences in response rates across station types, we also include a measure of the reacting-stations' ownership type.[28] This too is not predicted to have a significant effect on responsiveness.

4. Conclusion and remarks

A key feature of this paper is a dataset that collected prices and volumes over time for a sample of retail gasoline stations stratified by the number of rivals within two miles, where prices at a sub-sample of "treatment" stations were intermittently determined exogenously. Although there are notable limitations (e.g., a small number of treatment stations, a short period of time for price collection, restricted data collection during week-ends, and the existence of other shocks in the retail gasoline market during this period), our analysis of the dataset still reveals two key patterns: 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.

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 of a key folk theorem, namely that an increase in the number of competitors in a market will reduce prices. With respect to our reactions, 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. Our finding that rival-responses depend inversely on the number of sellers in the rival's market reinforces the importance of consid-ering the role of the number of sellers in price-setting behavior.

[28] Noel (2007) follows endogenously arising price changes and station responses for a sample of 22 retail stations.

Appendix A. Sample means for Table 1

Table 1
Descriptive statistics

Variable	Mean (Standard deviation)
Log of sales volume (self-serve gasoline)	8.38
at treatment station	(.344)
Log of self-serve price	.234
	(.168)
Price interacted with:	
Mid-level-density indicator	.080
	(.148)
High-density indicator	.073
	(.145)
Log of the number of stations	.696
within two miles	(.520)
Log of market-average self-serve price	.269
	(.155)
Log of market-average price interacted with:	
Mid-level-density indicator	.092
	(.156)
High-density indicator	.085
	(.152)
Log of the number of stations	.800
within two miles	(.485)
Mid-level-density indicator	.336
	(.472)
High-density indicator	.326
	(.469)
San Diego area indicator	.366
	(.482)
San Francisco area indicator	.170
	(.375)
Observations/number of treatment stations	4188/54

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

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.ijindorg.2007.03.002.

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