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Service time competition

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How can two physically identical gasoline stations differentiate themselves? In this article we develop and test a model of service time competition: some stations set higher prices and thereby offer shorter queues, whereas others offer lower price and longer queues. We find that retail demand is sensitive to service time: customers are, on average, willing to pay about 1% more for a 6% reduction in congestion. Consistent with the service time hypothesis, prices are more *dispersed at stations facing more direct competition.*

1. Introduction

■ A Chevron and a Shell gasoline station stand at two corners of the Le Conte/Gayley Avenue intersection in Westwood Village, Los Angeles, California. Any number of UCLA professors will testify that, for many years, the Chevron station has charged lower prices than has Shell. How could the price differential persist so long?

In many retail businesses—automated teller machines, barber shops, gasoline stations, restaurants, and supermarkets—sellers serve randomly arriving customers from fixed capacities. From time to time queues form and, as emphasized by Becker (1965), customers pay two prices—an (explicit) price to the seller and, in addition, an (implicit) price in the time spent waiting.

Such circumstances provide competing businesses with an opportunity to differentiate on price and thereby service time. Using discrete and continuous models respectively, Luski (1976) and Reitman (1991) derive theoretical conditions sufficient for such competition. In this article, we consider whether service time competition arises in practice.

Lott and Roberts (1991) mention service time as one of the dimensions on which gasoline stations compete.[1] Indeed, there are several reasons why gasoline retailing would

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[1] Deacon and Sonstelie (1985) monitored consumer choice at a gasoline station that was compelled by regulation to set lower prices than two competitors. Customers had to queue at the regulated station but not elsewhere. Those with relatively lower cost of time tended to choose the regulated station. In this case, service time competition was imposed by regulation.

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seem to provide a natural setting for such competition. Service stations—unlike banks, barbers, and supermarkets—sell fairly homogeneous products. Moreover, the value of the potential waiting time can be quite significant relative to price differentials among competing stations.[2] Finally, gasoline retailing is a mature industry, so any observed variation is more likely the result of equilibrium responses to differing conditions than it is of incomplete adjustment to a changing marketplace.

The service time competition model motivates two questions. First, how much does service time matter? Second, do similarly situated stations differentiate on price? We use Shepard's (1991) census of eastern Massachusetts service stations to investigate these issues.

Other things equal, a station that increases capacity will reduce average service time. Hence, under the service time hypothesis, *ceteris paribus*, demand should increase with a seller's capacity. The data indeed show a strong positive relation between demand and station capacity. The relation is robust to alternative measures of capacity. Moreover, demand is more sensitive to congestion in higher-income areas.[3] We interpret these findings to be strong evidence that service time is an important factor in retail gasoline demand.[4]

In contrast to the service time competition model, other theories of competition or collusion would predict that businesses in more direct competition would set more similar prices. Accordingly, to investigate the question of whether stations differentiate on service time, we compare the degree of price dispersion at stations that face more direct competition with dispersion at stations facing less competition. We find that, consistent with the service time competition model, prices are more dispersed at stations that face more direct competition.

This article is arranged as follows. In Section 2 we develop a service time model of gasoline retailing, and in Section 3 we describe the data. In Section 4 we estimate the effect of service time on station-level demand. Then in Section 5 we investigate whether competing stations differentiate on service time, and in Section 6 we discuss the extent of scale economies in station operations. Section 7 concludes the article with some general remarks on the role of service time in other businesses.

2. Model

■ Using discrete and continuous frameworks respectively, Luski (1976) and Reitman (1991) modelled competition among sellers for customers who vary in their opportunity cost of time. In equilibrium, each supplier's choice of price and capacity endogenously determines its service time. Assuming that (i) customers choose among sellers by their average rather than their actual service times,[5] and (ii) customers cannot trade positions in queues, Luski and Reitman showed that, in equilibrium, *ex ante* identical sellers would differentiate on price and capacity, and thereby on average service time.[6] With regard to

[2] At \$5 an hour, five minutes of time would be worth about \$.42. On a purchase of 10 gallons, a four-cent per gallon price differential means a saving of \$.40.

[3] This result distinguishes the service time hypothesis from an alternative explanation of the relation between station sales and capacity, i.e., that these are related simply because gasoline retailers build larger stations where they expect higher demand. The latter hypothesis, however, does not explain why the relation should depend on customers' incomes.

[4] Previous empirical research has identified many other important factors that influence demand at a gasoline station. These include location, brand identity, presence of a convenience store, customers' information costs (Marvel (1976)), and customers' switching costs (Borenstein (1991) and Shepard (1991)). None of these stories, however, suggest that service capacity per se should affect demand.

[5] That is, each customer chooses a seller once and for all, according to the seller's average service time, and cannot switch among sellers with the minute-by-minute development of queues.

[6] In related theoretical research on service time competition, Li and Lee (1991) allow customers to switch queues and also find that competing suppliers will differentiate on service time. See also Kalai, Kamien, and Rubinovitch (1992). De Vany and Saving (1983) and Scotchmer (1985) assumed that customers were identical, so, in equilibrium, sellers did not differentiate on either price or capacity.

gasoline retailing, their theory emphasizes that each station's demand will fall with average service time.

Deacon and Sonstelie (1985) monitored consumer choice at a gasoline station that was compelled by regulation to set lower prices than two of its competitors. Their observations validate (i) for gasoline retailing: customers' choice among the three stations depended on the average waiting time at the regulated station rather than on the actual wait. With regard to (ii), if sellers do differentiate by service time, then customers will sort into clienteles according to their individual value of time. The less heterogeneous the customers in a queue, the smaller will be the gains from exchanging places. Hence, to the extent that stations compete on service time, (ii) will tend to be satisfied endogenously.

Outside of peak hours, a station should be able to serve customers without significant delay. In general, average service time during peak periods is a complicated function of service capacity, distribution of customer arrivals, and queue discipline. We have, however, records only of capacity and total sales. Peak average service time will depend on these measurable characteristics in the following ways. First, it will increase with the average number of customers per unit of service capacity. Second, customers arrive randomly, so there is an economy of scale in service—if the total number of customers served and the station capacity are both doubled, average service time will fall. This motivates a peak demand function of the form

$$Q_p = AP^\alpha P_n^\omega \left(\frac{Q_p}{K^{1+\beta}}\right)^\gamma e^{\eta X}, \tag{1}$$

where Q_p is the number of peak-hour customers, A is a constant, P is the price, $\alpha < 0$ is the price elasticity of demand, P_n is the average price at nearby stations, $\omega > 0$ is the cross price elasticity of demand, K is service capacity, $\beta \geq 0$ measures the economy-of-scale effect, $\gamma < 0$ is the congestion elasticity of demand, and X is a vector of other station characteristics.

Let the number of peak-hour customers, Q_p, depend on the total number of customers, Q, and the station's total weekly operating hours, H, through

$$Q_p = \frac{Q}{H^\tau}, \tag{2}$$

where $\tau > 0$.[7] Substituting in (1), taking logarithms, and collecting Q terms on the left-hand side leads to

$$\ln Q = \frac{\ln A}{1-\gamma} + \frac{\alpha}{1-\gamma}\ln P + \frac{\omega}{1-\gamma}\ln P_n - \frac{\gamma(1+\beta)}{1-\gamma}\ln K + \tau \ln H + \frac{\eta X}{1-\gamma}. \tag{3}$$

We posit a short-run framework: a station can vary price and operating hours, but, with one exception, other attributes such as service type (full- vis-à-vis self-service) and brand affiliation are exogenous. The exception is station capacity, which, for reasons given later, we treat as endogenous.

3. Data

■ Our first source of data is Shepard's (1991) census of service stations in four eastern Massachusetts counties collected over 12 weeks in early 1987. For each station, there are records of the types of fuel sold (gasoline/diesel) and grades (regular/premium and leaded/unleaded), type of service (self-/full-service), prices, monthly sales volume, number of

[7] Generally, $Q_p < Q$, which by (2) implies that $H^\tau > 1$. Every station in our sample operated for at least 45 hours a week, i.e., $H \geq 45$, and hence $\tau > 0$.

islands, fueling places, nozzles, repair service bays, and whether the station included a convenience store.

Shepard's cross section also records each station's brand affiliation (if any), the source of its fuel, and its method of operation. Generally, a station can be operated either by employees of some larger organization such as a refiner or a distributor, by a lessee-dealer of such an organization, or directly by the owner of the station (i.e., an "open dealer"). Shepard used the stations' street addresses to construct a Cartesian grid with 3/8-mile steps over the stations. Her dataset also includes the average weekly wholesale price of regular unleaded gasoline in the Boston area as reported by the Oil Price Information Service.[8]

Our second source of data is the *Sourcebook of Zip Code Demographics*. This provides information on population, mean per capita income, and median rent of occupied housing units. We matched these data to the stations by zip code. See Table 1 for descriptive statistics of the data.

4. How much does service time matter?

■ The first issue that we address is whether, and to what extent, station-level demand for gasoline is sensitive to service time. We use the model (3) to address this question. Because the majority of gasoline sold during the sample period was regular unleaded, we treat the price of this grade as an index.[9] Most of the stations in the sample list only a credit or a cash price but not both. We set *PRICE* to be the cash price, unless the station had only a credit price, in which case we used the credit price.[10] As Shepard (1991) noted, gasoline prices rose steadily during the sample period. In order to reflect only relative price differences, we discount *PRICE* by the motor fuel component of the consumer price index.[11] The next variable in (3) is the average price at nearby stations, *PPROX*.[12] Demand at a station should rise with the average price at nearby stations.

With regard to service capacity, we focus on the stations' physical attributes and ignore the possibility that service speed might be determined by labor—whether to pump gasoline (at full-service islands) or to collect payment. Once all fueling places are occupied, the next customer to arrive must wait even if a nozzle is free. Accordingly, the measure of capacity that probably best fits the service time story is the number of gasoline fueling places, *FP*. Under the service time hypothesis, this should have a positive effect on demand. Another possible measure, however, is the number of gasoline nozzles and we do consider this alternative specification below.

[8] For a more detailed description of this dataset, please refer to Shepard (1991). See Temple, Barker & Sloane, Inc. (1988) for the general structure of the U.S. gasoline industry.

[9] Specifically, according to the *Petroleum Marketing Monthly* (1987), regular unleaded gasoline constituted 54% of December 1986 wholesale gasoline sales in Massachusetts, and 52% in the United States as a whole.

[10] It would seem natural to include a dummy variable to indicate stations that offered only a credit price, which presumably meant that they charged the same price for cash and credit sales. However, these were almost all stations belonging to a major refiner brand, as defined by *Oil Daily* (American Petroleum Institute, 1992). Thus "the same low price for cash or credit" is one of the benefits bundled with branded gasoline. As we explain later, we did include dummy variables to distinguish branded from independent stations.

[11] Shepard, by contrast, deflated retail prices by the wholesale price of gasoline. This assumes that gasoline stations pass along wholesale price changes proportionally with some fixed lag. Our approach assumes instead that retail gasoline prices move in step with inflation in the general product category, which seems more reasonable.

[12] We defined nearby stations according to the following hierarchy, using the first that applies: other stations along the same road in the same town; then, other stations with the same coordinates as defined by Shepard (1991); then, other isolated stations in the same town; and finally, all other stations in the same town. We tried several other definitions of nearby stations and found substantially similar results.

TABLE 1 Summary Statistics

Variable	Description	Source	Mean	Standard Deviation	Minimum	Maximum
PRICE	Price of regular unleaded (cents)	AS	89.175	8.517	70.9	168.9
VOLUME	Monthly sales (thousand gallons)	AS	61.711	40.184	0.5	258
HOURS	Weekly hours	AS	103.418	30.340	45	168
FP	Fueling places	AS	4.304	2.135	1	16
PUMPS	Gasoline nozzles	AS	8.041	4.630	1	30
LEADED	Sells leaded	AS	.875	.330	0	1
PREMIUM	Sells premium	AS	.944	.230	0	1
FULL	Full service	AS	.658	.475	0	1
MULTI	Multi- (full- and self-) service	AS	.157	.364	0	1
CSTORE	Convenience store	AS	.075	.264	0	1
PPROX	Average price of nearby stations	AS	89.123	5.938	70.9	123.9
HIWAY	On a highway	AS	.089	.285	0	1
POP	Population	SZD	26400.84	14774.15	178	64053
INCOME	Per capita income ($)	SZD	15715.68	2473.500	8465	23376
RENT	Median housing rental rate ($)	SZD	297.000	48.241	181	493
WHOLESALE	Average weekly wholesale price for unleaded (cents)	AS	52.862	1.423	50.44	55.01
BAYS	Number of service bays	AS	1.935	1.206	0	9
OPNDLR	Open dealer	AS	.491	.500	0	1
MAJSUP	Major supplier	AS	.622	.485	0	1
NOBRND	Unbranded fuel supply	AS	.239	.426	0	1
GULF	Brand dummy	AS	.085	.279	0	1
CITGO	Brand dummy	AS	.077	.267	0	1
EXXON	Brand dummy	AS	.073	.260	0	1
GETTY	Brand dummy	AS	.056	.230	0	1
MOBIL	Brand dummy	AS	.191	.393	0	1
SHELL	Brand dummy	AS	.085	.278	0	1
SUNOCO	Brand dummy	AS	.125	.331	0	1
TEXACO	Brand dummy	AS	.103	.304	0	1
MINOR	Regional or convenience store chain	AS	.126	.332	0	1
NOBRAND	Unbranded retailer	AS	.051	.219	0	1

Note: 1,501 stations. AS = Shepard (1991). SZD = *Sourcebook of Zip Code Demographics*.

Shepard's dataset records each station's aggregate monthly gasoline sales, *VOLUME*. Although stations' operating hours vary considerably, congestion matters only at peak times. As modelled in (3), we adjust for these differences by including the station's total weekly operating hours (*HOURS*) as an explanatory variable.

Finally, we discuss other characteristics that affect station demand. Product mix affects demand directly as well as indirectly through service time. For instance, Borenstein

(1991) observed that leaded and unleaded purchases were of similar size, but Lott and Roberts (1991) found that unleaded nozzles dispensed fuel more slowly than did leaded nozzles. Further, the average number of nozzles per fueling place tends to rise with the number of grades offered by the station.[13] Because all stations offered regular unleaded, we let this be the basis and adjust for product mix through the two fuel grade variables, *PREMIUM* (premium unleaded) and *LEADED* (leaded), which are dummy variables indicating whether the station sold these additional fuel grades.

The service time hypothesis probably applies most closely to the market for self-service gasoline. Some stations sell self- or full-service (*FULL*) exclusively, whereas multi-service stations (*MULTI*) offer both types of service. Because full service customers receive additional services, other things such as price being equal, we expect *FULL* to have a positive effect on demand. We make no prediction as to the effect of *MULTI* on station demand.[14]

Several other attributes that might affect station-level demand are brand affiliation, the presence of a convenience store, and location. Eight brands, each with at least 80 outlets, made up 79.5% of the sample. The next largest brand had 26 outlets. Because the large brands might have differed significantly in advertising expenditure and other marketing variables, we include a dummy variable for each of them. As for the smaller brands, *MINOR* denotes independent stations that belong to a regional chain or convenience store brand, and *NOBRAND* represents the remaining independent stations. The default then is major refiner brands, such as ARCO and Chevron, with a small presence in the sample. Demand should be lower in the case of either *MINOR* or *NOBRAND*.

Next, a convenience store (*CSTORE*) will raise demand, but will increase the time that each customer spends in the station, thus more than proportionately adding to congestion. *HIWAY* denotes stations that lie on or at intersections with divided highways.[15] Demand should be relatively higher at such locations. Demographic factors that should raise station demand are population (*POP*) and mean per capita income (*INC*).

To summarize, we implemented (3) as follows:

$$\begin{aligned} LOGVOLUME = {} & a_0 + a_1 LOGPRICE + a_2 LOGFP + a_3 LOGHOURS \\ & + a_4 PREMIUM + a_5 LEADED + a_6 FULL \\ & + a_7 MULTI + a_8 CSTORE + a_9 HIWAY \\ & + a_{10} LOGPOP + a_{11} LOGINC + a_{12} LOGPPROX \\ & + \mathbf{a}'_{13} BRANDVECTOR. \end{aligned} \tag{4}$$

Three of the independent variables, viz., price, capacity, and operating hours, are quite clearly endogenous: demand depends on all three, but station operators would also adjust price, capacity, and operating hours according to beliefs about demand. Hence, we estimate (4) using two-stage least squares. The ideal instruments would be variables that are correlated with price, capacity, and operating hours but not correlated with the error in estimating (4). The wholesale price and the station's source of fuel (refiner, jobber, or an unbranded source) are probably the most important determinants of a station's marginal

[13] The average number of nozzles per fueling place was 1.16 among eight stations offering only one grade, 1.63 among 254 stations offering two grades, and 2.01 among 1,239 stations offering three grades.

[14] For multi-service stations, we defined *PRICE* to be the self-service price. Shepard (1991) found that self-service prices at multi-service stations did not differ significantly from those at exclusively self-service stations.

[15] Shepard's (1991) records include the street address of each station. We matched these to the divided highways as identified by the American Automobile Association maps entitled "Boston and Vicinity" and "Connecticut, Massachusetts, Rhode Island."

cost of fuel.[16] We use these as instruments for retail gasoline prices. A very suitable instrument for capacity would be the cost of land. As an approximation, we used the median rent in the station's zip code. Another suitable instrument arises from differences in the cost of capital.

Generally, a station can be operated either by employees of a refiner, jobber, or regional or convenience-store chain ("employee operated"), by a lessee of a refiner, jobber, or chain ("lessee dealer"), or by the owner of the station ("open dealer"). Refiners, jobbers, and chains will, on average, have better access to capital than do open dealers. Accordingly, if a station is an open dealer, its capacity is likely to be smaller, which suggests using the indicator variable *OPNDLR* as an instrument for capacity.[17] To the extent that there are economies of scope in staffing repair service and fueling places, the number of service bays (BAYS) will also be a suitable instrument for capacity.

A persistent issue between major refiners and their franchisees has been operating hours, with franchisees clamoring for shorter hours (see for instance, Macauley (1990)). Accordingly, among stations selling branded fuel, we expect open dealers to have shorter operating hours, which motivates using the indicator variable for open dealer selling branded fuel as an instrument for operating hours.[18] The remaining instruments are the exogenous demand shifters in (4).

Column 2 of Table 2 reports the estimates.[19] Before discussing the results, allow us to reiterate that, when a station raises price, it expects two effects: a higher price will directly *reduce* demand, whereas the concomitant reduction in sales will increase service speed and hence *raise* demand. To maximize peak-hour profit, a station should raise price until its contribution margin just equals, in absolute value, the inverse of the responsiveness of peak demand to changes in price, *taking into account both effects*.[20] The responsiveness is the coefficient of *LOGPRICE*, which at -3.282 suggests that stations maximize profit at a contribution margin of 30%.[21]

The contribution margin may seem a little high for gasoline retailing. Note, however, that at peak hours congestion is greater, making it more difficult for customers to switch among stations. Hence, station-level demand will be much less price sensitive during peak hours. Because stations did not vary price between peak and off-peak hours,[22] their actual prices are a compromise between the ideal peak and off-peak prices. So, although we find that *peak* demand is not very sensitive to price, actual contribution margins must be lower than 30%.

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[16] Jobbers are wholesalers of fuel. A jobber may sell branded fuel, unbranded fuel, or both.

[17] A potential snag with using method of operation as an instrument is that franchisors might systematically choose to operate higher-volume locations directly and franchise only the less attractive sites. This problem applies only to employee or lessee stations. We would expect open dealers, like other station owners, to locate stations where they expect demand to be largest. As explained above, however, open dealer stations may face higher cost of capital, and hence be smaller for that reason.

[18] For the reasons given in footnote 17, we do not try to distinguish employee- from lessee-operated stations.

[19] Column 1 reports, for comparison, the ordinary least squares (OLS) estimate of (4).

[20] The contribution margin is price less marginal cost, expressed as a percentage of price.

[21] Notice that the OLS coefficient of *LOGPRICE* is closer to zero (-0.854 as compared with -3.282). This is consistent with the OLS equation combining the positive supply-side effect of price on sales with a negative demand-side effect.

[22] From conversations with Shell's District Manager for the area, we learned that it is quite costly to change prices. The station must reset prices on signboards, pumps, and computers. Moreover, a substantial portion of gasoline stations' business is conducted in cash, so frequent price changes complicate the monitoring of cashiers. In addition, to avoid disputes with customers over the correct price, it may be necessary to shut a station when changing prices. Only in 1992 did Shell introduce a five-cent discount for premium gasoline on Tuesdays, traditionally the slowest day of the week.

TABLE 2 **Demand Equation**
Dependent Variable: *LOGVOLUME*

	(1)		(2)		(3)	
Independent variables	OLS	*t*-statistics	2SLS	*t*-statistics	2SLS	*t*-statistics
INTERCEPT	−2.242	(−1.537)	8.396	(1.662)	6.166	(1.372)
LOGPRICE	−.854	(−4.716)	−3.282	(−3.134)	−2.116	(−2.254)
LOGFP	.378	(11.675)	.670	(2.677)	—	—
LOGNOZZ	—	—	—	—	.954	(2.892)
LOGHOURS	1.068	(17.782)	.725	(2.205)	.401	(.989)
PREMIUM	.470	(7.962)	.318	(3.601)	.114	(.869)
LEADED	.331	(7.097)	.303	(5.397)	.116	(1.263)
FULL	−.032	(−.718)	.138	(1.628)	.187	(2.124)
MULTI	.066	(1.338)	.019	(.300)	.056	(.993)
CSTORE	.024	(.482)	.032	(.561)	.053	(.935)
HIWAY	.088	(1.937)	.107	(1.830)	.089	(1.584)
LOGPOP	.039	(2.105)	.004	(.203)	−.011	(−.461)
LOGINC	−.008	(−.112)	−.028	(−.327)	−.089	(−1.012)
LOGPPROX	.784	(3.950)	1.191	(4.081)	.897	(3.869)
GULF	−.122	(−1.403)	−.004	(−.039)	−.044	(−.454)
CITGO	−.123	(−1.407)	−.098	(−1.008)	−.092	(−1.010)
EXXON	−.005	(−.065)	.057	(.561)	−.005	(−.056)
GETTY	.015	(.163)	−.060	(−.556)	−.062	(−.608)
MOBIL	.061	(.741)	.222	(1.920)	.107	(1.116)
SHELL	−.006	(−.069)	.066	(.585)	−.051	(−.529)
SUNOCO	−.014	(−.168)	.249	(1.654)	.448	(2.454)
TEXACO	−.126	(−1.485)	.001	(.019)	−.041	(−.423)
MINOR	−.218	(−2.554)	−.305	(−2.999)	−.197	(−1.924)
NOBRAND	−.292	(−3.119)	−.295	(−2.831)	−.239	(−2.395)
Observations	1501		1501		1501	
Adjusted R^2	.5910		.4731		.5060	

With regard to the service time hypothesis, the coefficient of *LOGFP*, at .670, is positive and highly significant. This implies that the marginal fueling place generates sales equal to 67% of the average fueling place.[23]

Another way to evaluate our results is to consider the implied demand elasticities. From (1), the *price elasticity*, α, measures the responsiveness of demand to *pure* changes in price, i.e., *holding service quality constant*.[24] To estimate the price elasticity, we equate

[23] Let Q and K represent sales and capacity respectively. One fueling place represents $1/K$ of total capacity. Then, referring to (3) and (4), the coefficient of *LOGFP* implies that raising capacity by $1/K$ will increase *total* sales by a proportion of $.67/K$, or $.67Q/K$ in absolute terms. Put differently, the marginal unit of capacity generates sales of $.67Q/K$, which is consistent with diminishing marginal returns.

[24] Our initial surprise at the persistent price differential between the two Westwood gasoline stations, of course, ignored concomitant differences in service speed.

TABLE 3 Demand Elasticities

Economy-of-Scale Effect, β	Congestion Elasticity, γ	Price Elasticity, α	Tradeoff
.1	−1.558	−8.396	.186
.2	−1.264	−7.431	.170
.3	−1.063	−6.772	.157
.4	−.918	−6.294	.146

the coefficients for price and service capacity in column 2 of Table 2 with those in (3). The elasticities, however, depend on the scale economy parameter, β, which we cannot directly estimate. Based on indirect evidence presented in Section 6, we believe that a reasonable range for β is [0.1, 0.4]. Table 3 reports the elasticities corresponding to values of β in this range. The price elasticity ranges from -6.29 to -8.40, which seems quite reasonable. Substituting the computed elasticities in (1), we infer that retail customers are willing to pay $\gamma/\alpha = 1.5$–1.9% more for a 10% reduction in congestion.

Finally, referring again to column 2 of Table 2, *MINOR*, *NOBRAND*, and *LOGPPROX* all have significant coefficients with the predicted signs. *HIWAY* has the predicted sign and is significant at the 10% level, whereas *FULL* has the predicted sign but is not quite significant at the 10% level. The two demographic variables, *LOGPOP* and *LOGINC*, however, did not have statistically significant coefficients. Upon reflection, it is perhaps not so surprising that these areawide demographic variables were not significant in *station*-level demand. Obviously, an increase in either population or income will raise market demand, but it may also attract new entry. So, at the level of individual stations, we may observe demand to rise at first, and then drop when the market grows sufficiently to accommodate another station.[25]

We used fueling places to measure service capacity. Many stations, however, consist of one or more islands with fueling places on both sides drawing on a common set of nozzles. Hence, at times, nozzles might be the binding constraint on service time. Further, fueling places may be subject to greater measurement error: whereas counting nozzles is quite simple, the surveyor must *estimate* the number of "cars that easily fit" to measure gasoline fueling places. Also, some stations may offer gasoline and diesel from common fueling places.

To check whether our results are sensitive to the specification of service capacity, we reestimated (4) with *LOGNOZZ* (logarithm of the number of nozzles) replacing *LOGFP* (column 3 of Table 2). Compared with the *LOGFP* regression, the fit is almost the same. Consistent with the service time hypothesis, *LOGNOZZ* has a significant positive coefficient. The coefficient of LOGPRICE is negative and significant, implying a contribution margin of 44%, which seems a little high. Note, however, that if nozzles measure capacity with error, then the price coefficient may capture the effect of changes in price as well as concomitant changes in capacity that are not reflected in terms of nozzles.[26]

The model of service time competition emphasizes that competing stations differentiate themselves by service time, thereby drawing customers according to their respective

[25] The *LOGHOURS* coefficient should be interpreted in light of theoretical (Klemperer and Padilla (1993)) and empirical evidence (Messinger and Narasimhan (1993)) that some consumers prefer to concentrate their purchases at a single supplier. When a station extends its hours, it not only draws additional business during that period, it also increases its business at other times as consumers attracted by the longer hours switch *all* their purchases.

[26] We also varied the model in a number of other ways, including the adjustments made to obtain peak volume, specifications of the base price, and which variables were taken to be endogenous. In all of these results (which, for brevity, we do not report), we found that capacity had a positive and statistically significant effect on demand.

opportunity cost of time. One factor that we have not considered is variation among customers in their opportunity cost of time. In particular, to the extent that this rises with income, the customers most sensitive to congestion will be those with the highest income. We measure customer income by the per capita income in the zip code containing the station.[27] Of course, congestion is not the only demand parameter that might depend on customers' incomes. Higher-income customers may be relatively more sensitive to other quality attributes and less sensitive to price. For simplicity, we focus on the effect of income on elasticities of congestion and price, and ignore the potential effects on other quality attributes. This leads to a demand specification of the form

$$Q_p = A(P^{\alpha}P_n^{\omega})^{(1+\mu_p(Y-\bar{Y}))}\left(\frac{Q_p}{K^{1+\beta}}\right)^{(\gamma+\mu_k(Y-\bar{Y}))} e^{\eta X}, \tag{5}$$

where Y is income, $\bar{Y}$ is mean income over the sample, μ_p and μ_k are the incremental effects of income on the elasticities of price and congestion, and, by (2), $Q_p = Q/H^{\tau}$.

Regarding price elasticity, we predict that $\alpha < 0$ and that the higher is income, the *less* sensitive demand will be to price, i.e., $\mu_p < 0$. With regard to congestion elasticity, we predict that $\gamma < 0$ and that the higher is income, the *more* sensitive demand will be to congestion. Now $1 + \beta \geq 1$, hence this means that $\mu_k < 0$.

The algebraic transformation that we used to linearize the earlier specification (1) no longer works, and consequently, we estimate (5) using nonlinear two-stage least squares. This allows us to estimate the demand coefficients directly, but requires a value for the scale economy parameter, β. Again, based on the analysis in Section 6, we assume that $\beta \in [0.1, 0.4]$. Table 4 reports the results. The estimates of μ_k are negative and statistically significant, consistent with the hypothesis that higher income customers are more sensitive to congestion.[28] According to these estimates, a station in an area with per capita income one standard deviation above the average will face a congestion elasticity 43–50% higher.

Although the estimates of μ_p are not consistent with our prediction, neither are they statistically significant. The remaining results are consistent with those from the specification (4), although standard errors are generally higher. To summarize, we have found substantial evidence that congestion matters in retail gasoline demand and it matters relatively more among customers with higher incomes.

5. Do competing stations differentiate on price?

■ Given that customers care about service time, do they differ enough that stations choose to differentiate on price, and thereby, service time? Motivated by the two stations at the Le Conte/Gayley Avenue intersection in Westwood Village, we approached this question in the following way. In contrast to the service time competition model, other theories of price competition or collusion would tend to predict that businesses in more direct competition would set more similar prices. This suggests testing our model by comparing the degree of price dispersion at stations that face more direct competition with dispersion at stations facing less competition.

To construct a subsample of stations facing more intense competition, we use Shepard's *VISIBLE* variable. A station from which at least one other station could be seen has *VISIBLE* = 1. Using each such station's address and nearest cross street, we grouped

[27] This very crude measure neglects the considerable mobility of customers across zip codes to purchase gasoline.

[28] In contrast, in Deacon and Sonstelie's (1985) study of a station compelled by regulation to set lower prices than did its competitors, choice among stations did depend on whether the customer was fully employed, but, among employed drivers, choice was not sensitive to their income.

TABLE 4 **Nonlinear Demand Equation Dependent Variable: *VOLUME***

	(1)		(2)		(3)		(4)	
Variable	β = .1	*t*-statistics	β = .2	*t*-statistics	β = .3	*t*-statistics	β = .4	*t*-statistics
CONSTANT	12.102	(1.08)	11.744	(1.15)	11.454	(1.21)	11.239	(1.27)
α	−5.548	(−1.74)	−5.328	(−1.88)	−5.141	(−2.00)	−4.988	(−2.12)
ω	1.999	(1.80)	1.910	(1.91)	1.828	(2.01)	1.757	(2.11)
τ	.903	(2.61)	.909	(2.58)	.915	(2.57)	.920	(2.57)
γ	−1.032	(−1.14)	−.889	(−1.20)	−.773	(−1.24)	−.680	(−1.29)
μ_k	−3.032	(−2.13)	−2.747	(−2.33)	−2.503	(−2.52)	−2.298	(−2.67)
μ_p	.338	(.92)	.346	(.98)	.353	(1.02)	.357	(1.06)
PREMIUM	.597	(2.36)	.556	(2.68)	.526	(2.97)	.504	(3.23)
LEADED	.648	(2.38)	.604	(2.68)	.569	(2.98)	.541	(3.29)
FULL	.157	(.68)	.153	(.72)	.149	(.76)	.145	(.80)
MULTI	.131	(1.16)	.108	(1.08)	.091	(.99)	.078	(.90)
CSTORE	.004	(.04)	.005	(.05)	.006	(.07)	.008	(.08)
HIWAY	.186	(1.25)	.166	(1.27)	.152	(1.28)	.140	(1.28)
LOGPOP	.020	(.42)	.015	(.33)	.011	(.25)	.007	(.18)
GULF	−.007	(−.03)	−.005	(−.02)	−.005	(−.02)	−.005	(−.03)
CITGO	−.120	(−.60)	−.118	(−.64)	−.117	(−.68)	−.117	(−.72)
EXXON	.020	(.10)	.024	(.12)	.027	(.14)	.028	(.16)
GETTY	−.039	(−.19)	−.052	(−.27)	−.061	(−.33)	−.067	(−.38)
MOBIL	.301	(.99)	.291	(1.04)	.282	(1.08)	.274	(1.13)
SHELL	.046	(.19)	.042	(.19)	.038	(.18)	.035	(.17)
SUNOCO	.386	(.99)	.369	(1.04)	.354	(1.09)	.342	(1.13)
TEXACO	−.010	(−.05)	−.002	(−.01)	.003	(.01)	.006	(.04)
MINOR	−.537	(−1.99)	−.514	(−2.13)	−.494	(−2.26)	−.477	(−2.38)
NOBRAND	−.427	(−1.89)	−.420	(−2.01)	−.413	(−2.13)	−.405	(−2.22)
Observations	1501		1501		1501		1501	
Adjusted R^2	.4594		.4680		.4739		.4776	

most of them into clusters of two to four. One result of this grouping was that the stations in a cluster were generally within one block of one another. To construct the control subsample of relatively isolated stations, we drew on stations from which no other stations could be seen (*VISIBLE* = 0). We selected all such stations for which there was at least one other such station on the same street in the same zip code.

Stations in both subsamples face competition. The stations in the clustered subsample, however, face more direct competition in the sense that approaching customers could also see one or more competitors. To the extent that customers who care about price or congestion collect information with their own eyes, competition at the clustered stations is more intense.

We first checked whether the clustered stations did indeed face more direct competition. Table 5 reports estimates of the demand equation (4) for the clustered stations in

TABLE 5 Demand at Clustered vis-à-vis More Isolated Stations
Dependent Variable: *LOGVOLUME*

	(1)		(2)	
Independent variable	Clustered	*t*-statistics	More Isolated	*t*-statistics
INTERCEPT	9.070	(1.211)	−.684	(−.101)
LOGPRICE	−2.754	(−1.664)	−1.711	(−1.265)
LOGFP	.487	(1.727)	.685	(2.746)
LOGHOURS	.713	(1.590)	1.007	(2.851)
PREMIUM	.608	(4.128)	.175	(1.401)
LEADED	.240	(2.231)	.182	(2.040)
FULL	.017	(.168)	.179	(1.365)
MULTI	−.028	(−.234)	.070	(.746)
CSTORE	.077	(.827)	−.010	(−.112)
HIWAY	.094	(1.228)	.067	(.632)
LOGPOP	−.032	(−.920)	.018	(.473)
LOGINC	−.127	(−.952)	.178	(1.106)
LOGPPROX	.866	(2.039)	.926	(2.264)
GULF	−.050	(−.332)	.051	(.307)
CITGO	−.157	(−1.038)	.100	(.676)
EXXON	−.007	(−.048)	.149	(.936)
GETTY	.065	(.382)	.094	(.556)
MOBIL	.229	(1.238)	.215	(1.322)
SHELL	−.014	(−.088)	.199	(1.190)
SUNOCO	.170	(.704)	.160	(.838)
TEXACO	.018	(.107)	.065	(.418)
MINOR	−.250	(−1.433)	−.081	(−.567)
NOBRAND	−.341	(−1.821)	−.242	(−1.547)
Observations	491		525	
Adjusted R^2	.4336		.4656	

column 1 and for the relatively isolated station in column 2.[29] The coefficient of price among clustered stations (−2.754) is 60% larger than that for isolated stations (−1.711). Although the two coefficients differ by a little less than one standard error, the result does suggest that stations in the clustered subsample face more direct competition than do those in the control subsample.

The next step is to compare the degree of price dispersion in the two subsamples. We focused on the price of regular unleaded.[30] The estimates in Table 2, however, show that gasoline consumers care not only about price, but also about product mix, brand affiliation, and availability of full service when choosing among competing stations. Accordingly, to measure pure price dispersion, we must adjust prices for all other station

[29] The corresponding estimated demand for the whole sample is in column 2 of Table 2.

[30] As discussed above, we used the cash price, unless the station had only a credit price, in which case we used the credit price.

attributes. We used the estimates in column 2 of Table 2 to make this adjustment. We also adjusted prices by the survey date to remove any spurious price differences resulting from general inflation.

Let the price set by station i within group s be a random variable $p_{si} = k_s + \epsilon$, where k_s is a constant for group s and ϵ is a random variable distributed normally with mean μ and standard deviation σ. The parameter k_s reflects common cost and market demand conditions that affect prices at every station in the group. Let group s consist of n_s stations with a mean price of p_s. Then $\Sigma_{i=1}^{n_s} (p_{si} - p_s)^2/\sigma^2$ is a χ^2 random variable with $(n_s - 1)$ degrees of freedom. Adding over all the groups, $\Sigma_s \Sigma_{i=1}^{n_s} (p_{si} - p_s)^2/\sigma^2$ is a χ^2 random variable with $\Sigma_s(n_s - 1)$ degrees of freedom. Because other theories of competition and collusion predict that stations in more direct competition would set more similar prices, the null hypothesis is that price of regular unleaded exhibits less variance among clustered stations.

Consistent with the service time model, the estimated variance was 50.1 at clustered stations and 42.2 at isolated stations which, by a (one-tailed) F-test, rejects the hypothesis that clustered stations exhibit less price dispersion at the 7% level.[31] We infer that there is evidence that, in a free-market setting, competing stations do find it worthwhile to differentiate on price, and by doing so, *endogenously* differentiate on service time.

6. Economies of scale

■ Our estimates of price and congestion elasticities in Section 4 depend on the economy-of-scale parameter, β. We would like, if possible, to gauge the extent of these scale economies. In the absence of a more direct method, we ask whether smaller or larger stations predominate in the fast-service niche and thereby infer the strength of the scale economies.

Although stations could, in principle, easily adjust service time by simply changing price, we do not expect much switching in practice because it is more costly to make the concomitant adjustments to capacity. Accordingly, we expect each station to remain in the niche to which it is best suited.

To the extent that there are economies of scale in serving randomly arriving customers, larger stations will be better suited to the fast-service niche for two reasons. First, a larger station can offer faster service even while utilizing capacity more intensively. Second, customers purchase different quantities of gasoline and hence take varying times to dispense fuel. So, if a station doubles both capacity and customer numbers, it will reduce both the *average* service time and the *variance* of service times.[32] If customers with higher average cost of time also have higher *marginal* cost of time,[33] then these customers will be more averse to variance in service times, thus reinforcing their attraction to larger stations.

On the other hand, if a station charges a relatively higher price and provides faster peak service, it will draw relatively little business outside of peak hours when congestion does not matter. So, if a high-price station adds capacity, the marginal return comes mainly from peak-hour customers. By contrast, a low-price station that adds capacity will derive

[31] Providing further support for the service time model, we found that the estimated sample variance of the raw price (not adjusted for other station attributes or survey date) was also higher among the clustered stations. The estimated variance was 67.2 among the clustered stations and 57.9 among the isolated stations, the difference of which was significant at the 11% level.

[32] Suppose that there is only one nozzle, and a customer, j, arrives to find another customer ahead in line. Then the variance of j's waiting time is the variance of one customer's dispensing time. On the other hand, if there were two separately accessible nozzles, and customer j arrived to find one customer ahead at both nozzles, the variance of j's waiting time would be the variance of the *minimum* of two customers' dispensing times.

[33] This "single-crossing" assumption underlies most self-selection models. See, for instance, Cooper (1984) or Maskin and Riley (1984).

additional profits from *both* peak and off-peak customers. Hence, the marginal return from additional capacity will diminish relatively faster for high-price stations. Thus, they can be expected to be relatively smaller.

By (1), we measure station congestion by $Q_p/K^{1+\beta}$. To investigate whether smaller or larger stations predominate in the fast-service niche, we consider the relationship, $Q_p/K^{1+\beta} = \nu K^{\sigma}$, with no hypothesis as to the sign of σ. Rearranging and taking logarithms, we have

$$\ln Q_p = \ln \nu + (\sigma + 1 + \beta) \ln K. \tag{6}$$

As column 2 of Table 2 shows, a station's peak-hour service time depends on its product mix. To adjust for this, we used the coefficients on *PREMIUM* and *LEADED* from column 2 of Table 2 to calculate each station's volume as if it had sold only regular unleaded. Next, we deflated this figure by operating hours (using the coefficient on *LOGHOURS* from column 2 of Table 2) to obtain peak volume, *PKVOLUME*. We then estimated (6) by ordinary least squares and obtained the following results (numbers in parentheses are t-statistics):

$$\begin{array}{llll} LOGPKVOLUME = & 3.795 \; + & 0.596 & LOGFP \\ & (96.144) & (21.543) & \\ & & & \text{1501 Observations} \\ & & & \text{Adjusted } R^2 = 0.2359. \end{array} \tag{7}$$

By (6) and (7), the coefficient of *LOGFP*, $\sigma + 1 + \beta = 0.596$. Now $\beta \geq 0$, hence $\sigma = -0.404 - \beta < 0$, implying that larger stations are better suited to providing fast service. Accordingly, we infer that scale economies are strong enough (β is large enough) to outweigh the costs of underutilization during off-peak times. Recall from (1) that, if both service capacity and the number of peak customers were to double, congestion would fall by a factor of $(1 - 1/2^{\beta})$. Given the results in (7), it seems reasonable to suppose that this factor will be at least 5%, or that $\beta \geq 0.074$. On the other hand, it appears unlikely that doubling both capacity and peak patronage would reduce congestion by more than 25%, implying that $\beta \leq 0.41$. To conclude, we believe that a reasonable guess is that $\beta \in [0.1, 0.4]$. We use this range of values to calculate the elasticities of demand with respect to price and congestion (Table 3) and the effect of household income on these elasticities (Table 4).

7. Concluding remarks

■ Our results should also be viewed in a broader context. As Becker (1965) has emphasized, time is an *input* into consumption. Many cross-sectional differences and secular changes in retailing practices can be best understood in terms of this factor. For instance, Messinger and Narasimhan (1993) attribute the rise of supermarkets to consumers' rising cost of time, hence demand for one-stop shopping. Pashigian and Bowen (1994) show that the increase in women's, relative to men's, cost of time since the mid-1970s can explain the growth of nationally advertised brand names relative to retail stores as sources of consumer information.

In the context of retail gasoline markets, we have shown that service time has a significant effect on demand and that competing stations use it as a point of differentiation. More generally, we expect service time to influence retailers' choice of capacity and, thereby, the number of firms in each market. The spread of multiple-island stations with wide aisles and computerized point-of-sale payment systems can be attributed to the rising cost of customers' time (Hogarty (1981)).

Service time competition arises in any business in which competing sellers serve randomly arriving customers from fixed capacities. A seller's price then determines two variables—the explicit amount that customers must pay, and the average service time. In service time competition, higher price does indeed mean higher product quality.

Examples of such competition abound. Customers of private security patrols and automobile breakdown services have random need for service, hence they necessarily must choose among suppliers on the basis of average response time. In industrial marketing, Eidinger, Goree, and Reisinger (1991) reported that physicians and clinics ranked next-day delivery in the event of stock-out to be the most important feature of service from distributors of medical supplies. Likewise, if a manufacturer that practices Just-In-Time (JIT) inventory meets a sudden surge in demand, he must forgo the additional orders unless his own suppliers have the capacity to respond quickly. Thus, contrary to popular discussion, a JIT system does involve a trade off—between the manufacturer holding inventory and his suppliers maintaining excess capacity.[34]

Supermarket operations illustrate discrimination as well as competition on service time. Many large supermarkets offer three checkout alternatives: (i) payment in cash with a limited number of items, (ii) payment in cash with any number of items, and (iii) all methods of payment. Line (i) responds to competition from "convenience stores" for small quick transactions, whereas lines (ii) and (iii) discriminate between customers with larger purchases according to their willingness to wait (for the customer, paying by check or credit card is more convenient and cheaper than paying in cash).[35]

Finally, discrimination by service time may also arise in retail gasoline sales. Shepard (1991) found that multi-service and exclusively self-service stations charged similar prices for self-service gasoline, whereas multi-service stations priced full service significantly above exclusively full-service stations. These observations are consistent with "full service" at a multi-service station bundling the "full service" of a full-service station plus an option to customers who encounter congestion at self-service.

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[34] Blinder (1991) asked a representative sample of U.S. firms what affected the frequency with which they adjusted prices. The explanation given most often and which carried the most weight was that rather than respond to variations in demand by changing prices, firms would adjust delivery time and improve other auxiliary services.

[35] Donaldson and Eaton (1981) analyze how a monopolist might discriminate by service time.

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