Measuring the Price Impact of Retailers' Locations and Brands

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Abstract

In this paper we examine the effect of the locations and brands of gasoline retail outlets in Tucson, Arizona on market prices. We apply a novel approach to model the impact of competing gas stations that allows all stations in the market to have an effect rather than limiting our analysis to predetermined nearby locations. We show that: (1) hypermarts reduce prices by a larger amount and over a greater distance than other types of gas stations; and, (2) reduced brand diversity is associated with lower prices. We demonstrate that our conclusions are robust to three alternative measures of distance.

Keywords: Econometric Spatial Analysis, Spatial Effects, Brands, Distance Metrics

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1 Introduction

In this paper we examine the impact of the locations and brands of gas stations on prices in the retail gasoline market in Tucson, Arizona. Our approach allows for absolute and relative spatial location and brand location effects. Unlike prior researchers, we flexibly model the impact of competing gas stations allowing all stations in the market to have an effect rather than limiting our analysis to predetermined nearby locations.

In this context a retailer's absolute spatial location refers to its physical location before taking into consideration the location of competing outlets. Relative spatial location accounts for a retail outlet's location with respect to its competitors. All other things being equal, we would expect a higher density of nearby competitors to be associated with lower prices. This is the case since the presence of a higher density of competitors means that consumers benefit from more close substitutes which in turn increases the price elasticity of demand and, assuming individual outlets behave as independent profit maximizers, reduces equilibrium prices.

In the case of brands, an analogous distinction between absolute and relative effects is pertinent. Absolute brand location refers to a retail outlet's brand without considering the brands of other outlets. Relative brand location takes into account the brands of other retailer's that are present in the marketplace. We limit our consideration of relative brand location effects to studying the relationship between market prices and brand diversity. Theoretically brand diversity's impact on prices is ambiguous. If consumers have preferences over brands, reduced brand diversity may increase the density of close substitutes leading to reduced equilibrium prices (we call this the "brand loyalty" effect). However, if retail outlets of the same brand follow a coordinated pricing strategy[2], then reduced diversity may result in less effective price competition and higher equilibrium prices (we call this the "brand collusion" effect). The net result from these two offsetting effects is theoretically unclear and is a matter for empirical investigation.

Relative spatial location effects have received only limited attention from empirical industrial organization economists. If they have been modeled, ease of data collection has tended to override other considerations. As a result, measures such as the shortest distance to a competitor, or the number of competitors located less than some critical distance from the outlet of interest have been employed. Our approach allows many surrounding outlets to have an impact and avoids the need to apply predetermined market sizes. The methodology is particularly appropriate for examining whether different categories of retailers have different market impacts. We use this feature to compare hypermarts[3] to other types of gas stations. As far as we are aware, relative brand location effects have not previous been studied empirically and we are the first to examine the

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[2] As a result of the range of prevailing ownership and contractual arrangements, the degree to which gas stations of the same brand would be expected to coordinate pricing is itself uncertain. The ownership of branded gas stations fall into three basic types. The first type is a company owned station. The refiner owns the station and an employee of the refiner runs the station. In this case retail prices are set by the refiner. The second type is a lessee dealer. The refiner owns the station and leases it to an operator. In this case the lessee is responsible for setting retail prices. The third type is a dealer owned station. In this case the operator owns the station and is responsible for setting retail prices. Hastings (2004) includes a more detailed discussion of ownership arrangements in the retail gasoline industry.

[3] Hypermart is an industry term used to describe non-traditional retail gasoline locations. Typically traditional gas stations are located on major streets and intersections and generally include amenities such as convenience stores, car washes, and repair shops. Common examples of traditional gas stations are Chevron, Shell, and Texaco. Hypermarts, on the other hand, are big-box stores, mass-merchandisers, wholesale outlets, and grocery stores, which over the last decade have entered the retail gasoline industry. Examples are Costco, Wal-Mart and Safeway. Hypermarts characteristically price low, sell high-volumes of gas, locate in the larger stores' parking lots and offer few of the amenities often offered by traditional gasoline retailers.

relative magnitudes of the brand loyalty and brand collusion effects.

Using our novel approach to modeling the impact of surrounding retail outlets, we show that in the Tucson retail gasoline market, on average hypermarts have a larger impact on prices over a greater distance than other types of gas stations.[4] This suggests that the low price strategy followed by hypermarts intensifies price competition locally leading to lower equilibrium prices. In addition, we demonstrate that reduced brand diversity is associated with lower prices. This is consistent with brand loyalty having a greater effect on equilibrium prices than brand collusion. Our findings are robust to three alternative measures of distance: Euclidean distance; road distance; and, travel time.

2 Relevant Literature

Two relevant areas of research are discussed below: (a) empirical studies of retail gasoline markets; and, (b) a study that investigates the use of alternative measures of distance.

A. The Retail Gasoline Market

There is a fairly extensive literature that considers industry structure and pricing in the retail gasoline market. In contrast to the analysis described later in this paper, in general researchers have used predetermined market areas based on Euclidean distances to evaluate the degree of competition faced by a retail outlet. In addition relative brand location issues have not been investigated.

[4] This result is consistent with the findings of Brewer (2006).

Shepard (1991) uses data from gas stations in the Boston area to investigate competition between multi-product and single product providers. The analysis uses the average price for competitors located within a specified Euclidean distance (half, one, one and a half or two miles) from the gas station of interest as an explanatory variable. Pinkse and Slade (1998) investigate supply contract choices of gas stations in Vancouver. The authors compare six metrics of competitive closeness (Euclidean distance, location on same street, a combination of the first two methods, nearest neighbor on street, nearest neighbor, and common boundary) and conclude that nearest neighbor is the most appropriate measure. Barron, Taylor and Umbeck (2000) investigate the relative pricing of regular and premium gasoline using data from the Los Angeles area. The authors use the Euclidean distance to the nearest competitor as an explanatory variable. Netz and Taylor (2002) investigate how firms locate as competition increases. Competition is measured based on the number of stations within either half, one or two Euclidean miles of the gas station of interest. Barron, Taylor and Umbeck (2004a) investigate the impact of different contractual supply arrangements between gasoline wholesalers and retailers on retail gasoline prices. The data used relate to the Los Angeles area. In the analysis the number of competitors within a specified Euclidean distance from the gas station of interest and the Euclidean distance to the nearest competitor are used as explanatory variables. Barron, Taylor, and Umbeck (2004b) examine the impact of the density of competitors on prices. The authors measure competitor density by counting the number of stations within one and a half Euclidean miles of the station of interest and find that as density increases, posted prices fall. Barron, Umbeck, and Waddell (2006) conduct a field experiment and demonstrate that competitor density impacts a station's price elasticity of demand and the responses of competitors to an exogenous change in another station's price. The authors measure competitor density by counting the number of stations within two Euclidean miles of a given station.

An exception to the pattern of relying on Euclidean distance measures is Hastings (2004) in which the number of competitors in market areas based on road distances are used to measure the level of competition a retail location experiences.

B. Alternative Distance Metrics

In general, industrial organization economists have not considered the importance of different distance measures in spatial analysis. This approach has been defensible in the past since in many applications spatial effects were of secondary importance only, and alternatives to Euclidean distances were prohibitively costly to collect. Given the improvement in cost and ease of use of geographical information system ("GIS") software and the greater availability of location coded data sets the usual approach may no longer be appropriate. Apparicio et al (2003) discuss the relative advantages and disadvantages of four measures of distance: Euclidean distance; Manhattan distance; shortest road distance; and, shortest road travel time. Euclidean distance is the straight line distance between two points. Manhattan distance is the distance along two sides of a right angle triangle, where one of the sides measured runs North/South and the other runs East/West and with the hypotenuse corresponding to the Euclidean distance. Shortest road distance takes into account the actual location of roads to estimate the shortest route between two points. Shortest road travel time takes into account road locations and estimates of actual travel speeds to estimate the time to travel between two points. Apparicio et al (2003) compare these four distance measures in eight Canadian metropolitan areas and finds that the measures are all closely correlated across the eight metro areas but that within each metro area the measures can vary substantially. The authors conclude that “for the study of general metropolitan phenomena Euclidean and Manhattan approximations are adequate, but as soon as specific sub-metropolitan areas or neighborhoods are considered there are substantial benefits to using network based distances and times.”

3 Econometric Model

Our econometric model is shown in Equation 1.

$$\begin{aligned} p_i = X_i\beta + (\text{hypermart count}_i)\lambda_h + (\text{non}-\text{hypermart count}_i)\lambda_n \\ +Log(\text{Herfindahl Index of brand counts}_i)\mu + \varepsilon_i \end{aligned} \qquad (1)$$

In Equation 1 p_i represents the posted prices for a gallon of regular gas at station i. X_i is a vector of exogenous station characteristics consisting of location specific characteristics (population density and traffic flow) and dummy variables for station characteristics (brand, convenience store, franchise food outlet, car wash and repair shop). The hypermart and non-hypermart counts are our measures of the density of competitors. Consistent with the findings of prior researchers we would expect market prices to decline as the density of competitors increases. As explained below, when calculating the counts we avoid applying a predetermined market definition and instead allow all the gas stations in the data set to have an impact on the prices at all other gas stations. In this way we expect to be better able to understand the relationship between market price impact and distance from the station of interest than is possible using less flexible methods. By calculating a separate count for hypermarts and non-hypermarts we are able to investigate whether or not hypermarts and non-hypermart gas stations on average have different effects on market prices. The Herfindahl Index of brand counts serves as our measure of brand diversity. As with the hypermart and non-hypermart counts, we avoid applying predetermined market definitions when calculating the Herfindahl Index of brand counts. As discussed earlier, theoretically the impact of a change in brand diversity is unclear since it depends on two potentially offsetting effects: brand loyalty; and, brand collusion. The final term in Equation 1, ε_i, is an i.i.d. disturbance term. The manner in which the hypermart and non-hypermart counts and the Herfindahl Index of brand counts were calculated is explained below.

In counting the gas stations surrounding the station of interest i, each station j is assigned a weighting factor w_{ij} that declines with distance from station i as shown in Equation 2.

$$w_{ij} = \frac{\phi\left(\frac{d_{ij}}{s}\right)}{\phi(0)} \tag{2}$$

In Equation 2 $\phi(.)$ is the probability density function for a standard normal distribution, d_{ij} is the distance from the station of interest i to station j and s is a distance normalization factor that is to be determined. In order to investigate if hypermarts have a different impact on prevailing prices than other types of gas stations different values of the distance normalization factor were allowed for hypermarts and non-hypermarts. (We designate these values s_h and s_n for hypermarts and non-hypermarts respectively.) The manner in which the counts for hypermart and non-hypermart gas stations were calculated for station i are shown in Equation 3.

$$\text{hypermart count}_i = \sum_{\substack{\text{all } j \text{ where } j \text{ is} \\ \text{a hypermart} \\ \text{and } j \neq i}} w_{ij}\ , \quad \text{non-hypermart count}_i = \sum_{\substack{\text{all } j \text{ where } j \text{ is} \\ \text{not a hypermart} \\ \text{and } j \neq i}} w_{ij} \qquad (3)$$

We believe that the use of a factor based on the normal probability density function to weight the count of surrounding gas stations as shown in Equation 2 is appropriate since: (1) it avoids imposing a predetermined market definition; (2) it allows all stations in the market to have an impact; (3) its form corresponds to the intuition that nearby stations have significant importance while distant ones do not; and, (4) its smooth character and parsimonious coefficient requirements facilitates estimation. For these reasons we prefer it to the traditional "distance to nearest competitor" or "number of stations within y miles" approaches. Finally, since many individuals are likely to purchase gas while making journeys that are primarily for other purposes, we would like the weighting factors to correspond to the probability that given an individual will be passing station i she will also be passing station j. The general form of the normal probability density function seems appropriate under these circumstances. Normalizing the weighting factors by $\phi(0)$ is consistent with the probability explanation. It also simplifies the interpretation of the coefficients of the counts for hypermarts and non-hypermarts, λ_h and λ_n, since it means that they correspond to the expected price impact of a hypermart and a non-hypermart respectively located arbitrarily close to the gas station of interest.

In order to calculate the Herfindahl Index of brand counts similar counts to those indicated in Equation 3 were undertaken for all the brands present in the market. For these purposes unbranded stations were treated as a single brand and all hypermarts were considered as a single brand. The count corresponding to the brand of the station of interest was adjusted to include the station of interest.

If Z is the set of all the brands in the marketplace, $share_{ix}$, the brand share of brand x for station i, was defined as shown in Equation 4.

$$share_{ix} = \frac{x \text{ count}_i}{\sum_{\text{all } z \in Z} z \text{ count}_i} \tag{4}$$

The Herfindahl Index of brand counts for station i was then calculated in the usual way as shown in Equation 5.

$$\text{Herdindahl Index of brand counts}_i = \sum_{\text{all } x \in Z} \left(share_{ix} \right)^2 \tag{5}$$

A value of the Herfindahl Index of brand counts of one would correspond to no brand diversity at station i and a value close to zero would correspond to very high brand diversity. Note that in calculating the Herfindahl Index of brand counts the station of interest i is included in the analysis and therefore this measure reflects both the variability in brands of the surrounding stations and the difference between the surrounding stations and the station of interest.

Since the hypermart count, the non-hypermart count and the Herfindahl Index of brand counts contain non-linear transformations of the observed data, we used non-linear least squares to estimate the model.

4 Description of the Data

Our data set includes posted prices, characteristics and locations for 235 retail gasoline outlets in Tucson, Arizona. The data were collected over a 14 hour period on March 12, 2005.[5] We believe that all gas stations in the metropolitan area of Tucson in service at the time the data were collected are included in the data set.

Table 1

Regular Gasoline Pricing Statistics by Brand or Type of Station

Brand/Type	Average Price	Standard Deviation	Minimum Price	Maximum Price	Observations
Arco	$1.969	$0.011	$1.95	$1.99	11
Diamond Shamrock	1.971	0.005	1.97	1.99	14
Hypermart	1.972	0.019	1.95	1.99	8
Conoco	1.983	0.028	1.96	2.05	11
Unbranded	1.993	0.026	1.94	2.13	116
Citgo	2.030	0.000	2.03	2.03	6
76	2.030	0.031	1.99	2.07	7
Exxon	2.043	0.028	1.99	2.08	8
Mobil	2.043	0.013	2.03	2.07	13
Shell	2.060	0.030	2.01	2.11	10
Texaco	2.060	0.020	2.04	2.09	5
Chevron	2.074	0.050	1.99	2.29	26

Table 1 shows price observations by brand and retailer type. The lowest price observed for one gallon of regular gasoline was $1.94 and the highest $2.29. In addition to a gas

[5] The data were collected by Jed and Jordan Brewer.

station's location, prices, and brand, the presence of a convenience store, franchise food restaurant, car wash or repair shop are recorded in the data set. For the 235 locations a total of 209 convenience stores, 18 franchise food restaurants, 14 car washes and 19 repair shops were observed.

Table 2

Population Density and Traffic Flow Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum	Observations
Population density	2,610	1,771	19	5,384	235
Traffic flow	46.52	24.43	3.10	107.25	235

Two additional variables were included in our models to control for demand effects: population density; and, traffic flow. The summary statistics for these variables are shown in Table 2. Population density is measured in units of individuals per square mile and traffic flow in terms of thousands of vehicles per day.[6]

5 Distance Measurement Methodologies

In order to investigate how sensitive our results are to the distance measure chosen we estimated the model using three distance measures: Euclidean distance; road distance; and, travel time.

Since we wished to allow for the possibility of all gas stations influencing prices at all

[6] Population density was collected from the US Census Bureau. We observed the zip code in which each gas station was located. We calculated the population density for each zip code and matched these with the respective stations. The traffic flow data were obtained from Pima County Department of Transportation. If a station was located at an intersection, then the station was credited with the sum of the traffic flows on both intersecting streets. We experimented with including median income as an additional control variable. Since we found the coefficient for this variable not to be statistically significantly different from zero, it was not included in the analyses shown in this paper.

other stations it was necessary to calculate the distances between all station locations and all other station locations. The first step in obtaining the distance matrices was to place the gas station locations in geographic space in a GIS. This required a reliable road network containing all roads in the greater Tucson area to use as our base for geocoding. We obtained the road GIS data from the Pima County Department of Transportation. We used local data rather than national level census road data because the census GIS is not updated regularly to reflect the changing road network. Setting up a GIS and geocoding locations can be time consuming. Differences in road names and abbreviations can require changes to the road GIS and in some cases requires the hand plotting of locations. In addition, even with the more accurate local data we had to correct some obvious addressing errors resulting from errors in the underlying road network. Once the gas stations were placed in geographic space, calculating the Euclidean distances was trivial. It took only a few seconds to calculate over 50,000 distance measurements. Finding road distances using a GIS is a more complicated process. In order to determine the routing necessary for road distance measurements, a geometric network must be created from the road GIS data. If there are errors in the GIS data, either in road attributes or geometric errors in road intersections, an erroneous geometric network is created. Even small errors in the network can cause significant measurement error in road distance.[7] The local road data compiled by the transportation authority had not been created for the purpose of

[7] An additional issue concerning road distances and travel times as compared to Euclidean distances is that the matrices using road distances and travel times are not symmetric. The Euclidean distance between two points, A and B, is the same regardless of whether one is moving from A to B or from B to A. With road distances and travel times, this is not necessarily the case. For example, consider two locations located on a one-way street, where station B is located farther down the one-way street than A. To get from A to B, one simply needs to drive down the street. However, to get from B to A, one would need to use an alternative and presumably longer route. In general, for a symmetric JxJ distance matrix, one needs to calculate $J(J-1)/2$ distances. For an asymmetric distance matrix, one needs to calculate $J(J-1)$ distances. (The diagonals do not have to be calculated because they are always equal to zero.)

routing. Given that we had already found some small mistakes in the data, the road GIS would need to be checked for accuracy, a labor intensive and time consuming process. Given our concerns about the applicability of our GIS for routing, we decided to use MapQuest.com, an Internet GIS specifically designed for routing, to obtain our road distance and travel time measurements. The advantages of using a service such as MapQuest are: (1) the routing is based on proprietary data that generally reflects the most accurate data available; and, (2) the complex task of routing is handled using efficient algorithms. The disadvantages are: (1) distance acquisition is relatively slow since each distance must be queried via the Internet[8]; and, (2) the routing algorithm is a black box; we do not known how road distances or travel times are derived. It may be important to note that the measurements of distance and time are not independent. The routing algorithm does not search for the shortest distance between two points and then search for the shortest travel time between the same two points rather the algorithm chooses the "best" route between two points and returns the corresponding distance and travel time.

Euclidean and road distances are measured in miles to the nearest foot. Travel times are measured in whole minutes with no times less than one minute.

[8] The number of distances to be calculated was rather large. Since we had 235 observations, we needed to fill out a 235x235 matrix of distances. This required 235x(235 – 1) = 54,990 distances to be calculated. It took approximately 24 hours for our computer program to extract all 54,990 road distances and travel times from the Internet.

6 Results from the Empirical Analysis

Table 3 summarizes the results from estimating the model using road distances as the measure of distance. Appendices 1 and 2 include similar information using Euclidean distances and travel times respectively.

Table 3

Results Using Road Distances

	Coefficient value	**s.e.**	**p value**	**90% confidence interval** low	high
Constant	1.994	0.009	0.000	1.979	2.009
Population density	2.819E-06	1.490E-06	0.058	3.690E-07	5.269E-06
Traffic flow	0.0002	0.0001	0.087	0.0000	0.0003
Hypermart	-0.030	0.012	0.014	-0.050	-0.010
Arco	-0.028	0.009	0.001	-0.043	-0.014
Chevron	0.071	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.198	-0.025	0.003
Citgo	0.035	0.011	0.002	0.016	0.053
Diamond Shamrock	-0.025	0.008	0.001	-0.037	-0.012
Exxon	0.044	0.010	0.000	0.027	0.061
Mobil	0.041	0.008	0.000	0.028	0.055
Shell	0.060	0.009	0.000	0.045	0.076
76	0.020	0.012	0.079	0.001	0.040
Texaco	0.060	0.013	0.000	0.039	0.082
Convenience store	-0.007	0.008	0.376	-0.019	0.006
Franchise food outlet	0.013	0.007	0.061	0.002	0.025
Car wash	0.004	0.009	0.650	-0.010	0.018
Repair shop	0.014	0.007	0.053	0.002	0.026
s hypermarts (s_h)	1.458	0.656	0.026	0.380	2.537
λ hypermarts (λ_h)	-0.014	0.007	0.050	-0.025	-0.002
s non-hypermarts (s_n)	0.872	0.208	0.000	0.530	1.215
λ non-hypermarts (λ_n)	-0.005	0.002	0.046	-0.009	-0.001
Log of HI of brand counts (μ)	-0.024	0.013	0.073	-0.045	-0.002

As expected, the results in Table 3 show that prices increase with population density and traffic flow each of which are expected to be associated with increased gasoline demand.

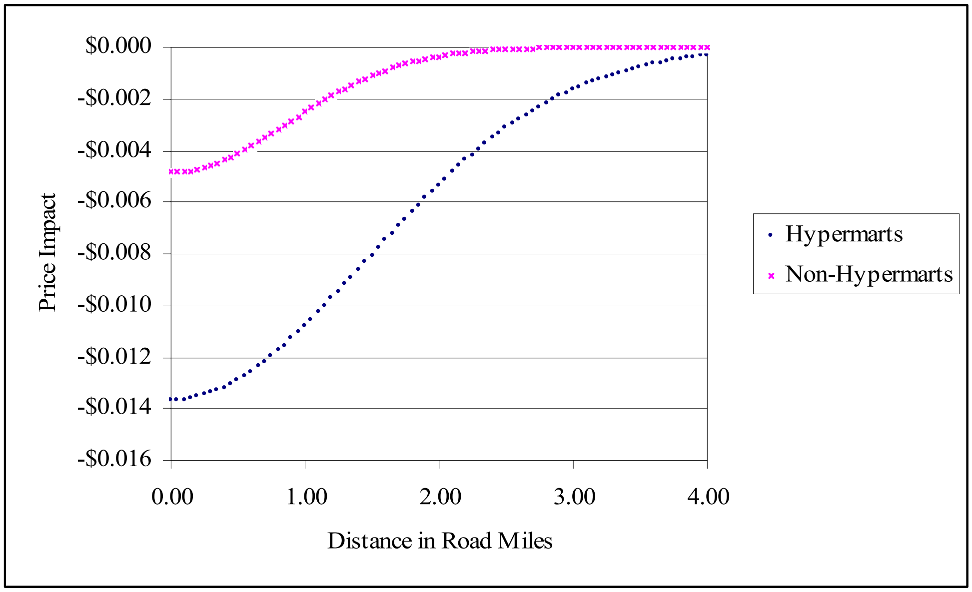
Both of these coefficients are statistically significant at the 10% level. The coefficients for the dummy variables for gas station type and brand are in general statistically significant and are of plausible signs and magnitudes. In terms of amenities located at the gas station, franchise food outlets and repair shops are associated with prices that are higher by 1.3¢ and 1.4¢ respectively. Both of these coefficients are statistically significant at the 10% level. In contrast the presence of convenience stores and carwashes are not associated with any statistically significant price difference.

The coefficients for hypermart and non-hypermart counts, λ_h and λ_n, and the corresponding distance normalization factors, s_h and s_n, are all statistically significant at the 5% level. As expected λ_h and λ_n are both negative and s_h and s_n are both positive indicating that an increase in the number of competing stations or a reduction in their distance from the station of interest results in a fall in posted price. λ_h is greater in absolute value than λ_n and s_h is greater than s_n indicating that a hypermart has a larger negative impact on prices and influences prices over a greater distance than a representative non-hypermart gas station.[9] Chart 1 illustrates how the implied price impact of hypermarts and non-hypermarts varies with distance.

[9] In light of the variables included in the model to control for demand and given the fact that costs are unlikely to vary significantly with location, we believe it is improbable that omitted variables relating to demand or costs are biasing our findings. If we are wrong on this point, we are of the view that the most plausible situation would be that our control variables fail to fully account for the higher demand associated with hypermart locations. If this is in fact the case our reported value of λ_h would be biased upwards towards zero. Therefore if bias is present it is likely that our reported results understate the difference between hypermarts and non-hypermarts and our conclusion that on average hypermarts have a larger negative impact on prices than non-hypermarts would still hold.

Chart 1

Estimated Price Impact of Hypermart and Non-Hypermart Gas Stations Based on Road Distance from Station of Interest



As shown in Table 3, the coefficient for the log of the Herfindahl Index of brand counts, μ, is statistically significant at the 10% level. The sign of the coefficient indicates that lower brand diversity is associated with lower prices and vice versa. For example, two otherwise identical gas stations where the first is in a market with no brand diversity (and therefore the Herfindahl Index of brand counts is equal to one) and the second has significant brand diversity such that the Herfindahl Index of brand counts is 0.1 would be predicted to have prices that differ by 2.4¢ with the station with the higher Herfindahl Index of brand counts posting the lower price.[10] This result suggests that the price impact resulting from brand loyalty more than offsets the effects of brand collusion.

[10] At the estimated values of s_h and s_n, the observed average value of the Herfindahl Index of brand counts was 0.39 and its standard deviation was 0.20.

Table 4 shows the estimated values of λ_h and λ_n and μ for each of our three measures of distance (road distances, Euclidean distances and travel times). Since the coefficients included in the table are all of the same units (dollars), their values do not depend on the metric used to measure distance and so a direct comparison of the absolute values is meaningful. As can be observed, the values are not materially changed by the choice of distance measurement metric.

Table 4

Comparison of Results

	Distance Metric Used		
	Road Distances	**Euclidean Distances**	**Travel Times**
λ hypermarts (λ_h)	-0.0137 (0.0070)	-0.0126 (0.0060)	-0.0120 (0.0080)
λ non-hypermarts (λ_n)	-0.0048 (0.0024)	-0.0051 (0.0027)	-0.0038 (0.0024)
Log of HI of brand counts (μ)	-0.0237 (0.0132)	-0.0210 (0.0139)	-0.0272 (0.0138)

Standard errors are indicated in parentheses.

In order to check the robustness of our results and to investigate if our findings might be influenced by the large number of unbranded stations included in the count for non-hypermart gas stations, we estimated a model which separated non-hypermarts into unbranded and branded stations and utilized separate counts for these new categories. The results of the model following this approach (the "adapted model") using road distances is shown in Appendix 3. Although the coefficient for the unbranded station count, λ_{ub}, and the distance normalization factor for branded stations, s_b, are not statistically different from zero at the 10% level, the results are generally consistent with those discussed earlier in this section and encourage us to believe that our approach is reasonable. Importantly for our purposes, the estimated values of the coefficients for the counts for hypermarts, unbranded stations and branded stations are all negative with λ_h being the largest in absolute value and the estimated values of the distance normalization factors are all positive with s_h being the largest. In addition, the coefficient of the log of the Herfindahl Index of brand counts is negative and is statistically significantly different from zero at the 5% level.

As a second robustness check of our findings we estimated an autoregressive spatial model as shown in Equation 6.

$$\begin{aligned} p_i &= X_i\beta + (\text{hypermart count}_i)\lambda_h + (\text{non}-\text{hypermart count}_i)\lambda_n \\ &+ Log(\text{Herfindahl Index of brand counts}_i)\mu + u_i \end{aligned}$$

$$\text{where } u = \rho M u + \varepsilon \qquad (6)$$

This model allows for residual spatial effects in the error terms. In the event that residual spatial effects are in fact present the coefficients estimated using our earlier model will be consistent but the estimates of standard errors will be incorrect and consequently inferences based on the results from the model could be erroneous. Residual spatial effects would be present if the model omits a relevant variable that is itself spatially correlated. M is a square matrix of the same dimension as the number of gas stations with a zero diagonal. We assumed that the off diagonal elements of M have the same form as w_{ij}. We chose the corresponding distance normalization factor (we designate this value s_u) to minimize the calculated sum of squared residuals. We estimated the coefficients in the autoregressive spatial model using the generalized method of moments technique described in Kelejian and Prucha (1999).[11] In estimating the autoregressive model, we used the values of s_h and s_n estimated using our original model.

Appendices 4, 5 and 6 show the results from estimating the autoregressive spatial model using road distances, Euclidean distances and travel times respectively. As discussed above, in each case the value of s_u was chosen so as to minimize the sum of squared residuals. In the model using road distances this value was 0.33. The corresponding value of ρ was estimated to be 0.0007. Taken together the estimated value of ρ and the value of s_u that minimized the calculated sum of squared residuals suggest that any residual spatial effects are small in magnitude and are limited in geographic scope. Consistent with this observation, the coefficient values calculated using the autoregressive spatial model are not materially different from those calculated earlier using our original model. We interpret this as implying that our choice of explanatory variables and the associated choices of weighting factors largely capture the spatial characteristics of prices. It should be noted that this conclusion is predicated on M having the correct structure. A comparison of the results shown in Appendices 4, 5 and 6 shows that this conclusion holds for all of our measures of distance.

7 Conclusions

As expected, our analysis shows that the locations and the brands of retail outlets both matter when analyzing market prices.

[11] Bell and Bockstael (2000) is an early example of an application of this technique to micro level data.

Our finding that prices decrease when the density of competitors is higher is consistent with prior work. Applying our new method of flexible weighting factors we are able to show directly how the impact on prices of an additional station varies with distance and we avoid the need to use arbitrary predetermined market definitions. Using flexible weighting factors makes clear that the effect of hypermarts is greater in magnitude and extends over a larger distance than representative non-hypermart gas stations.

We demonstrate that, in the market we analyze, reduced brand diversity as measured by the Herfindahl Index of brand counts is associated with lower prices. We are not aware of other researchers investigating this issue. This finding could be relevant in the context of anti-trust assessments since it implies that an increase in the relative presence of a particular brand of retail outlet is not necessarily associated with price increases as might instinctively be expected. Although we make no claims as regards to consumer welfare, our finding might make a policy maker evaluating a possible business transaction that would lead to a reduction in brand diversity more sanguine about the likely market implications than would otherwise be the case.

Our conclusions are robust to three ways of measuring distance. Although this is an observation regarding a single market, it should give some comfort to researchers investigating similar issues who are unable to check the robustness of their finding to alternative distance metrics.

References

Apparicio, Philippe; Richard Shearmur; Mathieu Brochu and Gaëtan Dussault. 2003. "The Measure of Distance in a Social Science Policy Context: Advantages and Costs of using Network Distance in Eight Canadian Metropolitan Areas." *Journal of Geographic Information and Decision Analysis.* Vol. 7, No. 2, pp. 105-131.

Barron, John M; Beck A. Taylor; and, John R. Umbeck. 2000. "A Theory of Quality-Related Differences in Retail Margins: Why There is a Premium on Premium Gasoline." *Economic Inquiry.* Vol. 38, No. 4, pp. 550-569.

Barron, John M; Beck A. Taylor; and, John R. Umbeck. 2004a. "Will Open Supply Lower Retail Gasoline Prices?" *Contemporary Economic Policy.* Vol. 22, No. 1, pp. 63-77.

Barron, John M; Beck A. Taylor; and, John R. Umbeck. 2004b. "Number of Sellers, Average Prices, and Price Dispersion." *International Journal of Industrial Organization.* Vol. 22, pp. 1041-1066.

Barron, John M; John R. Umbeck; and, Glen R. Waddell. 2006. "Consumer and Competitor Reactions: Evidence from a Field Experiment." *Working Paper.*

Bell, Kathleen P. and Nancy E Bockstael. 2000. "Applying the Generalized-Moment Estimation Approach to Spatial Problems Involving Microlevel Data." *The Review of Economics and Statistics.* Vol. 82, No. 2, pp. 72-82.

Brewer, Jed. 2006. "Spatial Interaction and the Effect of Hypermart Penetration on Retail Gasoline Prices." *Working Paper.*

Hastings, Justine. 2004. "Vertical Relationships and Competition in Retail Gasoline Markets: Empirical Evidence from Contract Changes in Southern California." *American Economic Review.* Vol. 94, No. 1, pp. 317-328.

Kelejian, Harry H. and Ingmar R. Prucha. 1999. "A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model." *International Economic Review.* Vol. 40, No. 2, pp. 509-533.

Netz, Janet S; and Beck A. Taylor. 2002. "Maximum or Minimum Differentiation? Location Pattern of Retail Outlets." *The Review of Economics and Statistics."* Vol. 84, No. 1, pp. 162-175.

Pinkse, Joris and Margaret E. Slade. 1998. "Contracting in Space: An Application of Spatial Statistics to Discrete-Choice Models." *Journal of Econometrics*. Vol. 85, pp. 125-154.

Shepard, Andrea. 1991. "Price Discrimination and Retail Configuration." *The Journal of Political Economy.* Vol. 99, No. 1, pp. 30-53.

Appendix 1: Results Using Euclidean Distances

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.994	0.009	0.000	1.979	2.009
Population density	2.911E-06	1.491E-06	0.051	4.585E-07	5.364E-06
Traffic flow	0.0002	0.0001	0.054	0.0000	0.0003
Hypermart	-0.026	0.012	0.037	-0.046	-0.005
Arco	-0.029	0.009	0.001	-0.043	-0.015
Chevron	0.072	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.197	-0.025	0.003
Citgo	0.034	0.011	0.003	0.015	0.052
Diamond Shamrock	-0.025	0.008	0.001	-0.038	-0.013
Exxon	0.044	0.010	0.000	0.027	0.061
Mobil	0.040	0.008	0.000	0.026	0.053
Shell	0.060	0.009	0.000	0.045	0.076
76	0.021	0.012	0.076	0.002	0.040
Texaco	0.059	0.013	0.000	0.038	0.080
Convenience store	-0.005	0.007	0.479	-0.018	0.007
Franchise food outlet	0.013	0.007	0.068	0.001	0.025
Car wash	0.004	0.009	0.653	-0.010	0.018
Repair shop	0.014	0.007	0.051	0.002	0.026
s hypermarts (s_h)	1.063	0.476	0.025	0.281	1.846
λ hypermarts (λ_h)	-0.013	0.006	0.037	-0.023	-0.003
s non-hypermarts (s_n)	0.698	0.172	0.000	0.415	0.980
λ non-hypermarts (λ_n)	-0.005	0.003	0.059	-0.009	-0.001
Log of HI of brand counts (μ)	-0.021	0.014	0.131	-0.044	0.002

Euclidean distances are measured in miles to the nearest foot.

Appendix 2: Results Using Travel Times

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.992	0.010	0.000	1.976	2.008
Population density	1.242E-06	1.245E-06	0.319	-8.064E-07	3.289E-06
Traffic flow	0.0001	0.0001	0.104	-0.0000	0.0003
Hypermart	-0.028	0.012	0.024	-0.048	-0.008
Arco	-0.027	0.009	0.002	-0.042	-0.013
Chevron	0.071	0.007	0.000	0.060	0.083
Conoco	-0.012	0.009	0.189	-0.026	0.003
Citgo	0.034	0.011	0.002	0.015	0.052
Diamond Shamrock	-0.023	0.008	0.002	-0.036	-0.011
Exxon	0.045	0.010	0.000	0.028	0.062
Mobil	0.041	0.008	0.000	0.028	0.055
Shell	0.061	0.009	0.000	0.045	0.076
76	0.022	0.012	0.056	0.003	0.042
Texaco	0.059	0.013	0.000	0.038	0.080
Convenience store	-0.004	0.008	0.553	-0.017	0.008
Franchise food outlet	0.014	0.007	0.047	0.002	0.026
Car wash	0.003	0.008	0.711	-0.011	0.017
Repair shop	0.013	0.007	0.078	0.001	0.025
s hypermarts (s_h)	2.654	1.523	0.081	0.149	5.159
λ hypermarts (λ_h)	-0.012	0.008	0.133	-0.025	0.001
s non-hypermarts (s_n)	2.091	0.570	0.000	1.153	3.028
λ non-hypermarts (λ_n)	-0.004	0.002	0.115	-0.008	0.000
Log of HI of brand counts (μ)	-0.027	0.014	0.050	-0.050	-0.004

Travel times are measured in whole minutes with no times less than one minute.

Appendix 3: Results of Adapted Model Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.995	0.009	0.000	1.980	2.010
Population density	2.098E-06	1.478E-06	0.156	-3.318E-07	4.529E-06
Traffic flow	0.0001	0.0001	0.091	0.0000	0.0003
Hypermart	-0.038	0.013	0.003	-0.060	-0.017
Arco	-0.039	0.011	0.000	-0.057	-0.022
Chevron	0.062	0.009	0.000	0.047	0.077
Conoco	-0.021	0.010	0.039	-0.037	-0.004
Citgo	0.032	0.012	0.007	0.012	0.051
Diamond Shamrock	-0.033	0.009	0.001	-0.049	-0.017
Exxon	0.037	0.011	0.001	0.018	0.056
Mobil	0.034	0.009	0.000	0.018	0.049
Shell	0.052	0.010	0.000	0.035	0.069
76	0.015	0.013	0.239	-0.006	0.036
Texaco	0.054	0.013	0.000	0.032	0.076
Convenience store	-0.007	0.007	0.377	-0.019	0.006
Franchise food outlet	0.012	0.007	0.092	0.000	0.024
Car wash	0.001	0.009	0.887	-0.013	0.015
Repair shop	0.012	0.007	0.090	0.000	0.024
s hypermarts (s_h)	1.374	0.615	0.026	0.362	2.386
λ hypermarts (λ_h)	-0.021	0.009	0.021	-0.035	-0.006
s unbranded stations (s_{ub})	1.121	0.219	0.000	0.761	1.480
λ unbranded stations (λ_{ub})	-0.002	0.002	0.291	-0.006	0.001
s branded stations (s_b)	0.361	0.234	0.123	-0.024	0.747
λ branded stations (λ_b)	-0.017	0.007	0.020	-0.028	-0.005
Log of HI of brand counts (μ)	-0.067	0.031	0.029	-0.118	-0.017

Road distances are measured in miles to the nearest foot.

Appendix 4: Results of Autoregressive Spatial Model Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.994	0.009	0.000	1.979	2.008
Population density	2.820E-06	1.327E-06	0.034	6.373E-07	5.002E-06
Traffic flow	0.0002	0.0001	0.080	0.0000	0.0003
Hypermart	-0.030	0.012	0.014	-0.050	-0.010
Arco	-0.028	0.009	0.001	-0.042	-0.014
Chevron	0.071	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.197	-0.025	0.003
Citgo	0.035	0.011	0.002	0.016	0.053
Diamond Shamrock	-0.025	0.008	0.001	-0.037	-0.012
Exxon	0.044	0.010	0.000	0.027	0.061
Mobil	0.041	0.008	0.000	0.028	0.055
Shell	0.060	0.009	0.000	0.045	0.075
76	0.020	0.012	0.078	0.001	0.040
Texaco	0.060	0.013	0.000	0.039	0.082
Convenience store	-0.007	0.008	0.376	-0.019	0.006
Franchise food outlet	0.013	0.007	0.060	0.002	0.025
Car wash	0.004	0.008	0.640	-0.010	0.018
Repair shop	0.014	0.007	0.052	0.002	0.026
λ hypermarts (λ_h)	-0.014	0.005	0.011	-0.023	-0.005
λ non-hypermarts (λ_n)	-0.005	0.002	0.001	-0.007	-0.002
Log of HI of brand counts (μ)	-0.024	0.013	0.071	-0.045	-0.002
ρ	0.00071				

Road distances are measured in miles to the nearest foot.

s_u = 0.33 was used since this value minimized the sum of squared residuals

Appendix 5: Results of Autoregressive Spatial Model Using Euclidean Distances

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.994	0.009	0.000	1.979	2.009
Population density	2.914E-06	1.329E-06	0.028	7.285E-07	5.099E-06
Traffic flow	0.0002	0.0001	0.050	0.0000	0.0003
Hypermart	-0.026	0.012	0.033	-0.045	-0.006
Arco	-0.029	0.009	0.001	-0.043	-0.015
Chevron	0.072	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.200	-0.025	0.003
Citgo	0.034	0.011	0.003	0.015	0.052
Diamond Shamrock	-0.025	0.008	0.001	-0.038	-0.013
Exxon	0.044	0.010	0.000	0.028	0.061
Mobil	0.040	0.008	0.000	0.026	0.053
Shell	0.060	0.009	0.000	0.045	0.075
76	0.021	0.012	0.076	0.001	0.040
Texaco	0.059	0.013	0.000	0.038	0.080
Convenience store	-0.005	0.007	0.480	-0.018	0.007
Franchise food outlet	0.013	0.007	0.066	0.001	0.025
Car wash	0.004	0.008	0.640	-0.010	0.018
Repair shop	0.014	0.007	0.049	0.002	0.026
λ hypermarts (λ_h)	-0.013	0.005	0.016	-0.021	-0.004
λ non-hypermarts (λ_n)	-0.005	0.001	0.001	-0.008	-0.003
Log of HI of brand counts (μ)	-0.021	0.014	0.125	-0.044	0.002
ρ	0.00582				

Euclidean distances are measured in miles to the nearest foot.

s_u = 0.34 was used since this value minimized the sum of squared residuals.

Appendix 6: Results of Autoregressive Spatial Model Using Travel Times

	Coefficient value	s.e.	p value	90% confidence interval low	90% confidence interval high
Constant	1.992	0.009	0.000	1.976	2.007
Population density	1.242E-06	1.176E-06	0.291	-6.925E-07	3.176E-06
Traffic flow	0.0001	0.0001	0.094	0.0000	0.0003
Hypermart	-0.028	0.012	0.024	-0.048	-0.008
Arco	-0.027	0.009	0.001	-0.041	-0.013
Chevron	0.071	0.007	0.000	0.060	0.083
Conoco	-0.012	0.009	0.186	-0.026	0.003
Citgo	0.034	0.011	0.002	0.015	0.052
Diamond Shamrock	-0.023	0.008	0.002	-0.036	-0.011
Exxon	0.045	0.010	0.000	0.028	0.062
Mobil	0.041	0.008	0.000	0.028	0.055
Shell	0.061	0.009	0.000	0.045	0.076
76	0.022	0.012	0.055	0.003	0.042
Texaco	0.059	0.013	0.000	0.038	0.080
Convenience store	-0.004	0.008	0.552	-0.017	0.008
Franchise food outlet	0.014	0.007	0.047	0.002	0.026
Car wash	0.003	0.008	0.709	-0.011	0.017
Repair shop	0.013	0.007	0.077	0.001	0.025
λ hypermarts (λ_h)	-0.012	0.006	0.036	-0.021	-0.003
λ non-hypermarts (λ_n)	-0.004	0.001	0.010	-0.006	-0.001
Log of HI of brand counts (μ)	-0.027	0.014	0.048	-0.050	-0.005
ρ	3.693E-06				

Travel times are measured in whole minutes with no times less than one minute.

$s_u = 0.21$ was used since this value minimized the sum of squared residuals.

Supplementary Materials

Not for Inclusion in Final Paper

Annex 1: Analysis of Impact of Common Ownership on Prices

Annex 2: Analysis of Impact of Same and Different Brand Stations on Prices

Annex 1: Analysis of Impact of Common Ownership on Prices

In order to investigate the possible impact of common ownership on prices, we collected information about the ownership of the gas stations in our data set from the Arizona Department of Weights and Measures ("ADWM") and the Arizona Department of Environmental Quality ("ADEQ"). These state authorities have responsibility for monitoring compliance with certain consumer and environmental laws and in this capacity they maintain records that are available for public inspection which include information about gas stations. The information we were able to obtain was neither fully complete nor necessarily up to date. In general we found the ADEQ data to be the more useful for our purposes and in most cases we relied on this source which we augmented by the ADWM data in the event of ambiguities or missing information. All gas stations in Arizona are required to obtain a permit to operate underground storage tanks. ADEQ maintains a directory of locations that have obtained such permits which includes the identity of the owner of the site. It should be noted however that it is not clear that the stated owner is necessarily the ultimate economic owner. It could for example be the case that two stations which have different corporate owners are in fact under common control via an entity that owns both of the disclosed owners. Using the information from ADEQ and ADWM we identified a total of 17 ownership groups for the gas stations in our data set. 38 gas stations were not part of any ownership group. Details of the ownership groups are shown in Table 5.

Table 5

Analysis of Gas Station Ownership Groups

Name of Ownership Group	# Stations
Circle K Stores Inc	83
Loma Catalina Co	16
Diamond Shamrock Arizona Inc	14
Quik-Mart Stores Inc	14
Giant Industries Arizona Inc	10
BP West Coast Products LLC	8
Shell Oil Products	8
AZ Portfolio Properties Group LLC	7
7-Eleven Inc	6
Reays Ranch Investors LLC	6
ConocoPhillips	5
Cox Investment Group LLC	5
C and T Oil Company	4
Chevron Products Co	4
Frys Food Stores of America Inc	3
Capin Enterprises Inc	2
Costco Wholesale	2
No ownership group	38
Total	235

Using the information summarized in Table 5, we estimated a revised version of the model (the "2nd adapted model") by adding an additional variable; the Herfindahl Index of ownership group counts. This new variable was calculated in the same way as the Herfindahl Index of brand counts discussed earlier except ownership groups rather than brands were used to differentiate between gas stations. A single distance normalization factor, s_{og}, was applied to all gas stations irrespective of their brands. The results from following this approach using road distances are shown in Table 6.

Table 6

Results of 2nd Adapted Model Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval Low	high
Constant	1.993	0.010	0.000	1.977	2.009
Population density	2.803E-06	1.555E-06	0.071	2.464E-07	5.360E-06
Traffic flow	0.0002	0.0001	0.095	0.0000	0.0003
Hypermart	-0.030	0.012	0.013	-0.050	-0.010
Arco	-0.028	0.009	0.001	-0.043	-0.014
Chevron	0.071	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.209	-0.025	0.003
Citgo	0.035	0.011	0.002	0.016	0.053
Diamond Shamrock	-0.025	0.008	0.001	-0.037	-0.012
Exxon	0.045	0.010	0.000	0.027	0.062
Mobil	0.042	0.008	0.000	0.028	0.055
Shell	0.061	0.009	0.000	0.046	0.076
76	0.020	0.012	0.079	0.001	0.040
Texaco	0.061	0.013	0.000	0.039	0.082
Convenience store	-0.007	0.008	0.368	-0.019	0.006
Franchise food outlet	0.013	0.007	0.063	0.002	0.025
Car wash	0.004	0.009	0.632	-0.010	0.018
Repair shop	0.014	0.007	0.059	0.002	0.026
s hypermarts (s_h)	1.458	0.644	0.024	0.398	2.518
λ hypermarts (λ_h)	-0.014	0.007	0.050	-0.025	-0.002
s non-hypermarts (s_n)	0.872	0.216	0.000	0.517	1.226
λ non-hypermarts (λ_n)	-0.005	0.003	0.049	-0.009	-0.001
Log of HI of brand counts (μ)	-0.020	0.019	0.288	-0.051	0.011
s ownership group (s_{og})	1.000	2.032	0.623	-2.342	4.342
Log of HI of ownership group counts	-0.005	0.020	0.786	-0.038	0.027

As can be observed from Table 6, when the log of the Herfindahl Index of ownership group counts is included in the model its coefficient and the coefficient for the log of the Herfindahl Index of brand counts are not statistically significantly different from zero. The same is true of s_{og}. It appears that, in the manner we are currently measuring it, common ownership has no discernable impact on prices that is not already reflected by the Herfindahl Index of brand counts. We hypothesize two explanations for this finding.

First, as discussed earlier in this annex, the information we have concerning ownership is incomplete and may not properly reflect whether or not gas stations are under common ownership. Second, as discussed in footnote 2, gas stations can be operated under a number of different contractual arrangements and therefore it may be the case that common ownership is simply not indicative of the likelihood of pricing coordination among gas stations. For example, although all other things being equal we might expect gas stations that are owned and operated by the same refiner to coordinate pricing, this would not be the case if the stations are leased to separate independent operators that are individually responsible for pricing polices. Since at present we have no information about lease arrangements we are unable to investigation this issue further.

Annex 2: Analysis of Impact of Same and Different Brand Stations on Prices

In order to investigate the possibly different impact of same brand and different brand competitors on prices at the station of interest, we estimated a revised version of the model (the "3rd adapted model"). This model used a single value of the distance normalization factor for all stations, s_{all}, and included separate counts for stations with the same brand as the station of interest and with a different brand from the station of interest. The coefficients for these two new variables were designated λ_s and λ_d respectively. For simplicity, the model did not include counts for hypermarts and non-hypermarts nor did it include the Herfindahl Index of brand counts. The results from following this approach using road distances are shown in Table 7.

As can be observed from Table 7, although s_{all}, λ_s and λ_d are all of the expected sign, λ_s is not statistically significantly different from zero. In light of the standard errors applicable to λ_s and λ_d it is not possible to draw any inferences concerning their true relative magnitudes. Consistent with our earlier findings, it appears that it is the degree of brand diversity that is important in determining overall prevailing prices not simply whether the station of interest is of the same or of a different brand than surrounding stations. Similar results are obtained if rather than considering a station's brand, stations are classified as branded versus unbranded or premium branded versus other stations.

Table 7

Results of 3rd Adapted Model Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	90% confidence interval high
Constant	1.995	0.009	0.000	1.980	2.010
Population density	1.225E-06	1.254E-06	0.329	-8.382E-07	3.288E-06
Traffic flow	0.0001	0.0001	0.118	0.0000	0.0003
Hypermart	-0.022	0.012	0.073	-0.043	-0.002
Arco	-0.023	0.009	0.011	-0.038	-0.008
Chevron	0.077	0.007	0.000	0.065	0.089
Conoco	-0.005	0.009	0.544	-0.020	0.009
Citgo	0.042	0.012	0.000	0.023	0.061
Diamond Shamrock	-0.019	0.008	0.020	-0.032	-0.005
Exxon	0.047	0.011	0.000	0.029	0.065
Mobil	0.047	0.009	0.000	0.033	0.061
Shell	0.068	0.010	0.000	0.052	0.084
76	0.032	0.012	0.007	0.013	0.051
Texaco	0.069	0.013	0.000	0.048	0.091
Convenience store	-0.005	0.008	0.533	-0.017	0.008
Franchise food outlet	0.011	0.007	0.116	-0.001	0.023
Car wash	0.007	0.009	0.425	-0.007	0.021
Repair shop	0.011	0.007	0.143	-0.001	0.022
s all stations (s_{all})	0.576	0.171	0.001	0.295	0.857
λ same brand (λ_s)	-0.003	0.005	0.530	-0.011	0.005
λ different brand (λ_d)	-0.007	0.003	0.012	-0.011	-0.002