Price Competition in Industries with Geographic Differentiation: Measuring the Effect of Location on Price in the Fast Food Industry

Raphael Thomadsen
Columbia Business School

December 7, 2001

Abstract

This paper analyzes the empirical relationship between prices in the fast food industry and the market structures and taste variations induced by the geography of the market. I do this by using price and location data, but no quantity data, to estimate a discrete choice model of demand and supply for fast food that accounts for the exact geographic configuration of firms. I use the estimated model to run counterfactual experiments to demonstrate how the location of a firm will affect its price. I find that consumers will travel about 1/3-mile to save $1. I also find that both geographic differentiation from competitors and the distribution of consumers around the outlet have significant effects on the equilibrium prices for fast food outlets. For example, I show that for one of the outlets in my market that moving the outlet to a location ½-mile away would change the price for a meal (with an average mark-up of $2.67) by 15¢. Also, joint ownership can significantly increase prices above those that would be charged under separate ownership, especially for the industry leader. This price increase can occur even when the co-owned outlets are located far enough apart that the firms would both charge monopoly prices had they been owned by different parties. Since the changes in prices that occur from joint versus separate ownership are the same as the differences that occur from a merger (of two franchisees belonging to the same chain), these results are suggestive of general anti-trust policy in markets with geographic differentiation.

1. Introduction

This paper analyzes the empirical relationship between the equilibrium prices in the fast food industry of Santa Clara County, CA (Silicon Valley) and the rich market structures and taste variations induced by the geography of the market. Retail outlets in this market, and any urban or suburban area, compete with firms that are located at different distances apart from them. Thus, the true market structures for these outlets consist of the exact layouts of the firms, and not the classic market structures such as pure monopolies, duopolies, or other traditional market structures.[1] Also, the many locations of consumers represent different tastes for the different outlets (on top of heterogeneity in tastes I include in other dimensions). Together, these two effects give rise to a complex set of substitution patterns between the outlets.

I use a two-step approach in this paper. First, I estimate a model of demand and supply. Then I use the estimated model to conduct counterfactual experiments that demonstrate the effect of geographic differentiation on price, and how the effect of geographic differentiation is dependent upon the identities of the firms in the market.

The approach I use is consistent with economic theory and accounts for the exact geographic locations of all of the firms in the market, capturing the true richness of any geographical configuration of competitors that can potentially exist. For example, the approach accounts for the different equilibrium prices that would emerge from a firm competing against two competitors that are on the same side of the outlet compared to the prices that would be observed if instead the two competitors were on opposite sides of the outlet, as well as the prices that result from any other configuration of competitors. Also, in a large market such as Santa Clara County, which has 39 Burger Kings and 64 McDonald's, it is not clear which outlets are close enough to be relevant competitors. The approach I use does not rely on arbitrary classifications to define which outlets are in this set. Instead, my approach allows any outlet in the county to be a potential competitor for every other outlet, and lets the data reveal the extent to which each of the outlets in the county are *de facto* competitors.

As is common in many industries, it is very difficult to obtain quantity data because the firms themselves keep this information as proprietary data, while price data is easy to obtain

[1] This contrasts with the small, isolated markets of Bresnahan and Reiss (1991) where the classic market structures remain intact.

because all the econometrician needs to do is to pose as a consumer. To accommodate the fact that this quantity data was not available to me, I have adapted the established models of differentiated industries to handle cases where the econometrician can observe the prices of goods, but not the quantities sold. In particular, I use the same set of first-order conditions for the firms as Berry, Levinsohn and Pakes (1995) (hereafter BLP). However, instead of creating moment conditions from matching the actual market shares and those identified in the model (as BLP do), I identify the parameters of the indirect utility functions of consumers and the marginal costs of firms from the price variation across outlets within each chain, along with the consumers' locations, and each outlet's location and static profit-maximizing behavior.

Using price data without quantity data gives estimates that are less efficient than one could obtain if accurate quantity data were available. However, one may choose to use my estimation approach if there is a high risk of measurement error in the quantity data. This occurs, for example, when a firm has incomplete records of sales, or when they only have records of total revenues or quantities from all of their outlets instead of from each outlet. Another common source of measurement error is that the market shares may be miscalculated. This can occur either because it is difficult to get quantity data from all of the firms in an industry, or because it is nearly impossible in most industries to obtain the market share of the outside good.[2] If the market share of the outside good is incorrectly specified then the implied demand elasticities obtained from quantity data for each product will be incorrect. Price data, on the other hand, is usually cleaner and easier to collect,[3] and the approach I use reveals the relevant market shares as output, rather than use them as input. While measurement error in prices causes problems in both my approach and BLP's approach to estimation, measurement error in quantities is avoided in my approach since I do not use this data. A reasonable guide is to use a BLP approach if one can obtain accurate quantity data, and use my approach if such data is not available.

The data I use consist of the prices, locations and outlet attributes of all of the Burger King and McDonald's outlets in Santa Clara County, California. Both of these chains exhibit significant price variation across their outlets in the county. These are the two largest fast food chains and together they sell $30 billion worth of food in the United States each year, and

[2] Or equivalently, to get the size of the total potential market.

[3] There are exceptions. For example, BLP's paper studies the automobile industry, where transaction prices are very difficult to obtain.

approximately $50 billion worldwide. Almost 6 percent of the Santa Clara population consumes a meal from McDonald's on a given day,[4] and over 80 percent of Americans eat at a McDonald's in a given year. The homogeneity of both the food and the ambiance across the outlets within each chain aids the estimation of the effect of geographic differentiation on price because it allows me to attribute the differences in prices between the different McDonald's outlets (or between the different Burger King outlets) to the differences in the local competitive environment of the restaurants rather than to unobserved differences in each outlet's products. Also, the locations of the outlets are especially important in the fast food industry because the value of fast food is lost through storage so consumers have to travel to the restaurant to obtain the full experience of the good.[5] This is consistent with the conventional wisdom in the industry that the majority of fast food business comes from consumers located within 3 minutes of the outlet, which corresponds to a distance of about 1 mile.[6]

The estimates indicate that consumers are willing to travel about 1/3 mile to save one dollar on a meal. The high concentration of fast food restaurants is consistent with the low willingness of consumers to travel; 68% of Burger King's are located within one mile of a McDonald's, while 54% of McDonald's are located within 1 mile of a Burger King, and the maximum distance from any of these outlets to the nearest McDonald's or Burger King is just over 2 miles.

I use the estimated model to run counterfactual experiments in order to analyze the effect of geographic differentiation on price. The experiments demonstrate that the location of the outlet affects the price for that outlet; for example, for one outlet in my sample the price of a meal with an average mark-up of $2.67 would increase by 15¢ if it moved to another location 1/2 mile away. The experiments also reveal that both geographic differentiation from competitors and the distribution of consumers in the area of the outlet significantly and jointly affect the pricing of fast food. The balance of these two effects can produce interesting results. For example, fast food outlets located at a mall where a competitor is present will charge higher prices than they would if the outlet were located slightly away from the mall,

[4] 6 percent figure is the daily average number of customers who eat in each McDonald's (nationwide), times the number of McDonald's in the county, divided by the population of Santa Clara county. Each outlet serves approximately 1540 people a day. Another 3.5% go to a Burger King on any given day.
[5] Even for drive-thru service, customers go to the outlet at approximately the same time as they eat the food.
[6] The time to distance conversion is calculated from driving throughout my study area to collect the data. This conversion is using surface streets and not freeways. The 3-minute rule was obtained in conversations with representatives of several fast food firms.

since the effect of being located further away from a large source of customers dominates the effect of being increasingly differentiated from their competitor. Also, I find that the identities of the firms affect both the equilibrium prices of the outlets and the degree to which geographic differentiation impacts prices.

The counterfactual experiments also demonstrate how mergers between different McDonald's franchisees or Burger King franchisees would affect the equilibrium prices. I find that co-ownership among McDonald's outlets can significantly increase prices. A McDonald's in my sample set is shown to have a price that is 13¢ higher because it is owned by the same owner as another McDonald's than it would have been if all of the outlets were independently operated. If the co-owned outlets were closer together then the effect of the merger could be much larger. Indeed, the experiments show that mergers can lead to significantly higher prices even under circumstances where the outlets were far enough apart that they each would have charged monopoly prices had they been under separate ownership. On the other hand, the experiments show that mergers between Burger King outlets, which are weaker competitors than McDonald's, have much smaller effects on prices.

The chapter proceeds as follows: section 2 outlines the model and estimation procedure. Section 3 describes the data. Section 4 presents the results and analysis. Section 5 concludes the chapter.

2. Model and Estimation

I analyze the role of geographic differentiation on the pricing of firms by estimating a model of supply and demand, and then using these estimates to conduct counterfactual experiments that highlight the effect of geography on competition. In this section I present my model of demand and supply and explain how I estimate the parameters in this model.

The approach of this paper builds upon work by Bresnahan (1987), Berry (1994) and Berry, Levinsohn and Pakes (1995) (BLP) that demonstrates how to estimate utilities and costs in differentiated industries from aggregate data. I model demand as being derived from consumers making a discrete choice of where to purchase their meal. Consumers each choose to consume a meal at the outlet that delivers the maximum utility, accounting for product attributes, prices and travel costs. Geography is incorporated into the demand-side of my model in a manner similar to Davis (1998), who added geography to the BLP framework in his study on the welfare effects of movie theater locations. However, while the demand model I use is similar to that of Davis (1998), the question of this paper is fundamentally different that that of Davis. I estimate the effect of geographic differentiation on price in an industry where there is large price variation at the outlet level, while Davis addresses welfare issues in an industry that exhibits little price variation within each market.

I model the supply of fast food meals by assuming that each franchisee maximizes their profits by setting prices at each of their outlets, which compete through Bertrand competition. As in Bresnahan (1987), BLP and others, the marginal costs of the firms are estimated as parameters rather than derived from cost data.

While I model demand and supply in a manner similar to BLP and Davis, the way that I estimate my model is different. I estimate my model using only price data and not quantity data. This is possible because both the parameterized utility functions from the demand side of the model and the first order conditions for each franchisee on the supply side provide relationships between observed prices and implied quantities that jointly identify the parameters of the model.

2.1 Demand

In this section I build a model of demand for fast food meals at each of the outlets in my sample area using a discrete-choice framework. Consumers choose either to purchase their meal from the outlet that maximizes their utility or to consume only an outside good.[7] Consumers are spread across the county, but have the same utility function except for different unobserved tastes for each location/chain combination. However, consumers with identical utility functions will make different choices if their locations are different because they have a disutility for travel. For example, a consumer who prefers McDonald’s over Burger King may choose to eat at Burger King if a Burger King outlet is located nearby but there is no McDonald’s in the area. The result is that although consumers are free to eat at any

[7] This is consistent with a two-staged decision process where consumers first decide where to eat based on their expected utility from their meal at each of the outlets. Once the consumer arrives at the chosen outlet, they consume their ideal bundle. By using a discrete-choice framework I am assuming that a firm’s prices have a greater impact on the number of consumers who make a purchase at the restaurant than on the quantity of food each consumer purchases.

restaurant in the county, they will mostly choose between the restaurants close to their location. In this way, the different locations of consumers represent different observable tastes for each of the outlets.

Formally, consumer i chooses which fast food outlet j to patronize and how much of the outside good, m, to consume, subject to a budget constraint. The consumer also has the option of consuming only the outside good. Their optimization problem is then:

$$\text{Max}_{j,m} \{U_i(j,m) \text{ s. t. } P_j + P_m m = Y_i \} \tag{1}$$

where $U_i(j,m)$ = the utility of consumer i when they eat at outlet j and consume m quantity of the outside good.
P_j = the price of a meal at outlet j,[8]
P_m = the price of the outside good,
Y_i = the income of consumer i, and
$j = 0,1,2, \ldots ,J$ indexes the J outlets $1, \ldots , J$ and the choice to consume only the outside good, $j = 0$.

Rearranging the budget constraint yields $m = \dfrac{Y_i - P_j}{P_m}$. I normalize the price of the outside good, P_m, to be \$1. This implies that $m = Y_i - P_j$. Plugging this value of m back into (1) reduces the consumer's problem to:

$$\text{Max}_j \ V_i(j, Y_i - P_j). \tag{2}$$

I parameterize the conditional indirect utility that consumer i derives from consuming from outlet j, $V_i(j, Y_i - P_j)$, as:

$$V_i(j,Y_i - P_j) = X'_j b - D_{i,j} d + (Y_i - P_j)g + h_{i,j} \tag{3A}$$

where X_j = a vector of dummies indicating the chain to which outlet j belongs, and dummies indicating the presence of a drive-thru or a playland,
$D_{i,j}$ = the distance between consumer i and outlet j,[9]
b, d, g = parameters to be estimated,
$h_{i,j}$ = unobserved portion of utility for individual i at outlet j.

The consumer can also choose not to eat at any of the outlets and to consume only the outside good.[10] Their indirect utility will then be:

[8] The price I use for the meal will be the price of the signature sandwich, which I explain in detail in section 3.1.

[9] Distances are measured by using the shortest route along existing streets, except for distances from malls, which are calculated using Euclidean distances because of inaccuracies caused by unusual official road patterns that exist around malls. However, using Euclidean and using street distances both gave very similar estimates.

$$V_i(0,Y_i) = b_0 + Y_i\, g + h_{i,o}. \tag{3B}$$

Because of the role of geography, the specification of the utility function above differs slightly from the standard assumptions in the discrete-choice literature. My specification implies that the outside good is located at the same location as the consumer, which is reasonable if the alternative is, for example, cooking a meal at home. By definition, the outside good must be unobservable since if one could observe the outside good then it should be specified explicitly in the model. Since I focus only on competition between McDonald's and Burger King outlets, one may hypothesize that instead of using an unspecified outside good I should instead use the locations of other fast food outlets. While I focus on these two chains partially because they are the largest chains in the hamburger segment of the fast food market, with a significant difference in the sales level of Burger King ($8b domestically) and Wendy's ($5b domestically),[11] I mostly focus on these two chains because I ran many other specifications with other competitors and the estimates revealed that the relevant set of competitors for these two chains are other Burger King and McDonald's outlets. When I add other hamburger chains into the model, for example, I find that the estimates that are returned imply that these outlets steal exceptionally little business from the two largest chains. I show these results and explain them in detail in Section 4. This matches both comments by these chains and the targeting of these chains' products. For example, both McDonald's and Burger King appeal largely to families with kids, as opposed to Wendy's, which has more appeal for adults, or Taco Bell, which primarily draws males 18-24 years of age. Jack In The Box, which has a large presence in Santa Clara County, also states on their web page that their food appeals primarily to adults. All of this evidence, both empirical and anecdotal, suggests that McDonald's and Burger King are primarily competing for the same set of consumers, while the other fast food chains are targeting a somewhat different set of consumers.

The consumer will purchase one meal from the restaurant that delivers the highest utility if that utility is greater than the utility of the outside good. If the consumer derives the greatest utility from the outside good then they will not purchase any fast food.[12] Since the

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[10] This is equivalent to setting $P_0 = 0$, which indicates that a consumer who chooses $j = 0$ will spend none of their income on fast food (by which I mean Burger King or McDonald's) and all of their income on the outside good, or that $m = Y_i$.

[11] According to each firm's 2000 annual report.

[12] I assume that consumers are perfectly informed about the prices, locations and food options of all outlets.

consumer must choose to either consume a meal from an outlet or consume only the outside good, only the relative, not absolute, levels of utility affect the consumers' choices. Therefore I normalize $b_0 = 0$ and interpret, for example, the coefficient of the McDonald's dummy to be the difference in utility of consuming McDonald's food over the utility of consuming only the outside good.[13]

The $Y_i g$ term appears linearly in the indirect utility functions for all outlets and for the outside good. The result is that the income does not affect the consumer's choice. This is a result of the way that I have modeled the utility function. There is no theoretical reason that the consumer's choice of fast food must be constant across income. However, if the utility that consumers derive from eating fast food comes from the physical properties of the food itself then these tastes should be independent of income, which means that rich and poor consumers will have equal probabilities of choosing a McDonald's over a Burger King. Income is more likely to affect the consumer's fast food choice through the utility of the outside good, which may be more attractive for a rich consumer than it would be for a poor consumer. However, estimating a more complete model with income effects required additional parameters that proved to be difficult to estimate precisely[14] because of the size of my dataset. I also believe that the income effect may not be as large as many readers may initially think. A study by the National Restaurant Association (1983) shows that the rates of fast food consumption are fairly constant across levels of income.[15]

I account for the different physical product characteristics of the food at the different outlets through the chain dummies that appear in the indirect utility function. Product differentiation papers have traditionally accommodated the physical differences in the products by defining utilities over each of the attributes of the product. However, the equilibrium prices in those models will depend upon the portion of utility that is unobserved by the econometrician but observed by the firms and consumers. I am able to circumvent this problem because a chain's food is nearly identical at each of its restaurants.[16] This allows me to get multiple

[13] The coefficient on the Burger King dummy is interpreted in a similar manner.
[14] A correct approach would require integrating across the income distribution of consumers, but even simple linear approaches to estimating income effect were unsuccessful.
[15] This study covered a wide-range of definitions of fast food but did not separate out the middle class from the wealthier classes.
[16] Not only is the food identical, but the chains also try to make the experiences at each of their outlets identical. For example, the outlets have a uniform appearance, the menu boards look very similar, and workers wear similar uniforms.

observations of the exact same item in a variety of competitive environments, compared to most papers that only observe each item in one set of market conditions. Thus, I exploit this homogeneity by estimating a fixed effect for each chain's food in the same manner as Nevo (2000), who also observes identical products in a variety of competitive environments. This fixed effect will capture the total utility for the food at each of the chains including not only the utility from the observable attributes, but also the utility obtained from unobservable attributes, including advertising, brand image, and Pokeman toys.[17]

I calculate each outlet's demand in two steps. First I integrate over the unobserved component of utility to get the percentage of consumers at a given location who patronize each outlet as a function of the utility parameters.[18] I then aggregate the choices of consumers across the different locations, giving me total demand for each outlet.

Consumers are spread across the continuum of space comprising of Santa Clara County.[19] Instead of integrating over a geographic space, I discretize the consumers' locations and sum over the decisions of the consumers located in each of the discrete locations. I do this by first dividing the county into 1119 small grid cells and ten mall locations. I then place all consumers in a grid cell at the centroid of that cell. Since I have consumer data at the census block-group level, I use census block-groups as my cells. These 1129 different locations represent 1129 different sets of preferences that the consumers have for each of the outlets, on top of the individual heterogeneity of preferences for each of the outlets. While I discretize the consumer locations, I use the exact locations of the outlets without distortion. Thus, I am able to capture the true richness of the exact layout of the firms to the extent that the grid cells are small enough that they do not significantly distort the distribution of consumers. With 1119 grid cells in the county, most of which are located in the densely populated area of the county,[20] plus an additional 10 mall locations, the distortion is likely to be small, and my model accounts for the 1129 different sets of consumer preferences, each of which will have a different cross-price

[17] If some chains tend to choose better locations (such as corner locations vs. middle of the block locations) than other chains then this difference will be reflected in the estimated dummies.

[18] I assume that there is a continuum of consumers at each location so I can integrate to get the demand. An alternative interpretation is that there are a discrete number of consumers, but that firms will maximize expected profits.

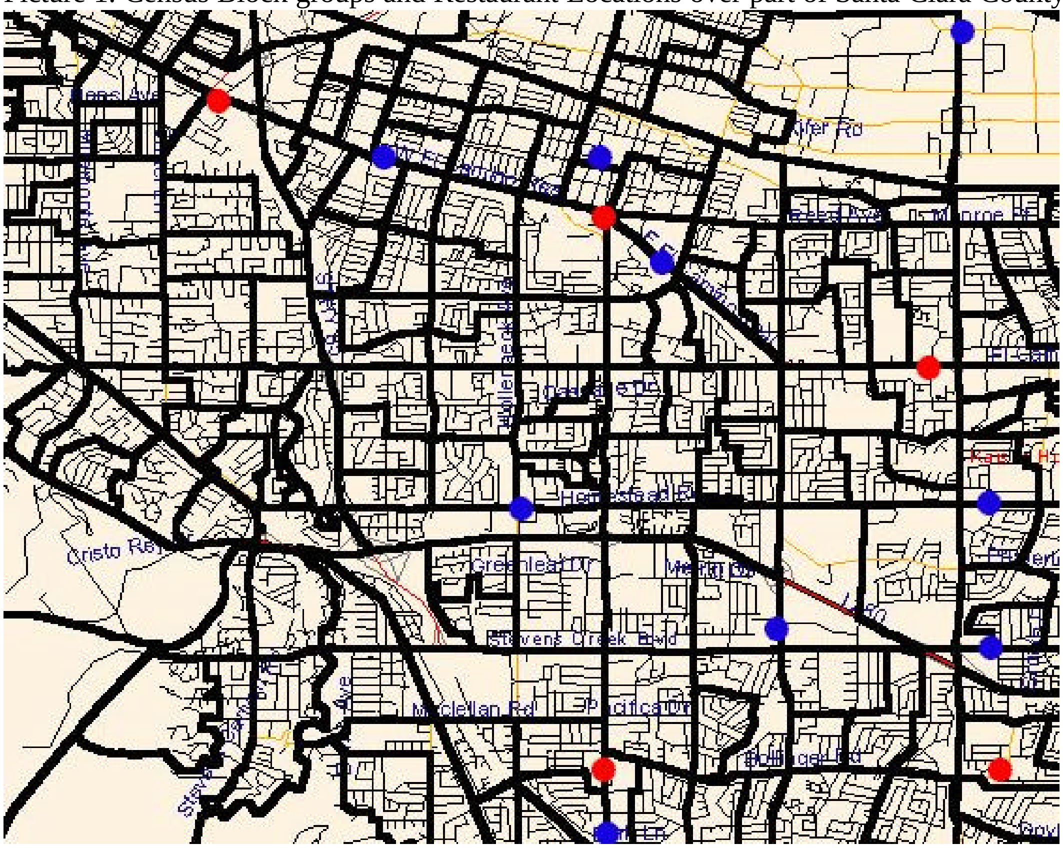
[19] The geography of the area is such that only two of the outlets whose price-setting behavior I use are within one mile of the county border. I ignore the demand and competition that could come from the other counties. However, the demand and competitive conditions are approximately equal on both sides of the border.

[20] The median area for each census block-group is about 0.18 square miles, while in the very sparse part of the county they can be much larger – over 100 square miles.

elasticity for every pair of outlets.

I have mapped part of my study area below to show that the census block-groups are relatively small areas. The dark outlined areas are the census block-groups, the light dots represent Burger Kings, and the darker dots represent McDonald's. To give a frame of reference, the width of map below is approximately 6 miles.

Picture 1: Census Block-groups and Restaurant Locations over part of Santa Clara County



As discussed above, the first step for estimating each outlet's demand is to calculate the percentage of consumers from each location who go to that outlet as a function of the utility function parameters. This is feasible once the distribution for the unobserved components of taste has been specified.

Formally, recall that consumers are choosing between the *J* outlets in the county and the outside good. Then, given a distribution on the (*J+1*)-dimensional **vector**, h_i, representing individual *i*'s unobserved tastes for every restaurant and the outside good, the share of the consumers located in a **particular** location, *b*, who consume from outlet *j* is:

$$S_{j,b}(P) = \int_{A_j} f(h_i)\, dh_i$$

where P is the J-dimensional **vector** of prices for **every** outlet in the market, $f(h_i)$ is the probability density of the unobserved portion of utility, and

$$A_j = \{h_i | \ (V_i(j,Y_i - P_j\ ) > V_i(t,Y_i - P_j\ )\ \text{"}\ t\ ^1\ j)\ Ç\ (V_i(j,Y_i - P_j\ ) > V_i(0,Y_i - P_j\ ))\}$$

is the set of match values, h_i, between consumers and firms such that the consumer derives a higher utility by consuming from outlet j than from any other outlet t or from the outside good. The exact functional form of the share equation depends on the distribution of h_i. I assume that h_i has an i.i.d. type I extreme-value distribution. Thus, the fraction of consumers located in location, b who choose to purchase a meal from outlet j is then:

$$S_{jb}(P) = \frac{e^{j_j}}{1 + \sum_t e^{j_t}} \qquad (4)$$

where $j_j = X'_j b - D_{i,j} d - P_j g$, and t indexes all of the J outlets in the sample. The 1 represents the normalized utility of zero assigned to the outside good.

Once I have calculated the percentage of consumers from each location who patronize a particular outlet, I then calculate the total demand for each outlet by summing up its demand across all locations. The demand for an outlet is the product of the fraction of the consumers at each location, b, who patronize the outlet multiplied by the mass of consumers at that location, $h(b)$. Thus, $h(b)$ gives the geographic distribution of consumer preferences.

There are two types of consumers in my model: those who are located at their residence, and those who are located at a mall.[21] I obtain the $h(b)$ for consumers located at their residence from a composite of data sources. I cannot accurately observe the number of consumers located at each mall, and even if I had accurate tallies of daily mall patronage I would need to know how to compare the number of people at a mall with the number of residents in a census block-group. Therefore, I estimate the number of people at each mall (in an equivalent measure as the residual population) as a parameter in the model. I explain how $h(b)$ is obtained for each type of consumer more precisely below.

I obtain the $h(b)$ for residential consumers from the data. However, instead of using the total number of people residing in each census block-group, I adjust this number according

[21] I ran specifications that also included weighting employment locations by a parameter and estimating that parameter, constraining the parameter to be non-negative. However, the estimates hit the zero constraint. This is consistent with information given to me by a Burger King franchisee (who used to be a corporate employee) who stated that worker location was not a primary factor in choosing outlet locations, and with the fact that McDonald's and Burger King tend to target families with children, while other hamburger chains appeal more to adults.

to the age of each resident. Age is one of the largest observable factors that determine whether a particular consumer is likely to consider eating at a fast food restaurant. Younger consumers tend to eat fast food more often than older consumers. Ignoring this difference in the propensity to eat fast food would add error into my model by incorrectly attributing a large number of consumers to locations with large concentrations of senior citizens when these locations would, in truth, not be attractive to the fast food chains. Theoretically, I could assign a set of parameters that represent the probability that a consumer in each age class eats fast food and estimate these parameters when I estimate the rest of the model. However, there is a high correlation between areas that are densely populated by older people and areas that are densely populated by younger people, so as a practical matter it takes a very large dataset (of fast food outlets) to precisely estimate these parameters.[22] Instead, I weight the number of consumers in each census block-group by the national probability that a consumer in each age category ate at a fast food outlet within a two-week period, as reported by a study in a survey by the National Restaurant Association (1983), using these weights as data.[23] This weighted population measure gives a better fit for the model than using either the unweighted residential population or a uniform distribution of consumers. Thus, I assign to each census block-group the following population mass:

h(b) = 0.82(number of children ages 5-17 in block-group) + 0.888(number of people ages 18-29 in block-group) + 0.77(number of people ages 30-49 in block-group) + 0.595(number of people ages 50-64 in block-group) + 0.363(number of people older than 64 in block-group)

Malls are also a significant source of demand for fast food. However, since I do not know how many consumers are located at the typical mall, I assign each mall a weight l, so $h(b) = l$ for each mall, and estimate this parameter jointly with all of the other parameters in the model. Note that this measure of consumers located at each mall will be estimated in units that are equivalent to those used for the residential population.

To summarize, I allow consumers to be located at their homes or at malls. I weight the consumer residential population according to the age of each person by the affirmative response rate for the given age group to whether survey respondents had eaten fast food in the

[22] Even the one parameter I use for the weighting between population and malls is very imprecisely estimated.
[23] There is nothing special about the two-week period. I show in Appendix 3 that using any period of time would lead to a theoretically consistent set of weights for each age group.

previous two weeks. I treat this response rate as data, and, thus, the density of residential consumers is given by the data. I also allow consumers to be located at one of the large malls in the county, but the number of consumers at each mall is estimated jointly with the other parameters in the model.

Given this distribution of consumers, the total demand for each outlet is the sum of the demand for the firm from each location:

$$Q_j(P) = \underset{b}{S} Q_j(P,b) = \underset{b}{S}\ h(b)\ S_{j,b}(P,b). \tag{5}$$

The derivative of demand with respect to price is computed in a similar manner:

$$\P Q_j/\P P_j(P) = \underset{b}{S}\ h(b)\ \{\P\ S_{j,b}(P,b)/\P P_j\ \}. \tag{6}$$

While the use of logit demands implies that the consumers located at a particular location have substitution patterns that have the Independence of Irrelevant Alternatives (IIA) property, the aggregate demands do not suffer from this problem. Instead, the geography guides the consumer choices among firms and yields a complex substitution pattern. When an outlet raises its price, the rates at which consumers substitute to other outlets will not be driven by the market shares in my model. Rather, most of the consumers who stop patronizing that outlet will switch to others nearby.

The difference between the traditional logit and the geographic logit is highlighted by comparing the ratio of the quantities sold by two outlets:

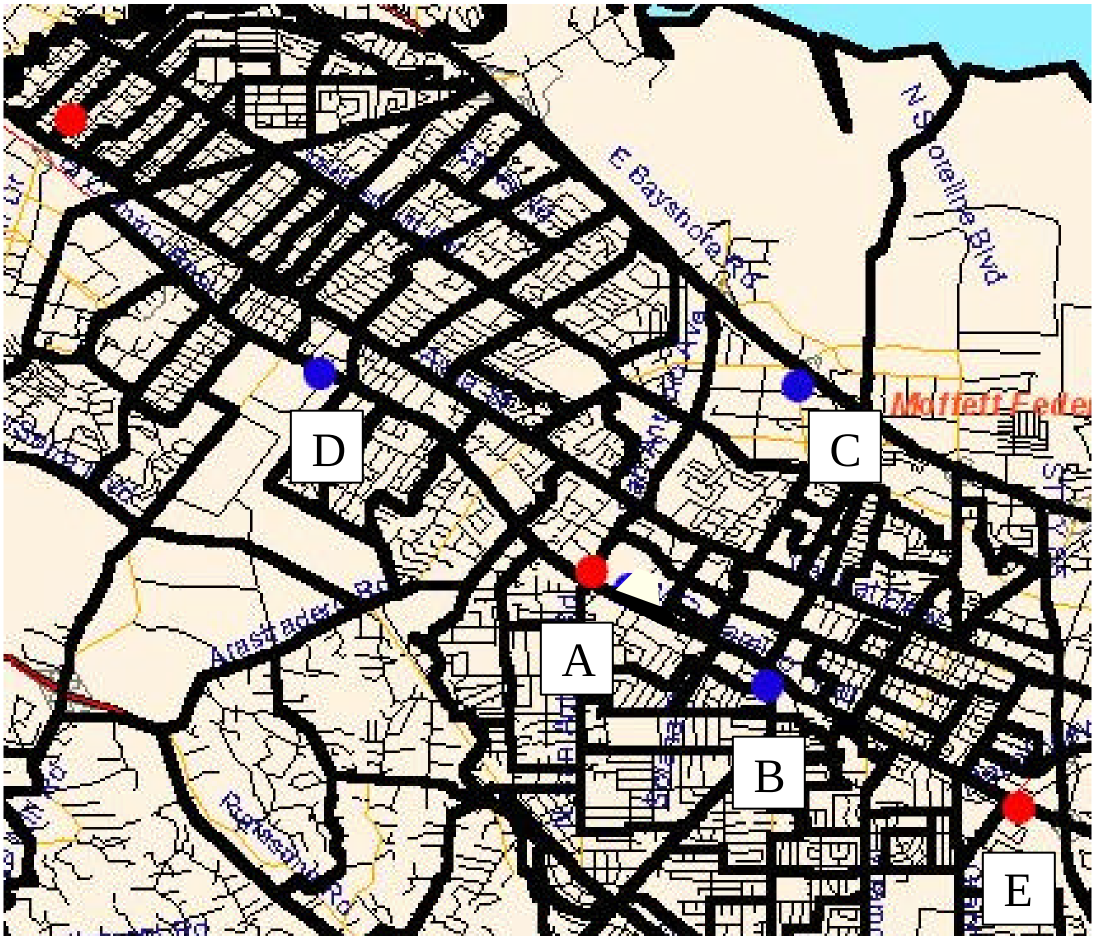
$$\frac{Q_1}{Q_2} = \frac{\displaystyle\sum_b h(b)\frac{e^{X'_j b - D_{b,1}d - P_1 g}}{1+\displaystyle\sum_t e^{X'_j b - D_{b,t}d - P_t g}}}{\displaystyle\sum_b h(b)\frac{e^{X'_j b - D_{b,2}d - P_2 g}}{1+\displaystyle\sum_t e^{X'_j b - D_{b,t}d - P_t g}}} \tag{7}$$

If there were no geography then the $1+\sum_t e^{X'_j b - D_{b,t}d - P_t g}$ terms in the numerator and denominator would cancel, and the ratio of the quantities of each good would only depend on the attributes of the two goods. This is why the standard logit model has the IIA property. However, with the 1129 different locations (or types) of consumers, it is not possible to cancel any terms because the set of distances between the consumers and outlets, $\{D_{i,j}\}$, differs for each location, so the relative market shares will depend not only on the attributes of the two firms, but those of every firm.

To demonstrate how geography guides the substitution patterns, I have mapped out a portion of the market area below in Picture 2. I first calculated how many consumers would patronize each outlet under the current prices using the quantities implied by my estimated model and the actual distribution of consumers.[24] Then I calculated how the number of consumers patronizing each outlet would change if outlet A increased its price by 40 cents. Outlet A would lose about 16% of its business from such a move. Of this 16%, most (about 2/3) would substitute away from fast food. However, 16% of the people who stop patronizing outlet A would substitute to outlet B, 9% would substitute to C, 6% would substitute to D, and 1% would substitute to E. Less than 1% of the customers would go to any of the other outlets. This simple experiment demonstrates that my model captures the complex substitution patterns that are induced by geography, which is that most consumers choose between outlets near their location. These substitution patterns will prove rich enough to give a strong fit to the data. As reported in Section 4, the correlation between the actual prices and the prices implied by the estimated model is 0.54.

[24] The estimated parameters are reported in Section 4.

Picture 2:



The parameters of the indirect utility function are traditionally estimated using the prices and quantities sold at the outlets.[25] However, while I have data on the locations and prices of the outlets, I have no data on the quantities sold at each of the outlets because quantity data is confidential. While not ideal, this is a common problem for retail data. Prices often can be observed because the economist can pose as a customer, but the firms' quantity data is kept as proprietary information. Since collecting quantity data would be very expensive, the demand for a particular outlet must be inferred. Instead of using the actual quantities sold, I use the assumption of static profit-maximization by firms to identify my model. I do this by substituting the implied demand quantities from the consumer side of the model into the first order conditions for the firms, and solve for both the demand and supply side parameters simultaneously. Both sides of the model are identified because I have demand and cost shifters, and I explain the estimation and identification in detail after I set up the supply side of

[25] The quantity data can come either in a micro format, where the econometrician observes individual choices, or in an aggregate format, where BLP-style methods are used.

the model.

2.2 Supply

I model the supply of fast food by assuming that each franchisee sets prices at each of their outlets to maximize the joint profits of all of their outlets according to a static Bertrand game. Different ways of modeling the supply could be used, but the assumed mechanism for supply identifies the model. Static Bertrand competition is a reasonable assumption because the firms offer to sell as many units of the good as are demanded at the posted prices, and because the firms can change their prices quickly and easily. Burger King and McDonald's suggest a price for the food to their franchisees, although the local franchisees are free to charge any price they want.[26]

Formally, each owner, n, maximizes profits across their outlets, j, by choosing the price for each outlet, P_j, that solves

$$Max_{P_j} \sum_{\substack{j \text{ owned} \\ \text{by } n}} \left(P_j Q_j(P) - C_j Q_j(P) - F_j \right) \tag{8}$$

where C_j, the marginal cost of a meal at outlet j, is dependent on the chain, k, to which the outlet belongs, P is the J-dimensional vector of prices for every outlet, and F_j is the fixed cost of operating outlet j.[27]

I assume that each outlet has a constant marginal cost, and that the outlet's marginal

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[26] McDonald's has an FAQ on their web site: "Why do your prices vary from one restaurant to another and why do some restaurants charge for extra condiments?" The answer McDonald's gives: "Approximately 85 percent of McDonald's restaurants are locally owned and operated. As independent businesspeople, each individual determines his or her own prices taking their operating costs and the company's recommendations into consideration. Therefore, prices do vary from one McDonald's restaurant to another. Also, for this same reason, charges for condiments may vary from McDonald's restaurant to another." (Source: http://www.mcdonalds.com/corporate/info/faq/index.html, September 6, 1999.) A former corporate employee of Burger King told me that while Burger King suggested prices on new items and used charts to show that when franchises increased prices their quantity went down, the corporate employees were instructed not to discuss exact outlet prices with their franchisees.

[27] For this maximization, I do not focus on agency problems and assume instead that the outlet is maximizing total profits at the outlet. However, this form of estimation can handle some simple contractual forms. The most common one is that the outlet pays the chain a percentage of revenues. Under this contract, only the marginal cost will be estimated incorrectly. Instead of estimating the true marginal cost, the estimate will be C_k/r, where r is the fraction of revenue the owners of the outlet keep. While the marginal cost is incorrect, the firm will behave as if the estimated marginal cost were the true marginal costs, so any behavioral implications of my estimates will still be valid. Since I only consider the pricing decision of franchised outlets, and since the interpretation of the marginal cost estimate does not affect the pricing predictions by the model, I remain agnostic about whether the estimated marginal cost is the true marginal cost or C_k/r.

cost is equal to a chain-specific marginal cost plus a zero-mean unobservable component. Thus, outlet *j*'s marginal cost is

$$C_j = (C_k + e_{\,j}) \tag{9}$$

where C_k represents the mean marginal cost for all outlets belonging to chain k, and $e_{\,j}$ represents the zero-mean, outlet-specific, portion of marginal costs. The different chains will have different marginal costs because they serve different food. I attribute the outlet-specific component of marginal cost to be due to the labor efficiency of the workers and the management of the outlet because the other sources of variable costs, food and materials, are very standard across all of the outlets. I assume that the franchisee knows their true marginal cost, including $e_{\,j}$, when they set their prices, but that the econometrician does not observe the outlet's marginal cost.

Substituting equation (9) into equation (8), and taking the derivative with respect to each outlet's price leads to the following first-order conditions for the price at each outlet:

$$Q_j(P) + \underset{\substack{i \text{ owned} \\ \text{by } j\text{'s owner}}}{S}\ [(P_i - C_k - e_{\,j})\{¶Q_i/¶P_j\}] = 0. \tag{10}$$

While I do not have data on quantity and derivative of quantity with respect to price, I solved for these variables as a function of the utility parameters in Section 2.1. I estimate the model by substituting these quantities and derivatives into equation (10) and rearranging for the $e_{\,j}$'s, which are the residuals I use for Generalized Method of Moments (hereafter GMM) estimation. This is solved for outlets whose owners own multiple outlets by using matrix inversion, but the formula for $e_{\,j}$ for the independently operated units is

$$e_{\,j}(q) = P_j - C_k - \frac{\displaystyle\sum_b \left[h(b)\ \frac{e^{j_j}}{1 + \sum_t e^{j_t}} \right]}{\displaystyle g \sum_b \left[h(b)\ \frac{e^{j_j}}{1 + \sum_t e^{j_t}} \left(1 - \frac{e^{j_j}}{1 + \sum_t e^{j_t}} \right) \right]} \tag{9}$$

where $j_j = X'_j b - D_{b,j} d - P_j g$ and t indexes all of the firms in the county. Note that both the demand and supply side parameters appear in this equation. The set of $\{C_k\}$ are the cost parameters, which represent the supply side of the model, and b, d, and g are the demand parameters. The population weight of the malls appears in this, too, since for the 10 mall locations, $h(b) = l$. For the 1119 census block-groups the $h(b)$ is the weighted population in the block-group, which is obtained from the data, as explained in Section 2.1.

The price-setting game exposited above can be embedded into a greater two-stage game that was proposed by Hotelling (1929) and has become standard in the theoretical product differentiation literature. In the first stage, firms (sequentially) enter the market. In the second stage, firms set prices to maximize profits. This framework for the entry game is fairly standard, and while firms can change their locations, doing so is both expensive and takes time. In contrast, firms can adjust their prices quickly. Therefore, I assume that the prices reflect the demand and firm locations at the time that I collected the data.

This paper focuses on the second stage of this game. However, while I do not explicitly model the entry decision that occurred before the firms set their prices, I use assumptions about entry to justify my instruments. As mentioned above, the deviation from chain-level marginal costs are likely to come from the different efficiencies of the workers and managers at each of the outlets. These are things that are likely to change over time as workers and managers are replaced or managers are retrained. The assumption that I make is that the values of e_j that existed when the firms entered are uncorrelated with the values of e_j that were true when the sample was taken. Instead, I assume that the e_j evolve over time and that the e_j have reached a steady-state distribution by the time the data was collected. This is a reasonable assumption since most of the outlets had been open for several years before the sample was collected.[28] While I rely on these assumptions to justify the validity of my instruments, one strength of my model is that if my assumptions are correct then my estimation procedure is consistent with endogenous location choices by the firms, where firms choose their locations to maximize expected profits based on the observable attributes of the location. This contrasts with most papers on product differentiation, which assume that the product attributes of each product is exogenously given.[29]

[28] 2 Burger Kings and 2 McDonald's opened two years prior to the sample. I am missing the dates of entry for 1 McDonald's and 2 Burger Kings. The rest of the outlets were open for at least three years before the sample was collected. Some readers have worried about exit, but this is not a concern in this market. Exit is very rare with these chains, and unlike the few markets where these chains have sometimes exited, which are generally declining markets, Silicon Valley was growing at ferocious rates at this time. (The census bureau states that the population grew 12.4% over 10 years at http://quickfacts.census.gov/qfd/states/06/06085.html.)

[29] An alternative hypothesis that would also be sufficient for the moment conditions I use would be that the firms do not observe (and are unable to back out) the values of ε for themselves or any outlet before entry.

2.3 Estimation

I estimate the model by interacting the deviations from the chain-level marginal costs with a set of instruments and using GMM. I need to use instruments to estimate this model for three reasons. First, prices are correlated with each outlet's marginal costs, so prices are endogenous. Second, parameters corresponding to chain dummies appear both in the demand and supply side of the model, so I need demand and supply shifters to capture both of these effects. Third, the travel cost parameter relates to distances that are specific to the consumer-firm pair, while the unit of observation is at the firm level.[30]

Appropriate instruments, Z, will be uncorrelated with e_j, but correlated with the cost or demand terms. A sufficient condition for this is that

$$E[e_j(q^*)|Z_j] = 0 \tag{10}$$

where q^* is the "true" value of q.

The first set of instruments I use are the chain dummies, which shift the costs of the outlet.[31] The unobserved components of costs are, by construction, independent of the chain affiliation of the outlet, but the chain dummies will be correlated with the marginal costs of the outlet. The second set of instruments I use describe the competitive environment of the outlets. These instruments are the distance to the nearest competitor, and a measure of the directions of the outlet's competitors, which is explained in Appendix 1. These instruments are demand shifters. For example, a firm that is further from its nearest competitor will, all else equal, have higher demand and be able to charge a higher price due to its greater market power. The model shows that most of an outlet's customers come from census blocks where j_j is high, which are the same census blocks where $D_{i,j}$, the distance between the consumers and firms, is small. If the nearest competitor is far away, then the values of j_t for the other firms will be small for the consumers in the same blocks where j_j is high, so the fraction of consumers that patronize the outlet, $\dfrac{e^{j_j}}{1+\sum_t e^{j_t}}$, will be very high for these census blocks. The competitive

[30] Steve Berry noted that one could theoretically use maximum likelihood if the observed price equilibrium were unique in the marginal cost disturbances. This condition holds over some range of parameter values. However, the fitted residuals from GMM fit most observations very well but a few observations extremely poorly, indicating that the residuals are not distributed normally.

[31] These will shift the demand, too, but the other instruments I use are demand shifters. Therefore these instruments are contributing mostly to the identification of the cost parameters.

environment of the firm will be uncorrelated with the outlet-specific component of marginal cost under my assumption that the deviation from chain-level marginal costs that existed when the outlet chose its location is independent of the deviation from chain-level marginal costs that existed when I collected the sample. The third set of instruments are dummy variables indicating the presence of drive-thrus and playlands in the outlets, and also dummies indicating the presence of drive-thrus and playlands in the outlets of their nearest competitors. While theoretically these variables could be related to marginal cost because they could change the amount of labor required per order, this is not mentioned in the literature as a factor in marginal cost by any of the sources I have seen discussing the economics of drive-thrus and playlands. I therefore assume that they have no effect on marginal cost. The final sets of instruments that I use consist of demographic data for each of the outlets. These are the population density of kids in the nearest census block-group, the weighted population density of adults in the nearest census block-group, and the distance to the nearest major mall. These factors shift demand because, all else equal, sales increase when firms are located near a cluster of potential customers.[32] Finally, I interact all of these instruments with the chain dummies to account for the asymmetries in how market conditions will affect the two firms.

Formally, I define a set of instruments $Z = (z_1, z_2, \ldots, z_N)$ to use in the estimation. These instruments must be uncorrelated with e_j, but correlated with demand or supply for the outlet. The population moment condition and corresponding sample analogue are given by:

$$E[Z_j e_j(q^*)] = 0$$

$$G_J(q) = \frac{1}{J}\sum_{j=1}^{J} Z_j e_j(?) \qquad (13)$$

where q^* is the true value for the vector of parameters, and J is the number of outlets in the estimation sample. The GMM estimator is then the value of $\hat{q}$ that solves

$$\arg\min_{\hat{q}} G_J(q)' A G_J(q) \qquad (14)$$

where A is a weighting matrix for the moments. The GMM estimator is consistent with any weighting matrix A. However, the optimal weighting matrix to use is an estimate of the inverse

[32] While the absolute population density of consumers is unimportant, the relative densities are. The higher the absolute density of a nearby block-group, the higher the probability that the density of consumers is higher near the firm than a little further away, and therefore a greater proportion of the outlet's consumers find that the outlet is located close to their ideal position. Therefore, they will be less willing to switch products than the average consumer, leading to higher prices.

of the asymptotic variance of the moment conditions $(E[G_J(q^*)\ G_J(q^*)¢])^{-1}$. Therefore I use a common two-step procedure, where I use GMM to get a consistent estimate, q_1, and then run GMM a second time using the weighting matrix

$$A = \left[\frac{1}{J} \sum_{j=1}^{J} Z_j Z_j' e_j^2 (q_1) \right]^{-1}$$

2.4 Intuition Behind Identification

The intuition behind the identification of the utility and cost functions comes from the idea that changing the parameters of these functions will change the equilibrium prices of the firms under some market configuration. While there may be more than one combination of parameter values which are consistent with the observed equilibrium prices under some market configurations (monopoly, duopoly with a particular competitor, crowded market, etc…), the different sets of parameters will lead to different equilibrium prices in other market conditions. For example, increasing both the average consumer's base utility for a good and price sensitivity could keep the profit-maximizing price of the good in a monopoly market unchanged. But the changed price sensitivity would lead to an equilibrium where the chain charged a different price in a duopoly market than it would have if both of these parameters had been smaller.

While I do not mathematically prove that it is never possible for two sets of parameters to generate the same pricing pattern across market structures, Thomadsen (2001) illustrates that in markets with two firms on a line, each giving consumers the same levels of base utility, any combinations of changes to base utility, price sensitivity, travel costs, and marginal costs will lead to changes in the equilibrium prices in at least some market structures. The market structures used in this paper have a much richer set of substitution patterns than can be achieved in a linear market. Also, firms in this paper compete against different numbers of competitors, and against competitors with different identities. Each of these differences leads to an even wider set of market structures whose pricing patterns can be exploited to identify the utility and cost parameters.

To gain intuition about how both supply and demand effects are identified through the observed prices, note that the price for each outlet is equal to a cost component plus a mark-up. The cost component will not vary in the different competitive environments, while the mark-up, which comes from the demand for the product, will.

I demonstrate this by parsing the residual into a price term, a supply term, and a demand term. This was done in equation (9),

$$e_j(q) = P_j - C_k - \frac{\sum_b \left[h(b)\, \frac{e^{j_j}}{1+\sum_t e^{j_t}} \right]}{g \sum_b \left[h(b)\, \frac{e^{j_j}}{1+\sum_t e^{j_t}} \left(1 - \frac{e^{j_j}}{1+\sum_t e^{j_t}} \right) \right]}, \tag{9}$$

which can be rewritten as

$$e_j(q) = P_j - C_k - \frac{Q_j(q)}{\left[\frac{\partial Q_j(q)}{\partial P_j} \right]}. \tag{9a}$$

(a) (b) (c)

Component (a), price, is data. The next 2 components are functions of the parameters that I am estimating. Term (b), the supply side of the model, consists of the chain-specific marginal costs. This term will not be related to the competitive environment of the firm. Term (c), the mark-up term, consists of the demand side of the model. This term will vary as the firm is closer or further from its competitors since the degree to which two products are substitutes, and therefore the price-elasticity of each of the outlets, is determined by the preferences of consumers. Thus, if one observes outlets belonging to the same chain in a wide variety of competitive environments, one can then separate the constant supply side of the model from the outlet-varying demand side of the model.

One corollary is that the econometrician must observe each chain's outlets in a wide variety of competitive environments in order to identify the model. If a chain's outlets are only observed in extremely competitive environments, or on the other extreme, only very monopolistic environments, then my approach to estimating the model will not work.

One assumption I rely on for identification is that the econometrician knows the families of the utility and cost functions. It is not possible to back out the true utility function if no structure is imposed. However, it is possible to distinguish between a wider variety of functional forms as the firm is placed in a more diverse set of market conditions.

3. Data

This study uses an original dataset consisting of all fast food restaurants in Santa Clara County that belong to chains, including all 64 McDonald's and 39 Burger Kings in the county. In this study, I focus on competition between Burger King and McDonald's, although I use the full dataset to confirm that limiting the market to McDonald's and Burger King is a valid assumption.

The data I have include the locations, complete menu prices, ownership and presence of drive-thrus and playlands for each of the outlets in my sample. I obtained the locations of the outlets from the Santa Clara Department of Environmental Health, the local yellow pages,[33] and each chain's web page's list of outlet locations. I geocoded each outlet's location into a computerized map and double-checked this location by physically visiting the restaurant, ensuring that its location was accurate and that the restaurant was still open.[34] While confirming the locations of the outlets, I collected data indicating whether a drive-thru or playland was present and the full menu of prices.[35] The menu was collected through photography where possible. Since some companies forbid the photographing of menus in their restaurants, I used drive-thru menus where they were available.[36] For outlets where photographs could not be taken, the complete menus were written down by hand.

I also collected data about consumers to support the firm data. This data includes demographic information by census block-group, including the population density and the age distribution in each census block-groups, in addition to the locations of the 10 major malls in Santa Clara County. Finally, I have the locations where consumers work by TAZ, which is an area defined locally and used by the US Department of Transportation. On average, the TAZs are about three times the size of a census block-group, although no strict ordering in size exists. I used this worker location data to test whether worker location was an important factor in determining demand, but my estimates showed it to be unimportant.

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[33] Online yellow pages, and paper yellow pages for the areas I could get them.

[34] I also looked to see that there were no outlets missing from the set.

[35] The prices were collected over a time frame of less than 2 months, mostly during the end of June and July of 1999. There were no observed price changes during this period except for specials, and these were not on items I use for the prices.

[36] Prices did not seem to vary between the drive-thru menus and the indoor menus, based on observations where I had both.

3.1 Prices

Each outlet is an observation. The prices used for this study are the prices of the extra value meals with the signature sandwich for each chain: the Big Mac for McDonald's and the Whopper for Burger King.[37] This is done because these items are the most purchased items, and I was not able to obtain data about the distribution of sales across all of the menu items.[38]

I use the price variation across different McDonald's outlets, and across different Burger King outlets, to estimate the model. I omit the pricing decisions of the 21 outlets owned by McDonald's corporation[39] because these outlets face different incentives than the franchised outlets, both because the marginal costs for the corporation are lower than the marginal costs for franchised outlets and because the parent chain profits from sales at every McDonald's outlets. However, I do account for the effect that their presence has on the demand for every other outlet in the market.

Note that using only the pricing decisions of outlets owned by franchisees, and not those of the parent corporation, does not introduce any sample selection bias into the estimates. I am not conditioning my choice of observations for the estimation on the endogenous variable, price (or e). Rather, I am conditioning on firms that have a similar set of costs and incentives and using these incentives to estimate the model. The only potential loss from omitting pricing decisions of the corporate-owned outlets is efficiency, because the e_j's still retain their properties of being mean zero and orthogonal to my instruments,[40] while the instruments I use are still correlated with each outlet's demand and chain-specific marginal cost. This is true even if the corporate-owned outlets are (i) systematically located in different competitive environments than franchised outlets or (ii) if they systematically price higher or lower than the franchised outlets. The reason for this is that I am estimating a Nash Equilibrium for a pricing

[37] These prices will be the transactions prices for the items. An advantage of studying the fast food industry is that all consumers pay the same price on the goods. There are rare exceptions, but not on the main items. (An example of an exception is that at many outlets seniors can get a coffee for 25 cents.)
[38] Numerous references state that these sandwiches are the chains' best sellers, but I could not find the exact sales figures. Figures on Burger King's website (April 5, 2001) say that Burger King sells 4-4.6 million whoppers a day to 15 million customers. This implies that over one-fourth of all Burger King customers eat a whopper. McDonald's notes that the Big Mac is their best seller on their website - http://www.mcdonalds.com/countries/usa/corporate/info/studentkit/index.html. Love (1995) reports that by 1969 the Big Mac accounted for 19% of all McDonald's sales.
[39] There are no Burger King outlets in this market that are not franchised.
[40] That is, $E[Z_j e_j(q^*)] = 0$ still holds.

game – which is consistent with the second stage of a two-stage entry game, such as the one proposed in the introduction of this paper, where firms first choose locations and then choose prices. Once the locations of franchised and corporate-owned outlets are chosen, the prices of the franchised outlets are the best responses for these outlets given the realized locations and prices of their competitors, regardless of how their competitors' locations or prices were chosen. While the only potential loss from excluding the information from the pricing decisions of corporate outlets is a loss of efficiency in the estimates, including the pricing decisions of these outlets when their objective functions are incorrectly specified introduces true error that destroys the consistency of the estimates.

There are a few other types of outlets that I treat specially. I completely omit the outlets located in the San Jose airport (one McDonald's and one Burger King – each in different terminals), and the McDonald's located on the Moffett Air Force Base, because I believe that these outlets do not compete with other fast food firms in the same manner as the other firms in my market. I also completely omit the four McDonald's outlets that are located in Wal-Marts since I believe that these are poor substitutes for other outlets. This conjecture is supported by the fact that two of the four Wal-Mart McDonald's have stand-alone outlets located in their parking lots, and a third has a stand-alone outlet located very close to the Wal-Mart. I also do not consider the pricing decision of the outlets located in malls (2 Burger Kings and 5 McDonald's) since these are likely to be poor substitutes to stand-alone outlets. However, I account for the competition that restaurants in malls provide against outlets located outside of the mall in most of the results that I report. As was the case with corporate outlets, efficiency is the only loss if I do not use the pricing decision of the mall outlets but they price their meals in the same manner as other outlets, but I would be introducing error into the estimates if I used their pricing condition in the estimation and they price differently. Supporting evidence that these mall outlets are in different markets includes the fact that McDonald's set up stand-alone outlets outside two of the malls where they have food court locations, and Burger King set up two stand-alone outlets within one mile of one of their two mall locations. Finally, I omit one of the McDonald's outlets, the one located in the food court of the great mall of Milpitas, because there is also a McDonald's located just outside of the mall, which is corporate owned. This means that I do not use the pricing decision of either of these McDonald's. However, I do not believe that other outlets in the area face twice as much competition from having two McDonald's outlets in essentially the same location, so I remove one of these outlets to indicate that the other outlets are competing against McDonald's but to avoid overstating this effect.

My estimation is based on the pricing conditions of the 36 Burger Kings and 33 McDonald's remaining after accounting for the special cases detailed in this section. In Table 1 below, I give some summary statistics about the degree of price variation in these two chains.

Table 1 – Summary of Price Variation in McDonald's and Burger King
Only the outlets included in the estimation are reported here.

Chain	N	Mean Price	Standard Deviation of Price	Minimum Price	Maximum Price	Note:
Burger King	36	$3.24	$0.08	$3.19	$3.49	
McDonald's	33	$3.48	$0.27	$2.99	$4.09	Omitting 2 outlets with price of $4.09 gives Max = $3.79.

4. Analysis

4.1 Estimates

The estimates of this model are reported in Table 2. The coefficient on travel costs is 3.58 times the coefficient on price, which indicates that consumers are willing to travel less than 1/3 mile in order to save $1.00. The estimated marginal costs indicate that the firms hold significant market power.[41] The average mark-ups are $2.32 for Burger King and $2.67 for McDonalds. This implies that, on average, marginal costs are 28% of price for Burger King and 23% of price for McDonald's, which is consistent with one Burger King franchisee's estimate that food plus paper costs represented about 31% of price.[42] A significant portion, $2.17 = 1/\gamma$, of this margin comes from the non-geographical product differentiation. This is the amount that each firm will price above their marginal cost, even in the presence of an infinite number of competitors that are located at the same location as the outlet. Comparing the mark-up of the average firm with this minimum price-cost margin, we find that the average price increase from geographic differentiation is 15 cents for Burger King and 50 cents for McDonald's, although some outlets will have much greater mark-ups. This is consistent with

[41] As defined by price above marginal cost. Tirole (1995), *The Theory of Industrial Organization*, compares different definitions of market power on page 284.
[42] Note that the relevant marginal cost for pricing purposes is the cost of delivering one more item, not the average variable cost.

the fact that the Burger King outlets are usually located near a McDonald's, but several of the McDonald's outlets are located far away from any Burger Kings.

The first column reports the estimates for the model that I have described throughout this paper, where the pricing decisions of malls are not used, but their competitive presence is. The second column reports estimates for the same model where mall outlets are assumed to compete in separate markets, and are therefore completely omitted from the model. The estimates reported in column 3 use the same assumptions as in column 1, except I allow the other large hamburger chains[43] to compete against McDonald's and Burger King. Finally, the fourth column reports the estimates of the same model as in column 1, except only prices from independently owned outlets are used to estimate the model. There are far fewer observations in this final case – 11 Burger Kings and 13 McDonald's.

Note that while the estimates vary somewhat across these specifications, the important characteristics of the estimates remain the same. McDonald's gives a significantly higher utility to consumers than Burger King.[44] Also note that the travel costs are all estimated to be about \$3/mile, although the higher estimates have greater standard errors. The estimate of \$3.58/mile in the first regression is has a t-statistic of 1.38, which is significant at the 10% confidence level for a one-sided test.[45] This travel cost estimate is reasonable and implies that consumers have an average opportunity cost of their time of approximately \$32/hour.[46]

The estimates reported in column 3 demonstrate that it was reasonable to limit the set of competitors to Burger King and McDonald's. The model estimated in column 3 allowed consumers to choose between not only Burger King and McDonald's, but also at any of the large hamburger chains in the area.[47] However, the average utility consumers obtain from

[43] Carl's Jr., In-N-Out, Jack In The Box and Wendy's.

[44] The difference is both statistically and economically significant. The difference between Burger King and McDonald's in column 1 is significant at the 1% confidence level, with a t-stat of 2.46. The reason for the significance is the high positive covariance of these two estimates.

[45] Travel costs are assumed to be positive.

[46] At the time that the data was collected Silicon Valley was very prosperous, and wages were larger on average than elsewhere. The median income (as estimated in 1997 by the census bureau) was \$59,639. (See http://quickfacts.census.gov/qfd/states/06/06085.html.) The Opportunity cost of time is calculated by noting that a person going to an outlet 1 mile away from them will travel a total of 2 miles round trip. One mile of travel takes approximately 3 minutes in my study area. Thus after subtracting the standard 31-cent per mile deduction as true costs (US General Services Administration – See May 23, 1996 Federal Register page 25802, Vol 61, No 101), the hourly cost of the time is \$32/hour. Thanks to Greg Rosston for pointing this out.

[47] Since I am only using prices from McDonald's and Burger King, the relevant set of consumers for this model are those who may be induced to eat at Burger King or McDonald's if the prices at these outlets were changed.

eating hamburgers from the other large hamburger chains is very negative.[48] This implies that the presence of the other large hamburger chains is not important to the pricing decisions of McDonald's or Burger King outlets since almost no McDonald's or Burger King customer consider eating at one of the other outlets. Other models with different combinations of additional competitors yielded the same qualitative results. These results are consistent with the market segmentation of these chains. For example, both McDonald's and Burger King appeal largely to families with kids, while Wendy's and Jack In The Box[49] both appeal more to adults, and Taco Bell appeals mainly to males 18-24 years of age.[50]

To give confidence to validity of the estimates, I examine how well the estimated model fits the data. There is no established method of measuring fit for structural models, so I studied how well the model predicted the actual prices observed in the data.

The estimates produce predicted prices[51] that are positively correlated with the actual prices. The correlation of predicted price with actual price for the whole sample is 0.54. The high correlation partially reflects the fact that the estimates of the model have successfully differentiated between McDonald's and Burger King. However, the correlations between predicted and actual prices within each of the chains are also high. For Burger King, the correlation of predicted prices with actual prices is 0.27, while the correlation between predicted prices and actual prices for McDonald's is 0.33.[52] The fit for most outlets is even better; if one ignores the fit for the two worst fitting McDonald's and the one worst fitting Burger King outlets, then the correlation of predicted versus actual prices jumps to 0.37 for Burger King, 0.57 for McDonald's, and to 0.70 for all observations.

Running OLS of actual prices on the predicted prices and the brands of the outlets gives the results shown in Table 3. The predicted prices explain a significant proportion of the price variation, improving the R-square from 0.285 to 0.360. The last two columns of Table 3

[48] The estimate is very imprecise because the estimate is so negative that the implied prices and quantities are almost identical when the estimate is –15 as when it is more negative. The standard error of e^{-15} is 2.25.

[49] As stated on their web page.

[50] I have tried to estimate models with a nesting structure between the different hamburger chains, but so far these have proven to be too difficult to estimate with the data I have. However, the focus on different demographic groups, along with the high correlations of predicted vs. actual prices reported in the next paragraphs suggest that limiting competition between McDonald's and Burger King is a reasonable assumption.

[51] Equals actual prices minus the residual from each outlet's idiosyncratic cost variation.

[52] The standard errors of the predicted and actual prices differ slightly. For Burger King, the standard deviation of predicted prices is 0.051, while the standard deviation of actual prices is 0.081. For McDonald's these numbers are 0.28 for the predicted prices, 0.27 for the actual prices.

show the fit of the estimates if the two worst fitting McDonald's and the one worst fitting Burger King outlets were ignored.[53] In this case, the R-square increases by 72%, from 0.302 to 0.518. While one can always improve the fit of any set of estimates by removing the worst-fitting predictions, the correlations between predicted and actual prices, and the R-squares for the OLS regressions in Table 3 for the restricted sample is high enough to indicate that this model fits the data very well for 95% of the sample.

Finally, I performed a test of over-identifying restrictions for the estimation. The p-values of the χ^2 tests for each version of the model are reported in Table 2. In all cases, the p-value is 0.37 or less. Thus, I conclude that over-identification is not a problem.

I use the set of estimates reported in the first column of Table 2 to conduct counterfactual experiments that illustrate how an outlet's location affects the market power of firms. It is useful to use the monopoly price for a meal at an outlet with the chain's average marginal cost as a benchmark in these experiments. However, this price depends upon the geography of the market. For example, if a McDonald's were located in a spaceless market[54] then the monopoly price would be \$4.90. If the McDonald's were instead located at the center of a 10-by-10 mile square market then the monopoly price would only be \$3.57. The reason for the difference in these prices is that McDonald's must decrease its price in markets with a geographic distribution of potential consumers in order to attract consumers that incur a travel cost when they patronize the outlet. In the counterfactual experiments that follow, the proper benchmark to use in Tables 4 and 5 is this \$3.57 figure for McDonald's, and \$3.33 for Burger King.

The rest of the analysis section reports the results of the counterfactual experiments. The goal of the analysis is to illustrate how an outlet's location affects the equilibrium prices that emerge from Bertrand competition. I first report the results of simple experiments in artificial markets with a uniform distribution of consumers in order to demonstrate the pure effects of geographic differentiation from competitors, and show how these effects are affected by the number and identity of the various firms. I then use the real market conditions and simulate how the prices would change for one outlet, the one located at 3128 El Camino Real in Palo Alto, if its location were different. These experiments demonstrate how price is

[53] These are the most expensive outlets for each chain.

[54] A spaceless market is a market where all consumers and firms are located at the same location, such as a Bresnahan and Reiss (1991) market.

influenced not only by the outlet's proximity to competitors, but how it is also jointly influenced by the outlet's proximity to consumers. The results will show that the price for the outlet will vary substantially when it is moved to alternative locations within 2 miles of the outlet.

4.2 Simple Experiments

The results of some simple counterfactual experiments are reported in Tables 4A-C and 5A-B. These counterfactual experiments are conducted in an artificial market that I have created, which is a 10-by-10 mile market with a uniform distribution of consumers.[55] I discretize the space by placing a grid of square cells with a width of 1/10 of a mile over the market and treat all consumers located in a particular cell as if they were located at the center of the cell. I then aggregate over the decisions of consumers each of the cells in the same manner as explained in Section 2.1. The marginal costs used in these experiments are the mean marginal costs for each chain's meal. Finally, the firm for which I am reporting prices is always located at the center of the market to ensure that the prices for these outlets are comparable across experiments.

Table 4A shows how the price would vary for a McDonald's if it were competing in a market against a single Burger King outlet. The first column shows the prices for the McDonald's outlet when consumers travel along the path that minimizes the Euclidean distance. When the two firms are located together then the price for a meal at McDonald's is eight cents lower than the monopoly price. When the Burger King is located 2.5 miles or more away, the McDonald's is essentially able to charge its monopoly price.[56] The second column shows the same experiment, except in the second column consumers must travel along a grid of roads and therefore their travel distance is measured using the taxicab metric rather than the Euclidean metric. The effect of geographic differentiation is almost identical under these two metrics, although the prices are always slightly higher when consumers must travel along a grid as compared to when they can use the shortest Euclidean distance. This pattern holds in all experiments.

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[55] I choose such large markets to avoid worrying about how the edge of a market affects the equilibrium prices. Real markets will have smaller areas from which the firms will be drawing large percentages of their consumers, and the results from Section 4.3 show the price variation in such a market. Using 4x4 miles markets does not change the results much.
[56] The prices appear to be 1 cent apart due to rounding.

Table 4B reports the same set of statistics as table 4A, except that the prices are now for a Burger King outlet competing against a McDonald's. The first column of the table shows that when both firms are located together then the price of a Burger King meal is 10 cents below its monopoly price. In this same situation the McDonald's price is only eight cents below its monopoly price because McDonald's is a stronger competitor than Burger King. One result is that the distance between the Burger King and the McDonald's is a larger factor in Burger King's equilibrium price than in McDonald's price.

Table 4C shows equilibrium prices for a market with two McDonald's. The first column assumes that the two McDonald’s are competing against each other. This is not unrealistic because most of the McDonald's are owned by different franchisees, and therefore these franchisees care about their own profits but not the profits of other McDonald’s. Indeed, there have been many lawsuits were franchisees have sued McDonald's for placing competitive franchises too close to their outlets. Table 4C shows that McDonald's would face tougher competition form another McDonald's than from a Burger King outlet. As a result, the degree of geographic differentiation between two McDonald's has a larger impact on price than geographic differentiation between a McDonald's and a Burger King. The result that geographic differentiation has the largest impact on prices in markets between firms that are similar held in all experiments that I ran, under a wide variety of parameter values.

The second column in Table 4C shows the prices that occur if the outlets are maximizing joint profits. The high price when the firms are located together reflects the i.i.d. assumption of tastes. However, the high prices in general have a strong economic foundation. If a firm has multiple locations then, at any fixed set of prices, the firm is closer to a larger percentage of the consumers who patronize each outlet. Since each outlet is more convenient to a higher percentage of its customers, the firm will charge higher prices at each outlet, not caring that some of the consumers will instead go to the owner’s other outlet. As the firms are located closer together a greater percentage of their customers will be deciding which of the two outlets to go to rather than whether to go to either of the outlets. Therefore, prices will be higher as the distance between the outlets fell.

Also, note that the differences in prices between the two columns in Table 4C represent the changes in prices that would occur if there were a merger between two outlets. The results indicate that mergers can lead to significant price increases, even when the outlets are located far enough apart that they would have been charging monopoly prices if they had been individually owned. For example, the price increase is 10¢ even when the outlets are 2.5. This increase in price occurs because many of the marginal consumers to the individual outlets (those who were in between the two outlets) are not marginal to the integrated firm, and so the joint firm faces a more inelastic demand.

So far the analysis has discussed markets with only two firms. However, most outlets compete against more than one competitor. Tables 5A and 5B show how the price of a McDonald's outlet changes with the degree of differentiation to multiple competitors. Table 5A reveals that prices for a McDonald's are lower when it competes against two Burger Kings as compared to when it competes against only one, and as a consequence, the effect of geographic differentiation is also larger. The second column in table 5A shows that when the McDonald's is competing against two Burger Kings, the layout of the competition affects a price at McDonald's charges; the prices are slightly higher when both Burger Kings are located to one side of the McDonald's as compared to when they are located on opposite sides of the McDonald's. The importance of the layout of competitors is slightly higher in table 5B where the McDonald's is competing against two other McDonald's outlets, which also have lower prices and larger differences from geographic differentiation than a McDonald's competing against a single McDonald's, as reported in Table 4C. However, the differences in prices from the geographic layout of firms still appear to be small in these counterfactual experiments. This is a result of the estimated parameters. I found that the layout of the firms had substantial effects when I ran the same experiments under different parameter values.

4.3 Real Market Conditions

The simulations from the previous section demonstrate how geographic differentiation of firms affects the equilibrium prices that emerge in a market. However, in real markets the equilibrium prices are affected by both geographic differentiation and the distribution of consumers around the outlet. In order to see these effects jointly affect price, I demonstrate in this section how equilibrium prices of a real outlet would change if its location were changed.

The featured outlet in these experiments is the McDonald's located at 3128 El Camino Real in Palo Alto. I provide a map of the outlet in Appendix 2. I calculate the equilibrium prices that would emerge if the outlet were instead located at different points between two of its nearest competitors along the approximate route of El Camino.[57] The nearest competitor on

[57] I recalculate new equilibrium prices for all of the outlets in the vicinity of this outlet.

one side is a McDonald's located in a mall, and on the other side it is a Burger King. The mall is about 2.4 miles from the actual restaurant, and the Burger King is about 1.9 miles away. The results of this counterfactual experiment are reported in table 6. The first column shows the predicted prices for the outlet if all the outlets were owned by individual franchisees. The prices vary for the outlet as its location is changed, ranging from \$3.41 to \$3.60. Even small changes in an outlet's location can have a large impact on price; the price of the outlet would increase 15¢ if its location were changed by just over ½ mile, from 0.97 to 1.51 miles away from the mall. Note that the prices move somewhat up and down for locations near the center of the section. This oscillation in prices is due to the different densities of consumers close to the different locations along the line, and demonstrates how much the distribution of consumers affects the price. For example, if the outlets had been independently owned then the price for a Big Mac varied from \$3.59 to \$3.52 and back to \$3.59 all along a 1.2-mile stretch of El Camino where no other competitors were present.

The fourth column gives the equilibrium prices that arise under the true ownership structure of the market, which is that the featured McDonald's is owned by the same owner as two of the other McDonald's in the area.[58] The predicted price at the true location is \$3.65, while the actual price of the outlet is \$3.69. Comparing the prices in columns 1 and 4 reveals that consumers at this McDonald's paid 13¢ more for their meals due to the joint ownership between some of the outlets than they would have paid if the outlet had been independently operated. Table 6 shows that prices under joint ownership are highest when the outlet is located near the Burger King, which occurs because the McDonald's is also closer to the other two McDonald's owned by the same owner, and the joint-profit maximizing effect of having all outlets closer to their customers dominates the effect of competition by the Burger King.

These results, that prices are higher in the jointly owned outlets, are supported by a quick glance at the data. The co-owned McDonald's in Santa Clara county do charger higher prices on average than the independently operated McDonald's; the average price for the Big Mac meal at the jointly owned outlets[59] is \$3.52, while the average price at the independently owned outlets is \$3.42.[60] Because Burger King outlets are generally close to McDonald's, and because McDonald's is a stronger competitor than Burger King, this effect does not occur in

[58] The two rightmost ones in Appendix 2.
[59] This does not count corporate owned outlets, which generally charge the lowest prices.
[60] The standard deviations for these numbers are large, however, 21¢ and 32¢, respectively.

the data for co-owned Burger Kings. This is also consistent with the estimated model. In Table 7 I estimate the equilibrium prices that would occur for the 3128 El Camino outlet along a variety of hypothetical locations, under both the independent and joint ownership structures, if **all** of the outlets in the area changed their chain affiliation (that is, if all McDonald's became Burger Kings and all Burger Kings became McDonald's). Thus, the featured restaurant is now a Burger King. Note that the qualitative properties about the equilibrium prices are the same as in Table 6, but the level of price variation under each of the ownership structures is smaller. Also, the differences in prices between the two ownership structures are smaller for Burger King than for McDonald's. For example, this difference is only 4¢ in Table 7 (for Burger King under different ownership structures), compared to 13¢ in Table 6 (for McDonald's).

The differences in prices under independent and joint ownership are equivalent to the differences in prices that would occur if several outlets merged into one firm. Thus, these counterfactual experiments give insight into evaluating merger policy. The counterfactual experiments highlight that mergers can have a significant impact on price, even when the co-owned outlets are far away, and that mergers among market leaders have a larger effect on price than the mergers between weaker firms. The first point can be seen from the 13¢ differences in prices that occurred when the outlet at 3128 El Camino was "merged" with two outlets over 2.5 miles away.[61] This price increase occurs even though the merging outlets are further away from the featured outlet than the closest competing McDonald's. The second point can be seen by comparing the differences in prices for Burger Kings under joint ownership compared to McDonald's under joint versus independent ownership. The price change for the featured outlet at its true location is over three times larger on a similarly priced item when the merger is between McDonald's compared to what it would have been if the merger had been between Burger Kings at the same location. These results together suggest that the government should be most wary of mergers among firms that are market leaders and less concerned about mergers among weaker firms. If the quality of the weaker competitors can be improved through a merger[62] then the results from Tables 4A-C, which were analyzed in the previous subsection, suggest that allowing such a merger would be beneficial as long as

[61] Compare columns 1 and 4 in Table 6. From experience, it would take about 7-10 minutes to drive from one outlet to the nearest of the other co-owned outlets if there were no traffic backups in this area.
[62] Even if it is through improvement in brand image from a stronger market presence.

the strongest competitor remained in the market and the outlets of the weaker outlets were far apart. In Table 4C, the non-cooperative price equilibrium for McDonald's food when the two competitors were located at the same location was \$3.38, while the price equilibrium when the McDonald's was competing against a Burger King was higher, \$3.48. If the quality of Burger King improved to that of McDonald's then the equilibrium price of Burger King food would increase from \$3.23 to \$3.38.[63] However, the increase in utility from improved quality for the average consumer would more than offset the utility loss from the price increase. Also, the majority of consumers were initially purchasing the stronger, more expensive brand, so, on average, the consumers are better off under this type of quality-improving merger.[64]

Note that being located near a mall substantially increases an outlet's sales. This is consistent with the conventional wisdom within the industry, with the observed clustering of fast food outlets near malls, and with the volume of traffic reported for major malls according to the directory of major malls. However, the data cannot precisely estimate the population weight that has been assigned to malls.[65] If the estimates of the population equivalence of malls are too large then the prices that are reported near the mall will also be too high because the firm will be primarily targeting the large number of consumers close to the outlets rather than the relatively fewer consumers located further away. If I use a weighted population equivalence of 8,000[66] instead of 28,000, then I get the prices and quantities as reported in Table 8. Note that in Table 8 the price increases as the firm is further from the mall after the first ½ mile of differentiation, in contrast to 0.86 miles in Table 6, and that the variable profits increase consistently with the level of geographic differentiation.

According to my estimates of variable profits, this outlet is not located at the optimal location.[67] This may occur for several reasons beyond incorrect weighting of the population equivalence of malls. First, this outlet was opened in 1974, and the demographic layout of the area was different at the time. If moving costs are high enough, then the outlet will not move even if the location is no longer optimal. Also, greater variable profits at one location do not imply that the total profits are higher in that location because variable profits do not account for

[63] See Table 4B and 4C.
[64] Because the total quality of Burger King improved, the quantity of Burger King purchases would increase, too.
[65] The standard error on the population weight of malls was very large (at least twice the size of the estimate) for all versions of the model that I ran.
[66] This number is closer to the estimates from the other versions of the model.
[67] Note these profits are only correct to a factor of proportionality, and therefore can only be compared to each other and not to any absolute number.

fixed costs, such as rent. Finally, the outlet may have wanted to locate closer to the mall but been unable to do this either due to zoning restrictions by the city of Palo Alto,[68] or because McDonald's refused to allow a second franchisee to locate an outlet too close to the McDonald's located in the Stanford shopping mall.

5. Conclusion

This paper estimates a model of supply and demand in the fast food industry by exploiting the geographic differentiation between firms. The estimation procedure preserves the exact layout of the firms, and the estimates are used to conduct counterfactual experiments that illustrate the effects of geography on the market power of retail firms both in hypothetical and actual markets.

The geographic arrangement of the outlets is a factor that affects the equilibrium prices that result from Bertrand competition, although in some market situations the degree of differentiation may have only a small impact on the price that an outlet charges. The identities of the firms and their competitors also determine the degree of market power they command. When there is a large disparity in the relative popularity of two firms (defined as the difference in the base-utility parameters of the utility function), the "more popular" firm will be able to charge a large mark-up, while the "less popular" firm will have less market power. The identities of the firms also determine how much geographic differentiation will affect prices, with the largest effects coming from competition among firms of similar appeal. For example, among department stores a Wal-Mart is likely to discipline the prices of a Target because these firms are of a similar quality, but it will have a smaller effect on the prices of a Macy's, which sells many of the same items but is of a higher quality.

The results also demonstrate that a firm's location can affect its market power not only because of its differentiation from consumers, but also because of the distribution of consumers near the outlet. This result strongly appears for outlets located at a mall, but also can be seen in the oscillating prices observed in the middle of the market area examined in Tables 6-8.

These results shed light on the optimal locations of firms. If there is a large demand

[68] A large percentage of the land between the mall and the outlet is part of the Stanford campus where there is no commercial activity. This also limited the choices of locations that the outlet had to choose from.

source, such as a mall, then it is better to locate there even if other competitors are already present rather than locate away from the mall. Indeed, if the concentration of consumers is concentrated enough, as it is at a mall, then both prices and quantities will be higher at the mall with a competitor present than they would be if the outlet were located somewhat away from the mall. However, firms will have incentives to differentiate themselves more when the demand is less concentrated. Also, my estimates can be used to study the entry decisions of firms. The estimation procedure that I used is consistent with firms choosing their locations endogenously to maximize profits, and the marginal costs and utility functions that I estimate in this paper can be used to infer the prices and quantities (and therefore variable profits) that would arise should a firm enter at any particular location. These variable profits, along with the past location choices of the outlets, can then be used to estimate a firm's fixed costs at any location as a function of rent and other observable factors. I have data on the entry dates of the outlets, so I can control for the set of firms that were present when the outlets entered the market. By dividing the county into grid cells, one can model the entry choice of firms as a discrete-choice problem where the potential location choices for the outlets are each of the grid cells. I leave this to future research.

Finally, the estimated utility functions can be used to calculate how much prices would change if some outlets were merged under common ownership. The FTC is concerned about how to evaluate the price effects of mergers in geographically differentiated markets. For example, the FTC, in order to preserve local competition, has required supermarket chains to sell stores in particular locations to competitors before approving mergers.[69] In the counterfactual experiments I ran, I found that the price increases from a merger could be quite high. The results in Table 4C demonstrated that a merger could lead to higher prices even when the firms were originally charging monopoly prices. Also, consumers at the outlet featured in my counterfactual experiments paid almost 13¢ more on a meal with an average price of $3.48 because the outlet was owned by the same owner as other McDonald's outlets over 2.5 miles away, even with another McDonald's owned by someone else about 2.4 miles away. If the co-owned outlets had been closer together then the price increase would have been even higher. While co-owned outlets from the dominant firm, McDonald's, charge higher

[69] As reported in Davis (1998) and http://www.ftc.gov/opa/1996/9607/ahold.htm (November 4, 1999), Ahold, the parent company of Stop and Shop, was required to sell several outlets (at specific locations) after they acquired Edwards food stores. The FTC website has many other examples.

prices on average than individually owned outlets, the same is not true for Burger King because the closest McDonald's generally provides sufficient competition to keep prices lower, a fact that is supported by the counterfactual experiments. The analysis supports being tough on accepting mergers among market leaders and less concerned about those among weaker brands. In fact, a merger among weaker brands could be good if the merger led to tougher competition for the market leader.

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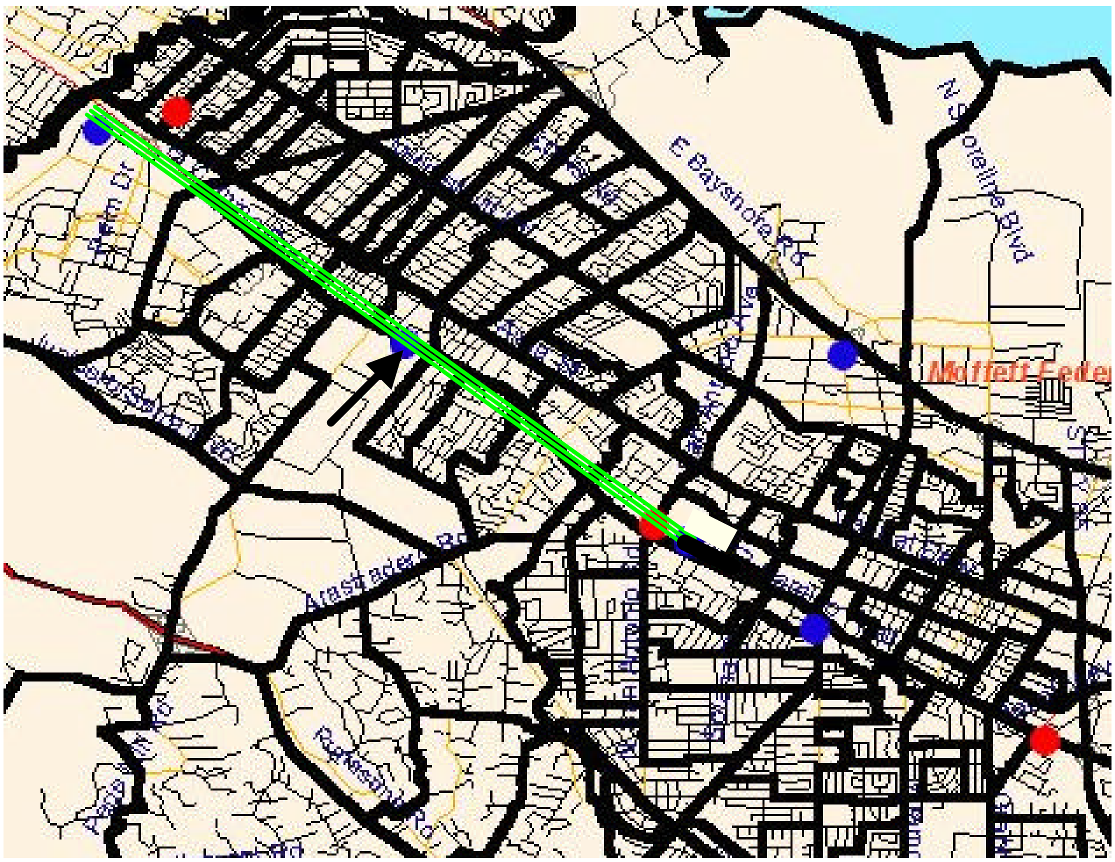
APPENDIX 1 – Moment Conditions: measure of the direction of nearby firms

The measure of the direction of nearby firms is as follows. I take a circle with a radius of 1.25 miles. Then I divide the circle into 4 regions – Northwest, Northeast, Southeast and Southwest. I count up the number of regions that have any firms in them. This instrument is then 4 - {number of regions with competitors}.

APPENDIX 2 – Picture of Market around 3128 El Camino Real



APPENDIX 3 – Justification of using two week period to measure percentage of consumers in age group who are potential fast food customers.

In the text, I weight the consumers in each age group by the percentage of consumers who had eaten at a fast food outlet in the previous two-week period. There is nothing special about the two-week period, and below I show that using any period of time would be reasonable.

I note first that it is not necessary to know the actual fraction of people in each age group who consume fast food, but rather it is only necessary to calculate this fraction to a factor of proportionality. For example, I get identical estimates if instead of using the correct number of potential fast food customers in each census block-group, I instead use a number that is 20% lower, as long as this factor of proportionality is consistent across <u>all</u> groups.

One strength of my model is that I do not need to know the relevant period of time over which consumers are deciding whether to eat fast food. It does not matter to me whether the relevant decision period is each meal, each day, each week, etc…. This contrasts with the methods used in other papers where the market share of the outside good is needed. For these other papers, it is only possible to calculate the outside share by calculating the amount of the good that is consumed in the relevant period of time over which the decision is made, and then getting the outside share as

outside share = (# consumers – purchases)/(# consumers)

However, in my model the outside share is output rather than input. Thus, I am agnostic to the relevant time period for my discrete choice.

The model I use is as follows. There are 2 types of people in each category: those who consider eating fast food and those who do not. For a given age group, consider that a fraction γ consider eating fast food. In each relevant time period for the discrete decision, a fraction β of the consumers who eat fast food consider eating at a fast food outlet actually make a purchase. I assume that γ differs across different age groups, but that β is constant across the different age groups.

My objective is to find a measure that is proportional to γ.

I assume that two weeks is T times as long as the relevant period of time over which consumers make their discrete choice. Then the fraction of consumers who respond that they ate fast food in the two-week period is

$$\gamma\beta + \gamma(1-\beta)\beta + \gamma(1-\beta)^2\beta + \gamma(1-\beta)^{T-1}\beta = (1 - (1-\beta)^T)\gamma$$

Note that this is proportional to γ. As longer periods of time are used, capital T will increase, so the coefficient on γ will increase, but each age group will be weighted in a manner proportionate with the fraction that considers eating fast food.

TABLE 2 – Estimation Results

$V_{i,j} = Xb - D_{i,j}d + (Y_i - P_j)g + h_{i,j}$

$MC_j = C_k + e_j$

		Pricing in malls not used, but presence is.	Outlets in malls omitted	Pricing in malls not used, but presence is.	Pricing behavior malls and jointly owned outlets omitted.
Variable Name	Variable	Estimate (Standard Error)	Estimate (SE)	Estimate (SE)	Estimate (SE)
Burger King base	b_1	0.88 (2.19)	2.32 (1.86)	0.76 (2.28)	2.69 (3.09)
McDonald's base	b_2	2.13 (2.65)	2.88 (2.00)	1.61 (2.61)	4.90 (3.93)
Other hamburger base	b_3			-15.0 (NA)	
Price Sensitivity	g	0.46 (0.40)	0.55 (0.33)	0.45 (0.39)	0.66 (0.59)
Burger King marginal cost	$C_{Burger\ King}$	0.92 (1.93)	1.11 (1.23)	0.80 (2.04)	1.51 (1.44)
McDonald's marginal cost	$C_{McDonald's}$	0.81 (1.93)	1.13 (1.25)	0.81 (2.01)	1.39 (1.44)
Travel costs	d	1.66 (0.33)	1.37 (0.10)	1.71 (0.40)	2.47 (0.68)
Playland effect	b_{play}	-0.34 (0.26)	-0.19 (0.19)	-0.21 (0.31)	-1.37 (0.72)
Drive-thru effect	b_{drive}	0.02 (0.26)	0.03 (0.25)	0.19 (0.29)	-0.31 (0.19)
Mall equivalent to weighted population (1000s)	l	28.0 (71.5)	12.62 (27.0)	8.9 (59.9)	0.19 (4.80)
Implied travel costs		\$3.58/mile (2.60)	\$2.50/mile (1.40)	\$3.85/mile (3.18)	\$3.76/mile (2.37)
Objective function		8.02	8.95	6.98	4.82
χ^2 p-value		0.29	0.37	0.27	0.15

TABLE 3 – Fit of Estimates

	All Observations				Omit Worst 3 Observations	
	Actual Price	Actual Price (control)	Actual Price		Actual Price	Actual Price (control)
Burger King Constant	2.23 (0.37)	3.24 (0.03)			1.78 (0.27)	3.23 (0.03)
McDonald's Constant	2.38 (0.40)	3.48 (0.03)			1.85 (0.30)	3.44 (0.03)
Predicted Prices	0.31 (0.11)		0.99 (0.01)		0.45 (0.08)	
R-squared	0.360	0.285	0.288		0.518	0.302

TABLE 4A: McDonald's fixed at center with a Burger King

Monopoly Price is $3.57. No drive-thru or playland for the McDonald's.

Distance from McDonald's	Price with Euclidean distances	Price with taxicab metric for distances
0 miles	$3.49	$3.49
0.5 miles	$3.50	$3.51
1 mile	$3.53	$3.54
1.5 miles	$3.55	$3.56
2 miles	$3.56	$3.57
2.5 miles	$3.56	$3.57

TABLE 4B: Burger King fixed at center with a McDonald's

Monopoly price is $3.33. No drive-thru or playland for the McDonald's.

Distance from Burger King	Price with Euclidean distances	Price with taxicab metric for distances
0 miles	$3.23	$3.23
0.5 miles	$3.25	$3.26
1 mile	$3.28	$3.29
1.5 miles	$3.31	$3.32
2 miles	$3.32	$3.33
2.5 miles	$3.33	$3.33

TABLE 4C: McDonald's fixed at center competing against a McDonald's

Using Euclidean Distances. Monopoly price is $3.57.

Distance from central firm	Price	Price if the firms are jointly-owned
0 miles	$3.38	$3.83
0.5 miles	$3.41	$3.82
1 mile	$3.47	$3.79
1.5 miles	$3.52	$3.75
2 miles	$3.55	$3.70
2.5 miles	$3.56	$3.66

TABLE 5A: McDonald's and 2 Burger Kings – price for McDonald's

Distance from McDonald's	Price when on opposite sides	Price when on same side
0 miles	$3.43	$3.43
0.5 miles	$3.45	$3.45
1 mile	$3.49	$3.50
1.5 miles	$3.53	$3.53
2 miles	$3.55	$3.55
2.5 miles	$3.56	$3.56

TABLE 5B: 3 McDonald's

Distance from McDonald's	Price when on opposite sides	Price when on same side
0 miles	$3.28	$3.28
0.5 miles	$3.30	$3.32
1 mile	$3.38	$3.40
1.5 miles	$3.46	$3.47
2 miles	$3.52	$3.52
2.5 miles	$3.55	$3.55

Monopoly Price in both tables = $3.57.

Note: Tables 5A and 5B assume that consumers travel using the route that minimized the Euclidean distance.

TABLE 6: 3128 El Camino

Price	Quantity (1000s)	Variable Profits	Price for joint profit-max.	Distance from Mall	Distance to Burger King
$3.59	13.14	36.52	$3.60	0	4.30
$3.58	13.42	37.15	$3.59	0.11	4.19
$3.54	13.36	36.45	$3.55	0.22	4.09
$3.50	13.15	35.32	$3.51	0.32	3.98
$3.46	12.89	34.15	$3.47	0.43	3.87
$3.43	12.60	33.05	$3.45	0.54	3.76
$3.42	12.30	32.08	$3.43	0.65	3.66
$3.41	12.01	31.28	$3.43	0.75	3.55
$3.42	11.72	30.63	$3.45	0.86	3.44
$3.44	11.44	30.15	$3.47	0.97	3.33
$3.47	11.18	29.78	$3.50	1.08	3.23
$3.51	10.93	29.49	$3.54	1.18	3.12
$3.54	10.70	29.22	$3.58	1.29	3.01
$3.57	10.47	28.89	$3.61	1.40	2.90
$3.59	10.25	28.47	$3.64	1.51	2.80
$3.60	10.03	27.94	$3.65	1.61	2.69
$3.59	9.81	27.33	$3.66	1.72	2.58
$3.59	9.60	26.63	$3.66	1.83	2.47
$3.57	9.38	25.88	$3.65	1.94	2.37
$3.55	9.17	25.12	$3.64	2.04	2.26
$3.53	8.97	24.42	$3.64	2.15	2.15
$3.52	8.77	23.80	$3.64	2.26	2.04
$3.52	8.58	23.27	$3.65	2.37	1.94
$3.53	8.41	22.85	$3.68	2.47	1.83
$3.54	8.25	22.52	$3.70	2.58	1.72
$3.56	8.10	22.25	$3.74	2.69	1.61
$3.57	7.97	22.01	$3.77	2.80	1.51
$3.58	7.86	21.78	$3.80	2.90	1.40
$3.59	7.76	21.56	$3.83	3.01	1.29
$3.59	7.68	21.35	$3.85	3.12	1.18
$3.59	7.62	21.17	$3.88	3.23	1.08
$3.59	7.57	21.03	$3.90	3.33	0.97
$3.58	7.54	20.90	$3.92	3.44	0.86
$3.57	7.52	20.75	$3.93	3.55	0.75
$3.55	7.52	20.60	$3.94	3.66	0.65
$3.53	7.53	20.50	$3.95	3.76	0.54
$3.52	7.56	20.48	$3.97	3.87	0.43
$3.51	7.60	20.50	$3.98	3.98	0.32
$3.49	7.66	20.54	$4.00	4.09	0.22
$3.48	7.72	20.59	$4.01	4.19	0.11
$3.46	7.80	20.67	$4.03	4.30	0

TABLE 7: 3128 El Camino if All Outlets Swapped Brand Affiliation

Price	Quantity (1000s)	Variable Profits	Price for joint profit-max.	Distance from Mall	Distance to Burger King
$ 3.36	6.06	14.81	$3.37	0	4.30
$ 3.36	6.14	14.96	$3.36	0.11	4.19
$ 3.33	5.97	14.41	$3.34	0.22	4.09
$ 3.31	5.72	13.67	$3.31	0.32	3.98
$ 3.29	5.47	12.95	$3.29	0.43	3.87
$ 3.27	5.23	12.30	$3.27	0.54	3.76
$ 3.26	5.02	11.76	$3.26	0.65	3.66
$ 3.26	4.85	11.32	$3.26	0.75	3.55
$ 3.26	4.70	11.00	$3.27	0.86	3.44
$ 3.27	4.59	10.78	$3.28	0.97	3.33
$ 3.28	4.50	10.64	$3.29	1.08	3.23
$ 3.30	4.43	10.54	$3.31	1.18	3.12
$ 3.32	4.36	10.46	$3.33	1.29	3.01
$ 3.33	4.29	10.34	$3.34	1.40	2.90
$ 3.34	4.21	10.17	$3.35	1.51	2.80
$ 3.34	4.11	9.94	$3.36	1.61	2.69
$ 3.34	3.99	9.65	$3.36	1.72	2.58
$ 3.33	3.86	9.32	$3.35	1.83	2.47
$ 3.32	3.73	8.95	$3.34	1.94	2.37
$ 3.31	3.59	8.58	$3.33	2.04	2.26
$ 3.30	3.47	8.25	$3.33	2.15	2.15
$ 3.29	3.36	7.97	$3.32	2.26	2.04
$ 3.29	3.27	7.75	$3.33	2.37	1.94
$ 3.29	3.20	7.59	$3.34	2.47	1.83
$ 3.30	3.14	7.47	$3.35	2.58	1.72
$ 3.31	3.09	7.39	$3.36	2.69	1.61
$ 3.32	3.05	7.32	$3.38	2.80	1.51
$ 3.32	3.01	7.23	$3.39	2.90	1.40
$ 3.32	2.97	7.14	$3.39	3.01	1.29
$ 3.32	2.93	7.03	$3.40	3.12	1.18
$ 3.31	2.90	6.94	$3.40	3.23	1.08
$ 3.31	2.87	6.87	$3.41	3.33	0.97
$ 3.31	2.85	6.80	$3.41	3.44	0.86
$ 3.30	2.82	6.71	$3.41	3.55	0.75
$ 3.29	2.79	6.60	$3.41	3.66	0.65
$ 3.27	2.77	6.53	$3.41	3.76	0.54
$ 3.27	2.77	6.50	$3.41	3.87	0.43
$ 3.26	2.78	6.50	$3.42	3.98	0.32
$ 3.25	2.79	6.51	$3.42	4.09	0.22
$ 3.25	2.80	6.53	$3.43	4.19	0.11
$ 3.25	2.83	6.57	$3.44	4.30	0

TABLE 8: 3128 El Camino – mall weighted population equivalent = 8,000

Price	Quantity (1000s)	Variable Profits	Price for joint profit-max.	Distance from Mall	Distance to Burger King
$3.47	7.93	21.10	$3.60	0	4.30
$3.47	8.27	21.96	$3.59	0.11	4.19
$3.45	8.50	22.42	$3.55	0.22	4.09
$3.43	8.67	22.72	$3.51	0.32	3.98
$3.42	8.81	22.97	$3.47	0.43	3.87
$3.41	8.92	23.22	$3.45	0.54	3.76
$3.42	9.01	23.49	$3.43	0.65	3.66
$3.43	9.08	23.79	$3.43	0.75	3.55
$3.45	9.14	24.15	$3.45	0.86	3.44
$3.48	9.18	24.55	$3.47	0.97	3.33
$3.52	9.22	24.98	$3.50	1.08	3.23
$3.56	9.24	25.38	$3.54	1.18	3.12
$3.59	9.24	25.70	$3.58	1.29	3.01
$3.62	9.22	25.89	$3.61	1.40	2.90
$3.63	9.18	25.92	$3.64	1.51	2.80
$3.64	9.12	25.77	$3.65	1.61	2.69
$3.63	9.04	25.48	$3.66	1.72	2.58
$3.62	8.93	25.06	$3.66	1.83	2.47
$3.59	8.82	24.54	$3.65	1.94	2.37
$3.57	8.69	23.98	$3.64	2.04	2.26
$3.55	8.56	23.45	$3.64	2.15	2.15
$3.54	8.42	22.98	$3.64	2.26	2.04
$3.53	8.29	22.58	$3.65	2.37	1.94
$3.54	8.16	22.26	$3.68	2.47	1.83
$3.55	8.03	22.02	$3.70	2.58	1.72
$3.57	7.92	21.82	$3.74	2.69	1.61
$3.58	7.82	21.65	$3.77	2.80	1.51
$3.59	7.73	21.48	$3.80	2.90	1.40
$3.60	7.65	21.31	$3.83	3.01	1.29
$3.60	7.59	21.14	$3.85	3.12	1.18
$3.59	7.54	20.99	$3.88	3.23	1.08
$3.59	7.50	20.88	$3.90	3.33	0.97
$3.59	7.48	20.77	$3.92	3.44	0.86
$3.57	7.47	20.64	$3.93	3.55	0.75
$3.55	7.48	20.51	$3.94	3.66	0.65
$3.53	7.50	20.42	$3.95	3.76	0.54
$3.52	7.53	20.41	$3.97	3.87	0.43
$3.51	7.58	20.44	$3.98	3.98	0.32
$3.49	7.64	20.49	$4.00	4.09	0.22
$3.48	7.71	20.55	$4.01	4.19	0.11
$3.46	7.79	20.64	$4.03	4.30	0