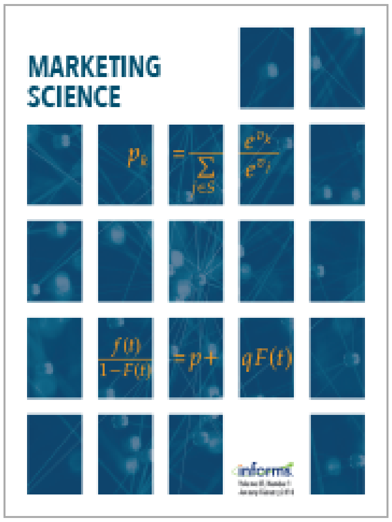

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Measuring the Impact of Negative Demand Shocks on Car Dealer Networks

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The goal of this paper is to study the behavior of consumers, dealers, and manufacturers in the car sector and present an approach that can be used by managers and policy makers to investigate the impact of significant demand shocks on profits, prices, and dealer networks. More specifically, we investigate consumer demand, substitution patterns, and price decisions across different cars and dealer locations to identify dealerships with low margins or high fixed costs and measure the value of closing down dealerships for manufacturers. We apply our model empirically to the San Diego area using a transactional data set with information about the locations of dealers and consumers, as well as manufacturer and retail prices. We find strong consumer disutility for travel and find that dealers have local demand areas that are shared with a small set of competitors. We show that a reduction of market demand by 30% over two years, similar to the economic crisis of 2008–2009, results in an annual drop in prices of approximately 11%. We discuss this price drop in the context of the 2009 federal policy measure known as the Car Allowance Rebate System program. We compare predictions and actual dealership closings in the General Motors and Chrysler dealer networks as an application of our approach.

Key words: automobile industry; spatial competition; models of demand and supply
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> GM intends to have the right number of brands, sold by the right number of dealers, in the right locations to obtain maximum profitability to GM and the retailer network. (General Motors Corporation 2008, p. 19)

1. Introduction

In 2009 and the first half of 2010, the car industry suffered a significant decline in demand as a result of the economic crisis that started in October 2008. The increase in the price of gas, combined with the real estate and financial crises, lowered the yearly number of vehicles sold from the usual number of 16.5 million in 2007 to a projected number of about 12 million in 2009 (General Motors Corporation 2008).[1] Because of the decline in demand, several companies, including General Motors (GM) and Chrysler, found themselves in a dire situation, with a significant number of unprofitable dealerships. To respond to the crisis, one of the proposed actions taken by car manufacturers was to announce a reduction in the size of dealer networks. An excessively large network of dealers imposes significant costs to the manufacturer, including distribution costs, marketing, and quality control. It can also have a negative impact on the demand for the manufacturer's brand. For example, if sales are too infrequent, a dealership owner does not have the resources to reinvest in the dealership, and the manufacturer loses potential buyers who see old-fashioned and poorly maintained showrooms. Additionally, having too many car dealerships of the same manufacturer in a geographic region leads to high competition intensity, which may result in lower margins for both dealers and manufacturers. To reduce the negative impact from having too many dealerships, car companies have the option to close the less profitable dealers in their networks. For example, GM plans to consolidate its dealer network, reducing the number of dealers from 6,450 in 2008 to 4,700 in 2012 (General Motors Corporation 2008).

In this context, the goal of this paper is to study the behavior of consumers, dealers, and manufacturers in the car sector and to present an approach that can be used by managers and policy makers to investigate the impact of significant demand shocks on industry profits, prices, and market structure. More specifically, in the context of dealer network reductions, we investigate consumer demand, substitution patterns, and

[1] The actual number, according to Reuters (Krolicki and Kim 2010), was 10.4 million in 2009.

firm price decisions across different cars and different dealer locations to provide guidance on closing down dealerships for manufacturers while taking into account margin adjustments and spatial substitution.

We start by studying demand in the automobile industry, which has been the focus of several studies in recent years, both in economics and in marketing. This literature has covered a variety of themes, such as the analysis of demand and supply in the auto industry (Berry et al. 1995, 2004; Sudhir 2001), the influence of the Internet on prices (e.g., Zettelmeyer et al. 2007, Scott Morton et al. 2001), and the impact of innovations on consumer demand—for example, the introduction of minivans (Petrin 2002) and SUVs (Luan et al. 2007). These studies provide considerable insights into how car manufacturers compete and how consumers react to product characteristics and marketing activities. However, central to our research, these studies tend to disregard the role played by the location of customers and retailers. In particular, little is known about how dealer location and the geographic distribution of consumers interrelate to shape demand and competition patterns in the car industry. In this paper, we allow that the location of customers and retailers plays an important role in the optimal size of a manufacturer's dealer network. To this end, we define each choice alternative as a combination of a car, with its product attributes, and a dealer, with its own characteristics and location; its utility is therefore informative about the trade-off between preferences for dealer location and car characteristics, including price.

We also model the pricing behavior of both manufacturers and dealers. Manufacturers move first and decide on the wholesale price for each car model. Retailers take the manufacturer price as given and set prices to maximize their own profits. From this analysis, we estimate the variable costs of manufacturers and retailers. Next, we estimate the fixed costs of dealerships, using the moment inequalities approach proposed in Pakes et al. (2008). With these estimates, it is possible to evaluate the impact of a negative shock on market demand, on the optimal dealer network size, and on the closings of dealerships. Our approach is suitable for such counterfactual analysis because we measure both the demand and supply of cars at the dealer level, and thus we can quantify the effects of closing a dealership on costs and margins.

To make these inferences, we use a unique individual-level data set with transaction information about dealer and manufacturer prices, car characteristics, and zip code locations of sellers and buyers. We augment this transactional data using census information on consumer demographics, and we estimate the demand parameters of our individual-level model using simulated maximum likelihood, while taking into account consumer heterogeneity and endogeneity between prices and unobserved car attributes. We use a demand model that accounts for observed heterogeneity at the zip code level, includes location and dealer effects, and accounts for correlation in the error term across similar alternatives.

We apply our methodology to the car industry in the San Diego area. In terms of demand, our results show that consumers treat alternatives of the same car type[2] as close substitutes, and they do so even more if cars share the same brand. When deciding where to buy a car, we infer that consumers dislike traveling a long distance to car dealerships and that most of the demand for a car dealership originates from consumers located in close proximity. As a result, dealers typically have their own local demand "backyard," the size of which is determined by the location of competitors. For instance, we find cases where the highest level of demand is not at the location of the dealer but instead is at locations that are farthest from direct substitutes. In addition to characterizing the geographic trading area of car dealerships, we also compute the geographic areas of demand at the manufacturer level by consolidating the market areas of its dealers, and we report some interesting patterns in location decisions. For instance, consistent with theories of spatial competition, we find that Honda and Toyota target different geographic areas to minimize overlap and create spatial differentiation between the two manufacturers.

Regarding the supply side, we find that the average manufacturer's gross margin per car is about $12,500, which includes both the immediate margin at the time of sale and other future cash flows related to the sale of the car. The margin for American manufacturers from premium SUV sales is estimated to lie between $5,000 and $15,000 (Lienert 2003). Our findings are in the higher end of this spectrum for margins. This seems reasonable because our estimates are for San Diego, a location where consumers have, on average, higher purchasing power, and most of the included car brands and types are in the medium- to high-end price segments.

Car dealers obtain a much lower margin on new cars. The observed gross margins of the dealers in the new cars divisions are 6.5%, with an average value of approximately $1,600. In addition to having consumer location data, we also observe wholesale prices, another unique aspect of our data set, which allows us to estimate other sources of retailer revenues, such as car servicing and parts. Taking our estimate of the latter into account, dealer margins go up to about $6,000 per vehicle. We estimate dealer fixed

[2] Car types are defined as large SUVs, small SUVs, midsize cars, and near-luxury cars.

costs to be, on average, \$3.6 million per year, similar in magnitude to the national average of \$2.8 million reported by the National Automobile Dealers Association (NADA 2008). The somewhat higher value of our estimate might be expected given land values in Southern California. Dealer fixed costs are estimated to drop outside the San Diego and Escondido city centers, where real estate prices are lower in the suburbs.

Combining demand and supply, we evaluate the impact of a significant reduction of demand on dealer network size and quantify changes in profit, prices, and demand. We simulate a negative shock of demand of the same magnitude as the one that occurred in the United States in 2008 and 2009—that is, a drop in demand of about 30% in those two years. In such a scenario, our model predicts that average dealer and manufacturer prices would decrease by an annual average of 11% and predicts a drop in the total gross margins of about 35%. We relate this price decrease to the Car Allowance Rebate System (also known as the "cash for clunkers" program) used by the U.S. government to provide temporary price discounts to consumers. Finally, we discuss actual dealership closings in the Chrysler and GM networks as a managerial application of our model, and we find that the implications of our model broadly agree with the closings of car dealerships implemented by the firms.

The rest of our paper is structured as follows. The next section discusses the relevant literature. The description of the model is included in §3. Section 4 provides details about the several data sets used in the paper. The estimation algorithm is presented in §5, and the results are discussed in §6. Section 7 describes managerial applications, and §8 concludes.

2. Background

Our work is related to previous papers about the car industry, spatial competition, and management of networks. Berry et al. (1995) develop a model of the automotive industry to analyze the demand and supply of differentiated cars using aggregate-level data. Berry et al. (2004) expand on this methodology to combine micro and macro data. Among other results, the authors are able to produce demand elasticities of price and other observed attributes, and they find considerable variability across types of cars and models. Sudhir (2001) suggests that manufacturer competitive behavior may depend on the car type. Regarding the introduction of new products in the car industry, Petrin (2002) analyzes the impact of the introduction of the minivan on consumer welfare, and Luan et al. (2007) evaluate the evolution of consumer preferences and market structure during the introduction and takeoff of SUVs. Whereas this literature provides valuable insights on the interaction among car manufacturers and between car manufacturers and consumers, it assumes that consumers trade off all alternatives based solely on car attributes and not on the locations of car dealerships.

In contrast, the location of customers relative to retailers is central in the literature on spatial competition. Indeed, location has been shown to serve as input for managerial decisions on pricing (e.g., Ellickson and Misra 2008), store customization (e.g., Hoch et al. 1995), and store locations (e.g., Duan and Mela 2009). Industry research has also shown that a large percentage of variance in consumer store choice in the grocery trade is explained by location (Hofbauer 2011). Finally, the role of the location of consumers has been investigated in several important industries, such as the hospitality (Mazzeo 2002, Venkataraman and Kadiyali 2007), fast-food (Thomadsen 2007), and movie theater (Davis 2001) industries.[3] We believe that the location of customers relative to dealerships is also of great importance to car manufacturers, especially in cases where manufacturers seek to change their dealer networks. However, a good understanding of this competitive environment and its characterization across geography is lacking in the literature. Our paper seeks to fill this gap by combining a spatial demand model in the auto industry with the analysis of both manufacturer and retailer pricing decisions as a means to provide a complete analysis of car dealer networks.

A third, important strand of literature is on the management of outlet networks. For example, Ishii (2008) studies networks of ATM machines, based on consumer demand and bank competition. Ho (2009) studies networks of hospitals managed by healthcare insurance and estimates the division of profits between health plans and hospitals. These studies use recent advances in empirical methodology from the studies on moment inequalities (Pakes et al. 2008). We combine such advances in the management of networks with our spatial demand and competition analysis to evaluate changes in dealer networks in the auto industry, in response to large demand shocks.

3. Model

On the demand side, we model the consumer's choice of purchasing a car as a function of car and dealer characteristics, as well as the geographic distance between consumer and dealer locations. On the supply side, we assume profit-maximizing behavior by manufacturers and dealers, which provides estimates

[3] There is a recent study on the demand effects of dealer accessibility and concentration in the auto industry (Bucklin et al. 2008). However, this study neither focuses on the supply side of dealer networks nor measures the impact of changes in demand for dealers and manufacturers.

of variable costs and margins. We then use the realizations of network size and locations to identify fixed costs of dealerships. Together, the demand and supply models are used to run counterfactual scenarios in policy simulations and provide guidance to managerial decisions.

3.1. Demand Utility Specification

A number of households H_z living in zip code z consider purchasing a car. The total number of households in the market is $H = \sum_{z=1,\ldots,Z} H_z$. Household i, living in zip code z, chooses either to purchase a car or to use a different means of transportation.[4] The households that buy cars may choose among j alternatives, each of them characterized by its dealer, brand, and car type. There are four car types in our data set: midsize cars, near-luxury cars, small SUVs, and large SUVs.[5] We define our observations at the quarterly level, with individuals who make car purchase decisions in the same quarter under the same market conditions, such as car prices and availability.

The indirect utility for consumer i of purchasing car j—a vehicle of brand b, type m, sold at dealer d—is given by

$$\begin{aligned} U_{ijt} &= \alpha_{ij} + \lambda_i x_{jt} + \beta_i p_{jt} + \gamma_1 g_{ij} + \gamma_2 g_{ij}^2 + \xi_{jt} + e_{ijt} \\ &= V_{ijt} + e_{ijt}, \end{aligned} \tag{1}$$

with

$$e_{ijt} = v_{im_jt} + (1-\sigma_M) v_{ib_jt} + (1-\sigma_B)(1-\sigma_M)\varepsilon_{ijt}. \tag{2}$$

The first component of the utility α_{ij} includes dealer- and car type-specific intercepts and the interaction of these intercepts with demographic characteristics. The term x_{jt} is a vector of observed car characteristics, such as engine size and transmission type. The term p_{jt} represents the price for alternative j at time t. The term g_{ij} is the geographic distance between individual i and the location of the dealer that sells j, measured as the Euclidean distance between the zip code centroid of i and j. The impact of distance on utility is modeled as a quadratic function to account for the nonlinear effects of distance on utility. The term ξ_{jt} captures the impact of car attributes unobserved to the researcher but taken into consideration by both consumers and supply agents. Typically, these demand shocks are positively correlated with prices, causing endogeneity bias if not accounted for.

Heterogeneity in coefficients α_{ij}, λ_i, and β_i is included using draws from known demographic distributions (e.g., income) for the zip code location of individual i. We allow for correlation within cars of the same type and within cars of same brand using a nested logit formulation for the components of the unobservable term e_{ijt}.[6] The parameter σ_B is a measure of unobserved correlation in brand tastes, and σ_M captures the correlation of tastes for car types, with $0 \le \sigma_B \le 1$ and $0 \le \sigma_M \le 1$. The utility function is derived from a variance components formulation, described in Cardell (1997) and Richards (2007). The distributions of v_{im_jt} and v_{ib_jt} are assumed to be conjugate to the extreme value distribution such that $v_{im_jt} + (1-\sigma_M)v_{ib_jt} + (1-\sigma_B)(1-\sigma_M)\varepsilon_{ijt}$ is also extreme value distributed (Cardell 1997).

This formulation can support flexible substitution patterns. Alternatives that share the same type will be more strongly correlated and be closer substitutes as σ_M approaches 1. Conditional on car type, the correlation between alternatives sharing the same brand will be higher than alternatives that do not share the same brand as σ_B approaches 1. In other words, substitution will be stronger within type or within brand as parameters σ_M and σ_B get closer to 1, respectively. The model reduces to the multinomial logit model with consumer heterogeneity if both parameters are equal to 0. We note that the independence of irrelevant alternatives (IIA) property of the aggregate logit model is avoided with the inclusion of the type and brand nests; individual distance between household and retailers; and heterogeneity in the preferences for dealers, car makes, and price sensitivities.

Our choice of nests is guided by the observed similarity of attributes within car type and brand. Cars differ more across types than across brands, leading us to choose a first level of nests defined by car type and a second level of nests composed of alternatives of same type and brand. Consumers are expected to segment the category in similar ways, substituting more readily among alternatives of the same type. We have also tested the use of demand models with other correlation structures, following Swait (2001), with more-complex nested logit trees. We did not find a significant improvement in fit and therefore chose the simpler nested logit model as described. For identification purposes, the deterministic part of the utility of the outside good is set to 0.

[4] The outside option also includes car purchases made at dealers that are not in our analysis and vehicles not covered in our data set.

[5] Each car type is defined as a set of car models using the classification defined by the research company that provided the data in our empirical section. Vehicles that belong to the same type have significant similarities across a number of dimensions.

[6] The errors e_{ijt} are assumed to be spatially independent, conditional on the distance effects included in the utility function. That is, we assume that spatial dependencies can be captured via a flexible function of distance.

With these assumptions, the probability of household i choosing alternative j, a car of type m, and brand b is[7]

$$\Pr_i(j) = \Pr_i(j \mid b(m)) \times \Pr_i(b(m) \mid m) \times \Pr_i(m), \qquad (3)$$

where $\Pr_i(m)$ is the marginal probability of choosing the car type m or the outside good; $\Pr_i(b(m) \mid m)$ is the probability of choosing brand b, given the choice of type m; and $\Pr_i(j \mid b(m))$ is the probability of buying j—a unique combination of dealer, car type, and brand—given that brand b in type m is chosen. The conditional and marginal probabilities are

$$\Pr_i(j \mid b(m)) = \frac{\exp((1/(1-\sigma_B)(1-\sigma_M))V_{ij})}{\sum_{j'\in b(m)}\exp((1/(1-\sigma_B)(1-\sigma_M))V_{ij'})}, \qquad (4)$$

$$\Pr_i(b(m) \mid m) = \frac{\exp((1-\sigma_B)IV_{ib(m)})}{\sum_{b'\in m}\exp((1-\sigma_B)IV_{ib'})}, \quad \text{and} \qquad (5)$$

$$\Pr_i(m) = \frac{\exp((1-\sigma_M)IV_{im})}{1+\sum_{m'}\exp((1-\sigma_M)IV_{im'})}, \qquad (6)$$

where $IV_{ib(m)}$ and IV_{im} are the inclusive values of brand nest b and type m, respectively, which are equal to

$$IV_{ib(m)} = \ln \sum_{j\in b(m)} \exp\left(\frac{1}{(1-\sigma_B)(1-\sigma_M)} V_{ij}\right) \qquad (7)$$

and

$$IV_{im} = \ln \sum_{b\in m} \exp((1-\sigma_B)IV_{ib}). \qquad (8)$$

3.2. Manufacturers and Dealers

To predict managers' decisions when faced with alternative demand conditions, we seek to obtain estimates of costs related to dealer networks. For this reason, we model the behavior of both manufacturers and dealers. The supply side of the market has K manufacturers and D dealers. Manufacturers first decide on the number of the dealers in the market. They then set wholesale prices. Next, dealers choose final prices taking wholesale prices as given.[8]

3.2.1. The Conduct of Manufacturers. Given a dealer network, manufacturers maximize profits by choosing the average wholesale price of each make–model at each dealer for each time period t (again, we remove the time subscript for clarity). The profit of manufacturer k is given by

$$\pi_k = \sum_{j\in k}(w_j - c_j)\cdot s_j \cdot H - (x_k\rho_1 + v_k)n_k - f_k, \qquad (9)$$

where w_j is the wholesale price of alternative j, and c_j is the manufacturer variable cost. The product of the market share[9] s_j and the number of households in the market H represents the total number of vehicles sold of alternative j. The fixed costs incurred by the manufacturer when managing and supplying its network of dealers are modeled as $(x_k\rho_1 + v_k)n_k$, where n_k is number of dealers of manufacturer k, x_k is a vector of cost shifters, and ρ_1 is a vector of parameters to be estimated. We allow for measurement errors in costs, v_k, that are unobserved to the manufacturer and the researcher and are assumed to be uncorrelated with x_k.[10] Finally, f_k are other fixed costs associated with manufacturer k not dependent on the dealer network.

We briefly discuss what is observed and estimated in Equation (9). In the first component of profits, $\sum_{j\in k}(w_j - c_j)\cdot s_j \cdot H$, we observe both w_j and H in our data, and s_j is obtained from the demand model. Therefore the only unobserved component is c_j, which is estimated using the first-order profit-maximizing conditions of manufacturers. In the second component, $(x_k\rho_1 + v_k)n_k$, we observe x_k and n_k and estimate the parameter vector ρ_1, and v_k drops out of our estimation. Further details on our estimation approach are provided in §5. Finally, we do not have any variation in the data that can identify f_k, and so this part of the manufacturer fixed costs is not estimated. We assume that the optimal dealer network size and price do not depend on f_k.

3.2.2. The Conduct of Car Dealers. Dealers take manufacturer prices as given and compete on prices charged to consumers. The profit function of the dealer is given by

$$\pi_d = \sum_{j\in d}[p_j - w_j + \delta_j]\cdot s_j \cdot H - f_d. \qquad (10)$$

The component in brackets represents the unit margin for each car sold and equals the difference between the consumer price p_j and manufacturer price w_j, plus any additional cash flows δ_j (such as car service revenues) associated with vehicle j. We assume δ_j are fixed quantities set on the basis of industry standards and manufacturing servicing manuals and are not strategically set by the retailer,[11] and f_d are the fixed costs of dealer d.

To obtain the optimal pricing decisions in the industry, we solve backward. The first-order conditions of the dealer's pricing problem are (in vector form)

$$P - W + \Delta = -(\Theta_D \odot \Omega_p)^{-1} S. \qquad (11)$$

[7] The subscript t was removed for clarity of exposition.

[8] Our assumption is consistent with industry reports that generally depict manufacturers as the leaders in setting prices. However, it is possible to test other pricing strategies, as in Villas-Boas (2007).

[9] In our model, the estimated market shares are obtained by averaging the choice probabilities $\Pr_i(j)$ across consumers.

[10] In §5, we also discuss a robustness check where we use instruments to account for a possible correlation between ν_k and x_k.

[11] It is possible that δ_j are in some way related to prices and are endogenous. If so, this would be an additional decision variable for dealers. We simplify our model by focusing only on the retailers' price decision and abstract from the decision to price additional services.

In this formulation, P and W are the vectors of consumer and manufacturer prices, respectively, and Δ is the vector of additional cash flows of dealers. The term Θ_D is a dealer ownership matrix where $\Theta_D(j, j') = 1$ if alternatives j and j' are sold by the same dealer. The term Ω_p is a matrix of derivatives of share with respect to final price, and a typical element j, j' of the matrix Ω_p is defined as $\partial s_{j'}/\partial p_j$. We use the symbol $\odot$ to represent element-by-element multiplication. Both P and W are observed in our data, which allows Δ to be evaluated (after using the demand estimates to compute Ω_p). Assuming a unique equilibrium,[12] Equation (11) defines the price charged by dealers as a function of manufacturer prices.

We now turn to the manufacturer pricing strategy. We assume that manufacturers maximize profits and play a Bertrand–Nash pricing game, taking into account that dealers set prices according to Equation (11). The optimal manufacturer margins are given by the first-order conditions, again presented in vector form:

$$W - C = -(\Theta_K \odot \Omega_w)^{-1} S, \tag{12}$$

where C is a vector of manufacturer variable costs, S is a vector of market shares, and Θ_K is a manufacturer ownership matrix. In this matrix, $\Theta_K(j, j') = 1$ if alternatives j and j' are sold by the same manufacturer. The term Ω_w is a matrix of derivatives of share with respect to wholesale price, and a typical element j, j' of the matrix Ω_w is defined as $\partial s_{j'}/\partial w_j$. To obtain these quantities, we use the chain rule and note that $\partial s_{j'}/\partial w_j = \sum_{j''}(\partial s_{j'}/\partial p_{j''} \cdot \partial p_{j''}/\partial w_j)$. The terms $\partial s/\partial p$ can be obtained numerically once the demand-side parameters have been estimated. To compute the relation between consumer and wholesale prices (i.e., $\partial p/\partial w$), we use the recent work by Villas-Boas (2007, pp. 633–634), who studies vertical interaction between retailers and manufacturers. Consider that these terms are arranged in a matrix Ω_r, with a typical element j, j' consisting of $\partial p_j/\partial w_{j'}$. When manufacturers set their prices first and retailers follow, Villas-Boas (2007) shows that the fth column of Ω_r is given by $\Gamma^{-1} G_f$, where Γ is a matrix of size $J \times J$, with element (j, j') given by

$$\Gamma(j, j') = \frac{\partial s_j}{\partial p_{j'}} + \sum_{l=1}^{J}\left(\Theta_D(l, j)\frac{\partial^2 s_l}{\partial p_j \partial p_{j'}}(p_l - w_l + \delta_l)\right) + \Theta_D(j', j)\frac{\partial s_{j'}}{\partial p_j}, \tag{13}$$

and G_f is a vector of size $J \times 1$, with elements

$$G_f(j, f) = \Theta_D(f, j)\frac{\partial s_f}{\partial p_j}. \tag{14}$$

[12] The assumption of the existence of a unique equilibrium is common in similar papers. For an example, see Villas-Boas (2007).

Finally, we can compute the unknowns in Equation (12) using the chain rule $\Omega_w = \Omega_r' \Omega_p$. Once the demand parameters are estimated, and Ω_p and Ω_r are evaluated numerically, we can obtain the implied manufacturer variable costs C, because we observe W in our data set.

3.3. Car Dealership Networks

To evaluate decisions regarding the size of dealership networks, we also estimate the fixed costs of each dealership. The manufacturer profits in Equation (9) can be rewritten in the following way:

$$\pi_k = R_k(\Lambda, n_k, n_{-k}) - (x_k \rho_1 + v_k) n_k - f_k. \tag{15}$$

Here, $R_k(\Lambda, n_k, n_{-k})$ are the variable profits of manufacturer k, n_k and n_{-k} are the number of dealers in the network of manufacturer k and of all other manufacturers $-k$, and Λ summarizes the information about the data and remaining parameters. As previously described, $(x_k \rho_1 + v_k) n_k$ represents the fixed costs incurred by the manufacturer that are a function of the size of the dealer network, where x_k is a vector of observed cost shifters, ρ_1 is a vector of parameters to be estimated, and v_k is an unobserved component.

3.3.1. Manufacturer Fixed Cost. We assume that each manufacturer maximizes its expected profit by choosing the optimal number of dealerships in its network n_k. Any deviation from the chosen n_k—for instance, $n_k - 1$ or $n_k + 1$—is assumed to result in lower profits. This is a necessary condition for profit maximization that is also sufficient when profits are concave in n_k (Ishii 2008). The choice of n_k satisfies the following conditions:

$$\pi_k(\Lambda, n_k, n_{-k}, x_k, \rho_1) > \pi_k(\Lambda, n_k - 1, n_{-k}, x_k, \rho_1),$$
$$\pi_k(\Lambda, n_k, n_{-k}, x_k, \rho_1) > \pi_k(\Lambda, n_k + 1, n_{-k}, x_k, \rho_1),$$

which implies

$$\begin{aligned} x_k \rho_1 + v_k &\le R(\Lambda, n_k, n_{-k}) - R_k(\Lambda, n_k - 1, n_{-k}),\\ x_k \rho_1 + v_k &\ge R(\Lambda, n_k + 1, n_{-k}) - R_k(\Lambda, n_k, n_{-k}). \end{aligned} \tag{16}$$

Once demand parameters and margins for manufacturers are estimated, we can compute manufacturer variable profits of counterfactual scenarios. In this particular case, we evaluate the cases when manufacturer k increases or decreases its network by one dealer; i.e., we compute $R_k(\Lambda, n_k + 1, n_{-k})$ and $R_k(\Lambda, n_k - 1, n_{-k})$.

3.3.2. Dealer Fixed Cost. To estimate the fixed costs of each dealer, we use a similar approach. The profit function for car dealership d can be rewritten as

$$\pi_d = \pi_d(\Lambda, d_z, -d_z) = R_d(\Lambda, d_z, -d_z) - f_d.$$

The term $R_d(\Lambda, d_z, -d_z)$ represents the variable profits of the dealer, with dealership d and all other dealerships $-d$ located at the observed zip codes. We add a subscript z to dealer d to represent its current zip code location. The fixed costs of operation are denoted by f_d. We model these costs as having cost shifters x_d and an unobserved (to the researchers) component v_d:

$$f_d = x_d \rho_2 + v_d, \tag{17}$$

where ρ_2 is a vector of parameters to be estimated.

To estimate the cost parameters ρ_2, we make two assumptions: first, dealers remain in operation if their expected profits are larger than 0; second, the expected profits of the observed dealer location z are higher than expected profits at other locations z'.[13] This means that any geographic configuration of dealers different from the observed one is assumed to produce lower profits. We note that this estimation approach does not directly quantify the costs of closing down or moving a dealership, but it instead compares the expectations about annual profits to estimate the fixed costs of keeping the dealer operating.

With these assumptions, we obtain the following conditions:

$$\begin{aligned} & x_{d_z}\rho_2 + v_{d_z} < R(\Lambda, d_z, -d_z), \\ & \quad (x_{d_{z'}}\rho_2 + v_{d_{z'}}) - (x_{d_z}\rho_2 + v_{d_z}) \\ & \qquad > R(\Lambda, d_{z'}, -d_z) - R(\Lambda, d_z, -d_z), \end{aligned} \tag{18}$$

where $z' \neq z$. In the estimation, we assume that agents act on expected values of profits and costs, and that the expected value of the unobserved costs v_k and v_{d_z} is assumed to be 0 in order to create the inequalities to estimate the vector of parameters ρ_1 and ρ_2. With these parameters in hand, combined with the remaining estimates of demand parameters and margins, we can provide estimates of profits for dealers and manufacturers, as well as run counterfactual scenarios to help manufacturer decide which dealerships to close, in response to negative demand shocks.

4. Data

We combine several data sets to estimate our model. Our main data set was obtained from a large automobile research company, and it includes details about individual car transactions occurring in the San Diego area and its suburbs between 2004 and 2006.[14] We have information about each car make and model, as well as the following car characteristics: transaction price, engine size, fuel, and transmission type. Our data also contain the zip codes of dealer and consumer locations. Additionally, we have retail and wholesale prices for each car, as well as any manufacturer rebate given. The data are drawn from a sample of car transactions in the San Diego area, including 20% of all transactions. We complemented these data with U.S. Census demographic data on the income and population density at the zip code level. Finally, we also collected latitude and longitude data of both retailer and consumer zip codes from the Zipinfo database.[15] With these data, we computed distances between consumers and dealers measured in 100 miles.

For each vehicle, we use the transaction date and the number of days that the vehicle was on the lot before being sold to compute the arrival date. With this information, we know if alternative j was available to consumers at time t. For the last year of data, we do not have complete data on car availability, because some cars for which transactions occurred in 2007 (unobserved to us) would have been on the lot during 2006. Therefore, we drop the data from 2006 and focus our attention on the data from 2004 and 2005.

We observe 26,720 transactions in and around San Diego. We limit our analysis to the most important brands in the area, which are General Motors (with Cadillac, Chevrolet, and GMC), Ford, Honda, Hyundai, Chrysler, Toyota, and Volkswagen (VW). We also remove car models with a very small market share (<0.4%). Finally, we exclude from our data the transactions by consumers living in zip codes where the number of purchases is fewer than 50 transactions per year. After filtering, we retain 15,795 observations, or about 60% of total observed transactions.[16] Our data used in estimation include 22 different dealerships covering 9 car makes and a total of $J = 62$ dealer–brand–car–type unique combinations.

[13] To create counterfactual scenarios in both the manufacturer and retailer cases, we implicitly assume that agents have passive expectations, i.e., that the increase or decrease in the number of dealers does not change the agents perceptions of the market or that of their competitors. This is also an assumption in Pakes et al. (2008).

[14] To do a national analysis, we could repeat the analysis for multiple regional markets. For instance, in our case, we also have data for the Los Angeles market (the closest and largest market to San Diego) and find that there is only a very small number of transactions between San Diego dealers and Los Angeles consumers. Hence it seems reasonable to view San Diego as a separate market from Los Angeles. Our study could be repeated for the Los Angeles area without becoming infeasible, as well as for other markets.

[15] Available at http://www.zipinfo.com (accessed 2009).

[16] Our raw data include 20% of all transactions made in the San Diego area. After the filtering described here, the final percentage of transactions included in our data set is 12% (60% × 20%) of all purchases made in the San Diego area.

Table 1 Car Models Included in Our Study and the Size of Dealer Networks

Manufacturer	Network size	Car models
General Motors	3	Cadillac CTS, Cadillac Escalade, Chevrolet Tahoe, GMC Yukon
Ford	4	Escape, Expedition, Explorer, Explorer Sport
Chrysler	4	Jeep Grand Cherokee, Liberty, Wrangler
Toyota	3	4Runner, Camry, RAV4, Sequoia
Honda	3	Accord, CR-V, Element, Pilot
Hyundai	2	Santa Fe, Sonata
Volkswagen	3	Jetta, Passat

The size of the dealership networks and cars included in the data for each manufacturer are presented in Table 1. The dealer network sizes vary from two to four dealers. Collectively, our data cover a large diversity of cars, from midsized cars to large SUVs or near-luxury cars.

Figure 1 shows the average dealer and manufacturer prices, for a sample of alternatives, grouped by car type, for the midsized and near-luxury cars and for large SUVs. It reveals the presence of significant price variation across brands, even within car type, whereas prices of the same type of car sold at different dealers show much less variation. The manufacturer price is the value in the invoice of the car sale to the consumer. Our data set does not include any trade-in values that might be involved in a transaction, which happen in about 30%–40% of the transactions in California, or any financial costs to the consumer (and financial revenues for manufacturer and retailers) if the car was purchased on credit. We discuss the impact of trade-ins in §7.

A unique feature of our data is that we observe the location of both consumers and car dealers for each transaction, which allows for a better understanding of the spatial distribution of demand and supply. As an illustrative example, we display the location of Ford and Toyota dealers in Figure 2, as well as the distance traveled by their clientele. Panel (a) shows the spatial distribution of Ford dealerships. Ford has four dealerships in the San Diego area. For one of these dealers, panel (c) shows the geographic origin and concentration of a random sample of its customers. Of consumers that bought a car at this dealer, 87% were located at a distance fewer than 20 miles from the dealership, whereas 35% traveled fewer than 10 miles to buy their car. Panels (b) and (d) show similar examples for the Toyota brand. Across all dealers included in our analysis, consumers travelled an average of 10 miles to buy a car, whereas the median travel distance is 7.3 miles. Only 10% of the consumers travelled more than 20 miles, whereas about 27% of the consumers purchased a car at a dealer located fewer than 5 miles from their residences.

Figure 1 Retail and Wholesale Prices by Car Types and Brand

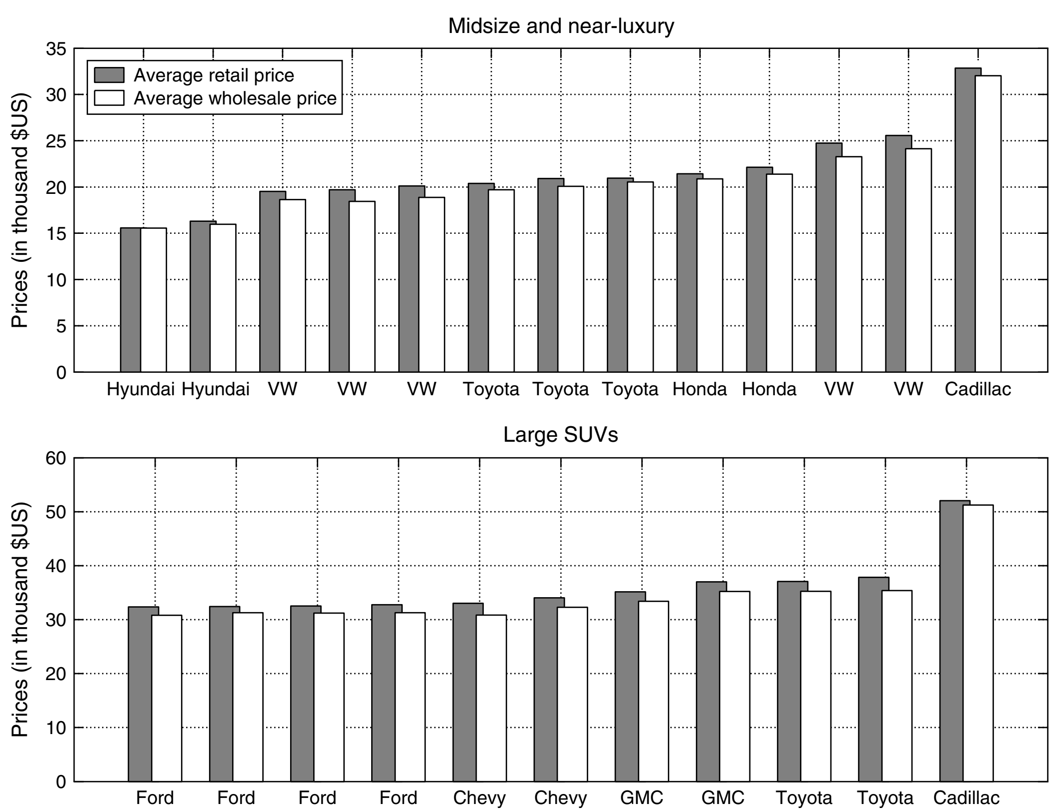
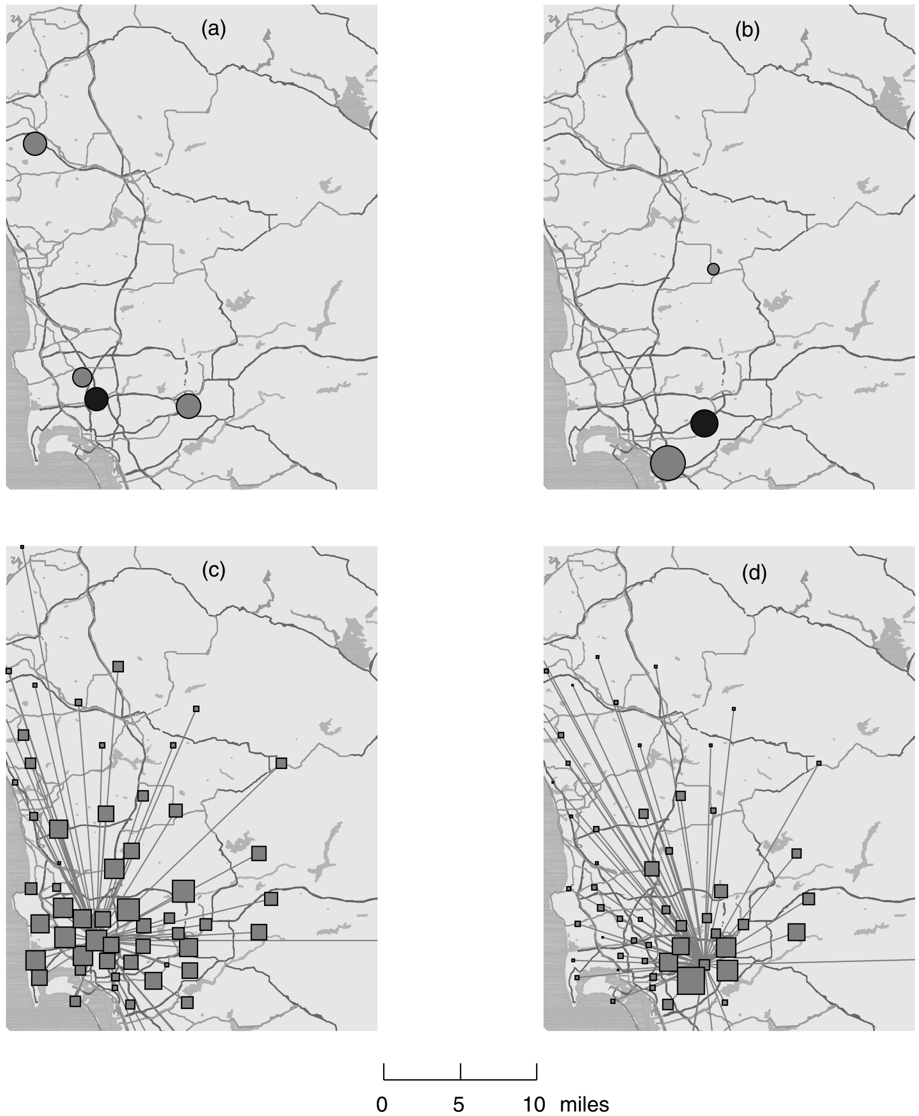


Figure 2 **Spatial Distribution of Dealers and Customers**



Notes. (a) Location of Ford dealerships, (b) location of Toyota dealerships, (c) location of customers who bought from the Ford dealer represented by the black circle, and (d) location of customers who bought from the Toyota dealer represented by the black circle. The plot symbols are proportional to how many cars were sold (dealers) or bought (consumers).

5. Estimation

5.1. Data Preparation

We address three aspects regarding the data before estimating the proposed model: (1) characteristics of alternatives not chosen, (2) total market size, and (3) unobserved attributes.

5.1.1. Characteristics of Alternatives Not Chosen. Transactional data sets commonly include information about the price paid by the consumer for the chosen alternative but not about prices that the same consumer would have been charged for alternatives not purchased. From the large number of transactions, we compute expected attribute values for the alternatives that were not chosen. Our data are similar in this respect to previous data sets used in the literature, such as Berry et al. (1995) and Petrin (2002), where only the average price and characteristics are known, not the specific characteristics of each car sold in the market. Our assumption is that consumers are aware of the average level of prices at each dealership but not of the exact prices of all available cars. Accordingly, we use the average price of cars of the same brand and model sold in the same quarter as the price of nonpurchased alternatives. Similarly, we also compute the average for the other car characteristics. If a car is not available, it is not part of the choice set of the consumers.

5.1.2. Total Market Size. Any analysis of spatial competition must take into account the location of potential demand, as consumers have the option of purchasing a car that is not in our data set or of not buying a car at all. We use census data to obtain the total number of households in each zip code, $\#Households_z$. The potential market for cars in each zip code will be a proportion of this number, for two reasons. First, our data cover only a part of all transactions, and therefore we limit the potential market to the same percentage of the total number of households. Additionally, we account for the fact that consumers who have purchased a car recently will not be looking for a car and will not be part of the potential market. We use the interpurchase time of cars to reflect this aspect on the total market potential (seven years; see Sudhir 2001 for a similar approach). Stated formally, the total market in zip code z is given by

$$H_z = [\#Households_z \times Observed\ transactions \\ /Total\ transactions \times Years\ of\ data] \\ \cdot (Interpurchase\ time)^{-1}. \tag{19}$$

For each zip code z, the sum of "observed" individuals who bought a car in our data set and "unobserved" individuals whose choice was the outside good will be equal to the total market at that location, H_z. The census data show 993,767 households living in the zip codes included in our study, which results in the observed number of households for our sample of $H = \sum_z H_z = 34{,}072$.[17] For reference, as mentioned in §4, our data include 15,795 households who buy a car, which means that alternatives considered as the outside good represent the remaining 18,277, or 56%, of the market. We assume that, for each zip code, consumers who choose the outside good have the same distribution in terms of demographic characteristics and price expectations as consumers who bought a car in our data set. Thus, we make draws from the empirical distributions, at the zip code level, of consumer demographics and assign the values to "outside good" individuals in that zip code.

5.1.3. Unobserved Attributes. One potential source of endogeneity comes from the fact that the dealer prices and unobserved car characteristics that influence consumer utility, e.g., car accessories, may be correlated. One way to avoid the bias created by this correlation is to use a control function approach (Pancras and Sudhir 2007, Petrin and Train 2010), making use of the information about unobserved attributes contained in prices. This approach has two stages. In the first stage, we recover ξ'_{jt}, a one-to-one function of ξ_{jt}, by regressing prices on observed exogenous variables and instrumental variables:

$$p_{jt} = \mathrm{E}[p_{jt} \mid z_{jt}] + \xi'_{jt},$$

where z_{jt} includes exogenous demand and cost shifters, as well as instruments. The exogenous cost shifters include dummy variables for the dealer and car type, and the exogenous characteristics are engine size, fuel, and transmission type. Our instruments are similar to the ones in Berry et al. (1995) and Petrin and Train (2010). We use the sum of each exogenous characteristic across all vehicles of the same brand sold in other dealers and the sum of each characteristic across all other vehicles of other brands but of the same type. This gives us six instruments for each alternative. Thus, our price equation is given by

$$p_{jt} = \omega z_{jt} + \xi'_{jt}. \tag{20}$$

When estimating the remaining demand parameters, $\delta_1 \xi'_{jt}$ replaces ξ_{jt} in the utility function, where δ_1 is a parameter to be estimated and ξ'_{jt} is kept fixed.

5.2. Demand Parameters

Because the demand model is fully identified from the choice data, and we wish to avoid imposing structure on the estimation problem if none is required, we start by estimating the demand parameters without making any assumptions on the behavior of dealers and manufacturers. Given our estimates for ξ', the estimation of the demand parameters can proceed via simulated maximum likelihood, using the following likelihood function:

$$L = \prod_i \prod_j \prod_t (\mathrm{Pr}_{ijt} \mid \mathrm{data}, \xi', \theta)^{y_{ijt}},$$

where y_{ijt} is an indicator variable that takes the value of 1 for the alternative chosen by individual i and 0 otherwise, and θ is the vector of demand parameters to be estimated. In our algorithm, we maximize the log likelihood function:

$$\log L = \sum_i \sum_j \sum_t y_{ijt} \cdot \log(\mathrm{Pr}_{ijt} \mid \mathrm{data}, \xi', \theta). \tag{21}$$

5.3. Supply Parameters

5.3.1. Variable Costs and Revenues. We start by evaluating manufacturer variable cost C and dealer revenues Δ, which can be computed directly from the data and the demand estimates. To compute the implied variable costs of the manufacturers, we use Equation (12). In this equation, we need to evaluate $\partial S/\partial P$, the derivative of shares with respect to prices, and $\partial P/\partial W$, the derivative of prices with respect to

[17] More specifically, 993,767 (number of households) × 12% (percentage of observed transactions) × 2/7 (interpurchase time, considering two years of data) = 34,072.

wholesale prices. The derivative $\partial S/\partial P$ can be computed directly from the demand estimates, whereas $\partial P/\partial W$ can be evaluated using the demand estimates and Equations (13) and (14). Along with the observed wholesale prices, we are in possession of all terms in the right-hand side of the resulting expression for manufacturer variable costs:

$$C = W - ([\Theta_K \odot \Omega_w]^{-1} S). \tag{22}$$

Next, we use the approach in Pakes et al. (2008), as it is applied, for instance, by Ishii (2008), to the case of ATM networks, to estimate the fixed costs of dealers using as input for the observed decisions in terms of size and location of the dealer networks, and the fixed costs of manufacturers directly related to the dealer network.

5.3.2. Retailer Fixed Costs. Our objective is to estimate the fixed cost parameters for dealers ρ_2. For the observed costs shifters at the dealer level x_{d_z}, we use an intercept, the population size at each dealer location and surrounding locations, the distance from downtown San Diego and the city center of Escondido, and a dummy for large dealers. Regarding the last item, we observe in the data two very different sizes of dealers, which we allow to have different fixed costs, and thus we include a dummy for being a large dealers, operationalized as having more than 500 cars in unit sales over the two years in our data. In total, we estimate six fixed cost parameters.

We have 22 dealers in our data set. In two instances, we observe two dealers of different brands that have the same owner (GM and Chrysler) within the same zip code, and we consolidate their profits and fixed costs for the estimation procedure. For each of the 20 dealers so defined, we relocate one and keep all others fixed at the observed location. The counterfactual locations are chosen to be zip codes where there is at least one other dealer, thus ensuring that it is a realistic target for location. In particular, we chose 11 alternative locations for each retailer to obtain $20 \times 11 = 220$ inequalities.[18] We compare each dealer's predicted profit at the current location with those at alternative locations. To satisfy the inequalities in Equation (18), profits at the current configuration should be larger than those of the counterfactual one. Additionally, each dealer's fixed cost needs to be larger than or equal to zero, which leads to an additional 20 inequalities. Finally, the profits of the dealer at the actual location have to be positive, which provides 20 more inequalities. In total, we define and use 260 inequalities.

[18] We could have constructed more inequalities based on other locations, but 11 alternative locations for each dealer already identify parameters to a point.

To construct each inequality, we need the variable profits (revenue-variable costs) for each dealer, at both the actual and counterfactual locations. This is obtained using the demand and supply estimates, so that both quantities and prices reflect the reaction of demand and supply to the relocation of the dealer in the counterfactual scenario. We note that when dealers relocate, their demand changes, leading some large dealers to become small dealers, and vice versa; through this, we identify the size-of-dealer parameter. Because the relocation also changes the distance from downtown San Diego and Escondido, that variation allows us to estimate the sensitivity of fixed costs to distance from these centers.

We assume that the errors v_k and v_d are measurement or expectation errors by the agents, assumed to be uncorrelated with x_k and x_d and of expectation 0 at the time of the decisions, eliminating endogeneity concerns. We argue that this conditional independence of the errors, given the observed characteristics of dealers, is reasonable because the population and distance from city centers serve as good summary statistics for the major decision factors of dealer location. If endogeneity is a concern, it is possible to interact each inequality with instruments. In that case, the number of inequalities is multiplied by the number of instruments. We present the results with instruments $Z = 1$, i.e., where we construct a sample analogue of the moment conditions directly from the inequalities. Parameters are estimated, minimizing the sum of the absolute value of inequality violations as in Ishii (2008). For example, if the parameters provide gains in the counterfactual configuration compared with the actual configuration, or if some parameters give a negative profit for the new location or a negative estimate of fixed costs, we take the absolute value of all these violations across all observations, sum, and minimize its total. This follows the approach in Pakes et al. (2008) and Ishii (2008). We carry out a robustness check using the population in surrounding zip codes as an instrument in addition to $Z = 1$. This instrument would control for any factors unobserved to the researcher related to the area of the dealership (for example, the existence of a nearby freeway) that may potentially be considered by the agents when choosing locations. The results for total fixed costs of dealers and manufacturers with this instrument do not differ substantively from the results we present here.

We compute standard errors in a fashion similar to Ishii (2008). That is, we sample from the distribution of the data by randomly drawing dealerships (with replacement) and for each draw reestimate the model. We took a total of 50 bootstrap samples and obtained estimates of the fixed cost parameters for each sample, again by minimizing the absolute value of the inequalities. Reported standard errors are the standard deviations of the parameters across samples.

5.3.3. Manufacturer Fixed Costs. Taking a similar approach, we now move to the estimation of manufacturer fixed cost parameters ρ_1. We model fixed costs using an intercept, a dealer size dummy, and the distance from the port of San Diego as cost shifters; i.e., we estimate three cost parameters. To formulate inequalities, we remove, in turn, an existing dealer from the market and compute the profits for the manufacturer of its brand of cars, i.e., compute manufacturer profits with a reduced dealer network. Additionally, we add a dealer to the manufacturer networks. To do so, we choose one of each of the 20 dealers, in turn, and "launch an exact copy" of that dealer at a different location, following the same rules for a location as outlined previously.[19]

In each counterfactual situation, we use the supply and demand parameters to compute the counterfactual prices, quantities, and profits. We then compare the difference in variable profits between the actual and the two counterfactual situations (one more or one less dealer), as in Equation (16). These counterfactual scenarios create a total of $20+20=40$ inequalities, from increasing or decreasing the size of the manufacturer networks. Additionally, we define 20 more inequalities, based on the fact that the fixed costs for each new dealer added in the counterfactual scenario where the car networks are expanded should be larger than 0. Thus, in total, we have 60 inequalities.

Finally, standard errors are computed using a similar procedure as noted previously.[20]

6. Model Estimates

In this section, we present and discuss the results of the demand and supply parameter estimates, price elasticities, geographic demand variation, and estimates of fixed costs of dealers. The next section describes managerial applications of our model.

6.1. Demand

Table 2 presents the results for the demand parameters and log likelihoods for four alternative models: (1) the logit model with no control for price endogeneity, (2) the logit model with endogeneity correction, (3) the nested logit with no control for price endogeneity, and (4) the proposed full nested logit.[21] Comparing the log likelihood of the different formulations, we observe that the nested logit models fit the data better than do the logit models. We also see an improvement in the log likelihood when we account for price endogeneity. Comparing models (3) and (4), the price coefficient becomes significantly more negative, approximately doubling in size, when endogeneity between unobserved attributes and price is accounted for. This corresponds to what is reported in Berry et al. (1995). Using the best-fitting model, the remainder of the analysis is done with the nested logit model that accounts for price endogeneity (4).

To illustrate the model's fit, Figure 3 shows the actual and estimated average market shares of each alternative j (excluding the outside option) for the total San Diego market (panel a) and for two randomly selected zip codes (panels b and c). We find that the model explains well the variations in car popularity, not only at the general market level but also at the zip code level, with a good match between estimated shares and actual shares. The model does equally well for other zip codes.

Additionally, we did a holdout test using several zip codes that were left out of the estimation. In total, these zip codes comprise 700 additional car purchases. We forecast shares among these 700 holdout purchases, and the actual and predicted shares correlate with $r=0.79$ ($R^2=0.62$). In view of the number of alternative cars and dealers, this is a good holdout validation result.

We now interpret the demand parameters. The price coefficient is negative and significant for all income levels, with the lowest income group (average annual income lower than \$24,000) being the most price sensitive. The parameters translate to an average own-price elasticity of −4.1. We analyze the cross-price elasticities in more detail in §6.3.

In terms of other car attributes,[22] consumers value engine size, automatic transmission, and cars that use higher-octane fuel. Regarding the car type, small SUVs, which include both compact and mini-SUVs, are more popular than both large SUVs and mid-sized cars.

We also observe that the residuals from the control function, which represent attributes unobserved to the researcher but considered by consumers, have a positive impact on choice, with cars that have higher levels of unobserved accessories being more appealing to the final consumer. Finally, we find that the

[19] As stated above, we can launch a dealer at many more locations, but we find the inequalities originated by testing one additional dealer to be sufficient to obtain point estimates.

[20] To be conservative, and because the number of manufacturers is low in our sample, we also study the distribution of our parameters across bootstrap samples of manufacturers, in addition to bootstrapping dealerships. We randomly select a sample of manufacturers and only use the observations associated with those manufacturers in estimation. We take draws of manufacturers from the data with replacement and estimate the parameters at each draw, obtaining an empirical distribution of the parameters.

[21] As described in §3, we also included dealer intercepts in our demand specification, but we do not list them to avoid cluttering.

[22] We code the variable *transmission type* as 0 if automatic and 1 otherwise. For fuel type, 0 is the basic type of fuel, and 1 is coded if the car uses higher-octane fuel.

Table 2 Mean and Standard Errors of Demand Parameters and Log Likelihood of Four Alternative Models

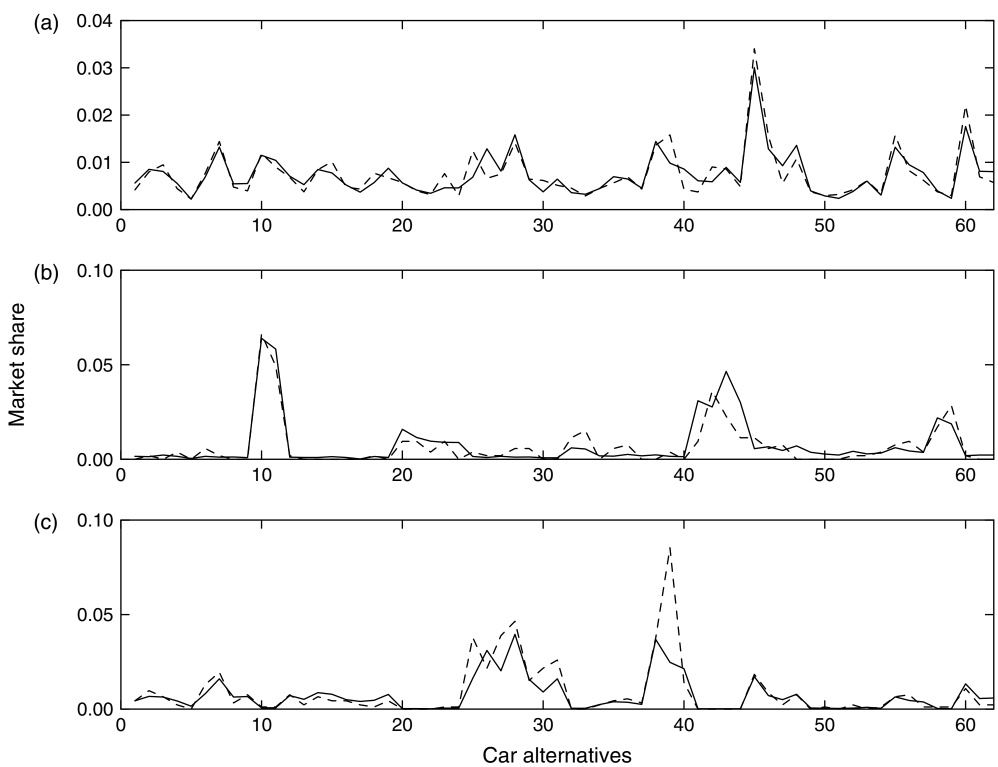
		(1) Logit I		(2) Logit II		(3) Nested logit I		(4) Nested logit II	
Category	Variable	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Car type	*Midsize and sedans*	−1.163	0.445	−0.802	0.451	−3.024	0.508	−2.847	0.465
	Small SUVs	1.428	0.322	1.286	0.317	−0.034	0.374	−0.130	0.325
	Large SUVs	−6.406	0.233	−5.750	0.220	−3.430	0.241	−3.032	0.205
Location	*Distance* (100 miles)	−11.896	0.149	−11.899	0.147	−3.577	0.214	−3.524	0.158
	Distance^2	8.503	0.182	8.503	0.179	1.552	0.214	1.511	0.151
Price	*Income* <$24K	−0.536	0.056	−1.158	0.117	−0.255	0.035	−0.596	0.047
	$25K < *Income* < $44K	−0.247	0.050	−0.869	0.116	−0.067	0.023	−0.410	0.040
	$45K < *Income* < $64K	−0.213	0.050	−0.836	0.116	−0.038	0.024	−0.382	0.040
	Income > $65K	−0.452	0.051	−1.076	0.118	−0.207	0.028	−0.550	0.043
Car attributes	*Engine size*	0.276	0.031	0.494	0.049	0.074	0.014	0.197	0.016
	Transmission type	−0.301	0.017	−0.378	0.021	−0.072	0.008	−0.116	0.008
	Fuel type	0.036	0.017	0.058	0.017	0.015	0.008	0.026	0.004
Control function	*Unobserved attributes*			0.075	0.013			0.039	0.004
Nest coefficients	*Car type*					0.720	0.015	0.725	0.012
	Car make					0.157	0.020	0.156	0.020
Log likelihood		−108,140		−108,124		−107,169		−107,119	

nest parameter for car type has a value of 0.72, which is consistent with stronger substitution between alternatives within car types versus across car types. For the brand nest parameter, the value is 0.16. These estimates suggest that consumers segment the alternatives by car type, with additional segmentation by brand. In the next subsections, we further analyze the impact of these estimates on car substitution patterns.

6.2. Dealer Demand Areas

From our estimation results, we find that distance between dealers and consumers plays an important

Figure 3 Actual Shares (Solid Lines) and Estimated Shares (Dashed Lines)



Note. (a) Average shares for each dealer across all zip codes, (b) shares for zip code 92008, and (c) shares for zip code 92154.

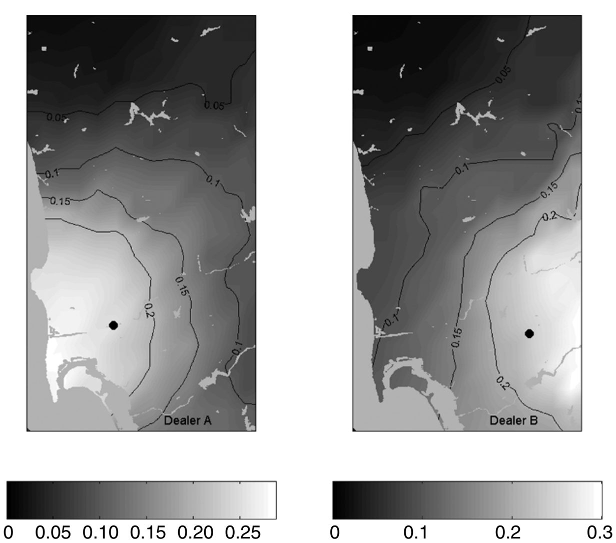
role in the decision of buying a car. The effect of distance is both highly significant and substantial—the longer the distance between the consumer and a dealer's location, the lower the utility and choice probability of an alternative. From the squared term of distance, we infer that the effect of distance is marginally decreasing, meaning that as distances increase, utility still declines but at a slower pace.

We display market areas for each car model, dealership, and manufacturer using geographic plots of the predicted choice probabilities of our model. As an example, panels (a) and (b) of Figure 4 show the average choice probabilities for the Ford Expedition, as a percentage of all full-size SUVs, at two Ford dealerships designated by A and B. The large dots represent the two dealers' locations. Other retailers are not shown for clarity.

As expected, we observe larger choice probabilities in areas surrounding the dealer locations, with the Expedition having an estimated share of about 25% of large SUVs in zip codes located five miles or fewer from the dealers' locations. However, the presence and location of the other dealer has a major impact on demand. In fact, average choice probabilities of consumers buying from dealer B are highest not at the zip code of the dealership, but to the right of its location, farther away from his strongest competitor, dealer A.

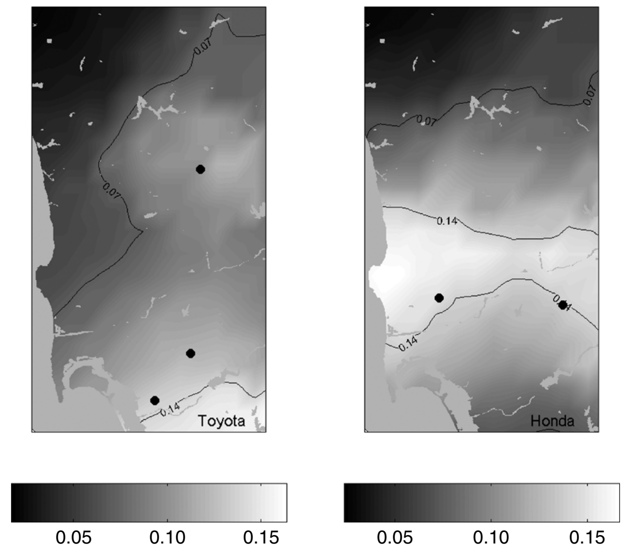
Figure 4 also outlines the market areas for the Ford Expedition, as defined by the geographic contours of the predicted choice probabilities. For instance, dealer A's market area for the Ford Expedition where choice probabilities exceed 15% among large SUVs covers an area of approximately 100 square miles, as outlined by the contours labeled 0.15. Choice probabilities above 10% are observed in an area covering about 300 square miles.

Figure 4 **Market Areas for Ford Expedition Sold at Two Different Dealers, Designated by A and B**



Note. The market shares are computed within large SUVs.

Figure 5 **Market Areas for Toyota and Honda in San Diego and Suburbs**

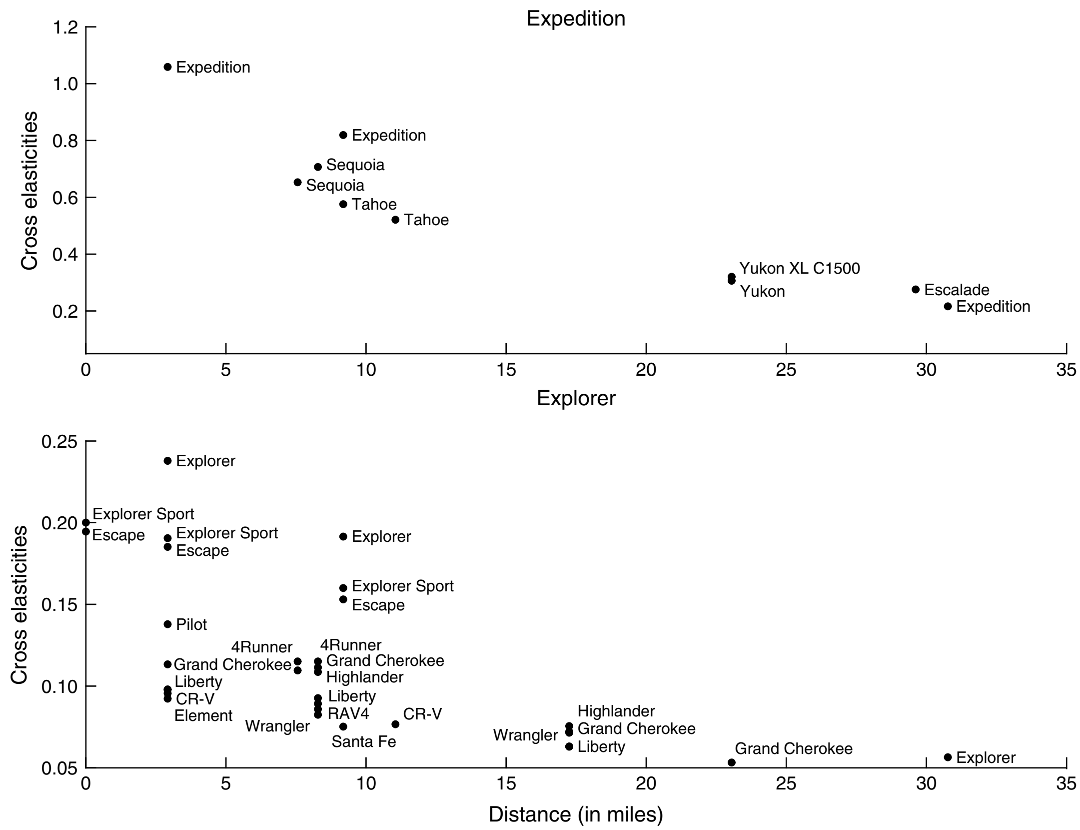


In addition to dealerships, we can also generate examples of market maps for car manufacturers. To do this, we plot the sum of the choice probabilities for all alternatives of a manufacturer. Figure 5 shows the market shares for Honda and Toyota, with the large dots representing dealership locations. Honda has two dealerships, located at almost the same latitude, one closer to the coast than the other. Toyota, on the other hand, has two dealerships located closer to downtown and a third located about 20 miles north. Because of their location, the market areas of the two Japanese manufacturers display an interesting pattern: demand for Honda is concentrated in a horizontal band, whereas Toyota has two areas of high demand, one close to downtown and the other inland, in the area of Escondido. These location choices can be discussed in the context of theoretical models of spatial competition. For instance, in the case of product choice involving multiple characteristics, Irmen and Thisse (1998) show that manufacturers choose one dimension to completely differentiate while minimizing differentiation on other characteristics. Given our results, it seems that location serves as the differentiation dimension, because, within a car type, attributes of cars by different manufacturers are strikingly similar. The patterns observed in Figure 5 are consistent with this theoretical prediction about location choice.

6.3. Substitution Patterns

To gauge how consumers trade off and substitute among car types, manufacturer brands, and dealer locations, we compute cross-price elasticities for automobiles. Across all alternatives, the cross-price elasticities range from values very close to 0 to

Figure 6 **Cross-Price Elasticity Between Car Dealerships, for a Ford Dealer, for Two SUV Types Sold**



a maximum of 1.2 for several cars that belong to the same type and brand. For illustration purposes, Figure 6 shows cross-elasticities for two cars at a single Ford dealership, which sells four different SUV models: the Escape, the Explorer, and the Explorer Sport (classified as small SUVs in our data); and the Expedition (a large SUV). The selected Ford dealership is placed at the origin of the x axis and other car dealers are located at the actual geographic distances from this dealership, in miles. In each panel of the figure, all alternatives with cross-price elasticity above 0.05 are presented, regardless of car type.

In most cases, the closest substitutes are cars of the same type. For example, the closest substitutes of the Expedition in the top panel of Figure 6 are other large SUVs, such as the Sequoia and the Tahoe (recall that the "car type" nest parameter is large). We also observe that the number of competitors with a cross-price elasticity larger than 0.05 is much higher for the Explorer than for the Expedition vehicles, although the magnitude of the cross elasticity is lower. It is interesting to note that in the top panel the cross elasticity to the largest Expedition is close to 1. Indeed, a consumer in the market for an Expedition has few alternatives to the selected dealership, and the cross-price effect expresses this. On the other hand, the much more crowded small SUV segment has many more substitutes available over which cross-price effects are smaller.

Besides car type, two forces affect the strength of competition: distance and brand name. Figure 6 shows that the shorter the distance, the higher the cross-price elasticities. For the two Ford cars (Expedition and Explorer), changes in prices at other Ford dealers have a stronger impact on demand than changes in prices of other brands. For example, a Ford Explorer sold at the dealership nine miles away is perceived as a stronger substitute than alternatives such as the Pilot or the CR-V sold at a dealership three miles away. We conclude that distance plays an important role in decreasing substitutability between alternatives. However, its differentiation impact is lower if cars share the same brand.

6.4. Supply

We find that the average manufacturer margin is \$12,513, which includes both the immediate margin at the time of sale and other future cash flows related to the sale of the car. American manufacturers are estimated to receive a margin between \$5,000 and \$15,000 from premium SUV sales (Lienert 2003). As we stated in §1, being in the higher end of this range seems reasonsable for San Diego, a location where consumers have, on average, higher purchasing power, and most of the included car brands and types are in the medium- to high-end price segments.[23]

For car dealerships, there are two quantities to discuss. First, in our data, we observe the direct gross margin for each car, i.e., the difference between the manufacturer price and the final price charged to the consumer by the dealership. On average, this value is \$1,630, about 6.5% of the final price. Thus, compared with dealers, manufacturers get the lion's share of gross margins in this industry. However, given that dealers will have future revenues from the servicing of cars, dealers also take those revenues into consideration in their pricing (denoted in Equation (11) as Δ). Our estimates imply that dealers get, on average, a total value of \$6,220 per car, which means that additional net revenues amount to \$4,590. This seems to be a reasonable result, because industry reports state that profits resulting from car servicing are about four times the value of profits from selling new cars (NADA 2008).

As described in §5, we obtain the parameters related to fixed costs by shifting the location of each dealer to 11 hypothetical locations. Our estimates satisfy over 98% of the inequality conditions used. The point estimates and standard errors are presented in Table 3. We observe that the most significant variables are the distances of the dealership from the two main urban centers. These variables are estimated to have negative effects, implying that a greater distance from the city centers lowers the fixed costs of the dealership. The number of inhabitants at the dealer zip code and surrounding zip codes does not play a significant role in explaining fixed costs.

With the estimates $\hat{\rho}_2$, we obtain estimated values for the fixed costs of dealerships using $\hat{f}_d = x_d\hat{\rho}_2$. On average, we estimate fixed costs with an annual value of \$3.6 million.[24] NADA states in its 2008 report that dealers spend on average about \$2.2 million on salaries and another \$600,000 in other fixed costs, such as advertising and rent (NADA 2008). Although our estimate is slightly above this national average, we focus on the most important brands in San Diego. The high cost of land in California adds further face validity.

In measuring fixed costs as a percentage of dealer variable profits, we find values ranging from 14% to 36%. Honda has the largest dealers in the area, which helps dilute their fixed costs, presenting the lowest percentage of fixed costs to variable profits at 14%. Most brands have fixed cost percentages of 20%–26% of profits, except GM. GM has smaller-than-average dealers in the area, and although it presents lower fixed costs than most brands in absolute values, it represents a considerably larger percentage of profits at 36%.

Table 3 Estimates of the Manufacturer Fixed Cost Parameters $\hat{\rho}_1$ and of the Dealer Fixed Cost Parameters $\hat{\rho}_2$

Agent	Variable	Mean	SE
	ρ_1		
Manufacturer	*Intercept*	359.57	124.48
	Relative size of dealer	748.70	74.05
	Distance from the Port of San Diego	−1.21	4.13
	ρ_2		
Dealer	*Intercept*	300.166	69.763
	Population in dealer's zip code	−0.027	0.121
	Population in adjacent zip codes	0.013	0.025
	Distance from center San Diego	−5.053	1.978
	Distance from center Escondido	−8.517	3.708
	Relative size of dealer	47.372	51.933

Finally, we estimate the fixed costs of the manufacturers supporting each dealership in terms of distribution and marketing activities. We find that the manufacturer fixed cost of supporting a larger dealer is significantly higher, whereas the distance from the Port of San Diego, where the arrival of some cars from other countries occurs, does not explain the difference in costs.[25] Using the estimates, and scaling to account for the fact that we only observe a portion of total transactions over two years, we find that, on average, manufacturers have costs between \$2 and \$3 million per year per dealership, representing about 27% of manufacturer costs. According to a *Wall Street Journal* report (Ball 2000), distribution costs (part of which are fixed manufacturer costs related to the network) may account for 20%–25% of a car's costs, providing validity to our results.

7. Evaluating the Impact of Lowering Demand

7.1. General Approach

Motivated by the quote at the beginning of this paper wherein General Motors plans to revise its dealer network configuration, we investigate the impact of lowering demand using two simulations. First, we analyze the impact of a reduction of market demand on profits of dealers and manufacturers, which can serve as potential justification for General Motors'

[23] We estimate markups that are slightly higher than the ones presented in Berry et al. (1995): 50% versus 30%. Besides for the previously described reasons, we conjecture that this is because larger and more expensive cars have been introduced and have become popular since 1990 (the time period of the Berry et al. data).

[24] Our data set includes only a portion of the total observations, as described in §4. We scaled the fixed costs obtained from the estimates to take into account the relative size of the observations in our data set.

[25] These conclusions continue to hold if we draw manufacturers instead of dealers to construct bootstrap samples.

desire for a leaner structure. We also discuss the results in the context of the so-called cash for clunkers program. Second, we analyze the impact of lower demand on the San Diego dealer networks of GM and Chrysler, and we compare our predictions of dealership closings to actual data. In each case, we consider the effects of lower demand on prices, quantities, and profits of retailers and manufacturers.

Our approach to measuring the effects of an economic crisis is to increase the appeal of the outside good and make consumers more likely to stay out of the category. To do this, we shift the utility of the outside good from an exogenously set value of 0 to a value of 0.7, leading to a market drop of about 30% in the general demand for automobiles over two years, similar to the effect of the 2008–2009 economic crisis. We note that this decrease is general to the entire market; i.e., it affects all zip codes similarly. We explore the robustness of this simulation using an alternative case where we increase price response to obtain a 30% drop in sales. We note that these scenarios are simulations of outcomes of model perturbations, such as the outside good preferences or the price sensitivity, but that the model does not explain the causes of such changes. Our increase in price sensitivity can be interpreted as the effect of an income reduction, because our model has income-specific price effects.

7.2. Prices and Margins in Response to an Economic Crisis

In this first simulation, we use our demand model with the more valuable outside option to obtain estimates of market shares, and we next use those estimates to obtain new dealer and manufacturer prices using the supply equations. We then iterate the demand and supply sides of the model until they converge; i.e., we stop iterating when $\max_{jd}(P^{\tau+1} - P^{\tau}) < \iota$, where P^{τ} and $P^{\tau+1}$ are the vectors of prices at iterations τ and $\tau + 1$, respectively, and ι is set to be very small ($\iota = 0.01$).

We find that lower demand levels cause lower equilibrium prices, with dealer and manufacturer prices decreasing by an annual average of 13% and 11%, respectively. The drop in equilibrium prices partially offsets the initial negative demand shock caused by the economic crisis, leading to a final market size that is 21% smaller after two years. Table 4 shows that a decrease in quantity sold and in prices results in total gross margins becoming about 53% smaller. A dealer's direct margin (consumer price minus manufacturer price) becomes negative for all brands, which implies that most dealers survive solely on their parts and services business during the crisis.

As a robustness check, we alternatively simulate an economic crisis by increasing consumers' price sensitivity rather than their taste for the outside good.

Table 4 **Average Margins for Manufacturers and Dealers and Estimates of Cars Sold Before and After a Negative Shock That Reduced Demand by 30% Over Two Years**

Manufacturer	Manufacturer margin/car ($)	Dealer margin/car ($)	Dealer margin and other revenues ($)	Cars sold
		Before demand shock		
GM	14,089	1,579	6,711	530
Ford	12,815	1,088	6,200	3,529
Honda	13,834	1,346	6,663	3,380
Chrysler	12,009	1,429	5,918	3,229
Toyota	14,853	1,039	6,345	2,872
VW	13,401	985	6,367	1,595
		After demand shock		
GM	9,505	(510)	4,619	430
Ford	8,773	(920)	4,198	2,750
Honda	9,556	(813)	4,563	2,661
Chrysler	8,089	(498)	3,989	2,474
Toyota	10,512	(987)	4,339	2,227
VW	9,048	(1,164)	4,220	1,279

We do this as a simple way to capture the effect of a change in disposable income, on which price response depends. In particular, we evaluate the consequence of raising price response by an amount that produces a 30% drop in units sold in the car market, the same amount as before. Empirically, this amounts to increasing the price coefficient by 50%, or the average own-price elasticity from −4.1 to −6.4. This implementation of a crisis affects expensive cars more than inexpensive cars and will lead to the substitution to the lower-priced cars and the outside good.

Substituting this enhanced price response into our model of demand and supply, we obtain counterfactual quantities and prices. Compared with the situation where the appeal of the outside is increased, final prices will be slightly lower, by an average of $550 less, than the prices in the previous scenario, while unit sales will recover more, leading to a final market reduction of 8% relative to the beginning of the recession. However, in terms of the net effect, this scenario of increased price sensitivity leads to total revenues for manufacturers and dealers similar to those shown in Table 4.

7.3. Car Allowance Rebate System

In 2009, the U.S. government introduced a stimulus program, the Car Allowance Rebate System (also known as the cash for clunkers program), to counteract the effects of the economic crisis on the auto industry. The program provided $3,500 or $4,500 to a consumer who traded in an old car for a new one. In the previous section, we showed that optimal prices go down by between $3,000 and $6,000 over two years as a result of the demand shock, leading to a strong reduction of profits for dealers and manufacturers.

Interestingly, the range of the predicted price reduction from our approach matches the amount given in the government program. With the financial situation of the American manufacturers and the effects of a severe economic crisis, it is unlikely that manufacturers could have survived if such a drastic price cut would have been implemented; it would have led to severe drops in margins while fixed costs would have remained at prerecession levels. Viewed in this way, the cash for clunkers program offered a temporary solution to the need to respond to the decrease in the demand for cars by shifting the final prices paid at the dealer closer to optimal prices without putting additional strain to the manufacturers' already dire financial situation.

An interesting related question that we can answer using our model pertains to the effects of such subsidies on retailer behavior—namely, prices. Given that retailers know that consumers each have an additional $4,500 in disposable income to spend on a new car, it is possible that retailers would adjust final prices to account for that subsidy. With our approach, we are able to form an opinion about how much of the subsidy offered to consumers would likely stay with the consumers and how much would be transferred to retailers by means of price changes.

To investigate the simultaneous impact of an economic crisis and a car allowance rebate program, we perform a counterfactual analysis. After reducing the demand by the amount equivalent to the economic recession, with an increase in the appeal of the outside good, we apply the subsidy and reduce the prices faced by consumers by $4,500, which is equivalent to the amount offered by the government. Thus, in this counterfactual analysis, there is a $4,500 difference between the price charged by retailers and the price faced by consumers. Demand takes into account the benefit of the car allowance, and manufacturers and retailers set their prices by taking into account this windfall in consumer demand. Given that consumers now face a lower price, the probability of buying a car goes up, and retailers are likely to move prices up to face this new increase in demand. With these two conditions, that is, (1) an increase in the popularity of the outside good that would cause a drop in the market by 30% and (2) a subsidy such that prices faced by the consumer are $4,500 lower than the ones charged by dealers, our results show that retailers would charge on average $1,542 more per car than in a situation without the subsidy program, leaving an average of $2,958 in the hands of consumers.

We note that in a related study, Li et al. (2010) also find that the cash for clunkers program provided incentives to consumers that lead to an increase in the number of cars sold for the duration of the program, with part of this increase being due to the anticipation of demand from posterior months. Our model abstracts from this intertemporal effect and measures the direct impact on prices and sales of the subsidy. Additionally, it is also likely that the program affected some consumer segments more than others, depending on the consumer's income level, whether the consumer owned a car that qualified as a possible "trade-in," or other demographic characteristics. For example, Bruce et al. (2006) show that providing cash rebates may attract consumers in negative equity situations. Trade-in or equity information is not present in our data set, but our model includes income effects on price sensitivity, making the impact of the program segment specific.

7.4. Reducing the Number of Dealers

The continuous decrease in demand led some manufacturers to close some of the less profitable dealerships. We show the effects of closing alternative dealerships for GM and Chrysler in Table 5. We implement a 30% drop in demand for GM and a 50% drop for Chrysler, matching industry reports (Zino 2009), and we obtain the respective unit sales and margins as previously described. In each row, for GM and Chrysler, we show the numbers for the current dealer networks and the results of removing a given dealership, identified by its zip code, from the market. For each case, we present the total number of cars sold, variable profits, and fixed costs across all the *remaining* dealerships in the manufacturer's network, as well as the actual decision if any, by the manufacturer to close the dealership.

Looking at the values presented in Table 5 for GM, we observe that the GMC dealership is the best candidate for closure from the dealer network side; i.e., if that dealership were closed, the remaining dealerships would net a profit of $675,000, larger than the current network profit of $305,000. At the same time, closing that dealership will yield only a small drop in the profit to the manufacturer, because fixed costs of both the manufacturer and dealer networks go down significantly when the GMC dealership is closed, and this leads to a much leaner structure, one of the desired objectives of GM's restructuring plan. Based on these results, our model supports GM's and the dealer's decisions to close down the GMC dealership, which happened at the end of 2009.

Consider now the case of Chrysler. Closure of the dealerships located within the 91950 and 92111 zip codes would lower the manufacturer and dealer profits of the remaining network considerably, leading us to conclude that these dealerships should not be closed in the near future. We predict that the other two dealerships, located within the 92029 and 92064 zip codes, are potential targets for closing because

Table 5 Variable Profits, Cars Sold, and Fixed Costs for the Remaining Dealers in the Market When General Motors and Chrysler Reduce Their Networks by a Selected Dealer

				Manufacturer ($K)			Dealer ($K)			
Manufacturer	Make	Code	Cars sold	Variable profits	Fixed costs	Profits	Variable profits	Fixed costs	Profits	Decision
GM	Current network		679	6,505	2,079	4,426	3,175	2,870	305	
	Chevy	92020	585	5,731	1,734	3,997	2,802	2,230	571	
	Chevy	91941	479	4,575	1,730	2,845	2,243	2,145	98	
	Cadillac	92008	491	4,650	1,765	2,885	2,270	2,565	(295)	
	GMC	92029	483	4,809	1,008	3,801	2,346	1,671	675	Closed
Chrysler	Current network		1,941	13,236	3,605	9,631	6,529	3,202	3,328	
	Jeep	92029	1,708	11,553	2,534	9,019	5,701	2,002	3,699	Closed
	Jeep	91950	1,323	8,889	2,497	6,392	4,393	2,422	1,971	
	Jeep	92064	1,788	12,124	3,274	8,850	5,979	2,865	3,114	
	Jeep	92111	1,402	9,581	2,534	7,047	4,734	2,315	2,419	

fixed costs for Chrysler would drop significantly, and manufacturer profits would stay almost constant. Between these two dealerships, our model recommends the closure of the dealership located within the 92029 zip code, with better numbers in terms of cost savings and dealer network profits, matching Chrysler's only closing decision in this market. We conclude that our predictions show face validity and demonstrate the usefulness of our approach regarding decisions on reducing the size of outlet networks of manufacturers.[26]

8. Conclusion and Future Research

This paper analyzes demand and supply for cars using transactional data. It provides insight into the effects of a severe reduction of demand, caused, for instance, by an economic crisis, on the car industry and more specifically on dealer networks. We provide a number of substantive insights and an approach that can help in the decision making of manufacturers and policy makers.

On the demand side, we define a purchase option as a combination of a car, with its product attributes, and a dealer, with its own characteristics and location. Utilities for such purchase options are therefore informative about the consumer trade-off between preferences for dealer location and car characteristics, including price. Using a large transaction-level data set, we show that the effects of physical distance between buyers and sellers are important and cannot easily be ignored when studying demand and substitution patterns in the car industry. Specifically, our analysis suggests that substitution even among pairs of cars of the same brand quickly fades as the dealers selling them are located farther away from each other. We find that each dealership has a localized demand area and that choice probabilities decrease at a fast rate with distance between buyers and sellers.

Using the demand estimates and assuming profit maximizing behavior of both manufacturers and dealers, we can estimate gross margins of agents and fixed costs of running a car dealership. We investigate the impact of a demand reduction, similar in size to the economic crisis that started in 2008. We find that dealer and manufacturer prices would decrease by an annual average of 13% and 11%, respectively, and that total gross margin would decrease by about 53%. Our second application focuses on network size choices, given the new demand conditions. We exemplify the usefulness of our model in measuring profits when a manufacturer considers reducing the size of its dealer network.

We followed the previous literature that modeled demand in the car industry as static (Berry et al. 1995, 2004; Petrin 2002). Therefore our analysis does not provide insights on intertemporal decisions of consumers, which can be important generally in durable goods and more specifically in the car industry. We leave this for future research.

Finally, we believe that our approach can be broadly applied to settings outside the car industry. Specifically, it can be used when manufacturers are interested in evaluating the effects of location of outlets on demand and competition, e.g., in the banking or gasoline industries, where store location plays an important role in the success of the products and services of a firm. It can also be applicable to categories in decline, where manufacturers must choose which outlets to remove from the market to maximize the profits of the manufacturer's dwindling products.

[26] We note that although immediate profits for both GM and Chrysler are predicted to go marginally down when they close these dealers, their decision is justified by two factors: First, we do not include in our analysis the savings from decreases in other fixed costs, such as production and related salaries, that happened in 2009 as a result of widespread reductions in production and in the dealer network. Second, both GM and Chrysler had the need to create much leaner and efficient structures to satisfy government regulation, which increases the importance of cutting fixed costs in the manufacturer and dealer networks.

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