Advertising in Vertical Relationships: An Equilibrium Model of the Automobile Industry

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Abstract

I estimate a model of demand for new cars and equilibrium pricing and advertising decisions of dealers and manufacturers. The estimated split of surplus between dealers and manufacturers differs from a model without advertising decisions because of a public goods advertising externality within the vertical relationship. I predict firm and consumer behavior if two state franchise regulations change. First, vertical integration leads to 20% lower retail prices and 30% higher advertising. Second, manufacturers substantially decrease brand advertising after dealer closures, and remaining dealers of the same brand can be worse off, even though they face less intra-brand competition.

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1 Introduction

Retailers and manufacturers commonly engage in promotional effort for the same product. Promotion by one level of a vertical structure benefits the other; for example, retail advertising shifts consumer demand and positively affects manufacturer surplus. However, promotional incentive concerns arise within vertical relationships akin to the well-studied pricing incentive problem of double marginalization. If the retailer considers only its own marginal benefit of promotion decisions, then a public goods externality exists and promotion is under-provided from the perspective of joint manufacturer-retailer surplus. As in the case of the double marginalization externality, the promotion public goods externality may have significant consequences for industry outcomes.

I present a model of vertical relationships where both the manufacturer and retailer choose both prices and advertising levels. The model bridges earlier theoretical work on inefficiencies in vertical relationships (Winter, 1993; Mathewson and Winter, 1984) with more recent work on the importance of adverting in differentiated goods markets (Sovinsky Goeree, 2008) and empirically quantifying the importance of vertical inefficiencies (Villas-Boas, 2007; Hortaçsu and Syverson, 2007; Mortimer, 2008). Specifically, I build on work by Villas-Boas (2007) by incorporating both pricing and advertising decisions by both retailers and manufacturers into an empirical model of vertical relationships. The model has similarities with the theoretical work of Winter (1993); the equilibrium choices of retailers are to under-provide advertising from the perspective of the manufacturer. I show how adding a non-price decision, such as advertising, analytically and empirically alters the pricing relationship between retailers and manufacturers, changes estimates of firm surplus, and implies different outcomes for policy predictions.

I apply the model to the new automobile market, where both dealers, the final goods retailers in this market, and manufacturers spend significant resources on advertising in local markets.[1] This is an ideal setting to study decisions of vertically related firms because the new automobile dealer-manufacturer relationship is heavily regulated in the United States at the state level. Lafontaine and Morton (2010) suggest that the complex set of regulations in this industry distort market outcomes and

[1]For example, in 2012 the automotive industry was the second most heavily advertised industry, with manufacturers collectively spending almost $9 billion and dealers collectively spending almost $6 billion to purchase advertising space on various media. Data come from Kantar Media and includes only costs associated with the purchase of advertising space/time. Kantar lists the top industry as "Retail."

may be detrimental to consumer welfare.

I use the model to asses the distortions created by two types of ubiquitous dealer franchise regulations. The first has to do with manufacturer-dealer integration. Dealers are required to be independent of the manufacturer, manufacturers are prohibited from selling directly to consumers, and manufacturers cannot contractually force dealers to set a specific price, sell a specific quantity, or spend resources on promotion. These regulations inhibit the ability of manufacturers and dealers to resolve price and promotional incentive issues that naturally arise in vertical relationships. This specific issue has recently gained attention because of a new wave of new car retailing over the Internet, which connects manufacturers directly to consumers, for example the business model of Tesla Motors, which has used loopholes in state regulations to sell cars directly to consumers in many states.

Second, manufacturers are, in most cases, prohibited from terminating a selling relationship with a dealer. This issue received attention during the 2008-2009 financial crisis, when two of the three major US automobile manufacturers, General Motors and Chrysler, lobbied US Congress to close dealers, arguing that terminating dealers would decrease costs, including costs associated with advertising and promotion.[2] Ford, the third major U.S. manufacturer, also has a policy of reducing its dealer network, and has eliminated thousands of dealers since the mid 20th century though attrition and facilitating consolidations.[3]

I estimate the structural model of demand and supply, and I use the model to predict how firms and consumers would behave if current state dealer franchise regulations were to change. The demand model is estimated using transaction level data for the population of new car sales in Virginia from 2007-2011. Among other things, I observe the transaction price, the location of the buyer and seller, the type of car sold, and the amount of local advertising by both dealers and manufacturers. Consumers incur a disutility for traveling to purchase a car which gives rise to spatial demand and competition among dealers. Also, dealer and manufacturer advertising affects the consumer purchase decision differently. I use the estimates and the model of dealer and manufacturer behavior to infer the costs and profits of firms in the spirit of Bresnahan (1987) and Berry, Levinsohn, and Pakes (1995) (henceforth BLP), and Villas-Boas (2007). The model incorporates two incentive issues between

[2] Although Chrysler is no longer a U.S. owned company, but was at the time of the time of the financial crisis.

[3] See `nytimes.com/2009/05/19/business/19ford.html` and Lafontaine and Morton (2010).

dealers and manufacturers: double marginalization which implies retail prices are too high from the perspective of joint dealer-manufacturer surplus, and an advertising public goods externality which implies advertising is too low from the perspective of joint dealer-manufacturer surplus. For example, when a dealer is deciding on how much to spend on advertising, it does not consider the marginal benefit of advertising to the manufacturer, and so supplies too little advertising from the perspective of the the manufacturer.

I present three main findings. First, incorporating advertising into an empirical model of vertical relationships changes estimates of how dealers and manufacturers split surplus. The advertising model implies dealers earn 6% more surplus in the vertical relationship, compared to 11% from a model without advertising decisions. Second, the pricing and advertising externalities are large. If a single dealer-manufacturer pair vertically integrates, the new integrated firm decreases retail prices by about 19% on average, and more than doubles advertising. Third, I close Ford dealers in Richmond in 2010 and predict that Ford would substantially decrease advertising in the local market. Even though the remaining Ford dealers face less same-brand competition, they are worse off because of the decrease in brand advertising.

A predecessor to more recent empirical work on vertical relationships that is closely related to my work is Bresnahan and Reiss (1985), who estimate a automobile dealer-manufacturer model for rural towns and find that markups between dealers and manufacturers is proportional across the product line. There is a more recent growing literature that analyzes outcomes in vertical relationships using structural empirical models including, Villas-Boas (2007), Goldberg and Hellerstein (2013), Mortimer (2008), Ho (2009), Bonnet and Dubois (2010), Crawford and Yurukoglu (2012), Grennan (2013), and Lee (2013). All of these studies either only consider pricing decisions, or pricing decisions and the decision of who to contract with. Villas-Boas (2007) shows how to solve for and identify cost functions in empirical models of vertical relationships in a similar way to previous studies that focus on a single level of the vertical structure, such as Berry, Levinsohn, and Pakes (1995).[4] I build on this work by modeling a second choice variable for both upstream and downstream firms, and I show how to solve the model analytically to recover the cost structure of dealers and manufacturers including an extra profit term that represents unobserved marginal

[4]See Villas-Boas and Hellerstein (2006) for a identification results for empirical models of vertical relationships.

profits from advertising activities.[5] Villas-Boas (2007) finds that retailers capture more of the rents than manufacturers in her context. However, my result suggest that if advertising is predominantly at the retail level, retailers may not be capturing the majority of rents in the market even if they charge high prices.

I also contribute to an extensive literature on the automobile industry. To my knowledge, I am the first to use complete transactions data to estimate a model of spatial demand in this industry. For example, BLP, Petrin (2002), and Train and Winston (2007) use aggregate data to estimate demand. Others have used micro level data from surveys, including Berry, Levinsohn, and Pakes (2004), Copeland, Dunn, and Hall (2011), and Langer (2011), but are not able to capture the complete competitive environment in a local geography. Most closely, Albuquerque and Bronnenberg (2012) estimate demand for automobiles using transactions data, but only for a sample of dealers in a local area.

I am also first to use a structural model to predict the effect of state dealer franchise regulations in this industry. Lafontaine and Morton (2010) provide an thorough overview of state franchise laws, and suggest that these laws have contributed to the decline of US automobile manufacturing. Examining the auto manufacturer and dealer relationship has been an interest U.S. policy authorities, for example the Federal Trade Commission in Rogers (1986) study state restrictions on vertical restraints, including a ban on direct to consumer sales, and conclude that state policies restricting vertical arrangements are harmful to consumers. This finding is echoed in a 2001 speech made by the former FTC chairman, Thomas Leary.[6] In Bodisch (2009), the Department of Justice advocates eliminating state bans on direct sales. They hypothesize that direct sales would reduce distribution costs and better match consumer preferences with car production.

The rest of the paper is organized as follows. In Section 2 I describe the industry and regulatory details in more detail. The model of demand and supply is presented in Section 3. I describe the data in Section 4 and discuss estimation and the results in Section 5. Section 6 contains two subsections: in the first I discuss vertical integration in the industry and present counterfactual results, and in the second I discuss and present counterfactual results for the closing of dealers. Section 7 concludes.

[5] There is also a recently developing literature on estimating demand and supply with multiple endogenous variables, although not in a setting with vertical relationships. For examples see Fan (2013) and Eizenberg (2014).

[6] See http://www.ftc.gov/speeches/leary/learystateautodealer.shtm.

2 Demand and Supply of New Cars

2.1 Demand

In this subsection I describe the demand for new cars. Each period, consumers make a discrete choice among differentiated products. I define a product as a car make/model from a particular dealer. Consumers decide which of the $j = 1..J_{tn}$ products to purchase in their home market, where $t = 1..T$ indexes time and $n = 1..4$ indexes the four markets: Richmond, Virginia Beach, Roanoke, Norhtern Virginia. I assume consumers can only purchase products located in their home geographic market. The consumer also has the option of no purchase, denoted as $j = 0$.

Consumer i's indirect utility for a new car j at time t in market n is a function of a vector of observed car characteristics, $\boldsymbol{x}_{jt}$, price, p_j, a function $g(a_{jt}, A_{jt}; \boldsymbol{\phi}_{it})$ of exposure to local dealer and brand advertising, a_{jt} and A_{jt} respectively, and a function $f(\mathcal{D}_{ijt}; \boldsymbol{\lambda}_{it})$ of the distance from the consumer location to the product location, $\mathcal{D}_{ijt}$. Indirect utility of product j for consumer i at time t is

$$u_{ijt} = \boldsymbol{\beta}_i \boldsymbol{x}_{jt} + \alpha_i p_{jt} + f(\mathcal{D}_{ijt}; \boldsymbol{\lambda}_{it}) + g(a_{r_j t}, A_{z_j t}; \boldsymbol{\phi}_{it}) + \xi_{jt} + \epsilon_{ijt}, \tag{2.1}$$

where $\boldsymbol{\beta}_i$ is a vector of consumer specific preferences for car characteristics, α_i represents a consumer specific preference for price, $\boldsymbol{\lambda}_{it}$ and $\boldsymbol{\phi}_{it}$ are preference parameters for distance and advertising , and ξ_{jt} represents a product-time specific preference that is known to the consumers and firms, but unobserved in the data.[7] Car dealers are indexed $r = 1..R_{nt}$ and car models are indexed $z = 1..Z_{nt}$. The index r_j maps product j to dealer r, and the index z_j maps product j to car model z. The term ϵ_{ijt} is distributed i.i.d. type I extreme value distribution, and represents unobservable idiosyncratic consumer tastes. I assume that utility from not purchasing is only a function of an unobserved consumer specific preference: $u_{i0t} = \epsilon_{i0t}$. Consumers choose the option with the highest indirect utility.

Consumers have heterogeneous preferences over product price and product characteristics. Preference for price has the following functional form: $\alpha_i = \alpha_{\Upsilon_i} + \sigma^p \epsilon_i^p$, where Υ_i represents the income bracket of consumer i, ϵ_i^p is distributed i.i.d standard normal, and σ^p represents the degree of heterogeneity in price preference across

[7]Notice that I omit the market index, n. By definition a product exists in only one market, so this index is redundant.

consumers.[8]

I allow for individual specific preferences for product characteristics. Letting $k = 1..K$ index characteristics, consumer i's preference for characteristic k is $\beta_{ik} = \bar{\beta}_k + \sigma_k^x \epsilon_{ik}^p$, where ϵ_{ik}^p is distributed standard normal and represents unobserved individual preferences for product characteristic k. As noted in BLP and subsequent related studies, this specification allows for realistic substitution patterns that do not suffer from the independence of irrelevant alternatives problem. For example, a consumer with a strong positive preference for horsepower will more likely substitute to products with high horsepower before products with low horsepower, all else equal.

To capture the idea that consumers may prefer to purchase cars from nearby dealers over dealers that are farther away, I allow indirect utility to be a function of the distance between the consumer and the location of the dealer that sell the product, $\mathcal{D}_{ijt}$. The distance function has the following functional form:

$$f(\mathcal{D}_{ijt}; \boldsymbol{\lambda}) = \lambda_1 \mathcal{D}_{ijt} + \lambda_2 \mathcal{D}_{ijt}^2 + \lambda_3 H_1 \mathcal{D}_{ijt} + \lambda_4 H_2 \mathcal{D}_{ijt}, \tag{2.2}$$

where $\boldsymbol{\lambda}$ is a vector of preference to be estimated, and H_1 and H_2 are consumer characteristics. I include travel time to work and a measure local population density as consumer characteristics that influence preferences for distance.[9] This formulation of spatial demand that includes distance in the utility function is a common treatment in the literature, including Davis (2006), Manuszak (2010), and Houde (2012), among others. Allowing for distance in the utility function creates spatial competition between dealers which implies that dealers with fewer geographic competitors have more market power, holding other things constant. Consumer preferences for distance have implications for cross-price elasticities between competitors of varying distances, and the aforementioned studies have found strong effects of distance on demand in a variety of industries.

I assume advertising enters indirect utility. I limit the analysis to television and print advertising and aggregate them into a single variable of advertising expenditures measured in dollars. Advertising is classified into two types: (1) *dealer* advertising, a_{jt}, and (2) *brand* advertising, A_{jt}. Brand advertising is model/make specific, and can represent either advertising for the entire brand or for the specific make. The

[8] I use three income brackets, $[0, \$50000]$,$[\$50000, \$100000)$,and $[\$120000, \infty)$

[9] For population density I use the land area of the consumer's Census Tract. Tracts are designed to have similar populations, so land area is highly correlated with population density.

two types of advertising have, potentially, different and linearly separable effects on utility. Dealer advertising influences the utility for every product at that dealer, and brand advertising influences the utility for every product of that brand or model.[10]

I allow for consumer specific preferences for advertising. This could either represent heterogeneity in tastes for advertising, or heterogeneity in exposure to advertising. The following is the functional form for advertising preferences:

$$g(a_{r_jt}, A_{z_jt}; \boldsymbol{\phi}) = \phi_i^{dealer} log(\underline{a} + a_{r_jt}) + \phi_i^{brand} log(\underline{A} + A_{z_jt}), \tag{2.3}$$

where the advertising parameters are distributed truncated normal,

$$\begin{pmatrix} \phi_i^{dealer} \\ \phi_i^{brand} \end{pmatrix} \sim TrN\Bigg(\begin{pmatrix} \phi_i^{\bar{dealer}} \\ \phi_i^{\bar{brand}} \end{pmatrix}, \begin{pmatrix} \sigma^{dealer} & 1 \\ 1 & \sigma^{brand} \end{pmatrix}, \mathbb{R}^+ \Bigg). \tag{2.4}$$

The parameters $(\bar{\phi}^{\text{dealer}}, \bar{\phi}^{\text{brand}})$ describe the scale of advertising preferences in the population, and $(\sigma^{\text{dealer}}, \sigma^{\text{brand}})$ describes consumer heterogeneity in advertising preferences.[11] The parameters $\underline{a}$ and $\underline{A}$ represent minimum levels of advertising resulting from normal business operations in a given market.[12]

Manufacturer advertising affects the utility for all of the manufacturer's products at all of the dealers in its dealer network. However, dealer advertising only directly affects the utility of products sold at that particular dealer. I allow for separate effects of dealer and brand advertising for the following reasons. First, typically these advertisements convey different types of messages about the product. Second, brand advertisements typically have a higher level of production quality, and so may have a different effectiveness in shifting consumer demand per dollar of media spending. On the other hand, dealer advertising may be better at reflecting local idiosyncrasies in preferences, and so may be more effective.[13]

[10] It is sometimes the case that dealer advertising is specific to a particular brand, even if the dealer sells more than one brand. When this happens, I make the strong assumption that this advertising perfectly "spills over" to the other cars sold by the dealer.

[11] $\bar{\phi}$ is the mean of the parent normal distribution, and σ is the standard deviation of the parent normal distribution.

[12] This is not observed and I do not estimate it. As an approximation, I use advertising rate data from Clear Channel for the value of a medium size billboard in each of the four markets and set this value as the minimum advertising level, the idea being that this approximates the value of a storefront with a sign. The minimum level of advertising could also include informal advertising like word of mouth.

[13] For a similar treatment of advertising in indirect utility see Dubé, Hitsch, and Manchanda (2005) and Anderson et al. (2012). I depart slightly by modeling advertising tastes as perfectly correlated across dealer and brand advertising for each consumer. This is more reasonable than a zero correlation assumption, and the aggregate nature of the data limits my ability to identify a correlation parameter.

2.2 Automobile Dealers

I model the supply of new cars by manufacturers and dealers as a full information two stage game. In the first stage, manufacturers simultaneously set wholesale prices and brand advertising levels. In the second stage, dealers observe the manufacturer decisions and simultaneously make retail pricing and advertising decisions. Each firm has complete information about its rival firms, and I assume there exits a sub-game perfect Nash equilibrium in prices and advertising.

First, I introduce additional notation to help deal with different combinations of dealers and brands. Manufacturers sell multiple car models through multiple dealers, and dealers can sell multiple models from multiple manufacturers. Recall that a product is a dealer/make/model combination. Let m_j denote the manufacturer m associated with product j, where manufacturers are indexed $1 \ldots M_{tn}$. Recall that r_j maps product j to dealer r and z_j denotes the car model z associated with product j. Indexing models is necessary because manufacturers make decisions at the model level, not the product level. For example, if j is a Toyota Camry from Mike Brown's Auto Mall, then $\{m, r, z\} = \{$Toyota, Mike Brown's Auto Mall, Camry$\}$.

Both manufacturers and dealers sell multiple products. Let the set of products sold by manufacturer m at time t in market n be $\mathcal{J}^M_{mtn}$. Let the set of products sold by dealer r be $\mathcal{J}^R_{rt}$. Also, let the set of all products of the same model z be Ω_{ztn} and the set of models from manufacturer m be $\mathcal{Z}_{mtn}$.

I solve the price and advertising game backwards, starting with the decisions of the dealers. The goal is to recover the unobserved costs of dealers and manufacturers. With costs in hand, I calculate producer surplus, and conduct counterfactual exercises.

Each dealer makes one retail price decision for each product and a single advertising decision, taking as given the wholesale price and manufacturer advertising decisions. A particular dealer faces the following profit maximization problem:

$$\max_{\boldsymbol{p_t}, a_{rt}} \pi_{rtn} = \mathcal{M}_{tn} \sum_{j \in \mathcal{J}^R_{rt}} (p_{jt} - W_{jt} - c_{jt}) s_{jt}(\boldsymbol{p}, \boldsymbol{a}, \boldsymbol{A}) - a_{rt} + a_{rt}\psi_{rt}, \tag{2.5}$$

where $\mathcal{M}_{tn}$ represents the size of the potential market, W_{jt} is the wholesale price charged by the manufacturer, c_{jt} represents constant marginal cost/revenues of distribution, and s_{jt} is the product market share. Unobserved advertising costs and revenues are a linear function of advertising and constant marginal cost/revenue parameter, ψ_{rt}. Note that the market share is directly a function prices and both types of advertising. The term c_{jt} could represent additional costs of distribution, or additional revenue from the sale of a car such as future warranty service, unobserved constant marginal rewards from the manufacturer, or other future business. The term ψ_{jt} represents unobserved revenue from advertising activities, like sales from trucks, used cars sales, or other dealer services that generate revenue, or unobserved costs associated with advertising, like production costs. Fan (2013) recovers a similar cost parameter that represents the costs of changing newspaper attributes.

All dealers simultaneously make price and advertising decisions. For a particular dealer, the solution involves one pricing first order condition for each product sold and one advertising first order condition.[14] The price first order condition for product j is

$$s_j + \sum_{k \in \mathcal{J}^R_{r_j}} (p_k - W_k - c_k) \frac{\partial s_k}{\partial p_j} = 0, \tag{2.6}$$

and the advertising first order condition for dealer r is

$$\mathcal{M} \sum_{j \in \mathcal{J}^R_r} (p_j - W_j - c_j) \frac{\partial s_j}{\partial a_r} - 1 + \psi_r = 0. \tag{2.7}$$

Let T^R be the dealer ownership matrix, with general element $T^R(g,h) = 1$ if product g and h are sold by the same dealer, and zero otherwise. Let ∇^s_p be a matrix containing all of the first partial derivatives of shares with respect to retail prices, with general element $\nabla^s_p(g,h) = \frac{\partial s_g}{\partial p_h}$. Also define ∇^a as a row vector with general element $\nabla^a(g) = \frac{\partial s_g}{\partial a_{r_g}}$. Following Bresnahan (1987) and BLP, I solve for dealer markups by stacking all of the pricing FOCs defined by equation (2.6),

$$(\boldsymbol{p} - \boldsymbol{W} - \boldsymbol{c}) = -(T^R * \nabla^s_p)^{-1} \boldsymbol{s}, \tag{2.8}$$

where $\boldsymbol{s}$ denotes the vector of product shares and the notation "$*$" refers to element-by-element multiplication. Once markups are recovered, I plug them into equation (2.7) and recover ψ directly.

Although optimal price and advertising decisions cannot be solved for analytically, the FOCs from equations (2.6) and (2.7) implicitly define functions for equilibrium

[14] For the remainder of this section, I drop the time subscript t for clarity.

choices of price and advertising given the decisions of manufacturers: $\boldsymbol{p}^\star(\boldsymbol{W},\boldsymbol{A})$ and $\boldsymbol{a}^\star(\boldsymbol{W},\boldsymbol{A})$. Equilibrium prices and ads imply a level of equilibrium shares, $s^\star(\boldsymbol{p}^\star(\boldsymbol{W},\boldsymbol{A}),\boldsymbol{a}^\star(\boldsymbol{W},\boldsymbol{A}),\boldsymbol{A})$, given manufacturer decisions. Notice that brand advertising affects shares directly because consumer utility is a function of brand advertising, as well as indirectly through dealer decisions. Wholesale prices affect shares indirectly though dealer decisions.

2.3 Automobile Manufacturers

Manufacturers make wholesale price and advertising decisions in the first stage with full information about how these decisions change equilibrium shares, $s_j^\star$, in the retail sub-game. Manufacturers solve the following problem:

$$\max_{\boldsymbol{W},\boldsymbol{A}} \Pi_m = \sum_n \Big[\mathcal{M}_n \sum_{j\in\mathcal{J}_m^M} (W_{z_j} - C_{z_j}) s_j^\star - \sum_{z\in\mathcal{Z}_m} A_z + \sum_{z\in\mathcal{Z}_m} A_{zt}\Psi_z\Big], \tag{2.9}$$

where C_{z_j} represents marginal costs of production for model z and the term Ψ_z represents unobserved constant marginal costs/revenues of advertising for model z. Notice that a manufacturer can choose to spend different amounts on advertising for a particular model z in different media markets, but W_z is not market specific because wholesale prices, by law, must be the same for every dealer in the state of Virginia.[15]

Manufacturers anticipate that changes in wholesale prices lead to changes in retail prices *and* changes in dealer advertising. For example, consider an increase in wholesale price that leads to a less than one-for-one increase in retail price. The dealer would sell less and make a lower markup per car, therefore it has less incentive to advertise, which in turn reinforces the lower retail price.[16] Also, rival dealers change prices and advertising in response to wholesale price and brand advertising changes. The sum of these effects depends on the parameters of demand and the market structure of local markets. A single wholesale pricing first order condition for a manufacturer is,

$$\sum_n \Big[\sum_{j\in\Omega_z} s_{z_j} + \sum_{f\in\mathcal{Z}_m} (W_f - C_f) \sum_{k\in\Omega_f} \frac{\partial s_k^\star(\boldsymbol{p}(\boldsymbol{W},\boldsymbol{A}),\boldsymbol{a}(\boldsymbol{W},\boldsymbol{A}),\boldsymbol{A})}{\partial W_z}\Big] = 0, \tag{2.10}$$

[15] See Lafontaine and Morton (2010).

[16] In the model, all of these effects happen simultaneously.

where I am explicit about the fact that retail prices and dealer advertising are a function of wholesale prices and manufacturer advertising.

A change in wholesale price directly affects the retail price decisions of dealers, as well as the advertising decisions of dealers. Both of these effects influence how a change in wholesale price changes equilibrium shares of a single product in a market:

$$\frac{\partial s_k^{\star}}{\partial W_z} = \Bigg[\underbrace{\frac{\partial s_k}{\partial p_1}\frac{\partial p_1}{\partial W_z} \cdots \frac{\partial s_k}{\partial p_J}\frac{\partial p_{J_n}}{\partial W_z}}_{\text{effect through dealer prices}} + \underbrace{\frac{\partial s_k}{\partial a_1}\frac{\partial a_1}{\partial W_z} \cdots \frac{\partial s_k}{\partial a_{R_n}}\frac{\partial a_{R_n}}{\partial W_z}}_{\text{effect through dealer ads}} \Bigg] \tag{2.11}$$

The manufacturer anticipates how changes in wholesale price will change retail prices and advertising and therefore change demand. There is the typical wholesale price pass-though to retail prices and in addition an advertising pass-through of wholesale price.

I recover the pass-through of wholesale price to retail price, $\frac{\partial p_j}{\partial W_z}$, and advertising, $\frac{\partial a_r}{\partial W_z}$, by applying the implicit function theorem to the *retail* pricing and advertising first order conditions. Villas-Boas (2007) suggests this for prices, and I extend her results to two choices of the retailer and manufacturer. Consider the system of implicit equations Q, where the jth equation is the retail pricing FOC of product j:

$$Q(j) = s_j + \sum_{k \in \mathcal{J}^r} (p_k - W_k - c_k)\frac{\partial s_k}{\partial p_j} = 0. \tag{2.12}$$

Define the following matrices of derivatives of Q with general elements: $Q_p(i,j) = \frac{\partial Q^j}{p_i}$, $Q_a(i,r) = \frac{\partial Q^j}{a_r}$ and $Q_{W_1}(j) = \frac{\partial Q^j}{\partial W_1}$. Also, consider the system of dealer advertising FOCs, K, with general element for the rth dealer:

$$K(r) = \sum_{j \in \mathcal{J}_r^R} \mathcal{M}(p_j - c_j)\frac{\partial s_j}{\partial a_r} - 1 + \psi_r = 0, \tag{2.13}$$

where I define matrices of derivatives of the FOCs as K_p, K_a, and K_{W_1} with general elements $K_p(r,j) = \frac{\partial K^r}{\partial p_j}$, $K_a(r,r') = \frac{\partial K^r}{\partial a'_r}$, and $K_{W_1}(r) = \frac{\partial K^r}{\partial W_1}$.

To recover the total effect of a wholesale price change on dealer pricing I apply a multivariate version of the implicit function theorem. I define the following block matrix with dimension $(J_n + R_n) \times (J_n + R_n)$,

$$\mathcal{G} = \begin{pmatrix} Q_p^p & Q_a^p \\ K_p & K_a \end{pmatrix}. \tag{2.14}$$

Next, I construct a block matrix with dimension $(J_n + R_n) \times Z_n$

$$\mathcal{H} = \begin{pmatrix} Q_{W_1} & \cdots & Q_{W_Z} \\ K_{W_1} & \cdots & K_{W_Z} \end{pmatrix}. \tag{2.15}$$

This matrix holds the derivatives of all the dealer price and advertising FOCs with respect to wholesale price.

The matrix of wholesale price pass-through, ∇_W, is the solution to the following system of equations, $\mathcal{G}\nabla_W = \mathcal{H}$, where the first J rows of ∇_W are the price pass-through terms, and the last R rows are the advertising pass-through terms.

Manufacturer markups can be expressed as

$$(\boldsymbol{W} - \boldsymbol{C}) = -1 * (T^M * \left(\nabla_W^{p\prime} \nabla_W^{a\prime}\right) \begin{pmatrix} \nabla_p^s \\ \nabla_a^s \end{pmatrix})^{-1} \tilde{\boldsymbol{s}}^\star. \tag{2.16}$$

If there is only one market, ∇_p^s is a $J_n \times Z$ matrix. With multiple markets, it is a $\bar{J} \times Z$ matrix, where recall J_n is the number of products in market n, and define $\bar{J} =\mid \mathcal{J}_1 \cap ... \cap \mathcal{J}_N \mid$ as the number of products across all markets. Similarly, ∇_a^s includes an element for each dealer in all markets. Also, $\tilde{\boldsymbol{s}}^\star$ is a vector of *model* market shares, with element, $\tilde{s}_z^\star = \sum_n \sum_{j \in \Omega_{zn}} s_j$. By writing markups this way, I am including the constraint that wholesale prices must be equal across markets.

Brand advertising by the manufacturer is at the model-market level, and therefore affects all products of the same model in a single market, regardless of the dealer. In this sense, brand advertising "raises all boats" with respect to the dealers. The number of advertising decisions equals the number of products multiplied by the number of local markets. The manufacturer advertising first order condition for model z in local market n is

$$\sum_n \Big[\mathcal{M}_n \sum_{k \in \mathcal{J}} (W_{z_k} - C_{z_k}) \frac{\partial s_k^\star(\boldsymbol{p}(\boldsymbol{W}, \boldsymbol{A}), \boldsymbol{a}(\boldsymbol{W}, \boldsymbol{A}), A)}{\partial A_z} - 1 + \Psi_{zt}\Big] = 0. \tag{2.17}$$

Even though car model level advertising decisions are market specific, the advertising decision is dependent across markets because wholesale price is not market specific.

The partial derivative of shares with respect to manufacturer advertising implies that the manufacturer anticipates changes in dealer price and advertising effort given changes in brand advertising:

$$\frac{\partial s_k^\star}{\partial A_{zn}} = \Bigg[\underbrace{\frac{\partial s_k}{\partial p_1}\frac{\partial p_1}{\partial A_{zn}} \cdots \frac{\partial s_k}{\partial p_J}\frac{\partial p_J}{\partial A_{zt}}}_{\text{effect through dealer prices}} + \underbrace{\frac{\partial s_k}{\partial a_1}\frac{\partial a_1}{\partial A_{zn}} \cdots \frac{\partial s_k}{\partial a_R}\frac{\partial a_R}{\partial A_{zn}}}_{\text{effect through dealer ads}} \Bigg]. \tag{2.18}$$

When the manufacturer changes its advertising, all dealers will respond with changes in prices and advertising, which in turn changes equilibrium shares. The sum of these effects is the total effect of a change in manufacturer advertising on quantity demanded. Recovering Ψ_{zt} is straightforward after solving for markup's in equation (2.16) and recovering $\frac{\partial s}{\partial A}$'s.

3 Data Description

For this study I have compiled a dataset on new car sales and the pricing and advertising behavior of dealers and manufacturers.[17] I obtain automobile sales data for the state of Virginia from the Virginia Department of Motor Vehicles for January 1, 2007 to September 31, 2011. The data are at the transaction level, and for each purchase I observe the make/model of car bought, date of transaction, transaction price, identity of the selling dealer, and the nine or five digit zip code of the buyer. I limit the sample to cars, SUVs, and vans sold to and from buyers and dealers in the four largest media markets in Virginia: Northern Virginia, Virginia Beach, Richmond, and Roanoke/Lynchburg. I also limit the sample to cars with a manufacturer suggested retail price below $70,000. I merge the transactions data with data on car characteristics and wholesale prices provided to me from Intellichoice.com. In the analysis I include horsepower, physical size in cubic inches, weight, miles per gallon, passenger capacity, and body style as car characteristics.[18] I aggregate the data to define a product as a model-dealer combination. I use the mode model characteris-

[17] For insitutional details about this industry, see Lafontaine and Morton (2010) and Murry and Schneider (2015).

[18] Following BLP I create an acceleration variable defined as horsepower divided by weight. I observe a number of aspects of wholesale price, including the invoice price from the manufacturer, delivery charges, and a post-sale kickback to the dealer called "holdback."

tics across model trims as the product characteristics, I use the average price for the model from the dealer in a particular quarter as the product price. The final sample consists of 57,557 product level observations across four markets and 18 quarters. I present sample moments in Table 1.

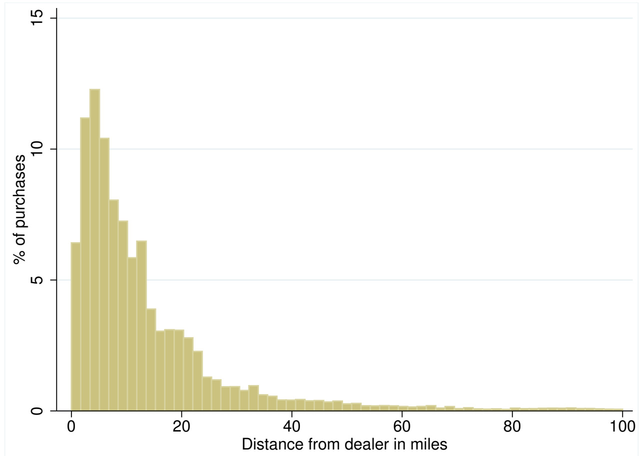
Table 1: Virginia New Car Transactions, Descriptive statistics

	Mean	SD	Q25	Median	Q75
Transaction Moments					
Purchase Distance	13.3	4.3	8.1	17.9	
Distance past closest dealer	9.2	1.8	4.3	14.6	
Price	29,489	11,116	22,038	27,054	34,096
Product Moments					
HP/100	2.086	0.628	1.62	2	2.61
MPG/10 (hwy)	2.668	0.463	2.3	2.7	3
Cubic Inches	8,756	1,803	7,568	8,424	9,859
Passenger Seats	5.192	1.083	5	5	5
Domestic Brand	0.434	0.496	0	0	1
Dealer Advertising	24,681	45,277	0	4,228	31,103
Brand Advertising	10,897	25,021	0	0	8,005
Total Sales of New Cars					
Year	2007	2008	2009	2010	
Quantity	186,598	168,633	149,020	169,792	

Note: From the selected sample of new automobile transactions, 2007Q1 - 2011 Q3, Virginia Department of Motor Vehicles. See text for selection details. Price is in 2006 dollars. Total sales are the sales included in my sample after the sample selection described in the text.

I geo-code the location of dealers and buyers in order to construct purchase distances. Figure 1 is a graph of the empirical density of transaction distances in the sample. Most consumers do not make purchases very far from home, and the distribution is heavily skewed. I present transaction distance moments in Table 1. The median purchase distance is about eight miles. Furthermore, median transaction distance past the closest dealer is only about four miles. As expected, transaction distances are much shorter in urban and suburban areas than rural areas, not shown in the table.

I merge the transactions data with information on dealer and manufacturer advertising from Kantar Media Intelligence. I observe quarterly advertising expenditures for automobile dealers, manufacturers, and dealer associations in the four largest media markets in Virginia. The data are broken down by type of media, and I use the sum of print and television advertising as the measure of advertising expenditures. I classify brand advertising as the sum of manufacturer and dealer association adver-



Note: Histogram of transaction distances for new cars, 2007Q1-2011Q3. Data from Virginia DMV.

Figure 1: Transaction Distance in Miles

tising. There is substantial variation in advertising across products. There are also substantial differences in dealer advertising, both within brands and across brands. Advertising moments, at a product level, are displayed in Table 1. For example, the average dealer advertising each quarter is \$24,681, and the average brand level advertising for a given product is \$10,897.

Next, I establish a link between advertising and sales in the data. I present a linear regression of log dealer sales on log advertising in Table 2. The dependent variable is sales, across models, of a particular make from a particular dealer in a single quarter. The first column includes market dummies, and the second column includes market and brand dummies. As expected, log-sales at a dealer is positively and significantly associated with both dealer and manufacturer advertising. In the structural model, the advertising parameters, $(\phi^{dealer}, \phi^{brand})$, are approximately elasticities and their magnitudes can be roughly compared to the regression results in Table 2.

Finally, in the structural estimation, I use tract level data from the 2010 American Community Survey to simulate households in the state of Virginia. The Survey uses Census data to provide estimates of income and other demographic information for every Census Tract. I use data on tract population, income, the geographic size of the tract (this is to control for population density) and travel time to work. The demographic data is from a single year, however, the sample period of five years is relatively short.

Table 2: Dealer Sales and Advertising

	Log Dealer Sales	Log Dealer Sales
Log Dealer Advertising	0.194	0.126
	(0.011)	(0.008)
Log Brand Advertising	0.106	0.013
	(0.008)	0.006
Constant	1.243	3.951
	(0.163)	(0.171)
Brand Dummies		✓
Market Dummies	✓	✓
Time Trend	✓	✓
Observations	2456	2456

Note: Regression of log sales on log advertising. An observation is a brand-dealer-quarter. Sales are total brand sales at a given dealer in a given quarter. SEs in parentheses.

4 Estimation and Results

I estimate the demand model using the Method of Simulated Moments, following closely Berry, Levinsohn, and Pakes (2004) and Petrin (2002). The parameters I estimate are the consumer preferences for car characteristics, price, travel distance, and advertising. I use three different types of moments to identify the parameters. First, as in BLP and Berry, Levinsohn, and Pakes (2004), I force the market shares predicted by the model to equal the market shares in the data. Second, I make a distributional assumption on unobserved quality, $\boldsymbol{\xi}$, namely that it is mean zero conditional on a set of instruments, $E[\xi \mid Z] = 0$, where Z represents a set of instruments. Third, I construct a set of micro-moments based on the individual transactions data. For example, I match the mean travel distance in the data to the mean travel distance predicted by the model. I do not use restrictions from the supply model to estimate the demand parameters. Details of how I construct the moments and other estimation details can be found in the Appendix.

4.1 Identification and instruments

I use moments that assume the unobserved quality, $\boldsymbol{\xi}$, is mean zero conditional on a set of instruments. For instruments, I use the set of exogenous variables included in the utility function, for example miles per gallon, as well variables that act as exclusion restrictions for the endogenous variables, price and advertising because the supply model implies that both price and advertising decisions are functions of the unobservable product specific quality parameter.

To identify the price coefficient I rely on the standard argument in the literature that the characteristics of other products are correlated with pricing decisions although uncorrelated with the structural error. For instruments I use the characteristics and number of other cars of the same style (mid-size, SUV, etc.), within a 10 mile radius. The rationale for interacting the typical instruments suggested by BLP with geography is that competition with rivals dissipates over space and over styles of cars, so I capture important restrictions placed on the geographic nature of competition in the supply model.

To identify the effect of dealer advertising, I rely on the fact that the first order conditions for dealer advertising imply that some notion of market size is correlated with advertising. To capture this, I use the total population within 5 and 10 miles of each dealer. Also, from the dealer advertising first order conditions, a dealer that offers more models and brands will, all else equal, find it optimal to advertise more, so I include this as an instrument as well.

To identify the effect of manufacturer advertising I include the number of dealers in a particular market selling each brand. More dealers leads to greater market coverage for the manufacturer, which implies a higher marginal benefit of advertising. I also include the population of each market. Additionally, I use a measure of the price of advertising in each local market constructed from data on total advertising expenditures and the number of units of TV Spot advertising for all industries.

The main overarching assumptions I rely on is that functions of geography and dealer entry and location decisions are not correlated with contemporaneous unobserved product quality, after controlling for product characteristics, location, and time effects. There is very little entry in this industry, and both entry and exit are regulated by states. Also, to the extent that local demographics and population change over time, initial decisions about entry may not reflect current demographics, population, and preferences for cars. Importantly, I include zip-code dummies to capture unobserved demand shocks at the dealer location level.

4.2 Demand Results

Here I present results of demand estimation. The estimates and standard errors are in Table 3. I find that consumers are very sensitive to travel distance. Consumers with longer travel times to work dislike distance more, as do consumers from more urban areas. Consequently, cross price elasticities between products at dealers located far from each other are substantially smaller than dealers located near each other. I present elasticities for selected group of cars in the Richmond market in the first quarter of 2007 in Table 4. An element of the table is the percent change in demand of the row product given a percent change in price of the column product. Three different geographic selling areas are represented in the table. Area “1” is approximately 15 miles from areas “2” and “3”, and the later two areas are approximately 25 miles from each other. We would expect, for the same car, cross elasticities to be smaller between areas “2” and “3” than between any other combination. For example, a price increase by Honda Accord 2 leads to greater substitution to Honda Accord 1 than Honda Accord 3. The pattern is similar for the Ford Fusion. Also, notice that the Ford Fusion 1 and the Ford Escape 1 are closer substitutes for the Honda Accord 1 than is the Honda Accord 3. The elasticity of demand with respect to distance is between -1.1 and -1.8 depending on the market and the time period. For example, a 1% increase in distance to a product for all consumers (or the equivalent increase in the cost of distance) leads to a decrease in demand by between 1.1% and 1.8%.

Own price elasticities are generally consistent with, or slightly more elastic than related studies of the automobile market. For example, the average price own price elasticity for the entire sample is -5.3, compared to Albuquerque and Bronnenberg (2012) who find an average price elasticity of -4.1 with a similar model using a 20% sample of transactions the San Diego area for 2004-2006. Additionally, I estimate that lower income households (<\$50k) are more price sensitive than medium and higher (<\$120k) income households. Notice that the two highest priced cars in Table 4 are each other’s closest substitutes, the Ford Escape and the BMW 3-series. High income consumers are less price sensitive, so they substitute to other high quality cars.

Both dealer and brand advertising have a meaningful affect on utility. On average, consumers value an increase in dealer (brand) advertising from \$20,000 to \$30,000 at about \$36 (\$44) in terms of the price of the car, and \$26 (\$32) for an increase from \$30,000 to \$40,000. There is substantial variation across households in their preference for advertising, and more heterogeneity for brand advertising than dealer advertising.

Given the functional form assumption of advertising preferences, this implies there is a mass of consumers that are not affected much by advertising. Sovinsky Goeree (2008) also finds substantial heterogeneity in advertising effectiveness using micro level data on advertising exposure in the personal computer industry, including many consumer who are not affected by advertising. Although the average effects of brand and dealer advertising are similar, there is a clear tension underlying these results.

Table 3: Demand Estimates

Variable	Parameter	Estimate	Standard Error
Distance	λ_1	-10.596	0.032
Distance^2	λ_2	-3.179	0.060
Dist×TravelWork	λ_3	0.537	0.032
Dist×Density	λ_4	0.021	0.060
Advertising	ϕ^{dealer}	0.051	0.006
	σ^{dealer}	0.064	0.001
	ϕ^{brand}	0.052	0.010
	σ^{brand}	0.101	0.017
Price	α^L	1.532	0.104
	α^M	0.893	0.037
	α^H	0.851	0.029
	σ^p	0.611	0.071
Acceleration	β_1	3.818	0.068
Size	β_2	7.796	0.164
MPG	β_3	-1.052	0.029
	σ_3	0.996	0.002
Seats	β_4	-2.148	0.010
	σ_4	0.997	0.001
US Brand	β_5	0.024	0.035
	σ_5	0.104	0.007
Constant	β_0	-8.367	0.259

Note: Note: The utility function includes car style dummies, dummies for the zip-code of the dealer, a dummy if the car is a luxury car, and a quadratic time trend. Estimates are from two-step GMM estimation. Standard errors are calculated directly.

In a somewhat similar empirical setting, Xu et al. (2014) argue that dealer association advertising is more effective than manufacturer advertising the more local an ad's sender, the more credible the information in the ad. This could explain the reason why preferences for brand advertising vary much more than dealer advertising. a dealer's advertisement only affects cars at that dealer, although a manufacturer's advertisement affects all cars of that brand in a local market. In this sense, dealer advertising is wasteful from the standpoint of the manufacturer because it doesn't spill over to all of the manufacturer's cars, or in other words, the manufacturer would prefer if the dealer advertising dollars were spent on brand advertising.

Table 4: Cross price elasticities between select products

Product	Honda Accord	Honda Accord	Honda Accord	Ford Fusion	Ford Fusion	Ford Ford	Ford Escape	BMW 3-series
Accord 1	-4.3494	0.0272	0.0157	0.0015	0.0087	0.0067	0.0037	0.0257
Accord 2	0.0253	-4.8433	0.0099	0.0015	0.0116	0.0047	0.0029	0.0189
Accord 3	0.0347	0.0234	-4.5209	0.0015	0.0076	0.0058	0.0035	0.0220
Fusion 1	0.0319	0.0331	0.0140	-4.4084	0.0100	0.0055	0.0061	0.0233
Fusion 2	0.0305	0.0437	0.0121	0.0017	-4.2988	0.0053	0.0038	0.0224
Fusion 3	0.0367	0.0276	0.0144	0.0014	0.0083	-3.9909	0.0034	0.0221
Escape 1	0.0282	0.0242	0.0123	0.0022	0.0083	0.0047	-4.8293	0.0250
3-series 1	0.0265	0.0210	0.0103	0.0011	0.0066	0.0042	0.0034	-6.7754

Note: For products sold in the Richmond area during 2007Q1. Area 1 is approximately 15 miles from area 2 and 3. Areas 2 and 3 are approximately 25 miles from each other.

4.3 Supply Results

I calculate markups, marginal costs, (c_j, C_z), and unobserved marginal advertising profits, (ψ_r, Ψ_z) using the demand estimates and the equilibrium model presented in Section 4. Table 5 includes summary statistics of product markups and costs for dealers and manufacturers across brands. The results presented are for the Richmond market for 2007-2011.

In total, mean dealer markups are \$5,238 on average. In contrast, manufacturer markups are \$4,736 on average, not weighted by sales). Markups tend to be higher for more expensive cars. Marginal cost to the manufacturer represent about 62% of the retail price of a car on average.

I compare the supply estimates to other studies of the automobile industry. Albuquerque and Bronnenberg (2012) is the only other paper that I am aware of that uses transaction data to estimate firm surplus. My results are similar to their results for dealer markups and dealer costs. However, I estimate smaller manufacturer markups.[19] Also, my finding that distributional costs to dealers, c_j, are often negative is consistent with Albuquerque and Bronnenberg (2012). There are a few potential reasons for this. First, dealers might price new cars expecting future revenues like warranty service. Second, there are issues with the measure of wholesale price. I do not observe the exact wholesale prices for the set of cars sold, but only an aggregate measure, exactly like I only observe aggregate characteristics. I use the median

[19] My data is slightly different. They only have a sample of manufacturers in a single metropolitan area, whereas I have the population of car sales in a state.

Table 5: Summary Statistics, Firm Behavior

	Dealer			Manufacturer		
Brand	Mean Price	Mean Markup	Mean Lerner Index	Mean Markup	Mean Marginal Cost	Mean Lerner Index
BMW	53,394	7,299	0.14	6,761	34,780	0.17
Buick	33,418	5,526	0.17	4,894	22,090	0.18
Cadillac	46,518	6,726	0.15	6,029	33,083	0.16
Chevrolet	28,660	5,076	0.19	4,542	17,893	0.22
Chrysler	28,521	5,126	0.19	4,452	17,668	0.21
Dodge	25,680	4,954	0.20	4,294	15,853	0.22
Ford	28,877	5,220	0.19	4,713	17,035	0.22
GMC	40,663	5,962	0.15	5,348	24,150	0.18
Honda	24,738	4,851	0.20	4,661	14,856	0.25
Hyundai	23,813	4,719	0.21	4,184	14,711	0.23
Kia	21,343	4,482	0.22	3,910	12,820	0.24
Lexus	52,512	7,035	0.14	6,479	36,151	0.16
Mazda	25,045	4,913	0.20	4,323	15,643	0.22
Mercedes-Benz	54,732	7,182	0.13	6,568	39,135	0.15
Nissan	28,190	5,111	0.19	4,646	17,647	0.22
Subaru	24,835	4,929	0.20	4,336	15,839	0.22
Toyota	28,909	5,189	0.19	4,975	16,671	0.24
Volkswagen	26,362	5,106	0.20	4,506	17,116	0.22
Volvo	35,098	5,789	0.17	5,165	26,161	0.17
Total (all brands)	29,532	5,238	0.19	4,736	18,455	0.22

Note: For the 2007Q1-2011Q3 in Richmond, Virginia. “Total” includes smaller brands not listed.

wholesale price across trims, which may overstate wholesale prices in some cases and lead to bias in the distribution costs, c_j. Third, I am not incorporating information on dealer rebates. These rebates can be quite large, anywhere from \$500 to \$10,000 per sale.[20]

It is a little more difficult to compare my results to previous studies that use aggregate data at the make/model level such as BLP, Petrin (2002), and Brenkers and Verboven (2006). In particular, BLP and Petrin (2002) do not model the vertical structure, and they interpret their results as the costs and markups of manufacturers. They implicitly assume retailers do not make strategic decisions. However, if both dealers and manufacturers have market power, these studies are estimating, using aggregate data, a measure of retail markups, and, as noted by Brenkers and Verboven (2006), the costs they estimate are the total costs of the entire vertical structure. Although the comparison is difficult because the time periods are different, I find slightly larger dealer markups than the markups in BLP and Petrin (2002). BLP find that “manufacturer” marginal costs are a much higher percentage of the final price

[20]According to NADA, service department revenues represented 14% of total revenues in 2010, and warranty revenues are about 10% of service revenues (http://tinyurl.com/azf6jey). Information on dealer rebates is from Automotive News, an industry data and analysis resource.

than I do, which is expected given that they do not split marginal costs between dealers and manufacturers.

4.3.1 Distance and Competition

The demand results imply that distance is important for consumer choice, but how does this translate into competition between firms? I re-solve the model for prices in the dealer sub-game assuming different counterfactuals about the effect of distance. First, I halve the preference for distance; second, I assume that there is no preference for distance in the model, which effectively reduces the distance to each dealer to zero. Mean prices decrease by around \$100 when the distance preference is cut in half and by \$250 if distance does not matter at all. As distance becomes less important, dealers start to compete more directly with each other because consumers are now willing to substitute to more distant dealers.

4.3.2 Advertising and the division of surplus

Typically, the relationship between a retailer and manufacturer is expressed as the relative size of price-cost markups. [21] However, this does not account for potentially important non-price decisions of firms, such as advertising. For example, although markups may look like they favor dealers, if dealers are doing the bulk of advertising then the division of surplus might favor the manufacturer.

I define the division of surplus within the vertical structure as the ratio of dealer to manufacturer average profits (including advertising expenses) for each product sold. Define η_j to be this ratio for a particular product using estimates from my model that incorporate advertising decisions,

$$\eta_j = \frac{(p_j - W_j - c_j) + (a_{r_j}\psi_r - a_{r_j})(\frac{1}{q_{r_j}})}{(W_j - C_j) + (A_{z_j}\Psi_z - A_{z_j})(\frac{1}{Q_{z_j}})}. \tag{4.1}$$

Compare this to $\hat{\eta}_j$, the ratio of dealer to manufacturer markups,

$$\hat{\eta}_j = \frac{(p_j - c_j)}{(W_j - \hat{C}_j)}. \tag{4.2}$$

[21] For example, Villas-Boas (2007) calculates the division of surplus in the yogurt industry, Albuquerque and Bronnenberg (2012) calculate markups with a similar model of pricing for auto dealers and manufacturers and Ho (2009) uses a price bargaining model to calculate the division of surplus between hospitals and insurers.

where $\hat{C}$ is an estimate of manufacturer marginal costs calculated from a model of supply where manufacturers do not account for the pass-through of wholesale prices to dealer advertising. Since advertising is not product specific (it is either dealer specific or model specific), I weight advertising equally across products. The term q_{r_j} represents total units sold by dealer r, and Q_{z_j} represents total units sold for model z by the manufacturer across all dealers.

Results for the division of surplus are displayed in Table 6. I include the six most popular brands in the sample. Although total brand advertising is greater than dealer advertising, dealers advertise more per car sold in local markets than manufacturers, which is the primary reason why the mean of η is smaller than the mean of $\hat{\eta}$. The difference is also partly due to the marginal cost estimates being different between specifications. The magnitude of difference reflects the extent to which advertising per car is relatively important compared to price-cost markups. On average, dealers earn about 6% more surplus from new car sales than manufacturers, contrasted to 11% for the case without advertising.

Table 6: Mean Division of Surplus by Make

	Without advertising ($\hat{\eta}$)	With advertising (η)
Chevrolet	1.12	1.06
Chrysler	1.15	1.11
Ford	1.11	1.03
Honda	1.04	1.01
Hyundai	1.13	1.04
Toyota	1.04	0.99
All Brands	1.11	1.06

Note: Dealer to manufacturer surplus as defined in the text. Calculated from supply results from the Richmond market, 2007-2011.

4.3.3 The marginal benefit of dealer advertising

At both the dealer and the manufacturer level I allow for the marginal benefit of a dollar of advertising to be different from the observed marginal cost of an ad, in this case $1. For dealers, this is captured as marginal *other* profit from advertising, ψ, in equation (2.7). Given that I estimate the demand model without restrictions from the supply equations, the extent to which the marginal benefit and cost of advertising diverge can tell me something about the fit of the model. For example, if the computed marginal benefit of advertising from the demand estimates is always equal to the observed marginal cost, then the demand estimates and the supply model completely explain advertising behavior.

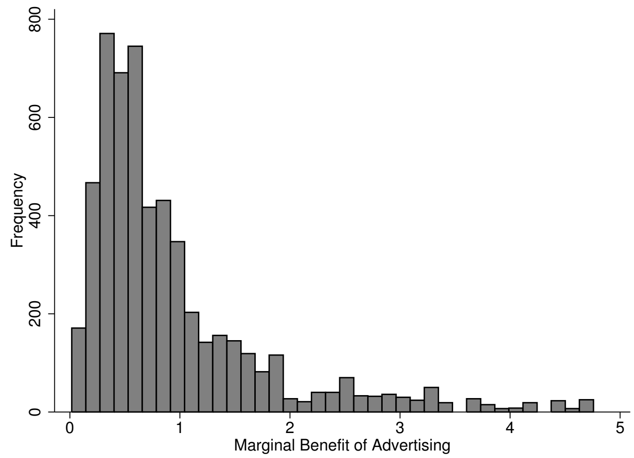


Figure 2: Marginal Benefit of Dealer Advertising

There are both revenue and cost components of ψ. On the revenue side, new car sales represent a little less than half of revenue for a dealership.[22] Other revenue comes from new truck sales, used car and truck sales, and the service department. There is no reason to believe dealer advertising does not benefit these other business lines. There are other costs associated with advertising besides the cost of buying media time/space, for example production costs. Also, there might be less advertising than expected at a dealer if the dealer is starting a showroom renovation project, employing more seasonal staff, or engaging in direct promotional activities not captured in the advertising data. In Figure 2, I present a histogram the computed marginal benefit of advertising, conditional on dealer advertising greater than zero. Specifically, this is the leftmost term from equation (2.7). The median of the distribution is close to one half, about 60% of dealers have marginal benefit less than one and about 78% less than two. Numbers below one suggest that dealers advertise more than just the benefit from new cars implies. Values above one suggest that there are net costs of advertising that the model does not explicitly capture, or in other words too little advertising when compared to model predictions.

[22] Information about dealership line of business are taken from the National Automobile Dealer Association website: http://www.nada.org/Publications/NADADATA/dealership_profile/

5 Policy Implications

5.1 Vertical coordination

One auto dealer-manufacturer regulation that has received attention recently from academics, policy makers, and the media, is a common regulation stipulating that manufacturers sell cars through an independent network of licensed franchised dealers. The details of these regulations vary slightly across states, but generally manufacturers are prohibited from selling directly to consumers, or owning controlling stakes in dealer operations. Manufacturers are also prohibited from using vertical restraints, such as price maintenance, non- linear pricing, or advertising requirements, in franchise contracts. However, a classic efficiency argument in favor of vertical coordination, or integration, whether from direct-to-consumer sales or through contractual restraints, is that coordination resolves the double marginalization externality and leads to lower retail prices.[23] The model I present also implies that coordination would resolve an advertising externality within the vertical relationship.

U.S. antitrust authorities have weighed in on the effects of vertical coordination in this industry. For example, Rogers (1986) concludes that state policies restricting vertical arrangements harm consumers. This conclusion is echoed in a 2001 speech made by Federal Trade Commission chairman Thomas Leary.[24] In a more recent analysis, Bodisch (2009) advocates eliminating state bans on direct sales. He predicts that direct sales would reduce distribution costs and better match consumer preferences with car production.[25]

The issue of direct-to-consumer sales and vertical coordination has recently emerged because of the actions of Tesla Motors, a luxury electric car company from California. Tesla has been sidestepping current regulations and selling directly to consumers by allowing customers to phone-order cars from "galleries." Dealer associations see Tesla as a threat: in multiple states, including New York, Texas, and Virginia, they have pushed legislation that further restricts the sales of cars to consumers by any means other than the established franchise system.[26]

How would the market for new cars change if manufacturers could coordinate

[23] See Rey and Vergé (2008) for an overview of the economics of vertical restraints.

[24] See `http://www.ftc.gov/speeches/leary/learystateautodealer.shtm`.

[25] Although the position of policy-makers is clear, federal antitrust agencies are likely powerless here because dealer franchise regulations fall under state action antitrust immunity.

[26] See the news media articles referenced in the introduction for more information.

with dealers, either by owning dealers and selling directly to consumers, or by writing contracts that coordinate dealer-manufacturer decisions? How large are the price and advertising inefficiencies from double marginalization and the public goods advertising externalities? Direct quasi-experimental evidence of coordination is not available because there exists little variation in regulations across states. However the recent behavior of Tesla Motors furnishes anecdotal evidence of the effect of coordination. Tesla's advertising- to-sales ratio as documented in annual reports is similar to that of other luxury vehicles, even though its market coverage is many times smaller. This implies that Tesla's marginal benefit of advertising is greater than that of a manufacturer in a traditional dealer franchise relationship.[27]Tesla's statements, both public and in their annual reports, about high levels of sales effort illustrates the effects of coordination. The incentive for advertising and sales effort are greater for Tesla because the coordinated firm makes pricing and advertising (and in Tesla's case, service) decisions based on the marginal benefit to the total vertical structure.

Using the estimation results and the model of firm behavior, I simulate the effects of dealer-manufacturer coordination, or integration. To simulate an integrated firm, I assume that the dealer makes decisions, but has a marginal cost equal to the sum of the marginal costs of both the manufacturer and the dealers and does not pay a wholesale price from the manufacturer. The dealer faces the following constant marginal cost: $c_j^{\text{total}} = c_j + C_j$. Therefore, the dealer faces the same marginal costs of the total vertical structure, but there is no surplus being extracted by the manufacturer, so the dealer's profits are the profits of the entire vertical structure. I simulate integration for dealers and manufacturers in the Richmond, Virginia market in the first quarter of 2007.[28]

I perform two different counterfactual simulations. The first involves simulating the effects of a single dealer-manufacturer pair integrating. I do this for each dealer-manufacturer pair at a time and record the subsequent changes in prices and advertising for the entire market. This exercise has two purposes. First, allowing a single deviation is a way to quantify the pricing and advertising externalities already discussed. In this sense, this counterfactual is like a comparative static for the size of the vertical pricing and advertising externalities. Second, this exercise simulates how competition would change if a single manufacturer took control of a dealer and

[27]Information on Tesla Motors' marketing activities is from various 10K statements available from their corporate investor website, `ir.teslamotors.com`.

[28]I assume that non-advertising dealers continue not to advertise after coordination. I make this assumption because I cannot infer the unobserved marginal revenue from advertising, ψ_r, for these firms. I also assume nothing changes in the manufacturer sub-game.

sold directly though its own “factory outlet,” while still competing against traditional dealers in the market. This is precisely the behavior of Tesla Motors, and this counterfactual predicts how competition would change if traditional manufacturers followed Tesla’s lead.

In the second counterfactual exercise, I simulate the effects of every dealer in the market integrating with manufacturers at the same time. This counterfactual captures the effect would be of a complete overhaul of dealer-manufacturer regulations.

Table 7: Results from Dealer-Manufacturer Integration

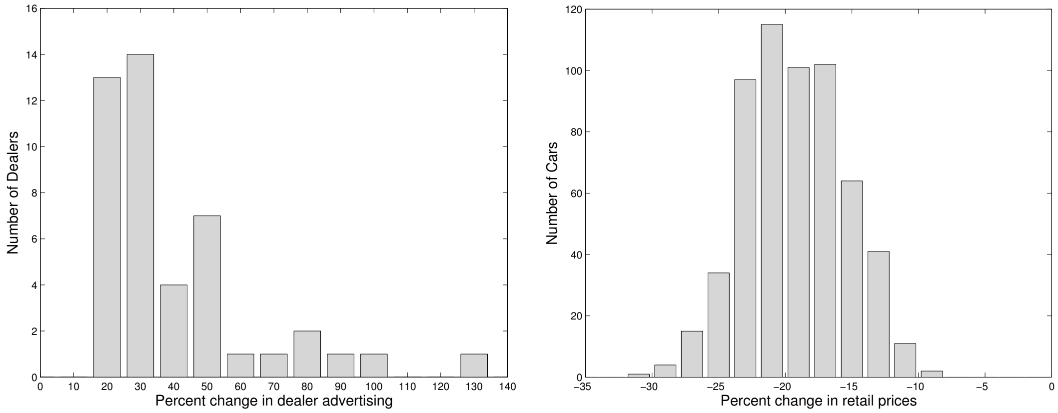
	Retail Price	Dealer Advertising
Single dealer integrates	-19.6%	+145%
Entire market integrates	-19.3%	+31%

Note: Results from counterfactual simulation show the median change in prices and advertising. First row: a single dealer coordinates with a manufacturer at a time, and the median is over all coordinated dealer- manufacturer pairs. Second row: All dealers and manufacturers vertically coordinate decisions. For both exercises I hold constant manufacturer decisions.

The results of the two counterfactual exercises are presented in Table 7. In both cases, the prices of the integrated firms fall substantially, by about 20%. This clearly suggests the the double marginalization externality is large in this industry. However, the advertising externality is large as well. In the case where one dealer-manufacturer pair integrates at a time, the median increase in dealer advertising is about 145%. The integrated firm has a significant advantage over the other firms because it does not suffer from the pricing externality, consequently the marginal benefit of advertising is much greater, and sales more than double on average. In the case when all dealer-manufacturer pairs integrate at the same time, the median dealer increases advertising by about 30% . This is not as great as the first case because a single integrated firm does not gain an advantage over the other firms, which are now integrated as well. However, advertising still raises because lower prices increase demand for products, in turn increasing the marginal benefit of advertising. The distribution of price and advertising changes is displayed in Figure 3 for the counterfactual where all firms integrate.

A classic defense of vertical mergers is the beneficial effects on retail price. Clearly this is seen in the counterfactual. However, advertising rises substantially. In the model, advertising directly affects preferences, which has often been viewed in the literature as wasteful because it distorts consumers’ true preferences for products.[29]

[29] See Bagwell (2007) for a detailed review of this argument, which is first attributed to Braithwaite (1928). See



(a) Dealer Advertising

(b) Retail Prices

Figure 3: Change in retail prices and advertising under full market integration

In general, the results suggest that policy-makers, when evaluating a vertical merger, should be aware of effects other than that on price.

5.2 Advertising and dealer terminations

In 2009, Chrysler and GM were asked to report on their activities to Congress as a requirement of receiving government funding from the Troubled Asset Relief Program (TARP). Both companies proposed terminating a total of about 3,000 dealers across the country. However, state laws generally prevent the termination of dealer franchise contracts, so GM and Chrysler were asking Congress to allow the proposed terminations. Ford, the third of the “Big 3” US car manufacturers, was in a similar position, as it had a clear policy of trying to reduce its dealer network.[30] Local and national dealer associations lobbied state and national legislators to prevent the proposed dealer terminations, and in the end end were successful in moderating the number of terminations. According to Congressional testimony, the second largest “cost” savings GM and Chrysler cite are is lower local advertising assistance. GM and Chrysler also claimed that one benefit of closing dealers is that the remaining dealers would be “stronger,” and thus able to provide a higher level of service to customers.

Dixit and Norman (1978) for a general analysis of how persuasive advertising tends to be excessive in equilibrium.

[30] For example, see Lafontaine and Morton (2010) for a historical trend in dealer reductions, or `nytimes.com/2009/05/19/business/19ford.html` for reports in the press. A summary of the dealer termination issue as it relates to the U.S. federal government is in a congressional report on TARP, see Barofsky (2010).

Here, I provide analysis of the effects of dealer network size on advertising and welfare. First, I discuss the effects predicted by the model. Second, I find evidence of these effects in the data. Third, I use the structural model to predict the effects of Ford closing dealers in the Richmond market.

There are two main effects in the model when a manufacturer shrinks its dealer network. First, there is a scale effect of sales on the manufacturer. The manufacturer will sell fewer cars, all else equal, because it has fewer retail locations. This decreases the marginal benefit of advertising for the manufacturer, and the manufacturer will decrease advertising. In turn, a decrease in manufacturer brand advertising has a negative effect on dealers. The second effect is a dealer competition effect. Remaining dealers, all else equal, are better off because they face less competition. Dealers have an incentive to charge higher prices, and because of this both dealers and manufacturers have a higher marginal benefit of advertising.

Table 8: Linear Regression: Relative Advertising and Market Structure[a]

	(1)	(2)
# of Dealers	3.47	2.91
	(1.04)	(0.78)
Constant	-22.98	-7.31
	(9.75)	(5.37)
Market Dummies	Yes	Yes
Observations	1815	123

[a] Standard errors in parentheses. Dependent variable (*ad ratio*) is brand advertising over median dealer advertising for dealers who sell that brand. Column (1) observation is a brand-market-quarter. Column (2) observations are aggregatedt to a brand-market.

The two effects just mentioned have competing implications for how advertising should vary with the size of dealer networks. I examine how dealer and manufacturer advertising co-varies with the size of dealer networks in the data. I construct a variable, *ad ratio*, which is equal to the ratio of brand advertising over mean dealer advertising, for dealers selling that brand in a given market. This variable captures the relative advertising effort of the manufacturer compared to its network of dealers in each market. Using OLS, I regress *ad ratio* on the size of the dealer network and market dummies. The results are displayed in Table 8. An observation for column (1) is make-market-quarter, and an observation for column (2) is averaged over all quarters. There is a significant positive association between a brand's *ad ratio* in a market and the number of dealers selling that brand of car in a market. The point estimate suggests that each extra dealer is associated with a three-fold increase in brand advertising relative to mean dealer advertising. In other words, manufacturers bear a larger share of the local advertising in markets with larger dealer networks suggesting that there are significant advertising savings to manufacturers by reducing dealer networks.

Overall, the co-variation between *ad ratio* and the number of dealers is consistent with what the model predicts. Both the scale effect and the dealer competition effect predict that the numerator of *ad ratio* goes up as the number of dealers increases. The dealer competition effect predicts that the denominator goes down as the number of dealers goes up. However, it is not possible to separately identify the two effects from one another or to understand how firm welfare changes from variation in the data alone. To gain a better understanding of the effects of dealer terminations, I use the model to simulate dealer closings by Ford in the Richmond area in 2010. Specifically, I close the 5 lowest selling Ford dealers to simulate what would happen if the Ford dealer network looked similar to the Honda and Toyota dealer networks. This leaves 6 Ford dealers in Richmond. I then re-solve the model for dealer advertising, retail prices, and manufacturer advertising.[31]

Table 9: Effect of Ford Dealer Closings in Richmond on Ford

	Pre-closing	Post-closing	Difference
Brand Advertising	277,464	117,750	-159,714
Sales	867	688	-179
Variable Profits	4,066,519	3,321,621	-744,898

Results from simulation exercises for first quarter 2010 in Richmond where I close five Ford dealers. Advertising and profits are in 2006 USD.

The results of the simulation exercises are in table 9. The dealer terminations result in a decrease in brand advertising by more than half, so there is indeed a significant cost savings to the manufacturer of fewer dealers. Because Ford is selling nearly 200 fewer cars, variable profits fall substantially. However, there may be other fixed costs to serving dealers not captured in my model.[32] Given my results, if Ford incurred equal fixed costs for serving each dealer of greater than $135,000 per quarter, then the decrease in dealers would be profitable. The decrease in advertising

[31] I hold constant wholesale prices because these are forced to be constant across the entire state by law. In practice, wholesale prices are often decided at the regional level.

[32] For example, see the TARP report to congress for a list of manufacturer suggested costs.

represents about $32,000 per closed dealer. If changes in advertising spending were ignored after closings, then per dealer fixed costs of about 23% more would be needed to rationalize dealer closings.[33]

A key argument of GM and Chrysler, for exaple see Barofsky (2010), around the time of the TARP bailout was that smaller dealer networks would make remaining dealer(s) stronger, so that they would be able to invest in sales effort, such as advertising, without manufacturer support. However, after the simulated closings, the remaining dealers are generally not more profitable. In fact, variable profits only increase for one remaining dealer, and slightly at that. Advertising decreases for all but a single dealer as well. The intuition is as follows. First, the decrease in brand advertising hurts the dealers by decreasing the willingness to pay for their products. This has a first order negative effect on sales and markups. Second, the only way to overcome the decrease in brand advertising is if consumers substitute from the closed dealers to the remaining dealers. However, I find that this is not the dominant effect. In general consumers substitute to closer dealers of different brands more than they substitute to Ford dealers far away. The overall impact on all but one of the remaining Ford dealers is negative.

6 Conclusion

I estimate demand for new cars in using transactions data in the state of Virginia, and I present a model of pricing and advertising decisions of both new car dealers and manufacturers. I estimate demand for new cars in using transactions data in the state of Virginia, and I present a model of pricing and advertising decisions of both new car dealers and manufacturers. Recent structural empirical models of vertical relationships do not model the promotional decisions of firms. However, there are many industries where promotion decisions are made by both retailers and manufacturers. I provide evidence that modeling the promotion decisions of vertically related firms is important for two reasons. First, estimates of relative surplus between manufacturers and dealers differs when advertising is included. Second, policy changes can induce large changes in advertising.

Specifically I find that dealers capture about 5% less surplus relative to manu-

[33] As a comparison, Albuquerque and Bronnenberg (2012) estimate dealer specific fixed costs of manufacturers of between $500,000 and $750,000 per quarter from a sample of dealers in southern California. To recover fixed costs the authors use a revealed preference approach based on current locations of dealers.

Table 10: Effect of Ford Dealer Closings in Richmond on Remaining Dealers

		Pre-closing	Post-closing	Difference
Profits	Dealer 1	1,142,647	1,120,830	-21,817
	Dealer 2	477,975	458,921	-19,054
	Dealer 3	568,596	539,916	-28,679
	Dealer 4	629,200	594,028	-35,172
	Dealer 5	595,182	596,274	1,093
	Dealer 6	1,190,528	1,157,509	-33,019
Sales	Dealer 1	190	186	-4
	Dealer 2	101	97	-4
	Dealer 3	89	85	-4
	Dealer 4	89	84	-5
	Dealer 5	103	103	-0
	Dealer 6	196	191	-5
Advertising	Dealer 1	65,582	65,582	0
	Dealer 2	20,438	19,539	-899
	Dealer 3	32,250	30,702	-1548
	Dealer 4	24,695	23,305	-1390
	Dealer 5	15,162	15,505	343
	Dealer 6	34,638	33,660	-978

Results from simulation exercises for 2007 Q2 in Richmond. In the second column I close two Chrysler dealers that never advertise; in the third column I close all but the best selling dealer.

facturers than from a specification without advertising decisions. Median prices are approximately 19% lower for a coordinated firm facing uncoordinated firms, and median dealer advertising is approximately 150% higher. If all dealer-manufacturer pairs integrate, advertising is approximately 30% higher. If a car manufacturer, for example Ford, were to make its dealer network look more like a Japanese firm's network, the remaining Ford dealers might be worse off because Ford would substantially decrease brand advertising in the local market.

I acknowledge that there are some limitations to the current study, and among them are the following. First, advertising may play a dynamic role as a stock variable. If the dynamic process for this stock is different between dealers and manufacturers then their advertising incentives differ from those captured in my model. Second, in the model dealers add little innate value to the vertical structure, so my results on vertical integration should be taken as an upper bound. Third, the buying process modeled is very simple, when in reality a complex search and negotiation process may more appropriately capture consumer incentives in this industry.

To be sure, the new car industry is not the only industry where non-price decisions within vertical relationships are an important consideration. Other industries where advertising is prominent by both retailers and manufacturers include groceries, retail clothing/accessories, and personal technology. Understanding how advertising is provided within these types of vertical relationships is important to understanding which firms hold economic power and the effect of regulatory or business policies.

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Appendix

A.1 Estimation Details

I estimate the demand model presented in section 2.1 using the car transaction and advertising data discussed in section 3. I follow the previous literature on demand for differentiated products by minimizing a GMM objective function of simulated moment conditions. The moment conditions originally proposed by BLP for these types of models are at the product level. More recently, like in this study, researchers supplement the poduct level moments, or macromoments, with moments constructed from individual level data on purchases. Examples of this include Berry, Levinsohn, and Pakes (2004), Petrin (2002), Sovinsky Goeree (2008), and Crawford and Yurukoglu (2012). In this appendix I discuss the details of estimation. First, I discuss details of the data, second I describe how deamnd is calculated, and lastly I present the moments used to estimate the demand parameters.

A.1.1 Market definition and product aggregation

I separate the state of Virginia into four separate markets. A geographical market consists of every dealer and household in a single media market, as defined by The Nielsen Company. I do not allow consumers to purchase outside of their market and I do not allow firms to sell outside of their market.

Each consumer's choice set includes every product available in the market. I aggregate over trim levels and options of cars to the model level. For instance I combine the Honda Accord EX and the Accord LX into a single product. To define a product's characteristics I use the mode product characteristics for trim levels and options offered. Without this aggregation the choice set would be unreasonably large.[34] Although I observe individual transaction prices, I do not observe the prices

[34] This aggregation is standard in similar studies of this industry, see Train and Winston (2007) and Berry, Levinsohn, and Pakes (2004)

consumers would have received for other products, so I assume consumers make decisions based on the average price for a particular product. In this sense, I ignore a more complicated negotiation process that generates the data.

To define the geographical market, I merge publicly available data from Nielsen on Designated Market Areas (DMAs) with the Census data from Virginia. I use DMAs to ensure that a market includes all consumers with access to local television stations for a given market. I define the market size as the total number of households in each market.

A.1.2 Consumer Choice

The probability that, in a given market, consumer i at time t chooses product j is

$$s_{ijt} = \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k \in \mathcal{J}_t} exp(\delta_{kt} + \mu_{ikt})}, \tag{A-1}$$

where δ includes all terms in the utility function that are not individual specific, and μ contains all individual specific utility terms.

$$\delta_{jt} = \bar{\beta} x_{jt} + \xi_{jt} \tag{A-2}$$

$$\mu_{ijt} = \alpha_{\Upsilon_i} + \sigma^p \epsilon_i^p + \sigma_k^x \epsilon_{ik}^p + f(\mathcal{D}_{ijt}; \boldsymbol{\lambda}) + g(a_{r_j t}, A_{z_j t}; \boldsymbol{\phi}) \tag{A-3}$$

The share of households that purchase a particular automobile, s_{jt}, is derived by summing up over individuals. Some individual attributes are unobserved, so during estimation I use simulation to integrate over the distribution of unobserved preferences and demographic characteristics. I use the 2010 ACS from American Fact Finder to simulate from the distribution of demographic characteristics and aggregate consumer into US Census Tracts. Next, I present the simulation details and a description of how I construct the moment conditions.

A.1.3 Moments

There are two types of product level macromoments: moments that match aggregate shares, and moments that are derived from a distributional assumption on unobserved product quality. First, following BLP, I restrict the aggregate product shares predicted by the demand model to exactly match the observed product shares in the data. Using the contraction mapping suggested in BLP, I solve for the mean utility parameters, $\boldsymbol{\delta(\theta)}$, that are the implicit solution to

$$S^{data} - s(\boldsymbol{\delta(\theta)}) = 0,$$

where S^{data} is the vector of observed market shares and $s(\boldsymbol{\delta(\theta)})$ is the corresponding vector of predicted shares from the model.[35] $\theta = \{\theta_1, \theta_2\}$ represents the vector of parameters and is partitioned into parameters that enter δ and μ respectively.

I use simulation to compute aggregate market shares. First, I draw a person from a Census Tract, then I conditional on each draw, I simulate unobserved preferences and demographic characteristics using the empirical distribution for demographic characteristics at the Tract level.[36] One difficulty is sampling from the geographic distribution of consumers. Because population densities are quite spread out and I use a relatively small unit of geography, taking a random sample of locations may lead to poor geographical coverage and require many simulations to reduce simulation bias.[37] Instead, I sample every Census Tract four times, and weight each draw by one-fourth Tract population. Conditional on the Census Tract, I simulate household demographics and the unobserved characteristics.[38]

Specifically, simulated market shares are

$$s_{jt} = \sum_{h}^{H} \frac{exp(\delta_j(\theta_1) + \mu_{hjt}(\theta_2))}{1 + \sum_{k \in \mathcal{J}_t} exp(\delta_k(\theta_1) + \mu_{hkt}(\theta_2))} \omega_h$$

where h is indexes simulation draws and ω is the population weight of each draw. The terms δ and μ are defined in equations (A-2) and (A-3).

After inverting demand using the BLP contraction mapping, I follow BLP by solving for the product specific demand unobservable as the residual of the following ordinary least squares regression:

[35] BLP show that there is a unique δ vector that solves this system of equations. There is a recent literature that criticizes the use of the BLP contraction mapping on computational grounds and suggests other methods. In my setting, the contraction mapping converges quite quickly for a given time period at a relatively strict tolerance, around 10 iterations.

[36] To construct market shares for the macromoments I *do not* use individual data. This step is analogous to BLP and other studies that only have aggregate data on market shares.

[37] I found estimates of $\boldsymbol{\delta}$ unstable in practice for small numbers of simulations without stratifying across geography.

[38] At this step I use antithetic acceleration to reduce variance due to simulation error when integrating over the distribution of demographics and unobserved household characteristics: see Stern (1997).

$$\delta_{jt}(s_{jt}, \theta_2) = \sum_k x_{jkt}\bar{\beta}_k + \xi_{jt}.$$

I use macromoments that set the expected value of $\boldsymbol{\xi}$ to zero, conditional on a set of instruments, Z,

$$G^{(1)}(\theta_2) := E[\xi \mid Z] \tag{A-4}$$

I supplement the standard product level BLP moments with micromoments derived from data on individual purchase decisions. These moments are most useful at identifying the parameters related to demographic characteristics, for example the dis-utility of distance traveled and the income specific preferences for price.

After recovering δ, I simulate *individual* purchase probabilities in the following way,

$$s_{ij}(\theta_2) = \frac{1}{R}\sum_{r=1}^{R} s_{ij}^r(\theta_2) = \frac{1}{R}\sum_{r=1}^{R} \frac{exp(\delta_j + \mu_{ij}^r(\theta_2))}{1 + \sum_{k \in \mathcal{J}} exp(\delta_k + \mu_{ik}^r(\theta_2))},$$

where I draw from the joint density of individual household demographics and unobserved preferences, conditional on Census Tract.[39]

Consider the residuals for each household, $y_{ij} - \hat{s}_{ij}$, where y_{ij} is a dummy of whether or not the household i purchases product j, and $\hat{s}_{ij} = \frac{s_{ij}}{1-s_{i0}}$ represents the choice probabilities *conditional* on purchase.[40] I interact this residual with data to form moments, for example household purchase distance, $\sum_j \sum_r (y_{ij} - \hat{s}_{ij}^r)d_{ij}$, or distance interacted with a demographic characteristic, $\sum_j \sum_r (y_{ij} - \hat{s}_{ij}^r)d_{ij}H_{1ij}^r$. Define $\mathcal{X}_{ij}$ as the vector of all the exogenous data entering the individual specific portion (μ_{ij}) of the utility function, for example distance traveled or distance traveled multiplied by travel-time-to-work. In general, the micromoments I construct take the following form:

$$G^{(2)}(\theta) = \sum_i \sum_j \sum_r (y_{ij} - \hat{s}_{ij}^r(\theta_2))\mathcal{X}_{ij}^r = 0$$

I stack the micromoments and macromoments and then minimize their weighted

[39] In practice, I use a sample of 10,000 individuals from the transaction data. Also, I see an individual's nine digit zip code, not Census Tract. I assign to each individual the Census Tract which has the closest center to the nine digit zip code.

[40] I make this adjustment following BLP (2004) because the individual level data is selected conditional on purchase.

distance by choosing θ_2:

$$\theta_2^{\star} = arg \min_{\theta_2} G(\theta_2)' \Gamma G(\theta_2)$$

where,

$$G(\theta_2) = \begin{pmatrix} G^{(1)}(\theta_2) \\ G^{(2)}(\theta_2) \end{pmatrix},$$

and Γ is a positive definite weighting matrix. I follow the two step procedure described by Hansen (1982) in order to obtain efficient estimates using the optimal weighting matrix. The weighting matrix is a block diagonal matrix, where the first block includes the weights for the macromoments, and the second block includes weights for the micromoments. For the first stage, I use the two-stage least squares weighting matrix, $(Z'Z)^{-1}$, for the product level moments and the identity matrix for the individual moments. I calculate standard errors directly using the expressions for asymptotic variance from Hansen (1982). In order to ensure that I have found the global minimum of the objective function, I start the estimation routine from 10 different randomly selected initial parameter values. Except in the case of the distance, advertising, and price parameter, I use a starting value from a simplified version of the model that I estimate ahead of time where the only dimension of heterogeneity is distance traveled.

A.2 Counterfactual Details

A.2.1 Vertical Integration

I simulate the model under different vertical integration scenarios. In each scenario, the vertically integrated firm face a constant marginal cost equal to the addition of distribution costs for the dealer and the production costs of the manufacturer: $c_j^{\text{total}} = c_j + C_j$. I resolve all of the price and advertising decisions at the downstream level. This is a very complicated non-linear system of equations. To deal with the dimensionality, I use a nested procedure. The outside nest uses Jacobi iteration over the advertising FOCS.[41] For each advertising FOC, I use a contraction mapping to solve for *all* retail prices. The contraction mapping iterates over the pricing first order

[41] For another example of Guass-Jacobi iteration see Pakes and McGuire (1994), which uses the Jacobi method to solve a dynamic investment problem.

conditions:

$$\boldsymbol{p}^{h+1} = \boldsymbol{c} + \boldsymbol{W} + \frac{-\boldsymbol{s}(\boldsymbol{p}^h)}{D\boldsymbol{s}(\boldsymbol{p}^h)} \tag{A-5}$$

The benefit of this procedure is that for each Jacobi step, the problem is a simple one dimensional non-linear equation: the solution to a single advertising FOC holding all other advertising constant. The price contraction mapping in the inner nest is extremely well behaved and converges quickly at each step. I repeat the Jacobi iterations over the entire system of advertising FOCs until the solution to the advertising FOCS no longer changes, up to some tolerance. The Jacobi method is not guaranteed to work, but in this application it works well because the system of advertising FOCs is diagonally dominant; in other words, the off-diagonal elements of the Jacobian are generally much smaller than the diagonal elements. The procedure is summarized as follows:

1. make a guess for a single dealer advertising term, a_1
2. given that guess, solve the pricing FOCs for all products
3. calculate the single advertising FOC for a_1, $K(1)$ (see equation (2.13)
4. update a_1 using Broyden's Method
5. repeat steps 1-4 until convergence to find a_1^{new}
6. follow steps 1-5 for a_2 through a_R, for each step using the *original* vector of $\boldsymbol{a}$
7. repeat steps 1-6 using the new vector of $\boldsymbol{a}^{new}$

A.2.2 Dealer Closings

I follow a similar procedure for dealer closings, except now there are a set of dealer advertising FOCs and manufacturer advertising FOCs. Solving the manufacturer level problem adds the complication of solving for all of the pass-though terms at each step, the procedure described in Section 3.3. Recall the effect of a change in manufacturer advertising on demand, equation (2.18) in the main text. I hold constant the pass-through terms, $\frac{\partial p_j}{\partial A_z}$ and $\frac{\partial a_r}{\partial A_z}$, and update the dealer terms, $\frac{\partial s_j}{\partial p_j}$ and $\frac{\partial s_j}{\partial a_r}$. After testing, I found that the former terms change very little during the procedure and were extremely computationally expensive to compute. The latter terms I already compute when I solve for retail prices and the dealer advertising FOCs.

Appendix References

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