Market Power in the US Automobile Industry

Mitchell Dubin*

31 March 2025

Abstract

This paper quantifies the extent and sources of market power in the U.S. automobile industry. I estimate a two level nested logit model of demand and a differentiated products oligopoly model of supply using S&P Global Mobility transaction-level data. Price endogeneity is addressed with BLP instruments. I recover a market-wide quantity-weighted average price-cost margin of 19%. I decompose this markup to reveal that product differentiation drives the vast majority of market power (90.8%), more than multi-product brands (5.8%) and multi-brand parent companies (3.5%). I also present the first formal analysis of the proposed Honda-Nissan merger. I find that Honda and Nissan markups will increase moderately (7%), while market-wide markups rise negligibly (1.2%). Subaru and Tesla, producers of Honda and Nissan's closest substitutes, emerge as the primary third-party beneficiaries of the merger. My findings suggest that the merger is unlikely to trigger antitrust scrutiny based on either substantial increases in prices or market concentration.

*I thank Phil Haile for his extensive guidance and Cormac O'Dea for his advice. I also appreciate Ken Gillingham and the Tobin Center for Economic Policy at Yale for support in data acquisition. Lastly, I am grateful to Carles Aules Blancher, Gian Luca Reti, and Rome Thorstenson for insightful discussions.

1 Introduction

In 2025, the US automobile industry will sell about 15 million new light vehicles to American consumers, contributing to the astounding fact that over 90% of American households own at least one vehicle (US Census Bureau). This makes automobiles one of the industries most penetrated into the daily lives of Americans. In this paper, I quantify the market power held by automobile firms in the United States, which affects nearly every American household.[1]

To this end, I ask two major questions. First, what are the sources of market power in the U.S. automobile industry, and what portion of markups (the component of price above marginal cost) do these sources generate? Second, how much additional market power will be generated by the recently proposed Honda-Nissan merger?

To answer the first question, I examine two major sources of market power: product differentiation and joint product ownership. In order to quantify these sources of market power, I decompose markups, following Nevo (2001). To do so, I need to first build and estimate a model of demand and supply in the market, then recover marginal costs, and finally run counterfactual simulations.

To model demand, I employ a two level nested logit model of consumer choice. Under the sequential decision making interpretation of this model, consumers first decide whether to buy a vehicle in a given year; then, if so, which type of vehicle to buy; and finally, which specific model within the type. This structure is a simple extension of the nested logit model in Berry (1994) and a form of the full random coefficients model found therein. On the supply side, I use a standard differentiated products oligopoly model, assuming each firm sets prices to maximize profits across all of their products. I estimate this model using transaction-level data from 14 representative US states over the period 2019-2022. In addition to transaction prices and quantities, these data provide many observable characteristics about the purchased vehicles. The central challenge in demand estimation, however, is the presence and importance of unobservable characteristics. To address this endogeneity of prices and quantities in estimating demand, I take and extend the instruments in Berry, Levinsohn, and Pakes (1995), henceforth referred to as BLP.

My demand results show that within-vehicle-type correlation is very strong, meaning that, say, consumers view all pickup trucks in their choice set as very close substitutes, as compared to cross-type substitution options. I also recover fairly sensible own-price elasticities, ranging from about -3 for lower-end products and firms to -9 for luxury products and firms. Using my demand estimates and my supply model, I recover marginal costs and therefore markups. I find that industry-wide

[1] Market power is the ability of a firm to profitably set prices above marginal cost.

price-cost margins (PCM) are about 19%.

One key contribution of my work is decomposing these 19% markups into their sources: product differentiation and joint ownership. By changing the product ownership matrix to reflect a counterfactual world where all products are owned by single product firms, I find that 90.8% of markups are due to product differentiation alone. This is likely due to a lack of joint ownership *within* particular vehicle-type nesting categories. I then perform a second counterfactual analysis to understand how much of the remaining 9% of markups is generated by joint ownership within multi-product brands as opposed to multi-brand parent firms (e.g. Dodge, Jeep, Ram, and Chrysler each setting prices for their suite of products vs. their collective owner, Stellantis, pricing all subsidiary products jointly). I find that 5.8% of markups are attributable to the joint pricing of models within brands, leaving about 3.5% of markups due to the large multi-brand parent companies. To the best of my knowledge, this depth of decomposition and quantification of market power has not yet been produced in the economics literature with regards to the US automobile industry (although it has been done quite robustly in other industries, see, for instance Nevo (2001)).

The same basic machinery that I develop to decompose and quantify the sources of market power can be easily retooled to provide the field's first prediction of the effects of the recently proposed Honda-Nissan merger. I answer this question by changing the product ownership matrix again to represent a counterfactual world with joint ownership of all products in the choice set currently owned by either the Honda or Nissan parent companies. My results suggest that the merger's effects would be quite limited, raising industry-wide prices by only 0.22%, and prices of the merged firm's products by about 2%. While I predict that Honda and Nissan will lose a sizable combined market share of 6.45%, this will be nearly fully recovered by other firms; market-wide purchases fall a negligible 0.1%. I find that Subaru and Toyota will be able to raise prices the most post-merger, outside of the merged firm, while Tesla will steal the greatest market share lost by the merged firm's price hikes (+ 2%).

The paper will proceed as follows. First I will discuss how my work is situated within the literature. Then, I describe the US automobile industry and provide a general theory of market power. Next, I provide my empirical specifications for estimating demand and supply, and discuss the data and estimation techniques. Results and counterfactual analyses follow, and a brief discussion concludes.

2 Literature

The random utility discrete choice model that I estimate in this paper is founded in the work of Berry (1994) and Berry, Levinsohn, and Pakes (1995). Berry (1994) begins with a classical framework of a discrete consumer choice model and endogenous firm price setting, but, importantly, allows for prices to be correlated with unobserved product characteristics. Berry shows that one can exploit the inversion of the market share equation to obtain an estimable (with instrumental variables) equation where market shares are regressed on price, a vector of observable product characteristics, and an error term representing unobservable product characteristics which are correlated with prices (hence the need for instruments). Berry presents estimating equations for both a simple multinomial logit model and a one level nested logit model. Recognizing the limitations of imposing a nesting structure on consumer choices — namely semi-restrictive substitution patterns — Berry provides the full random coefficients logit (RCL) extension allowing for fuller substitution patterns, but at a high computational cost. In the full random coefficients model, estimation by linear regression with instruments becomes impossible and there is no analytical solution. To balance these computational challenges with obtaining reasonable substitution patterns, I choose to employ an extension of Berry's single nested logit model — a double nested logit model — which still allows for linear estimation (with instruments), while also providing quite reasonable substitution patterns. The foundations of this nested logit model, a subclass of Generalized Extreme Value (GEV) models, are built in McFadden (1978) and Cardell (1991). My modeling choice follows that of Goldberg (1995) who models consumer choice in the automobile industry with a multi-level nested logit model with an initial layer for buying or not buying in a given year, and a subsequent layer of vehicle types (which she refers to as "classes"). Goldberg also includes additional layers for new vs. used and foreign vs. domestically produced vehicles, which I do not. I find that, for the automobile industry, my double nested logit model is both superior to the plain multinomial logit model and the single nested logit model, as well as quite parsimonious for the econometrician.

It is worth noting, however, that it is not obvious that the full random coefficients model is necessarily superior to the two level nested logit model that I utilize here. As noted in Berry (1994), the nested logit model is essentially a version of the RCL model with selective placement of random coefficients on specific variables. In the nested logit model, the characteristics, or features, given a random coefficient are indicators for their respective nests.

While the core demand model that I employ is an extension of Berry (1994) and not the full RCL model of BLP, I do rely heavily on BLP's empirical insights for working with product-level

and aggregate market share data in the automobile industry. While I follow BLP's conventions for separating utility into three components — price, observable characteristics, and unobservable characteristics — my data includes actual transaction prices, an improvement over MSRP figures that better reflect consumers' actual willingness to pay, as well as additional observable product characteristics beyond what was available to BLP. Most importantly, I take and extend the BLP instruments used for estimation of their standard IV logit model; BLP's instruments are useful for dealing with the price endogeneity problem, but my preferred double nested logit model introduces further endogeneity problems. I extend the BLP instruments to handle these issues in a similar fashion. On the supply side, my work most closely follows Bjornerstedt and Verboven (2013). I utilize both their differentiated products oligopoly model and counterfactual simulation algorithm in my work.

The two papers most closely related to my work are Grieco, Murray and Yurukoglu (2024) and Nevo (2001). Grieco et. al. produced the most recent analysis of market power in the US automobile industry. In their longitudinal study, they recover a strong downward trend in automobile markups, from a median of about 32.5% in 1980 to 18.5% in 2018. My quantity-weighted average estimate of approximately 19% markups falls in a similar range, especially considering their downward trend. My work here, in addition to corroborating these results, expands on Grieco et. al. by explicitly decomposing the markup into its two core sources: product differentiation and joint product ownership (both at the brand level and at the firm level). This sort of decomposition is a key contribution of Nevo (2001). Nevo decomposes markups in the ready-to-eat breakfast cereal industry to recover that the vast majority of market power is derived from product differentiation, a result which is mirrored here. It is important to note that both Grieco et. al. and Nevo employ a version of the full RCL model for their demand specifications. Grieco et. al. additionally employ micro-moments including demographic information linked to vehicle purchases as well as survey results on consumers' second choices.

Finally, the merger simulation falls into a broad swath of the economics literature concerned with estimating price effects of horizontal mergers. See, for example, Nevo (2000) on the cereal industry, Miller and Weinberg (2017) on the Miller-Coors beer merger, Fan (2013) on the Minneapolis newspaper market, Peters (2006) on U.S. airline mergers including Delta-Western and USAir-Piedmont, Dube (2005) on the carbonated soft-drink industry, or Werden and Froeb (1994) on hypothetical mergers involving AT&T.

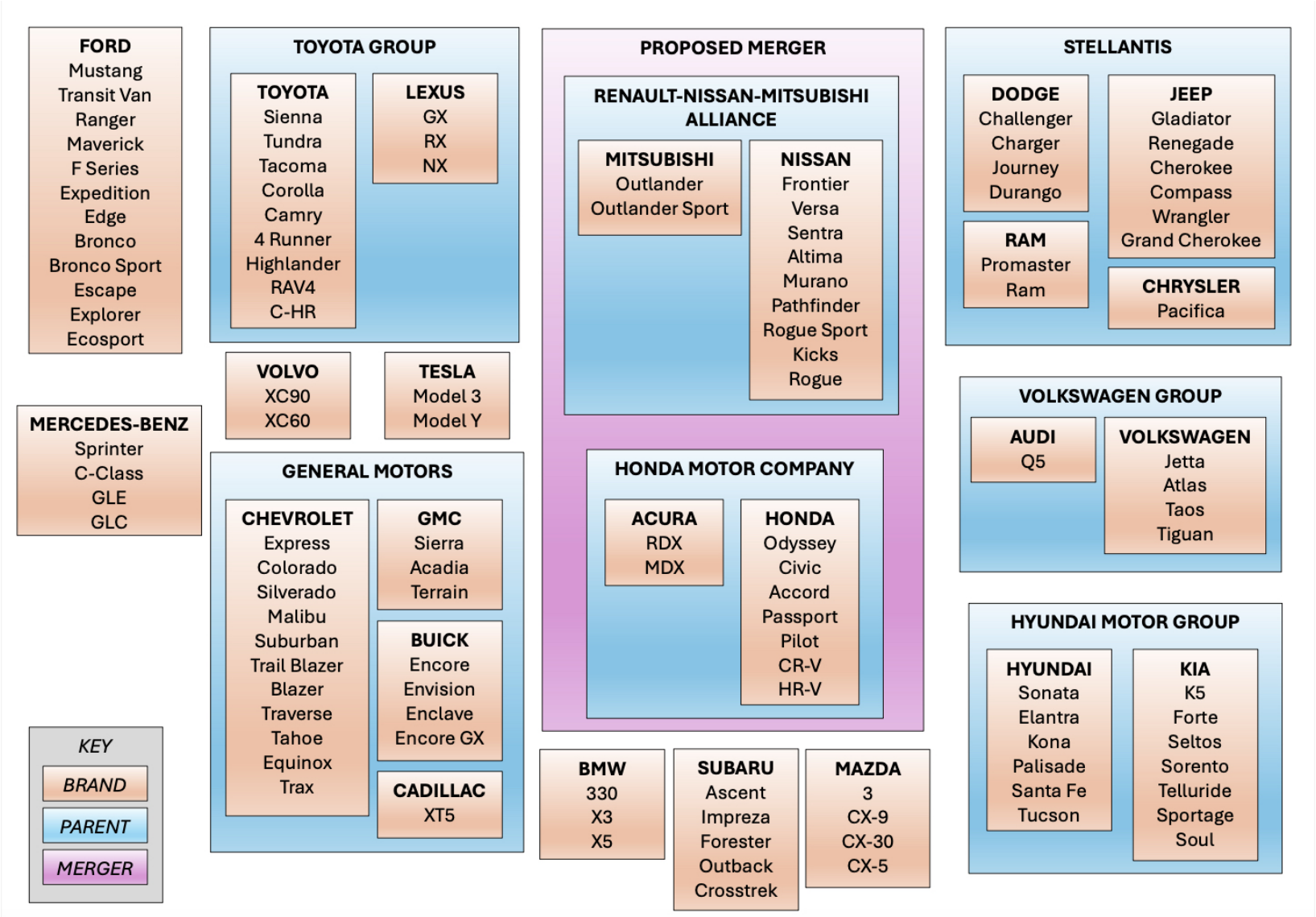
3 Industry Description

The US automobile industry is ripe with product differentiation. My data suggest that, since 2019, the prospective automobile consumer's choice set has included at least 390 unique models each year, and this may not be exhaustive. While these vehicles represent a wide choice set, remarkably, only about 25 models comprise 50% of all new vehicle sales. These are familiar names: the Ford F Series, Chevrolet Silverado, and Ram Truck pickup trucks occupy the top positions, with popular Toyota, Honda, and Tesla models not far behind.

One need not limit discussion of product differentiation in the industry to the wide diversity of available vehicle types, ranging from sedans, coupes, and wagons to SUVs, pickup trucks, and vans. Look no further than the two best selling vehicles, the Ford F Series and Chevrolet Silverado pickup trucks. Consumers in search of best-in-class towing, maximum payloads, modern stylings, and technology integration likely prefer the F Series, while those optimizing for ruggedness, durability, fuel efficiency and lower prices might opt for the Silverado. This sort of product differentiation, coupled with heterogeneity in consumer tastes, across a huge number of product characteristic dimensions, enables firms to set prices above cost.

Beyond product differentiation, the structure of the automobile industry — namely concentration into large multi-product firms — lends itself to additional market power. Figure 1 shows the structure of the top 115 models by quantity sold in 2022 and their respective owners.

Figure 1: Map of Top-Selling Models and their Owners in 2022



Notes: This market map shows the top 115 products by quantity sold in the US automobile market in 2022. Models are organized by brand (orange boxes) and, where applicable, parent company (blue boxes). The firm is considered the profit-maximizing entity, which, for a given model, is the outermost box to which it belongs. Contained in the pink box is the set of models that would become part of a single firm under the proposed Honda-Nissan merger.

Throughout this paper, I discuss both multi-product brands and multi-brand parent companies. Brands, the orange boxes in Figure 1, are most simply defined as the logo found in or on a vehicle, typically in the form of a badge or emblem. A vehicle's brand is generally synonymous with its manufacturer. In the F Series and Silverado case, the F Series belongs to the Ford brand, which also produces a suite of products ranging from the Ecosport to the Transit Van, and the Silverado belongs to the Chevrolet brand, which also produces popular models like the Malibu and the Suburban. Parent companies, the blue boxes in Figure 1, represent joint ownership of brands. While the Silverado belongs to the Chevrolet brand, it also belongs to the broader General Motors (GM) parent company, which sets prices not just for Chevrolet models, but also for Buick, General Motors Truck Company (GMC), and Cadillac branded products. Typically, the different brands within a parent company have specializations and/or are counter-positioned against one another. For instance, GMC specializes in trucks and SUVs and is positioned as a premium alternative to Chevrolet products. Note that certain brands — such as Ford, Tesla and BMW — are *not* subsidiaries of a multi-brand parent company.

Ultimately, a firm is a profit maximizing entity, and thus in this industry, I define a model's firm as the outermost box to which it belongs in Figure 1.

The pink box in Figure 1 shows how joint ownership in the automobile industry is expected to change in the coming year. In December 2024, the Honda and Nissan parent companies announced their intention to merge into Japan's second largest automaker (Komiya, Reuters 2024). They plan to negotiate the terms of the deal by mid-2025 and complete the merger by mid-2026.[2] If this merger proceeds, the merged firm will become the world's third largest automaker by vehicle sales, after Toyota and Volkswagen.[3] Honda and Nissan leadership have announced that their motivation to merge stems from a desire to collaborate against what they perceive as their most threatening competition: Tesla and other rapidly growing, largely Chinese, electric vehicle makers such BYD, Geely, Chery and Changan. Some industry experts have speculated that this merger is a rescue of Nissan which has faced a tough year of low sales and layoffs, but Honda leadership stresses that this is not the motivation.

[2]The last major merger of this type resulted in the creation of the Stellantis Group in January 2021.

[3]Despite negotiations between Honda and Nissan collapsing in February 2025, as of late March 2025, Nissan replaced its CEO to revive the merger's chance of success.

4 Theory

A firm has market power if it can profitably set prices above marginal cost. In this section I will review some relevant theory of market power and its two primary sources: non-homogeneous goods and joint ownership.

4.1 Product Differentiation

Suppose identical firms i and j are selling products in a shared market, both facing constant marginal costs c and market demand $Q(p)$. Assume i and j simultaneously set prices. Further suppose that i and j are offering differentiated substitute products. If consumers care about these differences, their choices are not made strictly based on price. To model this, suppose that $q_i(p_i, p_j)$ is decreasing in p_i (the law of demand) and increasing in p_j (i's and j's products are substitutes), but $q_i(p_i, p_j) > 0$ for at least some $p_i > p_j$ (allowing for product differentiation).

Firm i now maximizes its profit by choosing p_i:

$$\max_{p_i} \pi_i(p_i, p_j) = q_i(p_i, p_j)(p_i - c). \tag{1}$$

Taking the first order condition and rearranging reveals that firm i will set price

$$p_i^* = c - q_i(p_i, p_j) \left(\frac{\partial q_i(p_i, p_j)}{\partial p_i} \right)^{-1}. \tag{2}$$

Notice that the partial derivative $(\frac{\partial q_i(p_i,p_j)}{\partial p_i}) < 0$, so p_i^* consists of marginal cost plus a markup. Firm i is now acting as a monopolist against its residual demand, resulting in positive markups. Clearly, product differentiation, expressed here by the fact that $q_i(p_i, p_j) > 0$ for at least some $p_i > p_j$, can result in prices above cost, as intuition suggests.

4.2 Joint Ownership

Beyond product differentiation, firms can earn market power by producing multiple products and setting prices jointly. The intuition is that if a firm produces multiple products, it can recognize that each price affects demand for each good, and can therefore set prices strategically to account for these inter-dependencies. This is known as internalizing the pricing externality and will be discussed further below.

To illustrate this, consider the case of two substitute goods, 1 and 2, each with constant marginal

costs denoted as c_1 and c_2. Demand is given by $q_1(p_1, p_2)$ and $q_2(p_2, p_1)$. Since the goods are substitutes, demand for good 1 is increasing in p_2 and decreasing in p_1 (conversely for good 2).

Let's first suppose that there are two single product firms producing the two goods. Firm 1 maximizes its profit by choosing p_1, and firm 2 maximizes its profit by choosing p_2:

$$\begin{aligned} \max_{p_1} \pi_1(p_1, p_2) &= q_1(p_1, p_2)(p_1 - c_1) \\ \max_{p_2} \pi_2(p_2, p_1) &= q_2(p_2, p_1)(p_2 - c_2). \end{aligned} \tag{3}$$

This results in two first order conditions:

$$\begin{aligned} p_1^* &= c_1 - q_1(p_1, p_2) \left(\frac{\partial q_1(p_1, p_2)}{\partial p_1} \right)^{-1} \\ p_2^* &= c_2 - q_2(p_2, p_1) \left(\frac{\partial q_2(p_2, p_1)}{\partial p_2} \right)^{-1}. \end{aligned} \tag{4}$$

Now, compare these pricing decisions to a single multi-product firm which produces both products 1 and 2. The multi-product firm maximizes its profit by choosing both p_1 and p_2 simultaneously:

$$\max_{p_1, p_2} \pi_{multiproduct} = (p_1 - c_1) q_1(p_1, p_2) + (p_2 - c_2) q_2(p_2, p_1). \tag{5}$$

This results in two first order conditions:

$$\begin{aligned} p_1^{**} &= c_1 - q_1(p_1, p_2) \left(\frac{\partial q_1(p_1, p_2)}{\partial p_1} \right)^{-1} - (p_2 - c_2) \left(\frac{\partial q_2(p_2, p_1)}{\partial p_1} \right) \left(\frac{\partial q_1(p_1, p_2)}{\partial p_1} \right)^{-1} \\ p_2^{**} &= c_2 - q_2(p_2, p_1) \left(\frac{\partial q_2(p_2, p_1)}{\partial p_2} \right)^{-1} - (p_1 - c_1) \left(\frac{\partial q_1(p_1, p_2)}{\partial p_2} \right) \left(\frac{\partial q_2(p_2, p_1)}{\partial p_2} \right)^{-1}. \end{aligned} \tag{6}$$

Notice that these optimal prices are the same as those in the two single product firms case (see Equation 4), plus an additional term. Observe that the additional term contributes positively, such that $p_1^{**} > p_1^*$ and $p_2^{**} > p_2^*$, meaning that the multi-product firm can set higher prices than the single product firm. Clearly, p_1 and p_2 are strategic complements.

The key insight is that in the case of the two single product firms, there is a competitive externality resulting in lower prices. When firms are competing to set prices of substitute products, they have to consider how lowering prices both increases demand (since q_1 is decreasing in p_1) and decreases markups $(p_1 - c_1)$. When firms are concerned about diverting their demand to their competitor through higher prices, as is the case with substitute goods, prices are set "too low". This externality, though, is internalized by the multi-product firm. When pricing jointly, the firm can

consider the potential diversion from one product to another and ultimately raise both prices. This same reasoning, of course, produces an incentive for horizontal mergers, since a horizontal merger is merely joint pricing over a larger set of substitute products.

To illustrate this incentive to merge directly, suppose now that there are 3 products, $j \in [1, 2, 3]$. Each has marginal cost c_j. In the case of single product firms, as we've seen several times now, the first order condition sets the optimal price as

$$p_j^{***} = c_j - q_j(p_1, p_2, p_3) \left(\frac{\partial q_j(p_1, p_2, p_3)}{\partial p_j} \right)^{-1}. \tag{7}$$

Let's suppose that firms 1 and 2 merge, hoping to internalize the competitive pricing externality discussed above via joint profit maximization. Now, this merged firm maximizes its profit by choosing p_1 and p_2 jointly:

$$\max_{p_1, p_2} \pi_{merged} = (p_1 - c_1)q_1(p_1, p_2, p_3) + (p_2 - c_2)q_2(p_2, p_1, p_3). \tag{8}$$

The merged firm's optimal solutions are:

$$\begin{aligned} p_1^{***} &= c_1 - q_1(p_1, p_2, p_3) \left(\frac{\partial q_1(p_1, p_2, p_3)}{\partial p_1} \right)^{-1} - (p_2 - c_2) \left(\frac{\partial q_2(p_2, p_1, p_3)}{\partial p_1} \right) \left(\frac{\partial q_1(p_1, p_2, p_3)}{\partial p_1} \right)^{-1} \\ p_2^{***} &= c_2 - q_2(p_2, p_1, p_3) \left(\frac{\partial q_2(p_2, p_1, p_3)}{\partial p_2} \right)^{-1} - (p_1 - c_1) \left(\frac{\partial q_1(p_1, p_2, p_3)}{\partial p_2} \right) \left(\frac{\partial q_2(p_2, p_1, p_3)}{\partial p_2} \right)^{-1}, \end{aligned} \tag{9}$$

and firm 3, which did not merge, sets price

$$p_3^{***} = c_3 - q_3(p_3, p_1, p_2) \left(\frac{\partial q_3(p_3, p_1, p_2)}{\partial p_3} \right)^{-1}. \tag{10}$$

There are two key observations to make. First, the merged firm is able to set higher prices p_1^{***} and p_2^{***} due to joint profit maximization for the same reason discussed above. Second, more subtly, firm 3 which did not merge, benefits from the merger, and it too can set a higher price p_3^{***}. Notice that the term representing markup above marginal cost in the expression for p_3^{***} is increasing in p_1 and p_2, since the higher prices from the merged firm will cause some diversion of demand over to firm 3.

Ultimately, the merger of firm 1 and 2 into a single mega-firm is good for all of the firms. This will be borne out by the results of this paper: when Honda and Nissan merge, they will increase

their markups and prices, but so will the rest of the firms. The extent to which other firms can do so depends on the degree of substitutability between the products of a given firm and the merged firm.

Ultimately, both in theory and in my results, horizontal mergers are weakly dominant for all firms in the market. Furthermore, the horizontal merger is merely an extension of the joint-product ownership that we already observe in the market at both the brand and parent company levels. More generally, there exists an incentive for joint ownership and coordinated pricing whether at the brand, parent, or merger levels.

5 Empirical Specification

I will now describe my empirical specifications for demand and supply. As an overview, I first choose a functional form for demand that aligns with how consumers choose whether or not to buy a vehicle in a given year, and if so, which one. Here I will outline my preferred (double) nested logit model (alternative models are presented in the Appendix). From this model, own-price and cross-price elasticities can be derived, revealing substitution patterns. Second, I model the behavior of producers in a way that accurately reflects competition between automobile makers in the US market. I choose a standard non-cooperative differentiated products oligopoly model of supply. This allows me to recover marginal costs from the first order conditions of each firm's profit maximization problem, and therefore to infer markups. Crucially, I assume that firms profit maximize at the parent level (e.g. Stellantis jointly chooses prices for all of its models. Dodge and Chrysler, both owned by Stellantis, are not choosing prices separately).

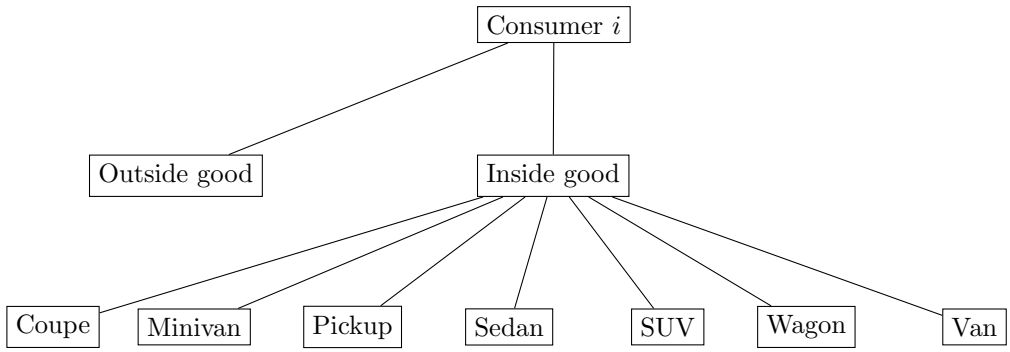
5.1 Demand

For the demand-side, as is now standard in the literature, I use a random utility discrete choice model in the form developed by Berry (1994). In particular, I employ a two level nested logit model, a simple extension of Berry's single nested logit model. I also estimate a plain multinomial logit model and single nested logit model, whose details and shortcomings, namely preposterous substitution patterns, are well known to the literature and are summarized in the Appendix.

In my preferred model, I partition the choice set into both groups and subgroups. Under the sequential decision making interpretation of this model, consumers first decide whether to buy a vehicle in a given year (the groups); then, if so, which type of vehicle to buy (the subgroups); and finally, which specific model within the type. Consumer preferences are thus allowed to be

correlated by vehicle type. Technically, this structure's strength is in allowing for different degrees of similarity/correlation within vs. across nests, relaxing the IIA restriction of the multinomial logit model. This form is shown in Figure 2.

Figure 2: Consumer Choice Model with Vehicle Types as Sub-Nests



Notes: The double nested logit discrete choice model allows for different degrees of similarity/correlation within vs. across nests and sub-nests, or the inside/outside good and vehicle types, respectively. This relaxes the IIA restriction of the multinomial logit model. Intuitively, the consumer's choice is split into two levels. First, whether to select an inside good or the outside good (which contains both not buying *and* buying a product outside of the choice set). Second, if the consumer chooses the inside good, she then selects a particular vehicle type and chooses a model from within that sub-nest.

Formally, I split the products into 2 groups $g \in [Inside, Outside]$, and then split the inside group into 7 subgroups, $h \in [Coupe, Minivan, Pickup, Sedan, SUV, Wagon, Van]$. The outside good $j = 0$ is the only member of the outside group.[4] Let the full set of products in subgroup h of group g be called $\Omega_{h,g}$ and the full set of subgroups in group g be called Ω_g. Consumer i's conditional indirect utility is given by:

$$u_{ij} = \delta_j + \zeta_{ig} + (1 - \sigma_2)\zeta_{ih} + (1 - \sigma_1)(1 - \sigma_2)\epsilon_{ij} \tag{11}$$

where, $\delta_j = -\alpha p_j + \beta \mathbf{X}_j + \xi_j$ and ϵ_{ij} is an i.i.d random variable with a Type I extreme value distribution representing the individual consumer's idiosyncratic component of utility due to heterogeneity in tastes. As is standard in the literature, product j's mean utility δ_j consists of price, a vector of product characteristics, and the error term, representing the unobservable characteristics of model j. The mean utility for the outside good, δ_0, is normalized to 0, without loss of generality. This turns out to be very helpful in inverting utility to an estimable linear regression, and is not restrictive since all that matters is the relationship between utilities of different choices.

The variables ζ_{ig} and ζ_{ih} follow distributions such that $\zeta_{ig} + (1 - \sigma_2)\zeta_{ih} + (1 - \sigma_1)(1 - \sigma_2)\epsilon_{ij}$

[4]The outside good includes both not buying any product, or buying a product outside of the defined choice set. See the Data section for more detail on the choice set and the outside option.

and $\zeta_{ih} + (1-\sigma_1)(1-\sigma_2)\epsilon_{ij}$ are also extreme value random variables. This is consistent with a consumer maximizing her utility if $1 \geq \sigma_1 > \sigma_2 \geq 0$ (McFadden 1978). In-subgroup correlation (e.g. within SUVs or within pickup trucks) is denoted by σ_1, and in-group correlation within the full set of inside goods or within the full set of outside goods (i.e. buying or not buying) is represented by σ_2. McFadden's derived parameter restriction is consistent with intuition; we expect higher in-subgroup correlation than in-group correlation.

Following Berry (1994), one arrives at the linear estimating equation:

$$ln(s_j) - ln(s_0) = -\alpha p_j + \beta X_j + \sigma_1 ln(s_{j|hg}) + \sigma_2 ln(s_{h|g}) + \xi_j \tag{12}$$

where $s_{j|hg}$ is product j's share conditional on being within j's group *and* subgroup, and $s_{h|g}$ is subgroup h's share conditional on being in h's group g.

For the purposes of obtaining clear expressions for selection probabilities and more easily calculating derivatives of these probabilities, it turns out to be convenient to define these three "inclusive values":

$$I_{hg} = (1-\sigma_1) log \sum_{j \in \Omega_{h,g}} e^{\delta_j/(1-\sigma_1)} \tag{13}$$

$$I_g = (1-\sigma_2) log \sum_{h \in \Omega_g} e^{I_{hg}/(1-\sigma_2)} \tag{14}$$

$$I = log(1 + \sum_g e^{I_g}). \tag{15}$$

Conditional selection probabilities are now as follows. The probability of selecting product j conditional on selecting both its group and subgroup is:

$$s_{j|hg} = \frac{e^{\delta_j/(1-\sigma_1)}}{e^{I_{hg}(/1-\sigma_1)}}. \tag{16}$$

The probability of selecting subgroup h conditional selecting its group is:

$$s_{h|g} = \frac{e^{I_{hg}/(1-\sigma_2)}}{e^{I_g(/1-\sigma_2)}}. \tag{17}$$

The probability of selecting group g is:

$$s_g = \frac{e^{I_g}}{e^I}. \tag{18}$$

The unconditional choice probability for product j is, by definition:

$$s_j = s_{j|hg} * \ s_{h|g} * \ s_g. \tag{19}$$

This identity (Equation 19), and the above expressions (Equations 13-18), can be used to derive own and cross-price elasticities (Equation 20). Note that there are three categories of cross-price elasticities; when products j and k are in the same group and subgroup (e.g. two SUVs), same group but different subgroups (e.g. an SUV and a sedan), and different groups (any inside product and the outside good):

$$\eta_{jk} = \begin{cases} -\alpha \frac{p_j}{s_j}[\frac{1}{1-\sigma_1} s_{j|hg}(1-s_{j|hg}) s_{h|g} s_g + s_{j|hg}(\frac{1}{1-\sigma_2} s_{j|hg} s_{h|g}(1-s_{h|g})) s_g + s_{j|hg} s_{h|g} s_j (1-s_g)]; k=j \\ \alpha \frac{p_j}{s_j}[(\frac{1}{1-\sigma_1}) s_{j|hg} s_{k_h|g} - s_{j|hg} \frac{1}{1-\sigma_2} s_{k|hg} s_{h|g}(1-s_{h|g}) s_g - s_{j|hg} s_{h|g} s_k (1-s_g)]; j \neq k, h_j = h_k, g_j = g_k \\ \alpha \frac{p_j}{s_j}[s_{j|hg} \frac{1}{1-\sigma_2} s_{h|g} s_{k|h^* g} s_{h^*|g} - s_{j|hg} s_{h|g} s_k (1-s_g)]; j \neq k, h_j \neq h_k^*, g_j = g_k \\ \alpha \frac{p_j}{s_j} s_{j|hg} s_{h|g} s_k s_g; j \neq k, h_j \neq h_k, g_j \neq g_k \end{cases} \tag{20}$$

These elasticity expressions yield far more reasonable substitution patterns than are possible under the standard logit or single nested logit model. Consumers' substitution patterns are weighted towards vehicles of the same type, as well as weighted towards their group (buying or not buying). If a consumer has set out to buy a vehicle this year and is substituting to a different model, we've imposed a preference for sticking to the chosen vehicle type and buying *a* car over no car at all. Still, this structure is restrictive, potentially yielding substitution patterns less realistic than BLP's full random coefficients model. However, the relative parsimony of this model makes up for the potential cost.

5.2 Supply

Compared to the demand model, it is quite straightforward to build a convincing model of supply. The supply side model, as mentioned briefly in the introduction to this section, is utilized in two ways: recover status-quo marginal costs using estimated demand parameters and, based on those marginal costs and estimated demand parameters, predict prices in the counterfactual scenarios.

The basic model is a standard differentiated-products oligopoly. Multiple firms set prices simultaneously and non-cooperatively.[5] As discussed before, I make the assumption that firms are profit maximizing at the parent level, where applicable, not the brand level. Here, I closely follow the work

[5]This non-cooperation assumption is widely used both for its relative simplicity and based on the assumption that in multi-period games, collusion is hard to sustain with differentiated products.

and notation of Bjornerstedt and Verboven (2013) and mirror the theory discussed in Section 4.

Suppose that each firm f owns products F_f. The firm maximizes its (variable) profits, which is given by the sum of profits across its portfolio of products. Profits are given by:

$$\Pi_f(\mathbf{p}) = \sum_{j \in F_f} (p_j - c_j) s_j(\mathbf{p}) \tag{21}$$

where c_j is product j's constant marginal cost, and $s_j(\mathbf{p})$ is the J x 1 market share vector, dependent on $\mathbf{p}$, the J x 1 price vector. Notice that price increases affect the firm's profit in three ways. A price increase of good j

1. raises profits proportional to demand $s_j(\mathbf{p})$
2. lowers product j's demand, lowering profits proportional to j's markup $(p_j - c_j)$
3. raises demand for products $k \in F_f, k \neq j$ (the multi-product firm benefit)

As we've seen, the profit-maximizing price for each product $j = 1, ..., J$ must satisfy the first order condition:

$$s_j(\mathbf{p}) + \sum_{j \in F_f} (p_j - c_j) \frac{\partial s_j(\mathbf{p})}{\partial p_j} = 0. \tag{22}$$

If this condition is satisfied for all products, there exists a Nash equilibrium. In the notation of Bjornerstedt and Verboven (2013), let θ^F be the product ownership matrix (dimensions J x J). Matrix element $\theta(j,k) = 1$ if both products j and k are produced by the same firm, and 0 if they are produced by different firms. If there are no multi-product firms, this is the identity matrix. Changing the values in this product ownership matrix will be at the heart of the simulations.

Note that $\mathbf{s}(\mathbf{p})$ is the J x 1 market shares vector, $\mathbf{c}$ is the J x 1 marginal costs vector, and define $\Delta(p)$ as the J x J matrix of first derivatives $\partial \mathbf{s}(\mathbf{p}) / \partial \mathbf{p}$.[6] Using $\odot$ to denote element-wise multiplication of the two J x J matrices (ownership and first derivatives), the first order conditions necessary for a Nash equilibrium can now be expressed in vector notation as

$$\mathbf{s}(\mathbf{p}) + (\mathbf{p} - \mathbf{c})(\theta^F \odot \mathbf{\Delta}(\mathbf{p})) = 0 \tag{23}$$

or equivalently

[6] The reader might want to observe that the expressions for the first derivatives can be easily taken from the elasticities in Equation 20, simply without the $-\alpha \frac{p_j}{s_j}$ component.

$$\mathbf{p} = \mathbf{c} - \frac{\mathbf{s}(\mathbf{p})}{\theta^F \odot \Delta(\mathbf{p})} \tag{24}$$

which is consistent with the intuitive forms of Equations 4,6,9 and 10 where price consists of marginal cost and a positive markup. Rearranging this equation allows me to recover the marginal cost vector $\mathbf{c}$:

$$\mathbf{c} = \mathbf{p} + \frac{\mathbf{s}(\mathbf{p})}{\theta^F \odot \Delta(\mathbf{p})}. \tag{25}$$

Finally, I calculate the J x 1 markup vector $\mathbf{m}$ using the price and cost vectors:

$$\mathbf{m} = \mathbf{p} - \mathbf{c}. \tag{26}$$

6 Data

The main source of data for my work is S&P Global Mobility automobile data (previously R.L Polk & Company) which includes transaction level details for all new automobile purchases between January 2019 and December 2022 in 14 states. Those states are Virginia, Texas, North Carolina, Michigan, Florida, California, Illinois, New Jersey, New York, Massachusetts, Pennsylvania, Arizona, Ohio and Georgia. Each transaction includes a unique Vehicle Identification Number (VIN) which has been decoded to reveal the make and model of the vehicle purchased, as well as many product characteristics. A given entry includes (among other details) the state of transaction, month of transaction, quantity purchased, make, model, transaction price, fuel type, body type, vehicle type, drive type, horsepower, curb weight, length, height, production location (city, state, country), and city and highway combined miles per gallon (MPG).

Since the data is at the transaction level, the first task is to aggregate the data. To do so, I define a market as a calendar year. For each year-model I determine the quantity sold as the sum of all vehicles sold of the given model in the given year. Since I have transaction prices, which reflect the actual price paid (a substantial improvement over BLP who only have MSRP), each year-model has a wide range of prices. I choose to define a year-model's transaction price as the median of all transaction prices for that year-model, to avoid the outsize influence of unusually high or low transaction prices. All nominal transaction prices are then inflated to 2024 USD using the CPI between July of the transaction year and July 2024.

For a year-model's make, weight, length, height, wheelbase, combined MPG, vehicle type, body

type, drive type, and fuel type, I use the mode across transactions involving that year-model. For horsepower I use a quantity-weighted mean since there is substantially more variation in the reported data as compared to the other characteristics. For each year-model, I synonymously define "brand" as make, and define "parent" firms according to brands by the market structure discussed in Section 3 and shown in Figure 1.

Following BLP, I define two additional characteristic variables. First, the horsepower weight ratio, $\frac{HP}{WT}$, a proxy for power and performance. Second, miles per dollar (MP$), which I consider instead of miles per gallon. Ultimately, when a consumer is deciding which vehicle to buy, she may not care about the raw miles per gallon, but she almost certainly cares about her bang-for-buck in fuel efficiency. For gas vehicles, $MP\$ = \frac{MPG}{\$\ per\ gallon}$ and for electric, plug in hybrid, and hybrid vehicles, $MP\$ = \frac{MPG}{\$\ per\ KwH} * \frac{33.7KwH}{Gallon}$. These should be interpreted as the number of miles that can be driven for 1 dollar of fuel spending. Herein, I make the assumption that purchasers of non-gas-only vehicles use exclusively electricity to power their vehicles (a great assumption for electric vehicles, and a necessary one for PHEVs and hybrids). Note that I calculate MP$ *before* aggregating the data into the year-level so I can take quantity weighted averages of MP$ that account for varying electricity and gasoline prices across states. At-pump gasoline prices are from the US Energy Information Administration's (EIA) Gasoline and Diesel Fuel Update. I have state-year level data for CA, FL, NY, OH, TX and MA, and Petroleum Administration for Defense Districts (PAAD) level prices for the remaining states (PADD 2: IL and MI; PADD 1B: NJ and PA; PADD 1C: VA, GA, and NC; PADD 5: AZ). Residential electricity prices at the state-year level come from the EIA's Electricity Data Browser. Both gas and electricity prices are inflated using the CPI to July 2024 USD, as with transaction prices.

Table 1 shows the range of continuous demand statistics and their associated models to illustrate the wide choice set.

To obtain market shares, I need to make an assumption about the number of consumers in the market. I follow BLP in defining the household as the consumer, under the rationale that vehicles are typically shared across household members. The American Community Survey reports that the average American household has about 2.5 people and less than 2 cars, so this is a reasonable assumption. Thus, I take state-year level number-of-households estimates from the US Census Bureau and divide a model-year's purchase quantity by the number of households in my 14 state sample in that year to generate market shares. The outside good's share for a given year/market t is then $s_0^t = 1 - \sum_{j \in J_t} s_j$.

Thanks to the completeness of the dataset, and without further simplification, I have data on

Table 1: The Range of Continuous Demand Characteristics and Associated Models

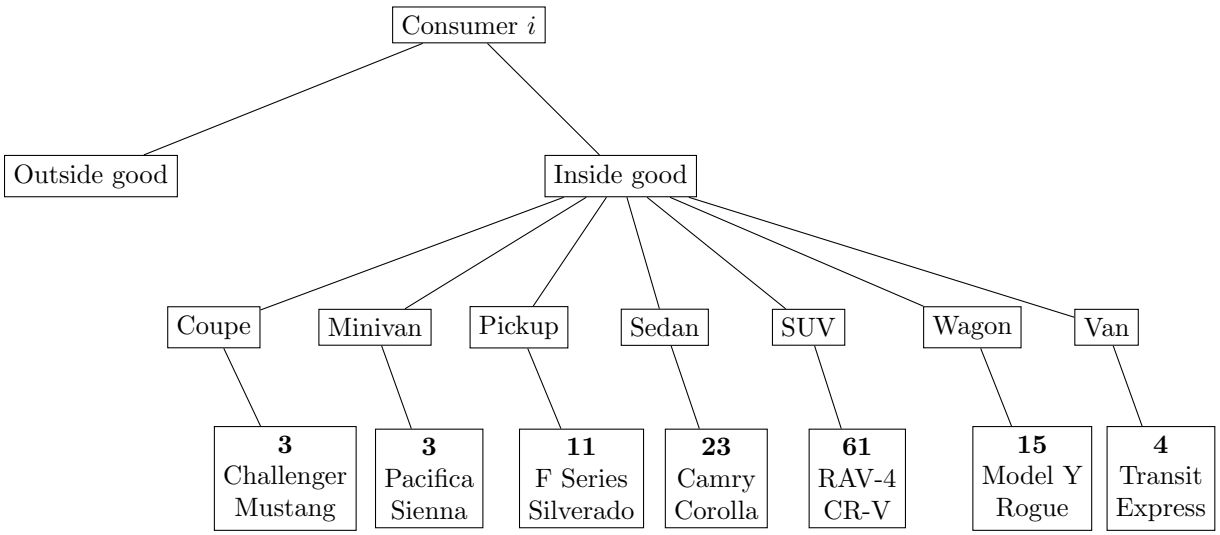
	Percentile				
Variable	0	25	50	75	100
Price	Nsn. Versa	Sub. Crstk	Ford Edge	Lexus NX	MB Sprinter
(2024 USD)	22,885	33,094	43,851	53,906	78,058
Quantity	Dodge Jrny	Nsn. Rogue Spt	Chev. Blazer	Chev. Malibu	Ford F Series
	148	32,442	53,197	87,182	383,699
Length	Ford Eco.	Buick Env.	Ford Brnc	Ford Expl.	GMC Sierra
(in.)	161.3	182.6	189.4	198.6	250.1
Height	Ford Must.	Sub. Crstk	Honda CR-V	Ford Brnc Spt	Ram Prom.
(in.)	54.3	63.5	66.5	70.15	105.9
Wheelbase	Ford Eco.	Mits. Outl.	Honda Acc.	MB GLE	MB Sprinter
(in.)	99.2	106.4	111.4	117.7	170.3
MPG	Chev. Exp.	Dodge Dur.	MB GLC	Mazda 3	Tesla M3
	13.0	21.0	24.0	29.5	131.0
MP$	Chev. Exp.	Dodge Dur.	MB GLC	Toyota C-HR	Tesla M3
	3.26	5.26	6.02	7.27	26.38
HP/Weight	MB Sprinter	Jeep Comp.	Jeep Glad.	Ford Brnc	Ford Must.
	0.040	0.050	0.060	0.070	0.110

Notes: This table shows the range of continuous demand characteristics and the associated models from the 2022 choice set consisting of the top 115 models by quantity sold. The variance in price, quantity, and miles per dollar (MP$) is particularly wide. Note that the 115th most popular model, also the least popular "inside" model in my restricted 2022 choice set, the Dodge Journey, only sold 148 units. This is strong evidence that restricting the inside good choice set to the top selling models is largely without loss.

approximately 395 models per year. However, the majority of these have extremely small market shares. This is problematic for obtaining sensible elasticities and substitution patterns. So, I restrict my dataset to the top 120 models by market share over the period 2019-2022. These 120 models comprise approximately 83% of all vehicle sales, and the remaining 17% are lumped into the outside good. Figure 3 shows how this restricted set of inside goods splits into the 7 inside good sub-nests for the 2022 choice set. The bold numbers indicate the number of products in each sub-nest, and the example models listed below are the best and second-best selling models in the given sub-nest in 2022. Note that not all of the 120 models are available in each year.

The choice of the 8 product characteristics to include in estimating the demand model was largely dictated by data availability and represents the best feasible option. While all of the characteristics are meaningful in and of themselves, a number of them are best understood as proxies for product characteristics. For instance, the $\frac{HP}{WT}$ ratio is a proxy for power, length and height are both indicators of size and proxies for safety, and MP$ represents fuel efficiency. The drivetrain configuration dummies, where the excluded category is front-wheel drive (FWD), are almost certainly correlated with other observables (e.g. RWD vehicles typically provide low fuel efficiency), so their signs when estimated are challenging to interpret independently. Readers may wonder why other characteristics

Figure 3: Number of Models Per Sub-Nest, with Top 2 Selling Models ($t = 2022$)



Notes: The inside good is split into 7 sub-nests by vehicle type. This figure shows the number of models within each of these vehicle types in the 2022 choice set, followed by the highest and second-highest selling models in the sub-nest.

are excluded. Data constraints are the primary answer. However, even setting aside data constraints, the careful treatment of characteristics unobservable to the econometrician — discussed next — should limit concerns about omitted variables. Finally, I also include a pandemic dummy variable for models purchased in 2020 and 2021, an important demand shifter.

7 Estimation

7.1 Demand

The fundamental challenge with demand estimation is the endogeneity of prices with the error term. Recall that the error term ξ_j represents the unobservable (by the econometrician) characteristics of choice j. Of course, the unobservable characteristics of vehicle choice j are correlated with p_j. For example, I do not observe the presence of hood ornaments or heated seats — both likely to be positively correlated with price — nor do I observe whether a vehicle has a high repair frequency or discontinued parts — likely to be negatively correlated with price.

To avoid parameter estimates that are biased towards 0 or even of the wrong sign, the standard procedure is to estimate with instrumental variables. All three models I estimate here — the multinomial logit, single level nested logit, and the preferred double level nested logit — thus require instruments for prices. The single level nested logit also requires instruments for the within-group

share $s_{j|g}$ and the double level nested logit requires additional instruments for both the within-subgroup and within-group shares, $s_{j|hg}$ and $s_{h|g}$ respectively.

As a baseline, I construct BLP instruments (BLP 1995) to interact with the error term and mitigate the endogeneity issue. For each product characteristic z_{jk} (product j's kth observable characteristic) in the characteristic vector $\mathbf{X}$, I construct the following three instruments:

$$z_{jk}, \sum_{r \neq j, r \in F_f} z_{rk}, \sum_{r \neq j, r \notin F_f} z_{rk} \tag{27}$$

where, as above F_f is the set of products produced by firm f. With K characteristics in $\mathbf{X}$, the instrument vector for product j, $\mathbf{z}_j$, has dimension $3K$. In my models, with 8 observed characteristics — $\mathbf{X}$ includes $\frac{HP}{WT}$, length, height, MP$, and 4 drive type dummies — this instrument vector $\mathbf{z}_j$ contains 24 instruments for each product.

To illustrate this, consider the first observed characteristic, the $\frac{HP}{WT}$ ratio. The instrument vector for product j includes the $\frac{HP}{WT}$ ratio of vehicle j, the sum of all $\frac{HP}{WT}$ ratios across all products owned by the same firm that owns product j (excluding j's own value), and the sum of all $\frac{HP}{WT}$ ratios across all products owned by all firms other than the firm that owns j. These three instruments are then constructed for all observed characteristics in $\mathbf{X}$.

For the instruments to be valid, they must satisfy the relevance and exclusion restrictions. Firms in an oligopolistic market set prices partially in response to the characteristics of other vehicles in their portfolio F_f and across their competitors' portfolios F_{-f}, ensuring instrument relevance. Moreover, j's unobservables contained in the error term ξ_j do not directly influence pre-existing characteristics of competitors' models, so there is no correlation between the instruments and the error term, fulfilling the exclusion restriction.

While these instruments suffice for the standard IV logit model, additional instruments are required for the within-group share $s_{j|g}$ in the single level nested logit model, and for the within-subgroup and within-group shares, $s_{j|hg}$ and $s_{h|g}$, in the double nested logit model. These shares are endogenous for the same reason prices are endogenous: the quantities purchased (from which these shares are derived) are correlated with unobservables contained in the error term.

For the single level nested logit, I add two within-group instruments:

$$\sum_{r \neq j,\, r \in F_f \cap g} z_{rk}, \quad \sum_{r \neq j,\, r \in g \setminus F_f} z_{rk} \tag{28}$$

For the double level nested logit, I, in theory, add two within-group and two within-subgroup in-

struments:

$$\sum_{r \neq j,\, r \in F_f \cap g} z_{rk}, \quad \sum_{r \neq j,\, r \in g \setminus F_f} z_{rk}, \quad \sum_{r \neq j,\, r \in F_f \cap g \cap h} z_{rk}, \quad \sum_{r \neq j,\, r \in g \cap h \setminus F_f} z_{rk} \tag{29}$$

However, due to the nesting structure that I have imposed where all products are within the same group (except the outside good),

$$\sum_{r \neq j,\, r \in F_f} z_{rk} = \sum_{r \neq j,\, r \in F_f \cap g} z_{rk} \quad \textit{and} \quad \sum_{r \neq j,\, r \notin F_f} z_{rk} = \sum_{r \neq j,\, r \in g \setminus F_f} z_{rk} \tag{30}$$

so in practice, I only add the latter two instruments from Equation 29 when estimating the double level nested logit. Thus I estimate the IV logit with $3K$ instruments per product, and both the single level and double nested logit with $5K$ instruments per product. Additionally, in practice, there are a handful of instances of near or perfect collinearity so some of the above candidate instruments are necessarily dropped from estimation.

7.2 Supply

Comparatively, the supply side is much simpler than demand. Marginal costs and markups are recovered using simple matrix algebra, as per these equations, derived in Section 5.2:

$$\mathbf{c} = \mathbf{p} + \frac{\mathbf{s}(\mathbf{p})}{\theta^F \odot \Delta(\mathbf{p})} \tag{31}$$

$$\mathbf{m} = \mathbf{p} - \mathbf{c}. \tag{32}$$

8 Results

8.1 Demand

8.1.1 Parameters

Column 4 of Table 2 contains the results from estimating my preferred double nested logit specification from which I will construct the remainder of the results in this paper. The price coefficient has the expected negative sign and is significant at the 1% level. The nesting parameters satisfy the requirement that $1 \geq \sigma_1 > \sigma_2 \geq 0$, although I am only able to reject the null hypothesis that $\sigma_2 > \sigma_1$ at the $p \approx .1$ level. Nonetheless, as expected, the nesting parameters suggest that products within the same subgroup are excellent substitutes (since σ_1 is near to 1), and for a consumer who is planning to buy any vehicle, buying any other vehicle as opposed to diverting to the outside option of not buying any vehicle is strongly preferred (high σ_2). Both of these are indicators that the structure imposed by the two level nested logit model in Section 5.1 is a reasonable representation of this market.

For comparison, I also estimate OLS, IV, and single nested logit models, whose setup can be found in the Appendix, Sections 11.1.1-2. Column 1 of Table 2 contains results from running the simple OLS regression without instruments, regressing $ln(sj/s_0)$ on price, the product characteristics, and the pandemic dummy. While the coefficients are of the expected signs (price < 0, $\frac{HP}{WT} > 0$, pandemic < 0, etc.), the low R^2 of .165 suggests that nearly 85% of the variance in mean utility is due to unobservables. Furthermore, as mentioned in Section 5.1 and in Section 11.1.1 in the Appendix, the elasticities and substitution patterns are completely preposterous. These estimates result in all models being quite inelastic, an implausible outcome.

The estimates in column 2 benefit from the introduction of instruments. In particular, the price coefficient nearly doubles, suggesting that the price coefficient in column 1 is a severe underestimate (in absolute value) due to the likely fact that unobservables which enter positively (i.e. high quality unobservables such as high end interior fabrics) cause higher prices. Not dealing properly with these unobservables leads to a price coefficient that is too low in absolute value. Unfortunately, the value added from the standard IV logit in column 2 ceases at proving the importance of properly handling endogeneity. The vast majority of models remain inelastic, and nearly all first substitute to the Ford F Series due to its high market share; an unlikely phenomenon for a consumer otherwise purchasing, say, the Chrysler Pacifica or the BMW 330.

Column 3 represents an attempt at estimating the single level nested logit with vehicle types as

groups, discussed in the Appendix, Section 11.1.2. While the price coefficient is of the expected sign and highly significant, and the coefficient on the group share is in between 0 and 1 as required, I am unable to obtain a significant coefficient for the group share. This leads to the conclusion that the structure imposed by the single level nested model with vehicle types as groups does not well define the actual structure of consumers' choices in the market. Attempts to define alternative single level structures such as broader vehicle types (car, SUV, truck, van) fail as well. Ultimately, I am unable to identify any sensible single nest structure of consumer choice.

The first stage F-statistics are presented at the bottom of Table 2. For all three of the models utilizing the instruments described in the previous section —- the standard IV logit (column 2), single level nested logit (column 3), and double level nested logit (column 4) — these F-statistics suggest that the instruments are sufficiently strong.

It is important to mention that the literature has not yet resolved how to evaluate the strength of instruments when instrumenting for multiple endogenous variables with multiple instruments, as is the case in columns 3 and 4. In the case of the full model in column 4, I have $5K$ or 40 instrument candidates, of which I use 36. Thus, there are 3^{36} ways to assign these instruments across the three first stage equations. I do not test all 150 quadrillion assignments, but I do search for acceptable combinations. This fishing does induce the potential for false security, but it is the best option that econometricians have in this case.

Note that discussion and results of a more flexible double nested logit model with unique nesting parameters for each subgroup (vehicle type) can be found in the Appendix, Section 11.1.3.

Table 2: Demand Estimation Results

	Dependent variable:			
	$ln(s_j/s_o)$			
	OLS	*IV*	*Single Nest*	*Double Nest*
	(1)	(2)	(3)	(4)
Price (in 10,000 USD)	-0.184^{***}	-0.320^{***}	-0.205^{***}	-0.114^{***}
	(0.051)	(0.100)	(0.074)	(0.024)
HP/WT	15.684^{***}	23.097^{***}	18.299^{***}	6.966^{***}
	(5.491)	(7.251)	(5.598)	(2.018)
Length	0.016^{***}	0.019^{***}	0.012^{**}	0.005^{***}
	(0.004)	(0.004)	(0.005)	(0.002)
Height	0.006	0.014	0.005	0.010^{***}
	(0.008)	(0.009)	(0.008)	(0.003)
MP$	0.098^{***}	0.095^{***}	0.082^{***}	0.043^{***}
	(0.017)	(0.017)	(0.018)	(0.007)
4X2	-0.123	0.050	-0.031	0.159
	(0.309)	(0.330)	(0.281)	(0.104)
4X4	0.622^{***}	0.684^{***}	0.602^{***}	0.084
	(0.146)	(0.152)	(0.136)	(0.059)
AWD	0.090	0.203	0.139	-0.017
	(0.111)	(0.133)	(0.107)	(0.038)
RWD	-0.361^{*}	-0.431^{**}	-0.421^{**}	-0.022
	(0.195)	(0.202)	(0.176)	(0.068)
Pandemic	-0.212^{**}	-0.202^{**}	-0.182^{**}	-0.096^{***}
	(0.085)	(0.086)	(0.077)	(0.029)
$ln(s_{j\|g})$			0.134	
			(0.083)	
$ln(s_{j\|hg})$				0.912^{***}
				(0.028)
$ln(s_{h\|g})$				0.861^{***}
				(0.030)
Constant	-11.393^{***}	-12.186^{***}	-9.940^{***}	-4.234^{***}
	(0.737)	(0.896)	(1.362)	(0.586)
Observations	461	461	461	461
Adjusted R^2	0.165	0.152	0.341	0.913
Residual Std. Error	0.862 (df = 450)	0.868 (df = 450)	0.765 (df = 449)	0.278 (df = 448)
1st Stage F Stat. (Price)	-	72.06	83.03	86.77
1st Stage F Stat. ($ln(s_{j\|g})$)	-	-	36.10	-
1st Stage F Stat. ($ln(s_{j\|hg})$)	-	-	-	29.41
1st Stage F Stat. ($ln(s_{h\|g})$)	-	-	-	144.35

Note: *p<0.1; **p<0.05; ***p<0.01

8.1.2 Elasticities

From here, I use the the price and nesting parameters (α, σ_1, and σ_2) from Table 2 column 4 to calculate own-price and cross-price elasticities as described in Equation 20. Individual model own-price elasticities are now exclusively elastic, between -2.95 and -9.93. For simplicity, Table 3 shows 2022-quantity-weighted-average own-price elasticities by firm, and Table 6 in the Appendix shows own-price elasticities, cross-price elasticities, and associated substitution patterns for all goods in the 2022 choice set.

Table 3: Quantity Weighted Average Own-Price Elasticity by Firm

Firm	Own Price Elasticity
Renault-Nissan-Mitsubishi Alliance	-4.44
Mazda Motor Corporation	-4.57
Subaru Corporation	-4.76
Hyundai Motor Group	-4.76
Honda Motor Company	-4.99
Volkswagen Group	-5.17
Toyota Group	-5.32
General Motors	-6.23
Ford Motor Company	-6.39
Stellantis	-6.56
Tesla, Inc.	-7.66
Mercedes-Benz Group	-8.17
BMW Group	-8.21
Volvo Group	-8.36
Proposed Merged Firm	-4.76
Aggregate Market Quantity-Weighted Average	-5.79

Notes: This table shows quantity-weighted average own-price elasticities for all firms in 2022. The proposed merged firm average uses pre-merger quantities. All elasticities are calculated using Equation 20 in conjunction with the parameters estimated in the double nested logit model found in column 4 of Table 2. Observe that, as expected, the higher end firms have higher absolute average elasticities, and the lower end firms have lower absolute average elasticities. For individual model elasticities, which range from -2.95 to -9.93, see Table 6 in the Appendix.

One can easily observe that the elasticities recovered are consistent with economic theory in that higher end products have higher (in absolute terms) elasticities. Mercedes, BMW, and Volvo models are characterized by high price sensitivity since they are generally producing luxury goods, while Nissan, Mazda, and Subaru models have relatively lower price sensitivities since their goods are more akin to necessities. While on the surface this might seem counterintuitive, consider what we would expect to happen if the prices of both the BMW X5 and the Nissan Versa double. My estimates suggest that if the BMW X5 doubles in price, demand will fall by nearly 10x, while if the

Nissan Versa doubles in price, demand will only fall by about 3x. This makes sense since the X5 is a luxury good — consumers will merely delay their purchases since they are not at all essential — while the Versa is the car of choice, according to Nissan itself, for first time car buyers, college students, and budget conscious consumers, all of whom are buying a car out of necessity, not in search of luxury. Conversely, consider if the prices of the Versa and X5 are halved. Many consumers for whom the X5 was previously too expensive will now be able to afford this luxury item and rush to purchase it, while the unattractive Versa will generate a relatively much smaller increase in demand as consumers upgrade to higher end models.

8.1.3 Substitution Patterns

Substitution patterns can now be determined by ranking cross price elasticities. In addition to obtaining sensible own-price elasticities, a central goal of upgrading from the standard logit to the (double) nested logit model of demand is to obtain substitution patterns that reflect our expectations of consumer behavior in the market. By construction, substitution in the two level nested logit model will be weighted towards within-subgroup products, producing much more sensible results. Indeed, we observe basically no substitution across sub-nests. A few representative substitution patterns are presented here in Figure 4, and the full set is available in the Appendix.

Clearly, the structure imposed by the double nested logit model aids significantly in generating reasonable substitution patterns. It remains the case, however, due to the fact that the IIA restriction has been only *partially* relaxed, that models with unusually dominant market shares still retain unusually common substitution positions (e.g. Ford F Series). Despite this, these patterns approximate intuition about what substitution patterns may exist in reality, and serve as evidence that this model is a sufficiently strong representation of consumer choice.

8.2 Supply

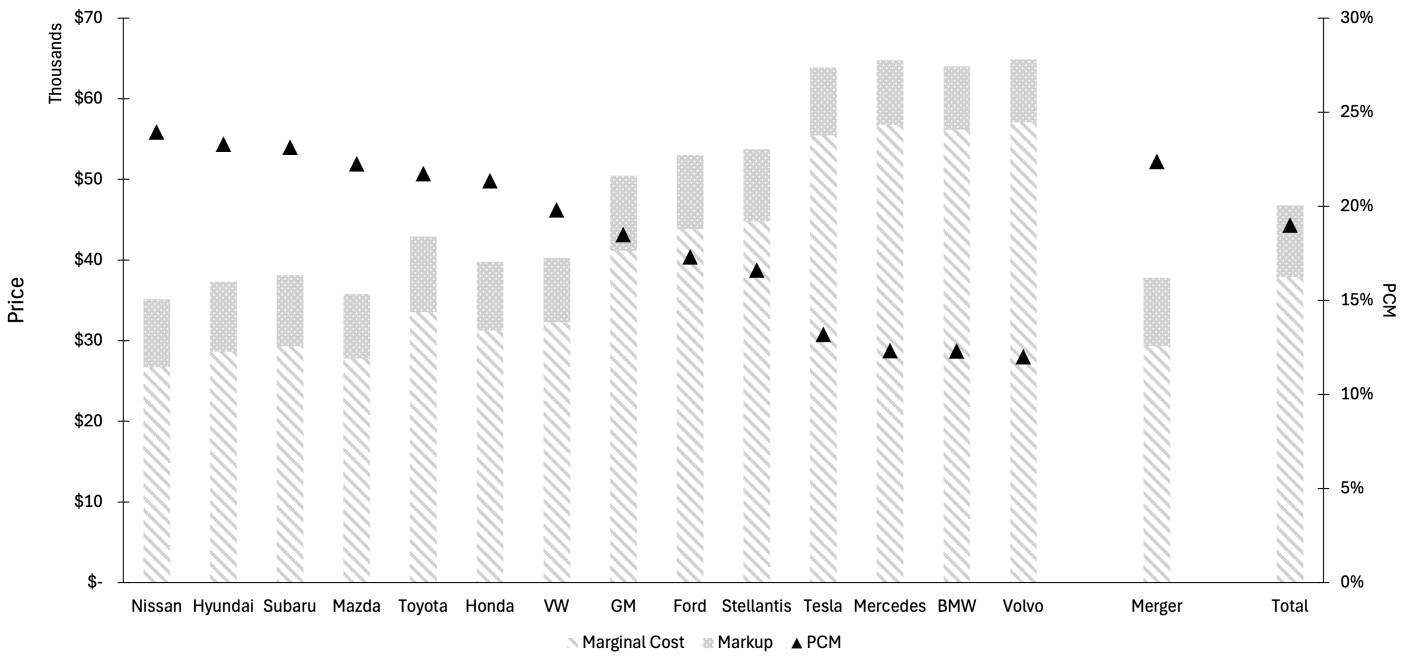
Now that demand parameters have been estimated, it is possible to recover marginal costs, as described by the procedure in Section 5.2. The purpose of recovering marginal costs is to derive price-cost margins (PCM), which is simply the markup as a percent of price, or $\frac{P-MC}{P}$.[7] This is a quantifiable measure of market power, a firm's ability to price above marginal cost. Firm-level results are presented in Figure 5, and individual product marginal costs, markups, and PCMs are presented in Table 7 in the Appendix.

[7] This is the same as the Lerner index.

Figure 4: Sample Substitution Patterns Generated by Preferred Double Nested Logit Specification

Notes: This figure illustrates the substitution patterns derived from the double nested logit model, as estimated in column 4 in Table 2. I show four different example starting models, each from a different subgroup/vehicle type: Chrysler Pacifica (minivan), Toyota Tacoma (pickup truck), Mitsubishi Outlander (SUV) and Mercedes Sprinter (van). This figure shows that, overall, substitution patterns are consistent with intuition; when prices rise on a preferred product, consumers deviate to the most similar products first. Recall that the nested logit model's key improvement over the standard logit model is the relaxation of the IIA assumption, but this is only partial, as evidenced by the appearance of the Ford F Series (pickup truck) as the second substitute to the Mitsubishi Outlander (SUV).

Figure 5: Decomposition of Price with Price-Cost Margins



Notes: This figure shows the decomposition of each firm's quantity-weighted average price in 2022 (in 2024 USD) into its two components, marginal cost and markup. All quantities are pre-merger quantities. Additionally, each firm's quantity-weighted average price-cost margin ($\frac{P-MC}{P}$, or equivalently, Lerner Index) is shown in the black triangles. Market-wide, I observe an average price of \$46,749, recovering \$37,864 as marginal cost and \$8,885 as markup, yielding an average PCM of 19%. This is well aligned with both publicly reported gross margins and the findings of Grieco et. al. (2024).

I recover an average price-cost margin across the entire market of approximately 19%, in line with Grieco, Murry, and Yurukoglu (2024) who estimate nearly the same median PCM across the aggregate US automobile industry. Furthermore, my findings are well aligned with publicly reported gross margins, defined as $\frac{Revenue-COGS}{Revenue}$, clearly a fair analogy for PCMs. 2021 and 2022 gross margins, where data was available, consistently hovered between 15-20% (SEC Filings and Yahoo Finance).

One important observation is that, by construction, there is a strong correlation between elasticity and PCMs. Firms that sell more elastic models have substantially less ability to profitably increase markups than those firms selling relatively inelastic models. In fact, PCMs nearly double from the most luxury firms (average PCMs $\approx$ 12%) to the firms with the most inelastic products (average PCMs as high as 23%). At the individual model level, PCMs range from 10% for the BMW X5 to nearly 37% for the Nissan Versa.

9 Counterfactual Analyses

In order to decompose the sources of market power and predict the price effects of a merger, I use the marginal cost vector $\mathbf{c}$ recovered in Equation 31 and alter the ownership matrix θ^F to reflect various scenarios which will be outlined here. Computationally, to simulate the new price equilibrium in my various counterfactual scenarios, I use fixed point iteration on Equation 23 with an algorithm from the *mergersim* Stata package made publically available by Bjornerstedt and Verboven (2013).

1. First, I am interested in how much market power comes strictly from product differentiation. To simulate this, I change θ^F to the identity matrix θ' where element $\theta'(j,k) = 1 \iff j = k$, and 0 otherwise. This is the case where every product is produced by a single product firm. This produces a new equilibrium defined by $\mathbf{p}'$ and $\mathbf{s}'(\mathbf{p}')$, yielding $\mathbf{m}'$. By construction, any markup above marginal cost observed in this scenario *cannot* be due to joint pricing by multi-product brands or firms and must be due *strictly* to product differentiation. $\frac{\mathbf{m}'}{\mathbf{m}}$ is this portion of markup due to product differentiation and $\frac{\mathbf{m}-\mathbf{m}'}{\mathbf{m}}$ is the (remaining) portion due to multi-product firms.

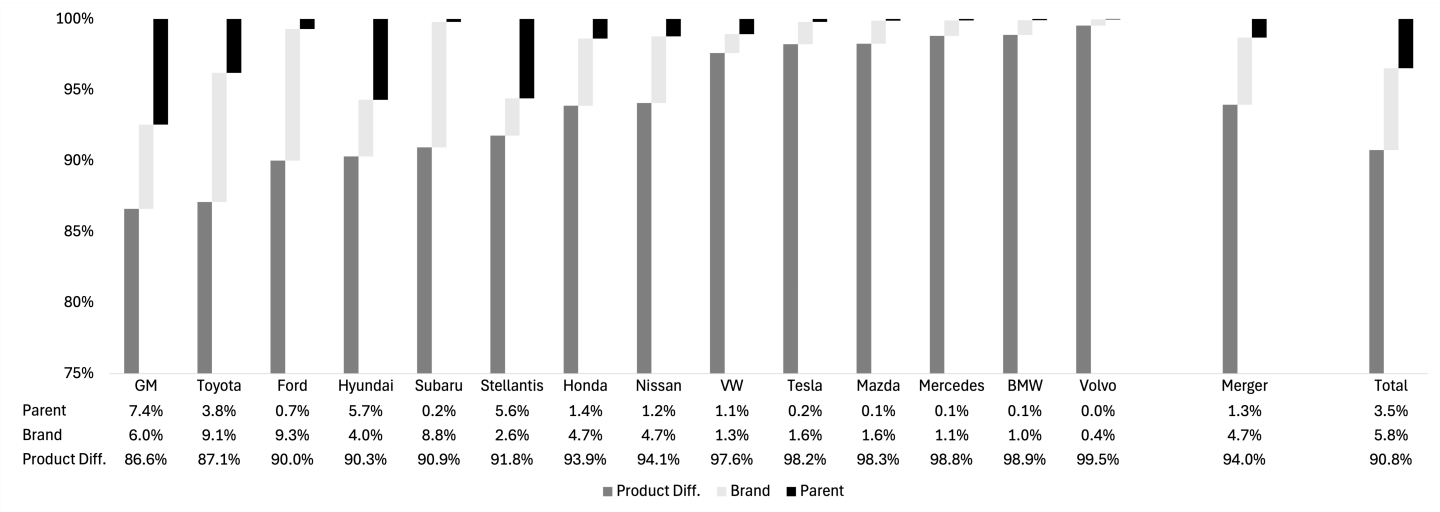
2. Next, I simulate what prices would be if profit-maximization occurred at the brand level instead of at the parent level. I define θ'' where element $\theta''(j,k) = 1 \iff j$'s brand is the same as k's brand, and 0 otherwise. This produces a new equilibrium defined by $\mathbf{p}''$ and $\mathbf{s}''(\mathbf{p}'')$, yielding $\mathbf{m}''$. $\frac{\mathbf{m}''-\mathbf{m}'}{\mathbf{m}}$ is the portion of markup describing the joint product ownership pricing benefit held by brands. The remaining portion of markup $\frac{\mathbf{m}-\mathbf{m}''}{\mathbf{m}}$ is thus attributable to the additional market power acquired by the larger multi-brand parents.

3. Finally, I simulate a merger between the Honda Motor Company and the Renault-Nissan-Mitsubishi Alliance by defining $\theta''' = \theta^F$ for all elements (j,k) *except* for the additional joint ownership that would exist under the hypothetically joint mega-firm. This produces a new equilibrium with one less firm than the other scenarios defined by $\mathbf{p}'''$ and $\mathbf{s}'''(\mathbf{p}''')$, yielding $\mathbf{m}'''$. $\frac{\mathbf{m}'''-\mathbf{m}}{\mathbf{m}}$ is the percentage increase in markups resulting from the merger and $\frac{\mathbf{p}'''-\mathbf{p}}{\mathbf{p}}$ is the percentage increase in prices. It will be worthwhile to differentiate between the price effects for products of the merging firms versus the rest of the products (recall Eq. 10 which suggests that even non-merging firms should obtain some positive price benefits from the merger).

9.1 Results and Discussion: Sources of Market Power

In order to decompose the recovered markup term into the portions due to product differentiation, multi-product brand market power, and multi-brand firm market power, I run the first two simulations described above. Firm-level 2022-quantity-weighted-average results are presented in Figure 6 and the accompanying table.

Figure 6: Decomposition of Markups (Product Differentiation and Joint Ownership)



	GM	Toyota	Ford	Hyundai	Subaru	Stellantis	Honda	Nissan	VW	Tesla	Mazda	Mercedes	BMW	Volvo	Merger	Total
Parent	7.4%	3.8%	0.7%	5.7%	0.2%	5.6%	1.4%	1.2%	1.1%	0.2%	0.1%	0.1%	0.1%	0.0%	1.3%	3.5%
Brand	6.0%	9.1%	9.3%	4.0%	8.8%	2.6%	4.7%	4.7%	1.3%	1.6%	1.6%	1.1%	1.0%	0.4%	4.7%	5.8%
Product Diff.	86.6%	87.1%	90.0%	90.3%	90.9%	91.8%	93.9%	94.1%	97.6%	98.2%	98.3%	98.8%	98.9%	99.5%	94.0%	90.8%

Notes: This figure illustrates the results of the first two counterfactual simulations. The first simulation (single product firms) reveals that, market-wide, 90.8% of markups are attributable to product differentiation alone. The second simulation, where profit-maximization occurs at the brand (not firm) level, reveals that 5.8% of markups are attributable to multi-product brands, and the remaining 3.5% to multi-brand firms. This figure uses pre-merger quantity-weighted averages.

The most notable takeaway here is that approximately 91% of markups can be attributed to product differentiation alone. One should be careful to take note that the difference in this proportion across firms is due principally to the number of products owned by each firm in the choice set. In any case, the result that, in the counterfactual world where each model is owned by a single-product firm, markups would be 91% of what they are today is remarkably telling about the competitive nature of the US automobile industry. In particular, only about 9% of markups, or 1.8% of total prices (given that markups comprise approximately 19% of prices) are due to concentration in the market. About two-thirds of this additional markup power is due to the concentration of models into multi-product brands — the orange boxes in Figure 1 — and the remaining portion (3.5% of markups or 0.66% of prices) is due to the parent conglomerates that own multiple brands — the blue boxes in Figure 1.

The reader might be surprised by the seemingly low (only 9.2%) amount of markup attributable

to joint ownership. One likely culprit is the limited joint ownership *within* the vehicle type nests. Figure 7 breaks down the owners of each of the models in the 2022 choice set. One can easily observe that within any given vehicle type, model ownership is remarkably disaggregated. Coupled with my finding that consumers feel very strongly about which type of vehicle (sub-nest) to buy (the coefficient on $ln(s_{j|hg}) \approx 91\%$), the disaggregated ownership helps explain why the main source of market power is product differentiation, not joint pricing. Consider a scenario in which, all else equal, consumers did not feel strongly about which type of vehicle to buy. Then, there would be competition across the entire market (see Figure 1) and firms with greater numbers of products would acquire more market power. Instead, though, since the vehicle type preference is so strong, competition between producers occurs primarily within vehicle type sub-nests, which, according to Figure 7 contain fairly limited joint ownership. Thus, the primary source of market power is product differentiation and not joint ownership.

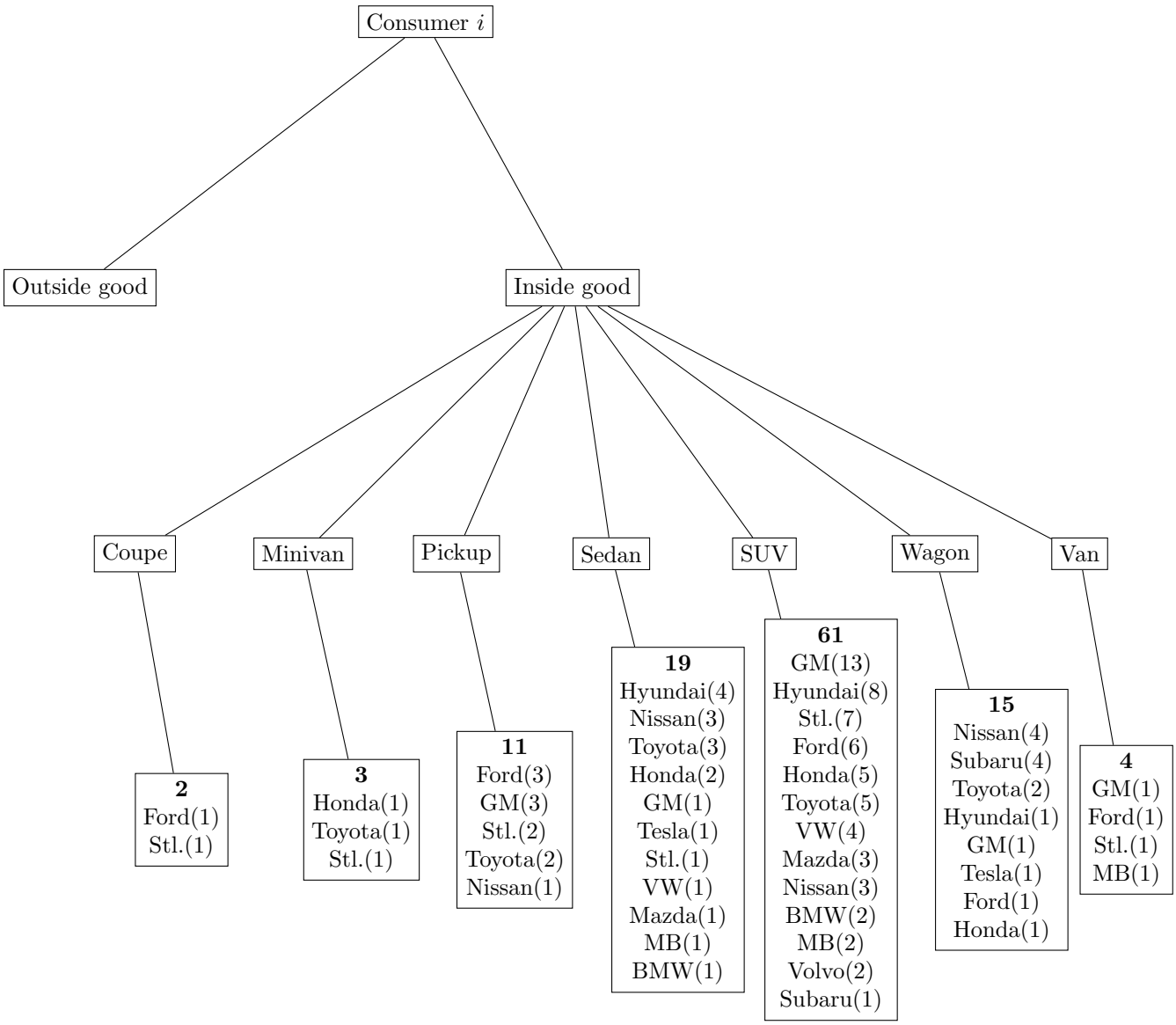
One further reason why the portion of market power attributable to product differentiation is quite high may be due to a modeling choice. My demand model allows for just one within-sub-nest correlation parameter (σ_1), imposing equality in this parameter across vehicle type sub-nests. One might expect, say, pickup trucks and vans to exhibit greater within-sub-nest correlation than sedans. To check, I construct and run a more flexible specification allowing for different nesting parameters across sub-nests, the details of which can be found in the Appendix, Section 11.1.3. The key result from this flexible model is that the single σ_1 parameter in the constrained model here is *not* statistically different from any of the flexible sub-nest parameters (with the exception of the van sub-nest). Furthermore, the price and group-share parameters are also not statistically different. While the specific point estimates from the more flexible specification may lead to a slightly lower share of markups attributable to product differentiation, these coefficients are by and large not statistically different from the constrained model, offering a reassuring robustness check.

In summary, the equality constraint of the within-sub-nest correlation parameter appears to not significantly impact the estimates. Thus, the overarching implication of my findings is clear and robust: market concentration is not a particularly strong, and certainly not the primary, source of market power in the US automobile industry.

9.2 Results and Discussion: Merger

Before presenting the formal results from the Honda-Nissan merger simulation, it is worth drawing some general lessons from the previous section as they pertain to mergers. In general, since the

Figure 7: Total Number of Models in Each Sub-Nest in 2022, with Firm Owners (Pre-Merger)



Notes: This figure illustrates how many products available in the 2022 choice set in a given vehicle type sub-nest are owned by a particular firm. Firms are listed in decreasing order. Importantly, this shows that joint ownership *within* vehicle type sub-nests is very limited. This may explain the high portion of markup due to product differentiation.

vast majority of market power is derived from product differentiation, not joint ownership, horizontal mergers are unlikely to cause substantial price increases. Furthermore, mergers that increase the joint ownership *within* one or more vehicle type sub-nests are likely to induce much greater upward pricing pressure than mergers that merely increase product ownership *across* vehicle types. A simple comparison of Figures 7 and 8 shows that the Honda-Nissan merger makes only minimal changes to within-nest joint ownership. Notice that the merger has the greatest effects on joint ownership in the sedan and SUV sub-nests, but does not at all give the merged firm any sort of unusually high amount of joint ownership in these, or any other, sub-nests.

In line with these expectations, the principal results of the merger are that market-wide prices will rise only one-fifth of one percent, while prices of the newly merged firm will increase by 1.67% (see Figure 9). The full set of product-level post-merger prices, markups, and PCMs is presented in the Appendix, Table 7.

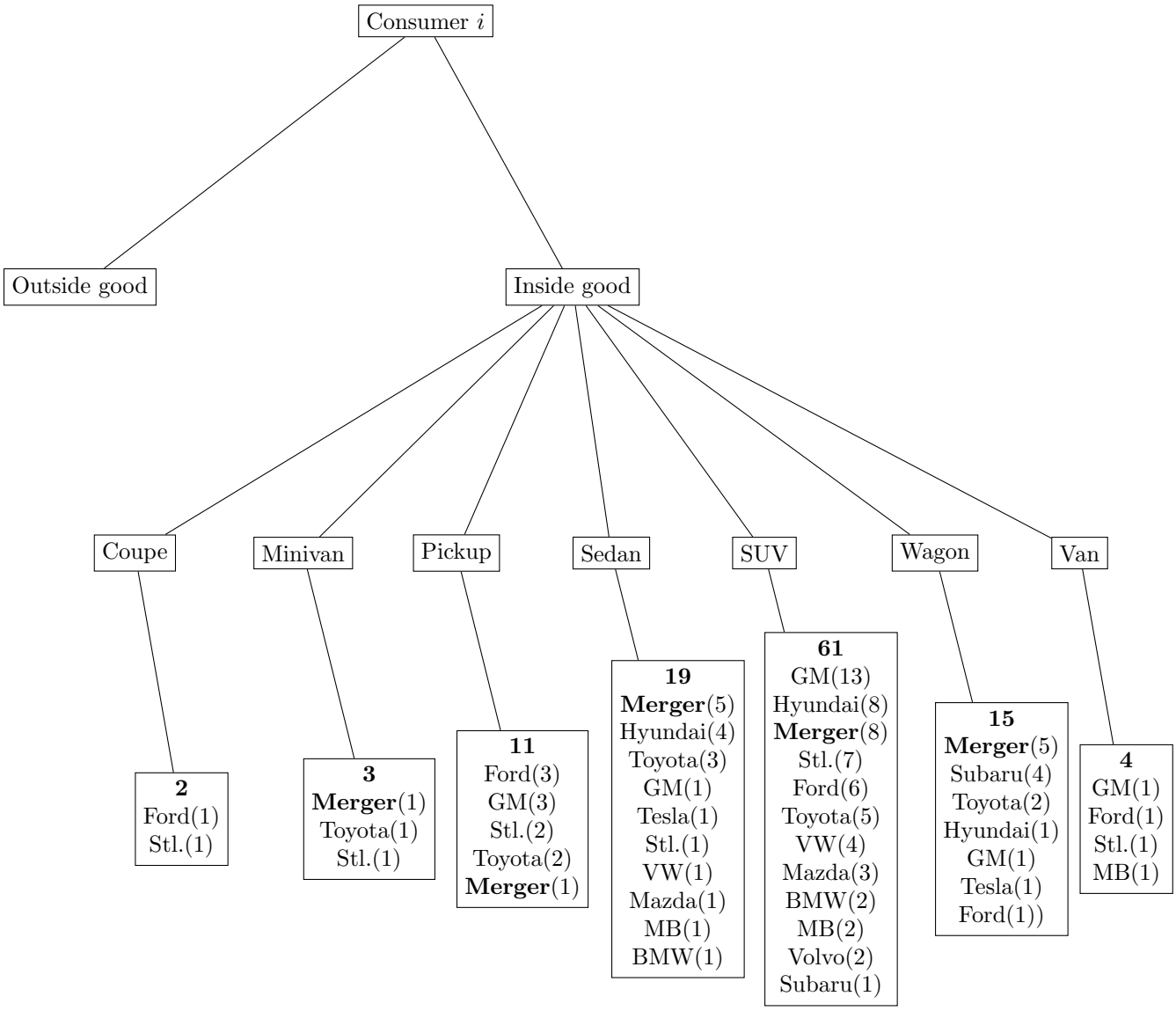
The firms that benefit the most from the merger, beyond the merging firms themselves, are Honda and Nissan's nearest competitors: Subaru, Toyota, Hyundai, and Tesla. However, this benefit is quite small. My estimates suggest that they can raise their prices by about one-tenth of one percent, and thus increase their markups by one-quarter of one percent. Luxury firms Volvo, Mercedes, BMW, and Volkswagen generate essentially zero additional market power from this merger.

Market shares, however, shift meaningfully for all firms. Figure 10 shows the percent change in market shares across firms in the new equilibrium with the merged firm. This simulation reveals that only the two merging firms raise prices substantially enough to lose market share. Nearly all of this loss in market share is recovered by the remaining firms; total purchase quantity falls by only one-tenth of one percent.

While Honda and Nissan are, respectively, the 6th and 7th largest firms in the pre-merger 2022 market, the merged firm will become the 3rd largest, behind only Toyota and General Motors (see Figure 11). I estimate that this merged firm will capture a 13.6% inside market share (that is excluding the outside good), which is a 6.45% decrease from the sum of both market shares as they stand pre-merger, explainable by predicted price increases and subsequent consumer substitution away from the merged firms' products.

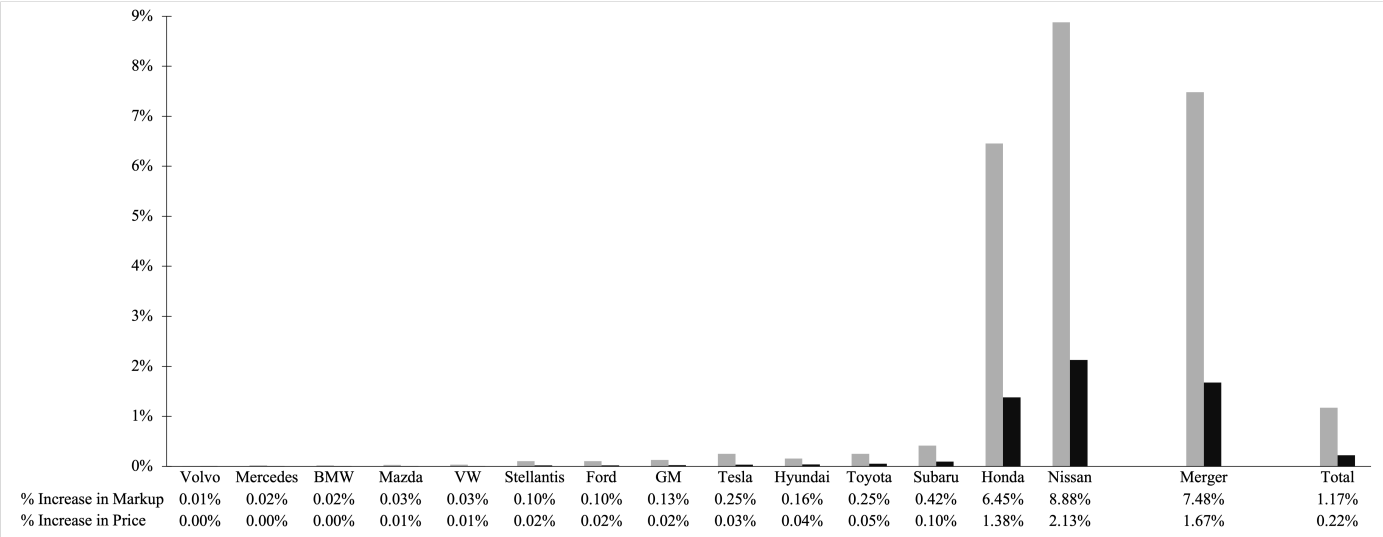
One measure of market concentration utilized by government anti-trust authorities is the Hirfindahl-Hirschfield Index (HHI). HHI is the sum of the squared (inside) market shares of all of the firms in the market.

Figure 8: Total Number of Models in Each Sub-nest in 2022, with Firm Owners (Post-Merger)



Notes: This figure, to be considered in comparison with Figure 7, shows how product ownership changes within each vehicle type sub-nest after the hypothetical merger. The combined Honda-Nissan firm is referred to in the figure as **Merger**. Clearly the merger does not significantly increase the amount of joint ownership in any given sub-nest. Consider the two cases where the merged firm displaces the existing leader: sedan and wagon. The previous leader held 4/19 and 4/15 models, respectively. The merged firm will hold 5/19 and 5/15, hardly an important increase. Clearly the merger will not markedly increase market concentration where it counts (within sub-nests) and thus will have only nominal price effects.

Figure 9: Percent Increases in Post-Merger Prices and Markups by Firm



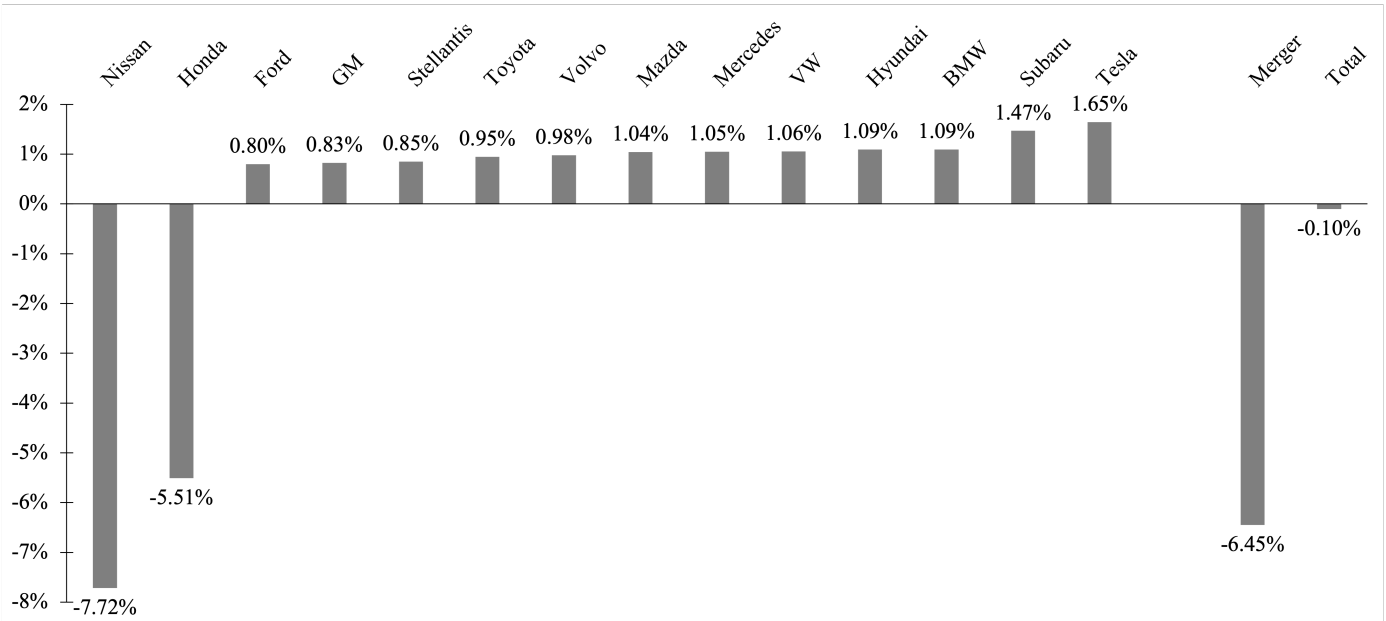
Notes: This figure shows the results of the Honda-Nissan merger simulation on prices and markups. Firms are ordered by percent increase in markup post-merger. Underlying calculations are quantity-weighted averages using the pre-merger 2022 quantities. Market-wide markups and prices are predicted to increase by 1.17% and 0.22%, respectively. The merged firm's markups and prices are predicted to increase by 7.48% and 1.67% respectively. Importantly, Subaru and Toyota emerge as the biggest third party beneficiaries of greater market power post-merger, while the luxury firms generate essentially zero marginal market power.

$$HHI = 10000 * \sum_{f \in F} s_f^2 \quad ; \quad \sum_{f \in F} s_f = 1 \tag{33}$$

HHI is measured on a scale of 0 to 10000, where, for example, 10000 represent a monopoly and 5000 represents a duopoly with two identical firms. Government agencies generally consider an HHI between 1000 and 1800 to represent a "moderately concentrated" industry, and an HHI above 1800 to represent a "highly concentrated industry" (DOJ/FTC 2023). One method of evaluating mergers is to examine their predicted changing of the HHI. I calculate a pre-merger HHI of 1123, indicating that this market is low-to-moderately concentrated. Using post-merger market shares, I calculate an HHI of 1221, an increase of just about 100. The DOJ and FTC typically flag mergers that are expected to increase the HHI by more than 100 points and/or produce a single firm with a market share in excess of 30%, but these are primarily applicable to markets already sufficiently concentrated. 1221 is almost certainly below this category. Thus, it is unlikely that this merger would be flagged for review by anti-trust authorities on the basis of substantially increasing market concentration.

The DOJ's *Horizontal Merger Guidelines* also asks whether any product's price is likely to rise

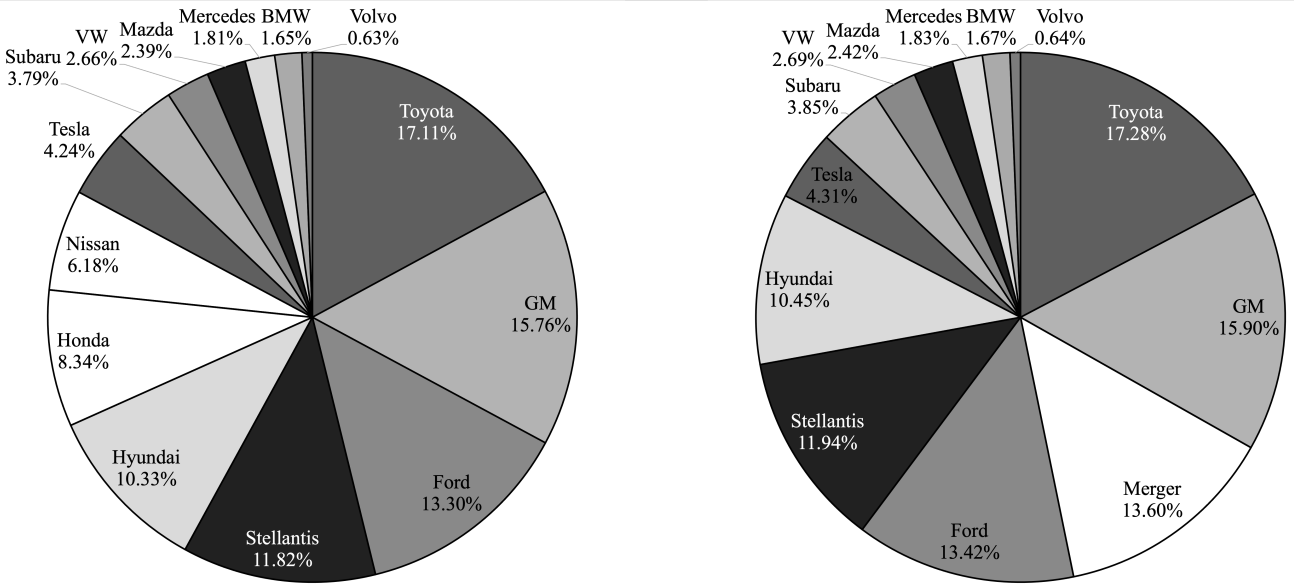
Figure 10: Percent Changes in Post-Merger Market Share by Firm



Notes: This figure shows the results of the Honda-Nissan merger simulation on market shares. Post-merger quantities are compared to observed 2022 quantities to obtain these estimates. As expected, price increases by the merged firm lead to diversion of demand to competitors. The merged firm loses 6.45% of the pre-merger Honda plus Nissan quantities, while competitors Tesla and Subaru capture the greatest of the diversion. Notably, total market quantity is practically unchanged post-merger.

by, generally, $\geq 5\%$. My predictions suggest that the greatest price increases will be on the Nissan Versa, Nissan Sentra, and Honda HR-V ($> 3\%$). Percent increases in price for all products owned by the merging firms are presented below in Table 4. The greatest price increases on non-merging-firm products will be for the Subaru Impreza and Toyota Corolla ($\approx .15\%$). Clearly, the 5% price increase threshold to trigger a flag on the basis of price increases will not be met.

Figure 11: Inside Market Shares of Parent Firms Pre- (Left) and Post- (Right) Merger



Notes: This figure shows the share of total purchase quantity of any inside good in the choice set belonging to each parent firm. The left panel uses observed 2022 pre-merger quantities, and the right panel uses predicted post-merger quantities. As per Figure 10, the total purchase quantity (the denominator) falls by a negligible 0.1% from the left to the right panel. The order of market shares is unchanged with the exception of the merged firm becoming the third largest, up from the 6th and 7th positions.

Table 4: Post-Merger Price Changes for Merged-Firm Products

Model	Percent Increase in Price
Nissan Versa	3.91%
Nissan Sentra	3.36%
Honda HR-V	3.25%
Nissan Altima	2.78%
Nissan Kicks	2.75%
Mitsubishi Outlander Sport	2.54%
Nissan Rogue Sport	2.38%
Honda Civic	2.10%
Nissan Rogue	2.02%
Honda Accord	1.79%
Mitsubishi Outlander	1.77%
Nissan Murano	1.47%
Nissan Pathfinder	1.33%
Nissan Frontier	0.95%
Honda CR-V	0.95%
Honda Passport	0.77%
Honda Pilot	0.76%
Acura RDX	0.70%
Honda Odyssey	0.59%
Acura MDX	0.56%

Notes: Percent increases in price are calculated by comparing a model's observed pre-merger price to the predicted post-merger price, as calculated by fixed point iteration on Equation 23. The full set of prices by model, pre- and post-merger, can be found in the Appendix, Table 7.

10 Conclusion

In this paper, I recover a 19% price-cost margin in the U.S. automobile industry, a value consistent with Grieco et. al. (2024), and then show that the vast majority — 91% — of this markup can be attributed to product differentiation. I find that the remaining 9% of markups are due to multi-product firms jointly setting prices to maximize profits, both at the brand level (5.8% of markups) as well as at the multi-brand parent firm level (the remaining 3.5% of markups). The relatively low proportion of market power derived from joint ownership appears to be due to the facts that (1) consumers' correlation between models of the same vehicle type (sub-nest) is extremely high and (2) joint ownership of products is quite limited within any given sub-nest. Taken together, this suggests that most market power comes from within-sub-nest product differentiation.

I also simulate the proposed merger between Honda and Nissan, where I find that market-wide markups will increase by 1.2% on average, and prices by only .22%. However, I do find that products within the merged firm will be priced 2% higher on average, with an increase of 7% on average in their markups. Among merged-firm products, the Nissan Versa, Nissan Sentra, and Honda HR-V will see the highest price increases ($> 3\%$), while the luxury brand Acura's RDX and MDX will see price increases only slightly above the market-wide average. Subaru and Toyota will be the greatest third-party beneficiaries of the merger in terms of their ability to increase markups — the Subaru Impreza and Toyota Corolla in particular will see the greatest percent increase in prices of any of the non-merging products — and Tesla will recover the most additional market share. However, I find that this horizontal merger fails to increase market concentration or prices substantially enough to trigger review by government agencies under usual standards.

Three limitations of my results are worth discussing now. First, while the substitution patterns derived from my demand model are quite reasonable, they lack complete flexibility due to the nesting structure imposed on the consumer's problem. A natural improvement might be to implement a full random coefficients model as in BLP (1995), but, as discussed above, one cost of doing so is the lack of an analytical solution. Moreover, I am confident in my model due to (1) the strong concordance of my results with Grieco et. al. (2024) despite their implementation of a more flexible demand model, as well as (2) the lack of statistically different parameter estimates between my preferred (constrained) model and the specification with flexible nesting parameters (details in Appendix, Section 11.1.3). Second, my data is limited to the 14 states named in Section 6. It is possible that certain patterns in these transaction data are not representative of the entire U.S. automobile industry, so, as in all industrial organization literature, results should not be over-extrapolated. However, my data does

include full transaction data for 9 out of the 10 most populated states which comprise roughly 70% of the US population, suggesting that my results should be a reasonable approximation for the U.S. market. Third, my merger simulation operates under the, potentially incorrect, assumption that there will be no gains in efficiency due to the merger. Considering that the headline result of the merger simulation is that market concentration and prices will not rise substantially, incorporating any efficiency gains (which are indeed likely to occur) should merely further mute the already low price effects of the merger. The results are at least directionally accurate, and likely most accurate in the short term before any efficiency gains could be realized.

11 Appendix

11.1 Alternative Models

11.1.1 Logit

In the basic multinomial logit model, consumer i selects from a set of $J+1$ products. There are J inside goods and 1 outside good. Consumer i's conditional indirect utility for model $j \in J$ consists of two components; the mean utility for model j across all consumers, and a term for random tastes — consumers have heterogeneous preferences. Consumer i's conditional indirect utility for product j is therefore given by:

$$u_{ij} = \delta_j + \epsilon_{ij} \tag{34}$$

where δ_j is the mean utility for model j which is homogeneous across consumers, and ϵ_{ij} is the individual consumer's idiosyncratic component of utility which is unobserved and assumed to take the form of an i.i.d random variable with a Type I extreme value distribution. Product j's mean utility, $\delta_j = -\alpha p_j + \beta \mathbf{X}_j + \xi_j$, consists of price, a vector of product characteristics $\mathbf{X}$, and the error term, which represents the unobservable characteristics of model j. The mean utility for the outside good, δ_0 is normalized to 0, without loss of generality. This turns out to be very helpful in inverting utility to an estimable linear regression, and is not restrictive since all that matters is the relationship between utilities of different choices.

Using the properties of the extreme value distribution, Berry (1994) shows that it is possible to transform the market share equation

$$s_j = \frac{e^{\delta_j}}{1 + \sum_{j=1}^{J} e^{\delta_j}} \tag{35}$$

into this linear equation:

$$ln(s_j) - ln(s_0) = -\alpha p_j + \beta \mathbf{X}_j + \xi_j \tag{36}$$

One can then easily estimate this equation using instrumental variables to deal with price endogeneity, since s_j, s_0, p_j and the vector of product characteristics $\mathbf{X}_j$ are all observable in the data.

Unfortunately, the cost of this simplicity is unrealistic substitution patterns. One can take derivatives to reveal an expression for own-price elasticity:

$$\frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = -\alpha(1-s_j)p_j \tag{37}$$

and for cross-price elasticity:

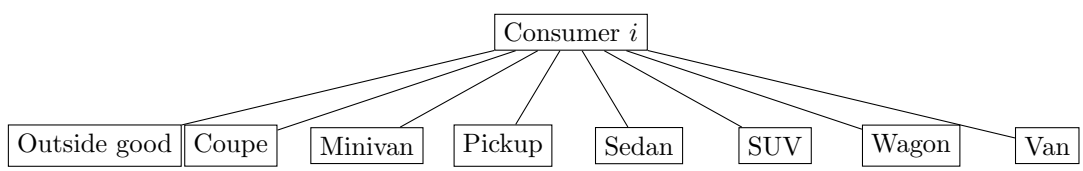
$$\frac{\partial s_k}{\partial p_j}\frac{p_j}{s_k} = \alpha p_j s_j \tag{38}$$

The fact that cross-price elasticities depend only on market shares and not on any product characteristics should raise alarm. The concerns over substitution patterns arise from the multinomial logit model's independence of irrelevant alternatives (IIA) property, which states that the probability of a consumer choosing between two products is independent of the other products in the choice set. I do estimate a basic multinomial logit model as an initial step, but the substitution patterns are so preposterous that I do not use this model for any analysis of market power or merger simulation.

The results from estimating this model are shown in columns 1 and 2 of Table 2, with and without instruments, respectively.

11.1.2 Single Level Nested Logit

The goal of the nested logit model is to, at least somewhat, relax the restrictive IIA assumption to allow for correlation between similar products by imposing a nesting/grouping structure on the choice set. We sort the choice set into $G+1$ groups, $g = 0, ..., G$, where the outside good $j = 0$ is the only member of group $g = 0$. The structure which I impose is shown in the figure below:



The conditional indirect utility of consumer i for product j in group g is now given by

$$u_{ij} = \delta_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij} \tag{39}$$

Again, $\delta_j = -\alpha p_j + \beta \mathbf{X}_j + \xi_j$ and ϵ_{ij} remains an i.i.d random variable with a Type I extreme value distribution. Notice that the term ζ_{ig} is the same for all products within a given group g, which allows for in-group correlation and is the crux of the improved substitution patterns. This group preference parameter has a distribution depending on σ where $0 \leq \sigma < 1$. Cardell (1991)

shows that if ϵ_{ij} is an extreme value random variable, so too is $\zeta_{ig} + (1-\sigma)\epsilon_{ij}$. Notice that as σ approaches 1 there is perfect in-group correlation, and as σ approaches 0, the model collapses into the basic multinomial logit.

The linear estimating equation, from Berry (1994), is now

$$ln(s_j) - ln(s_0) = -\alpha p_j + \beta \mathbf{X}_j + \sigma ln(s_{j|g}) + \xi_j \tag{40}$$

where $s_{j|g}$ is product j's share within its group g. The results from estimating this model are shown in column 3 of Table 2. Ultimately, I am unable to estimate this model with sensible and significant parameters, suggesting a rejection of this functional form as a reasonable representation of the market.

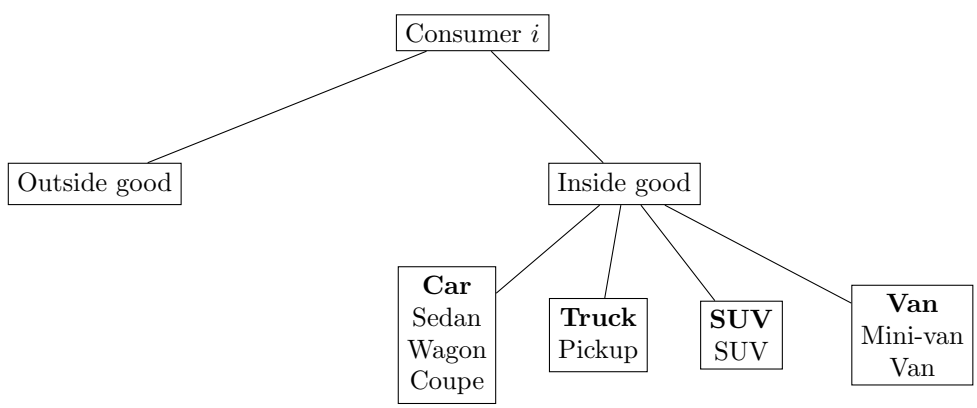
11.1.3 Double Nested Logit with Flexible Nesting Parameters by Vehicle Type

As mentioned in the discussion in Section 9.1, a natural extension of the demand model that I employ allows for variation in the within-sub-nest correlation parameter, as opposed to imposing equality across sub-nests as I do in the body of the paper. To implement this, I interact the sub-nest correlation parameter (previously σ_1) with a vector of dummy variables $\mathbf{D_h}$, one for each sub-nest h, as follows:

$$ln(s_j) - ln(s_0) = -\alpha p_j + \beta \mathbf{X}_j + \mathbf{D_h} * \sigma_h ln(s_{j|hg}) + \sigma_g ln(s_{h|g}) + \xi_j \tag{41}$$

This specification provides unique estimates of the within-sub-nest correlation parameter for each sub-nest and can be used as a robustness check of the restricted model that I use in the body of the paper. Since this specification allows for unique nesting parameters for each sub-nest, it is inappropriate to have extremely small sub-nests. As such, I slightly simplify the nesting structure as shown in Figure 12, combining like vehicle types.

Figure 12: Consumer Choice Structure in Flexible Nesting Specification



The results of estimating Equation 41 where the sub-nests h are as presented in Figure 12 are shown in Table 5. The results are extremely encouraging insofar as they align with the primary model (results in column 4 of Table 2) that I employ in the body of the paper. In comparing the primary constrained model with this flexible model, I find no statistical difference between the coefficients on price nor the group share ($ln(s_{h|g})$). More-so, the flexible nesting coefficients are not statistically different from the single sub-nest correlation parameter ($ln(s_{j|hg})$), with the exception of the van sub-nest. Additionally, as required for utility maximization, $\sigma_h > \sigma_g$ for all sub-nests, and $0 < \sigma_h < 1$ for all h, again with the exception of the van sub-nest.

The parameters for calculating elasticities are now, by construction, dependent on vehicle type,

Table 5: Flexible Nesting Parameters Specification Results

	Dependent variable:
	$ln(s_j/s_o)$
Price (in 10,000 USD)	-0.163^{***}
	(0.031)
HP/WT	5.869^{**}
	(2.591)
Length	0.012^{***}
	(0.003)
Height	0.022^{***}
	(0.006)
MP$	0.049^{***}
	(0.008)
‘4X2‘	0.373^{***}
	(0.125)
‘4X4‘	0.098
	(0.083)
AWD	-0.017
	(0.046)
RWD	-0.029
	(0.077)
Pandemic	-0.106^{***}
	(0.031)
$ln(s_{j\|Car,g=1})$	0.846^{***}
	(0.077)
$ln(s_{j\|SUV,g=1})$	0.835^{***}
	(0.070)
$ln(s_{j\|Truck,g=1})$	0.979^{***}
	(0.075)
$ln(s_{j\|Van,g=1})$	1.474^{***}
	(0.216)
$ln(s_{h\|g})$	0.793^{***}
	(0.076)
Constant	-6.299^{***}
	(0.940)
Observations	461
Adjusted R^2	0.898
Residual Std. Error	0.301 (df = 445)
Note:	*p<0.1; **p<0.05; ***p<0.01

not just nesting level as before. Evaluating Equation 20 with these flexible values for σ_1 (here σ_h) results in higher (in absolute value) own-price elasticities for pickup trucks and lower (in absolute value) own-price elasticities for cars and SUVs, all else equal. Effects on cross-price elasticities for goods within the same sub-nest are more ambiguous since the group and subgroup shares enter with opposite signs. Cross-price elasticities for goods in different sub-nests will fall, which, all else equal, will improve within-sub-nest substitution. Overall, these potential improvements — slightly more inelastic models for the bulk of the choice set and stronger within-sub-nest substitution — exemplify further benefits of this more flexible model.

While the issues with the van sub-nest make it infeasible to use this model as my preferred specification, the lack of statistical difference between the parameters in this flexible model and the parameters estimated in my preferred (constrained) model in the body of the paper lends strong support to the robustness of my preferred specification.

11.2 Tables

Table 6: Own-Price Elasticities and Substitutes with Cross-Price Elasticities

Model	Elasticity	Substitute 1	Substitute 2	Substitute 3	Substitute 4	Substitute 5
Bmw X5	-9.93	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Chevrolet Suburban	-9.85	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Mercedes-benz Gle	-9.53	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Ford Expedition	-9.50	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Chevrolet Tahoe	-9.43	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Mercedes-benz Sprinter	-9.34	Transit Van (1.09)	Promaster (0.5)	Express (0.44)	F Series (0.21)	Silverado (0.17)
Volvo Xc90	-9.23	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Gmc Sierra	-8.83	F Series (0.93)	Silverado (0.75)	Ram (0.66)	Tacoma (0.27)	Tundra (0.17)
Lexus Gx	-8.71	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Acura Mdx	-8.45	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Tesla Model Y	-8.24	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)	Hr-v (0.18)
Toyota Tundra	-7.90	F Series (0.93)	Silverado (0.75)	Ram (0.66)	Sierra (0.4)	Tacoma (0.27)
Lexus Rx	-7.77	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Volvo Xc60	-7.58	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Ford F Series	-7.56	Silverado (0.75)	Ram (0.66)	Sierra (0.4)	Tacoma (0.27)	Tundra (0.17)

Table 6: Own-Price Elasticities and Substitutes with Cross-Price Elasticities *(continued)*

Model	Elasticity	Substitute 1	Substitute 2	Substitute 3	Substitute 4	Substitute 5
Cadillac Xt5	-7.47	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Ram Ram	-7.45	F Series (0.93)	Silverado (0.75)	Sierra (0.4)	Tacoma (0.27)	Tundra (0.17)
Ford Bronco	-7.41	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Audi Q5	-7.23	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Jeep Gladiator	-7.16	F Series (0.93)	Silverado (0.75)	Ram (0.66)	Sierra (0.4)	Tacoma (0.27)
Buick Enclave	-7.14	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Jeep Wrangler	-7.10	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Tesla Model 3	-7.03	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)	Silverado (0.17)
Bmw X3	-6.97	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Mercedes-benz C-class	-6.94	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Hyundai Palisade	-6.93	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Chevrolet Silverado	-6.88	F Series (0.93)	Ram (0.66)	Sierra (0.4)	Tacoma (0.27)	Tundra (0.17)
Mercedes-benz Glc	-6.86	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Jeep Grand Cherokee	-6.86	Rav4 (0.23)	F Series (0.21)	Silverado (0.17)	Highlander (0.16)	Wrangler (0.16)
Lexus Nx	-6.82	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Lexus Es	-6.78	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Kia Telluride	-6.78	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Dodge Durango	-6.74	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)

Table 6: Own-Price Elasticities and Substitutes with Cross-Price Elasticities *(continued)*

Model	Elasticity	Substitute 1	Substitute 2	Substitute 3	Substitute 4	Substitute 5
Acura Rdx	-6.74	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Ram Promaster	-6.65	Transit Van (1.09)	Sprinter (0.76)	Express (0.44)	F Series (0.21)	Silverado (0.17)
Toyota 4 Runner	-6.63	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Ford Explorer	-6.39	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Nissan Pathfinder	-6.38	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Bmw 330	-6.34	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Toyota Highlander	-6.29	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Wrangler (0.16)
Gmc Acadia	-6.19	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Honda Pilot	-6.18	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Volkswagen Atlas	-6.14	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Subaru Ascent	-6.13	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Honda Passport	-6.11	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Mazda Cx-9	-6.01	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Honda Odyssey	-5.94	Pacifica (1.02)	Sienna (0.85)	F Series (0.21)	Silverado (0.17)	Ram (0.15)
Ford Transit Van	-5.84	Sprinter (0.76)	Promaster (0.5)	Express (0.44)	F Series (0.21)	Silverado (0.17)
Chevrolet Traverse	-5.81	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Chevrolet Blazer	-5.78	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Nissan Murano	-5.78	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)

Table 6: Own-Price Elasticities and Substitutes with Cross-Price Elasticities *(continued)*

Model	Elasticity	Substitute 1	Substitute 2	Substitute 3	Substitute 4	Substitute 5
Kia Sorento	-5.76	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Ford Edge	-5.62	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Toyota Sienna	-5.54	Pacifica (1.02)	Odyssey (0.57)	F Series (0.21)	Silverado (0.17)	Ram (0.15)
Chrysler Pacifica	-5.48	Sienna (0.85)	Odyssey (0.57)	F Series (0.21)	Silverado (0.17)	Ram (0.15)
Dodge Charger	-5.48	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Buick Envision	-5.46	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Chevrolet Express	-5.44	Transit Van (1.09)	Sprinter (0.76)	Promaster (0.5)	F Series (0.21)	Silverado (0.17)
Nissan Frontier /xe	-5.34	F Series (0.93)	Silverado (0.75)	Ram (0.66)	Sierra (0.4)	Tacoma (0.27)
Ford Ranger	-5.29	F Series (0.93)	Silverado (0.75)	Ram (0.66)	Sierra (0.4)	Tacoma (0.27)
Toyota Tacoma	-5.28	F Series (0.93)	Silverado (0.75)	Ram (0.66)	Sierra (0.4)	Tundra (0.17)
Jeep Cherokee	-5.26	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Hyundai Santa Fe	-5.22	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Subaru Outback	-5.18	Model Y (0.81)	Rogue (0.24)	F Series (0.21)	Crosstrek (0.2)	Hr-v (0.18)
Chevrolet Colorado	-4.99	F Series (0.93)	Silverado (0.75)	Ram (0.66)	Sierra (0.4)	Tacoma (0.27)
Ford Mustang	-4.96	Challenger (1.14)	F Series (0.21)	Silverado (0.17)	Ram (0.15)	Model Y (0.11)
Kia Sportage	-4.91	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Ford Bronco Sport	-4.90	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Honda Cr-v	-4.88	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)

Table 6: Own-Price Elasticities and Substitutes with Cross-Price Elasticities *(continued)*

Model	Elasticity	Substitute 1	Substitute 2	Substitute 3	Substitute 4	Substitute 5
Subaru Forester	-4.78	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Mitsubishi Outlander	-4.78	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Dodge Challenger	-4.73	Mustang (1.08)	F Series (0.21)	Silverado (0.17)	Ram (0.15)	Model Y (0.11)
Gmc Terrain	-4.73	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Hyundai Tucson	-4.71	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Toyota Rav4	-4.68	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)	Wrangler (0.16)
Jeep Compass	-4.66	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Volkswagen Tiguan	-4.66	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Nissan Rogue	-4.60	Model Y (0.81)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)	Hr-v (0.18)
Honda Accord	-4.55	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Silverado (0.17)
Mazda Cx-5	-4.50	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Kia K5	-4.45	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Hyundai Sonata	-4.42	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Ford Escape	-4.40	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Volkswagen Taos	-4.24	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Jeep Renegade	-4.22	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Chevrolet Equinox	-4.20	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Mazda Cx-30	-4.20	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)

Table 6: Own-Price Elasticities and Substitutes with Cross-Price Elasticities *(continued)*

Model	Elasticity	Substitute 1	Substitute 2	Substitute 3	Substitute 4	Substitute 5
Toyota Camry	-4.15	Model 3 (0.38)	F Series (0.21)	Corolla (0.2)	Accord (0.18)	Silverado (0.17)
Subaru Crosstrek	-4.09	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Hr-v (0.18)
Nissan Rogue Sport	-4.04	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Buick Encore Gx	-4.03	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Ford Maverick	-4.03	F Series (0.93)	Silverado (0.75)	Ram (0.66)	Sierra (0.4)	Tacoma (0.27)
Nissan Altima	-4.02	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Kia Seltos	-3.98	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Toyota C-hr	-3.90	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Chevrolet Trail Blazer	-3.90	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Honda Civic	-3.89	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Hyundai Kona	-3.89	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Mazda 3	-3.88	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Mitsubishi Outlander Sport	-3.82	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Honda Hr-v	-3.81	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Buick Encore	-3.78	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)
Chevrolet Malibu	-3.60	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Volkswagen Jetta	-3.59	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Dodge Journey	-3.55	Rav4 (0.23)	F Series (0.21)	Grand Cherokee (0.19)	Silverado (0.17)	Highlander (0.16)

Table 6: Own-Price Elasticities and Substitutes with Cross-Price Elasticities *(continued)*

Model	Elasticity	Substitute 1	Substitute 2	Substitute 3	Substitute 4	Substitute 5
Hyundai Elantra Sedan	-3.50	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Ford Ecosport	-3.49	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Nissan Kicks	-3.48	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Chevrolet Trax	-3.42	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Kia Forte	-3.42	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Subaru Impreza	-3.41	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Nissan Sentra	-3.38	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)
Toyota Corolla	-3.33	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Accord (0.18)	Silverado (0.17)
Kia Soul	-3.31	Model Y (0.81)	Rogue (0.24)	Outback (0.23)	F Series (0.21)	Crosstrek (0.2)
Nissan Versa	-2.95	Model 3 (0.38)	Camry (0.32)	F Series (0.21)	Corolla (0.2)	Accord (0.18)

Table 7: Full Supply-Side Results

		Pre-Merger			Post-Merger		
Model	MC	Price	Markup	PCM	Price	Markup	PCM
Nissan Versa	14520	22885	8365	0.37	23780	9259	0.39
Toyota Corolla	17573	27236	9663	0.35	27275	9703	0.36
Subaru Impreza	17655	26598	8943	0.34	26639	8984	0.34
Kia Forte	18380	27152	8772	0.32	27174	8793	0.32
Chevrolet Trax	18072	26686	8614	0.32	26697	8625	0.32
Kia Soul	17769	26142	8373	0.32	26154	8385	0.32
Nissan Kicks	18727	27433	8706	0.32	28187	9459	0.34
Dodge Journey	18767	27452	8685	0.32	27461	8693	0.32
Hyundai Elantra Sedan	18977	27749	8772	0.32	27770	8793	0.32
Nissan Sentra	18262	26627	8365	0.31	27521	9259	0.34
Ford Ecosport	18789	27274	8485	0.31	27284	8495	0.31
Buick Encore	20185	29267	9082	0.31	29279	9094	0.31
Chevrolet Malibu	19839	28557	8719	0.31	28571	8732	0.31
Chevrolet Trail Blazer	21277	30358	9082	0.30	30371	9094	0.30
Ford Maverick	22259	31642	9383	0.30	31651	9392	0.30
Mitsubishi Outlander Sport	20985	29691	8706	0.29	30444	9459	0.31
Toyota C-Hr	21509	30310	8801	0.29	30329	8819	0.29
Buick Encore Gx	22215	31296	9082	0.29	31309	9094	0.29
Hyundai Kona	21577	30264	8687	0.29	30274	8697	0.29
Volkswagen Jetta	20091	27993	7902	0.28	27996	7905	0.28
Kia Seltos	22241	30929	8687	0.28	30939	8697	0.28
Toyota Camry	24901	34563	9663	0.28	34603	9703	0.28
Honda Civic	22542	31149	8606	0.28	31802	9259	0.29
Nissan Rogue Sport	23013	31718	8706	0.27	32472	9459	0.29
Honda Hr-V	22429	30886	8457	0.27	31889	9459	0.30
Chevrolet Equinox	24216	33298	9082	0.27	33310	9094	0.27
Subaru Crosstrek	24228	33171	8943	0.27	33212	8984	0.27
Jeep Renegade	23995	32680	8685	0.27	32689	8693	0.27

Table 7: Full Supply-Side Results *(continued)*

		Pre-Merger			**Post-Merger**		
Model	MC	Price	Markup	PCM	Price	Markup	PCM
Mazda 3	22306	30181	7875	0.26	30184	7877	0.26
Nissan Altima	23760	32125	8365	0.26	33019	9259	0.28
Ford Escape	25736	34569	8833	0.26	34578	8842	0.26
Hyundai Sonata	25790	34562	8772	0.25	34584	8793	0.25
Kia K5	26155	34927	8772	0.25	34949	8793	0.25
Chevrolet Colorado	29500	39239	9739	0.25	39251	9751	0.25
Gmc Terrain	27809	36891	9082	0.25	36903	9094	0.25
Mazda Cx-30	24669	32638	7969	0.24	32641	7971	0.24
Volkswagen Taos	25025	33018	7992	0.24	33020	7995	0.24
Toyota Rav4	28790	37946	9157	0.24	37962	9172	0.24
Jeep Compass	27748	36432	8685	0.24	36441	8693	0.24
Honda Accord	27941	36547	8606	0.24	37200	9259	0.25
Hyundai Tucson	28466	37153	8687	0.23	37163	8697	0.23
Subaru Forester	29376	38319	8943	0.23	38360	8984	0.23
Nissan Rogue	28675	37381	8706	0.23	38135	9459	0.25
Ford Bronco Sport	29474	38307	8833	0.23	38317	8842	0.23
Ford Ranger	31934	41317	9383	0.23	41326	9392	0.23
Dodge Challenger	35069	45345	10276	0.23	45353	10283	0.23
Kia Sportage	29828	38515	8687	0.23	38525	8697	0.23
Mazda Cx-5	27466	35435	7969	0.22	35437	7971	0.22
Volkswagen Tiguan	28396	36389	7992	0.22	36391	7995	0.22
Ford Mustang	36435	46635	10200	0.22	46643	10208	0.22
Mitsubishi Outlander	29083	37174	8091	0.22	37834	8750	0.23
Honda Cr-V	30386	38770	8384	0.22	39136	8750	0.22
Buick Envision	33228	42310	9082	0.21	42322	9094	0.21
Subaru Outback	32855	41798	8943	0.21	41839	8984	0.21
Jeep Cherokee	32124	40809	8685	0.21	40818	8693	0.21
Hyundai Santa Fe	32195	40882	8687	0.21	40892	8697	0.21

Table 7: Full Supply-Side Results *(continued)*

		Pre-Merger			**Post-Merger**		
Model	MC	Price	Markup	PCM	Price	Markup	PCM
Toyota Tacoma	33764	42861	9097	0.21	42873	9110	0.21
Chevrolet Express	36205	45416	9211	0.20	45425	9220	0.20
Chevrolet Blazer	35970	45052	9082	0.20	45064	9094	0.20
Ford Edge	35018	43851	8833	0.20	43860	8842	0.20
Toyota Sienna	39468	49362	9894	0.20	49387	9919	0.20
Chevrolet Traverse	36363	45444	9082	0.20	45457	9094	0.20
Dodge Charger	34750	43188	8438	0.20	43197	8447	0.20
Chrysler Pacifica	40430	50236	9805	0.20	50257	9827	0.20
Nissan Frontier /Xe	33830	41942	8112	0.19	42339	8509	0.20
Kia Sorento	36294	44981	8687	0.19	44991	8697	0.19
Gmc Acadia	39010	48092	9082	0.19	48104	9094	0.19
Ford Transit Van	43570	53488	9918	0.19	53496	9926	0.19
Toyota Highlander	40689	49845	9157	0.18	49861	9172	0.18
Lexus Es	43333	52996	9663	0.18	53036	9703	0.18
Nissan Murano	36710	44801	8091	0.18	45460	8750	0.19
Honda Passport	39045	47429	8384	0.18	47795	8750	0.18
Toyota 4 Runner	42769	51926	9157	0.18	51941	9172	0.18
Honda Odyssey	41477	50355	8879	0.18	50652	9175	0.18
Ford Explorer	41729	50562	8833	0.17	50572	8842	0.17
Honda Pilot	39948	48332	8384	0.17	48698	8750	0.18
Mazda Cx-9	38708	46677	7969	0.17	46679	7971	0.17
Volkswagen Atlas	39790	47782	7992	0.17	47785	7995	0.17
Subaru Ascent	39706	47649	7943	0.17	47653	7947	0.17
Dodge Durango	43769	52453	8685	0.17	52462	8693	0.17
Chevrolet Silverado	49222	58961	9739	0.17	58973	9751	0.17
Buick Enclave	46292	55373	9082	0.16	55386	9094	0.16
Kia Telluride	44320	53007	8687	0.16	53017	8697	0.16
Lexus Nx	44957	53758	8801	0.16	53776	8819	0.16

Table 7: Full Supply-Side Results *(continued)*

		Pre-Merger			**Post-Merger**		
Model	MC	Price	Markup	PCM	Price	Markup	PCM
Nissan Pathfinder	41517	49608	8091	0.16	50268	8750	0.17
Ram Promaster	46408	55334	8926	0.16	55341	8933	0.16
Hyundai Palisade	45367	54055	8687	0.16	54065	8697	0.16
Acura Rdx	43856	52239	8384	0.16	52606	8750	0.17
Jeep Gladiator	47275	56264	8989	0.16	56272	8997	0.16
Jeep Grand Cherokee	45746	54431	8685	0.16	54440	8693	0.16
Bmw 330	41517	49359	7842	0.16	49361	7844	0.16
Cadillac Xt5	48860	57942	9082	0.16	57955	9094	0.16
Jeep Wrangler	47416	56100	8685	0.15	56109	8693	0.15
Ford Bronco	49315	58147	8833	0.15	58157	8842	0.15
Lexus Rx	51644	60801	9157	0.15	60816	9172	0.15
Mercedes-Benz Glc	45603	53482	7880	0.15	53484	7881	0.15
Toyota Tundra	53240	62336	9097	0.15	62349	9110	0.15
Mercedes-Benz C-Class	46233	54090	7857	0.15	54092	7859	0.15
Bmw X3	46478	54366	7888	0.15	54368	7889	0.15
Tesla Model 3	48983	57239	8256	0.14	57252	8269	0.14
Ram Ram	53727	62716	8989	0.14	62724	8997	0.14
Ford F Series	56221	65603	9383	0.14	65613	9392	0.14
Audi Q5	48296	56288	7992	0.14	56291	7995	0.14
Gmc Sierra	61588	71327	9739	0.14	71339	9751	0.14
Lexus Gx	58402	67559	9157	0.14	67574	9172	0.14
Volvo Xc60	51055	58851	7795	0.13	58851	7796	0.13
Acura Mdx	57301	65684	8384	0.13	66051	8750	0.13
Chevrolet Tahoe	64694	73776	9082	0.12	73788	9094	0.12
Tesla Model Y	61309	69896	8587	0.12	69925	8615	0.12
Ford Expedition	65118	73951	8833	0.12	73961	8842	0.12
Chevrolet Suburban	67471	76553	9082	0.12	76565	9094	0.12
Volvo Xc90	63804	71599	7795	0.11	71599	7796	0.11

Table 7: Full Supply-Side Results *(continued)*

		Pre-Merger			**Post-Merger**		
Model	MC	Price	Markup	PCM	Price	Markup	PCM
Mercedes-Benz Sprinter	69631	78058	8427	0.11	78060	8429	0.11
Mercedes-Benz Gle	66299	74179	7880	0.11	74180	7881	0.11
Bmw X5	69645	77533	7888	0.10	77534	7889	0.10

12 References

Berry, Steven T. "Estimating Discrete-Choice Models of Product Differentiation." The RAND Journal of Economics 25, no. 2 (1994): 242. https://doi.org/10.2307/2555829.

Berry, Steven, James Levinsohn, and Ariel Pakes. "Automobile Prices in Market Equilibrium." Econometrica 63, no. 4 (July 1995): 841. https://doi.org/10.2307/2171802.

Björnerstedt, Jonas, and Frank Verboven. "Merger Simulation with Nested Logit Demand - Implementation Using Stata." RePEc: Research Papers in Economics, April 15, 2013.

Cardell, N. Scott. "Variance Components Structures for the Extreme Value and Logistic Distributions." Mimeo, Washington State University, 1991.

Dube, Jean-Pierre H. "Product Differentiation and Mergers in the Carbonated Soft Drink Industry." Journal of Economics and Management Strategy 14, no. 4 (December 2005). https://doi.org/10.2139/ssrn.432940.

Fan, Ying. "Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market." American Economic Review 103, no. 5 (August 1, 2013): 1598–1628. https://doi.org/10.1257/aer.103.5.1598.

Goldberg, Pinelopi Koujianou. "Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry." Econometrica 63, no. 4 (1995): 891–951. https://doi.org/10.2307/2171803.

Grieco, Paul, Charles Murry, and Ali Yurukoglu. "The Evolution of Market Power in the U.S. Automobile Industry." The Quarterly Journal of Economics, Volume 139, Issue 2, May 2024, Pages 1201–1253, https://doi.org/10.1093/qje/qjad047.

Kantaro Komiya. “Honda, Nissan Aim to Merge by 2026 in Historic Pivot.” Reuters, December 23, 2024. https://www.reuters.com/markets/deals/honda-nissan-set-announce-launch-integration-talks-media-reports-say-2024-12-22/.

McFadden, Daniel. ”Modeling the Choice of Residential Location.” In A. Karlgvist, et al., eds., Spatial Interaction Theory and Planning Models. Amsterdam: North-Holland, 1978.

Miller, Nathan H., and Matthew C. Weinberg. “Understanding the Price Effects of the MillerCoors Joint Venture.” Econometrica 85, no. 6 (2017): 1763–91. https://doi.org/10.3982/ecta13333.

Nevo, Aviv. “Measuring Market Power in the Ready-To-Eat Cereal Industry.” Econometrica 69, no. 2 (March 2001): 307–42. https://doi.org/10.1111/1468-0262.00194.

———. “Mergers with Differentiated Products: The Case of the Ready-To-Eat Cereal Industry.” The RAND Journal of Economics 31, no. 3 (2000): 395. https://doi.org/10.2307/2600994.

Peters, Craig. “Evaluating the Performance of Merger Simulation: Evidence from the U.S. Airline Industry.” The Journal of Law and Economics 49, no. 2 (October 2006): 627–49. https://doi.org/10.1086/505369.

U.S. Department of Justice and the Federal Trade Commission. “Merger Guidelines,” December 18, 2023. https://www.ftc.gov/system/files/ftc_gov/pdf/2023_merger_guidelines_final_12.18.2023.pdf.

Werden, Gregory J and Froeb, Luke M, 1994. ”The Effects of Mergers in Differentiated Products Industries: Logit Demand and Merger Policy,” The Journal of Law, Economics, and Organization, Oxford University Press, vol. 10(2), pages 407-426, October.