Downstream Competition and Exclusive Dealing

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Abstract

This paper investigates empirically the role of downstream competition in the adoption of exclusive dealing and quantifies its effects in the car retail networks. I present a unifying model of supply and demand that includes the potential positive demand effects and the potentially exclusionary effects of exclusive dealing. I estimate a model of spatial demand and I analyze the incentives for dealerships to single-brand their establishments estimating cost differences between exclusive and non-exclusive stores.

Keywords: Exclusive Dealing, Retail Networks, Automotive industry, Geographic Competition, Downstream Competition

JEL Codes: L42, L62, L81

1 Introduction

Exclusive dealing contracts have a longstanding debate in competition policy because of their potential foreclosing effects. This controversy had its start in the literature with Posner (1976) and Bork (1978), whose work concluded that exclusive contracts could not deter entry from a more efficient competitor. A vast and rich theoretical literature developed trying to refute this view, leading to the general perception that contracts of this kind might have exclusionary effects, but their existence can be beneficial, aligning incentives along the supply chain. The question of whether exclusive contracts are welfare improving or welfare detrimental is, ultimately, an empirical one. In this paper, I focus on

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†Please contact me for an updated version of this work if you are willing to make comments on it or discuss it.

the role of retailers and their competition that may obstruct access of smaller manufacturers to points of sale in the presence of exclusive contracts.

I estimate a structural model of demand and supply of the car retail market in order to quantify the different effects of exclusive dealing and perform a welfare analysis. This model extends the literature allowing for retailers to endogenously determine their brands, and I use this feature to uncover fixed costs. I compare the estimated costs of exclusive and non-exclusive dealerships to determine the costs of such arrangements following a similar principle to that of Asker (2016). These costs arise when it is more costly to open a point of sale selling more than one brand than selling each of these brands separately.

The setup draws from the literature and presents a unifying approach to measuring the benefits and costs of exclusive contracts. The demand framework has similar characteristics to the one in Nurski and Verboven (2016), where dealers differentiate from each other spatially and exclusive contracts enter demand as a product characteristic. This demand shifter represents some kind of taste for exclusivity, due to premium service or additional promotional efforts.

On the supply side, I model retailers to endogenously choose their brand offerings in a simultaneous game setup. On the one hand, retailers want to differentiate from each other by offering different products to those of dealers geographically close. On the other hand, they want to sell popular products. Moreover, exclusive dealing appeals to downstream competitors because of its lower fixed costs.

In environments with no intense competition, exclusive dealing mostly limits the products offered and narrows demand for the retailer. Nevertheless, in the presence of fierce competition, single branding permits differentiation across dealers, facilitates their supply and makes them more competitive. This interaction between spatial and product differentiation downstream is also internalized by manufacturers, who set product prices in accordance to their distribution networks. Exclusive dealing eliminates competition among products of different brands within a retailer.

I assemble a novel dataset from a variety of sources so as to carry out my estimation. I use data from a Spanish official car registry spanning the whole country that allows me to observe purchases at the local market level. I complement them with self-collected data on retailers' locations and brands. This data required arduous and careful inspection to distinguish and classify multi-dealerships and exclusive dealers since many appear to be disguised under separate showrooms and names.

I estimate fixed costs using set identification methods (Pakes et al., 2015). I exploit the multiple equilibria of the brand choice game to estimate bounds on the parameters that do not suffer from selection on unobserved disturbances. The estimation using the model and the data allows me to illustrate the interplay between downstream competition, exclusive dealing and brand presence in the market in the counterfactual section. In a first experiment, all potential benefits from exclusive dealing are shut down and retailer structure is simulated again. A second counterfactual keeps the benefits for single branding, but simulates equilibrium in the dealer network relaxing downstream competition.

In summary, my contribution is threefold. First, I estimate a model that combines supply and demand to quantify the effects of exclusive dealing from an ample perspective. Second, retail brands are determined within the model, making it the first empirical framework to include such a feature. Finally, I introduce another strategy to deal with the selection problem that arises when using data realized from equilibrium play.

The paper proceeds as follows. In the next section I give an overview of the literature. Section 2 describes the data. The model is presented in section 3. Sections 4 and 5 describe estimation and results respectively. Section 6 performs counterfactuals and section 7 concludes.

1.1 Related Literature

This paper relates in its thematic to the literature that studies exclusive dealing and its potential exclusionary effects. The theoretical side of this literature has been very extensively developed, e.g., Bork (1978), Posner (1976), Aghion and Bolton (1987), Rasmussen et al. (1991), Segal and Whinston (1996), Bernheim and Whinston (1998). [1] Fumagalli and Motta (2006), and Simpson and Wickelgreen (2007) introduce the role of competition among firms in the downstream market as a force affecting the incentives to sign exclusive contracts and their potential for exclusion. Besanko and Perry (1994) explore the role of spatial differentiation across retailers.

There is also a recently expanding yet smaller literature on the empirics of exclusive dealing to which I relate more closely. Ater (2015) finds that exclusive contracts between fast-food restaurants and shopping malls impact competition negatively by lowering the number of restaurant, increasing prices and limiting total sales. Eizenberg et al. (2017) focus on the dynamic effects that the exclusive contracts between Intel and PC makers had on the development of its competitor AMD. Chen (2014) analyzes the entry of specialty beers and detects no foreclosing motives behind exclusive contracts by incumbent breweries.

Two papers from this literature are more closely related to my work. Asker (2016) develops a foreclosure test for the beer market in Chicago. He uses demand estimates and prices to infer distribution costs for brewers. He compares these costs between areas were Miller and Anheuser-Busch use exclusive contracts and areas where they do not and finds no statistical evidence of foreclosure. I employ an approach that share similarities with Asker (2016) because I use demand estimates to infer costs downstream and compare them between exclusive and non-exclusive dealers. Nevertheless, I focus on differences in fixed costs while he does on variable costs.

The industry and demand modeling link my paper to Nurski and Verboven (2016). They estimate a model of spatial demand and perform counterfactuals that assess the collective incentives for incumbent manufacturers to maintain these agreements. The two papers can be seen as complementary. While Nurski

[1] Sass (2005) provides a comprehensive overview of the main mechanisms used in the literature to rationalize the use of exclusive dealing.

and Verboven (2016) make an extensive analysis of demand and focus on manufacturers' incentives, I model explicitly the distribution network and estimate the fixed costs of these retailers. My model contains the channels for exclusive dealing of Nurski and Verboven (2016), where it shifted utility and it lowered product availability for rival brands. Nevertheless, it also incorporates supply side motives for exclusive dealing, where retailers might deal with only one brand because it is cheaper for them to do so. There exists no paper exploring jointly supply and demand side mechanisms for exclusive dealing.

This article is also related to the stream of literature that models product offerings or characteristics as endogenous. Examples include Fan (2013) in the newspaper market, Draganska et al. (2009) on the variety of vanilla ice cream, or Eizenberg (2014) in the PC market. My modeling of the supply side resembles the entry nature of many of these papers, but the fact that the endogenous choice are brands is a novelty on its own. Dealerships decide with their brand offerings what bundles of goods to offer and determine with them endogenously product availability in the market.

The estimation of fixed costs follow the literature that use moment inequalities to overcome the problem of multiple equilibria (Ciliberto and Tamer, 2009; Pakes, 2010; Pakes et al., 2015). This approach has been used recently in a number of empirical applications in industrial organization and trade (e.g. Holmes, 2011; Morales, Sheu, and Zahler, 2015; Wollmann, 2018). One main difference across these papers is how they deal with the potential selection issues induced by structural disturbances in the fixed costs. I contribute to these papers by introducing a new way to circumvent this issue

2 Data

My dataset spans the entire Spanish market from July 2016 until August 2017 and it was constructed from multiple sources. First, I supplemented car registry data with additional characterisics of cars that I collected from specialized magazines. Second, I collected data on car dealerships locations online. Third, I use information on population demographics and locations from Governmental Offices. I discuss each of these data in turn.

2.1 Car sales and characteristics data

I obtained data on car sales from the Spanish Directorate-General of Traffic (DGT)[2]. These data consist of daily information on all cars registered in the Spanish territory from December 2014. The data include a written description of the car model and its Vehicle Identification Number (VIN). They comprise a number of car characteristics such as engine displacement, horsepower, type of bodywork, number of seats or energetic propulsion. Unfortunately, the data do

[2] The data can be observed at `https://sedeapl.dgt.gob.es/WEB_IEST_CONSULTA/microdatos.faces`, and its documentation (in Spanish) at `https://sedeapl.dgt.gob.es/IEST_INTER/pdfs/disenoRegistro/vehiculos/matriculaciones/MATRICULACIONES_MATRABA.pdf`

not contain any owner information other than the postal code and municipality where the car was registered.

Since the registry is of general purpose, I removed registries that were not of enrollment of new cars, or whose registry was not for private use. I kept observations corresponding to new cars, 4x4s or small pickups used for non-commercial purposes. In total, in the period between July 2016 and August 2017, there are 1,091,932 entries from 7,712 different municipalities located. I chose this time window because it approximately coincides with the period in which I was able to collect the data on dealerships.

Table 1 shows market shares for car makes and models. It is notable that no make has a market share to the critical 30% that the General Vertical Block Exemption considers to be worrisome for legal vertical agreements[3]. In particular, no car make appears to dominate the market: no one market share being is 10% and the market leaders change across time periods and geographic regions[4]. I collected data on car characteristics from a series of specialized magazines; primarily autobild.es and autopista.es. These characteristics include list prices, measures of fuel consumption, car dimensions and weight. The data are detailed at the model (e.g. Ford Fiesta), version (e.g. Ford Fiesta 3P), and trim (e.g. Ford Fiesta 3P 2008 1.25 Duratec 82CV Trend) level.

Table 1: Market shares of best selling car makes and models

Make	Share	Sales	Model	Share	Sales
Peugeot	8.44%	70,805	Leon	2.51%	21,066
Renault	7.68%	64,416	Qashqai	2.44%	20,464
Volkswagen	7.22%	60,578	Sandero	2.22%	18,652
Seat	6.53%	54,790	Golf	2.19%	18,351
Ford	6.27%	52,570	Ibiza	2.16%	18,164
Opel	5.99%	50,266	Clio	2.01%	16,894
Citroen	5.90%	49,535	308	1.86%	15,594
Toyota	5.43%	45,577	Megane	1.82%	15,257
Nissan	5.15%	43,192	Corsa	1.79%	15,042
Kia	4.75%	39,817	Tucson	1.74%	14,613
Total	100%	839,086	Total	100%	839,086

I constructed baseline specifications for each model by merging the two datasets. First, I classified the models from the registry's string descriptions using automatized text analysis. Subsequently, I used information on bodywork type, measures, number of doors and horsepower to determine the car's version. Finally, I matched each registry entry to the car trim with the closest identifying characteristics. I define a baseline model specification as the mean of all merged trims. This linkage approach preserves a bigger part of price variation in the data and controls for the fact that, especially in higher-end cars, within-model

[3]OJ L 102, 23.4.2010, p. 1–7

[4]See Figure 5, where I present market leaders by year and administrative region for the years previous to the sample.

price dispersion plays a sizable role.

I excluded car models absent at more than 30 provinces[5] and car segments with a bigger part of close substitutes outside of the choice set (e.g. big vans, luxury sports cars). I aggregated the data at the province level in order to preserve the geographic disaggregation without incurring in "too small markets". I dropped provinces outside the Iberian peninsula (i.e. Canary Islands, Balearic Islands, Ceuta and Melilla), and Euskadi and Navarra since there are no available data on income.

Table 2 shows some descriptive statistics for different car characteristics after matching them with the registry data. The data comprise 43 provinces and 234 car models and they have significant variation on their characteristics. The average price is around 34,300 EUR, and the average horsepower around 144 CV, but they both have a great dispersion.

Table 2: Descriptive statistics of car characteristics

	Mean	Std. Dev	Min	Max	Obs
Model					
Horsepower	144.34	60.23	60	422	234
Weight (100 Kg.)	14.55	3.35	8.05	24.65	234
Size (m^2)	8.03	1.06	4.48	10.36	234
Fuel Cons. (l/km)	5.08	1.19	3.3	10.61	234
Price (10,000 EUR)	3.43	2.16	1.02	14.86	234
Markets					
Municipalities					6608
Provinces					43

2.2 Dealer data

I next require data on locations of dealerships as well as which brands are for sale at each dealership. This last part is particularly crucial as it drives the classification of a dealership as exclusive. Unfortunately, no registry existed for Spain with these characteristics so I collected them manually. I proceeded on the collection of data in two steps. First, I gathered the data on locations from the online applications that each manufacturer has available at their websites. These applications are normally used for manufacturers to inform about its available points of sale. Second, I manually matched the observations that were points of sale for more than one manufacturer.

I defined two observations from different makes to be a same dealership if they are observed to be contiguous and proven to be sharing ownership. This definition is based on the observed patterns for multi-dealers, where normally different car makes have separated showrooms and different names even if they are operated by the same owner. In an attempt to adapt the definition to the

[5]Spain is divided into 23 Autonomous Communities that are subdivided into 52 provinces

edification of urban and rural areas, I also consider observations separated by a street intersection as contiguous, but not by another building or dealership.

Using this definition, the data show 44.35% of dealerships offer more than one brand, which is a 66.21% of the total points of sale. There are some brands that have their dealership networks integrated with each other, i.e. Citroen and DS, or Renault and Dacia share all their points of sale. Figures change substantially if brands with integrated networks are excluded. In this case, the percentage of multi-dealers lowers to 21.57% (41.40% of points of sale)

Figure 1: Graph representation of shared dealership networks

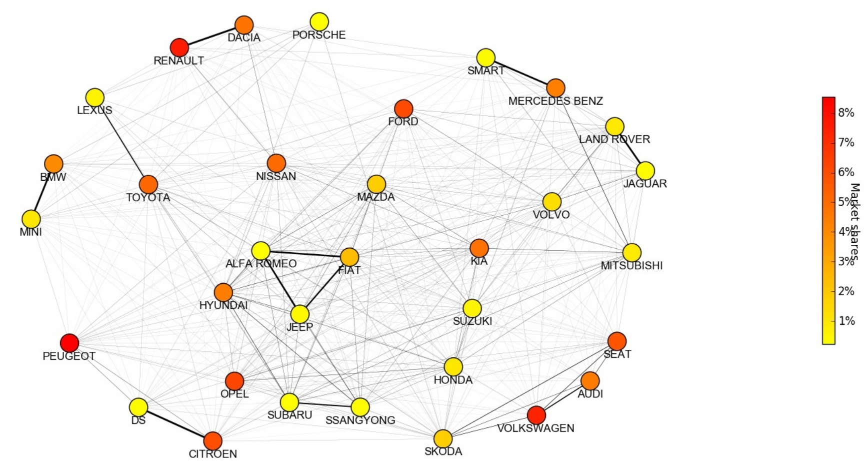
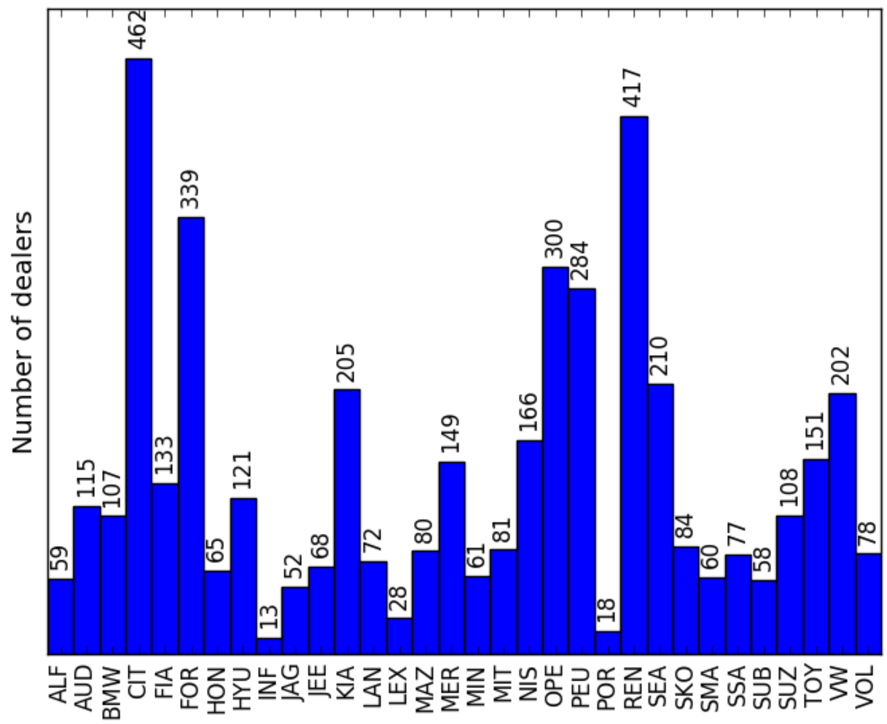


Figure 1 summarizes general patterns in distribution networks. Nodes colors represent the market share of the manufacturer in the market, whereas the thickness of node links are the percentage of shared dealerships between the two auto makes. This percentage is measured as the total number of shared dealerships over the number of dealerships for the smallest of the two brands. Particularly bold links between nodes of the same holding (e.g. VW Group, PSA, FCA) point to common dealerships being substantially more likely between makes belonging to the same company. Extreme cases are Renault/Dacia and Citroen/DS where distribution is observed to be completely integrated.

The second observable pattern is the higher *degree*, in the sense of more shared dealerships, of some brands with relatively low market shares. This phenomenon is more patent observing the Asian car makes (Honda, Mazda, Hyundai, Subaru), most of which do not belong to any particular holding group and share more dealerships and with more different brands than market leaders like Volkswagen or Renault.

Figure 2 shows the number of dealerships per brand. There are clear differences in terms of dealer density across car makes and reasons to think that these differences are not solely driven by demand concerns. For example, Re-

Figure 2: Number of dealerships per brand



nault/Dacia have as many as 417 dealers in the whole territory whereas Volkswagen has 202 and their differences in sales are of 0.46 percentual points. Differences in dealer density are more pronounced in scarcely populated areas, where Renault/Dacia, Citroen/DS, and Peugeot are spread, whereas the rest of manufacturers are only present in the few urban nuclei.

2.3 Geographic locations

One important consideration is how far consumers travel to purchase their cars. These data are not available, so in order to incorporate this I downloaded data on geographic positions at the municipality level from the National Geographic Institute (IGN). This dataset provides geocoordinates of the boundaries of each city and provides a large number of random geographic positions within those boundaries. For each province, I drew 2000 random locations for each province. These draws were weighted by population size of each municipality. More details on these simulations can be found in Section 4.

3 Model

I present the main framework of the paper in this section. The model consists of two stages. In the first stage, dealerships draw costs and decide what brands to offer taking into strategic consideration their local competitors. Prices are determined and consumers purchase their cars in the second stage.

The primitives of the model are the utility parameters for cars, the marginal costs for each model and fixed costs of establishing a dealership. In what follows, I introduce the model thoroughly in an inverse order from the timing of events.

3.1 Demand

I model demand with a random-coefficient-logit specification (Berry, Levinsohn, and Pakes, 1995). Individual i chooses what car $j \in J$ to buy. The indirect utility from buying product j at dealership d is given by

$$u_{ijd} = \begin{cases} x_{jm}\beta + \alpha_i p_j + \gamma_1 ED_d + \gamma_2 \text{dist}(i,d) + \xi_{jm} + \epsilon_{ijd}, & \text{if } j \neq 0, \\ \epsilon_{i0}, & \text{if } j = 0, \end{cases}$$

where p_j are car prices and x_j are different car characteristics as fuel consumption, size, or engine power. ξ_{jt} represents other car attributes that are relevant for the consumer, but unobserved by the econometrician. Finally, ϵ_{ijd} are consumer idiosyncratic disturbances that are assumed to be distributed according to a type I extreme value distribution. I allow the parameters α_i and β_i to vary across individuals. Following Nevo (2001), I parametrize this variation as $(\alpha_i, \beta_i)' = (\alpha, \beta)' + \Pi D_i + \Sigma v_i$, where the entries in matrices D_i and v_i represent simulated individuals. D_i are demographic characteristics, and v_i are unobserved individual components. α, β, Γ, Σ and Π are parameters to estimate.

The utility specification distinguishes between three parts. $\delta_{jm} = x_{jm}\beta + \alpha p_j + \xi_{jm}$ comprises observable and unobservable product characteristics together with prices, and $\mu_{ij} = (p_j, x_{jm})(\Pi D_i + \Sigma v_i)$ represents additive unobservable heterogeneity in taste. $\gamma_{id} = \gamma_1 ED_d + \gamma_2 \text{dist}(i,d)$ is the part of utility that the individual derives from the point of sale.

I follow Nurski and Verboven (2016) condensing these dealership characteristics into two attributes: distance to the dealer (dist_{id}) and a dummy variable that captures any effects in demand attributable to exclusive dealing (ED_d). Geographical distance to dealerships is also included in other work like Albuquerque and Bronnenberg (2012) and provides to the model a spatial dimension. It is expected to come out of negative sign as a result of the estimation. The magnitude of its parameter determines in turn the relevant market for a dealership and the intensity of its competition. If consumers are averse to driving for buying a car, dealership compete with each other locally, and more locally the higher this aversion is. The exclusive dealing dummy is suppose to capture any possible demand effects that an exclusive retailing can induce, e.g. being more prestigious, delivering a better service or enjoying additional promotional efforts

While I observe sales at very local areas, the exact point of sale where transactions take place and consumers' residences are unknown to me. To tackle this issue, I simulate distances by drawing locations in each market and computing the distance to the closest dealer for each product in their choice set. Locations are drawn from a population-weighted distribution for the different municipalities constituting a market. Consumers are assumed to be uniformly distributed within each municipality. While arbitrary, this distributional assumption within municipalities does not seem to be restrictive given that they are numerous and of small size.

Reducing the dealerships in the choice set to the closest simplifies computation, but imposes restrictions. First, it eliminates any dealership competition within car makes. The coordination of competition within a distribution network is the main focus of a number of theoretical papers (Lin, 1990; O'Brien and Shaffer, 1993) and it is a rationale for exclusive dealing akin to that of exclusive territories (Rey and Stiglitz, 1988, 1995). I believe this restriction is less relevant in the context of this paper, since the focus is on downstream incentives to engage in exclusive contracts.

Moreover, this assumption imposes a way how dealerships distribute their demand within a brand. I account for this issue using a large number of simulations. In this manner, an area that has many dealers will have different closest dealers, whereas areas with fewer dealers will have the same closest dealers in every simulation.

I use the simulations, the extreme value distribution error term, and the additional assumptions to aggregate from individual utilities to observable market shares of the form

$$s_{jm} = \int_{i\in m} \sum_{d\in D} s_{ijdm} = \int_{i\in m} \frac{\exp\{\delta_j + \mu_{ij} + \gamma_{id}\}}{1 + \sum_{(j',d')\in J_i} \exp\{\delta_{j'} + \mu_{ij'} + \gamma_{id'}\}},$$

3.2 Price Competition

This part of the model follows the empirical literature that uses market data to infer marginal costs and wholesale prices upstream, (e.g. Sudhir, 2001; Berto Villas-Boas, 2007). I assume that manufacturers set wholesale prices in order to maximize their profits and set list prices where retailers can extract a margin that is consistent with profit maximization. Since the list prices are one for each product, manufacturers maximize the profits of the whole network of retailers so that, on average, these are incentive compatible.

In particular, given that each dealership d has a profit function of the form

$$\pi_d = \sum_{m\in M} \sum_{j\in J_d} [p_j - p_j^w] q_{jdm}(\theta, p, a) - F_d(a_d),$$

where $q_{jdm} = MS_m s_{jdm}$ are the quantities of product j sold by dealer d in market m predicted by the demand model, and MS_m is the market size of market

m. These quantities are recovered integrating individual choice probabilities s_{ijdm}. q_{jdm} is a function of the demand parameters θ, but also of prices and the availability of products through retailers, which is endogenously determined in the model. p_j and p_j^w represent list and wholesale prices for product j, respectively. $F_d(a_d)$ are the fixed costs of the dealership, more detail on this will follow in subsections 3.3 and 4.

The profit function above produces first-order conditions

$$q_{jd} + \sum_{j' \in J_d} [p_j - p_j^w] \frac{\partial q_{jdm}(\theta, p, a)}{\partial p_j} \text{ for all } j \in J_d.$$

These first order conditions are used by manufacturers $b \in B$ to set their list prices so as to maximize the profits of its joint network.

$$\sum_{d \in E} \mathbb{I}\{b \in a_d\} \cdot \left(q_{jd} + \sum_{j' \in J_d} [p_j - p_j^w] \frac{\partial q_{jdm}(\theta, p, a)}{\partial p_j} \right) = 0 \text{ for all } j \in b \quad (1)$$

Such an assumption is mostly driven by data limitations, but it is sensible and it captures a series of interesting mechanisms. First, notice that, were all retailers allowed to set their prices independently, equation 1 would still be fulfilled and p_j would still be the average retail price for product j. Second, the derivatives at the dealer level in the first order conditions allow these list prices internalize the role of product competition within and across dealers given the geographic and brand structure of retailer networks. Finally, manufacturers profit maximization given list prices allows to back out for marginal costs of producing every model j

$$\max_{\{p^w\}_{jinb}} \Pi_f(p, p^w) = \sum_{b \in f} \sum_{j \in b} (p_j^w - c_j) q_j$$

3.3 Entry

A potential entrant $d \in E$ in a location l_d chooses what brands to deal (a_d) from the set $A_d \subset \mathcal{P}(B)$. It can choose to deal for one brand, e.g. $a_d = \{\text{Peugeot}\}$, for many brands, e.g. $a_d = \{\text{Peugeot, Suzuki, Subaru}\}$, or for no brand, i.e. $a_d = \emptyset$, in which case it means that the potential entrant decides to stay out. The set of entrants is $D \subseteq E$. Dealerships take these decisions in order to maximize their expected profits given the choices of competing rivals. This formulation is equivalent to,

$$\max_{a_d \in A_d} \mathcal{E}[\pi_d(a_d, a_{-d}) | \mathcal{I}_d] = \underbrace{\mathcal{E}\left[\sum_{m \in M} \sum_{j \in J_d} q_{jdm}(\theta, a)(p_j - c_j) \middle| \mathcal{I}_d \right]}_{EVP_d(a)} - F_d(a_d).$$

where $F_d(a_d)$ are the fixed costs of establishing a dealer of type a_d. These costs are a function of the brands in a_d, and whether the dealer is exclusive or not. They also include structural disturbances ν_d^b and ν_d^l which represent unobserved idiosyncratic cost components that dealer d observes and faces, but that I cannot see. I assume these costs to have $\mathbb{E}[\nu_{b,d}] = \mathbb{E}[\nu_{l,d}] = 0$. The term $EVP_d(a)$ are the expected variable profits the dealer has given its information set $\mathcal{I}_d$. Following Pakes (2010) and Pakes, Porter, Ho, and Ishii (2015), I denote the dealer's expectation $\mathcal{E}$ as opposed to the expectation of the sample moments $\mathbb{E}$.

This profit function condenses the main features of downstream competition in the model. Exclusive dealing enters both variable profits through market shares and fixed costs. Market shares bring strategic interactions between geographically close competitors. Multi-dealerships are more profitable in markets with higher isolation between points of sale as it allows the dealer to offer a larger selection of products and occupy a larger part of demand. In markets with dense dealership structure, exclusive dealing is favorable in a twofold manner: it reduces costs, allowing competitors to stay in the market even with smaller sales, and it differentiates dealerships from each other by offering different sets of products, relaxing competition (Besanko and Perry, 1994).

4 Estimation

I estimate the model in three steps. First, I estimate the demand parameters $\theta_1 = (\alpha, \beta)$ and $\theta_2 = (\Pi, \Sigma, \Gamma)$. Using the estimates to these parameters, I back out product unobservable characteristics $\hat{\xi}_{jt}(\hat{\theta}) = \delta(\hat{\theta}_2) - X_{jt}\beta + \alpha p_{jt}$ and manufacturers' wholesale prices. Finally, I use all estimated parameter together with equilibrium condition to estimate bounds on fixed costs.

4.1 Estimation of demand parameters $\theta = (\theta_1, \theta_2)$

I estimate the demand model following the methods proposed in Berry (1994) and Berry, Levinsohn, and Pakes (1995). These estimation methods are based on equating predicted and observed market shares for every product and market, so as to then back out the value of average utility δ and minimize the difference $\xi(\theta) = \delta(\theta_2) - X\beta - \alpha p$. The model is estimated by General Method of Moments (GMM) and it uses the moment condition $\mathbb{E}[Z'\xi(\theta)] = 0$, where Z is a matrix of instruments, and ξ is the vector of unobserved product characteristics. The estimates $\hat{\theta}$ are given by

$$\hat{\theta} = \arg\min_{\theta} \xi(\theta)' Z W^{-1} Z' \xi(\theta),$$

where W is an estimate of $\mathbb{E}(Z'\xi\xi'Z)$.

In addition to the instruments proposed by Berry et al. (1995), I incorporate as instruments neighboring demographics and rival dealer characteristics in a similar fashion as Fan (2013). These instruments make use of the geographic nature of dealer competition and modeling and can be better understood with an example.

For dealership A, income in some neighboring area might not affect it directly because it does not receive any demand from it. It can, though, affect directly the demand of some rival retailer B that is closer to that area. In this manner, since endogenous variables for rival dealer B are affected by the income of this area, then it also affects through competition, the ones of dealership A. Similarly, since dealerships are locally competing, the distance to rival points of sale determines to a great extent whether a given location is considered to be far by consumers or not.

Moreover, I assume models available at more than 80 kilometers of distance are not in the choice set of consumers. Put it differently, the consideration set is the set of all car models at their closest point of sale from the simulated location if its distance is below 80 km.

Two aspects can be noted from this assumption. First, the approach is computationally intensive[6] as it needs to draw locations and calculate distances, but it controls very flexibly for consumer locations not being directly observed.

Besides, the assumption on the maximum distance for the choice set of consumers provides additional variation for the identification of non-linear parameters. Two simulations for a same market can have a different consideration set depending on their distance to the closest dealers. This assumption seems to be sensible in the light of the very few cars that are bought from brands that are located far away.[7] Furthermore, robustness checks show that the chosen threshold does not play an important role.

Finally, it is importance to notice that, as in most of the literature on endogenous product characteristics, estimating demand on observed dealership might suffer from selection. In this case, the timing of the model alleviates these concerns. When choosing which brands to deal, retailers are assumed not to know the realizations of unobserved product characteristics (ξ) and can only condition their choices on variables that are also observable to the econometrician. This argument is used in Eizenberg (2014), where it is also formalized.

4.2 Estimation of wholesale prices and unobserved product characteristics (ξ)

I recover product characteristics that are unobserved to the econometrician as the residual $\xi(\hat{\theta})$ product of $\delta(\hat{\theta}_2) - X\hat{\beta} + \hat{\alpha}p$ from the demand estimation.

Marginal costs are backed out using demand parameters and the distribution of consumer locations. Unfortunately, I do not observe transaction prices in the different stores, which limits the possibility of inferring wholesale prices at the store level. Instead, I assume multi-product car manufacturers set wholesale prices so that on average dealerships are induced to set list prices. This assumption is similar to **?** and seems reasonable. Car manufacturers use list

[6]Alternatively, one can draw a large set of locations and compute the distances before the estimation in which case the approach is not computationally intensive, but demands large memory

[7]Tengo que redondear esto.

prices as a mechanism to set reference prices downstream and they do so in order to maximize their profits.

$$\sum_{d \in E} \mathbb{I}\{b \in a_d\} \cdot \frac{\partial \pi_d(a, \hat{\theta})}{\partial p_j} = 0 \text{ for all } j \in b \text{ and } b \in B.$$

Like in most of the demand estimation literature, this condition can be rearranged into matrix form

$$q + \left(\sum_{d \in E} \Delta_d \circ \frac{\partial q_d(a, \hat{\theta})}{\partial p} \right) (p - p^w) = 0,$$

where Δ_d is a $J \times J$ matrix where an element is equal to 1 if product j and k are sold by dealership d and $\circ$ denotes the Hadamard product between two equally sized matrices. A slight reordering of the matrices allows to solve for wholesale prices p^w

4.3 Estimation of fixed costs

I base my estimation of fixed costs on the literature using profit inequalities to estimate bounds on them (Pakes, 2010; Pakes, Porter, Ho, and Ishii, 2015). This approach has been used recently in a number of empirical applications in industrial organization and trade (e.g. Holmes, 2011; Morales, Sheu, and Zahler, 2015; Wollmann, 2018), and it allows to flexibly accommodate multiplicity of equilibria and big action spaces.

Following the notation of section 3.3, I assume the following functional form for the fixed costs

$$F_d(a_d, l_d) = \sum_{b \in a_d} F_b + \mathbb{I}\{|a_d| > 1\} \cdot C_{MD} + \nu_d^a + \nu_d^l, \tag{2}$$

where F_b is the cost dealership d has of offering brand b, C_{MD} are the potential costs of dealing with more than one brand. ν_d^a, ν_d^l are shocks to fixed costs owing to their actions and location that are observed by dealers, but not by the econometrician. This functional form is very simple, but the parameter C_{MD} allows to account for potential jumps in the cost function when transitioning from exclusive dealing to dealing with more than one brand.

In what follows, I proceed to describe the assumptions made for the estimation of the parameters in (2). Assumption 1 describes the common equilibrium assumption for this subgame. It entails that if a vector of dealership choices is observed in the data, these actions are profit maximizing from the their side and no unilateral deviation could make them better off. This assumption is common to the literature.

Assumption 1 (Best Response Condition) *If a_d is observed to be the strategy played by dealership d, then it must be the case that*

$$\max_{a_d \in A_d} \mathcal{E}[\pi_d(a_d, a_{-d}) | \mathcal{I}_d] \geq \mathcal{E}[\pi_d(a'_d, a_{-d}) | \mathcal{I}_d] \textit{ for every } a'_d \in A_d \textit{ and } d \in D.$$

This best response condition delineates the principle on which the moment inequality conditions of this estimation strategy are built. In a nutshell, I add and subtract brands to the observed offerings in order to estimate bounds to the parameters.

The presence of the structural disturbance ν permits to reconcile differences between model predictions and observed actions. However, a problem of selection arises when estimating this specification based on Assumption 1. Structural disturbances are not mean zero conditional on observed choices, even if they are unconditionally so. Pakes (2010) details several strategies to overcome this issue.

Location unobserved components are easy to control for given the separable functional form. Their disturbances are differenced out since I construct my moments by changing brands choices and keeping locations fixed.

I introduce Assumption 2 in order to construct a way to circumvents the selection problem occurring with ν_d^a. In essence, I aim at creating counterfactual inequalities that hold no matter what decision retailers make in order to be able to use the unconditional expectation of ν_d^a.

Let $a_d^{b-} = a_d \backslash \{b\}$, and $a_d^{b+} = a_d \cup \{b\}$. Furthermore, define $\mathcal{N}_d^L = \left\{ \tilde{d} \in D | \text{dist}(d, \tilde{d}) < L \right\}$.

Assumption 2 (Eventual (Un)Profitability) *Let $d, \tilde{d}$ be two observed dealerships with a_d and $a_{\tilde{d}}$ respectively, and suppose $b \in a_{\tilde{d}}$. Then if $d \in \mathcal{N}_{\tilde{d}}^L$ there exists at least one $i_d \in \{0,1\}^{|-d|}$ with $a'_{-d} = i_d \cdot a_{-d} + (1 - i_d) \cdot a_{-d}^{b-}$ such that*

$$\mathcal{E}[\pi_d(a_d^{b+}, a'_{-d}) | \mathcal{I}_d] \geq \mathcal{E}[\pi_d(a_d, a'_{-d}) | \mathcal{I}_d].$$

Conversely, let $b \in a_d$, then there exists at least one $i_d \in \{0,1\}^{|-d|}$ with $a'_{-d} = i_d \cdot a_{-d} + (1 - i_d) \cdot a_{-d}^{b+}$ such that

$$\mathcal{E}[\pi_d(a_d^{b-}, a'_{-d}) | \mathcal{I}_d] \geq \mathcal{E}[\pi_d(a_d, a'_{-d}) | \mathcal{I}_d].$$

Assumption 2 basically states that, in some areas, any dealership could potentially deal for any brand profitably (unprofitably) if intra-brand retail competition is sufficiently relaxed (tightened). The radius of maximum geographic distance (L) of the assumption is chosen small in order for this condition only to apply in areas where it is observed that there is enough demand for a dealership to offer the products of this brand.

It is useful to consider an example in order to illustrate the intuition of this assumption. A dealership might not find profitable to offer a brand (e.g. Nissan) in the current state of competition, but it might find it profitable if it were to be the only dealership offering Nissan in a radius of 80 kilometers.

I can construct moment conditions that are not selected combining assumptions 1 and 2. In particular, for brand b, I can construct the profit function $\Delta r(a_d, a'_d, a_{-d})$ such that

$$\Delta r_b(a_d, a_d^{b-}, a_{-d}) = \begin{cases} \mathcal{E}\left[\Delta\pi(a_d, a_d^{b-}; a_{-d}) | \mathcal{I}_d\right] + \Delta\nu_d^a, & \text{if } b \in a_d \\ \mathcal{E}\left[\Delta\pi(a_d^{b+}, a_d; a'_{-d}) | \mathcal{I}_d\right] + \Delta\nu_d^a, & \text{if } b \notin a_d. \end{cases}$$

leads to moment condition

$$m_{1,b} = |D|^{-1} \sum_{d \in D} \mathbb{I}\{d \in \mathcal{N}_b^L\} \cdot \Delta r_b(a_d, a_d^{b-}, a_{-d}) \geq 0$$

for i.i.d. disturbances provided that $|D|^{-1} \sum_{d \in D} \mathbb{I}\{d \in \mathcal{N}_b^L\} \cdot \nu_d^a$ follows the law of large numbers. Conversely,

$$\Delta r_b(a_d, a_d^{b+}, a_{-d}) = \begin{cases} \mathcal{E}\left[\Delta\pi\left(a_d^{b-}, a_d; a'_{-d}\right)|\mathcal{I}_d\right] + \Delta\nu_d^a, & \text{if } b \in a_d \\ \mathcal{E}\left[\Delta\pi\left(a_d, a_d^{b+}; a_{-d}\right)|\mathcal{I}_d\right] + \Delta\nu_d^a, & \text{if } b \notin a_d. \end{cases}$$

leads to

$$m_{2,b} = |D|^{-1} \sum_{d \in D} \mathbb{I}\{d \notin \mathcal{N}_b^L\} \cdot \Delta r_b(a_d, a_d^{b+}, a_{-d}) \geq 0$$

5 Results

5.1 Demand estimates

Table 3: Estimates for the demand model

	(1) Logit	(2) RC Logit	(3) RC Logit	(4) RC Logit
Price	-2.232	-1.130	-1.163	-2.291
	(0.220)	(0.118)	(0.115)	(0.618)
Fuel Cons.	-0.344	-0.342	-0.332	-0.214
	(0.041)	(0.048)	(0.048)	(0.067)
HP / Weight	-0.113	-0.028	-0.020	0.070
	(0.037)	(0.039)	(0.039)	(0.074)
Size	1.276	1.291	1.325	2.066
	(0.118)	(0.132)	(0.130)	(0.429)
Cons.	-15.200	-13.548	-13.914	-17.706
	(0.978)	(1.074)	(1.051)	(2.461)
Distance		-0.556	-0.546	-0.353
		(0.060)	(0.060)	(0.110)
ED			0.200	-0.021
			(0.100)	(0.154)
Price $\times$ Income				0.073
				(0.023)
Origin f.e.	Yes	Yes	Yes	Yes
Province f.e.	Yes	Yes	Yes	Yes

Table 4 presents demand estimates for different specifications. Column (4) is the most complete one of them since it includes all dealer variables (exclusivity and distance) as well as allowing for elasticity to depend on income. It is also the specification used for the supply side estimates. In line with what it is intuitive, the coefficients for distance and price are negative and significant. According to the estimates, 10km additional distance from a dealership has a comparable effect to EUR 1324 increase in the price of the car. The coefficient on exclusive dealing seems to be negative, although not significant. The random coefficient interaction between individual income and price is positive, implying that consumers become more inelastic as their wealth increases. Figure 3 represents the distribution of own price elasticities for the different products and markets.

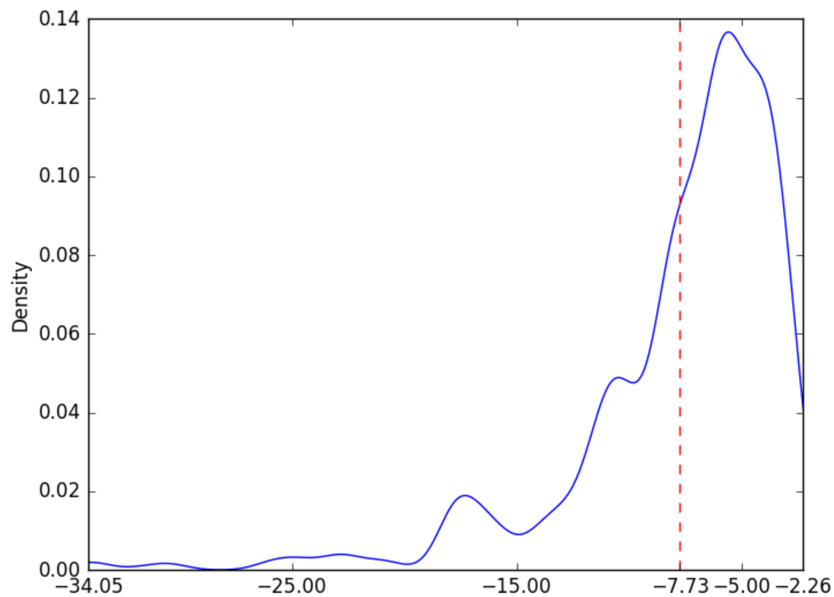


Figure 3: Distribution of elasticities at local markets

6 Counterfactuals

TBW

Counterfactual #1: No difference in costs for ED allowed Take away demand and supply differences for ED and resimulate the dealer equilibrium taking geographic locations as given. If c_{ED} are simulated to be negative, it is expected bigger number of multidealership depending on the level of downstream competition. In areas densely populated of dealerships, it might not have an effect.

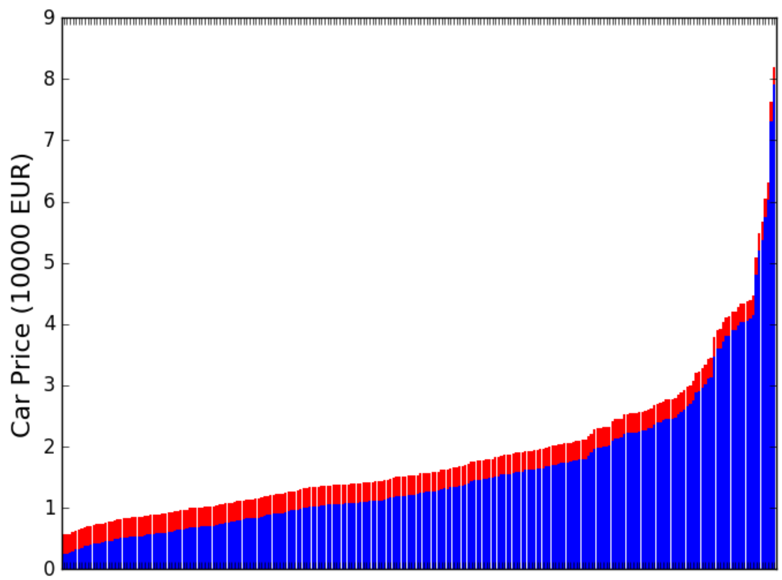


Figure 4: Distribution of dealer expected margin by car

Counterfactual #2: Relax downstream competition Eliminate a part of the dealers to allow dealerships to have more distance between each other and resimulate dealer equilibrium. Having competitors away, dealers must be choosing more often multi-dealing in order to cover greater portion of the market.

7 Concluding Remarks

References

Philippe Aghion and Patrick Bolton. Contracts as a barrier to entry. *American Economic Review*, 77(3):388–401, 1987.

Paulo Albuquerque and Bart J. Bronnenberg. Measuring the impact of negative demand shocks on car dealer networks. *Marketing Science*, 31(1):4–23, 2012.

John Asker. Diagnosing foreclosure due to exclusive dealing. *Journal of Industrial Economics*, 64(3):375–410, 2016.

Itai Ater. Vertical foreclosure using exclusivity clauses: Evidence from shopping malls. *Journal of Economics & Management Strategy*, 24(3):620–642, 2015.

Table 4: Estimates for the demand model

Variable	Lower Bound	Upper Bound
Alfa Romeo	-15.2026	104.0798
Audi	227.3829	1200.6678
BMW	228.8972	1744.7999
Citroen	132.9761	532.1270
Fiat	8.4770	196.3084
Ford	84.3753	469.3507
Honda	12.6588	241.0446
Hyundai	91.4429	544.5221
Infiniti	19.7331	289.1468
Jaguar	65.5609	731.0909
Jeep	12.0600	326.8334
KIA	91.4281	672.0341
Land Rover	91.0273	810.0314
Lexus	-10.5762	31.1274
Mazda	64.1384	528.7231
Mercedes	227.0218	1148.4970
Mini	5.5303	254.7788
Mitsubishi	32.1797	295.8697
Nissan	78.1137	525.1529
Opel	84.3210	575.5973
Peugeot	208.5584	1185.2976
Porsche	1130.4531	5588.0780
Renault	289.3478	1230.0370
Seat	238.0929	1015.9176
Skoda	48.1447	440.4564
Smart	-20.4028	95.5675
Ssangyong	3.1347	166.3182
Subaru	-0.0229	114.3118
Suzuki	6.1124	146.8747
Toyota	97.2771	556.5656
Volkswagen	195.2159	919.9906
Volvo	81.5017	648.5632
Multi-Dealing	7.4109	31.1963

B. Douglas Bernheim and Michael D. Whinston. Exclusive dealing. *Journal of Political Economy*, 106(1):64–103, 1998.

Steven Berry. Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262, 1994.

Steven Berry, James Levinsohn, and Ariel Pakes. Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, pages 841–890, 1995.

Sofia Berto Villas-Boas. Vertical relationships between manufacturers and retailers: Inference with limited data. *Review of Economic Studies*, 74(2):625–652, 2007.

David Besanko and Martin K. Perry. Exclusive dealing in a spatial model of retail competition. *International Journal of Industrial Organization*, 12, 1994.

Robert H Bork. *The Antitrust Paradox: A Policy at War with Itself*. 1978.

Chia-Wen Chen. Estimating the foreclosure effect of exclusive dealing: Evidence from the entry of specialty beer producers. *International Journal of Industrial Organization*, 37:47–64, 2014.

Federico Ciliberto and Elie Tamer. Market structure and multiple equilibria in airline markets. *Econometrica*, 77(6):1791 – 1828, 2009.

Michaela Draganska, Michael Mazzeo, and Katja Seim. Beyond plain vanilla: Modeling joint product assortment and pricing decisions. *Quantitative Marketing and Economics*, 7(2):105 – 146, 2009.

Alon Eizenberg. Upstream innovation and product variety in the us home pc market. *Review of Economic Studies*, 81(3):1003–1045, 2014.

Alon Eizenberg, Andras Pechy, and Michelle Sovinsky. The dynamics of technology adoption and vertical restraints: An empirical analysis. 2017.

Ying Fan. Ownership consolidation and product characteristics: A study of the us daily newspaper market. *American Economic Review*, 103(5):1598 – 1628, 2013.

Chiara Fumagalli and Massimo Motta. Exclusive dealing and entry, when buyers compete. *The American Economic Review*, 96(3):785–795, 2006.

Thomas J. Holmes. The diffusion of wal-mart and economies of density. *Econometrica*, 79(1):253 – 302, 2011.

Y. Joseph Lin. The dampening-of-competition effect of exclusive dealing. *Journal of Industrial Economics*, 39:209–223, 1990.

Eduardo Morales, Gloria Sheu, and Andrés Zahler. Extended gravity. *NBER Working Paper*, 21351, 2015.

Aviv Nevo. Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69(2):307–342, 2001.

Laura Nurski and Frank Verboven. Exclusive dealing as a barrier to entry? evidence from automobiles. *The Review of Economic Studies*, 83(3):1156–1188, 2016.

Daniel P. O'Brien and Greg Shaffer. On the dampening-of-competition effect of exclusive dealing. *Journal of Industrial Economics*, 41:215–221, 1993.

Ariel Pakes. Alternative models for moments inequalities. *Econometrica*, 78(6): 1783–1822, 2010.

Ariel Pakes, Jack Porter, Katherine Ho, and Joy Ishii. Moment inequalities and their application. *Econometrica*, 83(1):315–334, 2015.

Richard A Posner. *Antitrust law*. University of Chicago Press, 1976.

Eric B. Rasmussen, J. Mark Ramseyer, and John S. Wiley. Naked exclusion. *American Economic Review*, 81(5):1137–1145, 1991.

Patrick Rey and Joseph E. Stiglitz. Vertical restraints and producers' competition. *European Economic Review*, 32:561–568, 1988.

Patrick Rey and Joseph E. Stiglitz. The role of exclusive territories in producers' competition. *RAND Journal of Economics*, 26:431 – 451, 1995.

Tim R. Sass. The competitive effects of exclusive dealing: Evidence from the us beer industry. *International Journal of Industrial Organization*, 23(3-4): 203 – 225, 2005.

Ilya R. Segal and Michael D. Whinston. Naked exclusion and buyer coordination. *Harvard University, Institute of Economic Research Working Papers: No. 1780*, 1996.

John Simpson and Abraham L. Wickelgreen. Naked exclusion, efficient breach, and downstream competition. *American Economic Review*, 97(4):1305–1320, 2007.

Karunakaran Sudhir. Structural analysis of manufacturer pricing in the presence of a strategic retailer. *Marketing Science*, 20(3):244–264, 2001.

Thomas G. Wollmann. Trucks without bailouts: Equilibrium product characteristics for commercial vehicles. *American Economic Review*, 208(6):1364 – 1406, 2018.

Appendix A Computing Expected Variable Profits

Assume I add brand Citroen to dealership d, who already deals with Renault and Dacia.

1. Compute for each simulated location in the whole country, what the closest dealer offering Citroen, Renault or Dacia is.

2. Simulate sales for the municipalities containing the locations for which dealership d is in the choice set.

   (a) Draw locations and other demographics for each individual in the municipality.

   (b) Draw ξ for the market from the empirical distribution function over markets.

   (c) Draw ϵ for each individual from T1EV.

   (d) Compute utility maximization for each individual and recover sales.

   (e) Repeat NS times

Assumptions: (1) ξ are distributed jointly for all products. (2) Locations are distributed uniformly.

Computing time: Dividing the computations between 12 computers with 16 nodes each, it took some 6 hours and a half.

Figure 5: Market leader at the regional level for the years 2015 (left) and 2016 (right)

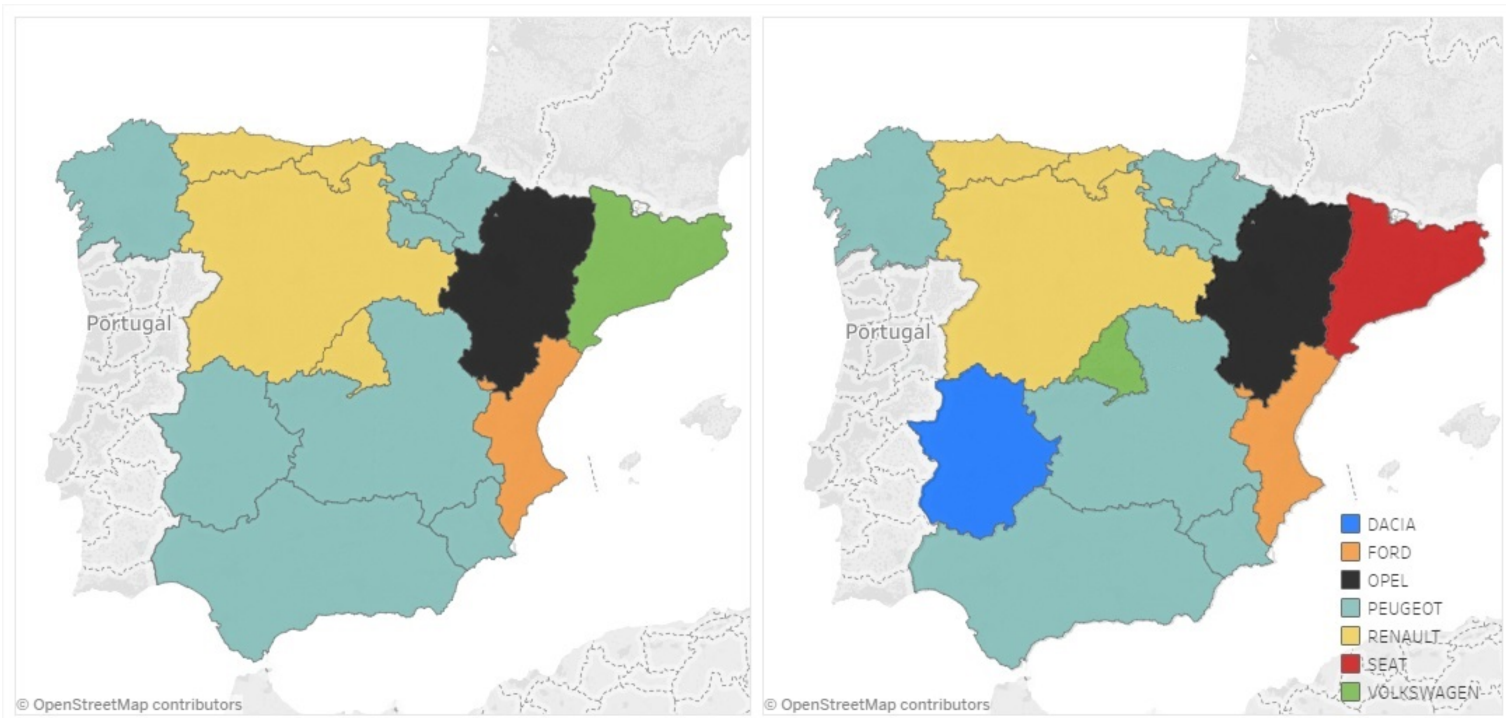


Figure 6: Exclusive and Non-Exclusive dealerships for Volkswagen (left) and Honda (right)