Essays on Empirical Industrial Organization

Inauguraldissertation
zur Erlangung des akademischen Grades
eines Doktors der Wirtschaftswissenschaften
der Universität Mannheim

vorgelegt von

Franco Esteban Cattaneo

im HWS 2019

Abteilungssprecher:	Prof. Dr. Hans Peter Grüner
Referent:	Prof. Michelle Sovinsky, Ph.D.
Korreferent:	Prof. Emanuele Tarantino, Ph.D.

Tag der Verteidigung: September 24, 2019

Acknowledgements

I would like to express my gratitude to my supervisors, Michelle Sovinsky and Emanuele Tarantino, for their guidance. Michelle contributed to the development of this thesis since its inception. She organized and led the Ph.D. group meetings that gave me the time and space to discuss research, develop ideas, and express myself. She also provided with lots of comments, advice, and chocolate. Emanuele also saw the development of my research from very early presentations. He taught me to form and motivate research ideas to answer relevant economic questions, which was not easy for me to understand, and gave me always an honest opinion on my work.

I am deeply grateful to my co-author Hidenori Takahashi, who always found time to discuss our joint project, and helped me develop new research interests. I am also indebted to the whole microeconomics group at the Department of Economics of the University of Mannheim that directly or indirectly contributed to my research with comments, advice, and the organization of conferences and seminars.

My adventure in Mannheim was a very challenging one, but I am lucky to have shared it with very kind people. I will be forever grateful to Johannes Bubeck, who was always very helpful and taught me how to behave like an adult. I treasure in my memory the conversations, coffees, beers, and dinners shared with him, and many times joined by mutual friends like Florian Fischer, Torben Fischer, Ian Hilgendorff, Jonas Kröger, or Julia Schmieder, during the early years of my Ph.D. path. Nowadays, I continue this "coffee and babble" tradition more sporadically in the company of the younger Tobias Kuhn.

I am also delighted to have shared part of these six years with Niklas Garnadt and Ruben Hipp. Niklas impressed me with his combination of brightness and down-to-earth personality since our time in Barcelona. I do not recall any dull moment with Ruben. I enjoy his humor and openness to talk and theorize about anything and appreciate his thoughtfulness. We went through the job search process together, and it could not have been a nicer madness.

I was lucky to share my Ph.D. group meetings with Alessandra Allocca and Yihan

Yan. They were my partners in this crime, together with Robert Aue. Not only they listened to my ideas, but they also took care of me and put up with my short temper many times. Alessandra glued the group together with her sympathy, and Yihan refreshed everyone's days with her funny and easy-going personality. I am also very thankful to Francesco Paolo Conteduca with whom I always enjoyed spending time with and always gave me his selfless support, both academically and personally.

I would also like to thank Albrecht Bohne, Enrico Camarda, Tobias Etzel, Ekaterina Kazakova, Niccolò Lomys, and Yasemin Özdemir for the time, and lunches shared during these years.

My parents, Natalia and Marcelo, and my sister, Giulia, deserve the greatest of my gratitudes. Ours is a lifelong of challenges since our time in Argentina. I thank them for all their sacrifices, understanding, and love. Their courage and constant learning make me proud and inspired me to persevere and complete this process.

My final acknowledgments are to my girlfriend, Hannah Jantsch, and her family. I was very lucky to meet Hannah during my time in Mannheim. She is a great partner with whom I look forward with enthusiasm to our future together. I thank her for her immense love, company, and tolerance through this journey. Together we built a relationship based on mutual respect and love that engages me to strive every day. I would also want to express my gratitude to her parents, Eva and Winne, for their generous support and hospitality. They made me feel at home, despite being far away from my family.

Contents

List of Figures

List of Tables

General Introduction

This dissertation consists of three self-contained chapters. The common theme is the analysis of the role that endogenous and strategic participation decisions play forming market structure and the design of regulatory policy that takes such responses into account.

The first two chapters are concerned with the effects of vertical restraints in the entry and brand positioning by dealerships in the car retail industry. In Chapter 1, I look at the effects of exclusive dealing and analyze whether car manufacturers use exclusivity with foreclosing motives. In Chapter 2, I explore the consequences of allowing for territorial protections in the formation of retail networks.

The third part of this dissertation is co-authored with Hidenori Takahashi and Yuya Takahashi. In Chapter 3, we study participation decisions in the procurement of public infrastructure project. We analyze the role that information about potential entry has coordinating entry among firms.

In what follows, I present summaries of the chapters.

Chapter 1
Downstream Competition and Exclusive Dealing

In this chapter, I empirically investigate the role of downstream competition in the use of exclusive dealing and quantify its effects in the formation of the car retailing networks. For this purpose, I develop and estimate a structural model where exclusivity can impact both supply and demand to be able to capture the diverse channels through which exclusive dealing plays a role.

In innovation to the previous literature, I allow dealers to choose which brand to offer strategically. These participation choices frame product and brand availability in the market and the retail networks for manufacturers. Dealers face a trade-off in this framework. They have incentives to add more brands to sell a broader set of products, but their interest to differentiate from local rivals limits this option. Moreover, manufacturers could raise costs anticompetitively to deter dealers from selling products of rival brands and foreclosing them.

I estimate the demand parameters, marginal costs, and fixed costs of the model in three stages. In my econometric estimation, I introduce a strategy to circumvent the selection issue that arises when using outcome data to form moment inequalities. I analyze the potential for upstream foreclosure, comparing the estimated fixed costs between exclusive and non-exclusive stores. I find that multi-dealing has an average cost advantage between -€10,000 and €620,000. These numbers indicate that downstream competition, instead of anticompetitive motives, explains a more substantial part of the prevalence of exclusive dealing in the market.

Chapter 2
Exclusive Territories and Brand Proliferation: A Simulation Study

In this chapter, I extend the model from the previous chapter to perform a simulation analysis. I investigate the role that territorial restrictions play in brand offerings in the car retail industry when combined with exclusive dealing. I experiment with the effects of implementing a policy by which dealers of the same brand cannot be closer than a certain distance from each other.

In particular, I look at whether forcefully spacing out intra-brand competition would give incentives for dealerships to substitute selling product from larger to smaller manufacturers. This scenario would lead to better access to points of sale by small competitors and higher product variety. Alternatively, territorial restrictions could reduce global competition without retailers substituting brands, and harming consumer welfare.

I find that, while territorial restrictions decrease the number of dealerships for larger manufacturers, it does not incentivize them to replace them with smaller manufacturers. Moreover, it causes an overall reduction in the number of dealers in the market that is detrimental to consumers. These patterns indicate that the current limits to the use of exclusive territories in the car retail market are a right regulatory approach, and its repeal would be positive neither for consumers nor for small manufacturers.

Chapter 3
Entry Signal and Market Segregation

This chapter is joint work with Hidenori Takahashi and Yuya Takahashi. In it, we examine the role of information design in procurement auctions using data from transport infrastructure projects in Florida.

In our setup, the procurer requires that interested firms request for a construction plan to participate in an auction. Plan requests become common knowledge before the auction takes place. We use this institutional feature to examine the impact of disclosing the number and identity of interested bidders on bidders' behavior and auction outcomes. We are interested in whether this institutional design leads strong contractors to signal their intention to bid for projects and preempt the entry of smaller firms to their advantage.

We find that the potential entry of an additional strong firm reduces the probability of participation of weak rivals by a 2.7%. We suspect that the signaling is a result of contractors substitution across projects. We find that each additional participation raises a strong firm's bid by 1% and a weak firm's bid by 3.8%.

Chapter 1

Downstream Competition and Exclusive Dealing

1.1 Introduction

Despite attempts by the competition authorities to encourage car retail outlets to sell more than one brand, multi-brand dealerships are a rarity in Europe[1]. Manufacturers often force their retailers to sell other brands under dedicated corporate identities using separate showrooms and with different personnel. These requirements increase the costs of multi-brand dealing and deter retailers from taking such options. However, multi-dealing reduces the incentives for manufacturers to invest in their retail stores, especially with respect to marketing and brand image. This is an important consideration, as investments in promotional efforts can be substantial: for example, in the case of car retailing, in Spain alone, they account for 13.4% of total sales revenue.

In this paper, I study how the presence of exclusive contracts shapes the competition between retailers from an empirical perspective. On the one hand, it can be in the interest of the retailer and the manufacturer to sign exclusive dealing agreements in order to preserve the returns from investments in brand promotional activities (Besanko and Perry, 1993), and differentiate from competing retailers (Besanko and Perry, 1994). On the other hand, the manufacturer may use exclusivity to soften competition by raising the retailers' costs to offer other brands[2]. In par-

[1]MEMO 10/217 by the European Commission: "The old rules have had little impact on favouring multi-dealerships, which continue to be determined by the size of the dealers and their geographical location – multi dealerships are more likely to happen in remote areas and within large dealer groups that have buyer power."

[2]Anticompetitive motives for exclusive dealing have been addressed extensively. E.g., Aghion

ticular, I assess the question of whether the prevalence of exclusive dealing between manufacturers and retailers emerges as a result of competition shaping the market or whether there is a scope for manufacturers to indirectly deter intra-dealer competition by increasing the costs for dealerships to sell for other brands.

The existing empirical literature has studied these two forces in isolation. More specifically, Asker (2016) looks at the possibility that exclusive dealing gives rise to foreclosure of competing brands, while Nurski and Verboven (2016) study the role of exclusivity as a means to achieve higher demand for the retailer. However, only a combined analysis can help competition authorities to quantify the merits of exclusive contracts.

I estimate a structural model of demand and supply of the car retail market that quantifies the diverse effects of exclusivity. Including both sides of the empirical model to analyze exclusivity helps to construct a full picture for regulation of this kind of vertical restrictions. On the one hand, only modeling demand misses the potential effects of exclusive contracts endogenously shaping market structure for distribution. On the other hand, focusing on capturing supply differences in retail between exclusive and non-exclusive dealers does not allow for other motivations for exclusive dealing other than excluding rivals. My results indicate that downstream competition, instead of anticompetitive motives, explains a more substantial part of the prevalence of exclusivity in the car distribution market.

There are several challenges associated with this exercise. First, in order to estimate a model where exclusive dealing impacts both supply and demand, I require data on (i) car sales registrations, (ii) dealer locations, (iii) brands sold at each dealer, as well as (iv) demographics of consumers. I collected this information by combining existing sources with comprehensive self-collected data. The main difficulty in constructing these data was to distinguish and classify multi-dealerships and exclusive dealers since many appeared to be disguised under separate showrooms and names. To address this ambiguity, I define a firm as a multi-dealer when it has adjacent showrooms which belong to the same owner. These classification efforts resulted in a novel dataset, whose features I discuss in detail shortly.

Second, I model retailers' choices of which brands to offer, making my empirical framework the first one to include such a feature. I use these firm choices to uncover the fixed costs of operating a dealership. Specifically, following a similar principle to that of Asker (2016), I compare the estimated costs of exclusive and non-exclusive dealerships to estimate the difference in the costs of signing such arrangements for

and Bolton (1987), Rasmussen et al. (1991), Segal and Whinston (1996), Bernheim and Whinston (1998), or Calzolari and Denicolò (2015) the retailers. These costs arise when it is more costly to establish a dealer selling more than one brand than a dealer selling each of these brands separately.

Similarly to entry games, local competition across dealers leads to a multiplicity of equilibria of the simultaneous move game in which retailers decide what brands to deal for, making maximum likelihood methods unfeasible for estimation. I estimate bounds to fixed costs using moment inequalities defined by equilibrium play (Pakes, 2010; Pakes, Porter, Ho, and Ishii, 2015) and methods developed to draw inference in these cases (Andrews and Soares, 2010). This approach enables me to overcome the problem of multiplicity at the cost of losing point identification of the parameters.

Another challenge related to the use of moment inequalities and equilibrium play for estimation is selection on unobservables. This problem arises when one makes inference based on observed choices to estimate fixed costs. In particular, when estimating fixed costs of selling for a particular brand, the upper bounds are identified by those dealers selling for that brand and the lower bounds by those who do not. Using this principle alone yields biased estimates since the dealers selling a particular brand most likely have better (lower) fixed costs than the dealers not selling it. The resulting (biased) estimates present themselves in the form of upper bounds for the parameters that are too low and lower bounds that are too high. Therefore, the estimated sets may not contain the true parameters.

A methodological contribution of this paper, then, is to introduce a strategy to deal with the selection problem that arises in these situations. The approach I propose is grounded on the observation that, conditional on observables, equilibrium play by dealers reflects their need to differentiate from neighboring rivals, and on the fact that these equilibrium choices are likely to replicate permuting brand offerings across dealers. The intuition is that the differentiation between dealers within a local market is a stable equilibrium prediction, and not which dealer sells what brand. Based on this idea, I propose conditions under which I can create new inequalities using multiple perturbations from equilibrium play. These inequalities allow me to derive moment conditions that are not dependent on choice and hence are free from selection.

In my empirical model, exclusive dealing comes into play in three ways. First, it enters the demand as a parameter in the consumers' utility of purchasing a car. This parameter captures enhanced consumer experience owing to improved customer service or better promotion. Second, multi-dealing enters the fixed costs paid by dealers as a cost shifter that I estimate. This parameter captures potential additional costs (or costs savings) related to selling for more than one brand. Finally, the choices of whether to deal exclusively are endogenous to the model, meaning that these decisions take the effects above into account, as well as the competitive environment in the market.

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 a taste for exclusivity, due to premium service or additional promotional and retailing efforts.

As mentioned above, I complete the model by allowing retailers to endogenously choose their brand offerings in a simultaneous move game setup. On the one hand, retailers want to differentiate from each other by offering different products to dealers geographically close. On the other hand, they want to sell popular products. Moreover, in the case of manufacturers raising costs of multi-dealing, exclusive dealing may appeal to downstream competitors because of its lower fixed costs.

In environments without intense competition, exclusive dealing has the effect of limiting the variety of products offered and narrowing demand for the retailer. Nevertheless, in the presence of fierce competition, single branding permits differentiation across smaller dealers. This interaction between spatial and product differentiation downstream is internalized by manufacturers, who set product prices in accordance with their distribution networks. Exclusive dealing eliminates competition among products of different brands within a retailer.

There is a longstanding debate about exclusive dealing contracts 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. My paper relates to the vast and rich theoretical literature that developed trying to refute this view. The main takeaway of this literature is that, although contracts of this kind might have exclusionary effects, their existence can be beneficial, by boosting investment and retailing efforts[3].

There is also growing literature on the empirics of exclusive dealing. My work links most directly to two papers in this literature and complements them. 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

[3]Apart from the previously mentioned papers, 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. Sass (2005) provides a comprehensive overview of the main mechanisms used in the literature to rationalize the use of exclusive dealing.

between areas where Miller and Anheuser-Busch use exclusive contracts and areas where they do not and finds no statistical evidence of foreclosure. My approach shares similarities with Asker (2016) because I also use demand estimates to infer costs downstream and compare them between exclusive and non-exclusive dealers. However, I additionally include demand-side effects of exclusive dealing, and I focus on differences in fixed costs and allow for endogenous market structure, while he focuses on variable costs and keeps the market structure fixed.

The industry and demand modeling links 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. While Nurski and Verboven (2016) make an extensive analysis of demand and manufacturers' incentives for exclusive contracts, I model the distribution network and estimate the fixed costs borne by these retailers. My model contains the channels for exclusive dealing of Nurski and Verboven (2016), where it shifts utility and it lowers product availability for rival brands. In addition, my model incorporates supply side motives for exclusive dealing, where retailers might deal with only one brand because it is cheaper for them to do so. To the best of my knowledge, this is the first paper that explores jointly supply and demand side mechanisms for exclusive dealing.

Other work in this area includes Ater (2015) who finds that exclusive contracts between fast-food restaurants and shopping malls impact competition negatively by lowering the number of restaurants, increasing prices and limiting total sales. Eizenberg et al. (2017) focus on the dynamic effects that exclusive contracts between Intel and PC makers had on the development of its competitor AMD. Chen (2014) analyzes the entry of specialty beers and does not find any foreclosing motives behind exclusive contracts by incumbent breweries.

This article is also related to the stream of literature on endogenous product offerings. 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. In my model, the strategic considerations that determine dealers' endogenous choice of brands are analogous to those shaping firms' decision to introduce a product in these papers. Dealerships decide with their brand offerings what bundles of goods to offer and with them determine (endogenous) product availability in the market.

Finally, the estimation of fixed costs relates to the literature that uses moment inequalities to overcome the problem of multiple equilibria (Ciliberto and Tamer, 2009; 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; Houde, Newberry, and Seim, 2017; 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 this literature by introducing a new way to circumvent this issue.

In summary, my contribution is manifold. First, I estimate a model that combines supply and demand to quantify the effects of exclusive dealing. Second, I determine retail brands within the model. Third, I introduce another strategy to deal with the selection problem common in the literature using choice data. Finally, I construct a novel dataset containing data on car sales and retail points in Spain.

The paper proceeds as follows. In the next section I describe the data. The model is presented in section 1.3. Sections 1.4 and 1.5 describe estimation and results respectively. Section 1.6 concludes.

1.2 Data

My dataset concerns the market for cars in Spain from July 2016 until August 2017. First, I use data on car registrations from the traffic registry. Second, I supplemented these car registry data with additional characteristics of cars that I collected from specialized magazines. Third, I collected data on car dealerships locations from web searches. Finally, I use information on population demographics and locations of consumers from Governmental Offices. I discuss each of these data in turn.

1.2.1 Car sales and characteristics data

I obtained data on car sales from the Spanish Directorate-General of Traffic (DGT)[4]. These data consist of daily information on all cars registered in the Spanish territory starting in 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, energetic propulsion, and the postal code and municipality where the car was registered.

I use observations corresponding to new cars, 4x4s or small pickups used for non-commercial purposes. In total, in the period between July 2016 and August

[4]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`

2017, there are 1,091,932 registrations from 7,712 different municipalities. I chose this time window because it approximately coincides with the period on which I was able to collect the data on dealerships.

Table 1.1 shows market shares for car makes and models. It is notable that no make has a market share close to the 30%, which the General Vertical Block Exemption considers to be worrisome for legal vertical agreements[5]. In particular, no car make appears to dominate the market: all market shares are below 10% and the market leaders change across time periods and geographic regions.

Table 1.1: 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 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.

I constructed a baseline 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 as the mean of all merged trims. This linkage approach preserves a larger part of price variation in the data and controls for the fact that, especially in higher-end cars, within-model price dispersion plays a sizable role.

I excluded car models absent at more than 30 provinces[6] and car categories that are not in direct competition with passenger cars (e.g. big vans, luxury sports cars).

[5] OJ L 102, 23.4.2010, p. 1–7

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

I aggregated the data at the province level. This market definition preserves the geographic disaggregation of the data without having markets with market share of zero for products with low probability of being chosen. I dropped provinces outside the Iberian peninsula (i.e. Canary Islands, Balearic Islands, Ceuta and Melilla) because they are geographically apart from the rest of the country.

Table 1.2 shows some descriptive statistics for different car characteristics after matching them with the registry data. The data comprise 43 out of a possible 52 provinces[7] and 234 car models with significant variation in their characteristics. The average price is around €34,300, and the average horsepower around 144 CV, but they both have a large dispersion.

Table 1.2: 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)	3.43	2.16	1.02	14.86	234
Markets					
Provinces					43

1.2.2 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, these data were not available in Spain so I collected them manually. First, I gathered the data on locations from online applications that each manufacturer has available on their websites. These applications are normally used for manufacturers to inform about their available points of sale. From them, I obtained a list of dealerships with their location and services for each car brand. Second, I manually combined the observations that were points of sale for more than one brand.

I consider two observations from different brands to be available at the same dealership (making it a multi-dealer) if they are (i) located adjacent to each other geographically and (ii) have the same owner. This definition is based on the observed

[7] These 43 provinces include 40.3 million inhabitants out of the total of 46.5 million in Spain.

patterns for multi-dealers, where normally different car makes have separated showrooms and different names even if they are operated by the same owner. Since construction and geographic distribution varies across urban and rural areas, I also consider observations separated by a street intersection as contiguous, but not those separated by another building or dealership.

Using this definition, the data show 44% of dealerships are multi-dealers, i.e., offer more than one brand (which constitutes 66% of the total points of sale). There are some brands that have their dealership networks integrated. For example, Citroen and DS, or Renault and Dacia share all their points of sale. However, if I count brands with integrated networks as exclusive dealing, the percentage of multi-dealers declines substantially to 22% (41% of points of sale)

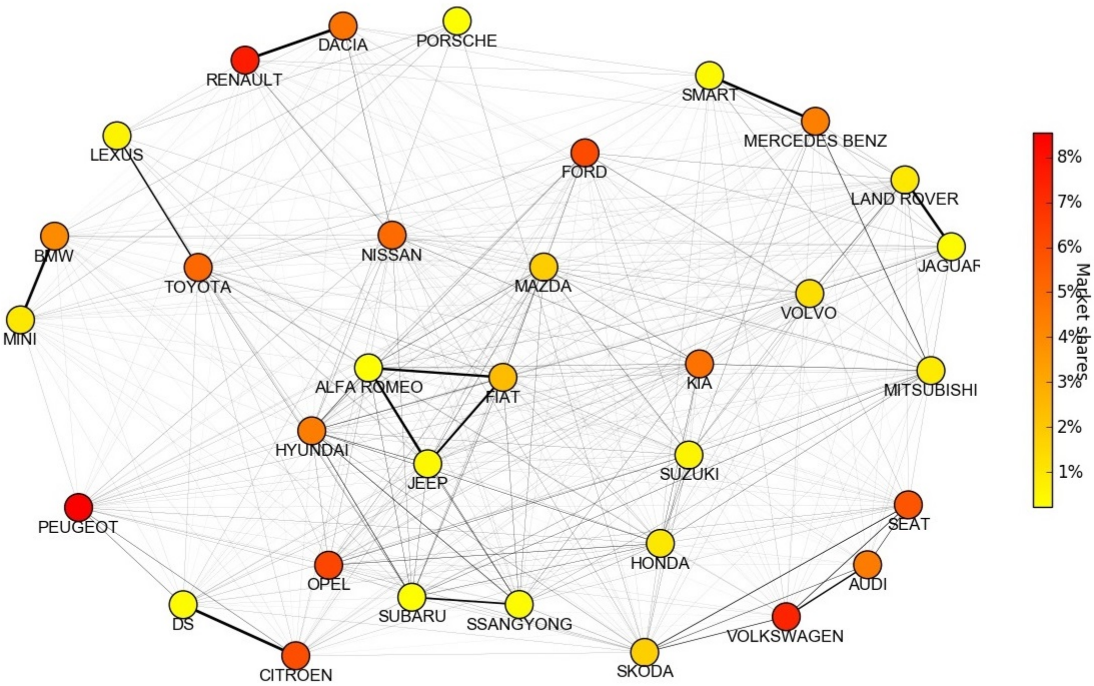

Figure 1.1: Shared dealership networks

Figure 1.1 summarizes general patterns in distribution networks. Node 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) indicate that common dealerships are substantially more likely between makes belonging to the same company - extreme cases are Renault/Dacia and Citroen/DS where distribution is 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 prominent among Asian car makes (Honda, Mazda, Hyundai, Subaru), most of which do not belong to any particular holding group and share more dealerships with more different brands than market leaders like Volkswagen or Renault.

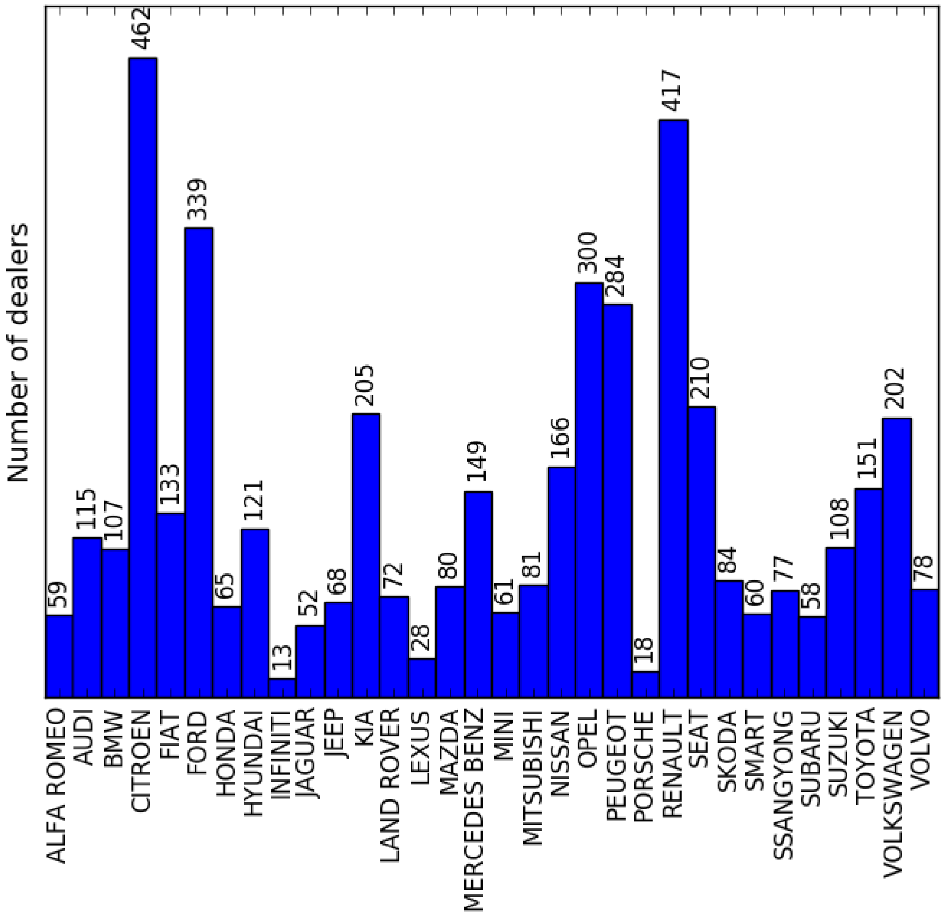

Figure 1.2: Number of dealerships per brand

Figure 1.2 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, Renault/Dacia have as many as 417 dealers in the whole territory whereas Volkswagen has 202 and their differences in sales are only 0.46 percentage points. Differences in dealer density are more pronounced in scarcely populated areas, where Renault/Dacia, Citroen/DS, and Peugeot are spread across provinces, whereas the rest of manufacturers are only present in urban areas.

These differences in geographic coverage are also reflected in Figure 1.3, where the points of sales for Honda, Volkswagen and Renault are plotted. Red points denote exclusive dealerships, while blue points are multi-dealerships. Another empirical regularity observable from Figure 1.3 is a larger tendency towards multi-dealerships in rural areas as compared to more densely populated areas. This tendency is normally attributed to the higher buyer power of the dealers present in these places due to the lower competition that they face.

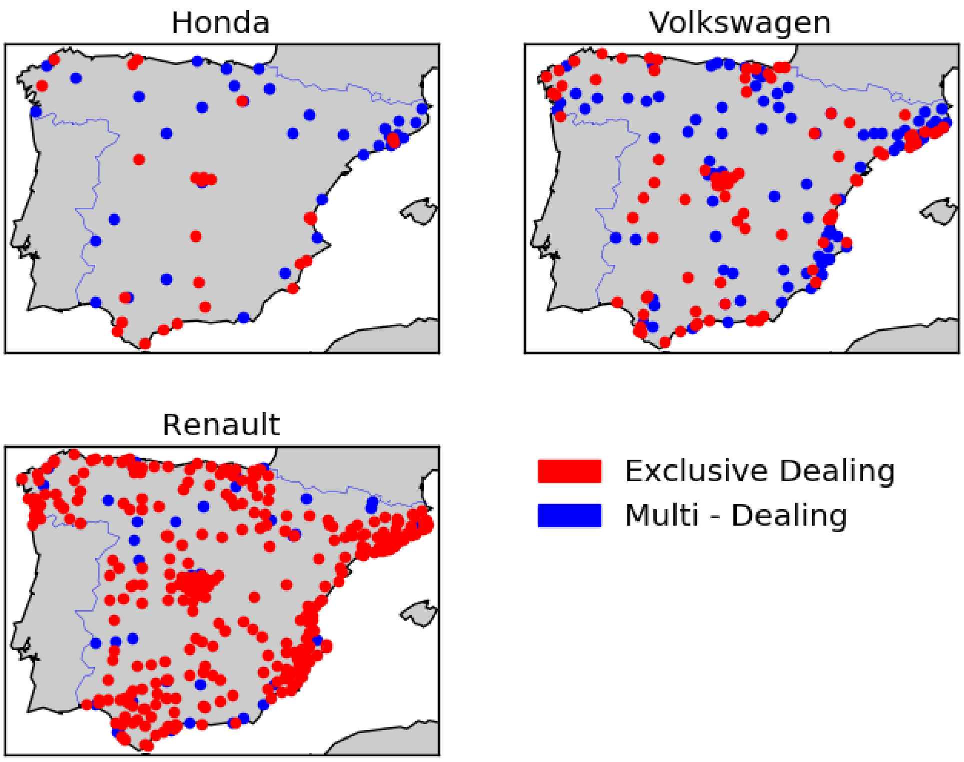

Figure 1.3: Exclusive and Non-Exclusive dealerships for Honda, VW and Renault

1.2.3 Geographic locations

One important consideration is how far consumers are willing to travel to purchase their cars. In order to incorporate this I use data on geographic positions at the municipality level from the National Geographic Institute (IGN). This dataset provides geocoordinates of the boundaries of each city. Using these boundaries, I drew a large number of random locations in each province. I weighted the draws by population size of each municipality within every market, so that the geographic distribution of consumers is consistent with the actual one within a province.

Table 1.3 shows the average simulated distance to the closest dealers for a number of brands in a number of provinces. The brands in the table have different levels of dealer density and are placed in the columns from most dense (Renault) to less

Table 1.3: Descriptive statistics of distance to closest dealer (in km)

	Renault	**Volkswagen**	**Mercedes**	**Mitsubishi**	**Infiniti**
Madrid	5.74	6.39	6.94	9.00	11.08
Barcelona	2.70	3.32	3.66	6.12	12.32
Murcia	8.51	12.19	12.86	15.21	23.93
La Coruña	7.28	8.05	12.95	14.92	23.87
Cáceres	15.39	21.54	22.85	35.43	148.44
Cuenca	23.34	25.70	24.75	46.25	98.75

dense (Infiniti). The provinces on the rows consist of the two most densely populated markets (Barcelona and Madrid), two middle sized provinces (Murcia and La Coruña), and two very sparsely populated provinces (Cáceres and Cuenca).

It is visible that highly populated areas have greater dealer supply, and thus transport distances are significantly shorter. This pattern is consistent across brands. However, the change in distances is more than proportional when departing from more to less populated areas. This fact confirms the previous observation that differences in dealer density are more pronounced in areas with less urban development.

1.3 Model

The model consists of four stages. In the first stage, dealerships draw costs and decide what brands to offer taking into strategic consideration their local competitors. After dealer configurations are determined in the first stage, manufacturers determine their wholesale prices in the second stage. In the third stage, manufacturers set cars' list prices. Finally, consumers purchase their cars.

The primitives of the model are the utility parameters, the marginal costs for each car model and the fixed costs of establishing a dealership. In what follows, I introduce the model starting from the demand side.

1.3.1 Demand

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

$$u_{ijdm} = \delta_{jm} + \mu_{ijm} + \gamma_{idm} + \epsilon_{ijdm},$$

where $\delta_{jm} = x'_{jm}\beta + \alpha p_j + \xi_{jm}$ is the base utility for product j in market m. This term contains observable car characteristics x_{jm} and p_j that include fuel consumption, size, engine power, and price. The characteristics also include dummy variables for province and country of origin of the car. I use these fixed effects to proxy for unobserved effects that are market and brand specific. The ξ_{jm} includes car attributes that are observed by the consumer, but unobserved to the econometrician.

The heterogeneity in consumers is captured by $\mu_{ijm} + \gamma_{idm} + \epsilon_{ijdm}$, which consists of the ϵ_{ijd}, idiosyncratic consumer disturbances that are assumed to be distributed according to a type I extreme value distribution. Heterogeneity in consumers' sensitivity to prices are captured in the interaction term $\mu_{ijm} = \sigma y_{im} p_j$, where y_{im} represents income of consumer i.

The term $\gamma_{idm} = \gamma_1 \mathrm{ED}_d + \gamma_2 \mathrm{dist}_{id}$ explains the heterogeneity in consumers' access to dealerships in their choice sets. I follow Nurski and Verboven (2016) and capture the impact of these characteristics by using two attributes: distance to the dealer and a dummy variable equal to 1 if the dealer is exclusive (ED_d). The exclusive dealing dummy contains any possible demand effects that exclusive retailing can induce, e.g., being more prestigious, delivering a better service or enjoying additional promotional efforts.

Geographical distance to dealerships is also included in Albuquerque and Bronnenberg (2012) and adds a spatial dimension to the model. Its coefficient explains the impact that traveling distance to a point of sale has on the utility of consumers. I anticipate that coefficient is negative, as in Nurski and Verboven (2016) and Albuquerque and Bronnenberg (2012), meaning that consumers value proximity to dealers.

While I observe sales at a very local level, the exact point of sale where transactions take place as well as consumers' residences are unknown to me, so I need to simulate them. I simulate random consumer locations in each market from a distribution that draws with higher probability locations from municipalities that are more populated.[8] I compute for each of these simulated locations the distance to every dealer to get $\mathrm{dist}(i, d)$, and I set ED_d equal to 1 if a dealer is exclusive and 0 otherwise.

An issue that arises with modeling purchases as a combination of product and dealer is that it expands the choice set for consumers exponentially, posing a substantial computational burden. I take a similar approach to Nurski and Verboven (2016) and assume the choice set to contain all possible car models from their clos-

[8]Consumers are assumed to be distributed uniformly within a municipality. This distributional assumption does not seem to be restrictive given that Spain is characterized to have numerous small municipalities.

est available dealer. This assumption reduces the choice set in each market to a maximum of 238 products.

Reducing the dealerships in the choice set to the nearest simplifies computation, but imposes restrictions. This assumption eliminates a large part of dealership competition within car brands because no consumer can take two dealerships selling the same car into consideration. Competition among two retailers dealing for the same brand boils down to the spatial dimension, i.e., which of the two is closer to a consumer[9].

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, I limit its effects 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 complete the discrete choice model of demand by introducing an "outside" option, which includes not purchasing a car, purchasing a car outside of the 238 models considered, or purchasing a car from a dealer-product combination outside of the ones allowed by the model. I assume this outside product to have a base utility that is normalized to zero, i.e., $u_{i0m} = \epsilon_{i0m}$.

Following Nevo (2001), I group parameters into $\theta_1 = (\alpha, \beta)$, and $\theta_2 = (\sigma, \gamma_1, \gamma_2)$. Assuming that consumers purchase their most preferred car, the distribution of unobservables y_i, $\text{dist}(i, d)$, ED_d, and ϵ_{ijdm} define the simulated individual choice probability. Let x_m, p, and δ_m denote the vectors containing x_{jm}, p_j, and δ_{jm} for every car j and market m, then

$$A_{jm}(x_m, p, \delta_m; \theta_2) = \{(y_i, \epsilon_{ijdm}, \text{dist}(i, d), \text{ED}_d) \mid u_{ijdm} \geq u_{ikdm} \; \forall k = 0, 1, ..., J_m\}$$

defines the set of unobservables for which product j is chosen. Given parameters, the market shares for each product are defined as

$$s_{jdm} = \int_{A_{jm}} \frac{\delta_{jm} + \mu_{ijm} + \gamma_{idm}}{1 + \sum_{k \in J} (\delta_{km} + \mu_{ikm} + \gamma_{idm})} dG_y(y) dG_d(\text{dist}, \text{ED}),$$

where the fraction term denotes the individual choice probability s_{ijdm}. Its formula comes from the assumed distribution function for ϵ_{ijdm}. The $G(\cdot)$ functions are the

[9] The coordination of competition within a distribution network is the focus of some theoretical papers (e.g. 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).

distribution functions for each unobservable. For simplicity, they are assumed to be independent of each other.

1.3.2 Price Competition

This part of the model follows the empirical literature that uses market data to infer marginal costs and upstream wholesale prices, (e.g. Sudhir, 2001; Brenkers and Verboven, 2006; Berto Villas-Boas, 2007). I assume that price setting takes place in two stages and that manufacturers set both. First, I assume that manufacturers set wholesale prices in order to maximize their profits. These wholesale prices are realized and observed. Subsequently, manufacturers set list prices such that retailers can extract a margin that is consistent with profit maximization.

Data limitations drive this assumption. I do not observe transaction prices, and therefore I use list prices to approximate them. Since there is one list price for each product across markets, manufacturers maximize the profits of the whole network of retailers so that, on average, retailers have incentives to comply with manufacturers' pricing instructions.

I explain the pricing of the model in an inverse order and start with the list prices. Let each dealership d have a profit function of the form

$$\pi_d = \sum_{m \in M} \sum_{b \in a_d} \sum_{j \in b} \left(p_j - p_j^w\right) \mathcal{M}_m s_{jdm}(\theta, p, a) - F_d(a_d),$$

where $\mathcal{M}_m$ is the size of market m in the set of all markets M. $q_{jdm} = \mathcal{M}_m s_{jdm}$ are the quantities of product j sold by dealer d in market m predicted by the demand model. I denote p_j and p_j^w as list and wholesale prices respectively.

I denote by $b \in B$ a brand in the set of all car brands. The set of brands that dealership d sells for is denoted by a_d, which is chosen from A_d - a subset of the power set of brands $\mathcal{P}(B)$. Finally, $a = (a_1, ...a_D)$ displays all brand offerings for all the dealers in the market, and $F_d(a_d)$ are the fixed costs of opening a dealership selling a_d. More detail on this will follow in subsections 1.3.3 and 1.4.

The profit function above yields list-pricing first-order conditions

$$\frac{\partial \pi_d}{\partial p_j} = \sum_{m \in M} \left(q_{jdm} + \sum_{b \in a_d} \sum_{k \in b} \left(p_j - p_j^w\right) \frac{\partial q_{kdm}(\theta, p, a)}{\partial p_j} \right) = 0 \text{ for all } j \in b \text{ and } b \in a_d.$$

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.

$$\sum_{d \in D} \mathbb{I}\{b \in a_d\} \cdot \frac{\partial \pi_d}{\partial p_j} = 0 \text{ for all } j \in b, \tag{1.1}$$

where $\mathbb{I}\{b \in a_d\}$ is an indicator variable that is equal to 1 if dealer d offers brand b (i.e., $b \in a_d$). From equation (1.1), one can rearrange its terms in matrix notation to get

$$q + \left(\sum_{d \in D} \Delta_d \right) (p - p^w) = 0, \tag{1.2}$$

where Δ_d is a $J \times J$ matrix where an element is equal to $\frac{\partial q_{jd}(a,\theta)}{\partial p_k} = \sum_{m \in M} \frac{\partial q_{jdm}(a,\theta)}{\partial p_k}$ if product j and k are sold by dealership d.

Notice that this expression is similar to the standard multi-product firms' pricing equations in many papers estimating demand (e.g. Berry, Levinsohn, and Pakes, 1995), except for the term including $\sum_{d \in D} \Delta_d$. In my model, this term emphasizes the role of dealer networks internalizing manufacturers' incentives. This conceptual difference can be best explained with an example. For two brands with integrated dealership networks (e.g., Renault and Dacia), the entries in this term are always going to be different from zero, and the sum is going to entail the same derivative as in a standard ownership matrix. In this case, integrated points of sale make compatible downstream pricing with common ownership. In general, common ownership is more prevalent in the pricing equation the more dealers the brands share.

Despite being restrictive, this modeling of list prices is sensible and captures a series of mechanisms that are important when studying exclusive dealing in a spatial market. First, notice that equation (1.1) is equivalent to the equilibrium condition arising from a model where all retailers set prices independently: p_j would still be the average retail price for product j. Second, list prices derived from these first order conditions capture the spatial dimension for product competition through the derivatives at the dealer level.

Finally, having solved for list prices, one can go back to the stage where wholesale prices are decided. Manufacturers' profit maximization for a firm f selling a series of brands b is

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

1.3.3 Entry

A dealer d in the pool of potential entrants E is located at l_d and chooses what brands to offer (a_d) from the set $A_d \subset \mathcal{P}(B)$. It can choose to offer one brand, e.g. $a_d = \{\text{Peugeot}\}$, or many brands, e.g. $a_d = \{\text{Peugeot, Suzuki, Subaru}\}$, or none, i.e. $a_d = \emptyset$. The last option corresponds to the case in which the entrant decides to stay out of the market. The set of entrants is $D \subseteq E$. Dealerships take their entry decisions a_d to maximize their expected profits given the choices of competing rivals $(\pi_d(a_d, a_{-d}))$ and their information set $\mathcal{I}_d$:

$$\max_{a_d \in A_d} \mathbb{E}[\pi_d(a_d, a_{-d})|\mathcal{I}_d] = \underbrace{\mathbb{E}\left[\sum_{m\in M}\sum_{j\in J_d} q_{jdm}(\theta, a)(p_j - c_j)\right]}_{\mathbb{E}[\text{VP}(a)]} - F_d(a_d). \tag{1.3}$$

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. I assume the fixed costs to have a simple function of the form

$$F_d(a_d) = \sum_{b\in a_d}(F_b + \nu_d^b) + \mathbb{I}\{|a_d| > 1\} \cdot C_{MD} + \nu_d^l, \tag{1.4}$$

where, as explained in the previous subsection, F_b is the cost dealership d faces when offering brand b and C_{MD} are the potential additional costs that can occur when dealing with more than one brand. They also include structural disturbances ν_d^b and ν_d^l which represent unobserved idiosyncratic cost components that dealer d observes, but that I do not. ν_d^b are unobservable shocks to fixed costs that depend on the brand choices of dealer d, while ν_d^l are unobservable components to dealers' locations. I assume that these costs are such that $\mathbb{E}\left[\nu_d^b\right] = \mathbb{E}\left[\nu_d^l\right] = 0$. This functional form is very simple, but the parameter C_{MD} accounts for potential jumps in the cost function when transitioning from exclusive dealing to multi-dealing.

The term $\mathbb{E}[\text{VP}(a)]$ denotes the expected variable profits of dealer d, and it entails two assumptions that facilitate estimation and are commonly shared in most applications (e.g. Holmes, 2011; Eizenberg, 2014; Houde, Newberry, and Seim, 2017). First, it implies that the expectations of the dealers are correct[10]. Second, it assumes that the dealers' information set does not contain any additional unobservable knowledge about its expected variable profits.

[10]Pakes (2010) and Pakes, Porter, Ho, and Ishii (2015) point out that a weaker condition on agents' expectations can also work. It is enough to assume that dealers do not have any systematic bias or deviation in their expectations. In other words, they can have wrong expectations, as long as they are not consistently wrong.

This profit function captures 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 into account. The estimated magnitude of the distance parameter in the demand determines, in turn, the relevant market for a dealership and the intensity of competition. If consumers are averse to driving far to buy a car, dealerships compete with each other locally, and more locally the higher this aversion is.

Multi-dealerships are more profitable in markets with higher isolation between points of sale as it allows the dealer to offer a more extensive selection of products and occupy a more substantial part of demand. In markets with a dense dealership structure, exclusive dealing is favorable in that (i) it reduces costs, allowing competitors to stay in the market even with smaller sales, and (ii) it differentiates dealerships from each other by offering different sets of products, relaxing competition (Besanko and Perry, 1994).

1.4 Estimation

I estimate the model in three steps. First, I estimate the demand parameters $\theta_1 = (\alpha, \beta)$, and $\theta_2 = (\sigma, \gamma_1, \gamma_2)$. Using these estimates, I back out product unobservable characteristics $\hat{\xi}_{jm}(\hat{\theta}) = \delta(\hat{\theta}_2) - X_{jm}\beta + \alpha p_j$ and manufacturers' wholesale prices. Finally, I use all previous estimates together with equilibrium condition to estimate bounds on fixed costs and its parameters $F = (F_1, ..., F_B, C_{MD})$.

1.4.1 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, BLP). 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 (Henceforth GMM, Hansen, 1982) using 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 order to control for potential correlation between unobservables ξ_{jm} and prices p_j, I use the set of instruments proposed in Berry, Levinsohn, and Pakes (1995). These BLP instruments include own car characteristics, sums of characteristics from the same manufacturer, and sums of car characteristics for rival products. I classified all car models into their market segments and performed these operations within segments for additional variation.

In addition to the BLP instruments, I incorporate as instruments neighboring demographics and rival dealer characteristics similar to Fan (2013) and Gentzkow and Shapiro (2010). These "Waldfogel" instruments (Waldfogel, 2003; Berry and Haile, 2009) make use of the geographic nature of dealer competition and modeling. For any dealership, its rival points of sale are those for which there exists at least one simulation draw with both of them in its choice set. Given this definition, I use as an instrument for a product in a dealership the demographics of simulation draws that have some of its rivals in their choice set, but not the original dealership.

The intuition of these instruments can be best described 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.

I require an additional assumption on the choice set of consumers to use the BLP instruments for the reason that their identification hinges on changes in the characteristics of rival products (Berry and Haile, 2014). I let the choice set of consumers be all models available at less than 80 kilometers of distance[11]. This assumption is sensible in the light of the very few cars that are bought from brands that are located far away and the low number entries that are registered in a province other than the one of purchase. It is also in line with empirical evidence, Murry

[11] I performed robustness checks with 60 and 70 kilometer and they did not present any strong difference.

and Zhou (2017) observe that less than 5% of car purchases take place at a distance further than 48 kilometers.

Finally, it is important to note that, as in most of the literature on endogenous product characteristics, estimating demand on observed dealerships might suffer from selection. This issue arises because choosing a brand for which to retail might be correlated with unobservable characteristics of the products offered by it. 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.

1.4.2 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 parameters. The collection of all residuals ξ for a given product over all markets (i.e., the set $\{\xi_{jm}(\hat{\theta})\}_{m\in M}$), defines the empirical distribution function for the unobservables of that product that I use later for the simulation of expected variable profits.

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. Following Section 1.3.2, I use the equality in equation (1.2) to solve for the vector of wholesale prices p^w given the vector of list prices (p), the realized profile of brand offerings (a), demand parameters ($\hat{\theta}$), and the inferred unobservables ($\hat{\xi}_{jm}$)

$$p^w = p + \frac{q}{\sum_{d\in D} \Delta_d}.$$

I compute the product derivatives over prices at the dealer level approximating them via Monte Carlo integration. The derivatives are given by

$$\frac{\partial q_{jdm}(a, \hat{\theta})}{\partial p_k} = \mathcal{M}_m NS^{-1} \sum_{i}^{NS} \mathbb{I}\left\{d \in J_i\right\} \frac{\partial s_{ijdm}(a, \hat{\theta})}{\partial p_k},$$

where aside from previously introduced notation, I denote $\mathbb{I}\left\{d \in J_i\right\}$ an indicator function equal to 1 when dealer d is in the choice set of consumer i (characterized by J_i).

1.4.3 Estimation of fixed costs

I follow the literature using profit inequalities to estimate fixed costs (Ciliberto and Tamer, 2009; Pakes, 2010; Pakes, Porter, Ho, and Ishii, 2015). This approach flexibly accommodates multiplicity of equilibria and large action spaces. However, this comes at the expense of partial identification of fixed costs. In what follows, I describe the assumptions necessary to estimate the parameters in (1.4).

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*

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

Assumption 1 describes the common equilibrium assumption for this subgame. It says that if a vector of dealership choices is observed in the data, these actions are profit maximizing and hence no unilateral deviation could make them better off. This assumption is common to the literature. This best response condition delineates the principle on which the moment inequality conditions of this estimation strategy are built. That is, I add (and subtract) brands to the observed offerings in order to estimate bounds on the parameters.

The presence of structural disturbances ν_d^l, ν_d^b reconciles differences between the model predictions and observed actions. However, a problem of selection arises in that 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 circumvent the selection problem occurring with ν_d^b. In essence, I create counterfactual inequalities that hold no matter what decision retailers make in order to be able to use the unconditional expectation of ν_d^b. Since $\mathbb{E}[\nu_d^b] = 0$, these unconditional moments eliminate the selection effect. Let $a_d^{b-} = a_d \backslash \{b\}$, and $a_d^{b+} = a_d \cup \{b\}$.

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 $dist(d, \tilde{d}) < L$ 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*

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

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

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

There are two points to note about Assumption 2. First, it specifies the area close to a dealer offering a specific brand (henceforth neighboring area). In these neighboring areas, the demand for a product of this brand is very similar for the original dealer as it would be for any neighboring dealer, should they also offer it. Logically, if a dealership is observed to be in a location, it means that there is enough demand around that area to sustain that dealership.

The spatial structure of the model implies that, in equilibrium, neighboring dealers normally tend to choose brands that their rivals are not choosing. This aspect is implied by the fact that, if two points of sale cannot relax their competition in the model through location choices, they are going to do so by their product offerings. This anti-coordination motive between dealers best responses could likely lead to a multiplicity of equilibria where the brand offerings are kept fixed, but what dealer offers which brand can be permuted.

It is useful to consider an illustrative example. In a completely isolated market with two dealerships and two brands (e.g., Renault and Seat), assume that the first dealership offers Renault and the second offers Seat. It is likely that, if the dealerships are similar in their observables, there is also another candidate equilibrium where the first dealership offers Seat and the second Renault. A dealership might not find it profitable to offer a brand (e.g. Seat) because there is another Seat dealer neighboring, but it might find it profitable were that competitor not offering Seat.

The second part of assumption 2 assures that there exist alternative profiles for which these profitable deviations can exist regardless of the unobservable ν^b_d within these neighboring areas. Assumption 2 basically states that, in these areas, any dealership could potentially deal for this brand profitably (unprofitably) if intra-brand retail competition is sufficiently relaxed (tightened). The radius of maximum geographic distance (L) for neighboring retailers 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.

Following the previous example, the assumption states that the neighboring dealership will surely find profitable to offer Seat if the rival dealer did not offer Seat and he was the unique dealer for that brand in a large area (a^{b-}_d).

I use the two assumptions to construct moment conditions that do not suffer from selection. The strategy I employ consists of first creating a function that subtracts a given brand b from each dealership whenever it is possible, i.e., when that brand is offered. For dealers for which the brand is not offered, I create a multilateral deviation for which they could potentially offer b. This deviation is a perturbation of the equilibrium play because it subtracts brand b from all local competitors within a radius L[12] in order to make the choice of b attractive to these dealers. I finally select those observations that offer b profitably with a weight function and average over dealers to construct moment conditions. I repeat the same procedure in the opposite direction, i.e., adding a brand if possible and creating multilateral deviations if not, and for all brands.

Let $\Delta x\left(a_d, a'_d; a_{-d}\right)$ be defined as $x\left(a_d, a_{-d}\right) - x\left(a'_d, a_{-d}\right)$ for a function x and any $a_d, a'_d \in A_d$. I construct the function $\Delta r^u_b(a_d, a^{b-}_d, a_{-d})$ as

$$\Delta r^u_b(a_d, a^{b-}_d, a_{-d}) = \begin{cases} \mathbb{E}\left[\Delta \mathrm{VP}_d(a_d, a^{b-}_d; a_{-d})\right] - F_b - \mathbb{I}\left\{|a_d| \neq 2\right\} \cdot C_{MD}, & \text{if } b \in a_d, \\ \mathbb{E}\left[\Delta \mathrm{VP}_d(a^{b+}_d, a_d; a'_{-d})\right] - F_b - \mathbb{I}\{|a^{b+}_d| \neq 2\} \cdot C_{MD}, & \text{if } b \notin a_d, \end{cases} \tag{1.5}$$

where $\mathbb{I}\left\{|a_d| \neq 2\right\}$ is an indicator function equal to 1 if dealer d offers a quantity of brands (denoted as $|a_d|$) different from 2. These indicators multiply the multi-dealing costs, which are only relevant in the fixed costs function (1.4) whenever a dealership transitions from selling for one brand to selling for two brands, or vice versa.

For a dealership d, I define it to be in the neighborhood of b if there is another dealer d' selling b within a distance L from d. This definition is formalized by

$$\mathcal{N}^L_b = \left\{d \in D \mid \mathrm{dist}(d, d') < L \text{ for some } d' \in D \text{ such that } b \in a_{d'}\right\}.$$

With these neighborhoods, I construct the weight functions $g^1_d(b, a_d, a_{-d})$ and $g^2_d(b, a_d, a_{-d})$ with which I define two sets of B moment conditions. In particular, let g^1_b and g^2_b be

$$\begin{aligned} g^1_d(b, a_d, a_{-d}) = &\quad \mathbb{I}\{b \in a_d\} \cdot \mathbb{I}\{|a_d| \neq 2\} + \mathbb{I}\{b \notin a_d\} \cdot \mathbb{I}\{d \in \mathcal{N}^L_b\} \cdot \mathbb{I}\{|a^{b+}_d| \neq 2\}, \quad \text{and} \\ g^2_d(b, a_d, a_{-d}) = &\quad \mathbb{I}\{b \in a_d\} \cdot \mathbb{I}\{|a_d| = 2\} + \mathbb{I}\{b \notin a_d\} \cdot \mathbb{I}\{d \in \mathcal{N}^L_b\} \cdot \mathbb{I}\{|a^{b+}_d| = 2\}. \end{aligned} \tag{1.6}$$

The weight functions in (1.6) basically selects observations that lie within a $\mathcal{N}^L_b$ and divides them into two groups. The first one has all observations that do not transition from 2 to 1 brands in equation 1.5, and thus only carry information about the component F_b in the fixed costs. The second one contains the observations that

[12]The results I report use L=15 kilometers, but they are robust to radius of 1, 5, 10, 20 and 30 kilometers.

transition from 2 to 1 brands when a brand is taken. These ones contain information about F_b and C_{MD}. Using (1.5) and (1.6), I construct the moment conditions

$$\begin{aligned} m_b^1 =& \quad |D|^{-1} \sum_{d \in D} g_d^1(b, a_d, a_{-d}) \Delta r_b^u \left(a_d, a_d^{b-}, a_{-d}\right) \geq 0, \quad \text{and} \\ m_b^2 =& \quad |D|^{-1} \sum_{d \in D} g_d^2(b, a_d, a_{-d}) \Delta r_b^u \left(a_d, a_d^{b-}, a_{-d}\right) \geq 0, \end{aligned} \tag{1.7}$$

for i.i.d. disturbances provided that the terms $|D|^{-1} \sum_{d \in D} g_d^1(b, a_d, a_{-d}) \cdot \nu_d^b$ and $|D|^{-1} \sum_{d \in D} g_d^2(b, a_d, a_{-d}) \cdot \nu_d^b$ vanish to 0 following the law of large numbers.

Similarly, I also define moments that determine the lower bounds for the parameters in a similar but opposite manner by defining function $\Delta r_b^l(a_d, a_d^{b+}, a_{-d})$, and weights $g_d^3(b, a_d, a_{-d})$ and $g_d^4(b, a_d, a_{-d})$ as

$$\Delta r_b^l(a_d, a_d^{b+}, a_{-d}) = \begin{cases} \mathbb{E}\left[\Delta \text{VP}_d(a_d^{b-}, a_d; a'_{-d})\right] - F_b - \mathbb{I}\{|a_d^{b-}| > 1\} \cdot C_{MD}, & \text{if } b \in a_d, \\ \mathbb{E}\left[\Delta \text{VP}_d(a_d, a_d^{b+}; a_{-d})\right] - F_b - \mathbb{I}\{|a_d| > 1\} \cdot C_{MD}, & \text{if } b \notin a_d, \end{cases} \tag{1.8}$$

$$\begin{aligned} g_d^3(b, a_d, a_{-d}) =& \quad \mathbb{I}\{b \in a_d\} \cdot \mathbb{I}\{d \notin \mathcal{N}_b^L\} \cdot \mathbb{I}\{|a_d^{b-}| > 1\} + \mathbb{I}\{b \notin a_d\} \cdot \mathbb{I}\{|a_d| > 1\}, \quad \text{and} \\ g_d^4(b, a_d, a_{-d}) =& \quad \mathbb{I}\{b \in a_d\} \cdot \mathbb{I}\{d \notin \mathcal{N}_b^L\} \cdot \mathbb{I}\{|a_d^{b-}| = 1\} + \mathbb{I}\{b \notin a_d\} \cdot \mathbb{I}\{|a_d| = 1\}. \end{aligned} \tag{1.9}$$

In this case, the critical inequality to identify the potential cost of multi-dealing is when adding a brand to an exclusive dealer. Converse to (1.6), the weight functions in (1.9) select all the observations that do not have $b \in a_d$ and add to them those that are unprofitable using Assumption 2. Using (1.8) and (1.9), I form the B moment inequalities

$$\begin{aligned} m_b^3 =& \quad |D|^{-1} \sum_{d \in D} g_d^3(b, a_d, a_{-d}) \Delta r_b^l(a_d, a_d^{b-}, a_{-d}) \geq 0, \quad \text{and} \\ m_b^4 =& \quad |D|^{-1} \sum_{d \in D} g_d^4(b, a_d, a_{-d}) \Delta r_b^l(a_d, a_d^{b-}, a_{-d}) \geq 0. \end{aligned} \tag{1.10}$$

These inequalities also hold provided that the terms $|D|^{-1} \sum_{d \in D} g_d^3(b, a_d, a_{-d}) \cdot \nu_d^b$ and $|D|^{-1} \sum_{d \in D} g_d^4(b, a_d, a_{-d}) \cdot \nu_d^b$ converge to 0.

The way moment inequalities (1.7) and (1.10) are constructed resembles Eizenberg (2014) on one side, and Pakes (2010) on the other. Eizenberg (2014) proposes an estimate that overcomes selection by replacing the missing values with conservative estimates of them. In his case, he uses the maximum and minimum of the differences in expected profits for the observed cases as an estimate to the missing upper and lower bounds. My approach shares some similarities in that it also approximates the value of unobserved choices and it does so conservatively. However, the big action set that dealers face in my game and the geographic component of supply and demand in the model do not allow this approach to yield any kind of informative result. This problem might be better described with an example. Following Eizenberg (2014), the fixed cost for a Nissan dealer will have 166 observed upper bounds and around 3,200 that are estimated to be the upper bound of these 166. Furthermore, this upper bound might come from a Nissan dealer in Barcelona or Madrid, which does not correspond to the possible expected revenues in less densely populated areas. The empirical content of such an estimate might come from below 5% of the observations.

Pakes (2010) discusses several ways to overcome selection. One these strategies uses unconditional averages due to inequalities that hold no matter what decision the agent has made[13]. My assumption is also formulated independent of agents own choices, but instead uses that of neighbors, which should not be inducing selection if these errors are independently distributed. Using this assumption, I can be conservative on which dealerships can eventually profitably offer products of a brand and still account for selection. While it is easy to justify that a Volkswagen dealer could eventually be profitable in some local geographic position in Barcelona, it is difficult to justify the same for an Infiniti dealer in Cáceres. Table 1.3 shows that the average consumer in that province needs to travel 148.44 kilometers to its closest point of sale of that brand. These traveling times imply that, so far, no dealership found offering Infiniti profitable there, even having no local rival.

In addition to these moments, I employ other moment inequalities based on Ho and Pakes (2014). I pair couples of observations d_1 and d_2 where d_1 subtracts brand b while d_2 adds it in order to form additional moments to identify C_{MD}. In order to avoid selection in these moments, I pair couples of equations in (1.5) and (1.8) to define

$$\Delta w(d_1, d_2, b) = \Delta r_b^u(a_{d_1}, a_{d_1}^{b-}, a_{-d_1}) + \Delta r_b^l(a_{d_2}, a_{d_2}^{b+}, a_{-d_2}), \tag{1.11}$$

which I combine with Assumption 1 and Assumption 2 and the weight functions defined before to form

$$\begin{aligned} m^5 = \quad & NM^{-1} \sum_{b \in B} \sum_{d_1 \in D} \sum_{d_2 \neq d_1} g_{d_1}^2(b, a_{d_1}, a_{-d_1}) g_{d_2}^3(b, a_{d_2}, a_{-d_2}) \Delta w(d_1, d_2, b) \geq 0, \quad \text{and} \\ m^6 = \quad & NM^{-1} \sum_{b \in B} \sum_{d_1 \in D} \sum_{d_2 \neq d_1} g_{d_1}^1(b, a_{d_1}, a_{-d_1}) g_{d_2}^4(b, a_{d_2}, a_{-d_2}) \Delta w(d_1, d_2, b) \geq 0, \end{aligned} \tag{1.12}$$

[13]see assumption PC4b in Pakes (2010)

where NM denotes the total number of matches formed. Intuitively speaking, moments in (1.12) select observations that transition from multi- to exclusive dealer dropping one brand with some multi-dealer that adds that brand. The average of these pairings should be bigger than or equal to zero if we take into account equations (1.7) and (1.10). However, these new inequalities only depend on C_{MD} and add a further restriction by matching independent observations.

For the estimation of parameters $F = (F_1, ..., F_B, C_{MD})$, I define $m(F)$ to be the vector containing moments $[m_1^1, ..., m_B^1, ..., m^6]$. The identified set of parameters must satisfy each of these inequality or, equivalently, be a part of the space of parameters minimizing the objective function

$$\left[m(F)_{\_}\right]' \Sigma(F)^{-1} \left[m(F)_{\_}\right], \tag{1.13}$$

where equation (1.13) is similar to the objective function in Chernozhukov et al. (2007). $m(F)_{\_}$ is a loss function that is different from zero whenever $m(F)$ is below 0, and it is 0 otherwise. $\Sigma(F)$ is the variance covariance matrix for the moments [14].

I use the method developed in Andrews and Soares (2010) to construct confidence sets that contain the true F_o in 95% of the cases. In practical terms, this methodology includes in the confidence set all vectors of parameters whose test statistic cannot reject the null hypothesis that these vectors are equivalent to the true parameter F_o. The acceptance and rejection regions are delimited by the 95% percentile of the distribution of test statistics from a large number of bootstrapped subsamples. In my application, I set the bootstrap subsamples to be one fourth of the total sample (subsample size of around 836 observations), and the number of bootstrap repetitions at 10,000.

I perform a search for parameters in the confidence sets as a problem of constrained optimization where, starting from a value within the set, I look for the minimum and maximum values for each parameter independently subjected to the vector not being rejected by the test. Since the set of parameters is large, I cannot search for all parameters at the same time and I tackle this issue in two steps. In a first step, I pair moments including pairs of parameters (F_0, C_{MD}), (F_1, C_{MD}), ..., (F_B, C_{MD}) and perform a search for parameters independently. From the first step optimization, I collect the sets $\underline{C} = \{\underline{C}_0, ..., \underline{C}_B\}$ and $\overline{C} = \left\{\overline{C}_0, ..., \overline{C}_B\right\}$. Clearly,

[14] In this application, I assume all off-diagonal entries to be zero. i.e. I do not take correlation across moments into account.

pairs of F_b and C_{MD} such that

$$C_{MD} \in \left[\sup \underline{C}, \inf \overline{C}\right] \tag{1.14}$$

were accepted for all optimization in the first step. In the second step, I search for parameters in the same pairs as in the first step, but with the bounds defined in (1.14) as additional constraints on the parameters.

1.4.4 Computing expected variable profits

In Subsection 1.4.3, I laid out the estimation strategy for fixed costs. This procedure requires knowledge of the expected variable profits for each dealership. I simulated these profits for both the observed equilibrium and the perturbed strategy profiles using inferred margins, demand estimates and demographic data.

In the first step, I reorganize the dealerships according to the profile to be simulated. In the case of $\mathbb{E}[\text{VP}(a)]$ no change is needed, while for unilateral perturbations $\mathbb{E}[\text{VP}(a_d^{b-}, a_{-d})]$ or $\mathbb{E}[\text{VP}(a_d^{b+}, a_{-d})]$ the change is simply subtracting or adding a point of sale[15] respectively. When simulating multilateral perturbations $\mathbb{E}[\text{VP}(a_d^{b+}, a_{-d}^{b-})]$, I subtract brand b for all dealers within a circle of 15 kilometers around dealer d and add the brand to it.

After reorganizing dealers' offerings, I recalculate the distances from the simulated consumer locations to dealerships for each brand. Two additional assumptions are used in order to simulate individuals and their purchase decisions: (i) I assume that consumers are allocated uniformly within a municipality given a large set of simulated locations, and (ii) I use the recovered empirical distribution function of ξ, where these ξ are jointly distributed for all products across markets.

The simulation process for consumer purchases is as follows. First, I draw ξ_{jm} for each product in each market. Second, I draw locations and other demographics for each individual in every municipality within each market. For every simulated individual, I also draw disturbances ϵ_{ijmd} for each product from a Type 1 Extreme Value distribution. With these draws I assemble consumers' utility and compute the car purchases for each individual as the utility maximizing product that yields a utility higher than 0. This procedure is repeated a total of NS times.

Since all of these simulations are done in order to get the expected variable profits for some particular dealership, I can make some simplifications that reduce

[15] These changes may also entail a change in exclusivity status along the process, which is considered.

the computational expenses from these operations. First, I do not have to compute sales for municipalities where dealer d is not in any choice set. Furthermore, I do not need to simulate the purchases for products not sold in this dealership. It suffices to find one product (or outside option) yielding a higher utility than any of the products sold by this dealer in order to finish the simulation for an individual that does not buy from d. This practical shortcut is substantially less computationally intensive than finding the utility maximizer of the products sold by other dealers.

Finally, I calculate expected variable profits by multiplying inferred margins by the sales for each product, and average it over the number of simulations.

1.5 Results

1.5.1 Demand estimates and inferred margins

Table 1.4: 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 1.4 presents demand estimates for different specifications. Column (1) is the baseline Logit without any random coefficients. Columns (2) and (3) add dealership characteristics. Column (4) includes all dealer variables (exclusivity and

distance) and interactions of price with income. It is the specification used for the supply side estimates.

In line with intuition, the coefficients for distance and price are negative and significant across the different specifications. Consumers dislike paying more for their cars and traveling longer distances. The positive sign of the interaction term of income with price means that demand becomes less sensitive to price as income increases. According to the estimates, for a consumer with an annual income of €20,000, a price increase of €1,000 for a car has a comparable effect to 6.07 kilometers of additional travel distance to the point of sale for this car. Exclusivity enters positively in specification (3), but loses significance when income random coefficients are added in column (4).

The rest of parameters have signs in line with what is expected: fuel consumption reduces the utility for the car while size has a positive sign. Horsepower over weight has a changing sign and it appears to be not significant in many of the specifications.

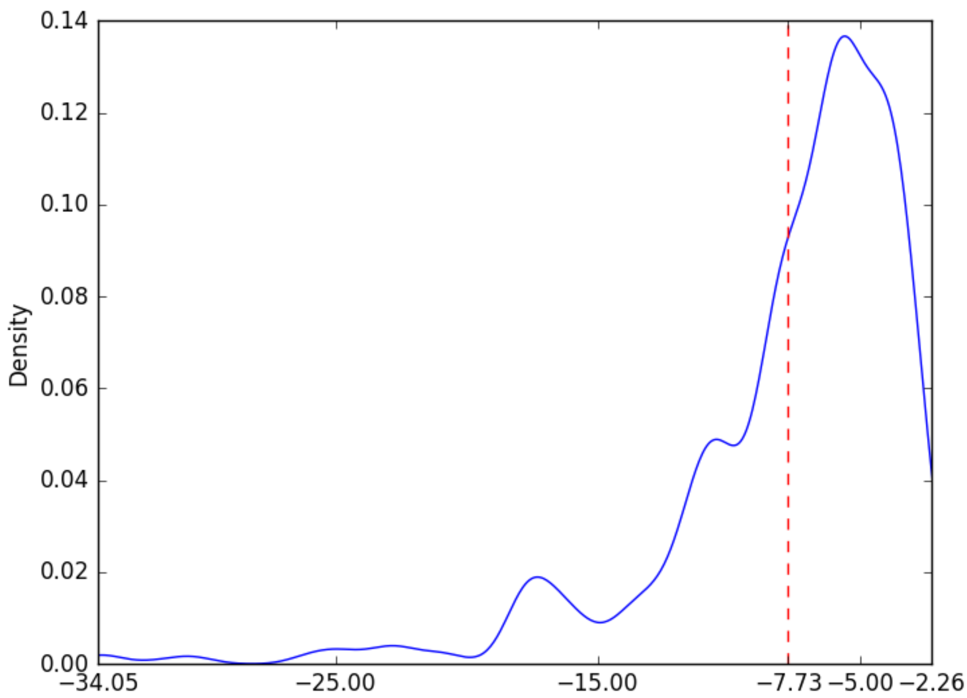

Figure 1.4: Distribution of elasticities at local markets

Figure 1.4 represents the distribution of own price elasticities for the different products and markets, while Table 1.5 shows which car models are pricing at the highest and lowest elasticity segments. Aside from luxurious cars, most of the local elasticities oscillate between -15% and -2.26%, with an average of -7.73% (median

Table 1.5: Top 5 Highest and Lowest Elasticities

Brand	Model	Elasticity	Brand	Model	Elasticity
Highest 5 Elasticities			**Lowest 5 Elasticities**		
Land Rover	Range Rover	-33.78	Dacia	Dokker	-2.56
Porsche	Panamera	-30.70	Ford	Ka	-2.48
BMW	Serie 6	-25.75	Dacia	Logan	-2.33
Mercedes	Clase S	-24.62	Dacia	Sandero	-2.30
BMW	Serie 7	-23.05	Skoda	Citigo	-2.30
Median					
Volkswagen	Beetle	-6.39			
Mini	Paceman	-6.30			

6.30%) decrease in demand for a 1% price increase. Whereas demand estimates show that distance has a sizable effect on utility, most elasticity differences across products are driven by prices.

Figure 1.5 shows the inferred marginal costs and margins for all cars. On the horizontal axis there are all car models ordered by price. The blue bars are all the inferred marginal costs, whereas the red area on top of them are the margins. The relatively small magnitude of the utility estimates for all car characteristics except price imply a relatively constant markup in absolute terms, or in other words, a markup that proportionately reduces as car list prices increase. The average markup is around €3,130.

1.5.2 Fixed Costs' estimates

Table 1.6 reports the fixed costs' estimates for the model. Columns Upper and Lower report the bounds corresponding to the 95% confidence set for these parameters. The confidence sets for the different brand related cost components show a very large difference across brands. In all cases, these bounds are relatively large, but in most cases they are bounded away from zero. Brand cost can be separated into three groups: brands like Alfa Romeo, Ssangyong, Subaru and Suzuki, whose costs are rather small (below €1 million) and their intervals not very wide; middle brands, with wider parameter intervals and higher upper bounds (e.g. Ford, Hyundai, Opel, Nissan, below €7 million). Finally, the third group is composed by popular brands and higher class manufacturers (e.g. Audi, BMW, Peugeot, Volkswagen, Mercedes) and their fixed costs can exceed the €7 million.

The parameter for the cost of multi-dealing is negative, but not significantly dif-

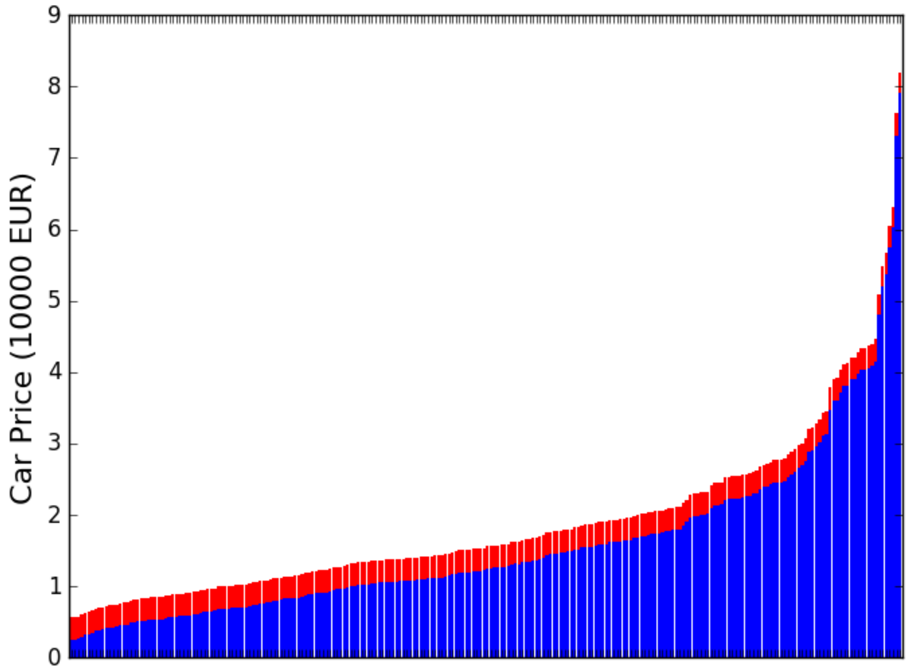

Figure 1.5: Distribution of dealer expected margin by car

ferent from zero. This result rejects the hypothesis that manufacturers use exclusive contracts to deter other brands from their points of sale by raising their costs to offer products from other manufacturers. It is dealerships who choose to deal exclusively in their trade-off between differentiating from rival dealerships and offering more products.

The results in Table 1.6 are robust to different radius for the neighboring dealers and they also do not seem to vary substantially under alternative algorithms. A natural robustness check is to perform in the first step the parameter search jointly for several brands, instead of doing these searches parallely, in order to account for potential correlations remaining unaccounted by the estimates. I tested several of these combinations without finding qualitative differences.

Another potential concern with these estimates arises from the side of the specification. It is plausible to think that some manufacturers might have more power or more interest in raising costs than others, and therefore the parameter C_{MD} captures an average cost of multi-dealing across brands. Accommodating this heterogeneity across groups of brands is possible, although it would entail a reformulation of the moment conditions in (1.7) and (1.10) so as not to count the C_{MD} twice.

Table 1.6: Fixed costs' estimates (in €10,000)

	Lower	Upper		Lower	Upper
Alfa Romeo	10.3750	112.3477	Mini	31.0048	233.3680
Audi	248.9550	967.3268	Mitsubishi	57.6487	253.7285
BMW	240.7112	1427.9737	Nissan	105.1268	453.3960
Citroen	158.1234	409.9916	Opel	112.3373	473.0761
Fiat	31.8118	199.4893	Peugeot	232.2222	982.2118
Ford	109.0567	382.4699	Porsche	1049.9087	5929.1565
Honda	35.2027	221.0466	Renault	314.3647	950.5661
Hyundai	110.0356	515.8113	Seat	243.6576	840.3873
Infiniti	43.2850	299.4948	Skoda	63.6640	367.2605
Jaguar	90.1613	601.0930	Smart	-9.9428	60.6519
Jeep	37.5273	266.4081	SsangYong	17.8420	118.3771
KIA	114.6440	580.4779	Subaru	1.9487	78.3876
Land Rover	116.1576	623.2758	Suzuki	15.3060	98.6510
Lexus	20.3505	35.8169	Toyota	117.6452	443.0447
Mazda	86.8278	440.2257	Volkswagen	213.7001	746.6376
Mercedes	248.3775	906.8245	Volvo	92.0989	499.0274
			Multi-Dealing	-62.5631	1.1340

1.6 Concluding Remarks

This paper has added to the debate on the potential anticompetitive effects of exclusive dealing from an empirical perspective. I estimated a structural model that combined demand and supply, and incorporated the manifold effects of exclusivity. Exclusive contracts can boost demand through increased promotional effort and better dealer service, but it can also be used to raise the fixed costs of distributing for rival brands, and deter competition from other brands within dealers. Moreover, exclusive dealing can be used by dealers as a means to differentiate from their local competitors. In order to capture this differentiation motives, my model extended the literature allowing for dealers to choose the brands that they sell endogenously.

For estimating this model, I assembled a novel dataset that combines information on car sales and car retailers from Spain. These data contain sales for a large number of car models in the market, and the specific location and brand offerings for all the dealers for the 32 most popular car brands in the country.

Furthermore, my estimation of the supply side contributed to the recent literature using moment inequalities to estimate fixed costs. In particular, I proposed a way how to circumvent the potential selection on unobservables that might happen when using equilibrium choices to estimate parameters. My approach is well-suited to spatial markets and it can be used in problems where the agents have large action spaces. It is based on using counterfactual dealer offerings for those observations that are selected out in order to account for them.

The results of my estimation suggest that (i) there are no particular effects in utility derived from exclusive dealing, (ii) there are no sizable costs additionally when multi-dealing. These two findings lead to conclude that (iii) spatial competition among downstream competitors creates the conditions for which they take up exclusive dealing in order to differentiate from their rivals in the products they offer. These conclusions are in line with the Chicago school view that exclusive contracts are not anticompetitive because they are not used to exclude rivals, and have large implications for regulatory policy in retail markets.

Two questions for future research are whether there actually exist difficulties for smaller manufacturers to access to retailing points, even if driven by competitive forces, and, if so, what is the impact of this exclusion on welfare. The model and estimation of this paper laid the foundations to answering questions of this kind, and more generally to analyze the effects of vertical restraints on market structure and product variety.

Chapter 2

Exclusive Territories and Brand Proliferation: A Simulation Study

2.1 Introduction

Vertical restraints are subject of much interest and debate for policy-makers and researchers both in the U.S. and in Europe. However, the regulation and study of them are complex. It is difficult to know the kind of relationship in which parties are formally engaging because vertical contracts are usually private. Furthermore, such agreements typically include several restraints, so it is hard to analyze the effect of each of them in isolation. These issues are present in the empirical literature, where researchers are forced to proxy vertical restraints with other variables. Nevertheless, they are also pervasive in the theory literature, where most papers analyze the effect of one restraint at a time, limiting the validity of their predictions.

In this paper, I use the model and estimates from Cattaneo (2018) to simulate counterfactual market configurations under a combination of vertical restraints. In particular, I evaluate the consequences that relaxing local competition through exclusive territories would have in terms of exclusive dealing and gaining access to points of sale by smaller manufacturers.

Most of the regulation regarding the distribution of new cars in the past few years was aimed at facilitating the access to points of sale to smaller manufacturers while allowing all manufacturers to establish their networks flexibly. The ultimate goal of such regulations is to prevent an anti-competitive use of distribution networks and guarantee competitiveness in the market. For this purpose, a policy study that introduces products from smaller manufacturers for commercialization at different dealers in an exogenous fashion (as in Nurski and Verboven, 2016) might prove successful at fulfilling this aim. However, it ignores that these dealers could have potentially commercialized these products before and decided not to.

In contrast, I introduce a policy that relaxes competition by restricting brand choices and let the dealers form the new distribution networks in equilibrium play. In so doing, any change in the reach of the distribution network of smaller manufacturers is an endogenous consequence of the model.

Moreover, evaluating such a policy is interesting from a regulatory stance. The framework and estimates in Cattaneo (2018) suggest that local competition could potentially play an essential role in the use of exclusive dealing and access to points of sale by smaller manufacturers. The intervention that I analyze in this paper bears a resemblance to exclusive territories in that it grants intra-brand territorial protection to dealers by restricting neighboring dealers' choices of brands. These practices are, in general, accepted in the European market. However, they are prohibited when selective distribution is in place, as it is the case for car retailing.

Contrary to what Cattaneo (2018) suggests, I find a modest increase in the number of points of sale for smaller manufacturers as a result of this policy intervention. The territorial restriction reduces the number of dealers for those manufacturers with denser networks, and thus it mechanically increases the market share of smaller manufacturers. However, there are very few smaller brands being incorporated to dealers' offerings in equilibrium, and there is a general reduction in the total number of dealerships. These results suggest that the proposed policy intervention would not be effective or profitable and that the current limits to the use of exclusive territories in the industry are a sensible regulatory choice.

Aside from a clearer interpretation of the estimates, the possibility of experimenting with policies using simulation analyses is the main appeal of empirical structural models. Some of the most popular applications of these kinds of policy experiments in the literature are implemented using demand models and limiting supply responses to adjustments on the intensive margin. Examples of these policy experiments include simulating the effects of an exogenous merger (Nevo, 2001), analyzing the welfare impact of a new product introduced exogenously (Petrin, 2002), or studying the introduction of different taxes, subsidies or trade quotas taking product offerings as given (Goldberg, 1995, 1998).

Counterfactuals acquire a particular relevance within the literature on endogenous entry and product offerings. They allow generating supply responses at the extensive margin to changes in model primitives. These reactions might mitigate or exacerbate the original effects of policy interventions and introduce the strategic considerations that shape market structure. In the context of car dealerships and manufacturers, simulating an endogenous market structure permits to predict what would be the brand presence that would result in equilibrium after a policy intervention. Such an exercise allows bridging the gap between policy measures and their objectives.

Despite the importance of considering endogenous market structure responses, using the framework of Cattaneo (2018) for this purpose presents several challenges that I tackle in this paper. More concretely, I adapt the model in this paper to allow for a feasible computation of equilibria under the alternative policy scenario. First, I provide with additional conditions to sidestep the issue of making predictions in the presence of set estimates as it is the case in Cattaneo (2018). Second, I reduce the number of potential actions for every player by proposing an alternative representation of the strategy space. This representation allows for a vast strategy space for players while reducing the number of alternative computations substantially. Finally, I use a heuristic iterative process to compute the equilibria of the model. The use of such dynamic processes reduces processing time further, as well as the number of equilibria.

I organize this paper as follows. In Subsection 2.1.1, I review the related literature. I present the data and the subsample that I use for the analysis in Section 2.2. Sections 2.3 and 2.4 describe the modeling and computational underpinnings of this exercise. Finally, I come to an end by presenting the results in Section 2.5, and concluding in Section 2.6.

2.1.1 Related Literature

This paper is closely related to a companion paper (Cattaneo, 2018). While I use the same model and data in both articles, the topics developed in each are complementary. In Cattaneo (2018), I estimate a model of supply and demand to analyze and quantify the effects that exclusive dealing has in the car retail industry. I do not find evidence in Cattaneo (2018) to support the hypothesis that exclusive dealing is used with foreclosing purposes in this industry. By contrast, the central exercise of this paper is not to estimate a model, but to use the model in Cattaneo (2018) to analyze a policy intervention simulating endogenous market structures.

Aside from this very clear relation, this work is very much related to the vast literature using entry models to endogenize market structure. Some first attempts at these exercises predicted the number of entrants to a market (Bresnahan and Reiss, 1991; Berry, 1992). The literature developed to answer more challenging questions.

Mazzeo (2002) introduced entry and endogenous product offerings, Seim (2006) used an entry model to explain location choices, and Ciliberto and Tamer (2009) studied the competitive effects in the airline industry posing particular emphasis on the importance of firm heterogeneity in markets with few participants.

The literature on endogenous product offerings developed largely in the number and complexity of applications. Papers like Draganska et al. (2009), Fan (2013), Eizenberg (2014), and Wollmann (2018) include not only a fully characterized model of supply but also incorporate demand. This extension allows to develop richer competition patterns in their simulations. Finally, a last strand of the entry literature deals with dynamic entry games. This literature normally uses a framework similar to Ericson and Pakes (1995), and has blossomed in the last few years with a large number of applications (e.g., Collard-Wexler, 2013; Igami, 2017).

For the computation of equilibria, I relate to the popular literature on learning models (e.g. Fudenberg and Levine, 1998; Young, 2004, and the references comprised in these books). This literature explores the use of learning heuristics to learn about the different epistemological properties from equilibria in general classes of games. Recently, many papers in the applied and empirical literature have used these dynamics (e.g., Wollmann, 2018) following the suggestions and work from Lee and Pakes (2009). These learning dynamics help to construct a feasible strategy for equilibrium computation and selection.

Finally, the policy that I implement for the counterfactual simulation relates to the literature on exclusive territories. A large part of this literature points at the potential anti-competitive effects of exclusive territories (Rey and Stiglitz, 1995; Piccolo and Reisinger, 2011; Asker and Bar-Isaac, 2014), although there are other papers that argue that exclusive territories could reduce the incentives to free-ride and increase demand (Klein and Murphy, 1988; Mathewson and Winter, 1994). There is also a developing literature on the empirics of exclusive territories both in a reduced form (Sass and Saurman, 1993; Burgdorf, 2019), and in a structural approach (Brenkers and Verboven, 2006).

Unlike all of these papers, my work does not aim to answer any efficiency-related question about exclusive territories. Instead, I use this restraint to create a mandatory separation between dealers of the same brand. This separation, in turn, relaxes intra-brand competition and induces dealerships to deal for smaller manufacturers.

2.2 Data

The data are from a variety of sources. The whole data contains car sales and dealerships in Spain from July 2016 until August 2017. Due to computational limitations, I will limit the scope of this paper to the territory, including the region of Asturias, and its neighboring areas. In what follows, I start by describing how I collected the data on car dealerships and the choice of the subsample that I use for the policy experiment. Finally, I describe the data on car sales and characteristics, and I characterize the main descriptive statistics of the relevant market.

2.2.1 Dealer Data and Clustering

I collected data on dealers' locations and brands for sale manually due to the lack of an available survey comprising all of them. First, I web-scraped the services that each dealer offers and their geographic coordinates. This information is available at the webpage of each manufacturer, where they construct interactive applications with maps to locate their points of sale.

These online applications list the points of sale of their manufacturer, but they do not provide any information about whether there are other brands sold in the same dealership. Moreover, it is often the case that the same owner uses two different corporate names to sell products of two different manufacturers. For this reason, I combined manually the observations gathered from these applications to know whether a dealership sold one brand exclusively or whether it did so with more than one. I classified two observations from different brands to be a joint dealership (i.e., a multi-dealership) if I find them to be (i) located next to each other, and (ii) owned by the same proprietor. The full sample contains 3345 dealers for the 32 most popular manufacturers in Spain. Around 22% of them are multi-dealerships.

I chose to extract a subsample of dealers from the vicinity of Asturias for the analysis of this paper. This region is suitable for several reasons. First, Asturias has two big cities (Oviedo and Gijón) with a rich and diverse network of dealers situated close to each other. Second, while it is relatively populated with dealers to its West (Ourense), its East (Cantabria), Southeast (Palencia) and South (León) have very few dealers. The aspect of this relative isolation is essential because it guarantees that the resimulated dealers are not significantly affected by dealers outside of the subsample.

I subdivided the whole sample into geographic clusters using a hierarchical agglomerative clustering algorithm, as shown in Figure 2.1. This unsupervised machine

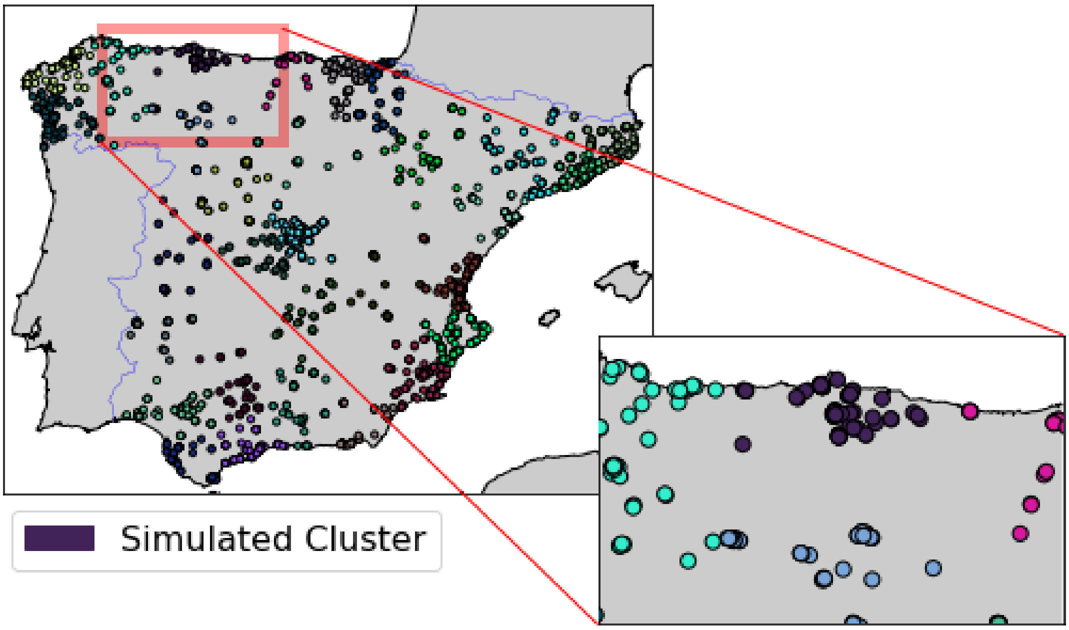

Figure 2.1: Map of Geographic Clusters

learning algorithm matches dealers spatially starting from single observations, and moving up in the size of clusters. It does a better job at recognizing the uneven patterns of agglomeration in metropolitan areas than other algorithms based on minimizing the distance from a centroid.

After dividing the dataset into several clusters, I extracted the cluster that corresponds to the territory of Asturias. The selected sample of dealers can be best summarized in Figures 2.1 and 2.2, and Table 2.1. Figure 2.2 shows the geographic distribution of exclusive and multi-dealers in the selected cluster. The large majority of the 77 dealers is located around the metropolitan areas of Gijón and Oviedo with 16 and 27 dealers within 15 km from the city center, respectively. There is another smaller focus of dealers located in Avilés (12 within the same radius). These three cities are at a distance of 20 to 25 km to each other.

In Table 2.1, I show some descriptive statistics related to dealer co-location and branding. The large average distance to the closest dealer in the cluster (1.08 km) is a result of the large heterogeneity that there is in density between rural and urban areas, whereas the median distance (0.25 km) shows the prevalence of some large areas of tight competition. There is a large prevalence of exclusive dealing that corresponds proportionally to the whole sample (79.22 % in the subsample of Asturias against a 78.43 % of dealers in the whole sample).

The distances of dealers to their closest competitor outside of the cluster is a good measure to see the adequacy of the subsample. The average dealer finds its

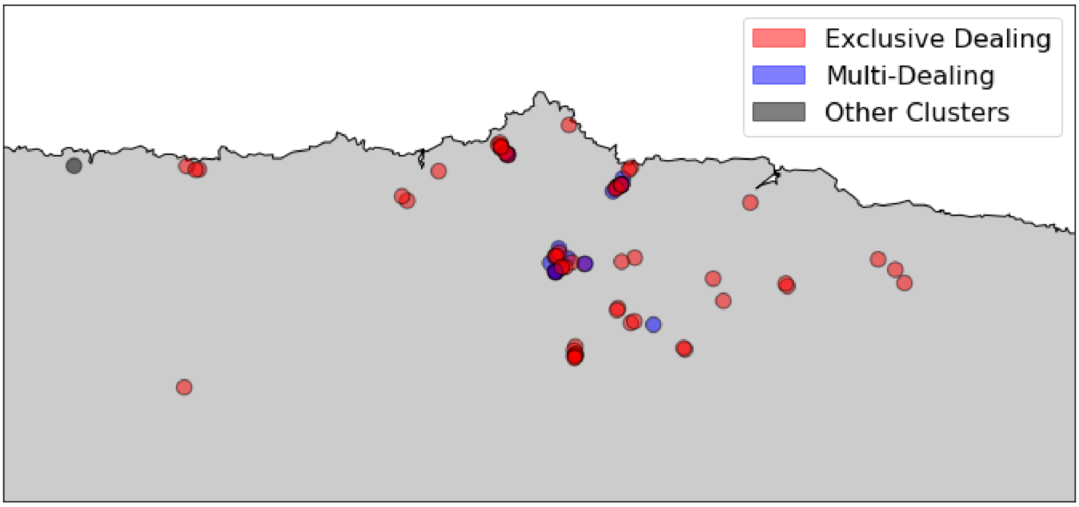

Figure 2.2: Exclusive and Non-Exclusive dealerships for all brands in the simulated cluster

nearest competitor at a distance of 51.61 km. This distance shows that, within the sample used for the simulation, there is almost no outside cluster competition given a disutility from traveling distance as the one estimated in Cattaneo (2018). Moreover, the entire cluster is somewhat isolated as dealer closest to an external competitor is still at a distance of 15.20 km.

Finally, I show the distribution of brands in the market in Figure 2.3. I use a similar definition as Nurski and Verboven (2016) and distinguish between entrant (yellow) and incumbent (black) car manufacturers. The classification aims at differentiating between the manufacturers that are well established and popular in the Spanish market from the rest. Figure 2.3 displays a sharp contrast in the dealer capillarity between one group and the other. Moreover, the subsample preserves the differences in dealer capillarity across manufacturers that exist in the whole Spanish territory. Renault, Citroen, and Peugeot have particularly dense networks, while other established brands have around half as many dealerships. Luxurious brands (Audi, BMW, and Mercedes Benz) have more selective distribution networks and thus less numerous dealerships.

2.2.2 Car sales and characteristics data

I built the data on car sales using the registry from the Spanish Directorate-General of Traffic (DGT). This registry contains daily information on all new cars circulating in Spain from December 2014 until the current day. While the data contain interesting individual information like the postal code and municipality where the

Table 2.1: Geographic descriptive statistics

Geographic Statistics

	Min	**Mean**	**Std. Dev.**	**Median**
Distance to closest dealer inside the cluster (kms)	0.009	1.088	3.129	0.245
Distance to closest dealer outside the cluster (kms)	15.202	51.613	11.015	54.797

Dealers Statistics

	Total
Average Number of Points of Sale (Incumbents)	5.667
Average Number of Points of Sale (Entrants)	2.100
Number of Exclusive Dealers	61.000
Number of Dealers	77.000

buyer registered its car, it does not provide the actual address of the buyer or the dealership in which he or she acquired it.

To overcome this issue, I simulated consumer locations from a distribution that I created using data from the National Geographic Institute (IGN). These data contain information about municipality boundaries that I used to draw numerous geographical coordinates for every province and weight them by the population size of each of these towns and cities within each province. Then I matched them to the closest dealer of each manufacturer within a radius of 70 km to form the choice set of each simulated consumer.

The registry data also comprises a written description of the car model and trim, and its Vehicle Identification Number (VIN). Moreover, the data include car characteristics like engine displacement, horsepower, bodywork, energetic propulsion, and the number of seats. To reduce the number of available models for the demand model, I classified each of the entries into a car model (e.g., Ford Fiesta) using the written description of the registry, and text analysis techniques. Following the classification into models, I used other car characteristics to distinguish across car version (e.g., Ford Fiesta 3P), and I matched these car versions to the closest trim (e.g., Ford Fiesta 3P 2008 1.25 Duratec 82CV Trend) in terms of horsepower. Finally, I defined a baseline car model as the sales-weighted average over the different trims that I recognized in the data. In total, I have 234 different car models from the

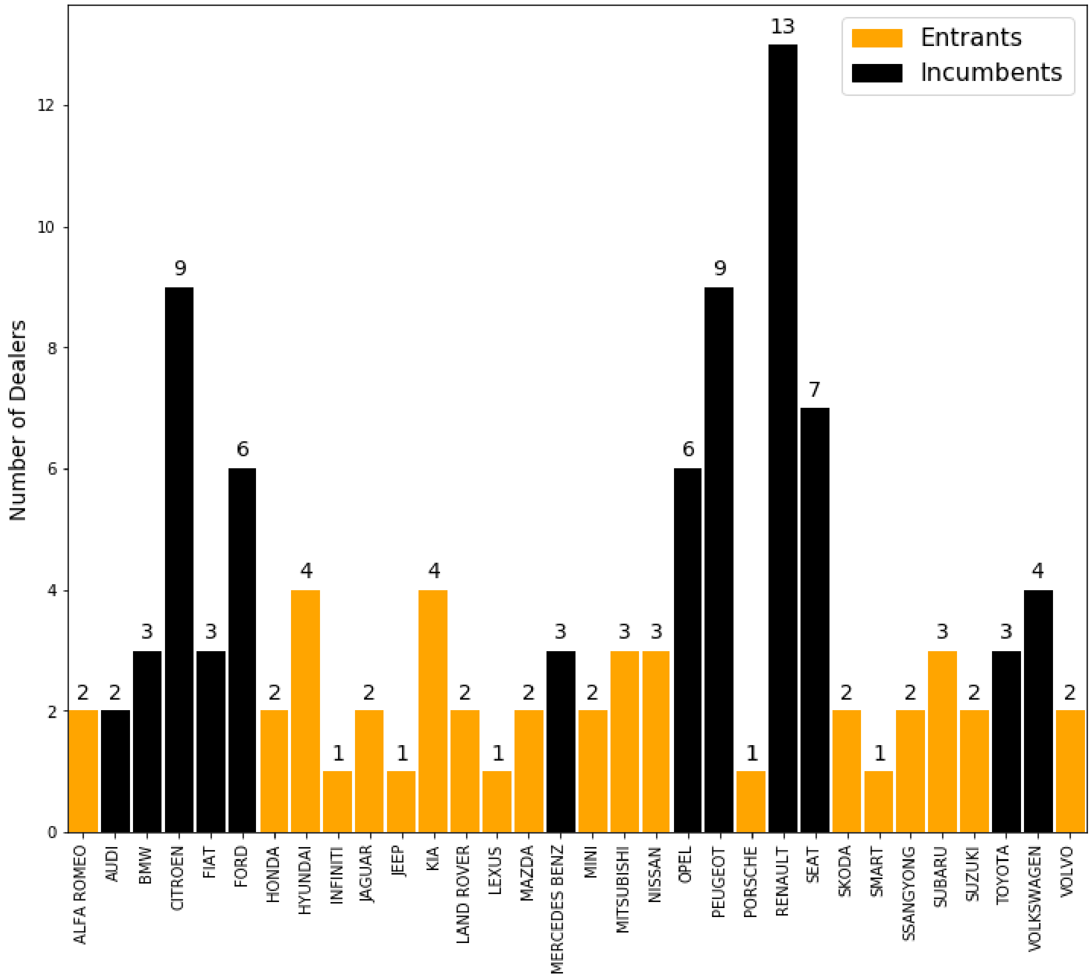

Figure 2.3: Number of dealerships per brand in the simulated cluster

32 most popular manufacturers comprised in the data that I merged with other car characteristics like list prices or weight using data from specialized car magazines.

Table 2.2 displays the ten most popular car makes and models in Asturias, and shows their market shares conditional on car sales. The region follows similar patterns as the total Spanish territory. No brand holds more than a 9% market share, and Renault is the most popular with 1,717 cars sold during the period and around an 8.70% conditional market share. The lack of a dominant car manufacturer assures that there should in principle not be any concerns regarding the competitiveness of the market, and contrasts with other regions where a single producer has a market shares over 18% (e.g., Palencia - Renault 18.6%, Toledo - Peugeot 24.2%, and Valladolid - Renault 22.2%). Moreover, the most sold models are also of similar cuts and characteristics as the ones that are popular for the whole country.

These similarities in terms of preferences give additional validity to the use of Asturias as a representative sample for the policy experiment. Table 2.1 comple-

Table 2.2: Market shares of best selling car makes and models in Asturias

Make	Share	Sales	Model	Share	Sales
Renault	8.70%	1,717	Qashqai	3.17%	626
Peugeot	7.95%	1,569	Astra	2.71%	535
Opel	7.70%	1,520	Sandero	2.67%	528
Nissan	6.25%	1,234	Leon	2.65%	523
Seat	6.20%	1,224	Megane	2.22%	438
Kia	6.11%	1,206	Golf	2.16%	427
Citroen	6.09%	1,202	Ibiza	2.16%	426
Volkswagen	6.00%	1,186	Corsa	2.13%	421
Ford	5.69%	1,123	Clio	2.10%	414
Dacia	5.30%	1,047	308	2.04%	402
Total	100%	19,740	Total	100%	19,740

Table 2.3: Sales-weighted descriptive statistics for the whole and selected samples

Asturias

	Mean	Std. Dev.	Min	Median	Max	Total Sales
Horsepower / Weight	8.85	1.15	6.35	8.65	22.47	19,740
Size (m^2)	7.76	0.71	4.48	7.91	10.36	19,740
Fuel Cons. (l/km)	4.66	0.79	3.31	4.60	10.61	19,740
Price (€ 10,000)	2.54	1.02	1.02	2.45	13.81	19,740

Spain

	Mean	Std. Dev.	Min	Median	Max	Total Sales
Horsepower / Weight	8.88	1.17	6.35	8.73	22.47	999,163
Size (m^2)	7.80	0.74	4.48	7.91	10.36	999,163
Fuel Cons. (l/km)	4.65	0.80	3.31	4.60	10.61	999,163
Price (€ 10,000)	2.62	1.11	1.02	2.49	14.86	999,163

ments this view showing sales-weighted descriptive statistics for Asturias and Spain as a whole. The country has a very diverse demography that, in turn, leads to a lot of local diversity in preferences. Rural areas have on average bigger and heavier cars that are less fuel-efficient, whereas urban areas display an opposite pattern. In contrast, the table shows that there are minimal differences in the average characteristics of the cars that are purchased and that there are no significant changes in their distribution. The average price is slightly lower in Asturias (€ 800), and a bit less dispersed, but the rest of the characteristics have almost identical distributions.

2.3 Model and Simulation Process

The model primitives, timing, and information structure follow from the framework developed in Cattaneo (2018). In this section, I explain in detail the model of supply and demand that lays the foundations for the policy experiment. The model is built on four different stages. In the first stage, all the dealerships decide simultaneously on the brands that they offer, given the costs that they draw and playing equilibrium strategies with their local competitors. After retail networks are determined, car manufacturers determine wholesale prices in the second stage and set cars' prices in the third stage. In the final stage, once all prices and points of sale are realized, consumers buy their preferred cars taking into account both products' and dealers' characteristics.

2.3.1 Demand

In my framework, I use a random-coefficient discrete-choice model for the demand of my framework (Berry, Levinsohn, and Pakes, 1995). The indirect utility for an individual i in market m buying a product j from a dealership d is

$$u_{ijdm} = \delta_{jm} + \mu_{ijm} + \gamma_{idm} + \epsilon_{ijdm}, \tag{2.1}$$

where $\delta_{jm} = x'_{jm}\beta + \alpha p_j + \xi_{jm}$ is the part of utility that is common to all individuals buying product j in market m. The term x_{jm} thereby contains different product characteristics like car size, horsepower divided by weight, and fuel consumption. It also includes a full set of province and car make origin fixed effects to control for additional characteristics that are inherent to the market or brand, but that remain unobservable to the econometrician. The elements in vector p_j are the cars' list prices that are assumed throughout the paper to coincide with the transaction prices. I model unobserved product heterogeneity with the term ξ_{jm} that captures all possible remaining characteristics that influence consumer choices, but that I cannot possibly observe.

The remaining terms are consumer-specific, and thus form part of the random coefficients of the utility. The idiosyncratic disturbance term ϵ_{ijdm} is assumed to be distributed as a Type I extreme value distribution so that the applied discrete-choice model is a Logit model. I use the term $\mu_{ijm} = \sigma y_{im} p_j$ to introduce heterogeneity in the price sensitivity owing to differences in consumers' income (y_{im}).

I model the dealers' characteristics that consumers take into account for their car purchases following Nurski and Verboven (2016). I do not allow every consumer to have all dealerships in his or her consideration set due to computational limitations. For this reason, I assume the set of possible dealers from which a consumer can buy to consist of the closest one of each car make that this consumer has available. This assumption can be regarded as rough but is not any stricter than assuming some other substitution pattern between dealerships, and it fits well with the random coefficient nature of the model. In this way, areas with a relatively low density of dealers will have the same closest dealer for the different consumer locations in the whole market, whereas those areas with lots of intra-brand dealer competition will have different consumers' draws buying from different dealerships.

These characteristics enter in the term $\gamma_{idm} = \gamma_1 ED_d + \gamma_2 \text{dist}_{id}$. ED_d is a dummy variable that is equal to 1 when the dealership is an exclusive dealer and 0 otherwise. It comprises demand effects that might arise as a result of the dealer being exclusive, better service, or higher promotional efforts. The variable dist_{id} is the geographical distance from the simulated consumer location of consumer i to the point of sale d, and it captures the distaste against traveling far to purchase their cars.

Finally, I bring the demand model to a close by introducing an "outside" good that includes the possibility of not buying any car, buying a car outside of the ones considered in the dataset, or buying a car from a dealer-car combination that is not considered in the model. I normalize this outside good to have a total utility $u_{i0m} = \epsilon_{i0m}$, where ϵ_{i0m} is also distributed as a type I extreme value.

The primitives of this demand model can be grouped into $\theta_1 = (\alpha, \beta)$ that enter δ_{jm} linearly, and the random coefficients $\theta_2 = (\sigma, \gamma_1, \gamma_2)$ that depend on the simulated variables. Let x_m, p, and δ_m denote the vectors containing x_{jm}, p_j and δ_{jm} for every car j and market m. Then it is the distribution of the simulated variables y_{im}, dist_{id}, ED_d, and ϵ_{ijdm} that define the individual choice probabilities of the simulated consumers. In particular, I define

$$A_{jm}(x_m, p, \delta_m; \theta_2) = \{(y_i, \epsilon_{ijdm}, \text{dist}_{id}, \text{ED}_d) \mid u_{ijdm} > u_{ikdm} \; \forall k = 0, 1, ..., J_m\}$$

to be the set of individual characteristics for which product j is preferred over any alternative. Given the demand primitives, the market shares are defined as

$$s_{jdm} = \int_{A_{jm}} \frac{\delta_{jm} + \mu_{ijm} + \gamma_{idm}}{1 + \sum_{k \in J_d} (\delta_{km} + \mu_{ikm} + \gamma_{idm}},$$

where the individual choice probabilities are denoted by s_{ijdm} that take this form due to the distribution of the error terms ϵ_{ijdm}. The functions $G_d(\cdot)$, and $G_y(\cdot)$ are the distribution functions for dealer characteristics and income, respectively, and are assumed to be independent of each other.

2.3.2 Price Competition

I base the price competition on the literature that uses market data to study vertical relations and infer the determinants of competitive behavior upstream (Sudhir, 2001; Brenkers and Verboven, 2006; Berto Villas-Boas, 2007). I model price setting to be decided by manufacturers both upstream and downstream, and in two stages. In the first stage, manufacturers set wholesale prices to maximize their profits as multi-product oligopolists. Once these wholesale prices are realized and observed, I assume that manufacturers place list prices for their products to maximize the profits of their networks. These list prices are in turn the final transaction prices.

The lack of transaction price data determines this modeling assumption, but it encompasses properties that make it sound for this framework. First, maximizing the profits of the joint network by the manufacturer assures that all dealerships extract a margin from the list prices, unlike in the scenario where manufacturers set both prices maximizing their profits. Second, on average, dealerships do not want to deviate from these prices, as it would be the case if they were allowed to set their prices separately. Finally, the cross-derivatives that enter the derivatives over each dealerships' profits interiorize the intra-dealer competition that manufacturers face when selling their products through shared dealerships.

Following this assumption, the first order conditions of a manufacturer $b \in B$ that sets the list prices of its products (denoted with a slight abuse of notation $j \in b$) to maximize the joint networks' profits are given by

$$\sum_{d \in D} \mathbb{I}\{b \in a_d\} \cdot \frac{\partial \pi_d}{\partial p_j} = 0 \text{ for all } j \in b, \tag{2.2}$$

where π_d are the profits of dealership d, and $\mathbb{I}\{b \in a_d\}$ is an indicator function equal to 1 if brand b is in the brand offerings the dealer (a_d). The brands offered by d are chosen from the set A_d which is a subset of the power set of brands $\mathcal{P}(B)$. The profits of a dealer d take the form

$$\pi_d = \sum_{m \in M} \sum_{b \in a_d} \sum_{j \in b} \left(p_j - p_j^w\right) \mathcal{M}_m s_{jdm}(\theta, p, a) - F_d(a_d), \tag{2.3}$$

where p_j and p_j^w denote list and wholesale price, respectively. The sales of a product j by dealer d in market m that the model predicts are $q_{jdm} = \mathcal{M}_m s_{jdm}$, where $\mathcal{M}_m$

is the total number of consumers in market $m \in M$. The market shares s_{jdm} depend on all brands offered by all the dealers in the market $a = (a_1, ..., a_D)$. The last term of the profit function are the fixed costs $F_d(a_d)$ that are specific to the products offered when commercializing the brands in a_d.

I plug in the derivatives of the profit function in equation (2.3) into the first order conditions of the joint network in (2.2), and rearrange the terms of it in matrix notation to get the expression

$$q + \left(\sum_{d \in D} \Delta_d \right) (p - p^w) = 0, \tag{2.4}$$

that I will later use to back out wholesale prices using observed list prices and the optimality conditions from the model. The matrix Δ_d is a series of $J \times J$ matrices where their jk-th element is $\frac{\partial q_{jd}}{\partial p_k} = \sum_{m \in M} \frac{\partial q_{jdm}}{\partial p_k}$ for those dealerships where both products j and k are sold. This term represents the role that dealers' brand offerings play for internalizing manufacturers' incentives. For brands that do not share any dealerships, this term is 0. In contrast, for two brands with integrated networks, e.g., in the case for Renault and Dacia, the entries of these matrices are always positive, and they collapse into the standard ownership matrix that is employed in most of the literature.

Finally, a firm f owning different car brands b sets wholesale prices to maximize its profits

$$\max_{\{p^w\}} \Pi_f (p, p^w) = \sum_{b \in f} \sum_{j \in b} \left(p_j^w - c_j \right) q_j, \tag{2.5}$$

where c_j are the costs that the firm faces when producing a particular car j.

2.3.3 Entry

Dealers decide on their entry into the market and the brands that they sell in the first period. Each potential entrant d from the set E is endowed with a location l_d, and chooses simultaneously whether to enter the market or not ($a_d = \emptyset$). The choice of entering the market comprises at the same time the brands that dealer d chooses to offer from the set $A_d \subset \mathcal{P}(B)$, and in turn, whether dealer d becomes an exclusive dealer or not. For example, a dealership d that chooses to sell only Peugeot ($a_d = \{\text{Peugeot}\}$) becomes an exclusive dealer of that brand, whereas one that sells many brands, e.g. $a_d = \{\text{Peugeot}, \text{Suzuki}, \text{Subaru}\}$, becomes a multi-dealer.

Dealerships draw idiosyncratic cost components ν_d^b for each brand $b \in B$, and ν_d^l for their location. These costs are assumed to have $\mathbb{E}[\nu_d^b] = \mathbb{E}[\nu_l^b] = 0$, and to be common knowledge amongst dealers, but unobserved by the researcher. In total, a dealer faces fixed costs of the form

$$F_d(a_d) = \sum_{b \in a_d} \left(F_b + \nu_d^b\right) + \mathbb{I}\left\{|a_d| > 1\right\} \cdot C_{MD} + \nu_d^l. \tag{2.6}$$

In this simple functional form, each brand offered has a total cost $F_b + \nu_d^b$, while there is an additional cost (or cost efficiency) C_{MD} when the dealership offers more than one brand (i.e., $|a_d| > 1$).

After observing its fixed costs, a dealership maximizes the expectation of its profits considering its brands to offer (if entering at all)

$$\max_{a_d \in A_d} \mathbb{E}[\pi_d(a_d, a_{-d})|\mathcal{I}_d] = \mathbb{E}\left[\sum_{m \in M} \sum_{j \in J_d} q_{jdm}\left(\theta, a\right)\left(p_j - p_j^w\right)\right] - F_d(a_d). \tag{2.7}$$

The expression in (2.7) represents the expected profits of dealer d conditional on its information set $\mathcal{I}_d$. In this expectation, I assume that, apart from the idiosyncratic costs ν_d^l and ν_d^b, the information set does not contain any additional unobservable knowledge about the dealer's profits. In particular, it does not contain information about demand unobservables which are denoted byξ_{jm}.

The term in the expectation operator are the variable profits which I denote as $\mathbb{E}[\mathrm{VP}(a)]$ henceforth. This expectation is taken over the unobserved product heterogeneity ξ_{jm} and the consumer idiosyncratic utility component ϵ_{ijdm}. The fact that ξ_{jm} is not part of the information set of the dealerships at the moment of entry is crucial and in line with Eizenberg (2014). It implies that dealers cannot observe whether a particular product is more profitable or popular in a particular area or not, and thus, they can enter the market only based on cost unobservables. Moreover, I assume that the expectation operator in $\mathbb{E}[\mathrm{VP}(a)]$ is correct like it is the case in most of the related literature (e.g. Holmes, 2011; Eizenberg, 2014; Houde et al., 2017). This assumption facilitates the simulation process and prevents modeling a particular kind of bounded rationality for the dealerships.

The expected profit function captures the way downstream competition frames market structure in the model. Strategic considerations in the brand offerings and exclusivity are contained in $\mathbb{E}[\mathrm{VP}(a)]$ through the relative distance to consumers that competitors inside and outside the brand have.

The expression also summarizes the mechanisms that are going to be at work at my policy simulation. Relaxing spatial competition increases the incentives to establish multi-dealerships since they are more profitable in markets where the distance between competitors is higher. Exclusive dealing turns out to be more convenient in markets where dealerships are closer to each other as they operate under lower costs, permitting dealers to stay in the market, reducing their scale. Furthermore, it allows competitors to differentiate from each other by offering different products, and thus it relaxes competition (Besanko and Perry, 1994).

Unlike other spatial regulations, the policy experiment that I implement with exclusive territories relaxes intra-brand competition in particular. This aspect provides an additional mechanism for smaller manufacturers to access points of sale. The spatial restriction to establish dealers within one brand favors the appearance of dealerships of alternative manufacturers. Some dealers that prefer a brand that is subject to a territorial restriction would tend to substitute this brand by an alternative manufacturer.

2.4 Policy Experiment

After having introduced the data and the theoretical framework, I develop a policy application around which I center this paper. First, I describe how I introduce exclusive territories for the distribution of manufacturers in the model. In addition to that, I also include these exclusive territories in the data taking into account that the observed data is in equilibrium without territorial protection.

I devote the latter part of this section to bridge the gap between the theoretical foundations of the model and the implementation of the policy experiment. In particular, I describe the additional assumptions and practical aspects, which are required for the computation of the expected profits, equilibria, and the selection among these equilibria.

2.4.1 Description and Implementation

As mentioned earlier, I consider the introduction of intra-brand territorial restrictions in the form of exclusive territories for dealerships. Exclusive territories are a permitted practice under the competition law of the European Union. The Vertical Block Exemption Regulation permits the general use of partial territorial protection in the contracts between suppliers and distributors under fairly relaxed criteria so long as they do not violate the so-called "hardcore restrictions".

In specific terms, a supplier can grant territorial exclusivity and protection to a seller in an area to preserve it from the competition by any other seller of that supplier. These clauses prohibit setting any other distributor that sells products of the same supplier in the area and also forbid active selling (e.g., targeting customers) in the territory by sellers placed elsewhere. However, passive sales (e.g., attending unsolicited customers' requests) cannot be restricted and place absolute territorial protection as a "hardcore restriction".

The case of car distribution is one exception to the permissive use of exclusive territories in the European market. The Vertical Block Exemption prohibits to combine the use of selective distribution criteria and exclusive dealing with any territorial restriction.

Within my framework, I explore the scenario of allowing for territorial restrictions in this market, prohibited in practice. With this exercise, I evaluate what would be the consequences in exclusivity and brand proliferation of restricting intra-brand geographic competition. In particular, I include endogenous responses by dealers when joining a distribution network to changes in policy. This feature is crucial in the design of policies targeted at promoting access to points of sale for smaller manufacturers. Naturally, there are other additional policy targets in the regulation of the European Union that might not be fully captured by this analysis, such as the creation of a common market or guaranteeing low prices.

I implement this policy experiment in two stages. First, I start with all the dealers having their current equilibrium play offerings as observed in the data. I perturb this equilibrium eliminating points of sales from all manufacturers randomly so that they comply with being at least at a 10 km radius distance from each other. I sequentially introduce this random perturbation. I order the dealerships randomly in the sample, and following that permutation, I calculate the distance to the closest point of sale of the same brand. If one or more brands have competitors within the critical radius, I eliminate at most one of these brands from the dealership at random and proceed the same way with the next dealer. The perturbation process finishes when there are no more points of sales of the same brand at a distance below 10 km.

After I have perturbed the equilibrium in the first stage, I simulate the best responses by every dealer in terms of adding or subtracting brands from their offerings in the second stage. I do this until a new equilibrium that is compatible with the territorial restrictions is reached. I also simulate the best responses after the perturbation in the case where no territorial restrictions are in place to have a benchmark for the simulated results. In the following subsections, I describe the different practical aspects and assumptions of these simulations.

2.4.2 Computing Expected Profits.

The first challenge when transitioning from the estimated model to a simulated model is computing the total expected profits. I henceforth refer to total expected profits as the sum of expected variable profits and fixed costs.

Given dealers' offerings (a_d, a_{-d}), the computation of expected variable profits follows a simple, yet computationally expensive, procedure. For each simulation, I draw ξ_{jm} randomly from the joint empirical distribution function of product unobserved heterogeneity and I update prices. Then, for each individual and product of the simulation, I draw idiosyncratic disturbances ε_{ijdm} and sum the virtual margin that the dealer would obtain if he offered the utility maximizer product for that individual.

Following the implementation in Eizenberg (2014), I can separate the expectation over ξ_{jm} and ε_{ijdm} which simplifies matters. In this manner, I first compute the equilibrium expected prices with different draws of ξ_{jm}. Then, I take the expectation over the ε_{ijdm} using the Logit reduced form integral for the Type 1 extreme value disturbances with each set of ξ_{jm} and updated prices. Finally, I take the integral over the ξ_{jm} by averaging out over the different draws.

For the price updates, I solve for the first order conditions in equation (2.2). I follow work by Morrow and Skerlos (2011) and Conlon and Gortmaker (2019), and separate the term Δ_d in (2.2) into a series of $|D|$ $|J| \times |J|$ diagonal matrices Λ_d with $\lambda_{jjd} = \frac{1}{NS}\sum_i^{NS}(\alpha + \sigma y)\mathcal{M}_m s_{ijdm}$, and a series of full matrices Ψ_d with elements $\psi_{jkd} = \frac{1}{NS}\sum_i^{NS}(\alpha + \sigma y)\mathcal{M}_m s_{ijdm} s_{ikdm}$. With these matrices I construct the mapping

$$p^w + \left(\sum_{d \in D} \Lambda_d(p)\right)^{-1} \left(\sum_{d \in D} \Psi_d(p)\right) [p - p^w - q(p)] \mapsto p.$$

This mapping is a contraction mapping and thus can be solved using some starting value for p and iterating until convergence.

I assume throughout this paper that a single dealership cannot change prices significantly when deviating to any other brand offering or leaving the market. While this is a sensible assumption in a big market as the Spanish, it also helps to reduce the computational burden. Otherwise, the price updating procedure has to be carried out for each dealer, each deviation, and each iteration, which makes the whole simulation unfeasible. For the entire subsample of Asturias, I also assume that the prices remain unchanged after all the simulations are finished due to its relatively small size. An alternative that is feasible, though computationally more costly, is to apply an iterative feedback between prices and brand offerings.

A more conceptually challenging aspect is subtracting the fixed costs from the simulated expected variable profits. These issues are intimately related to the flexibility that the use of moment inequalities permits when estimating the identified set for the average fixed costs. First, the estimation approach allows neither to back out idiosyncratic shocks ν_d^l, and ν_d^b, nor to estimate a reasonable distribution of them. Second, while I estimated sets of average fixed costs in Cattaneo (2018), there is no explicit distribution that determines which costs are more or less likely within those sets.

There are several sets of assumptions that could close these two gaps. One could assume the disturbances to be $\nu_d^l = \nu_d^b = 0$ for all dealers and further assume a distribution for the mean costs F_b and C_{MD}. In this manner, the assumed distributions create a probability over the most profitable strategy for dealer d from which it randomly chooses over the simulations.

An alternative option is to assume that dealers make their choices on the expected fixed costs. Then, one can compute them assuming a distribution for mean costs and using $\mathbb{E}[\nu_d^l] = \mathbb{E}[\nu_d^b] = 0$ from the model. This approach does not need additional assumptions for the idiosyncratic disturbances but is slightly inconsistent with the timing of the original setup. I use this approach because, given that none of the two is consistent with the selection on unobservables, the second set of assumptions also reduces the number of possible outcomes.

2.4.3 Strategies.

The original model assumes that the set of possible strategies could be any possible subset A_d from the powerset of the set of all brands $\mathcal{P}(B)$. While it is a positive aspect that the estimation strategy accommodates such a big strategy space, the simulations would need to compute $2^{|B|}$ possible deviations given a particular market structure to determine the best response.

I tackle this issue restricting the number of strategies and using recursive methods to search for equilibria. For each dealer d, I define the set of possible actions to be dependent from the action taken in the previous iteration with the set

$$A_d \mid a_d = \{a_d\} \ \cup \ A_d^+ \mid a_d \ \cup \ A_d^- \mid a_d. \tag{2.8}$$

$\{a_d\}$ represents the action of playing a_d in the following iteration, whereas

$$\begin{aligned} A_d^+ \mid a_d &= \{a_d \cup \{b\} : \text{ for each } b \in B \text{ if } b \notin a_d\}, \text{ and} \\ A_d^- \mid a_d &= \{a_d \setminus \{b\} : \text{ for each } b \in B \text{ if } b \in a_d\}, \end{aligned}$$

represent brand offerings that require adding one brand that is not offered, or subtracting one brand offered in the current iteration.

This modified strategy space interacts with recursion to find best responses in a way that can be best described with an example. Let dealer d offer a_d, all rivals offer a_{-d} and the best response to a_{-d} be $a'_d = a_d \cup b \cup b'$ for some $b,\ b' \in B$. Keeping all rivals constant, adding b will be the preferred action in the first iteration, and adding b' will be optimal in the second iteration (or vice versa). From the second iteration on, it will be optimal to keep the same action. The benefits of using this strategy become apparent in this simple example: whereas under normal circumstances one has to compute $2^{|B|}$ different payoffs, this particular example finds a best response after $2 \times |B|$ calculations.

Additionally, since the interest of the counterfactual analysis is to understand the presence of smaller manufacturers, I keep those manufacturers categorized as incumbents in Figure 2.3 fixed and consider deviations only for those brands that are entrants. Furthermore, since some subsidiary brands have their points of sale always connected to the main manufacturer (e.g., Smart and Mercedes Benz or Mini and BMW), dealers that do not offer the main brand are not able to incorporate the subsidiary brand to their offerings.

2.4.4 Game representation and heuristic dynamics.

Aside from the burden entailed in a large strategy space and referenced in the previous subsection, there are also other difficulties that arise from the number of players and the number of equilibria that this setup has in practice.

On the one hand, a large number of players entails a similar computational burden as a large action space. If keeping all rivals fixed, finding the best response for an individual player needs to compute $2^{|B|}$ payoffs, finding an equilibrium where everyone is playing mutual best responses in a sample of players J calls for $2^{|B| \times |J|}$

operations. On the other hand, the number of players multiplies the number of equilibria as they are all ex-ante equivalent, which calls for a reasonable selection mechanism to produce more powerful predictions from the counterfactuals.

In this regard, I follow Lee and Pakes (2009) and use heuristic dynamics to search for equilibria. The benefits of such an approach are twofold. They allow using much simpler rules that still converge to equilibrium[1], and they provide an intuitive principle by which to select equilibria.

I transform the one-period simultaneous-move game into an infinite-period sequential-move game. Each period the order of play permutes randomly across players given a starting profile a. At its turn of play, each dealership believes that all rivals keep the same strategy as thus far, and therefore best respond to last period's play. This kind of heuristic behavior is known as a *best response* dynamic and is crucial for my computational approach. Equilibrium play ($a^{\star}$) is reached when no player wants to deviate from their previous offerings, and all possible turn permutations are exhausted.

2.5 Results

In this section, I present the results from the simulated policy. Tables (2.4) and (2.5) introduce the parameter values used for the experiment. While I take the demand parameters from Cattaneo (2018), I estimated the supply-side parameters using the approach described therein but using the relevant subsample of dealers.

I ran a total number of 200 simulations using the procedure described in the previous sections.[2] Each of these simulations permutated the order of move allowed for the different dealers starting from the observed situation of the data described in Section 2.2. Most heuristic playing simulations converged to an equilibrium situation between the third and the fifth iterative round, and the incentives to deviate for any dealer reduced drastically after the second round.

In what follows, I present some summary statistics resulting from the simulation. I show these results and compare them in three different points in time. First, I analyze them before the policy intervention. The second reference point I take is right after I introduce the policy intervention by randomly eliminating the points

[1] When not to the set of Nash Equilibria, many of these heuristic rules are proven to converge to weaker equilibrium concept as the Hannan Set or the set of Correlated Equilibria.

[2] The complete computations took slightly less than nine days in total using the computing cluster provided by the University of Mannheim. These computations were run over 140 processors.

Table 2.4: Demand side parameters used for the policy simulations

Demand Parameters			
Regular Parameters		**Origin Fixed Effects**	
Price	-2.292	France	-1.527
Fuel Cons.	-0.214	Japan	-0.642
HP / Weight	0.070	Germany	-1.397
Size	2.066	Korea	-0.279
Cons.	-17.706	England	-1.207
		Eastern Europe	0.175
Province Fixed Effects		United States	-2.098
León	-0.952	Others	-1.389
Lugo	-0.719		
Ourense	-1.010	**Random Coefficients**	
Asturias	-0.486	Distance	-0.354
Palencia	-1.500	ED	-0.021
Salamanca	-1.573	Price × Income	0.073
Cantabria	-0.854		
Valladolid	-0.788		
Zamora	-2.348		

Table 2.5: Supply side parameters used for the policy simulations

Supply Parameters			
Alfa Romeo	[11.785, 42.807]	Mitsubishi	[58.606, 221.639]
Audi	[103.321, 373.705]	Nissan	[80.749, 324.562]
BMW	[131.934, 484.504]	Opel	[144.473, 611.422]
Citroen	[144.505, 642.340]	Peugeot	[181.442, 800.008]
Fiat	[44.363, 149.358]	Porsche	[11.778, 44.242]
Ford	[85.900, 392.744]	Renault	[251.769, 1115.822]
Honda	[16.540, 62.634]	Seat	[524.367, 1140.437]
Hyundai	[116.819, 434.200]	Skoda	[63.201, 235.503]
Infiniti	[4.834, 13.673]	Smart	[17.441, 61.908]
Jaguar	[1617.295, 4720.331]	Ssangyong	[40.860, 142.257]
Jeep	[33.114, 101.831]	Subaru	[7.452, 26.186]
KIA	[183.023, 687.766]	Suzuki	[24.652, 82.545]
Land Rover	[54.160, 138.102]	Toyota	[221.608, 793.871]
Mazda	[88.109, 338.254]	Volkswagen	[106.219, 398.231]
Mercedes Benz	[138.414, 538.795]	Volvo	[155.923, 559.679]
Mini	[17.825, 70.123]	Multi-Dealing	[-9.7841, 16.1923]

of sale that are not compatible with the territorial protection. Finally, I show the results after I allow dealers to converge to a new equilibrium.

2.5.1 Sales

In Tables 2.6 and 2.7, I present predicted market shares before, during, and after the policy intervention.[3] The first columns simulate market shares using the market structure observed in the data. One can interpret these columns in both tables as a measure of goodness-of-fit of the demand model with respect to Table 2.2.

Although it qualitatively matches pretty well which are the popular brands and models, the model predicts the market to be way more concentrated than it is observed in reality. For example, Renault and Dacia are predicted to concentrate around a 29% of the total cars sold, whereas in the sample it is observed to be a dominant group, first in terms of sales, but with a total market share close to a 15% only. One possible way to improve the fit of the demand model to these simulations is to cater it more to the market of Asturias either by including a more extensive set of random coefficients that interact with demographics or by interacting the Asturias fixed effect to different car characteristics.

Table 2.6: Top 10 most popular brands in the policy experiment

Initial	Share	Intermediate	Share	Final	Share
Renault + Dacia	29.440	Renault + Dacia	29.059	Renault + Dacia	27.038
Hyundai	11.344	Hyundai	15.033	Hyundai	13.440
Citroen + DS	7.450	Citroen + DS	8.783	Citroen + DS	8.172
Seat	6.453	Seat	8.098	Seat	7.532
KIA	5.202	KIA	6.985	KIA	6.497
Peugeot	4.901	Peugeot	5.277	Peugeot	4.909
Opel	4.263	Volvo	4.884	Volvo	4.537
BMW	3.905	Nissan	4.525	Nissan	4.207
Volkswagen	3.388	Opel	4.336	Opel	4.034

Table 2.7: Top 10 most popular models in the policy experiment

Initial	Share	Intermediate	Share	Final	Share
Hyundai Tucson	8.850	Hyundai Tucson	11.728	Hyundai Tucson	10.486
Renault Mégane	8.299	Renault Mégane	8.192	Renault Mégane	7.622
Dacia Duster	6.554	Dacia Duster	6.469	Dacia Duster	6.019
Renault Clio	4.484	Renault Clio	4.426	Renault Clio	4.118
Seat Ibiza	3.243	Seat Ibiza	4.070	Seat Ibiza	3.786
Kia Sportage	2.455	Volvo XC60	3.438	Volvo XC60	3.194
Dacia Sandero	2.422	KIA Sportage	3.296	KIA Sportage	3.066
Renault Scénic	2.119	Seat León	2.588	Seat León	2.408
Seat León	2.063	Dacia Sandero	2.391	Dacia Sandero	2.225

[3]These market shares are computed over total sold cars, not over the total market size.

The jump from the first column to the second, and from the second to the third in both tables uncovers the other main pattern from these simulations. Most of the variations appear when eliminating the points of sale that violate the imposed territorial protection, i.e., from the first to the second column. As a result of these modifications, brands with a high presence in the market (e.g., Citroen/DS, Peugeot or Renault/Dacia) reduce their sales substantially, although they remain prevalent. The decrease in total sales shows that the outside option replaces a part of these sales. However, another sizable portion of these buyers migrates to manufacturers that have now an increased relative presence in the market.

The third column does not introduce significant differences when compared to the second column, but it shows a moderation of the patterns arising from column one to two. The tendency towards moderation is intuitive from the perspective of equilibrium: starting from an equilibrium allocation and perturbing it, it is natural to expect the new equilibrium allocation to go in the direction of the old. Still, the lack of significant equilibrium effects that is evidenced by the relatively fast converge to an equilibrium of the simulations is relatively surprising. I comment on this in the following subsection.

2.5.2 Dealers' structure

I present a bar chart summarizing the main patterns in dealers' offering as a result of the policy intervention in Figure 2.4. Following the convention that I established in Figure 2.3, I denote entrant and incumbent manufacturers in orange and black, respectively. Moreover, I indicate the initial and final dealer configurations in light and dark colors. The numbers denote the initial, intermediate, and final number of points of sale for each brand. Incumbent manufacturers have only an initial and final number, as they were not allowed to update their points of sale in the simulations.

The policy simulation might be prone to two potential biases. One is a higher number of smaller manufacturers than usual because I do not allow adding incumbents to dealers' offerings. The other main potential criticism might be an excessive proportion of multi-dealers with respect to exclusive dealers. The way I construct the simulation does not contemplate the possibility for new dealerships to serve as new points of sale for brands, so entry forcefully appears within all dealerships, overstating the incentives to become a multi-dealer.

The plot confirms the intuition presented in the previous subsection. The territorial protection mechanically eliminates many points of sales for brands that are densely present in the market (e.g., Renault/Dacia, Citroen/DS, Peugeot), but it

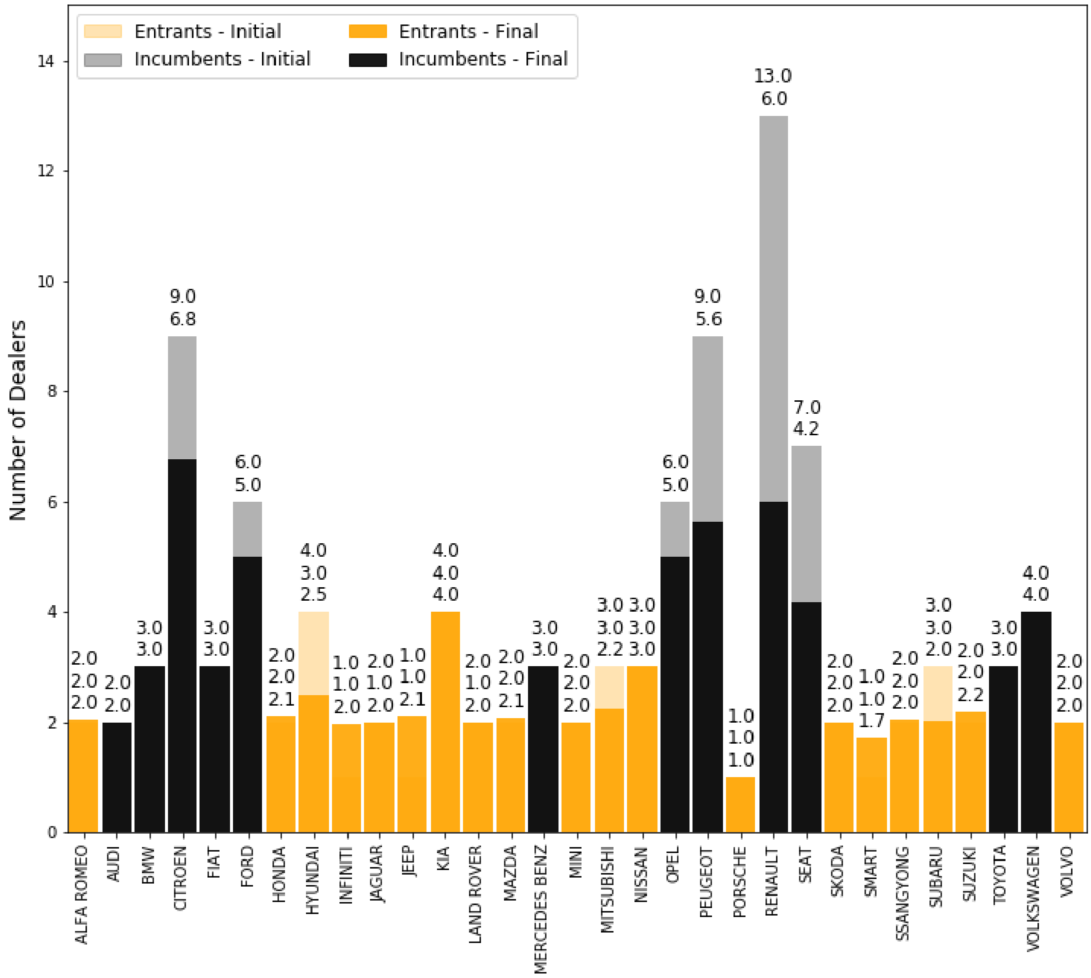

Figure 2.4: Number of dealerships per brand in the simulated cluster

does not translate into any other more prominent equilibrium effects for the dealerships. In particular, there is almost no increase in points of sales by entrant manufacturers, and their sales rise mostly because of the reduced competition.

Counting a point of sale as a manufacturer that sells its products through a dealership, the original subsample had a total of 109 points of sale distributed in 77 dealerships. Another piece of evidence that reinforces this view is that, although the initial random elimination of points of sale leads to an average total of 88.59 points of sale, the final average number of points of sale rose marginally to only 91.55.

The comparison between exclusive and multi-dealerships is a bit more complicated through the simulations because there is a fair amount of dealerships that have an average number of points of sale that range between one and two brands, as well as other dealerships with average points of sale below one. In table 2.8, I present the total average points of sale by dealer rounded up to the integers.

The results are pretty straightforward. The policy does not provide incentives to

Table 2.8: Total number of points of sale by dealer.

# Points of Sale	0	1	2	3	4	5	6	7	8
Initial	0	61	11	2	0	1	0	1	0
Intermediate	24	43	6	1	0	1	1	0	1
Final	28	40	6	1	0	1	1	0	0

multi-dealing, but instead causes a high level of exit from the market as territorial restrictions prevent dealers from accessing their most preferred manufacturers. In total, there is little room to see any potential benefits from such a policy.

2.6 Concluding Remarks

The use of moment inequalities to estimate the model used in Cattaneo (2018) proved effective at determining the potential costs of exclusive dealing and flexibly identifying many parameters. It also allowed bypassing the issue of multiplicity of equilibria in this context without leaving the question of selection unattended. However, this empirical tactic and that of its related literature shy away from providing a straightforward use of the estimated model for simulating counterfactuals.

In this paper, I extend the framework and estimation proposed and employed in Cattaneo (2018) to create useful counterfactuals usable for policy simulation and evaluation. In doing so, I deal with several conceptual issues to implement a feasible computation of the simulations for a subsample of dealers.

I use the framework and simulation procedure to study the effects of a policy intervention in the car retailing market. I analyze the results of territorial restrictions in dealers' strategies for what brands to commercialize. This policy is attractive for two main reasons. First, territorial restrictions are forbidden in combination with exclusive dealing, and more in general with selective distribution. The combination of vertical restraints usually is a complex puzzle to analyze, and this work is a first attempt to do that. Second, territorial restrictions could be used as a way to disincentive dealers to commercialize products of brands with dense networks and make dealing for smaller manufacturers more attractive.

The results of the policy experiment do not support this last vision. In total, the effects of territorial restrictions are a substantial decrease of points of sales by those manufacturers with large networks, but very marginally compensated by an increase in points of sale by smaller manufacturers. Sales of these manufacturers logically increased because their rivals have reduced network coverage, so these changes in consumers' preferences come mostly at the expense of their welfare. Moreover, several exclusive dealers do not replace their offerings, thus leaving the market.

My results indicate that it is not advisable to implement such a policy in the car retail industry given the overall impact of it in my simulations. Even though there are mechanisms by which it would have been able to increase the presence of smaller manufacturers in the market at the cost of some consumer welfare, these mechanisms do not materialize in practice using the parameters estimated in Cattaneo (2018). It is thus advisable to continue with the current prohibition for the development of a diverse distribution network for automobiles.

Chapter 3

Entry Signal and Market Segregation

joint with Hidenori Takahashi and Yuya Takahashi

3.1 Introduction

The development and maintenance of a safe and connective transportation system are fundamental to the economic performance of a nation. In the period comprised between FY 1993 to FY 2013, US spending in transportation at the federal, state and local level accounted for between 1.55 and 1.85% of total GDP, averaging a total of $220 billion per year. Designing and securing a competitive procurement of public transportation projects is of great importance for the government to make use of its resources efficiently.

In this paper, we examine the role of information design in procurement auctions using data from transport infrastructure projects in Florida. We make use of an institutional feature of our data to investigate the impact of disclosing the number and identity of interested bidders on bidders' behavior and auction outcomes. The Department of Transportation in Florida requires contractors to solicit an information brochure for the projects in which they are interested. The request of a project plan qualifies a contractor as a potential bidder. This information is collected and made publicly available before the auction for that contract takes place, so any interested contractor knows which are the prospective bidders for any project.

The issue of coordination and collusive behavior among bidders in procurement auctions is a subject of much interest for policymakers. There is a large literature trying to develop techniques to distinguish collusive from competitive behavior in auctions (e.g. Porter and Zona, 1993, 1999; Bajari and Ye, 2003). In our case, we evaluate the institutional design of the procurement process instead of firm conduct. The effect of revealing information about interested firms adds to the transparency of the procurement process (Ohashi, 2009), but it could have additional consequences in terms of efficiency as it can lead to some implicit coordination.

On the one hand, strong contractors might have incentives to use this institutional feature to signal their interest in some projects and relax competition by preempting rivals from submitting a bid. While requesting an information brochure and letting other firms know about the interest in a project is for free, entering an auction and submitting a bid are costly. In this context, both strong and weak contractors would benefit from some possibility of tacit coordination. The big firm would receive a higher pay from the auction due to reduced competition. Moreover, weak contractors would not sink costs unnecessarily participating in auctions for which they have little chances. The impact of this part of the coordination is harmful to the buyer.

On the other hand, weak contractors can use their saved bidding costs to instead focus on entering auctions for which there is no strong firm in contention. In this case, revealing this information could also benefit the buyer since it improves the matching between contractors and projects, and it increases competition in these projects.

An extreme example of these two mechanism would be a project that has two bidders, and another (probably smaller) project that remains unassigned because no bid was submitted. If there was some way to coordinate, the bidders would probably prefer to assign each one to one project. The original winner would be better off because in the new situation he would receive a higher price. The original loser would also benefit because he does not sink costs for nothing, and gets allocated now to one project. The auctioneer could benefit from this coordination depending on the balance between the outcomes of the two auctions. It will benefit if the increase in the price paid in the first project is less than the increased surplus from being able to procure the second project.

We develop our analysis in two steps. First, we provide with evidence that large firms' commitment to forego a project could signal interest in other projects. We argue that this signaling arises in equilibrium because bidders face some degree of substitutability across projects. This substitutability could arise from bidders' congestion or capacity constraints.

In the institutional context of this paper, requesting a plan keeps the option to compete for a project open. Instead, not seeking a plan is a commitment not to compete for it. It is the substitutability across projects that allows the commitment not to bid for a plan to become more informative about the intentions of the bidder in the projects for which it keeps an option. Foregoing a project also implies that the bidder is more capable of becoming competitive for other projects procured at the same time.

In the second stage of our analysis, we show evidence of coordination among bidders . We find that there is a negative and significant relationship between the number of strong contractors that are in the list of potential entrants and the actual entry of smaller contractors. This relation is robust and maintains its sign after controlling for a full set of fixed effects. We additionally test for the effect of strong potential bidders in the bidding distribution for those bidders that entered the auction after establishing the relationship between entry and signal. We find that the threat of entry does not affect the bidding behavior of firms after controlling for actual entry, which is expected, given the timing of the institutional framework.

Finally, we test for our proposed coordination mechanism in a reduced form setup estimating the bid distribution for weak bidders and analyzing what is the effect of participating in concurrent auctions. We find some evidence backing the idea that there is substitution across projects. Specifically, we find that unsuccessful bids, those bids that do not win an auction, cause an increase in the bid distribution for both strong and weak bidders.

We account for two main challenges in our simple empirical model. First, the bid of each contractor is a function of the number and type of rivals that bid for the same project which leads to reverse causality. The other challenge is that the sample of bids submitted for a project are a self-selected subsample from all contractors that decided to endogenously enter into the auction. We use the techniques developed by Heckman (1979), and frame this setup as a latent variable model where bids are observed contingent on a selection equation that encompasses entry effects.

For our empirical strategy to work, both the endogeneity and selection issues require excluded variables that provide with an exogenous variation. We propose the use of plan requests by rival firms and the sum of estimated costs for simultaneous projects as excluded variables and argue their adequacy and limitations as instruments.

This paper is organized as follows. Section 3.2 presents the related literature. In Section 3.3, we describe the institutional details present in the letting process of public projects by the Florida Department of Transportation. We also describe the data that we use and present some descriptive statistics in this section. We introduce a very simple stylized model in Section 3.4 where we summarize the mechanisms at work in our setup. These mechanisms and predictions are tested and commented in Section 3.5. Finally, we conclude with Section 3.6.

3.2 Literature Review

Our paper originates from the strand of literature analyzing the effects of endogenous entry in auctions (Bajari and Ye, 2003; Li, 2005; Li and Zheng, 2009; Athey et al., 2011). Unlike these papers, we consider the endogenous formation of the set of potential entrants.[1]

The aspect of endogenous interest and participation in procurement auctions is intimately intertwined with the idea that the identity of the competing firms might have a different impact on participation and bidding behavior. This factor is especially relevant in our setting because there is a relatively small number of firms that regularly provide services for the Florida Department of Transportation. Thus, there is a general awareness among competitors about which firms are more competitive in these markets.

Our interest to identify the differences in behavior between strong and weak bidders relates our work to the literature that explores the relationship between ex-ante bidder asymmetry and procurement design (Krasnokutskaya and Seim, 2011; Athey et al., 2013). They consider the distributional effects of policies aimed at giving preference to small contractors over top contractors using bid subsidies and set aside contracts, respectively. We study the distributional effects of an institutional design that does not target any particular group of bidders but has the potential to produce similar distributional outcomes.

Our setup is a very strategic one, where actions can convey messages. Although there is some developing literature, these kinds of setups are uncommon in empirical research. A fascinating example is Kawai, Onishi, and Uetake (2018). They develop and estimate a model of signaling in online credit markets where the borrowers' reserve interest rate is used to convey information about their creditworthiness.

In our paper, the request for projects' plans also discloses information to other agents, but it differs in two fundamental aspects from Kawai, Onishi, and Uetake (2018). First, the information transmitted here does not facilitate coordination between supply and demand, but instead can tacitly coordinate the supply. Second, we do not view our environment as one of transmission of private information.

[1] Outside of the auction literature, Fan and Xiao (2015) also consider endogenous potential entrants in the context of entry to the U.S. local telecommunication industry.

When a contractor chooses the plans to be requesting, it selects to keep an option to participate in those projects for which it holds a plan, and *commits* not to submit any bid for the others.

The idea that lies behind our stylized model and the proposed mechanism for coordination relates our paper to the theoretical literature on commitment. The value of commitment has a long tradition in game theory. The concept of commitment as a tactic in strategic situations dates back to Schelling (1960). He pointed out that a player could receive higher payoffs by reducing the number of possible strategies through some commitment device previous to the game. This idea is underlying several papers in applied theory. Caruana and Einav (2008) develop a dynamic model of endogenous commitment. Renou (2009), Bade et al. (2009) or Lazarev (2019) consider an environment more similar to ours. They model a two stages game where the first stage serves for players to display their commitment strategies that frame their options for the second stage.

There is a large body of empirical research about the lack of competition, cartelization or tacit collusion in public procurement due to its economic significance. Kang and Miller (2017) examine the role of government preferences and discretion, limiting the scope for competition in public procurement.

A larger body of literature is devoted to cartel detection in auctions using diverse approaches. Some of these papers develop tests for collusion using documented cases of detected cartels. Two early examples of this literature are Porter and Zona (1993, 1999) that analyze detection of cooperation comparing between the bids of firms inside and outside the bidding ring.

Other papers test for collusion without having prior information about bidder conduct. Bajari and Ye (2003) develop a test for bid-rigging comparing the predictions from competition and collusion models with the data. More recently, Kawai and Nakabayashi (2018) use variations in bid patterns in reauctions for unsuccessfully procured projects to develop a test for collusion in public construction projects in Japan. Another interesting example in this literature is Chassang and Ortner (2019) that use the effect that variations in the cartel's ability to implement punishments have on bidding behavior to detect collusion among bidders.

Our paper does not tackle the issue of cartelization in public procurement, and thus is less closely related to these papers. However, commitment serves as a tool to coordinate contractors in our setup, which connects our work to the concept of tacit collusion.

3.3 Institutional facts, data, and evidence

3.3.1 Institutional facts

We use a sample of procurement auctions for infrastructure projects procured by the Florida Department of Transportation (FDOT) over the period 2003-2014. The FDOT is an executive agency depending from the State of Florida in charge of providing a safe and well-planned transportation network for the mobility of goods and people with roadway, bus, air, rail, sea, bicycle, and pedestrian facilities. The duties of the FDOT include the construction of roads, bridges, signaling, and other transportation facilities, as well as the maintenance, resurfacing and rehabilitation of the ones that are already in place.

The FDOT has a decentralized organizational structure divided into seven independent district offices that span all 67 counties of the State as represented in Figure 3.1. Each district office independently procures between 1 to 16 infrastructure projects almost every month. We define the set of projects procured in a given month by a specific district office as a "procurement set". Procurement sets are composed by the FDOT's project managers, together with various department personnel based on district offices' workload and availability of staff.

Every project is advertised 1 to 2 months before its project letting date. These bid solicitation notices include diverse information for interested bidders about the items (tasks) contracted, and the location of the project. They also include estimates about the contract duration and construction costs developed from past data on bid prices and costs of equipment, labor, and materials. These documents might be modified and supplemented throughout the time to the letting process and notified publicly.

After bid solicitation notices are posted for the month, interested firms can request brochures for project plans and specifications, as well as bid documents. Asking for a project plan is free of charge and required for a firm to bid for the project. Some projects can additionally request a mandatory pre-bid meeting attendance for discussion and information purposes or other prerequisites.

If a firm requests for a project plan and fulfills all requisites, this information becomes publicly available online, and the firm becomes a potential bidder for that particular project. When the procurement auction takes place, all prospective bidders are allowed, but not obliged to submit their bids in a sealed-bid first-price auction that automatically awards the contract to the firm providing the lowest bid. These bids need to be specific breaking down the proposal to the prices that they

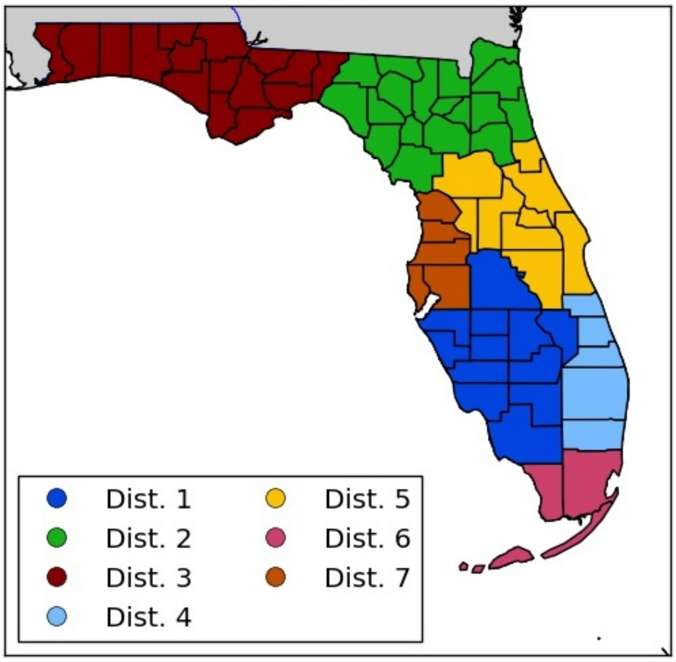

Figure 3.1: Map of the district offices of the FDOT

charge for each task in the project's plan. Changes in the working quantities and prices might appear throughout the completion of the contract and are handled in different ways depending on whether they are issued with fixed-price or unit-price contracts (Luo and Takahashi, 2019).

3.3.2 Data

The data contains detailed information about the characteristics of each project and auction outcomes, such as engineer's project's cost estimates, final payments to the contractor, the number of days it took to be completed, and a brief description of the tasks that were contracted. The dataset includes the identity and bids of all auction participants as well as contractors' traits such as bidder's backlog, the number of participated projects, and the location of its headquarters.

A significant feature of the data is that it contains the identity and characteristics of all contractors requesting a plan, including those firms that ended up not submitting a bid for the project. There are a total of 1935 different firms registered to have solicited information for a project during the sample. A sizable fraction of them (1435 firms) is never observed to participate in any single auction. We remove these firms to construct the set of potential bidders. The selected sample contains 1945 projects that are spread across all counties, although a bigger part of these plans is concentrated in the west coast of the State. Summary statistics for these variables can be found in Table 3.1.

Table 3.1: Projects' summary statistics

Variable	Mean	Std.	Min.	Max.	N
Winning Score ($1,000)	3,139.63	6,271.92	7.52	148,000	1,945
Engineer's Cost Estimates ($1,000)	3,781.10	7,608.44	5	164,000	1,945
Expected Contract Duration (# of Days)	196.12	173.85	15	2,034	1,945
Final Payment to Contractor ($1,000)	3,277.69	6,747.02	7.50	159,000	1,945
# of Participating Bidders / Auction	4.76	2.61	1	19	1,945
# of Plan Holders / Auction	39.80	22.48	1	159	1,945

There is more than apparent heterogeneity across projects. The very different tasks that these contracts can demand also reflect inevitably in the size of these projects. While the average winning score takes a value of $3.1 million, there are projects as small as $7,500 and as big as $148 million. These differences also reflect in the expected duration of the contracts: while the average lasts little more than half a year, the total range spans from two weeks until over five and a half years.

The data also reveal a substantial variation in plan requesting behavior across construction firms, as shown in Table 3.2. The average firm solicits 75 plans for procurement auctions and submits more than 18 bids, though the data suggests that it depends mainly on the identity of the contractor.

There are firms requesting over 1600 plans and placing over 400 bids, whereas the median holds five plans and makes four bids. In order to capture a part of this heterogeneity from the side of bidders, the nine contractors with most projects procured are considered as top contractors throughout the paper. Top contractors request more plans on average (460), but they are also more prone to submit bids (around 70% entry) and win it.

It is though still revealing to observe that, even though requesting for a plan is something that comes at no cost whatsoever, potential bidders are not remotely close to doing so for all available projects. Out of the 500 potential entrants in the data, only an average of 19.38 firms request the plan and bid information for a given project. Furthermore, no project is requested by more than 69 potential bidders.

3.3.3 Descriptive Evidence on Market Segregation

The existing literature typically assumes the set of potential bidders, i.e., firms that request project plans, as exogenous. In this section, we demonstrate that this assumption is firmly rejected in our data. To see this, we consider the entry

Table 3.2: Summary statistics for plan request and auction entry

Variable	Mean	Std.	Min.	Med.	Max.	N
Firm level						
# of Plans / Potential Bidder	75.39	167.27	1	17.50	1690	500
# of Plans / Top Firm	459.89	186.95	245	439	875	9
# of Bids / Potential Bidder	18.43	50.26	1	4	488	500
# of Bids / Top Firm	332.67	107.64	192	298	488	9
Project level						
# of Plan Holders / Auction	39.80	22.48	1	38	159	1945
# of Potential Bidders / Auction	19.38	10.27	1	18	69	1945
# of Top Firm as Pot. Bidders / Auction	2.13	1.32	0	2	7	1945
# of Bidders / Auction	4.76	2.60	1	4	19	1945
# of Top Firm as Bidders / Auction	1.54	1.18	0	2	7	1945

and bidding behavior of weak potential bidders with and without the presence of strong prospective bidders. Table 3.3 compares the bid submission frequency of weak bidders when at least one strong bidder requested the project plan with the one when there is no strong bidder requested the project plan. Asking for a plan by top contractors seems to have an impact on the entry of small firms. While about a 39% of small plan holders submit a bid when there is no strong potential bidder present, this number reduces to a 24% when at least one strong firm appears on the list.

Table 3.3: Presence of Strong Firms and Entry of Weak Firms

	Submit Bid	Do Not Submit Bid	Total
At least one strong firm on the list	831	2616	3447
			(0.24)
No strong firm on the list	1595	2501	4096
			(0.39)
Total			7543

Although this correlation is meaningful suggesting that there is some kind of market segregation across strong and weak bidders, it does not tell whether this phenomenon is due to preemption through the threat of entry, because of harder competition, or because of other project characteristics. In what follows, we will provide additional descriptive evidence about project segregation based on project characteristics and lay the foundations to the empirical approach that we will develop in the next sections.

One potential alternative explanation for the threat of entry is that market segregation happens through differences in project size. In other words, weaker contractors cannot undertake large projects, and top contractors have no interest in small projects.

In Table 3.4, we present the distribution of potential bidders, actual bidders, and top bidders per project divided into the different project size deciles as measured by the project costs estimates of the FDOT. One first pattern is that the total number of active bidders remains relatively unchanged throughout the different deciles and centered around 4.5 participants, although the number of potential bidders increases with project size. Top contractors seem to be more interested in participating in auctions for larger projects: while for the first two deciles the average participation of big firms is below 1, the last four deciles see an average of almost 2 top contractors bidding for the projects.

Table 3.4: Number of bidders by project size and bidder type

	Proj. Cost	# Pot Bidders		# Bidders		# Top Bidders	
	up to ($ 1,000)	Mean	Std. Dev.	Mean	Std. Dev	Mean	Std. Dev
10%	246.17	15.76	8.17	5.61	2.99	0.41	0.72
20%	471.75	14.80	6.93	4.47	2.25	0.78	1.01
30%	818.00	15.92	7.75	4.51	2.37	1.27	1.10
40%	1,201.64	17.61	8.04	4.84	2.63	1.50	1.17
50%	1,763.76	17.94	8.22	4.41	2.20	1.69	1.21
60%	2,448.08	18.93	8.85	4.34	2.34	1.78	1.04
70%	3,477.00	20.77	8.70	4.76	2.29	1.95	1.06
80%	5,167.78	21.28	10.03	4.53	2.18	2.09	1.10
90%	7,984.41	21.58	10.92	4.55	2.63	1.98	0.98
100%	163,700.00	29.22	14.83	5.60	3.55	1.96	1.09

Another possibility for market segregation could be that weak and strong contractors specialize in different tasks. In this case, projects that only have small contractors interested would be systematically different in that they would contain different tasks to fulfill. Figure 3.2 illustrates these differences comparing the distribution of tasks contracted in projects that have at least one top contractor in the set of potential bidders against those that do not have any. The percentages in this distribution can sum to more than one since more than one task can be contracted in the same project.

Projects that are only contended by small contractors tend to contain items such as signalization, lighting, signing, and other small tasks. Instead, the projects that attract top contractors usually include items like resurfacing and milling that require heavier machinery. From both Table 3.4 and Figure 3.2 one can qualitatively observe that there are specific differences in terms of project characteristics and size that might explain a part of the market segregation across contractors. However,

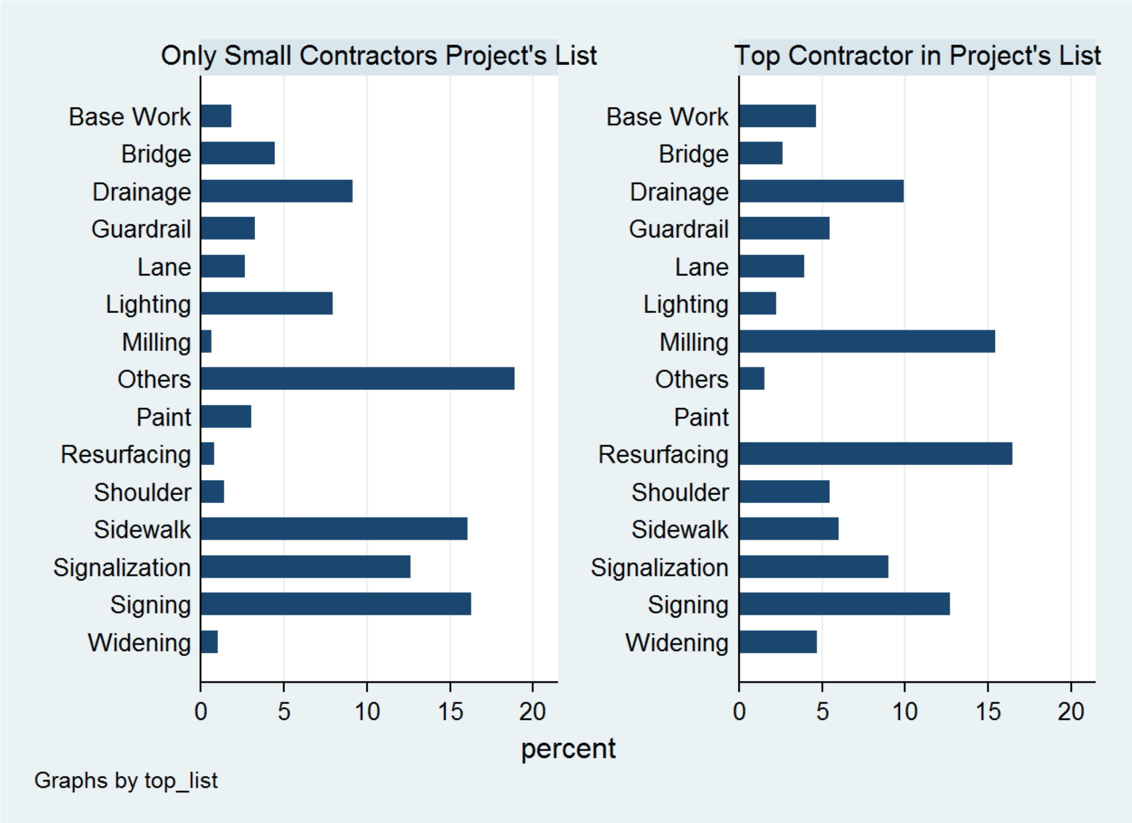

Figure 3.2: Distribution of tasks by potential bidder

these patterns do not seem striking enough to exclude the idea that there is some preemption from top contractors to smaller ones.

3.4 Commitment and incentives to forego a project

In this section, we present a stylized model that captures the institutional details and stylized facts of Section 3.3. We introduce a simplified model of entry to illustrate the mechanisms working behind signaling in this environment. We also discuss the incentives that contractors might have to forego being a potential entrant even if it comes at no monetary cost. We then test the predictions and mechanisms proposed in this stylized model in Section 3.5.

3.4.1 Stylized model

Consider the case of two firms where one is a strong contractor B and the other is a weak contractor W. They compete for two infrastructure projects at the same time: a large one L and a small one S.

To win these projects, they must enter them at some cost. If one contractor enters to the large project, and the other stays out of content, it earns $\pi^L > 0$. The same happens if only one contractor enters the small project, although we assume $\pi_i^L > \pi_i^S > 0$. We abstract, for the time being, to specify what is the allocation mechanism in case both enter a project simultaneously. However, we assume that if both of them participate, the project is earned by either of them, but they both incur losses of c. These losses represent the intensity of competition and, to make them relevant to our analysis, we assumed them to be such that $c > \pi^L - \pi^S$.

Furthermore, we crucially assume that there is some externality between projects. In particular, if the same contractor enters the two projects at the same time, its profits are reduced by e. This externality could be understood as some congestion due to possible capacity restrictions.

Equilibrium without commitment. Consider first the case where no contractor could credibly forego being a potential entrant to a project. Equilibrium in this game depends on the size of the project externality e. If $e < \pi^S - c$ the externality is very small and it does not play any sizable role, thus being the dominant strategy of each player to enter both projects. When the externality is moderate ($\pi^S - c \leq e < \pi^L - c$), the costs of entering into both projects are starting to be significant, and there are two equilibria: in each of them one of the two contractors enters at both projects, and the other enters only at the big one.

The more interesting case arises when the externality is large (i.e. $e > \pi^B - c$). In this situation, both contractors find too costly to enter into both projects, and have to decide on one of the two. Furthermore, given the intensity of competition (i.e., the value of c), they aim at avoiding the competing contractor. As a result, there are two pure-strategy equilibria: one where the strong contractor enters the large project and the weak enters to the small project, and one where the converse is true.

Equilibrium with commitment. Let now assume that the strong contractor can credibly commit not to participate in the small project. When the externality is low or moderate, this option does not play a particularly important role. In essence, it foregoes the small project to the weak contractor, who would still want to enter to the big project. In these cases, the strong contractor would not have incentives to take this commitment.

Instead, this device becomes essential when the externality is high. If $e > \pi^B - c$, and the strong contractor makes clear that he will not enter the small project, then the only equilibrium of this game becomes the one in which the strong contractor takes the large project, and the weak contractor undertakes the small project. Under these conditions, the strong contractor has incentives to coordinate with its weaker rival and get the best possible equilibrium outcome of the original game.

3.5 Empirical Strategy and Results

In this section, we test empirically for the mechanisms and predictions of section 3.4. We provide a simple and descriptive empirical analysis of the different patterns that arise in this setup. First, we inspect whether there is evidence for entry preemption taking place from strong bidders to weak bidders. The second aspect that we examine is whether a firm requesting for plan information and qualifying as a potential bidder to a project carries any possible information to its rivals about its intention to bid on a particular project.

These two fundamental aspects shed light on the relevance of signaling entry and how the request for project plans could be strategic. Still, they do not explain why would a firm forego any option to contend for a project in equilibrium. For this reason, we analyze whether there is evidence for substitutions across projects to be taking place in our sample.

3.5.1 Entry preemption

The descriptive statistics and the suggestive evidence of the previous sections do not tell if the observed difference in entry probabilities is due to the actual entry of strong firms or due to the threat of entry by strong firms. To see if weak bidders act on the risk of entry by strong bidders, we compare those cases in which strong bidders enter with those cases in which they do not.

In Table 3.5, we look at how small firms' entry and bidding behavior are associated with the number of strong participating and non-participating plan holders. The first three columns contain a linear probability model where the dependent variable is an indicator variable that is equal to one when a potential bidder has submitted a bid. In these regressions, we examine what is the effect that rival strong non-participating prospective bidders have on the auction participation of small firms.

The results show that irrespective of a strong firm submitting a bid or not, its request for a plan diminishes the propensity for a small firm to submit a bid by a 2.7%. The result here suggests that weak bidders act on strong firms' request for project plans and not on the actual entry of strong firms. Another finding here is that weak bidders are 1.38% more likely to submit a bid when the project is the only project from which they have solicited a project plan. These results persist after controlling for many other factors that might weight in as the size of the project, or the type of project. Moreover, we control for different kind of firm, district, and time-period unobservables using a broad set of fixed effects.

Table 3.5: Entry and Bidding Behavior of Weak Firms

Dependent Variable	1{submit a bid}			log(bid)		
# of strong non-participating	-0.0179**	-0.0266**	-0.0272**	0.0152**	0.0011	-0.0036
firms on the same list	(0.0034)	(0.0038)	(0.0038)	(0.0080)	(0.0073)	(0.0072)
# of strong participating		-0.0310**	-0.0298**		-0.0055	-0.0115
firms on the same list		(0.0029)	(0.0031)		(0.0069)	(0.0068)
1{no other projects}			0.0138**			0.0033
			(0.0053)			(0.0092)
Engineer's cost estimate	Yes	Yes	Yes	Yes	Yes	Yes
District Office Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Project Type Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.377	0.395	0.396	0.972	0.976	0.977
N	33556	33556	33556	6216	6216	6216

These findings are consistent with the hypothesis that plan requests are not only used by firms to acquire information about projects' characteristics but also to separate the markets by sending a signal of entry to weak firms.

In columns (4) to (6), we examine whether the entry signal mechanism is also carried on to the bidding behavior of smaller firms. We regress the logarithm of the bidding score submitted by these firms on the number of strong non-participating firms, and the same series of controls as in the first three columns. In this case, there does not seem to be any effect of the non-participating big firms to the bidding patterns of weak contractors after controlling for the actual entry. This finding is in line with the initial hypothesis: entry signals lose any effect on smaller contractors once parties have revealed entry behavior.

3.5.2 Signal of entry

Once having shown empirical evidence of small firms reacting to the possibility of entry by big firms, we focus on the signals of entry. In Table 3.6, we present a linear probability model of entry for weak and strong bidders regressed on a broad set of observables and fixed effects to control for unobservables. One first aspect to notice is that the impact of strong potential bidders on weak bidders remains throughout all specifications at around a 2%.

The parameters of the linear and squared term for the bidder utilization rate show that there are two groups with reduced entry into auctions. There is a large set of weak bidders that never win a project, and have very low utilization rates. These bidders have a lower probability of entry that is reflected in the coefficients. Other bidders do win projects and have utilization rates close to 1. These bidders also have a lower probability of entry mostly because they have low free capacity to employ.

Table 3.6: Entry Behavior by Firm Type

	(1)	(2)	(3)	(4)	(5)	(6)
	1{submit a bid} - Weak Bidders			1{submit a bid} - Strong Bidders		
# of weak potential entrants	-0.003***	-0.003***	-0.004***	-0.006***	-0.006***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
# of strong potential entrants	-0.021***	-0.021***	-0.020***	-0.012	-0.011	-0.010
	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.007)
Bidder Utilization Rate	1.829***	1.830***	1.827***	2.219***	2.219***	2.206***
	(0.040)	(0.040)	(0.040)	(0.075)	(0.075)	(0.075)
(Bidder Utilization Rate)^2	-1.527***	-1.527***	-1.525***	-2.093***	-2.089***	-2.078***
	(0.047)	(0.047)	(0.047)	(0.089)	(0.089)	(0.089)
# of projects requested simultaneously		-0.002***	-0.002***		-0.007***	-0.007***
		(0.001)	(0.001)		(0.002)	(0.002)
FDOT Utilization Rate		-0.024**	-0.024**		-0.012	-0.010
		(0.008)	(0.008)		(0.027)	(0.026)
Close Project		0.040***	0.040***		0.107***	0.105***
		(0.006)	(0.006)		(0.020)	(0.020)
Contract Duration			0.000***			-0.000***
			(0.000)			(0.000)
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Project Type Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Square	0.549	0.550	0.551	0.817	0.819	0.820
N	33556	33535	33521	4139	4137	4137

The parameter of interest in table 3.6 is the one associated with the number of simultaneous project plans requested. This variable is the number of project plans that the bidder requested for projects in the same district auctioned within a time window of three days before and after the auction. We group these projects because they have letting processes that occur relatively parallel to each other.

The coefficients for this variable both for weak and strong bidders are negative and significant. The sign means that the probability of entry by a bidder is lower the more projects it has shown interest in at the same time. We can invert the reasoning and interpret these results in terms of information. The negative coefficient implies that a bidder requesting few project plans is more likely to enter in these projects, and that certainty reduces the more plans the bidder requests. The effect is sizable for strong bidders with a reduction of a 0.7% for each plan requested in the same district.

It is interesting to join together the evidence of Tables 3.5 and 3.6. We showed in Table 3.5 that requesting a plan by big contractors reduces the contesting of small firms. The natural question taking this evidence face value is why does every strong bidder not request a plan for every project if it reduces its competition.

We complete this picture in Table 3.6. A high number of plans decreases the threat of entry by the firm requesting them. In other terms, if every strong bidder would request a plan for every available project, this signal would not be effective, and the effect on auction entry explored in Table 3.5 would not be as significant as it is currently.

3.5.3 Substitution across projects

We have shown that there exists evidence of strong contractors using their plan requests to signal their interest in specific projects. However, the channel through which these actions become valid signals requires profound inspection, since the cost of requesting a plan is none in itself.

In this subsection, we look for empirical evidence for the channel that we propose in the model of section 3.4. In it, foregoing a second project gives a signal to the rivals of the firm in a first project since there exists some substitution across projects. This substitution is present in the form of a less competitive bidding behavior for firms that are bidding more aggressively in other projects. In this manner, a bidder that decides not to bid in some project is probably also going to bid more aggressively in those projects that it can enter.

We propose the following simple approach to test for this mechanism in our data. First, we approximate the bidding distribution function for both strong and weak constructors using a complete reduced form regression that controls for many aspects that affect bidding behavior. After getting these bid distributions, we add to them the number of other simultaneous projects for which the firm has entered the auction.

We expect the sign for the coefficient of this last regressor to be positive to back our hypothesis of substitution across projects. Were it positive, it would imply that the more auctions a firm enters simultaneously, the least competitive it becomes in each of them.

We model the reduced-form bidding function as a linear function of its regressors and account for two main types of endogeneity that might arise in this setup. First, bidding depends on the number and identity of rival firms that have decided to participate in the auction, and the firms themselves decide this entry. There is a high probability that the unobservables that make a contractor bid aggressively are also the reason why many other contractors choose to submit a bid. This kind of endogeneity would lead us to overstate the competitive effects across firms in the procurement process.

Second, each observation that we have is a result of the decision of a firm to enter an auction. This remark also implies that we could probably have many missing observations that correspond to firms that would have submitted a less competitive bid, but decided instead not to submit any at all. This issue of selection would overestimate the competitiveness of firms when submitting their proposals.

We account for the selection effect using a selection model based on Heckman (1979). Let X and W be vectors of project and bidder characteristics, while the attributes in W are exogenous, the ones in X might be endogenous. For us to observe a bid, a firm should have decided to enter the auction and to participate in it. We define the variable SUBMIT BID as an indicator variable equal to 1 if the latent variable y is positive and 0 otherwise. We define additionally Z to be a set of exogenous variables relevant for entry. We consider the following equations

$$\begin{aligned} y &= Z\gamma_1 + W\gamma_2 + \epsilon_y, \\ \log(\text{bid}) &= X\beta_1 + W\beta_2 + \epsilon_b, \\ X &= Z\pi_1 + W\pi_2 + \epsilon_x. \end{aligned}$$

The first equation is the entry equation, and the second is the one of interest. The third equation regresses the endogenous characteristics over a set of exogenous variables for an instrumental variables approach. We assume β, γ, and π to be vectors of parameters to estimate. Finally, we take ϵ_y, ϵ_b, and ϵ_x as zero-mean normal random unobservables with $\text{Var}(\epsilon_y) = 1$, $\text{Var}(\epsilon_x) = \sigma_x^2$, and $\text{Var}(\epsilon_b) = \sigma_b^2$. We assume all the correlations to be 0, except $\text{Corr}(\epsilon_b, \epsilon_y) = \rho_{by}$ to be estimated.

This setup allows us to regress for the bids using our selected sample. We get a closed form expression for the conditional expectation of the log(bid)

$$\mathbb{E}[\log(\text{bid})|\text{SUBMIT BID} = 1, Z] = X\beta_1 + W\beta_2 + \rho_{by}\sigma\frac{\phi(Z\gamma_1 + W\gamma_2)}{\Phi(Z\gamma_1 + W\gamma_2)}, \tag{3.1}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability density and cumulative distribution functions of a standard normal random variable, and their ratio constitute what is normally referred as the inverse Mills' ratio. We expect the parameter ρ_{by} to be negative because less competitive firms (with higher potential bids) would tend to shy out from submitting a bid.

We estimate this model in two stages. In the first stage, we regress the endogenous variables on the exogenous characteristics and estimate the entry equation as a Probit model. We get estimates $\hat{X}$, and $\hat{\phi(\cdot)}/\hat{\Phi(\cdot)}$ from these first-stage regressions. In the second stage, we regress the log(bid) on the different exogenous variables, the predicted $\hat{X}$, and the predicted inverse Mills' ratio. We bootstrap our standard errors to account for the additional noise added by the predicted variables in the first stage of the estimation.

For the identification of our parameters to work in this model, we need as many excluded variables as the number of endogenous variables plus an additional one for the entry equation. It is difficult to find many such variables in such a strategic environment as this one. In what follows, we propose a series of instruments using our institutional framework and discuss their limitations.

We propose to use the number of potential bidders, the number of simultaneous projects requested by the bidder, and the estimated cost of all concurrent projects as excluded variables for our estimation. The number of potential bidders is an endogenous variable since the firms themselves also decide them. After all prospective bidders choose whether to enter the auction and submit a bid, this decision is observed by every competitor, and the status as a potential bidder is no longer relevant. For this reason, the relevance of the number of prospective bidders affects the bidding strategies only through the actual number of bidders, making it a suitable instrument. The number of simultaneous project requests follows a similar line of argument as the total number of potential bidders.

The total projected costs of all simultaneous projects let in a time window of 3 days should approximate for the opportunity cost that a contractor faces when deciding to contest for one project and foregoing another one. We need to assume that the set of projects posted every month by the FDOT are exogenous for this variable to work as a valid instrument. An example that might violate this assumption would be if the FDOT released its list of projects to procure in separate packages of complementary contractible units at the beginning of the month.

We show the results of our regressions in Table 3.7. The first four columns correspond to specifications including only weak bidders, while the last four columns include only strong bidders. In each of the two sets of four columns, there are different estimation strategies. The first one corresponds to a naïve least squares estimation of the logarithm of the bid on a series of regressors. The second column

Table 3.7: Bidding Behavior by Firm Type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	IV+Heck	IV+Heck	OLS	IV	IV+Heck	IV+Heck
	Log(Bid) - Weak Bidders				Log(Bid) - Strong Bidders			
# Weak	-0.014***	-0.017***	-0.015***	-0.017***	-0.016***	-0.013**	-0.011*	-0.011**
	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)	(0.004)
# Strong	-0.018***	-0.026***	-0.023***	-0.023***	-0.004	-0.000	-0.000	-0.003
	(0.004)	(0.006)	(0.006)	(0.006)	(0.004)	(0.006)	(0.006)	(0.006)
% Bidder Utilization	0.054***	0.054***	0.053**	0.068***	0.062***	0.060***	0.052**	0.059**
	(0.012)	(0.012)	(0.018)	(0.018)	(0.017)	(0.017)	(0.019)	(0.019)
% FDOT Utilization	-0.056***	-0.060***	-0.059***	-0.061***	-0.035*	-0.032	-0.031	-0.033
	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
Log(Contract duration)	0.070***	0.073***	0.078***	0.086***	0.191***	0.185***	0.183***	0.182***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.013)	(0.015)	(0.015)	(0.015)
Close Project	-0.029**	-0.031***	-0.029**	-0.023*	-0.021	-0.021	-0.023	-0.020
	(0.009)	(0.009)	(0.010)	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)
Inverse Mills			-0.015	0.007			-0.011	0.000
			(0.015)	(0.015)			(0.019)	(0.020)
# Proj. Entered				0.038***				0.010**
				(0.004)				(0.003)
# Proj. Won				-0.052***				-0.015***
				(0.004)				(0.003)
Engineer's cost estimate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project Type Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Test (Weak)		2259.51	2259.51	2330.65		302.05	302.05	301.88
F-Test (Strong)		7934.36	7934.36	7924.95		806.71	806.71	840.45
χ-Test (Entry)			557.29	544.17			15.83	104.45
Adj. R-Square	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
N	6213	6213	6213	6213	2987	2987	2987	2987

uses the instruments discussed before to account for the endogeneity of the number of participants. Finally, the third and fourth columns combine the use of instruments with the Heckman selection technique. The F-Tests and χ-Tests for instrument relevance of the first stages are reported in the lower part of the table.[2]

The regression coefficients for weak bidders are all in line with the general intuition. Weak firms react to a higher number of competitors by submitting a more competitive bid. This effect is more pronounced when the entrants are strong bidders. Specifically, weak bidders decrease their bids by a 2.3% for every additional strong participant as opposed to a 1.5% - 1.7% for every additional weak firm. They also tend to bid more competitively when the project is in the same district as their headquarters. Conversely, they bid less aggressively for long projects, and even when they are working at high capacity. The results look qualitatively similar for strong bidders except for their competitive effects. They seem not to be reacting at all to the presence of other strong firms bidding in the same auction.

The most interesting parameters are the ones at the end of Table 3.7 in columns (3), (4), (7), and (8). The coefficient on the inverse Mills' ratio is in neither of

[2]The first stage regressions can be found in Tables 14 and 15 of the appendix.

the columns significant. We would have expected it to have a significantly negative coefficient that implied that the bidders left out of the auction to be those that would have submitted less competitive bids. This lack of significance is in line with the standard modeling assumption in the structural literature where unobservable shocks to entry costs are independent of shocks to bidding strategies.

Finally, the last two coefficients are the number of simultaneous auctions entered, and the number of simultaneous auctions won by the bidder. We are interested mainly in the first one. We could interpret its coefficient as the impact that unsuccessful entry into other auctions happening at the same time have on bidding behavior. Its positive and significant estimate implies that entering to another concurrent auction and not winning it is associated with less competitive bidding by the firm in other projects. In quantitative terms, a weak contractor that participates unsuccessfully in another letting auction increases its bid by a 3.8%, while a strong contractor does so by a 1%.

We understand these results only as weak suggestive evidence of substitution across projects. First of all, there is little room for causal claims in such a strategic environment. Moreover, we find less competitive bidding for unsuccessful bids, which is a selected subsample of all bids.

3.6 Concluding Remarks

In this paper, we inspect the role of information design in procurement auctions. We use data from transport infrastructure auctions in Florida that contain not only the bids from all auction participants, but also the identity and number of all firms interested in a project. The list of interested firms is publicly known and no contractor can submit a bid without first qualifying as a potential bidder.

We use our data to analyze how common knowledge of the list of potential entrants affects the development of the letting process. In particular, we look at the possibility that strong bidders might use this institutional feature to signal interest in some projects and keep competition away from them.

We develop a stylized framework of the letting process to illustrate how a contractor could commit to giving up participating in some auctions to signal strongly that it wants to participate actively in other auctions. We then test for these predictions in our data.

We find strong evidence that knowing the list of potential entrants affects entry behavior in these procurement auctions. A normal bidder reduces its participation probability in a project by around 2.7% when an additional prominent bidder is in the list of potential entrants.

Furthermore, we find evidence that this information transmission is built upon the choice of projects for which a firm wants to appear as a potential bidder. In other words, a bidder that chooses to appear as a contender for many projects is less likely to enter any of them, whereas a bidder that shows interest in very few projects is expected to be more prone to submit a bid. Our estimates show that a strong bidder that request information for an additional project reduces its probability to enter any of the projects he is a potential bidder for by 0.7%.

After showing the existence of entry signals and their substantial effect in auction participation, we turn our attention to finding the mechanism that allows for this behavior in equilibrium. In particular, we propose that there exist some substitution effect among projects that reduces the competitiveness for a contractor submitting bids for several auctions at the same time. We test for this mechanism and find weak evidence of it. Each unsuccessful bid for a simultaneous project increases by a 3.8% and a 1% the bid score for weak and strong bidders respectively.

Our work is the first one to pay attention to the institutional design of information in project procurement and finds that it has sizable effects on participation and bidding behavior. We provide a different insight compared to much of the existing literature. While it is essential to detect potential collusive behavior among bidders, it is also vital to prevent the institutional framework to facilitate coordination among bidders. The optimal information design and the monetary cost of this coordination could be better quantified estimating a structural model.

Appendix to Chapter 2

Table 8: Predicted Number of Dealers by Manufacurer

Brand	Obs.	After Elimination		Eq'm	
		Mean	**(SD)**	**Mean**	**(SD)**
ALFA ROMEO	2.000	2.000	(0.000)	2.030	(0.171)
AUDI	2.000	2.000	(0.000)	2.000	(0.000)
BMW	3.000	3.000	(0.000)	3.000	(0.000)
CITROEN / DS	9.000	6.775	(0.418)	6.775	(0.418)
FIAT	3.000	3.000	(0.000)	3.000	(0.000)
FORD	6.000	5.000	(0.000)	5.000	(0.000)
HONDA	2.000	2.000	(0.000)	2.105	(0.307)
HYUNDAI	4.000	3.000	(0.000)	2.490	(0.500)
INFINITI	1.000	1.000	(0.000)	1.970	(0.243)
JAGUAR	2.000	1.000	(0.000)	2.000	(0.000)
JEEP	1.000	1.000	(0.000)	2.110	(0.313)
KIA	4.000	4.000	(0.000)	4.000	(0.000)
LAND ROVER	2.000	1.000	(0.000)	2.000	(0.000)
MAZDA	2.000	2.000	(0.000)	2.080	(0.271)
MERCEDES BENZ	3.000	3.000	(0.000)	3.000	(0.000)
MINI	2.000	2.000	(0.000)	2.000	(0.000)
MITSUBISHI	3.000	3.000	(0.000)	2.235	(0.424)
NISSAN	3.000	3.000	(0.000)	3.000	(0.000)
OPEL	6.000	5.000	(0.000)	5.000	(0.000)
PEUGEOT	9.000	5.640	(0.641)	5.640	(0.641)
PORSCHE	1.000	1.000	(0.000)	1.000	(0.000)
RENAULT / DACIA	13.000	5.995	(0.908)	5.995	(0.908)
SEAT	7.000	4.180	(0.384)	4.180	(0.384)
SKODA	2.000	2.000	(0.000)	2.000	(0.000)
SMART	1.000	1.000	(0.000)	1.700	(0.458)
SSANGYONG	2.000	2.000	(0.000)	2.040	(0.196)
SUBARU	3.000	3.000	(0.000)	2.010	(0.099)
SUZUKI	2.000	2.000	(0.000)	2.185	(0.388)
TOYOTA	3.000	3.000	(0.000)	3.000	(0.000)
VOLKSWAGEN	4.000	4.000	(0.000)	4.000	(0.000)
VOLVO	2.000	2.000	(0.000)	2.000	(0.000)

Table 9: Predicted Sales by Car Model (Part 1)

Model	Obs.	After Elimination Mean	(SD)	Eq'm Mean	(SD)
ALFA ROMEO GIULIA	0.0881	0.0233	(0.0031)	0.1592	(0.0061)
ALFA ROMEO GIULIETTA	0.1304	0.0344	(0.0031)	0.2356	(0.0061)
ALFA ROMEO MITO	0.0279	0.0074	(0.0031)	0.0505	(0.0061)
ALFA ROMEO STELVIO	0.1882	0.0497	(0.0031)	0.3401	(0.0061)
AUDI A1	0.1453	0.0385	(0.0034)	0.0357	(0.0034)
AUDI A3	0.2421	0.0642	(0.0034)	0.0595	(0.0034)
AUDI A4	0.1268	0.0336	(0.0034)	0.0312	(0.0034)
AUDI A5	0.1272	0.0337	(0.0034)	0.0313	(0.0034)
AUDI A6	0.0842	0.0223	(0.0034)	0.0207	(0.0034)
AUDI A7	0.0000	0.0000	(0.0034)	0.0000	(0.0034)
AUDI A8	0.0000	0.0000	(0.0034)	0.0000	(0.0034)
AUDI Q2	0.1146	0.0304	(0.0034)	0.0282	(0.0034)
AUDI Q3	0.2615	0.0693	(0.0034)	0.0643	(0.0034)
AUDI Q5	0.1411	0.0374	(0.0034)	0.0347	(0.0034)
AUDI Q7	0.1404	0.0372	(0.0034)	0.0345	(0.0034)
AUDI TT	0.0000	0.0000	(0.0034)	0.0000	(0.0034)
BMW SERIE 1	0.3053	0.0812	(0.0026)	0.0756	(0.0027)
BMW SERIE 2	0.2984	0.0793	(0.0026)	0.0739	(0.0027)
BMW SERIE 3	0.4557	0.1211	(0.0026)	0.1129	(0.0027)
BMW SERIE 4	0.1657	0.0440	(0.0026)	0.0410	(0.0027)
BMW SERIE 5	0.3696	0.0983	(0.0026)	0.0916	(0.0027)
BMW SERIE 6	0.0675	0.0180	(0.0026)	0.0167	(0.0027)
BMW SERIE 7	0.3051	0.0811	(0.0026)	0.0756	(0.0027)
BMW X1	0.7097	0.1887	(0.0026)	0.1758	(0.0027)
BMW X3	0.5692	0.1513	(0.0026)	0.1410	(0.0027)
BMW X4	0.4696	0.1248	(0.0026)	0.1163	(0.0027)
BMW X5	0.1084	0.0288	(0.0026)	0.0268	(0.0027)
BMW X6	0.0807	0.0215	(0.0026)	0.0200	(0.0027)
CITROEN BERLINGO	0.5776	0.6810	(0.0184)	0.6336	(0.0183)
CITROEN C-ELYSEE	0.8048	0.9488	(0.0184)	0.8828	(0.0183)
CITROEN C1	0.0239	0.0282	(0.0184)	0.0263	(0.0183)
CITROEN C3	1.0969	1.2931	(0.0184)	1.2033	(0.0183)
CITROEN C4	1.9116	2.2536	(0.0184)	2.0970	(0.0183)
CITROEN C4 AIRCROSS	0.3001	0.3538	(0.0184)	0.3292	(0.0183)
CITROEN C4 CACTUS	0.4876	0.5748	(0.0184)	0.5349	(0.0183)
CITROEN C4 PICASSO	1.6029	1.8897	(0.0184)	1.7584	(0.0183)
CITROEN C5	0.0910	0.1073	(0.0184)	0.0999	(0.0183)
CITROEN NEMO	0.0000	0.0000	(0.0184)	0.0000	(0.0183)
RENAULT DOKKER	0.5998	0.5921	(0.0268)	0.5509	(0.0267)
RENAULT DUSTER	6.5537	6.4689	(0.0268)	6.0190	(0.0267)
RENAULT LODGY	0.2900	0.2862	(0.0268)	0.2663	(0.0267)
RENAULT LOGAN	0.2315	0.2285	(0.0268)	0.2126	(0.0267)
RENAULT SANDERO	2.4223	2.3910	(0.0268)	2.2247	(0.0267)
CITROEN DS3	0.0826	0.0973	(0.0184)	0.0906	(0.0183)
CITROEN DS4	0.2252	0.2655	(0.0184)	0.2470	(0.0183)
CITROEN DS5	0.2456	0.2895	(0.0184)	0.2694	(0.0183)

Table 10: Predicted Sales by Car Model (Part 2)

Model	Obs.	After Elimination		Eq'm	
		Mean	(SD)	Mean	(SD)
FIAT 124 SPIDER	0.0661	0.0177	(0.0022)	0.0165	(0.0023)
FIAT 500	0.2439	0.0652	(0.0022)	0.0609	(0.0023)
FIAT 500L	0.0695	0.0186	(0.0022)	0.0173	(0.0023)
FIAT 500X	0.2122	0.0567	(0.0022)	0.0529	(0.0023)
FIAT DOBLO	0.0324	0.0087	(0.0022)	0.0081	(0.0023)
FIAT PANDA	0.1103	0.0295	(0.0022)	0.0275	(0.0023)
FIAT PUNTO	0.4644	0.1241	(0.0022)	0.1159	(0.0023)
FIAT TIPO	0.4902	0.1310	(0.0022)	0.1223	(0.0023)
FORD B-MAX	0.0183	0.0235	(0.0033)	0.0219	(0.0033)
FORD C-MAX	0.0946	0.1215	(0.0033)	0.1130	(0.0033)
FORD ECOSPORT	0.1479	0.1899	(0.0033)	0.1766	(0.0033)
FORD EDGE	0.0000	0.0000	(0.0033)	0.0000	(0.0033)
FORD FIESTA	0.1855	0.2382	(0.0033)	0.2215	(0.0033)
FORD FOCUS	1.4967	1.9213	(0.0033)	1.7871	(0.0033)
FORD GALAXY	0.0000	0.0000	(0.0033)	0.0000	(0.0033)
FORD KA	0.2611	0.3351	(0.0033)	0.3117	(0.0033)
FORD KUGA	0.2914	0.3741	(0.0033)	0.3479	(0.0033)
FORD MONDEO	0.1353	0.1737	(0.0033)	0.1615	(0.0033)
FORD S-MAX	0.0458	0.0588	(0.0033)	0.0547	(0.0033)
FORD TOURNEO CONNECT	0.0244	0.0313	(0.0033)	0.0291	(0.0033)
FORD TOURNEO COURIER	0.2827	0.3629	(0.0033)	0.3375	(0.0033)
HONDA CIVIC	0.0159	0.0042	(0.0034)	0.0265	(0.0078)
HONDA CR-V	0.0332	0.0088	(0.0034)	0.0552	(0.0078)
HONDA HR-V	0.0000	0.0000	(0.0034)	0.0000	(0.0078)
HONDA JAZZ	0.0000	0.0000	(0.0034)	0.0000	(0.0078)
HYUNDAI ELANTRA	0.1452	0.1924	(0.0036)	0.1720	(0.0074)
HYUNDAI GRAND SANTA FE	0.0000	0.0000	(0.0036)	0.0000	(0.0074)
HYUNDAI I10	0.1488	0.1972	(0.0036)	0.1763	(0.0074)
HYUNDAI I20	0.5089	0.6744	(0.0036)	0.6030	(0.0074)
HYUNDAI I30	1.3205	1.7499	(0.0036)	1.5645	(0.0074)
HYUNDAI I40	0.1122	0.1487	(0.0036)	0.1330	(0.0074)
HYUNDAI IONIQ	0.1815	0.2405	(0.0036)	0.2150	(0.0074)
HYUNDAI IX20	0.0212	0.0280	(0.0036)	0.0251	(0.0074)
HYUNDAI SANTA FE	0.0552	0.0731	(0.0036)	0.0654	(0.0074)
HYUNDAI TUCSON	8.8504	11.7283	(0.0036)	10.4860	(0.0074)
INFINITI Q30	0.0430	0.0112	(0.0044)	0.1243	(0.0174)
INFINITI Q50	0.0000	0.0000	(0.0044)	0.0000	(0.0174)
INFINITI QX30	0.0000	0.0000	(0.0044)	0.0000	(0.0174)
JAGUAR F-PACE	0.0353	0.1171	(0.0023)	0.1226	(0.0106)
JAGUAR XE	0.0000	0.0000	(0.0023)	0.0000	(0.0106)
JAGUAR XF	0.0000	0.0000	(0.0023)	0.0000	(0.0106)
JEEP CHEROKEE	0.0262	0.0070	(0.0033)	0.1161	(0.0047)
JEEP GRAND CHEROKEE	0.0731	0.0196	(0.0033)	0.3242	(0.0047)
JEEP RENEGADE	0.4122	0.1106	(0.0033)	1.8279	(0.0047)
JEEP WRANGLER	0.0079	0.0021	(0.0033)	0.0351	(0.0047)

Table 11: Predicted Sales by Car Model (Part 3)

Model	Obs.	After Elimination		Eq'm	
		Mean	(SD)	Mean	(SD)
KIA CARENS	0.4498	0.6040	(0.0017)	0.5618	(0.0017)
KIA CEE'D	0.8137	1.0927	(0.0017)	1.0162	(0.0017)
KIA NIRO	0.3073	0.4126	(0.0017)	0.3837	(0.0017)
KIA OPTIMA	0.0549	0.0737	(0.0017)	0.0685	(0.0017)
KIA PICANTO	0.1422	0.1910	(0.0017)	0.1776	(0.0017)
KIA RIO	0.3126	0.4198	(0.0017)	0.3904	(0.0017)
KIA SORENTO	0.6223	0.8356	(0.0017)	0.7772	(0.0017)
KIA SOUL	0.0000	0.0000	(0.0017)	0.0000	(0.0017)
KIA SPORTAGE	2.4547	3.2962	(0.0017)	3.0656	(0.0017)
KIA VENGA	0.0446	0.0599	(0.0017)	0.0558	(0.0017)
LAND ROVER DISCOVERY	0.0000	0.0000	(0.0024)	0.0000	(0.0092)
LAND ROVER DISCOVERY SPORT	0.0467	0.1551	(0.0024)	0.1633	(0.0092)
LAND ROVER RANGE ROVER	0.0000	0.0000	(0.0024)	0.0000	(0.0092)
LAND ROVER RANGE ROVER EVOQUE	0.0996	0.3305	(0.0024)	0.3480	(0.0092)
LAND ROVER RANGE ROVER SPORT	0.0150	0.0499	(0.0024)	0.0525	(0.0092)
LAND ROVER RANGE ROVER VELAR	0.0300	0.0996	(0.0024)	0.1049	(0.0092)
MAZDA CX-3	0.1097	0.0291	(0.0031)	0.2107	(0.0087)
MAZDA CX-5	0.1452	0.0384	(0.0031)	0.2788	(0.0087)
MAZDA MAZDA2	0.3396	0.0899	(0.0031)	0.6524	(0.0087)
MAZDA MAZDA3	0.0746	0.0198	(0.0031)	0.1433	(0.0087)
MAZDA MAZDA6	0.1020	0.0270	(0.0031)	0.1960	(0.0087)
MAZDA MX-5	0.0234	0.0062	(0.0031)	0.0449	(0.0087)
MERCEDES BENZ CITAN	0.0216	0.0058	(0.0029)	0.0054	(0.0029)
MERCEDES BENZ CLASE A	0.7681	0.2041	(0.0029)	0.1902	(0.0029)
MERCEDES BENZ CLASE B	0.0526	0.0140	(0.0029)	0.0130	(0.0029)
MERCEDES BENZ CLASE C	0.2895	0.0769	(0.0029)	0.0717	(0.0029)
MERCEDES BENZ CLASE CLA	0.5610	0.1491	(0.0029)	0.1389	(0.0029)
MERCEDES BENZ CLASE CLS	0.0000	0.0000	(0.0029)	0.0000	(0.0029)
MERCEDES BENZ CLASE E	0.1030	0.0274	(0.0029)	0.0255	(0.0029)
MERCEDES BENZ CLASE GLA	0.4646	0.1235	(0.0029)	0.1150	(0.0029)
MERCEDES BENZ CLASE GLC	0.3837	0.1020	(0.0029)	0.0950	(0.0029)
MERCEDES BENZ CLASE GLE	0.0952	0.0253	(0.0029)	0.0236	(0.0029)
MERCEDES BENZ CLASE GLS	0.0000	0.0000	(0.0029)	0.0000	(0.0029)
MERCEDES BENZ CLASE S	0.0000	0.0000	(0.0029)	0.0000	(0.0029)
MERCEDES BENZ CLASE SLC	0.0000	0.0000	(0.0029)	0.0000	(0.0029)
MINI 5 PUERTAS	0.0427	0.0113	(0.0031)	0.0772	(0.0018)
MINI CABRIO	0.0000	0.0000	(0.0031)	0.0000	(0.0018)
MINI CLUBMAN	0.0000	0.0000	(0.0031)	0.0000	(0.0018)
MINI COUNTRYMAN	0.1090	0.0288	(0.0031)	0.1972	(0.0018)
MINI HATCH	0.0290	0.0077	(0.0031)	0.0525	(0.0018)
MINI PACEMAN	0.0429	0.0113	(0.0031)	0.0776	(0.0018)
MITSUBISHI ASX	0.4562	0.1212	(0.0029)	0.5243	(0.0099)
MITSUBISHI MONTERO	0.0000	0.0000	(0.0029)	0.0000	(0.0099)
MITSUBISHI OUTLANDER	0.1256	0.0334	(0.0029)	0.1443	(0.0099)
MITSUBISHI SPACE STAR	0.0161	0.0043	(0.0029)	0.0185	(0.0099)
NISSAN 370Z	0.0207	0.0298	(0.0018)	0.0277	(0.0018)
NISSAN JUKE	1.0894	1.5684	(0.0018)	1.4581	(0.0018)
NISSAN MICRA	0.1649	0.2374	(0.0018)	0.2207	(0.0018)
NISSAN NOTE	0.0000	0.0000	(0.0018)	0.0000	(0.0018)
NISSAN PULSAR	0.1122	0.1615	(0.0018)	0.1501	(0.0018)
NISSAN QASHQAI	0.9973	1.4358	(0.0018)	1.3348	(0.0018)
NISSAN X-TRAIL	0.7589	1.0925	(0.0018)	1.0157	(0.0018)

Table 12: Predicted Sales by Car Model (Part 4)

Model	Obs.	After Elimination		Eq'm	
		Mean	(SD)	Mean	(SD)
OPEL ADAM	0.0581	0.0591	(0.0044)	0.0549	(0.0044)
OPEL ASTRA	1.8106	1.8418	(0.0044)	1.7132	(0.0044)
OPEL CORSA	0.6486	0.6598	(0.0044)	0.6137	(0.0044)
OPEL CROSSLAND X	0.1586	0.1613	(0.0044)	0.1501	(0.0044)
OPEL INSIGNIA	0.5383	0.5475	(0.0044)	0.5093	(0.0044)
OPEL KARL	0.0718	0.0730	(0.0044)	0.0679	(0.0044)
OPEL MERIVA	0.0285	0.0290	(0.0044)	0.0270	(0.0044)
OPEL MOKKA X	0.7017	0.7138	(0.0044)	0.6640	(0.0044)
OPEL ZAFIRA	0.2469	0.2512	(0.0044)	0.2336	(0.0044)
PEUGEOT 108	0.1336	0.1438	(0.0219)	0.1338	(0.0219)
PEUGEOT 2008	1.0025	1.0796	(0.0219)	1.0042	(0.0219)
PEUGEOT 208	0.7297	0.7858	(0.0219)	0.7309	(0.0219)
PEUGEOT 3008	0.5591	0.6021	(0.0219)	0.5600	(0.0219)
PEUGEOT 308	1.5152	1.6317	(0.0219)	1.5177	(0.0219)
PEUGEOT 5008	0.3171	0.3415	(0.0219)	0.3176	(0.0219)
PEUGEOT 508	0.2158	0.2324	(0.0219)	0.2161	(0.0219)
PEUGEOT BIPPER	0.0551	0.0593	(0.0219)	0.0552	(0.0219)
PEUGEOT PARTNER	0.3726	0.4012	(0.0219)	0.3732	(0.0219)
PORSCHE 718 BOXSTER	0.0000	0.0000	(0.0040)	0.0000	(0.0098)
PORSCHE 718 CAYMAN	0.0000	0.0000	(0.0040)	0.0000	(0.0098)
PORSCHE CAYENNE	0.0424	0.0115	(0.0040)	0.1495	(0.0098)
PORSCHE MACAN	0.0116	0.0031	(0.0040)	0.0408	(0.0098)
PORSCHE PANAMERA	0.0000	0.0000	(0.0040)	0.0000	(0.0098)
RENAULT CAPTUR	1.3304	1.3131	(0.0268)	1.2218	(0.0267)
RENAULT CLIO	4.4840	4.4259	(0.0268)	4.1181	(0.0267)
RENAULT ESPACE	0.1996	0.1970	(0.0268)	0.1833	(0.0267)
RENAULT KADJAR	1.7018	1.6797	(0.0268)	1.5629	(0.0267)
RENAULT KANGOO	0.8244	0.8138	(0.0268)	0.7572	(0.0267)
RENAULT MEGANE	8.2994	8.1920	(0.0268)	7.6222	(0.0267)
RENAULT SCENIC	2.1192	2.0918	(0.0268)	1.9463	(0.0267)
RENAULT TALISMAN	0.2498	0.2466	(0.0268)	0.2294	(0.0267)
RENAULT TWINGO	0.1340	0.1323	(0.0268)	0.1231	(0.0267)
SEAT ALHAMBRA	0.0304	0.0381	(0.0073)	0.0355	(0.0073)
SEAT ATECA	1.0322	1.2953	(0.0073)	1.2049	(0.0073)
SEAT IBIZA	3.2434	4.0704	(0.0073)	3.7861	(0.0073)
SEAT LEON	2.0625	2.5885	(0.0073)	2.4077	(0.0073)
SEAT MII	0.0452	0.0567	(0.0073)	0.0527	(0.0073)
SEAT TOLEDO	0.0391	0.0490	(0.0073)	0.0456	(0.0073)
SKODA CITIGO	0.0000	0.0000	(0.0018)	0.0000	(0.0018)
SKODA FABIA	0.1825	0.3921	(0.0018)	0.3643	(0.0018)
SKODA KODIAQ	0.4079	0.8763	(0.0018)	0.8142	(0.0018)
SKODA OCTAVIA	0.1442	0.3098	(0.0018)	0.2878	(0.0018)
SKODA RAPID	0.4475	0.9612	(0.0018)	0.8931	(0.0018)
SKODA SUPERB	0.1625	0.3492	(0.0018)	0.3244	(0.0018)
SKODA YETI	0.0402	0.0864	(0.0018)	0.0803	(0.0018)
SMART FORFOUR	0.0000	0.0000	(0.0034)	0.0000	(0.0274)
SMART FORTWO	0.0052	0.0014	(0.0034)	0.0243	(0.0274)
SSANGYONG KORANDO	0.0753	0.0199	(0.0031)	0.1360	(0.0039)
SSANGYONG REXTON W	0.3393	0.0896	(0.0031)	0.6125	(0.0039)
SSANGYONG RODIUS	0.0503	0.0133	(0.0031)	0.0908	(0.0039)
SSANGYONG TIVOLI	0.2705	0.0714	(0.0031)	0.4883	(0.0039)
SSANGYONG XLV	0.0153	0.0040	(0.0031)	0.0276	(0.0039)

Table 13: Predicted Sales by Car Model (Part 5)

Model	Obs.	After Elimination		Eq'm	
		Mean	**(SD)**	**Mean**	**(SD)**
SUBARU FORESTER	0.0237	0.0063	(0.0026)	0.0297	(0.0042)
SUBARU LEGACY	0.0000	0.0000	(0.0026)	0.0000	(0.0042)
SUBARU LEVORG	0.0000	0.0000	(0.0026)	0.0000	(0.0042)
SUBARU OUTBACK	0.0000	0.0000	(0.0026)	0.0000	(0.0042)
SUBARU WRX STI	0.0000	0.0000	(0.0026)	0.0000	(0.0042)
SUBARU XV	0.0242	0.0064	(0.0026)	0.0305	(0.0042)
SUZUKI BALENO	0.0215	0.0057	(0.0036)	0.0262	(0.0112)
SUZUKI CELERIO	0.0000	0.0000	(0.0036)	0.0000	(0.0112)
SUZUKI IGNIS	0.1520	0.0400	(0.0036)	0.1847	(0.0112)
SUZUKI JIMNY	0.1543	0.0406	(0.0036)	0.1874	(0.0112)
SUZUKI SWIFT	0.0788	0.0207	(0.0036)	0.0958	(0.0112)
SUZUKI SX4	0.0674	0.0177	(0.0036)	0.0819	(0.0112)
SUZUKI VITARA	0.3046	0.0802	(0.0036)	0.3700	(0.0112)
TOYOTA AURIS	1.1288	0.3006	(0.0026)	0.2802	(0.0026)
TOYOTA AVENSIS	0.1616	0.0430	(0.0026)	0.0401	(0.0026)
TOYOTA AYGO	0.3830	0.1020	(0.0026)	0.0951	(0.0026)
TOYOTA C-HR	0.3129	0.0833	(0.0026)	0.0777	(0.0026)
TOYOTA GT86	0.0000	0.0000	(0.0026)	0.0000	(0.0026)
TOYOTA LAND CRUISER	0.2298	0.0612	(0.0026)	0.0570	(0.0026)
TOYOTA PRIUS	0.0000	0.0000	(0.0026)	0.0000	(0.0026)
TOYOTA VERSO	0.1888	0.0503	(0.0026)	0.0469	(0.0026)
TOYOTA YARIS	0.7448	0.1983	(0.0026)	0.1849	(0.0026)
VOLKSWAGEN ARTEON	0.0000	0.0000	(0.0025)	0.0000	(0.0025)
VOLKSWAGEN BEETLE	0.0505	0.0134	(0.0025)	0.0125	(0.0025)
VOLKSWAGEN CADDY	0.0783	0.0208	(0.0025)	0.0194	(0.0025)
VOLKSWAGEN CC	0.0000	0.0000	(0.0025)	0.0000	(0.0025)
VOLKSWAGEN GOLF	0.9619	0.2556	(0.0025)	0.2380	(0.0025)
VOLKSWAGEN JETTA	0.0000	0.0000	(0.0025)	0.0000	(0.0025)
VOLKSWAGEN PASSAT	0.2082	0.0553	(0.0025)	0.0515	(0.0025)
VOLKSWAGEN POLO	0.3684	0.0979	(0.0025)	0.0912	(0.0025)
VOLKSWAGEN SCIROCCO	0.1176	0.0312	(0.0025)	0.0291	(0.0025)
VOLKSWAGEN SHARAN	0.0000	0.0000	(0.0025)	0.0000	(0.0025)
VOLKSWAGEN TIGUAN	0.6193	0.1645	(0.0025)	0.1532	(0.0025)
VOLKSWAGEN TOUAREG	0.1207	0.0321	(0.0025)	0.0299	(0.0025)
VOLKSWAGEN TOURAN	0.8635	0.2294	(0.0025)	0.2137	(0.0025)
VOLKSWAGEN UP!	0.0000	0.0000	(0.0025)	0.0000	(0.0025)
VOLVO S60	0.0729	0.1340	(0.0018)	0.1245	(0.0018)
VOLVO S90	0.0659	0.1211	(0.0018)	0.1125	(0.0018)
VOLVO V40	0.1985	0.3650	(0.0018)	0.3391	(0.0018)
VOLVO V60	0.2976	0.5472	(0.0018)	0.5084	(0.0018)
VOLVO V90	0.0378	0.0695	(0.0018)	0.0646	(0.0018)
VOLVO XC60	1.8696	3.4377	(0.0018)	3.1938	(0.0018)
VOLVO XC90	0.1136	0.2090	(0.0018)	0.1941	(0.0018)

Appendix to Chapter 3

Table 14: First Stage Regressions for Weak Bidders

	FS #Weak	FS #Strong	FS Probit	FS #Weak	FS #Strong	FS Probit
# Weak Potential	0.159***	-0.012***	-0.010***	0.160***	-0.012***	-0.012***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
# Strong Potential	-0.301***	0.608***	-0.189***	-0.285***	0.608***	-0.194***
	(0.012)	(0.004)	(0.012)	(0.012)	(0.004)	(0.012)
Sum of Concurrent	-0.005	-0.016***	0.078***	-0.044***	-0.013***	0.060***
Project Costs	(0.012)	(0.004)	(0.008)	(0.013)	(0.004)	(0.009)
% Bidder Utilization	0.743***	-0.003	6.178***	0.122	-0.005	6.022***
	(0.081)	(0.027)	(0.214)	(0.083)	(0.028)	(0.216)
(% Bidder Utilization)^2			-5.105***			-4.989***
			(0.244)			(0.246)
% FDOT Utilization	-0.617***	0.039**	-0.339***	-0.594***	0.044**	-0.364***
	(0.057)	(0.019)	(0.052)	(0.056)	(0.019)	(0.053)
Log(Contract duration)	0.801***	-0.223***	-0.016	0.805***	-0.225***	-0.023***
	(0.038)	(0.013)	(0.032)	(0.038)	(0.013)	(0.033)
Close Project	-0.061	0.032**	0.203***	-0.093***	0.035***	0.180
	(0.040)	(0.013)	(0.035)	(0.038)	(0.013)	(0.035)
# Proj. Entered				0.614***	0.005	0.075***
				(0.022)	(0.007)	(0.003)
# Proj. Won				-0.600***	-0.018**	
				(0.022)	(0.007)	
Engineer's cost estimate	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Project Type Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Square	0.538	0.668		0.539	0.698	
N	33,521	33,521	33,521	33,521	33,521	33,521

Table 15: First Stage Regressions for Strong Bidders

	FS #Weak	FS #Strong	FS Probit	FS #Weak	FS #Strong	FS Probit
# Weak Potential	-0.143***	-0.012***	-0.000	0.143***	-0.011***	-0.007**
	(0.005)	(0.002)	(0.003)	(0.005)	(0.002)	(0.004)
# Strong Potential	0.137***	0.644***	-0.038	-0.138***	0.643***	-0.053*
	(0.033)	(0.013)	(0.029)	(0.033)	(0.013)	(0.030)
Sum of Concurrent	-0.035	-0.059***	-0.103***	-0.020	-0.110***	-0.308***
Project Costs	(0.033)	(0.013)	(0.028)	(0.036)	(0.014)	(0.031)
% Bidder Utilization	0.005	0.572***	7.738***	0.034	0.439***	5.659***
	(0.128)	(0.052)	(0.327)	(0.132)	(0.052)	(0.359)
(% Bidder Utilization)^2			-7.191***			-5.200***
			(0.380)			(0.414)
% FDOT Utilization	-0.724***	-0.032	-0.176***	-0.730***	0.007	0.015
	(0.131)	(0.053)	(0.111)	(0.131)	(0.052)	(0.118)
Log(Contract duration)	1.157***	-0.301***	-0.277	1.151***	-0.285***	-0.248***
	(0.098)	(0.053)	(0.084)	(0.098)	(0.039)	(0.089)
Close Project	0.074	0.015**	0.478***	-0.079	0.012	0.505
	(0.098)	(0.040)	(0.098)	(0.098)	(0.039)	(0.102)
# Proj. Entered				-0.021	0.124***	0.567***
				(0.027)	(0.011)	(0.032)
# Proj. Won				0.009	-0.123**	-0.529***
				(0.027)	(0.007)	(0.032)
Engineer's cost estimate	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Project Type Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Square	0.516	0.574		0.516	0.588	
N	4,137	4,137	4,137	4,137	4,137	4,137

Bibliography

Aghion, P. and P. Bolton (1987): "Contracts as a Barrier to Entry," *American Economic Review*, 77, 388–401.

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

Andrews, D. W. K. and G. Soares (2010): "Inference for parameters defined by moment inequalities using generalized moment selection." *Econometrica*, 78, 119–157.

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

Asker, J. and H. Bar-Isaac (2014): "Raising retailers' profits: on vertical practices and the exclusion of rivals." *American Economic Review*, 104, 672–686.

Ater, I. (2015): "Vertical Foreclosure Using Exclusivity Clauses: Evidence from Shopping Malls." *Journal of Economics & Management Strategy*, 24, 620–642.

Athey, S., D. Coey, and J. Levin (2013): "Set-asides and Subsidides in Auctions," *American Economic Journal: Microeconomics*, 5, 1 – 27.

Athey, S., J. Levin, and E. Seira (2011): "Comparing Open and Sealed Bid Auctions: Evidence from Timber Auctions," *Quarterly Journal of Economics*, 126, 207 – 257.

Bade, S., G. Haeringer, and L. Renou (2009): "Bilateral commitment," *Journal of Economic Theory*, 144, 1817 – 1831.

Bajari, P. and L. Ye (2003): "Deciding between competition and collusion." *Review of Economics and Statistics*, 85, 971 – 989.

Bernheim, B. D. and M. D. Whinston (1998): "Exclusive Dealing," *Journal of Political Economy*, 106, 64–103.

Berry, S. (1994): "Estimating discrete-choice models of product differentiation," *The RAND Journal of Economics*, 242–262.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile prices in market equilibrium," *Econometrica: Journal of the Econometric Society*, 841–890.

Berry, S. T. (1992): "Estimation of a Model of Entry in the Airline Industry." *Econometrica*, 889–917.

Berry, S. T. and P. Haile (2009): "Nonparametric identification of multinomial choice demand models with heterogeneous consumers," *National Bureau of Economic Research*, w15276.

——— (2014): "Identification in differentiated products markets using market level data." *Econometrica*, 82, 1749–1797.

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

Besanko, D. and M. K. Perry (1993): "Equilibrium incentives for exclusive dealing in a differentiated products oligopoly," *RAND Journal of Economics*, 646–667.

——— (1994): "Exclusive dealing in a spatial model of retail competition," *International Journal of Industrial Organization*, 12.

Bork, R. H. (1978): *The Antitrust Paradox: A Policy at War with Itself.*

Brenkers, R. and F. Verboven (2006): "Liberalizing a distribution system: The European car market," *Journal of the European Economic Association*, 4, 216–251.

Bresnahan, T. F. and P. C. Reiss (1991): "Entry and competition in concentrated markets." *Journal of Political Economy*, 977–1009.

Burgdorf, J. (2019): "Impact of mandated exclusive territories in the US brewing industry: Evidence from scanner level data." *International Journal of Industrial Organization*, 63, 376–416.

Calzolari, G. and V. Denicolò (2015): "Exclusive contracts and market dominance." *American Economic Review*, 105, 3321–3351.

Caruana, G. and L. Einav (2008): "A Theory of Endogenous Commitment," *Review of Economic Studies*, 75, 99 – 116.

Cattaneo, F. E. (2018): "Downstream Competition and Exclusive Dealing," .

Chassang, S. and J. Ortner (2019): "Collusion in Auctions with Constrained Bids: Theory and Evidence from Public Procurement," *Journal of Political Economy*, Forthcoming.

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

Chernozhukov, V., H. Hong, and E. Tamer (2007): "Estimation and confidence regions for parameter sets in econometric models," *Econometrica*, 75, 1243–1284.

Ciliberto, F. and E. Tamer (2009): "Market structure and multiple equilibria in airline markets," *Econometrica*, 77, 1791 – 1828.

Collard-Wexler, A. (2013): "Demand fluctuations in the ready-mix concrete industry." *Econometrica*, 81, 1003–1037.

Conlon, C. and J. Gortmaker (2019): "Best practices for differentiated products demand estimation with pyBLP." .

Draganska, M., M. Mazzeo, and K. Seim (2009): "Beyond plain vanilla: Modeling joint product assortment and pricing decisions," *Quantitative Marketing and Economics*, 7, 105 – 146.

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

Eizenberg, A., A. Pechy, and M. Sovinsky (2017): "The Dynamics of Technology Adoption and Vertical Restraints: An Empirical Analysis," .

Ericson, R. and A. Pakes (1995): "Markov-perfect industry dynamics: A framework for empirical work." *Review of Economic Studies*, 62, 53–82.

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

Fan, Y. and M. Xiao (2015): "Competition and Subsidies in the Deregulated U.S. Local Telephone Industry," *RAND Journal of Economics*, 46, 751 – 776.

Fudenberg, D. and D. K. Levine (1998): *The Theory of Learning in Games*, MIT Press.

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

Gentzkow, M. and J. M. Shapiro (2010): "What drives media slant? Evidence from US daily newspapers." *Econometrica*, 78, 35–71.

Goldberg, P. K. (1995): "Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry," *Econometrica*, 63, 891–951.

——— (1998): "The effects of the corporate average fuel efficiency standards in the US," *The Journal of Industrial Economics*, 46, 1–33.

Hansen, L. P. (1982): "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica*, 50, 1029–1054.

Heckman, J. J. (1979): "Sample Selection Bias as a Specification Error," *Econometrica*, 47, 153 – 161.

Ho, K. and A. Pakes (2014): "Hospital Choices, Hospital Prices, and Financial Incentives to Physicians," *American Economic Review*, 104, 3841–3884.

Holmes, T. J. (2011): "The diffusion of Wal-Mart and economies of density," *Econometrica*, 79, 253 – 302.

Houde, J.-F., P. Newberry, and K. Seim (2017): "Economies of Density in E-Commerce: A Study of Amazon's Fulfillment Center Network," *National Bureau of Economic Research*.

Igami, M. (2017): "Estimating the innovator's dilemma: Structural analysis of creative destruction in the hard disk drive industry, 1981–1998." *Journal of Political Economy*, 125, 798–847.

Kang, K. and R. A. Miller (2017): "Winning by Default: Why is There so Little Competition in Government Procurement," *Working Paper*.

Kawai, K. and J. Nakabayashi (2018): "Detecting Large-Scale Collusion in Procurement Auctions," *Working Paper*.

Kawai, K., K. Onishi, and K. Uetake (2018): "Signaling in Online Credit Markets." *Working Paper*.

Klein, B. and K. M. Murphy (1988): "Vertical restraints as contract enforcement mechanisms." *Journal of Law and Economics*, 265–297.

Krasnokutskaya, E. and K. Seim (2011): "Bid Preference Programs and Participation in Highway Procurement Auctions," *American Economic Review*, 101, 2653 – 2686.

Lazarev, J. (2019): "Getting More from Less: Understanding Airline Pricing." *Working Paper*.

Lee, R. S. and A. Pakes (2009): "Multiple equilibria and selection by learning in an applied setting," *Economics Letters*, 104, 13–16.

Li, T. (2005): "Econometrics of First-Price Auctions with Entry and Binding Reservation Prices," *Journal of Econometrics*, 126, 173 – 200.

Li, T. and X. Zheng (2009): "Entry and Competition Effects in First-Price Auctions: Theory and Evidence from Procurement Auctions," *Review of Economic Studies*, 76, 1397 – 1429.

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

Luo, Y. and H. Takahashi (2019): "Bidding for Contracts under Uncertain Demand: Skewed Bidding and Risk Sharing." *Working Paper*.

Mathewson, F. and R. Winter (1994): "Territorial restrictions in franchise contracts." *Economic Inquiry*, 181–192.

Mazzeo, M. J. (2002): "Product choice and oligopoly market structure." *RAND Journal of Economics*, 221–242.

Morales, E., G. Sheu, and A. Zahler (2015): "Extended gravity." *NBER Working Paper*, 21351.

Morrow, W. R. and S. J. Skerlos (2011): "Fixed-point approaches to computing Bertrand-Nash equilibrium prices under mixed-logit demand." *Operations Research*, 59, 328–345.

Murry, C. and Y. Zhou (2017): "Consumer Search and Automobile Dealer Co-Location." .

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

Nurski, L. and F. Verboven (2016): "Exclusive dealing as a barrier to entry? Evidence from automobiles," *The Review of Economic Studies*, 83, 1156–1188.

O'Brien, D. P. and G. Shaffer (1993): "On the dampening-of-competition effect of exclusive dealing," *Journal of Industrial Economics*, 41, 215–221.

Ohashi, H. (2009): "Effects of Transparency in Procurement Practices on Government Expenditure: A Case Study of Municipal Public Works," *Review of Industrial Organization*, 34, 267–285.

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

Pakes, A., J. Porter, K. Ho, and J. Ishii (2015): "Moment Inequalities and Their Application," *Econometrica*, 83, 315–334.

Petrin, A. (2002): "Quantifying the benefits of new products: The case of the minivan," *Journal of Political Economy*, 110, 705–729.

Piccolo, S. and M. Reisinger (2011): "Exclusive territories and manufacturers' collusion," *Management Science*, 57, 1250–1266.

Porter, R. H. and J. D. Zona (1993): "Detection of Bid Rigging in Procurement Auctions," *Journal of Political Economy*, 101, 518 – 538.

——— (1999): "Ohio school milk markets: an analysis of bidding," *RAND Journal of Economics*, 30, 263 – 288.

Posner, R. A. (1976): *Antitrust law*, University of Chicago Press.

Rasmussen, E. B., J. M. Ramseyer, and J. S. Wiley (1991): "Naked Exclusion," *American Economic Review*, 81, 1137–1145.

Renou, L. (2009): "Commitment Games," *Games and Economic Behavior*, 66, 488 – 505.

Rey, P. and J. E. Stiglitz (1988): "Vertical restraints and producers' competition," *European Economic Review*, 32, 561–568.

——— (1995): "The role of exclusive territories in producers' competition," *RAND Journal of Economics*, 26, 431 – 451.

Sass, T. R. (2005): "The competitive effects of exclusive dealing: Evidence from the US beer industry," *International Journal of Industrial Organization*, 23, 203 – 225.

Sass, T. R. and D. S. Saurman (1993): "Mandated exclusive territories and economic efficiency: An empirical analysis pof the malt-beverage industry," *Journal of Law and Economics*, 36, 153–177.

Schelling, T. C. (1960): *The Strategy of Conflict.*

Segal, I. R. and M. D. Whinston (1996): “Naked exclusion and buyer coordination,” *Harvard University, Institute of Economic Research Working Papers: No. 1780.*

Seim, K. (2006): “An empirical model of firm entry with endogenous product-type choices.” *RAND Journal of Economics*, 37, 619–640.

Simpson, J. and A. L. Wickelgreen (2007): “Naked Exclusion, Efficient Breach, and Downstream competition,” *American Economic Review*, 97, 1305–1320.

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

Waldfogel, J. (2003): “Preference Externalities: An Empirical Study of Who Benefits Whom in Differentiated-Product Markets.” *RAND Journal of Economics*, 34, 557–568.

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

Young, H. P. (2004): *Strategic Learning and its Limits*, Oxford University Press.

Curriculum Vitae, Franco Esteban Cattaneo

2013 – 2019	PhD Studies in Economics, Center for Doctoral Studies in Economics, University of Mannheim.
2012 – 2013	M.Sc. in Economics, Barcelona Graduate School of Economics, Barcelona, Spain.
2008 – 2012	B.Sc. in Economics, Universitat Pompeu Fabra, Barcelona, Spain.
09/2010 – 01/2011	Visiting student, University of Amsterdam, Amsterdam, the Netherlands.

Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig angefertigt und mich keiner anderen als der in ihr angegebenen Hilfsmittel bedient zu haben. Insbesondere sind sämtliche Zitate aus anderen Quellen als solche gekennzeichnet und mit Quellenangaben versehen.

Mannheim, December 15, 2019: ______________________________

Franco Esteban Cattaneo