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# Incumbency advantages, distribution networks and exclusivity – Evidence from the European car markets<sup>☆</sup>

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## ABSTRACT

This paper investigates the role of distribution networks in explaining incumbency advantages in the European car market. We compare three approaches to incorporate the size of distribution networks in discrete choice models of product differentiation: as an extra product characteristic, as a new dimension of product differentiation in a nested logit framework, or as a measure of the expected travel cost under a spatial Poisson distribution of locations. We obtain robust conclusions across all three approaches: distribution networks play an important role in explaining car producers' market shares, but they only appear to explain part of the bias towards domestic brands in the car market. We also report on an ongoing research project where we analyze the role of distribution networks at a much more detailed local market level, and investigate the specific role of exclusive dealing as a possible entry barrier.

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## 1. Introduction

Car manufacturers across the world make use of a variety of vertical restraints to organize their dealer networks. In European countries, two forms of exclusivity are common. Territorial exclusivity provides dealers the right to sell a certain brand in a designated territory without competition from other dealers selling the same brand. Brand exclusivity, usually referred to as exclusive dealing, provides manufacturers the right to mandate their dealers not to sell competing brands within the same outlet. Theoretical work has stressed that incumbents may use this second form of exclusivity to foreclose new entry. When dealers cannot sell other brands, new entrants are forced to set up their own costly distribution networks; see for example, [Aghion and Bolton \(1987\)](#) and [Segal and Whinston \(2000\)](#). In ongoing work, we empirically analyze the incentives of incumbent car producers to foreclose entry through exclusive dealing. We take into account that new entrants may compensate the incumbents and their dealers for not signing exclusive dealing contracts ([Nurski and Verboven, 2013](#)). This work is based

on a rich dataset on demand and dealer locations at the level of local markets in one country (Belgium).

In the present paper we address a preliminary question using more aggregate data for a panel of nine European countries during 2000–2009. We ask to what extent the size of car producers' distribution networks contributes to explaining the car producers' market shares. We find that the distribution networks play an important role, although they only appear to explain part of the bias for domestic brands as observed in countries with local car producers.

Analyzing the role of distribution networks on demand is of broader interest to understand the mechanisms behind incumbency advantages emphasized in industrial organization, and behind market entry or penetration costs recently emphasized in international trade.<sup>1</sup> We therefore first present three possible approaches on how one may incorporate distribution networks in discrete choice models of product differentiation. We then present the data and empirical results. Finally, we conclude and report on an ongoing research project that aims to investigate the subsequent question whether exclusive dealing acts as a specific entry barrier in the car industry.

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<sup>1</sup> [Geroski \(1995\)](#) discusses the stylized fact that even successful new entrants require a considerable amount of time to reach market shares comparable to incumbents. [Berger and Dick \(2007\)](#) and [Bronnenberg et al. \(2009\)](#) provide recent analyses of early mover advantages and the persistence of market shares. In international trade, [Das et al. \(2007\)](#) provide an empirical analysis of market entry costs, and [Arkolakis \(2010\)](#) provides a model to analyze the trade implications of these costs.

**2. Incorporating distribution networks in discrete choice models**

Discrete choice models have become very popular to estimate substitution patterns between differentiated products. Berry (1994) and Berry et al. (1995) showed how to estimate these models with aggregate data on sales per product. Most work has focused on the role of price and product characteristics, and some work also considered the impact of advertizing. In this Section we show how one may incorporate the role of distribution networks. For clarity of exposition, we base the discussion on a simple logit model where consumers have uncorrelated preferences for different products. In our empirical analysis we extend the model to incorporate the possibility that consumers have correlated preferences for products of the same segment and subsegment.

A total number of  $L$  potential consumers choose among  $J$  differentiated products,  $j = 1, \dots, J$ , or alternatively they may choose not to buy in which case they purchase the outside good  $j = 0$ . The indirect utility of an individual  $i$  for product  $j$  is given by

$$u_{i,j} = \delta_j + \varepsilon_{i,j}.$$

The first part is the mean utility  $\delta_j$ , common to all consumers:

$$\delta_j \equiv x_j\beta + \alpha p_j + \xi_j.$$

This depends on a vector of observed product characteristics  $x_j$  (such as horsepower), price  $p_j$  and an unobserved quality term  $\xi_j$ . The second part is the individual-specific deviation around that mean  $\varepsilon_{i,j}$ , modeled as a mean zero random variable. In the simple logit model,  $\varepsilon_{i,j}$  is distributed i.i.d. extreme value. This assumption implies that consumers substitute symmetrically to other products when one product becomes less attractive.

Assuming that consumers choose the product  $j = 0, 1, \dots, J$  that gives the highest utility, one can obtain the individual choice probabilities or approximately the aggregate market shares  $s_j$  for every product  $j$  (where the market shares are sales divided by the potential number of consumers  $L$ ). Following Berry (1994), this gives rise to the following simple demand system:

$$\frac{s_j}{s_0} = \frac{\exp(\delta_j)}{\exp(\delta_0)} \quad j = 1, \dots, J,$$

where  $s_0 = 1 - \sum_{j=1}^J s_j$ . Using the above definition of  $\delta_j$  for  $j = 1, \dots, J$  and normalizing  $\delta_0 = 0$  for the outside good, one obtains the estimating equation

$$\ln s_j / s_0 = x_j\beta + \alpha p_j + \xi_j. \tag{1}$$

There are several ways to incorporate the role of distribution networks in this demand framework. An obvious first approach would simply consist of including the number of dealers of the product's brand,  $N_j$ , as an additional variable in the product characteristics vector  $x_j$ . In this case, consumers have a (mean) valuation for the number of dealers per se. While this approach is attractive because of its simplicity, it entails some difficulties, such as the choice of functional form in which  $N_j$  should enter. A practical difficulty also arises when the model is estimated with pooled data over different countries to exploit cross-country variation, as in our application. In this case, the number of dealers of a given brand may systematically differ across countries because of differences in market size or population density. An ad hoc solution is to normalize the number of dealers per country, for example by dividing it by the country average,  $N_j/\bar{N}$ . We follow this as our first approach to incorporate distribution networks.

Our second and third approach incorporate the number of dealers in a different way, giving rise to natural functional forms without requiring an arbitrary normalization of the number of dealers. Our second approach explicitly starts from a more disaggregate choice level. The consumer's

unit of choice is no longer the product (car model)  $j$ , but rather the dealer  $k$  selling product  $j$ . Consumers may have correlated preferences for dealers  $k$  selling the same product  $j$  according to a nested logit model. More specifically, suppose that each product  $j$  is sold by  $N_j$  dealers, so  $k = 1, \dots, N_j$ . Individual  $i$ 's utility for dealer  $k$  selling product  $j$  is given by

$$u_{i,kj} = \delta_j + \varsigma_{i,j} + (1 - \sigma_j)\varepsilon_{i,kj}.$$

This specification assumes that consumers have the same mean utility for all dealers of the same product,  $\delta_{kj} = \delta_j$ . The individual-specific deviation around that mean is the sum of two random variables  $\varepsilon_{i,kj}$  and  $\varsigma_{i,j}$ , which follow the distributional assumptions of a nested logit model (Cardell, 1997). First,  $\varepsilon_{i,kj}$  is an idiosyncratic valuation that is distributed i.i.d. extreme value across products and dealers. Second,  $\varsigma_{i,j}$  is a common valuation across all dealers of product  $j$ , with the unique distribution such that  $\varsigma_{i,j} + (1 - \sigma_j)\varepsilon_{i,kj}$  is also an extreme value random variable. The parameter  $\sigma_j$ , with  $0 \leq \sigma_j \leq 1$ , measures the degree of preference correlation for dealers  $k$  selling the same product  $j$ . If  $\sigma_j = 1$ , then dealers selling the same product are perfect substitutes. In contrast, if  $\sigma_j = 0$ , dealers of the same product are equally differentiated as dealers from different products (if they belong to the same subgroup).

Following similar steps as in Berry (1994), the nested logit model gives rise to the following inverted market share system

$$\frac{s_{kj}}{s_0} \left( \frac{s_{kj}}{s_j} \right)^{-\sigma_j} = \frac{\exp(\delta_j)}{\exp(\delta_0)}, k = 1, \dots, N_j, j = 1, \dots, J$$

where  $s_{kj}$  is the market share of dealer  $k$  of product  $j$ , and  $s_j = \sum_{k=1}^{N_j} s_{kj}$  is the market share of product  $j$ . In contrast with Berry (1994), we do not observe market shares at the level of the dealer ( $s_{kj}$ ), but only at the level of the product ( $s_j$ ). However, since we assumed  $\delta_{kj} = \delta_j$ , we can easily aggregate the market shares up to the level of the product  $j$  as in (Ben-Akiva and Lerman, 1985). After some rearrangements, this gives

$$\frac{s_j}{s_0} = N_j^{1-\sigma_j} \frac{\exp(\delta_j)}{\exp(\delta_0)}.$$

Since  $\delta_0 = 0$ , the estimating equation becomes

$$\ln s_j / s_0 = x_j\beta + \alpha p_j + (1 - \sigma_j) \ln N_j + \xi_j. \tag{2}$$

This specification extends the base model in Eq. (1) with one additional variable, the logarithm of the number of dealers,  $\ln N_j$ . The coefficient of this variable may be expected to be between 0 and 1, and has the interpretation of preference correlation for dealers of the same product. If consumers perceive dealers of a given product as perfect substitutes ( $\sigma_j = 1$ ), the coefficient of  $\ln N_j$  is 0. If consumers have uncorrelated preferences for dealers of the same product ( $\sigma_j = 0$ ), the coefficient is 1. Note that one can easily generalize this approach to include nests at higher levels such as segments (as we do below) or to include random coefficients on continuous variables: in both cases, one simply uses standard models and adds  $\ln N_j$  as an additional variable.

A third approach to incorporate the number of dealers starts from the assumption that consumers value the distance to the nearest dealer. The total price for consumer  $i$  purchasing product  $j$  is equal to the purchase price plus the expected travel cost to the nearest dealer,  $p_j + kd(N_j)$ , where  $k$  is the travel cost per unit of distance and  $d(N_j)$  is the expected distance of a consumer to the nearest dealer selling product  $j$ , a decreasing function of the number of dealers in the country. If one assumes that consumer and dealer locations follow a spatial Poisson process, then the expected distance to the nearest dealer follows a "square root law" in dealer density,  $d(N_j) = 0.5\sqrt{M/N_j}$ , where  $M$  is total surface area in the country. Kolesar and Blum (1973) provide a derivation for this square root law, and Ferrari et al. (2010)

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