WORKING PAPERS

N° 16-733

November 2016

"Strategic Obfuscation and Retail Pricing"

Timothy J. Richards, Gordon Klein, Celine Bonnet,
and Zohra Bouamra-Mechemache

Toulouse School of Economics

Strategic Obfuscation and Retail Pricing

Timothy J. Richards, Gordon Klein,
Celine Bonnet, and Zohra Bouamra-Mechemache*

November 16, 2016

Abstract

Retailers often stock items that are only slightly differentiated from others' – different sizes of a popular brand, or different flavors in a common product line for instance. We argue that this practice is a form of strategic obfuscation, intended to raise consumer search costs, and margins on non-comparable products. We test our hypothesis using examples from several product categories in German and French retail scanner data. We find that, after controlling for other explanations for how margins can vary with package size, we cannot rule out strategic obfuscation as a feature of our retail sales data.

keywords: differentiation, price discrimination, retail pricing, search model, strategic obfuscation

JEL Codes: D43, L13, M31

*Richards is Professor and Morrison Chair of Agribusiness, Morrison School of Agribusiness, W. P. Carey School of Business, Arizona State University; Klein is Junior Professor at the Westfälische Wilhelms University Münster and DICE Research Affiliate at the Heinrich-Heine University, Düsseldorf, Germany; Bonnet and Bouamra-Mechemache are Researchers in the Toulouse School of Economics, INRA, University of Toulouse Capitole, Toulouse, France. Contact author: Richards, Address: 7231 E Sonoran Arroyo Mall, Mesa, AZ, 85212. Ph. 480-727-1488, email: trichards@asu.edu.
The research leading to these results has received funding from the European Research Council under the European Community's Seventh Framework Programme (FP7/2007-2013) Grant Agreement no. 340903. Support from the Agricultural and Food Research Initiative (NIFA, USDA) is also gratefully acknowledged.

1 Introduction

Consumer product manufacturers tend to offer retailer-specific variants of common brands. While they may be targeting different segments of the market by doing so, it also effectively prevents direct price-comparison (Wilson-Jeanselme and Reynolds 2005). For example, General Mills Honey Nut Cheerios are offered online through one major US retailer in 12.25 oz, 17.0 oz, and 21.6 oz packages, while the same product is offered online through a different retailer in 12.25 oz, 21.6 oz, and 26.6 oz sizes. Whether such differentiation amounts to strategic obfuscation in the sense of Ellison and Ellison (2005, 2009), however, is largely an empirical question.

Strategic obfuscation describes decisions made by suppliers that are designed to prevent comparison among vendors, or by service providers to prevent comparing their products relative to others. For example, insurance providers tend to provide subtly different contract terms in order to prevent consumers from comparing the true coverage per dollar of premium among firms. Strategic obfuscation is more than simple differentiation. Product differentiation is intended to create products that appeal to heterogeneous preferences, but many product attributes provided by sellers cannot be justified on the basis of either vertical or horizontal differentiation, because they appeal to differences that would be trivial from the perspective of preferences, and are more reasonably due only to the prevention of direct comparisons. By offering different package sizes, suppliers – retailers and manufacturers both – raise the cost of comparing prices among similar products. If search costs are higher, search intensity will fall, and equilibrium prices, and margins, will rise (Ellison and Wolitzky 2012). In this paper, we examine whether there is evidence that consumer-product suppliers offer slightly differentiated items relative to their competitors as a means of strategic obfuscation, and margin enhancement.

Retailers may offer different package sizes for reasons other than strategic obfuscation. Because retailers are likely to target different market segments, and consumers have heterogeneous preferences for package sizes (Subramanian and Gal-Or 2009), package sizes may differ simply due to horizontal differentiation. Second, retailers and manufacturers both tend to practice second-degree price discrimination by offering larger packages at lower unit prices (Cohen 2008). Third, individual items may come in different aggregations – six-packs versus twelve-packs of soda, for example – due to variations in block-pricing strategies among retailers. Cakir and Balagtas (2012) argue that package downsizing is used as a means of passing along input price increases without losing market share, while Yonezawa and Richards (2016) show that this argument is incomplete as it does not allow for strategic behavior among retailers and manufacturers. Because there are many reasons for offering different packages, identifying strategic obfuscation in consumer packaged goods requires that other motivations for package variation must be adequately controlled in the empirical model.

We assume the goal of any attempt at strategic obfuscation is to raise equilibrium prices, and margins. Estimating margins, in turn, requires a structural model of demand that accounts for variation in package size among brands, and equilibrium price responses among competing retailers. In this study, we estimate the demand for a closely-related set of items using a random-coefficient logit (RCL) model, and then derive retailers' optimal pricing decisions, allowing for deviations from pure Bertrand-Nash competition. Conditional on other possible explanations for how package-variation can influence demand, we then estimate the effect of "product uniqueness" on equilibrium retail margins. While retailers offer many items that are by definition unique – store-brands – we focus on subtle variants of a well-known national brand in order to isolate the effect of uniqueness on equilibrium margins.

Our data experiment exploits observed variation in package sizes, and package forms, for the same brands across a sample of retailers. Namely, we compare variants of the same brands in the soft-drink category offered by 5 retailers in France that are sold in various package sizes or forms. Within these brands, we choose a sample of 18 variants offered among the retailers, 7 of which are offered in common, or by all 5 retailers, and 11 that are offered by only 1 of the 5.[1] We evaluate the robustness of our findings using a similar sampling procedure

[1] We define a unique offering as one in which a particular retailer is the dominant supplier. We provide more details on our experimental design below.

applied to different packages of ground coffee across retailers in Germany. Because some of the variation in package offerings may be due to either heterogeneity in package-preference or retailers' use of second-degree price discrimination, we control for variation in consumer demand and retailer strategy through a structural econometric model of demand and retailer pricing. We interpret the remaining variation in package size as retailers' attempt to raise consumers' costs of searching otherwise identical products across retailers, and estimate the effect of this lack of comparability on retail margins.

We find that consumers in our French data do indeed have heterogeneous package-size (and form) preferences, and that retailers vary in their tendencies to use package size strategically. We find that offering a package-variant that is unique to a particular retailer is associated with a higher willingness-to-pay among consumers, and equilibrium margins that are nearly 10% greater than those that are offered by all retailers. Our findings, however, may be specific to the food retailing industry in France, so we examine the data from a similar sampling strategy in German coffee sales.[2] Our results are largely confirmed in the German case, and are remarkably similar quantitatively. After controlling for other plausible reasons for why prices may differ across pack size, we interpret our findings as evidence of strategic obfuscation in consumer packaged goods.

The remainder of the paper is organized as follows. In the second section, we provide some background on what is known about strategic obfuscation, in terms of both theoretical expectations, and empirical evidence. In section 3, we describe our data, how we designed our data experiment, and provide some summary evidence of price differentials between items offered across retailers, and those offered by a single retailer. In the fourth section we present a formal econometric test of strategic obfuscation, and explain our identification strategy. Our estimation results and discussion are given in the fifth section, while the sixth offers some more general conclusions, and implications for retailing in general.

[2] German retailing differs from that found in France mainly in the more substantial presence of hard discounters, such as Aldi, that may influence the ability to strategically obfuscate.

2 Conceptual Background

Ignorance as a source of market power has been well understood since Scitovsky (1950). Indeed, Diamond (1971) shows that if search costs rise even a small amount above zero, a competitive equilibrium can devolve into a monopolistic one, with the attendant reduction in efficiency. If firms are able to make comparisons of their price with rivals' difficult or costly, then they will be more likely to sell to consumers unwilling to search for the true price. However, our notion of strategic obfuscation is different. In the extant literature, there are two types of obfuscation: (1) adding attributes to obscure the true nature of the product (Ellison 2005; Gabaix and Laibson 2006; Ellison and Ellison 2009; Kalayci and Potters 2011; Persson 2016), or (2) making the pricing structure itself sufficiently complex that consumers have difficulty determining the true price (Carlin 2009; Wilson 2010; Wilson and Waddams-Price 2010; Chioveanu and Zhou 2013; Muir, Seim, and Vitorino 2013).[3] Our concept is a combination of the two in that package types are inherent attributes of the item being purchased, and the pricing structure is typically by the package, not by the unit-of-measure. While our concept of obfuscation is clearly related to the others, there are important differences.

Much of what we know about strategic obfuscation is based on settings in which firms are able to vary the attributes of their product such that direct price comparisons are difficult, or at least more costly (Ellison 2005; Gabaix and Laibson 2006).[4] If firms have the ability to "add-on" features that raise the final price, but are not necessarily advertised, they can use these features to price discriminate in a competitive environment (Ellison 2005). Add-ons give rise to an adverse selection effect: The additional profits due to add-ons are not bid away because prices are pushed sufficiently far apart that the firm attracts a large number

[3] Ellison and Wolitzky (2012) describe a more general form of obfuscation that can include both attribute and pricing obfuscation as special cases. They show that it is individually-rational for firms to obfuscate in a competitive model of costly search and oligopolistic rivalry.

[4] "Versioning" is a type of obfuscation through attribute variation in which the intent is to induce consumers to self-select into higher or lower-priced variants where the difference is unrelated to cost (Varian 1997).

of "cheapskates" to the base product, and sufficient others willing to buy the add-on so that profits are sustainable in a competitive equilibrium. However, competitors should still be able to reveal the nature of these add-ons and remove any profit opportunities. Nonetheless, Gabaix and Laibson (2006) show that when the market consists of a substantial number of naive consumers who are unaware of the add-on premium, add-ons can proliferate in equilibrium. Essentially, add-ons are a form of strategic obfuscation as they are intended to raise the effective price of an item without affecting the "shelf price" or the price that consumers initially see when searching for the product. Because adding features to mass-produced consumer products is often not possible, these models describe a special case that is not typical of most retail markets. Moreover, empirically, strategic obfuscation through attribute complexity is difficult to identify independent from mere differentiation (Kalayci and Potters 2011). Therefore, we focus on obfuscation through costly search for prices.

Prices are not transparent in many, important markets. For example, Carlin (2009) studies price dispersion in financial markets. Using an oligopoly search model, he shows that prices rise in the complexity of the price structure, and interprets complexity as strategic obfuscation. Somewhat counter-intuitively, he shows that as the number of firms grows, then market does not necessarily become more competitive as the degree of complexity, and hence obfuscation, rises accordingly. The reason is straightforward: As more firms enter, each firm receives a smaller share of expert buyers. Therefore, their best response is to increase the level of complexity in order to increase rents from uninformed consumers when they do not "win" the expert consumers. As each firm has an incentive to do the same, the fraction of informed consumers falls as firms enter – complexity tends to reduce competition more generally. Firms actively manage the level of obfuscation as the proportion of uninformed consumers is endogenously determined by the complexity choices made by the firms.

Further emphasizing the strategic nature of obfuscation, Wilson (2010) describes a theoretical model in which firms are asymmetric, and use obfuscation in order to separate themselves from other firms, which he terms "prominent" firms, that choose to remain easily searchable and transparent. Agents with positive time costs first search the rival (prominent firm), which raises its price, and softens competition for the customers that choose to search beyond the most immediately transparent firm. The prominent firm has no incentive to obfuscate because doing so reduces profits to both firms, so the profits due to obfuscation are not bid away in a Nash equilibrium. However, equilibrium prices are lower with obfuscation in his model, so he describes a different outcome than we have in mind here.

Others predict that complex pricing structures can lead to higher equilibrium prices. In fact, how prices are framed can affect complexity (Spiegler 2006; Piccione and Spiegler 2012; Chioveanu and Zhou 2013), where price framing refers to how prices are presented to the consumer – in retail gasoline, prices are defined on a per-gallon basis, but are offered per box, or per unit, in the retail consumer packaged good industry. Chioveanu and Zhou (2013) find that, in equilibrium, firms randomize their choice of price frame in order to reduce the elasticity of demand, and sustain positive profits. Firms choose both frame differentiation, and frame complexity, so there is 2 separate dimensions as to how obfuscation enters the model. Similarly, using the bounded-rationality assumption of Spiegler (2006), Piccione and Spiegler (2012) argue that when firms compete in prices and complexity, prices will not fall to the competitive level, even when the products are homogenous. The same holds true in a service conext as Muir, Seim, and Vitorino (2013) find empirical evidence that more complex pricing structures are responsible for higher search costs, greater price differences among suppliers, and higher markups. Obfuscation in services such as this is common, but it is difficult to disentangle what is horizontal differentiation from complexity in pricing schedules.[5]

Clear separation between complexity and differentiation is perhaps best achieved in the lab. For example, Kalayci and Potters (2011) induce subjects' preferences for an hypothetical consumer good, so are able to hold willingness-to-pay constant while varying the complexity of the pricing terms. Complexity is still described in terms of the number of attributes

[5] Piccione and Spiegler (2012) argue that their approach provides a new interpretation of differentiation that admits perceptual differentiation through framing complexity.

their subjects must consider in comparing products, but attributes do not affect utility. Allowing complexity to vary randomly over a series of product choices is another alternative (Sitzia and Zizzo 2009). Using this approach, Sitzia and Zizzo (2009) attempt to disentangle subjects' aversion to complexity from their sense of being exploited, and find no evidence of complexity aversion, and only weak evidence in support of their exploitation hypothesis.

Experiments do contribute to a growing body of literature that examines whether there is empirical support for strategic obfuscation – a literature that also includes investigation using secondary data (Ellison and Ellison 2009; Wilson and Waddams-Price 2010). Other than Sitzia and Zizzo (2009), the evidence shows that strategic obfuscation is an empirical regularity in many real-world markets, whether online or offline. However, there is no empirical research that considers the role that simple variation in packaging plays in obscuring comparisons between otherwise identical products. While we do not model obfuscation in a lab environment, our data experiment achieves sharp identification of the effect of obfuscation by comparing equilibrium pricing strategies between items offered in common, and those offered by a single retailer.

3 Data and Identification Strategy

Our primary demand data are drawn from two sources. The first consists of a large-scale, household-panel data set of soft-drink purchases by consumers in France (Kantar TNS Worldpanel). The second is from a similar household-panel data set, the Consumer Panel by GfK Panel Services, which describes coffee purchases in Germany. The French data includes purchases made by panelists during 2013, while the German data includes purchases made during 2009 and 2010.[6] Both data sets are collected by panelists on a purchase-occasion basis, and include the full complement of purchase records (brand, item, price, quantity, purchase attributes), household demographics (age, income, education, household size, and place of residence), and a small set of store attributes (store size, and parent company).

[6] GfK Panel Services data are not available beyond the 2010 calendar year.

Although both data sets include purchases from a large number of categories and retailers, we draw data to define very specific choice environments in which strategic obfuscation is likely to be identified, if it indeed exists. In the analysis to follow, we present summary data and detailed results from the French case, and then corroborating evidence from the German sample.

In the case of France, we choose a set of variants offered by a single carbonated soft-drink manufacturer, across three different brands, sold through five different retailers.[7] We chose these brands because of their wide distribution across nearly all retailers, the number of variants offered within each, and the large number of purchase-transactions in our household-panel data. While the brands are widely distributed throughout the country, the manufacturer offers a range of variants, differentiated by the type of container (bottle or can), the size of the container, and the size of the multi-pack "brick," if not purchased as a single item. From these 3 brands, we selected several that were offered in common across all five retailers, and another sub-set that were offered in only one of the retailers over the sample period. In this way, our data forms a natural experiment, with the items offered in common serving as control, and those unique to individual retailers as the treatment items. Control items were chosen as they were the best-selling variants, while the treatment items were chosen according to the protocol described below. Our final sample, therefore, consists of 18 different items, sometimes differing only in container form, container size, or pack size, and sometimes not differing at all. Of the 18 items, 11 are unique to one retailer, while 7 are offered in various combinations across either all or subsets of the other retailers. In total across the 5 retailers, there are 69 retailer / item combinations.

For the German coffee data, a similar approach was taken in isolating unique variants of popular brands. Namely, we chose 2 coffee brands, sold through 5 of the largest retailers. These brands were chosen specifically because one brand offered sub-brands that embodied

[7] The specific identity of the manufacturer, brands, and retailers in our sample are not disclosed for confidentiality reasons. However, the manufacturer is a major multi-national firm with many brands that are in wide distribution. The retailers are among the top 10 in France.

attributes unique to one of the sample retailers, while the other one was similar in size, thereby serving as a control. Because coffee is generally offered in only one type of container, the unique attributes were some combination of package size, and whether the packages were offered together in a "multi-pack." Because each parent brand has several other sub-brands, there are 10 variants, leading to 38 retailer / item combinations. Of the 38 retailer / item combinations 4 are unique variants.

The design of the data experiment is important as truly unique items are purposefully rare. We selected the items to include in the experiment using the following approach: In the French data, there were 84 separate items (brands, containers, sizes, and packs) among the three brands sold at the 5 retailers, so we needed to select down to a tractable experiment size. From these 84 items, several did not sell frequently over the sample period, so were eliminated. Among the items that remained, over 76% were sold by at least 2 retailers, and most items sold at least a few times in each retailer. Therefore, the definition of "unique" includes items with 80% or greater of their sales volume through only one retailer. This is reasonable because the data set is a panel over retailers and time, so items that sold only a few times in a particular retailer were simply out of the market for much of the sample period. In effect, therefore, the "80%" rule means that an item was truly unique 80% of the time.[8] Because this rule limits the number of unique items, in order to maintain representation for both types of items, unique items were over-selected so that the final sample consists of 11 unique items and 7 items offered in common. Selecting items in this way means that our data represents a natural experiment in obfuscation, with 7 control items, and 11 treatment items. In the German data, this approach generates 8 control items and 2 treatment items.

As a first step, we calculated the unit prices for each item in order to determine whether there was any summary evidence of price differences between unique and non-unique, common, items. The summary data for the French soft-drink case are presented in the upper part of table 1. For brand 1, the average unit prices for unique items is 1.40 euros / litre,

[8] We estimated a version of the model using a "70% rule" instead and the results were not qualitatively different, although the sample of unique items was larger.

while the average price for items offered in common is 1.12, or a 25% difference in prices. For brand 2, the price difference is slightly smaller, with unique items selling for an average of 1.07 euros / litre and common items for 0.99 euros / litre (8.1% difference). For brand 3, the price differential is 0.15 euros / litre (1.16 versus 1.01), or 14.9% of the selling price. Each of the price differences is statistically significant at a 5% level. The same general pattern can be seen in the German case (lower part of table 1). In the data sample, unique items sell for more than 1.00 euros / kg more than items sold in common across all retailers (9.49 versus 8.24), or 15.1%. Based on this summary evidence, therefore, items sold at a single retailer sell for a higher price. Because this difference may be due to simple differentiation, or perhaps second-degree price discrimination, however, it is necessary to control for variation in product attributes, and retailer pricing strategies, in order to test more rigorously for the likelihood that the price differentials are due to strategic obfuscation.

[table 1 here]

Price-premia for unique items may, however, be due to a variety-effect rather than strategic obfuscation. That is, a larger store may simply offer unique items merely because it has more shelf-space, and an ability to sell a range of items that other retailers do not have. To examine this possibility, we categorized each retailer in the French data as either a "small store" (< 400 m^2), a supermarket (between 400 m^2 and 2,500 m^2), or a hypermarket (greater than 2,500 m^2).[9] In table 2 below, we show that the 5 retailers in our sample consist of 3 hypermarkets, and 2 that are predominantly supermarkets. However, because we capture purchases on a household-level, there is considerable heterogeneity even within the same "banner" or retailer-name recorded in the Kantar data. Within these different store formats, the data in table 2 show that unique items are less likely to be found in hypermarkets, so uniqueness does not appear to be due to a variety-effect alone. On the other hand, unique items may also be driven by shelf-space constraints in smaller stores as 4-packs of soda take up less space than a 6-pack, and are more likely to be purchased by a shopper carrying a

[9] These definitions are well-supported in the literature on retailing in France (Bonnet and Bouamra-Mechemache 2016; Turolla 2016).

small amount of groceries in an inner-city environment. Nonetheless, despite this summary evidence, we control for the possibility that uniqueness is driven by store format by including store size in our econometric models of demand, and pricing, described below.[10]

[table 2 here]

In table 3, we provide a summary of the variables that enter the soft-drink demand model, while the data used in the pricing model are summarized in table 4. Note that the number of observations for the supply model differs from the number in the demand model, because we aggregate over households to model market outcomes in the supply model. In terms of the demand data, there are 38,542 observations for the demand model. This table shows that there is substantial cross-item variability in price, attributes, and market share, while there is also considerable variation across brands, and retailers. Given the panel nature of our data set, there appears to be sufficient variation in the data to identify demand parameters at the item level.[11]

[table 3 here]

In terms of the supply data, we use input price indices from the French National Institute for Statistics and Economic Studies for the soft drink case, and input prices of Arabica and Robusta coffee, from the Thompson Reuters database, for the German coffee case. Both sets of input prices are used to estimate their respective marginal cost functions, and to instrument for endogenous prices in the demand model. In the soft-drink application, we use a set of primary inputs in the soft-drink manufacturing process, which includes water, sugar or sugar substitutes, an index of packaging prices created by averaging the price indices for aluminum, plastic, and glass, an index of wages in the beverage industry to account for the labor content of items in each category, and an index of energy prices from gasoline, and electricity. In the pricing model, we aggregated the data by brand and retailer each week (or month in the German case) across all household purchases. These averages were weighted by the volume of purchase to arrive at an average price across all participating households.

[10] Similar store-size data were not available for the German coffee application.

[11] The German coffee data exhibits similar variability. Summary tables are available upon request.

From the data presented in table 2, the resulting average prices contain sufficient variation to identify any variation in retail pricing over time, and over brands offered by different retailers. Based on the data shown in table 4, we are confident that there is sufficient variation in input prices over the 52 week sample period to identify variation in marginal cost.

[table 4 here]

4 Empirical Model of Strategic Obfuscation

4.1 Overview

In this section, we describe our empirical strategy designed to test for the presense, and effect of, strategic obfuscation. Because retailers may differ in terms of the packages they offer for a number of reasons, the purpose of our demand model is to control for motivations other than raising consumer search costs. Our empirical model has a number of unique features that are necessary to identifying the effect of strategic obfuscation on equilibrium retail prices. Specificaly, in order to formally test whether the pricing pattern shown in table 1 is likely due to strategic obfuscation, we estimate a structural model of item-level demand, and strategic pricing among retailers. Estimating a structural model is necessary because differences in observed prices may be due to retail pricing strategies not related to strategic obfuscation, the additional cost of selling specific items through individual retailers, or other idiosyncratic pricing factors. Further, while differences in unit-prices provide evidence that retailers consciously set different prices for items that are unique to their store, the strategic obfuscation argument concerns differences in margins more specifically, and not simply prices. That is, differences in price are only relevant if they are able to generate higher margins for the same brand, sold through the same retailer, in a slightly differentiated form from other retailers. Our empirical model accomplishes this task by controlling for attribute-based demand factors through a random coefficient model of demand, and a model of strategic pricing that controls for differences in marginal cost, rival pricing, and departures from the maintained Bertrand-Nash pricing assumption.

4.2 Model of Item-Level Demand

Our demand model controls for item-level attributes that differentiate each choice from all other choices: unit prices, the size of each individual container, the number of containers in each multiple-container pack, and whether each container is a can or bottle. We also control for the retailer each item is sold through, whether the item is unique to a specific retailer, or common among all retailers, a set of household attributes that account for the effect of observed heterogeneity on choice variation, and unobserved heterogeneity through a comprehensive set of household-varying random parameters. The primitives of our model are consumer utility, brand preferences, and a set of heterogeneous product attribute preferences. We assume consumers search among variants within a single brand, and search among stores for variants that satisfy their package and container preferences at least cost. Consumers are indexed by $i = 1, 2, ..., I$ and items by $j = 1, 2, ..., J$.[12] Utility depends on household-specific brand preferences, μ_{ij}, item attributes that are observed by the econometrician (x_j), household-level attributes that account for observed heterogeneity among households (z_i), a shelf price that varies by item (p_j),and a random term capturing random variation in preferences among households (ε_{ij}). Therefore, the utility derived by household i is written as:

$$u_{ij} = \mu_{ij} + x_j\beta_i + \alpha_i p_j + z_i\gamma + \varepsilon_{ij} = Z_{1ij}\theta_1 + Z_{2j}\theta_{i2} + \varepsilon_{ij}, \tag{1}$$

where the brand-preference intercept (μ_{ij}), marginal utility of income (price response) (α_i), and item-attribute preferences (β_i) are assumed to vary randomly over individual households. We collect all of the variables with non-random effects (θ_1) in the vector Z_1, and the variables with mean effects (θ_{i2}) in the vector Z_2 to make the notation more compact. The vector of item attributes consists of a measure of the size of each container (SIZ), the number of containers in the package (NUM), whether each container is a can or bottle (PCK), whether the item is unique to a retailer (UNQ), and a set of indicator variables for each of the four

[12] To clarify terminology, we refer to an "item" as a specific product-retailer combination. For example, a 330 ml can of brand 1 at retailer 1 is a separate item from a 330 ml can of brand 1 offered at retailer 2.

retailers (r) in the data ($RT_r, r = 1, 2, 3, 4$).[13] Further, the elements of z_i include the age of the household head (AGE), the education level of the household head (ED), household income (INC), and the number of household occupants ($HHSIZ$). Although this is the most general form of the model, we estimate several alternative specifications in order to test whether this level of complexity is necessary.

Allowing the brand preference, price-response, and item-level attributes to vary randomly accounts for any unobserved heterogeneity in item purchase behavior that is not captured by the observed arguments of the model. Formally, the parameters are modeled as random-normal variates such that: $\mu_{ij} = \mu_0 + \sigma_\mu \nu_{ij}^1$, $\alpha_i = \alpha_0 + \sigma_\alpha \nu_i^2$, and $\beta_i = \gamma_0 + \sigma_\gamma \nu_i^3$, where the $v^k, k = 1, 2, ..., K$ are distributed joint normal such that $(v^1, \nu^2, \nu^3)\tilde{} MVN(0, \Sigma)$ where Σ is, in its most general form, a symmetric $KC \times KC$ covariance matrix.[14]

We assume the errors in (1) above are extreme-value distributed, and consumers adhere to the random utility assumption, choosing the single item that provides the maximum utility, so that item choices are estimated using a multinomial logit model. As is well-understood, the random-parameter specification does not have a closed-form expression, so the probability of choosing item j is given by:

$$P(j = 1|\theta) = \int\int\int \frac{\exp(Z_{1j}\theta_1 + Z_{2j}\theta_{i2})}{(\sum_{l \in J} \exp(Z_{1l}\theta_1 + Z_{2l}\theta_{i2})} f(v_{ij}^1) g(\nu_i^2) h(v_i^3) dv_{ij}^1 d\nu_i^2 dv_i^3, \tag{2}$$

which we solve using simulated maximum likelihood methods (Train 2003). Others estimate models similar to ours using Bayesian methods, however, Train (2003) argues that random parameter logit models of the type we estimate here are observationally equivalent to Bayesian models, and are more easily estimated using simulated maximum likelihood. We use 50 Halton draws (Bhat 2003) in order to make the estimation routine more efficient. Although estimating a logit model of item choice implicitly assumes the errors are iid across consumers and items, by assuming household-specific preferences are distributed

[13] The identities of the sample stores are not disclosed for reasons of confidentiality.
[14] In the estimated form of the model, Σ was constrained to a diagonal matrix.

joint-normal, we induce preference correlation independent of sample households' choice behavior. That is, preferences for individual attributes can be correlated over households without violating the iid assumption that underlies the logit model.

In the demand model, prices are likely to be endogenous. That is, at the household level, the error term for each demand equation contains some information that the retailer observes in setting equilibrium prices: advertising, in-store displays, preferred shelf-space, or a number of other factors that we do not observe in our data. Therefore, we estimate the demand model using the control function method (Petrin and Train 2010). Essentially, the control function approach consists of using the residuals from a first-stage instrumental variables regression as additional variables on the right-side of the demand model. Because the residuals from the instrumental variables regression contain information on the part of the endogenous price variable that is not explained by the instruments, they have the effect of removing the correlated part from the demand equation. Because input prices are expected to be correlated with retail prices, and yet independent of demand, our first-stage control function regression uses the set of input price variables as instruments. We also include brand and retailer fixed-effects in order to account for any endogenous effects that are unique to each item. Although these variables should represent effective instruments, whether they are weak in the sense of Staiger and Stock (1997) is evaluated on the basis of the F-test that results from the first-stage instrumental variables regression. In this case, the F-statistic is 619.5, which is much larger than the threshold of 10.0 suggested by Staiger and Stock (1997). Therefore, we conclude that our instruments are not weak (table A1).

[table A1 in here - intended as appendix]

4.3 Model of Strategic Pricing

Our focus is on retail pricing only, so we model the interaction among oligopolistic retailers in the downstream market.[15] Retailers maximize profit by choosing prices for each item within

[15] More precisely, retailers and manufacturers are assumed to play a three-stage package-development and pricing game. We assume the retailers in our sample compete in a multi-retailer oligopoly environment, and

the product line of our focal brand, taking into consideration both the wholesale price and marginal cost of retailing. Because our focus is on strategic pricing at the retail level, we assume contracts written between retailers and manufacturers are designed to maximize the total surplus between the retail price and the manufacturing cost. The strategic-obfuscation hypothesis implies that some of the observed margin is due to the fact that the item is unique, even after controlling for its impact on consumer demand. That is, there is a premium per unit, ψ, associated with a unique item that is not a manifestation of either higher costs of production, retailing, or demand-effects (higher or less elastic) alone. Dropping time subscripts for clarity, and including retailer subscripts to describe the broader retail environment, the profit equation for retailer r selling item j is written as:

$$\pi_r = M \sum_{j \in J_r} [w_{r_j}(p_{r_j} - c_{r_j} - g_{r_j} - \psi UNQ_{r_j}) - F_{r_j}], \tag{3}$$

where M is the size of the aggregate market for all products, w_{r_j} is the market share of item j in retailer r, c_{r_j} is the marginal cost of producing item j sold by retailer r, g_{r_i} is the marginal cost of retailing, UNQ_{r_j} is the unique-item indicator variable introduced above, and F_{r_j} reflects the retailer's fixed cost of stocking item j. For tractability, we consider the marginal costs of producing and selling each item to be linear in a set of soft-drink manufacturing (v_j^m) and retailing (v_j^r) input prices so that: $c_{r_j} = v_j^m \lambda$ and $g_{r_j} = v_j^r \gamma$, which is consistent with the retailing literature (Villas Boas 2007; Richards and Hamilton 2015).

Conditional on its prior stocking decision, retailer r's first order condition for the price of item j is given by:

$$\frac{\partial \pi_r}{\partial p_{r_j}} = M w_{r_j} + M \sum_{k \in I} (p_{r_k} - c_{r_k} - g_{r_i} - \psi UNQ_{r_j}) \frac{\partial w_{r_k}}{\partial p_{r_j}} = 0, \ \forall k \in I, r \in R. \tag{4}$$

Notice that equation (4) implies that each retailer internalizes all cross-sectional pricing externalities across products within the soft-drink category, but does not take into account

rival retailers play a Bertrand-Nash pricing game. Container sizes, number of containers in a package, and container type (can or bottle) all vary over items in our sample, but we assume they are determined in a prior, unobserved, stage of the game, set by retailer-specific contracts with manufacturers. Therefore, we assume that retailers choose prices in response to expectations regarding rival behavior in the second stage. In the third stage, rivals interact in the consumer market and equilibrium prices and quantities are realized. We solve the game using backward induction, solving for equilibrium prices conditional on consumer demand.

the effect of his pricing on the sales of items sold by other retailers. Stacking the first order conditions across retailers, defining an ownership matrix as Ω, which has element $\Omega_{jr} = 1$ if item j is sold by retailer r (and zero otherwise), and introducing a conduct parameter, φ, that measures any departure from the maintained Bertrand-Nash assumption, provides an estimable form of the pricing model. Making use of this notation, we write the estimated pricing equation as:

$$\mathbf{p} = \mathbf{c} - \psi UNQ - \varphi(\boldsymbol{\Omega}\mathbf{W}_p)^{-1}\mathbf{w}, \tag{5}$$

where bold notation indicates a vector (or matrix), and $\mathbf{W}_p$ is the matrix of share-derivatives with element $\partial w_{r_j}/\partial p_{r_k}$ for items j and k,where the specific form of these derivatives for the logit model are well-understood in the literature. The conduct parameter in this equation, φ, represents a means of measuring the extent of departure from the maintained Bertrand-Nash nature of the game played among retailers.[16] An estimate of $\varphi = 1$ means that retailers price in a manner consistent with Bertrand-Nash rivalry, while estimates below 1 suggest that conduct is more competitive, and above 1 less competitive than Bertrand-Nash. In this specification, our primary hypothesis involves tests of the statistical significance of the ψ parameter. If ψ is significantly greater than zero, then retailers earn greater margins on items they offer, but their rivals do not. If ψ is negative, then the margins are lower.

Given that we estimate a structural model of item-level pricing, the implied margin is presumed to be endogenous to the pricing decision.[17] Therefore, we instrument for retail margins using demand-shifting variables that consist of lagged markups implied by the demand model (up to four weeks), lagged prices (single week), fixed retailer effects, fixed brand effects, and a set of "Hausman" instruments formed from the prices of other items offered at different retailers. In a first-stage instrumental-variables regression, these instruments

[16] The use of a conduct parameter has been criticized in the theoretical literature (Corts 1999), but nonetheless represents a concise way of nesting a wide range of observed price behaviors. Moreover, the criticism that it mis-represents the true dynamics of oligopolistic rivalry can be applied to any static model of firm or consumer behavior.

[17] A Hausman test of the exogeneity of retail margins (Hausman 1978) produces a Chi-square statistic of 5.72, which is greater than the critical Chi-square value of 3.84 with one degree of freedom. Therefore, we are led to reject the null hypothesis of exogeneity.

explain fully 82.4% of the variation in margins, with an F-statistic of 530.7. Therefore, the instruments are not "weak" by the Staiger and Stock (1997) criteria.

5 Results and Discussion

In this section, we present the results from our soft-drink demand model, followed by tests of the pricing model shown in equation (5) above. In terms of the demand model results, we first conduct specification tests to determine whether our preferred model consists of fixed or random parameters. Based on the findings of these tests, we use the preferred specification to estimate the pricing model. We also conduct specification tests of the pricing model in order to determine whether OLS estimation is sufficient. With our preferred pricing model, we then conduct a series of counter-factual simulations in order to illustrate the practical effect of strategy obfuscation on equilibrium prices in this category. Following the complete presentation of the results from the French soft-drink data, we then present an examination of the robustness of our findings from a similar sample drawn from German coffee sales.

5.1 Demand Model Results

Our demand estimates are shown in table 5 below. In this table, we show estimates from both a fixed-coefficient model without the control function, and random-coefficient logit demand specification that corrects for the likely endogeneity of prices. We compare the fixed- and random-coefficient specifications using both a likelihood-ratio (LR) test, and a simple t-test of the scale parameters in the random-coefficient model. A LR test is a valid comparison method in this case, because the fixed-coefficient model is nested within the random-coefficient version. Based on the estimates reported in table 5, the LR test statistic value is $4,059.6$, which far exceeds the critical Chi-square value for a model with 7 degrees of freedom (14.067), so we reject the fixed-coefficient model based on the LR criterion. Moreover, 6 of the 7 scale parameters are significantly different from 0, so we also reject the fixed-coefficient model based on the t-test criterion as well. Unobserved heterogeneity is clearly a feature of our demand-side data. Endogeneity is also important as the t-statistic for the control function parameter is greater than the critical value. Based on this t-test, we reject the null hypothesis of exogeneity, and use the random-coefficient, control function model for estimating equilibrium prices.

[table 5 here]

Comparing the fixed and random-coefficient models also reveals substantial bias in the former. While the marginal utility of income estimates are similar between the two models (-5.6 for the fixed-coefficient versus -5.5 for the random-coefficient model), the marginal utility of package size, and the number of units in a package differ sharply between the two models. Moreover, the estimates differ qualitatively in terms of the marginal effects of income and store-size on item-level demand. Most important to our objectives here, the marginal value of finding a unique item is much smaller in the preferred specification, yet still positive and statistically significant (2.9 versus 7.5). This finding suggests that the "unique item effect" is driven by household's demand for items they find in one particular store, but not others. Using the mean marginal-utility of income estimate, the premium for unique items shown in this table implies a willingness-to-pay for uniqueness of over 0.52€ per litre, which is a substantial premium given the average soft-drink prices reported in table 2. Whether this premium is supported as an equilibrium outcome, however, depends upon estimates from the equilibrium pricing model below.

The primary purpose in estimating the demand model is not in determining the structure of demand, *per se*, but rather to provide input to the equilibrium prices described in the next section. However, it is first necessary to assess whether the demand elasticities are at least comparable to those found in the literature in order to evalulate whether the demand estimates appear, at least on an intuitive level to "make sense." We present the full own- and cross-price elasticity matrix in table 6 below. Because the model is estimated at the item-level, we expected the own-price elasticities to be relatively large, as the estimates in the table show. Further, because the items are only subtly differentiated, the cross-price elasticities show perhaps less willingness to substitute across minor attribute variations than is typical in a brand-level analysis. Most revealing, however, is the comparison of own-price elasticities for unique items (Items 11 - 14 in table 6) relative to non-unique items (all others). The elasticity estimates in table 6 show that unique items are far more elastic in demand than items offered in common so, absent strategic pricing by retailers, we would expect to see lower retail markups for unique items.

[table 6 here]

Our demand estimates allow us to compute the margins implied by Bertrand-Nash rivalry from the right-most term in equation (5) above. That is, the implied margin over the total marginal cost of purchasing and retailing the sample items. As an additional robustness check, we can compare this estimate to those in the literature for similar products. We find that the average margin, calculated using the demand estimates described above, is approximately 0.63 euros / litre, which is both reasonable and consistent with previous research using similar data (Bonnet and Bouamra Mechemache 2016). Whether this margin is consistent with that actually charged by retailers, however, remains to be answered by the equilibrium pricing model estimates.

5.2 Pricing Model Results

Estimates of the equilibrium retail pricing model are shown in table 7 below. In this model, the parameters of primary interest are the conduct parameter (ϕ), which measures the departure from the maintained assumption of Bertrand-Nash rivalry among retailers, and the parameter ψ that measures the effect of uniqueness on equilibrium margins. Because we control for variation in demand, and other motivations for pricing unique items different from those offered in common, through our structural approach, we interpret this parameter as a test for strategic obfuscation in our sample of soft drink items. That is, if the ψ parameter is significantly different from 0, then offering items that other retailers do not provides a means of raising consumers' costs of comparing similar items across stores, and raising margins as a result.

In the pricing model, however, the equilibrium margins derived from the demand-side estimates are clearly endogenous. As described above, we address the ensuing identification problem by instrumenting for the endogenous margins with the set of variables described above, through a control-function procedure (Petrin and Train 2010). Whether the control function method is appropriate in this case is tested by examining the t-statistic on the control-function term in the pricing model. Based on the estimates in table 7, we show that our control function is statistically significant, so is able to account for much of the endogeneity bias that would otherwise affect the parameters of interest.

[table 7 here]

Based on the preferred, control-function estimates in table 7, we find that the ψ parameter is indeed significantly different, and greater than, zero. More specifically, the estimate of 0.107 implies that items sold in one store only are able to earn margins that are 0.107 euros per litre larger than when an item is sold in common, or at least in multiple stores. Based on the average imputed margin of 0.488 euros per litre, the "unique premium" is nearly 20% of the usual margin, so is both statistically and economically significant. After controlling for other factors that may explain why unique items sell for higher prices than those offered in common, we interpret this estimate as a measure of the extent to which consumers' inability to compare unit prices across stores allows retailers to raise prices, and earn higher margins. In this regard, higher search costs are a source of market power for retailers.

Retailers, however, are not able to offer unique variants of national brands on their own. Indeed, our findings have important implications for vertical relationships between retailers and manufacturers as offering unique items must be facilitated by a manufacturer that is both willing, and able, to produce and ship a variety of items. Only large, sophisticated manufacturers, and equally large, sophisticated retailers are likely to be able to benefit from developing a strategy of offering retailer-specific items (that are not private labels). If there is additional profit to be made from offering unique items, it is likely that manufacturers' bargaining power is greater for these items, so there are incentives to develop a mass-customization program on both sides. Indeed, finding that unique items are relatively elastic in demand, and yet command a margin-premium at retail, suggests that some of the margin premium found hee is likely absorbed by higher wholesale prices, and hence, manufacturing margins (Bonnet and Bouamra-Mechemache 2016). Modeling the vertical channel completely, however, is beyond the scope of this research.

5.3 Simulating Equilibrium Prices

Counter-factual simulations are useful in demonstrating the economic importance of our econometric estimates. That is, while individual parameter estimates may be statistically significant, if they are small they may have little practical significance for equilibrium prices, and consumer welfare. Our counter-factual simulations compare the fitted prices for both unique and common items (fitted from the equilibrium pricing model) under the existing mix of each, to prices that would emerge if retailers either each offered only unique items, or were restricted from offering items that were different from other retailers. We also compare the equilibrium margins that result, both for retailers that appear to be offering unique items in order to prevent comparison, and those that offer only items in common with other retailers. All of the findings from our counter-factual simulation are shown in table 8 below.

[table 8 here]

In this table, Scenario 1 describes the status quo, where Retailers 3 and 4 are the most intensive users of a unique-item strategy, and Retailer 2 enjoys large margins as the dominant retailer in most markets (see market shares in Table 4). Scenario 2 describes the case where all retailers offer unique products, so no price comparison can be made, while Scenario 3 shows the effect of moving to an all-common strategy on margins and equilibrium prices. Our results show that margins rise, in general, by moving to an all-unique strategy, and prices rise accordingly (Scenario 2). Indeed, margins rise by an average of 3.3% over all 5 retailers, and prices rise by 4.3%. Essentially, equilibrium prices and margins are affected in two ways: (1) prices rise through a direct effect by increasing demand, and (2) margins widen through in indirect, or strategic, effect by softening price competition engendered by consumers' relative inability to compare prices. In Scenario 1, each retailer has some price premia from their unique items, and for other reasons that are not observed, and margins are enhanced by some softening of price competition. In Scenario 2, retailers benefit from both the competitive effect of uniqueness, and price-premia once consumers are in the store. But, this effect is not uniform as margins actually fall in Retailer 2, which enjoyed the highest margins prior to all retailers moving to an only-unique strategy. In this case, some of their competitive advantage is clearly eroded, while Retailers 3 and 4, the largest providers of unique items, see only marginal gains as the change in strategy is only incremental for them. In Scenario 3, only Retailer 1 does not lose margin, because it used a common-item strategy before the change by all others. Because other stores lose their advantage, this retailer experiences a small rise in margins. Price, however, are lower overall as consumers can search more efficiently, and compare prices more accurately across all retailers.

In summary, we find that offering unique items tends to raise prices directly due to the demand-enhancing effect of uniqueness cited above, and due to their tendency to soften price competition as consumers find it harder to compare prices among retailers.

6 Robustness Check: German Coffee

We conducted a similar analysis using coffee purchases by German households as a means of corroborating the evidence from France, and serving as an evaluation of the robustness of those findings in a sharply different retail environment. Our German data experiment was designed as closely as possible to the French case, namely we sampled 38 items from the universe of coffee brands available in Germany, and selected some from two major brands that were offered uniquely in one of the five major food retailers. We then compared the prices for identical items in different stores with the prices of items that were offered in common across several stores.

Our summary findings show that prices for unique items are again dramatically higher than those that are offered in all stores as homogeneous items. Because these items are relatively minor variants on well-known national brands, retailers are able to retain the attractiveness of stocking national brands, while preserving the ability to price their own variants as differentiated products. Whether this summary evidence constitutes statistical evidence of strategic obfuscation, as we interpret our findings from France, however, requires the same model of statistical control that we present above.

We first estimate the demand for a number of variants from two major coffee brands in Germany. Each brand offers slight variants among the top five retailers, so our data experiment is similarly able to identify the premium associated with uniqueness as in the French case presented above. First, note that we again prefer the random coefficient logit estimates to fixed-coefficient alternatives as the LR test statistic of 546.39 is far greater than the critical Chi-square value of 24.995.[18] Again controlling for price endogeneity, the estimates obtained from a random coefficient logit model, similar in to the one used for the French soft drink data above, are shown in table 9 below. From these estimates, it is clear that there is again a demand-premium associated with uniqueness. That is, items that are offered in only one retailer are associated with a 2.04€ per kg. willingness-to-pay premium relative to non-unique items.[19] Because we control for brand-and-retailer fixed effects, as well as other elements of differentiation that may lead to a higher willingness-to-pay, we interpret this premium as the result of consumers' inability to search for lower-priced equivalents at the retailer.

[table 9 in here]

Whether this premium results in higher equilibrium prices, however, remains for an estimate of an oligopolistic-pricing model equivalent to the one presented above. With

[18] Note that the scale parameter is relatively large compared to the French estimate (10.0848 versus 0.919). This difference is due to the fact that the German demand model was estimated with a log-normal distribution for the marginal utility of income parameter (Hole 2007). While this assumption rules out positive estimates for the price-parameter, the log-normal distribution has notoriously fat tails.

[19] The willingness-to-pay premium is found by dividing the "Unique" parameter estimate by the mean marginal utility of income estimate.

the demand estimates from table 9, we then calculated retail margins under an assumed Bertrand-Nash pricing game, and estimated retail cost parameters using the coffee-input prices available in Germany.[20] The parameter estimates obtained from estimating the German equilibrium-pricing model are shown in table 10. As in the French example, the preferred model (estimated using the control function method) again finds a substantial premium associated with uniqueness, even after retailers' equilibrium price-responses are taken into account. In fact, because the average retail selling price for coffee in Germany is 7.21€ per kg in our sample, the estimate of 0.57€ per kg implies that margins for unique items are roughly 3% greater than for non-unique items. Further, the conduct parameter (ϕ) estimate of 2.03 suggests that German coffee retailing is substantially less competitive than Bertrand-Nash, at least in our data sample. In general, therefore, our findings in the German coffee example are broadly consistent with those found in French soft drinks, and suggest that strategic obfuscation is, while perhaps implicit, is more common than may be commonly understood.

[table 10 in here]

7 Conclusion and Implications

In this paper, we present a formal test for strategic obfuscation in frequently-purchased consumer packaged goods. Retailers, together with manufacturers, have an incentive to offer variants of commonly-purchased items that are unique to their store in order to raise the costs of searching among stores. If an item cannot be directly compared to another sold at a different store, then price-comparisons are more difficult, and the opportunity for profit will be greater.

We test our hypothesis using a sample of data taken from the French carbonated soft-drink market, and corroborate our findings with a similar sample from German coffee retail-

[20] Note that a full set of input price indices similar to those used in French model were not available for Germany. Brand and retailer fixed effects, and indicators of package variants, are used to identify any cost differences associated with selling through a different outlet, producing through different manufacturing facilities, or using a different package.

ing. Using demand-and-pricing information from 3 major brands of soft-drink sold in France, focusing on 18 package and container variants – 7 of which are offered in common among all stores and 11 offered uniquely in others – we are able to cleanly identify the treatment effect associated with strategic obfuscation, and the margin premium that results. Assuming supermarket retailers price carbonated soft drinks as Bertrand-Nash oligopolists, we control for both the marginal costs of buying and retailing soft drinks, as well as equilibrium responses to rival pricing behavior.

We find that retail margins are 14.5% higher when an item is sold at only one store, compared to when it is sold at all stores. In the German coffee data we find that equilibrium prices are approximately 3% higher for unique items relative to those variants sold in common across all stores. Controlling for item-level attributes and retailer-fixed effects, we eliminate other plausible explanations as to why margins on unique items may be higher than otherwise. Contracts with manufacturers that specify packages unique to their store are not uncommon, and the incentives to negotiate these arrangements are clear.

For consumer-packaged-good (CPG) retailers, our findings suggest that offering unique items may be an effective method to generate higher margins than would otherwise be the case. However, our analysis is confined to the effect of strategic obfuscation on competition among retailers, and not on the nature of vertical relationships among retailers and manufacturers. Manufacturers likely realize the value retailers derive from offering unique items, so can use their ability to flexibly produce different package sizes, or combinations of individual items, in order to enhance their bargaining power with retailers. We leave this analysis for future research. Our findings also imply that consumer search is perhaps more important than was once thought. While others examine the cost of searching in a retail food environment (Mehta, et a. 2003; Richards and Hamilton 2016), few consider the impact of impeding search in equilibrium price-and-margin outcomes. If our findings are robust across categories, the broader impact of package-customization may be important for consumer welfare as well.

Our findings are more general than the specific instance we use to illustrate the strategic obfuscation effect. Ellison and Ellison (2009) demonstrate a similar motive for obscuring items online, while more anecdotal evidence from services such as healthcare insurance, banking fees, and household mortgages are more commonplace. Any time an item or service cannot be directly compared among vendors, the ability to search and compare prices for like products is impaired. Without the ability to search with full information, one of the basic requirements for a competitive market fails to exist. If market power increases, and market performance declines, in the extent to which firms are able to obfuscate the price of their product from others, then the policy implications are clear. Namely, if anti-trust authorities are interested in maintaining the competitiveness of markets, then it is not necessarily the volume of information on items in the market that is important, but rather the comparability and simplicity. Consumers need to be able to compare products quickly and easily if search behavior is to be rewarded with relevant information. Standardized price-comparison information should be both more prominent and relevant to the specific attributes of each item.

Our analysis is not without weaknesses. First, we identify only one manufacturer offering slight variants through different retailers. While there are most certainly others, in categories for which we do not have data, if we were lucky enough to identify a "black swan" in retail pricing, then the practical implications of our findings may be minor in the context of the tens of thousands of items found in every supermarket. Second, our findings are conditional on a specific model of demand, and assumptions regarding the nature of competition in the retail industry. Although our approach is well-accepted in the empirical industrial organization literature, it may well be the case that a different model of demand, or different assumptions regarding the nature of retail competition, would generate different results. Finally, despite controlling for many different reasons that may explain why unique items sell for higher prices, there may be others that are grounded in the institutional detail of the contracts between manufacturers and retailers in our sample that we are not aware of.

References

[1] Baye, M. R., Morgan, J., Scholten, P., and Jansen, D. (2006). Persistent price dispersion in online markets. The New Economy and Beyond: Past, Present and Future (DW Jansen, ed.). New York: Edward Elgar Publishing, 122-143.

[2] Bonnet, C., and Bouamra-Mechemache, Z. (2016). Organic label, bargaining power, and profit-sharing in the French fluid milk market. American Journal of Agricultural Economics, 98(1), 113-133.

[3] Cakır, M., Balagtas, J. V. (2014). Consumer response to package downsizing: Evidence from the Chicago ice cream market. Journal of Retailing, 90(1), 1-12.

[4] Carlin, B. I. (2009). Strategic price complexity in retail financial markets. Journal of Financial Economics, 91(3), 278-287.

[5] Chioveanu, I., and Zhou, J. (2013). Price competition with consumer confusion. Management Science, 59(11), 2450-2469.

[6] Cohen, A. (2008). Package size and price discrimination in the paper towel market. International Journal of Industrial Organization, 26(2), 502-516.

[7] Corts, K. S. (1999). Conduct parameters and the measurement of market power. Journal of Econometrics, 88(2), 227-250.

[8] Diamond, P. A. (1971). A model of price adjustment. Journal of Economic Theory, 3(2), 156-168.

[9] Ellison, G., and Wolitzky, A. (2012). A search cost model of obfuscation. The RAND Journal of Economics, 43(3), 417-441.

[10] Ellison, G., and Ellison, S. F. (2005). Lessons about markets from the Internet. Journal of Economic Perspectives, 139-158.

[11] Ellison, G., and Ellison, S. F. (2009). Search, obfuscation, and price elasticities on the Internet. Econometrica, 77(2), 427-452.

[12] Gabaix, X., and Laibson, D. (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. Quarterly Journal of Economics, 121(2), 505-540.

[13] Grubb, M. (2014). Failing to choose the best price: theory, evidence, and policy. Review of Industrial Organization, forthcoming.

[14] Gu, Y., and Wenzel, T. (2014). Strategic obfuscation and consumer protection policy. Journal of Industrial Economics, 62(4), 632-660.

[15] Gu, Y., and Wenzel, T. (2015). Putting on a tight leash and levelling playing field: An experiment in strategic obfuscation and consumer protection. International Journal of Industrial Organization.

[16] Hausman, J. A. (1978). Specification tests in econometrics. Econometrica: Journal of the Econometric Society, 43, 1251-1271.

[17] Hausman, J., Leonard, G., and Zona, J. D. (1994). Competitive analysis with differenciated products. Annales d'Economie et de Statistique, 34, 159-180.

[18] Hole, A.R. (2007). Fitting mixed logit models by using maximum simulated likelihood. Stata Journal, 7(3), pp. 388-401.

[19] Kalaycı, K., and Potters, J. (2011). Buyer confusion and market prices. International Journal of Industrial Organization, 29(1), 14-22.

[20] Latek, M., and Kaminski, B. (2009). Social learning and pricing obfuscation. In Artificial Economics (pp. 103-114). Springer Berlin Heidelberg.

[21] McDonald, S., and Wren, C. (2013). Multiple price posting and consumer search obfuscation: Evidence from an online market. Working Paper, newcastle University Business School.

[22] Mehta, N., Rajiv, S., and Srinivasan, K. (2003). Price uncertainty and consumer search: A structural model of consideration set formation. Marketing Science, 22(1), 58-84.

[23] Muir, D., Seim, K., and Vitorino, M. A. (2013). Price obfuscation and consumer search: An empirical analysis. Working paper.

[24] Persson, P. (2016). Attention manipulation and information overload. Working paper, Department of Economics, Stanford University, Stanford, CA.

[25] Petrin, A. and K. Train. (2010). A control function approach to endogeneity in consumer choice models. Journal of Marketing Research, 47, 3-13.

[26] Piccione, M., and Spiegler, R. (2012). Price competition under limited comparability. Quarterly Journal of Economics.

[27] Richards, T. J. and Hamilton, S. F. (2016). A nested model of search and retail pricing. Review of Industrial Organization, forthcoming.

[28] Scitovsky, T. (1950). Ignorance as a source of oligopoly power. The American Economic Review, 40(2), 48-53.

[29] Sitzia, S., and Zizzo, D. J. (2011). Does product complexity matter for competition in experimental retail markets?. Theory and Decision, 70(1), 65-82.

[30] Staiger, D., and Stock, J. H. (1997). Instrumental variables regression with weak instruments. Econometrica, 65, 557-586.

[31] Subramaniam, R., and Gal-Or, E. (2009). Research note - quantity discounts in differentiated consumer productarkets, Marketing Science, 28(1), 180–192.

[32] Train, K. (2003). Discrete-choice methods with simulation. Cambridge, UK. Cambridge University Press.

[33] Turolla, S. (2016). Spatial competition in the French supermarket industry. Annals of Economics and Statistics, 121-122(June), 213-259.

[34] Wilson, C. M. (2010). Ordered search and equilibrium obfuscation. International Journal of Industrial Organization, 28(5), 496-506.

[35] Wilson, C. M., and Price, C. W. (2010). Do consumers switch to the best supplier? Oxford Economic Papers, gpq006.

[36] Wilson-Jeanselme, M., and Reynolds, J. (2005). Competing for the online grocery customer: the UK experience. in Grocery e-commerce: Consumer behaviour and business strategies, eds. Kornum, N. and Bjerre, M. Edward Elgar, Northampton, MA. p. 10.

[37] Yonezawa, K., and Richards, T. J. (2016). Competitive package size decisions. Journal of Retailing, forthcoming.

Table 1. Summary of Retail Prices: Unique vs Common Items

		Unique			Common		
Brand	N	Mean	Std. Dev.	N	Mean	Std. Dev.	t-ratio
French Soft-Drink Data							
1	1,985	1.40*	0.48	22,580	1.12*	0.25	25.40
2	583	1.07*	0.28	5,326	0.99*	0.28	6.36
3	453	1.16*	0.23	7,615	1.01*	0.32	13.24
German Coffee Data							
1	0			20,161	6.51	1.15	2.95
2	256	9.49*	0.87	13,653	8.24*	1.61	11.05

Note: Data are pooled over 5 retailers in each case; a single asterisk indicates prices are significantly different at 5% level. Soft drink prices are euros / l, and coffee prices are euros / kg.

Table 2. Store Format by Retailer

	% Unique	Small	Supermarket	Hypermarket
Retailer 1	1.26%	0.00%	0.00%	100.00%
Retailer 2	7.30%	9.24%	90.42%	0.34%
Retailer 3	14.79%	0.01%	72.61%	27.38%
Retailer 4	5.87%	0.00%	3.60%	96.40%
Retailer 5	1.92%	0.00%	0.02%	99.98%

Note: Value in % Unique column is % of items sold by retailer over households and time.

Table 4. Summary of Pricing Data

Variable	Measure	Mean	Std. Dev.	Min.	Max.	N.
Aluminum Price	Index	93.800	4.989	86.700	102.400	3484
Plastic Price	Index	106.300	0.332	105.700	106.900	3484
Glass Price	Index	104.967	0.661	103.500	105.700	3484
Sugar Price	Index	147.106	7.636	134.100	158.500	3484
Gasoline Price	Index	113.156	2.265	110.300	118.000	3484
Electricity Price	Index	115.331	4.921	107.300	121.300	3484
Sugar Substitute Price	Index	104.588	0.700	103.510	106.010	3484
Wages in Beverage Mfg	Index	110.650	0.415	110.000	111.100	3484
Retail Margin	Euro / litre	0.681	0.125	0.000	0.863	3484
Retailer 1	Market Share	0.219	0.041	0.136	0.302	3484
Retailer 2	Market Share	0.351	0.048	0.256	0.447	3484
Retailer 3	Market Share	0.144	0.035	0.074	0.214	3484
Retailer 4	Market Share	0.169	0.038	0.094	0..244	3484
Retailer 5	Market Share	0.117	0.032	0.052	0.087	3484

Note: Data from French National Institute for Statistics and Economic Studies.

Table 3. Summary of French Soft-Drink Demand Data

Variable	Units	Mean	Std. Dev.	Min	Max	Variable	Units	Mean	Std. Dev.
Income	Euro / mo	$3,120.95	$1,422.56	$525.00	$8,000.00	Item 1	%	31.11%	46.30%
Educ.	Years	12.282	2.648	6.000	18.000	Item 2	%	10.20%	30.26%
Age	Years	46.285	13.067	18.000	92.000	Item 3	%	2.26%	14.86%
HH Size	#	2.976	1.335	1.000	9.000	Item 4	%	17.27%	37.80%
Unique?	%	0.078	0.268	0.000	1.000	Item 5	%	1.46%	11.98%
Price 1	Euro / l	1.017	0.105	0.202	2.057	Item 6	%	1.18%	10.78%
Price 2	Euro / l	0.980	0.082	0.183	1.893	Item 7	%	0.26%	5.09%
Price 3	Euro / l	2.027	0.089	0.869	2.853	Item 8	%	11.69%	32.13%
Price 4	Euro / l	1.396	0.117	0.225	2.794	Item 9	%	8.07%	27.23%
Price 5	Euro / l	1.105	0.080	0.140	1.395	Item 10	%	0.83%	9.06%
Price 6	Euro / l	1.516	0.081	0.238	2.121	Item 11	%	0.35%	5.89%
Price 7	Euro / l	1.706	0.073	1.159	2.331	Item 12	%	8.88%	28.45%
Price 8	Euro / l	0.893	0.128	0.148	4.886	Item 13	%	4.93%	21.66%
Price 9	Euro / l	1.190	0.105	0.335	2.146	Item 14	%	0.44%	6.65%
Price 10	Euro / l	1.303	0.075	0.460	1.836	Item 15	%	0.33%	5.75%
Price 11	Euro / l	1.365	0.072	0.533	2.062	Item 16	%	0.30%	5.43%
Price 12	Euro / l	0.868	0.095	0.140	1.792	Item 17	%	0.10%	3.14%
Price 13	Euro / l	1.231	0.090	0.362	2.208	Item 18	%	0.34%	5.84%
Price 14	Euro / l	1.327	0.073	0.472	1.667	Store 1	%	14.51%	35.22%
Price 15	Euro / l	0.978	0.073	0.336	1.148	Store 2	%	17.00%	37.57%
Price 16	Euro / l	1.381	0.071	0.436	1.642	Store 3	%	20.33%	40.25%
Price 17	Euro / l	1.392	0.071	0.788	1.524	Store 4	%	36.65%	48.19%
Price 18	Euro / l	1.385	0.073	0.529	1.778	Store 5	%	11.50%	31.90%
						Brand 1	%	60.84%	48.81%
						Brand 2	%	17.08%	37.63%
						Brand 3	%	22.08%	41.48%

Note: Data from Kantar TNS Worldpanel.

Table 5. Model of Item Demand

	Fixed Coefficient		Random Coefficient	
	Estimate	t-ratio	Estimate	t-ratio
Brand 1	4.2011	0.1080	5.8395*	3.0453
Brand 2	6.0627	0.1559	7.5149*	3.9183
Brand 3	1.8137	0.0466	3.4950	1.8228
Price	-5.6434*	-108.2980	-5.5477*	-96.6006
Package	1.7858*	56.1941	1.2990*	37.1356
Size	-8.5106*	-54.9968	-24.1444*	-57.3870
Number	-18.9526*	-47.8177	-0.0032	-0.0056
Age	0.1180*	8.2802	4.8154*	5.5546
Income	-1.2788*	-9.8028	9.5452	0.9499
Education	0.5317*	7.4680	5.7355*	9.7984
HH Size	0.9809*	7.5612	0.8442	0.9962
Unique	7.4897*	13.5523	2.8982*	11.0830
Store Size	-9.6831*	-12.7112	0.3925	0.5904
Retailer 1	4.9787	0.1280	9.4406	0.0555
Retailer 2	3.6579	0.0941	6.3684	0.1718
Retailer 3	8.0393	0.0355	-4.6744*	-2.9450
Retailer 4	-6.2265	-0.1602	-3.7286*	-2.2934
Std (Brand 1)			0.6803*	2.6315
Std (Brand 2)			0.9934*	3.7777
Std (Brand 3)			0.6780*	2.6129
Std (Price)			0.9198*	13.8024
Std (Pkg)			-0.1049*	-4.1416
Std (Size)			-9.1759*	-45.6561
Std (Num)			-0.4459	-1.1767
Control Function			1.3047*	3.2528
LLF	-59,460.3		-57430.48	
AIC	33.0856		32.9802	

Note: A single asterisk indicates significance at a 5% level.
N = 38,542. Std() indicates scale parameters.

Table 7. Model of Strategic Pricing with Obfuscation

	OLS		Control Function	
	Estimate	t-ratio	Estimate	t-ratio
Constant	-5.7633	-1.0154	-4.4424	-0.7802
Aluminum	-0.1235	-0.3245	-0.0092	-0.0241
Plastic	-0.7373	-0.3137	-1.6766	-0.7056
Glass	1.9473*	2.3563	1.6212	1.9412
Sweetener	0.4521*	23.4964	0.4481*	23.2291
Gas	0.7861*	2.8707	0.7375*	2.6894
Electric	-0.8823*	-2.8945	-0.8410*	-2.7577
Wages	0.4138	0.9226	0.4137	0.9232
Retailer 1	-0.1417*	-3.0226	-0.1421*	-3.0331
Retailer 2	-0.1094*	-2.9543	-0.1127*	-3.0449
Retailer 3	0.0448*	2.9249	0.0397*	2.5749
Retailer 4	-0.1808*	-7.1714	-0.1836*	-7.2815
Store Size	-0.0799*	-1.9721	-0.0852*	-2.1004
Conduct	0.1456*	6.1010	0.1702*	6.6361
Unique	0.1050*	12.7451	0.1068*	12.9274
Control Function			0.0009*	2.6074
LLF	30.6651		34.0766	
AIC	111.5912		105.1877	

Note: A single asterisk indicates significance at a 5% level.

Table 6. Elasticity Matrix: Partial

Item No.	1	2	3	4	5	6	7	8	9	10	11^U	12^U	13^U	14^U
1	-5.5523	0.0134	0.0162	0.0142	0.0160	0.0101	0.0106	0.0106	0.0103	0.0083	0.0073	0.0072	0.0071	0.0070
2	0.0142	-5.1627	0.0161	0.0140	0.0159	0.0099	0.0105	0.0105	0.0101	0.0082	0.0072	0.0070	0.0069	0.0069
3	0.0167	0.0156	-6.1013	0.0165	0.0182	0.0123	0.0129	0.0127	0.0125	0.0104	0.0096	0.0095	0.0093	0.0093
4	0.0143	0.0133	0.0161	-5.3687	0.0159	0.0100	0.0105	0.0105	0.0102	0.0083	0.0072	0.0071	0.0070	0.0069
5	0.0166	0.0156	0.0184	0.0164	-5.3983	0.0122	0.0128	0.0127	0.0125	0.0103	0.0096	0.0094	0.0092	0.0092
6	0.0104	0.0097	0.0124	0.0103	0.0122	-5.2326	0.0067	0.0070	0.0064	0.0048	0.0034	0.0033	0.0032	0.0032
7	0.0108	0.0100	0.0127	0.0106	0.0126	0.0066	-5.0767	0.0073	0.0068	0.0051	0.0037	0.0036	0.0036	0.0035
8	0.0116	0.0108	0.0135	0.0114	0.0133	0.0074	0.0078	-5.6026	0.0075	0.0058	0.0045	0.0044	0.0043	0.0043
9	0.0105	0.0098	0.0124	0.0103	0.0123	0.0063	0.0068	0.0071	-5.1158	0.0049	0.0034	0.0033	0.0033	0.0032
10	0.0093	0.0087	0.0113	0.0092	0.0112	0.0052	0.0057	0.0060	0.0054	-5.6666	0.0023	0.0022	0.0022	0.0021
11	0.0073	0.0068	0.0093	0.0072	0.0092	0.0032	0.0036	0.0041	0.0034	0.0020	-9.1408	0.0002	0.0002	0.0001
12	0.0072	0.0067	0.0093	0.0071	0.0092	0.0032	0.0036	0.0041	0.0033	0.0020	0.0002	-10.9171	0.0001	0.0001
13	0.0073	0.0067	0.0093	0.0071	0.0092	0.0032	0.0036	0.0041	0.0033	0.0020	0.0002	0.0001	-9.3846	0.0001
14	0.0072	0.0067	0.0092	0.0071	0.0091	0.0032	0.0036	0.0041	0.0033	0.0020	0.0001	0.0001	0.0001	-11.5516

Note: All elasticities are significant at a 5% level. All items are from Brand 1. U superscript indicates unique item.

Table 8. Simulation of Equilibrium Prices and Margins

	Scenario 1		Scenario 2		Scenario 3	
	Margins	Prices	Margins	Prices	Margins	Prices
Retailer 1	0.4211	1.1662	0.4582	1.2300	0.4340	1.1191
Retailer 2	0.5120	1.2603	0.5011	1.3119	0.4301	1.1930
Retailer 3	0.4369	1.4574	0.4420	1.5081	0.4033	1.3947
Retailer 4	0.4340	1.2145	0.4502	1.2671	0.4151	1.1544
Retailer 5	0.4673	1.4433	0.4903	1.5095	0.4520	1.3962

Note: Scenario 2 is "All Unique," and Scenario 3 is "All Common."

Table 9. Estimates of German Coffee Demand Model

	Fixed Coefficient		Random Coefficent	
	Estimate	t-value	Estimate	t-value
Size	-0.0018*	-16.2362	-0.0011*	-9.8422
Unique	3.0927*	31.4944	2.0400*	17.0626
Promotion	9.6274*	60.9982	12.5868*	68.0320
Income	-0.3879*	-14.7155	-0.1349*	-4.7187
Education	0.7480*	41.3799	1.5484*	36.9729
Kids	-2.5753*	-20.3339	-2.6418*	-18.6729
Age	-0.2116*	-11.4419	0.4252*	12.6081
Package	-5.4132*	-66.4712	-4.7405*	-50.0817
Brand 1	-4.0145*	-70.7499	-4.6517*	-74.5104
Retailer 1	0.0471*	2.4071	-0.2101*	-9.3469
Retailer 2	-0.7904*	-35.1952	-0.8018*	-35.1018
Retailer 3	0.7956*	30.7057	1.0590*	36.7392
Retailer 4	-1.0269*	-40.9702	-1.2876*	-47.0079
Control Function	0.6668*	8.9795	0.4721*	6.0168
Price	-7.2171*	-58.3397	-10.0848*	75.3507
Std(Price)			10.9077*	20.9178
AIC	205,402.8		204,858.4	
LLF	-102,686.41		-102,413.22	

Note: A single asterisk indicates significance at a 5% level.

Table 10. Strategic Pricing with German Coffee Data

	OLS		Control Function	
	Estimate	t-ratio	Estimate	t-ratio
Coffee Input	0.0003*	20.7668	0.0003*	20.9104
Multipack	-0.0195*	-4.3321	-0.0234*	-4.8276
Conduct	2.1046*	78.5408	2.0315*	50.7302
Brand 1	0.0235*	4.7321	0.0323*	5.1381
Retailer 1	0.0044	1.5171	0.0039	1.3528
Retailer 2	0.0030	0.6221	0.0057	1.1447
Retailer 3	0.0045	1.4250	0.0037	1.1892
Retailer 4	0.0029	0.9677	0.0031	1.0312
Unique	0.0138*	3.0659	0.0200*	3.9156
Package Size	0.2810*	-4.1513	0.0316*	-4.4075
Control Function			0.0930*	2.5235
Constant	0.3451*	40.2060	0.3549*	37.0118
F	2666.91		2479.48	
R^2	0.969		0.9692	

Note: A single asterisk indicates significance at a 5% level, with heteroscedastic robust standard errors.
Prices are in cents / gram for estimation purposes, so are scaled to euros / kg for interpretation purposes.

Table A1. First-Stage IV Estimates

	Estimate	t-ratio
Constant	0.9604	0.4711
Brand 1	0.0931*	6.8888
Brand 2	-0.0561*	-4.1216
Retailer 1	-0.2949*	-53.7732
Retailer 2	-0.3036*	-57.3763
Retailer 3	-0.1191*	-23.5283
Retailer 4	-0.2917*	-61.8596
Aluminum	0.1527	0.9213
Plastic	-1.7776	-1.1551
Glass	1.0450	1.3971
Sweetener	0.1454*	1.9818
Gas	0.6545*	4.6473
Electric	-0.3305*	-4.6681
Wages	-0.8067	-1.0511
Insurance	1.1303	1.8939
R2	0.1852	
F	619.5	

Note: A single asterisk indicates significance at a 5% level.