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Antitrust Market Definition and the Sensitivity of the Diversion Ratio

Lydia Cheung

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Antitrust Market Definition and the Sensitivity of the Diversion Ratio [*]

Lydia Cheung
Auckland University of Technology [†]

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Abstract

The diversion ratio is a key ingredient for merger analysis, as mentioned in the new *Horizontal Merger Guidelines* (2010) in the U.S. and similar documents abroad. It is a measure of substitutability between merging goods, which determines the potential for price increase post-merger. There is little existing research on how the diversion ratio is to be estimated. This paper is the first one to explore estimation issues through standard demand estimation techniques and how changes in the antitrust market definition affect the resultant diversion ratios. I use random draws of supermarket products from a supermarket dataset to show that the estimated diversion ratios are, in fact, not greatly affected by market definition. They have the same magnitude as baseline estimates and the first significant figures vary within a small range.

JEL classification: D12; L11; L13; L41

Keywords: horizontal merger; unilateral price effect; differentiated products; upward pricing pressure; diversion ratio; elasticity

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[†] School of Economics, Faculty of Business, Economics, and Law, Auckland University of Technology. `lydia.p.cheung@aut.ac.nz`.

1 Introduction

The Upward Pricing Pressure (UPP) test popularized by Farrell and Shapiro (2010) signifies a new emphasis in merger analysis on price effects. While there has always been a need for easy-to-compute shortcuts for screening merger proposals, the old shortcuts that rely on market definition, market shares, and concentration are theoretically proven to be problematic and, in practice, often subjective. The new UPP test is designed to overcome these flaws. From a theoretical perspective, a focus on post-merger price change is much more appealing than a focus on market share or concentration change, because the former has a much more predictable relationship with consumer surplus than the latter. From a practical point of view, UPP no longer requires a definition of the market boundary. In addition, UPP addresses a salient feature of the modern retail industry: that most consumer products are highly differentiated, and consumers are keenly aware of the products' differences. In other words, two mergers with identical pre-merger market shares, but different characteristics on the two pairs of merging goods, are likely to have sufficiently different outcomes. The UPP is designed to detect these differences, where the old shortcuts ignore.

The UPP is an approximation of the post-merger price change for each product. This approximation can be viewed as the change in first order condition for each product, in a Bertrand oligopoly market, from pre-merger to post-merger, as detailed in Cheung (2016). Intuitively, before the two firms merge, competition between them imposes a constraint on price increase in terms of diverted profits: should one of the firms increases its price, some of the lost sales will divert to the competitor, increasing the competitor's profit. The more substitutable these two products are, the larger the diverted sales. However, after merger, this constraint or opportunity cost on price increase disappears, because profits are no longer "diverted", but jointly maximized. In summary, the larger the pre-merger constraint on price increase, the larger the opportunity for actual post-merger price increase.

One key ingredient in the UPP is the diversion ratio, a measure of substitutability between the two merging goods, first coined by Shapiro (1996). Intuitively, this is a crucial input to merger analysis because a merger between two close substitutes causes a larger reduction in competition than a merger between two distant substitutes. The larger the diversion ratio, the more lost sales will be diverted to the competitor should the firm increases its price. Thus, two products with high diversion ratios between them will have a large pre-merger constraint on price increase, and subsequently, a large opportunity for actual post-merger price increase. The actual calculation of the UPP requires few other inputs: the competitor's (pre-merger) price-cost margin, and optionally, the product's own reduction in marginal cost from the merger. Farrell and Shapiro (2010) are rather open-ended on where or how to obtain the diversion ratio, giving suggestions like company internal documents ("to whom do we lose our business?") or customer surveys.

Ten Kate and Niels (2014) is the first paper to clarify two distinct interpretations of the diversion ratio among practitioners since its popularization. This recent and timely paper is a direct inspiration for my empirical analysis—once there is a consensus on *what* to measure in the diversion ratio, the natural follow-up question would be *how* to measure it, preferably using commonly found store sales data. The authors point out that Shapiro's "diversion ratio" (between products A and B) has been interpreted in two distinct ways: firstly, as the fraction of customers leaving A that switch to B; and secondly, as the increased sales of B as a fraction of the lost sales of A. For clarity, they call the former the *switching-customers ratio* and the latter the *capture ratio*. For the purpose of establishing a relationship between lost and captured profits post-merger and its implied pricing incentive, only the *capture ratio* works. Lastly, the authors list four necessary conditions for these two ratios to coincide. In this paper I follow ten Kate and Niels's terminology throughout. In my empirical exercise I compute two estimates of the *capture ratio*, measured in *volume* and *value* respectively, as defined by these authors. It is worth mentioning that these capture ratios are mentioned earlier, under slightly different names, in Werden (1998), Table 5, among other alternative measures for ranking substitute products.

Stemming from the widespread discussion on the UPP, a number of researchers have explored different ways to estimate the diversion ratio, or consumer substitution patterns in general, with methods that are deemed to have a stronger theoretical or empirical basis. There are two main approaches. The first is an econometric approach, where the diversion ratio is derived from various demand parameters. This is the approach taken by this paper. The second is an experimental approach, where the diversion ratio is derived from observed substitution patterns when some products are taken away, either by natural or designed experiments. Conlon and Mortimer (2013) exogenously remove snack foods from vending machines and record how customers switch. Raval, Rosenbaum, and Wilson (2015) exploits natural disasters and the subsequent unexpected shut downs of hospitals to track patients' substitution patterns using extensive micro-level data.

To the best of my knowledge, this is the first paper that explores the econometric approach to the estimation of the capture ratio, and its accompanying paradox: in order to estimate a demand system (albeit a simple one), the researcher must define the market boundary on what products are "in" or "out" (of both the antitrust market and the dataset), which is precisely the subjective decision that plagued the old shortcuts and that UPP is designed to avoid. This paper shows that the choice of market boundary actually has little empirical influence on the estimated capture ratios. I experiment with market definitions of various sizes and randomly drawn sets of supermarket products, and compute the implied elasticities and capture ratios in each set of experiment. I use the full list of products from a supermarket category as the baseline, against which all experiment outcomes will be compared. My results show that the elasticities and capture ratios from all experiments have the same magnitude as the baseline estimates, and their first significant figures vary within a small range.

2 Demand Model and Diversion Ratio

The simple nested logit model is one of the most commonly used empirical demand models, and the foundation to other more flexible and sophisticated demand models. Its functional forms are detailed in many papers (such as Berry (1994), whose notation I follow), and are therefore not repeated here. The simple nested model uses only one nest (g), containing all inside goods. When a consumer substitutes away from an inside good, he is more likely to substitute towards another one of the inside goods, rather than the outside good ("not buying"), due to correlation in the random terms in the utilities of inside goods. However, there is no more distinction among the inside goods when the model has only one single nest.

The primary advantage of the simple nested logit demand model is that all market shares, elasticities, and capture ratios have tractable functional forms. I follow ten Kate and Niels's mathematical forms for the volume and value capture ratios, while adapting them to the discrete choice demand framework by changing quantities to market shares. The volume and value capture ratios from goods 1 to 2 can be derived explicitly, in terms of estimated model parameters:

$$\text{Volume capture ratio} = \left|\frac{\partial s_2}{\partial s_1}\right| = \frac{\partial s_2}{\partial p_1}\left(\left|\frac{\partial s_1}{\partial p_1}\right|\right)^{-1} = \frac{\varepsilon_{21}}{|\varepsilon_1|}\cdot\frac{s_2}{s_1},$$

$$\text{Value capture ratio} = \left|\frac{p_2\partial s_2}{p_1\partial s_1}\right| = \frac{\partial s_2}{\partial p_1}\left(\left|\frac{\partial s_1}{\partial p_1}\right|\right)^{-1}\frac{p_2}{p_1} = \frac{\varepsilon_{21}}{|\varepsilon_1|}\cdot\frac{s_2 p_2}{s_1 p_1},$$

$$\text{where } \varepsilon_1 = -\alpha p_1\left[\frac{1-s_{1|g}}{1-\sigma} + s_{1|g} - s_1\right] \text{ and } \varepsilon_{21} = -\alpha p_1 s_{1|g}\left[1 - s_g - \frac{1}{1-\sigma}\right]$$

The above simple nested logit model is easy to estimate, but researchers often want richer substitution patterns. The usual next step in enriching the model is by random coefficients: each demand parameter (representing consumer taste for a product attribute or product group) is fitted to a distribution, often interacted with demographic variables. The resultant elasticities and capture ratios will then be less dependent on the price coefficient. Random coefficient distributions can be discrete or continuous: discrete consumer types are often used for airline products (leisure vs. business travellers), while continuous taste distribution has been used for many consumer goods, from breakfast cereal to automobiles. This paper has not estimated elasticities and capture ratios based on random coefficient demand models due to their computational burden: my experiments require more than 800 instances of demand estimation. But random coefficients are a natural extension for future research, perhaps in markets with a smaller number of products to reduce computational time. Alternatively, if consumer-level micro data is available, random coefficient models can be estimated without the time consuming fixed-point algorithms.

3 Data and Results

I use a supermarket scanner dataset that contains complete categories of consumer products to estimate demand, and then derive the implied capture ratios from the estimated parameters. The data used is the IRI Academic dataset, which spans 11 years, from 2001 to 2011. It contains weekly prices and sales in 30 product categories, with complete UPC (Universal Product Code) coverage under each category. In terms of store types, this data mainly consists of supermarkets, but also includes convenience stores and warehouses. Stores that belong to the same chain are identified. In terms of geography, these stores provide good coverage on 47 major metropolitan areas in the U.S. In addition, there are individual panel shopping data, covering the same product categories, in two small cities, and some limited advertising data. For a complete description, please see Bronnenberg, Kruger, and Mela (2008).

Supermarket consumer products are a good example of subjective market boundaries due to product proliferation. In this supermarket data, even the smallest product category has more than 25 distinct UPC's; the large categories contain hundreds. Within each category, it is often possible to further divide UPC's into sub-categories. This creates many possible market definitions: should the antitrust market be the entire product category, or just selected

Table 1: Major Vendors and Brands in the Sugar Substitutes Category

Vendor		Brand	
McNeil Specialty Products Comp	46%	Splenda	49%
Cumberland Packing Corp	17%	Private Label	12%
Private Label	12%	Sweet ‘n’ Low	11%
Cargill Inc	9%	Truvia	9%
Merisant	7%	Equal	7%

Market shares are based on 2010 data, measured in sales revenue

categories, or articular combinations of UPC’s? For this study, I have chosen a medium-sized product category with distinct sub-categories: sugar substitutes. In the 2010 data that I use, there are a total of 320 unique UPC’s, with 1300+ supermarkets carrying this category on record. The average store is seen to have carried 120 distinct UPC’s throughout 2010, with a minimum of 70 and a maximum of 180 UPC’s. One possible way to sub-categorize these products is via active ingredients. However, I have not pursued this because, as sugar substitute products proliferate in the past decade, a sizable number of UPC’s contain multiple active ingredients, and many active ingredients have slight chemical variations, all recorded in a rather vague manner in my dataset. Instead, I exploit two other dimensions that products might be categorized: vendors and brands. Table 1 shows the major vendors and brands in sugar substitutes. In total, there are 53 active vendors and 75 active brands in 2010.

To test how the estimated diversion ratios vary with market definition, I will use the entire category as the baseline market definition, and experiment with using different subsets of vendors and brands in the category, as alternative market definitions that a hypothetical merger analysis might use. To compare diversion ratios across the different market definitions, I identify the two largest selling UPC’s in the category as focal products: “Splenda (packets) 3.5oz” (henceforth “Splenda”) and “Sweet ‘n’ Low (packets) 3.5oz” (henceforth “Sweet ‘n’ Low”). (Throughout this paper, “Splenda” and “Sweet ‘n’ Low” are shorthand for these two best-selling UPC’s, not the brands, which produce many other UPC’s.) In all experiments with market definitions, I compute the following variables between Splenda and Sweet ‘n’ Low: own-price elasticities, cross-price elasticities, volume capture ratios, and value capture ratios. This allows me to explore how these variables change with the number and identities of vendors / brands used.

Experiments with vendor subsets are conducted separately from those with brand subsets, but their procedures are the same, thus I will only describe the experiments with respect to vendors below. I start with the full list available: 53 vendors (or 75 brands). The elasticities and capture ratios computed from this list of UPC's are benchmarks from which I will compare against. I then subsequently decrease the total number of vendors used in steps of 3: namely 53, 50, 47, etc. (I do not cover all integer values in the number of vendors due to computational burden.) Within each number of vendors used, I make 25 sets of random draws over the identities of vendors. (It is impossible to cover all possible combinations, as their numbers increase dramatically. For example, $C^{53}_{50} = 23426$ and C^{53}_{47} exceeds 22 million!) In each experiment, after the vendors are drawn, the respective vendors for Splenda and Sweet 'n' Low are added to the list (if they are among the randomly drawn), to ensure the presence of these two focal products, so that elasticities and capture ratios between them can be computed. With this list of vendors, I retrieve all UPC's associated with them, which form the hypothetical antitrust market and dataset for demand estimation. I estimate a simple nested logit demand model in each experiment, with one nest N over all "inside goods" (sugar substitutes), with the "outside good" being "not buying". I use the same specification across all experiments. Within each experiment, I consider each (store, week) combination to be an independent market in which market shares are calculated for demand estimation. In each and every market where Splenda and Sweet 'n' Low are present, their elasticities and capture ratios are calculated. The elasticities and capture ratios reported for each experiment are simple averages from all markets within that experiment.

In terms of econometrics, changing the list of UPC's in each experiment does not only change the particular observations used in that demand estimation, it changes a few of the derived variables that are used in the demand estimation as well. I choose to fix the total market size M throughout, which is a multiple of each store's estimated total annualized sales, as a rough indication of catchment population. With this asumption, as the number of UPC's change, the market share of the outside good s_0 and shares within the nest $s_{j|g}$ will change too. Lastly, the derived "BLP instruments" (from Berry, Levinsohn, and Pakes (1995)) for the endogenous price, defined as the average price (or other product characteristics) over all *other* UPC's in the same market, will also change. Since this is not a bootstrap exercise (where non-changing observations are randomly drawn for computation), it is non-trivial to theoretically derive how estimated parameters (and subsequently, elasticities and capture ratios) will change when the observations used, dependent variable, one of the regressors, and the instrumental variable all change. My empirical experiments below will attempt to shed light on this question.

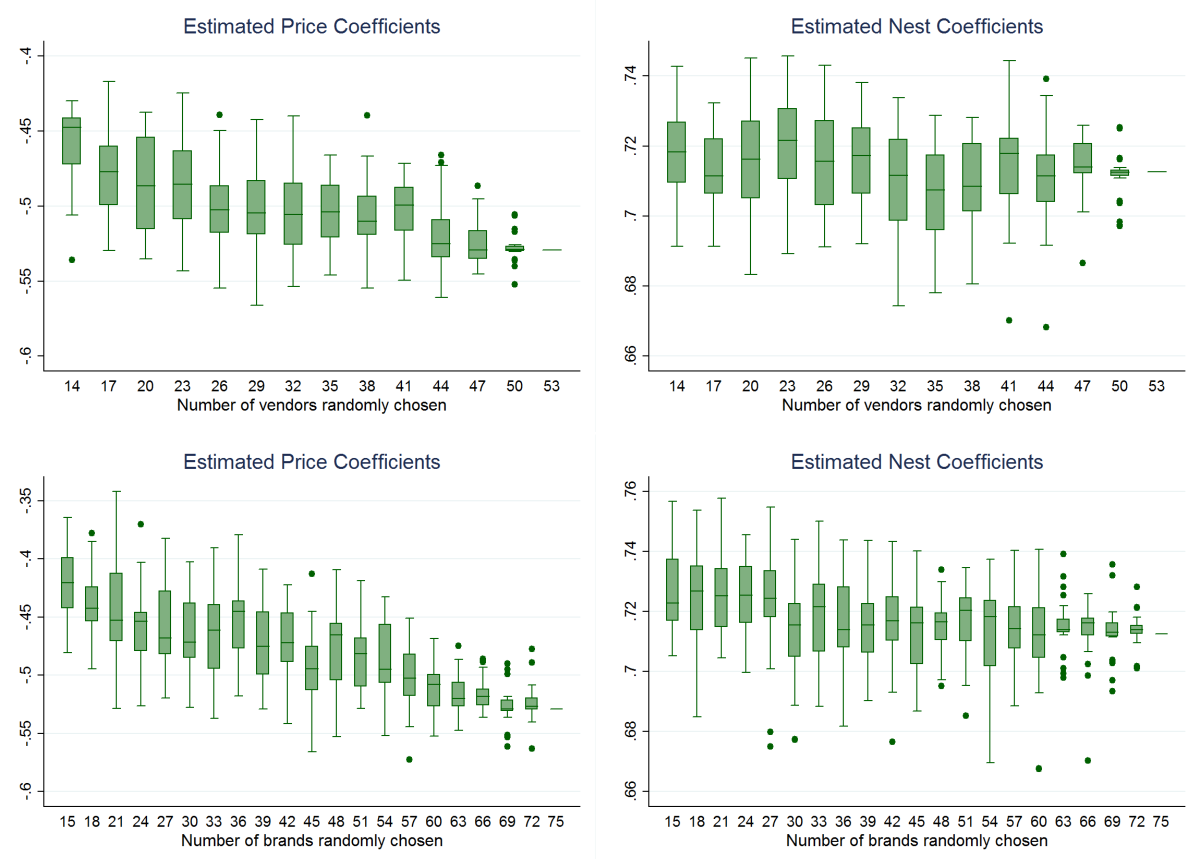
Table 2: Baseline Demand Estimation Results

Dependent variable: $\ln(s_j) - \ln(s_0)$	
Price	-0.5291518***
	(0.0015628)
Volume	0.229413***
	(0.000718)
$\ln(s_{s\|N})$	0.7125893***
	(0.0009359)
Constant	0.7125893***
	(0.5712917)
Vendor dummy variables	yes
Active ingredient dummy variables	yes
N	1534108
R^2	0.1745
Own-price elasticity, Splenda	-3.43346
Own-price elasticity, Sweet'n'Low	-1.866828
Cross-price elasticity, Splenda to Sweet'n'Low	0.1130081
Cross-price elasticity, Sweet'n'Low to Splenda	0.0612848
Volume capture ratio, Splenda to Sweet'n'Low	0.0328053
Volume capture ratio, Sweet'n'Low to Splenda	0.033508
Value capture ratio, Splenda to Sweet'n'Low	0.0256131
Value capture ratio, Sweet'n'Low to Splenda	0.063094

Notes:
"BLP instruments" are used to control for price endogeneity.
Elasticities and capture ratios are averages across all (store, week) markets

Table 2 shows the baseline demand estimation results, using the complete set of UPC's in the sugar substitute category, including the derived elasticities and capture ratios between Splenda and Sweet 'n' Low. All coefficients are statistically significant, due to the large sample size, and have the expected sign. Coefficient for $\ln(s_{j|g})$ gives the nest parameter σ in Berry (1994), and a value of 0.7 reflects a moderately strong tendency to for consumers to substitute between inside goods, rather than to "not buying". The bottom panel of the table shows the eight elasticities and capture ratios derived from estimated demand parameters; all figures displayed are averaged from market-level values, each computed at values in each market. The average own-price elasticities for both focal products are negative, elastic, and in line with estimates from many other consumer goods studies. The cross-price elasticities are one to two magnitudes smaller, but are in line with other supermarket UPC-level measures (for example, Nevo (2001)). All capture ratios, measured either in volume or value, are in comparable magnitude with cross-price elasticities, largely because the latter is a key input to the computation of the former. Unlike demand elasticities, there is virtually no existing research on what the "typical values

Figure 1: Price and Nest Coefficients, over Number of Vendors / Brands Randomly Chosen



or magnitudes" of diversion ratios between consumer goods are. One way to rationalize their seemingly small values is that the average supermarket carries 23 UPC's in this category every week, thus each UPC's share of diverted sales is small. It should also be reminded that the capture ratios include only consumer switching due to a change in price, instead of switching due to any other number of reasons: product attributes, unobserved characteristics, exploration, or sheer randomness. These other factors should not be included in the calculation of the UPP, either because they are present both before and after the merger, or that they are not substitutions that can be induced post-merger by a change of price alone.

These eight elasticities and capture ratios are computed in similar fashion in each and every product subset experiment. But before presenting them, it is worthwhile to look at the demand estimation results from these experiments, particular the price coefficients (α), which has major influence on the elasticities. Figure 1 presents the price and nest coefficients from the two sets of experiments: random draws over vendors (top two graphs) and brands (bottom two graphs).

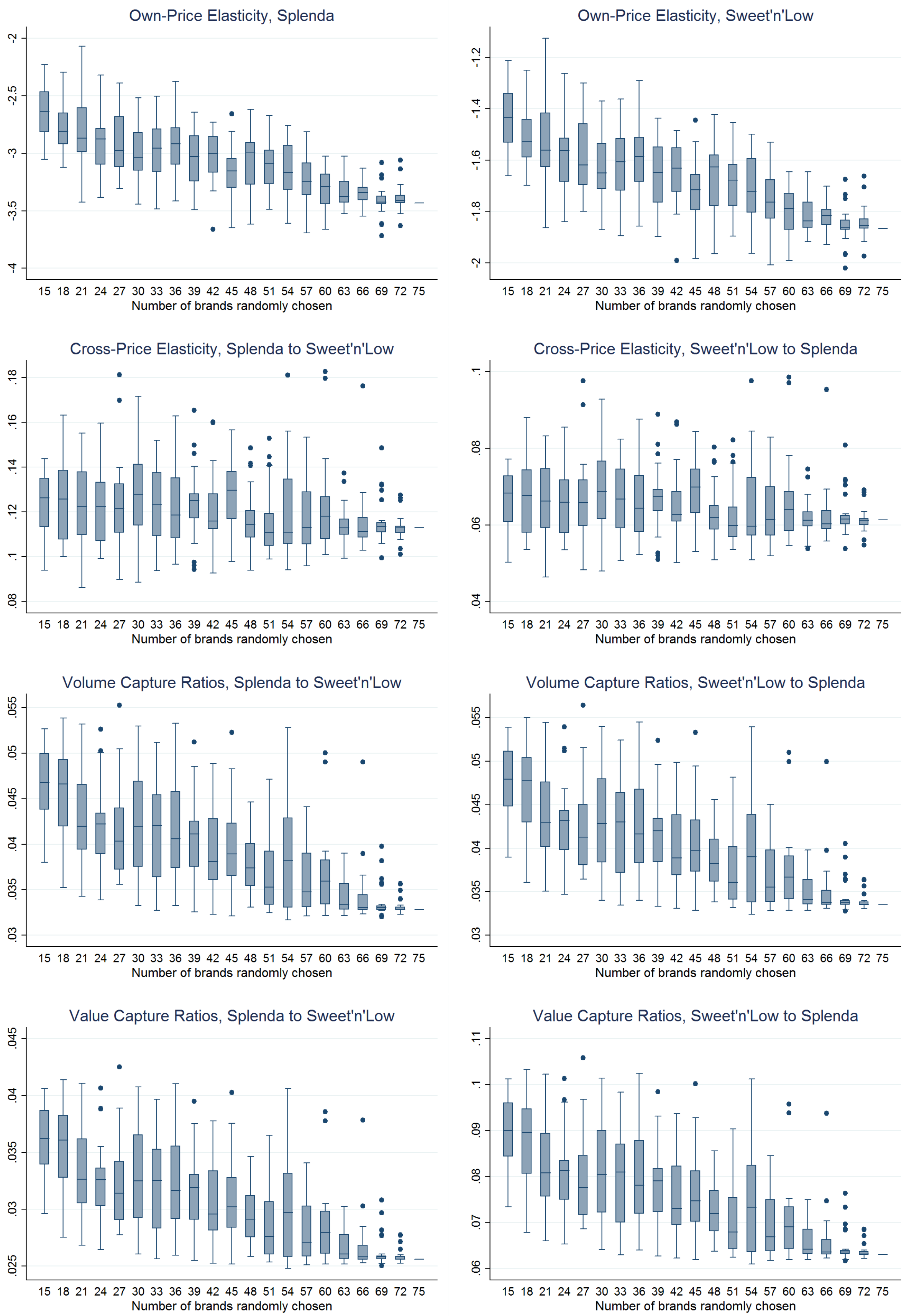
Each graph is organized by the number of vendors or brands randomly chosen; within each set of experiment that contains equal number of vendors or brands, there are twenty-five random draws, yielding twenty-five sets of demand estimation results, each set displayed as a box plot. All figures that follow are organized in the same manner. In all graphs, the baseline value computed with the full dataset, seen in the bottom panel of table 2, can be found in the last column, which contains a single value instead of a box plot. The price coefficients all show a slight upward drift as the number of randomly drawn vendors or brands decreases. In fact, the first one or two box plots are entirely above the baseline values. In contrast, the nest coefficients are not showing any drift pattern; almost every box plot includes the respective baseline value within its range.

The upward drift pattern on price coefficients could come from two sources: firstly, the decreasing number of randomly drawn vendors; secondly, the newly computed market variables s_0 and $s_{j|g}$, and the instruments for price, in each set of experiment. Here I consider the effect of the second; I will explore the effect of the first at the end of this section. When market size M is assumed unchanged while the number of UPC's included is gradually reduced, the market share of the outside good (s_0) gradually increases, thus the dependent variable in the demand estimation increases. Among the explanatory variables, the market share within the nest ($s_{j|g}$) increases, because the market share of the nest (s_g) decreases. The "BLP instrument" for the price is less likely to change in a systematic way with the number of UPC's present, because the instrument is an average of prices, which do not vary systematically with the number of UPC's drawn.

Figures 2 and 3 show the resulting elasticities and capture ratios derived from the estimated demand parameters. Figure 2 are random draws by vendors, and figure 3 are random draws by brands. These two sets of box plots look remarkably similar in shape, likely because brands are not of a substantially finer grain than vendors (53 vendors vs. 75 brands), and the relationship between them is mostly many-to-one, with some being one-to-one. Thus I will focus my following discussion mainly on figure 2, noting that results from figure 3 are remarkably similar. All own-price elasticities graphs resemble the price coefficient graphs in their upward drift pattern. This upward drifting pattern seems to have preserved, albeit more mildly, in the capture ratios graphs. Since the capture ratios (measured in either volume or value) are inversely related to the absolute values of own-price elasticities, the smaller the absolute value of the own-price elasticity, the larger the capture ratios. In contrast, the cross-price elasticities are not showing

Figure 2: Elasticities and Capture Ratios, over Number of Vendors Randomly Chosen

Figure 3: Elasticities and Capture Ratios, over Number of Brands Randomly Chosen



any drift pattern; almost every box plot includes the respective baseline value within its range.

There is little existing empirical research on capture ratios for comparison on whether my experimental values show excessive variation. Compared with Walters (2007), which is an early study on estimating diversion ratios between supermarkets, my experiments show less variation: all variables (elasticities and capture ratios) remain the same magnitude across all experiments, and the first significant figures do not vary widely. But this comparison should not be taken further as Walters estimates his diversion ratios very differently, using fascia counts, market shares, and geographical proximity, while I explore the effects of product market definition. If one considers the use of the capture ratio in the UPP test, the capture ratio is multiplied to the rival good's price-cost margin, from which the magnitude of cost saving is optionally subtracted. For supermarket products such as sugar substitutes, if the price-cost margin is in the magnitude of 10^{-1} dollars, then a change in the volume capture ratio from, say, 0.035 to 0.05 will at most change the UPP in its second decimal point. This magnitude change is relatively small and inconsequential if one imposes the "default" 10% cost savings suggested by Farrell and Shapiro (2010).

As mentioned before, there are two main sources of variation between the data that generate each box plot in each graph: firstly, the number of randomly drawn vendors; secondly, the newly computed market variables in each set of experiment. To isolate the effect of the first, I have repeated the entire set of experiments using the *same* randomly drawn vendors and brands as before, but *without* newly computed market variables. Instead, in each experiment I retrieve the market variables already computed for the full dataset used for calculating baseline values. In other words, this alternative set of experiments is a "pure bootstrapping" exercise, where all market variables are pre-calculated before random draws; after the list of vendors are randomly drawn, the market variables will *not* reflect the hypothetical market formed by this subset of vendors. The results of these alternative "pure bootstrapping" experiments are shown in figures 4 and 5. Both of them show milder drifting patterns than figures 2 and 3; figure 4 in particular shows almost no drift. The difference between them may be due to the fact that the random draws on brands have gone to more extreme in terms of reducing the number of UPC's selected, since brands are of a finer grain than vendors. In other words, if the leftmost two or three box plots are erased from each graph in figure 5, it will look much alike figure 4. Comparing figures 4 and 2, the former shows almost no (or very mild) upward drift in its own-price elasticities graphs, and no drift pattern in its capture ratios. The difference between figures 5 and 3 is greater. In figure 5, own-price elasticities still show an upward drift, albeit milder; cross-price elasticities actually show a *downward* drift as the number of brands decreases. Likely as a result of these two patterns, the capture ratios, which is partly consisted of the cross-price elasticity divided by the absolute value of the own-price elasticity, do not show any drift pattern. These comparisons suggest that both of the aforementioned sources of variation contribute to the upward drift in own-price elasticities, but the second source of variation (in computed market variables) is necessary for this upward drift to propagate from the own-price elasticities to the capture ratios.

4 Conclusion

The diversion ratio is a key ingredient to the calculation of the Upward Pricing Pressure (UPP) test, which is a new shortcut for screening mergers. When the *Horizontal Merger Guidelines* were released in 2010, there was much ambiguity in the mathematical form of the diversion ratio, and many different approaches to its estimation, such as company internal documents or consumer surveys. Recently, Ten Kate and Niels (2014) clarifies the mathematical form of the diversion ratio appropriate for estimating pricing incentive, and distinguishes it from other interpretations by calling it the capture ratio. Since the capture ratio, at its core, is a partial derivative of sales with respect to rival's price, it is natural to estimate it through established demand estimation techniques in the empirical industrial organization literature. However, demand estimation requires the list of products in the "antitrust market" to be defined. This is in contrast to the spirit of the UPP test, which was designed to de-emphasize the often contentious issue of market definition. The paper experiments with markets of various sizes and shows that the elasticities and capture ratios remain the same magnitude as that in the baseline (full) market; moreover, the first significant figure is not seen to change by more than two digits (e.g. from 0.032 to 0.049). This paper hopes to ease one potential obstacle—market definition—from the empirical estimation of the diversion ratio through standard demand estimation techniques. Future research should explore other empirical estimation methods, such as through natural or artificial experiments with product removals.

Figure 4: Elasticities and Capture Ratios, in Alternative “Pure Bootstrapping” Experiments

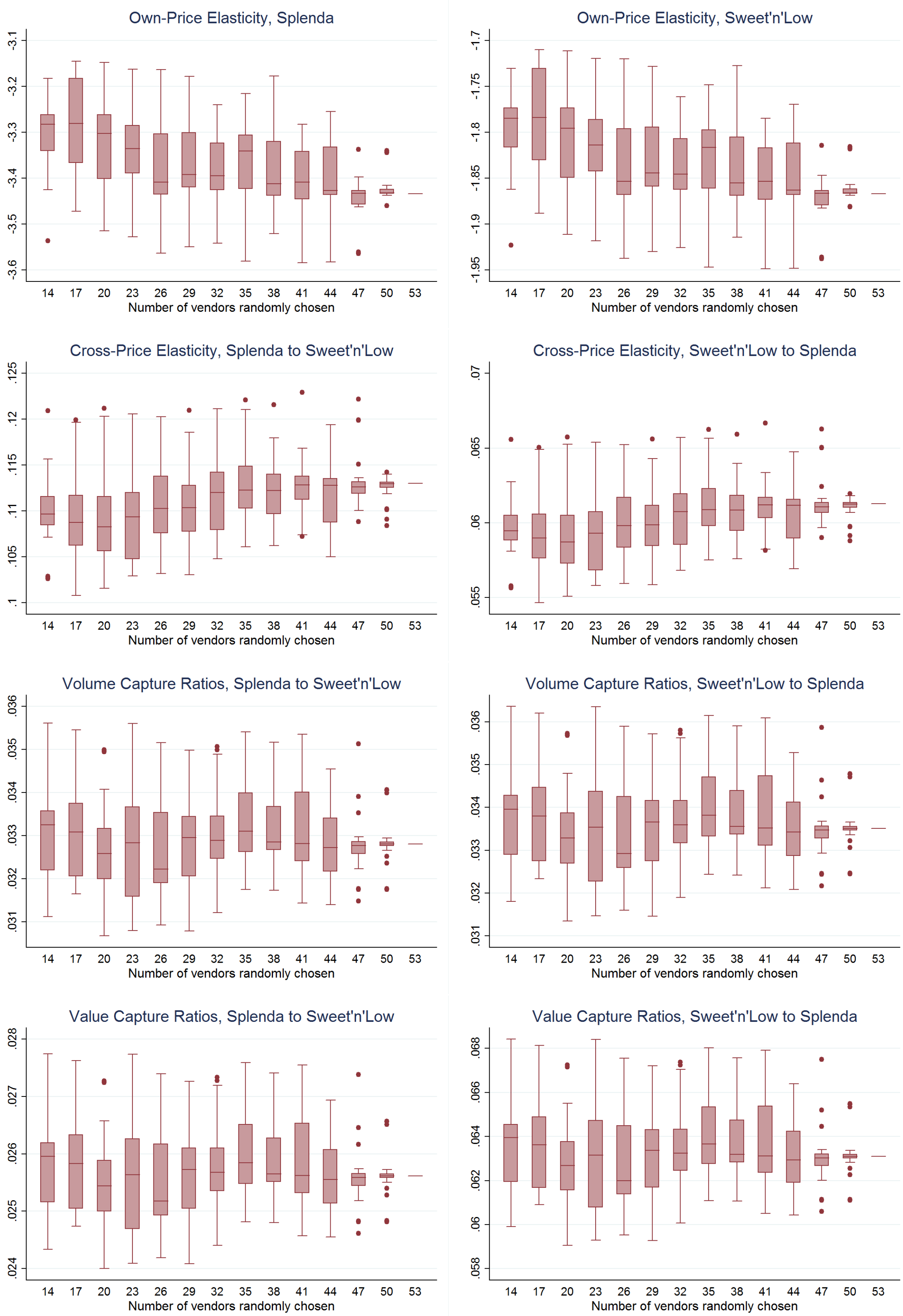
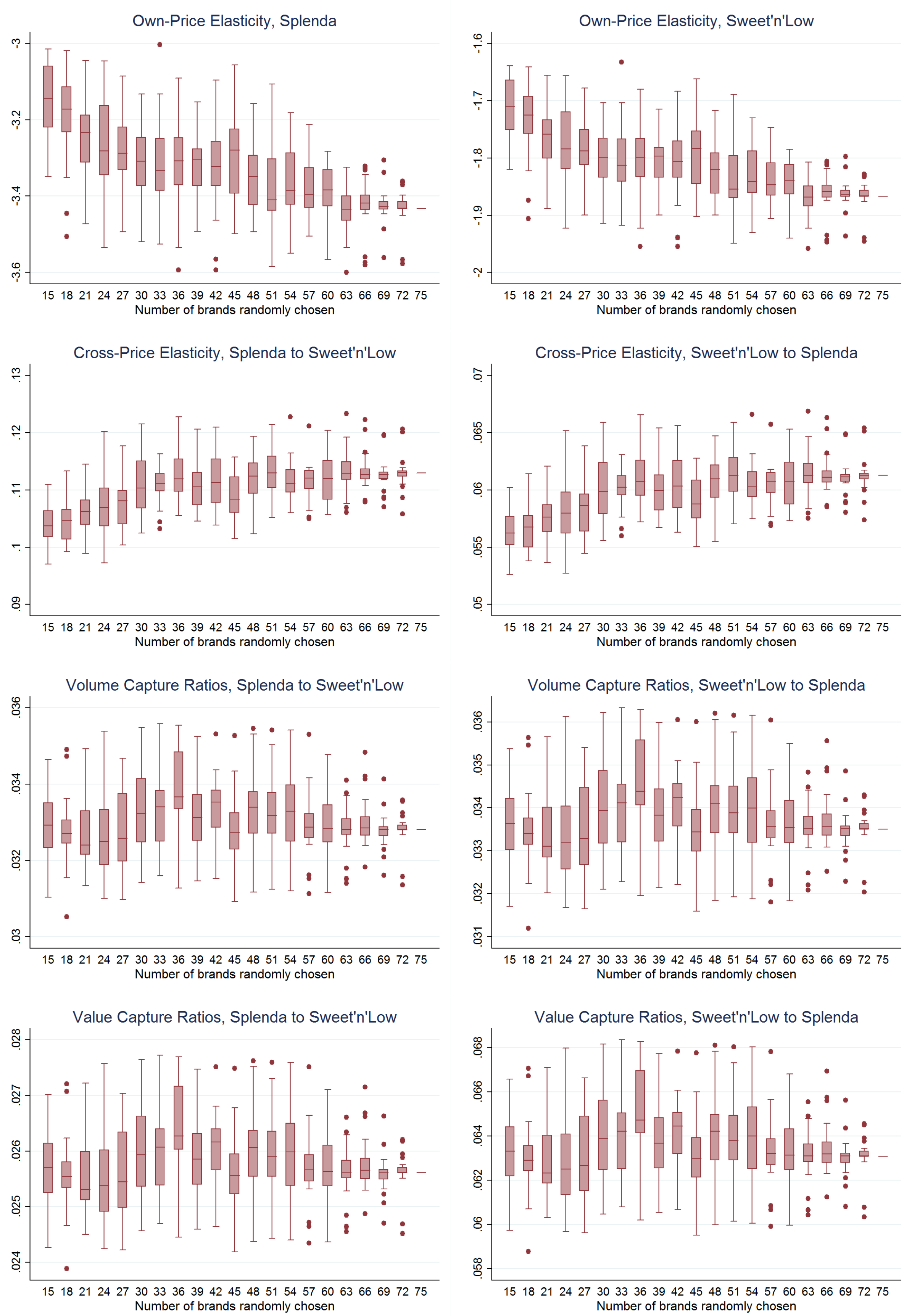


Figure 5: Elasticities and Capture Ratios, in Alternative "Pure Bootstrapping" Experiments



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