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Working Paper

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CSIO Working Paper, No. 0080

Provided in Cooperation with:

Department of Economics - Center for the Study of Industrial Organization (CSIO), Northwestern University

Suggested Citation: Salvo, Alberto (2006) : Testing for heterogeneous business practices across firms in developing countries: The case of the Brazilian soft drink industry, CSIO Working Paper, No. 0080, Northwestern University, Center for the Study of Industrial Organization (CSIO), Evanston, IL

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THE CENTER FOR THE STUDY
OF INDUSTRIAL ORGANIZATION
AT NORTHWESTERN UNIVERSITY

Working Paper #0080

Testing for Heterogeneous Business Practices
across Firms in Developing Countries:
The Case of the Brazilian Soft Drink Industry

By

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This Draft: July, 2006

^{*} This project began while I was pursuing a Ph.D. at the London School of Economics. I am very grateful to my supervisors Peter Davis and John Sutton for their early advice. I am greatly indebted to Ricardo Fort at the Coca-Cola Company for facilitating access to ACNielsen's proprietary data. I also thank Claudia Pessoa (Coca-Cola Co.), Rodrigo Motta (Coca-Cola Femsa) and, in particular, Bruno Gouvea (ACNielsen), for the many iterations of data provision and auditing. I am grateful to Alaor Dall'Antonia Junior and Maria Cristina Costa at the National Institute of Meteorology (INMET) for access to proprietary climatic data. I further thank seminar audiences at the LSE and Kellogg, and Allan Collard-Wexler, Tom Hubbard, Cristian Huse, Mike Mazzeo, and Scott Stern, for comments. Financial support from CAPES and from the LSE, and the provision of research facilities by STICERD, are gratefully acknowledged. The usual disclaimer applies.

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Abstract

This paper estimates a structural model of the Brazilian carbonated soft drink industry to test the claim that the observed low prices of low-end entrants owe to marginal cost advantages over the large, established brands, allegedly stemming chiefly from tax evasion. Such entrants, numbering in the hundreds, are typically small-scale operations, with limited geographic reach and no advertising. In addition to the low-cost hypothesis, advocated by the incumbent duopolists, the model allows for other (complementary or substitute) explanations: that consumers have different preferences for the low-price entrants over the established brands, and that firm-level strategic behavior is heterogeneous. The paper draws on a rich original panel dataset to structurally inform the relative weight of each hypothesis in explaining the observed price differences. The paper finds some support for the low-cost hypothesis, but finds strong support for the demand side hypothesis: the established brands' market power almost single-handedly explains the price premium they command over the entrants. It provides an innovative application of structural IO modeling and estimation within the realms of international business strategy, public finance, and development.

Keywords: Structural IO estimation; Demand estimation; Business practices in developing countries; Firm-level heterogeneity; Informal economy

JEL classification: L10, L40, L66, F23

1 Introduction

There is a view among marketing professionals in the so-called “fast moving consumer goods” industries that established global firms, such as Coca-Cola, Nestlé and Procter & Gamble, have been somewhat slow to respond to the needs of the fast-growing sea of low-income consumers that are emerging from below the poverty line in the developing markets of regions such as Southeast Asia, China, India, and Latin America. Over the past fifteen years of relative prosperity, one observes numerous examples, particularly in food and beverage, and household and personal cleaning, where established brands have seen their market share erode in the face of competition from low-price entrants. In contrast to the established brands, commonly owned by multinational corporations or by large traditional domestic firms, such “low-end” entrants typically offer low-price, low-quality, largely unadvertised products to low-income consumers, often times distributing their products within limited geographic areas, such as a few counties or a fraction of a state or province.

Possible explanations for this anecdotal rise of the so-called “B” brands range from a lack of local market focus on the part of the large established firms, to falling barriers to entry due to shifts in packaging and distribution technologies. Pundits further speculate that the observed growth in share of retailers’ “private labels” is a connected phenomenon, given the natural resistance by established firms – owners of “premium” brands – to manufacture private labels under contract for retailers. A more cynical explanation that has been put forward centers on the heterogeneous business practices that the established firms and the low-price entrants adhere to in developing countries. By this explanation, while the established firms – more visible to consumers, taxmen, regulators, and activists, among other communities – pay their taxes and abide by labor (and environmental) laws, the less visible makers of B brands allegedly are able to get away with evading taxes and subjecting their workers to “sweatshop” labor conditions and compensation. Naturally, scarce monitoring and enforcement resources are deployed where the tax revenue base is concentrated. And, clearly, a multinational corporation such as Coca-Cola will worry about its image. Such an asymmetry, so goes the claim, confers a competitive advantage, in developing countries, on the small entrants at the expense of the large law-abiding established firms^{1 2}.

A case in point is provided by the Brazilian carbonated soft drink industry, the third largest in the world by volume. As in most countries, the industry in Brazil is dominated by Coca-Cola, with a 50 – 60% volume share (and an even higher value share). Over the course of the 1990s, Coca-Cola (along with two traditional domestic firms, one of whom

¹The informal sector in developing countries can be substantial. For example, the World Bank’s report on *Doing Business in 2004: Understanding Regulation* states that “In Bolivia, one of the most heavily regulated economies in the world, an estimated 82 percent of business activity takes place in the informal sector. There, workers enjoy no social benefits and cannot use pension plans and school funds for their children. Businesses do not pay taxes, reducing the resources for the delivery of basic infrastructure. There is no quality control for products. And entrepreneurs, fearful of inspectors and the police, keep operations below efficient production size.” (p. xv) Schneider (2002) estimates that the average size of the informal economy in developing countries amounts to 41% of official GDP, compared to (a still high) 18% for OECD countries.

²Lewis (2004) cites “When taxes are included, it costs more productive companies as much to do business as it costs less productive, informal ones, which don’t pay taxes. Modern, productive enterprises can’t easily take market share from their unproductive counterparts, and the economy’s natural evolution is stymied.” (p.6)

distributes the Pepsi brand, both of which were later to merge into American Beverages Co. – Ambev) saw their established soft drink businesses come under attack from low-price entrants. The aggregate market share (in volume) of (ultimately) hundreds of local B-brand producers grew from less than 10% in 1990 to 32% by 2000. The entry and growth of B brands was particularly acute between 1996 and 1999, following an economic stabilization plan in mid 1994 where very high and chronic inflation was successfully brought down to single-digit levels. Price stability boosted the purchasing power of low-income households, as it represented a reduction in the “inflation tax” borne disproportionately by the poor, who did not have access to price-indexed savings accounts. Consumption of soft drinks almost doubled from 6 billion liters in 1994 to 11 billion liters in 1997.

Alongside the growth in the aggregate share of B brands were growing complaints by the established soft drink makers (Coca-Cola in particular) that their low-price counterparts were engaging in “unfair trading practices”, chiefly through tax evasion. As in other consumer goods industries, tax rates in the Brazilian soft drink industry are very high: in total, taxes correspond to as much as 40% of retail prices, with sales taxes (of five complementary types) amounting to around three-quarters of this total (the balance owes to taxes on payroll, income, etc). Coca-Cola and Ambev claimed that B brands could afford to undercut their prices – by as much as 40-50% – as a result of their lower (marginal) costs, attributed to tax evasion.

Underscoring their stated belief in the importance of reestablishing a “level” playing field, the established soft drink makers – jointly with established brewers, through various industry outfits – intensively lobbied the government on creative ways to reduce tax evasion among B brand makers. One such idea, finally bought into by the government, and surprising in its operational complexity, is to require by law that by the end of 2006 all soft drink makers (bottlers) install flowmeters along their filling lines to better monitor output – and hence enable the auditing of plant-level tax liabilities by the tax authorities³.

This paper estimates a structural model of the soft drink industry to test the claim that the low prices observed for local B brands are due to lower marginal costs (stemming chiefly from tax evasion) as compared to those of the large nationwide bottlers such as Coca-Cola. The paper draws on original panel data from the Brazilian soft drink industry during a period (December 1996 through March 2003) which covers the dramatic growth in share of the B brands. More appropriately, while remaining agnostic about the source of possible cost heterogeneity, the paper verifies whether the claim of tax evasion and thus low marginal cost is consistent with the data. Indeed, one possible explanation for the low price of B brands owes to low marginal cost. But there are other possible (complementary or substitute) explanations to the low-cost hypothesis. On the demand side, consumers may have different preferences over the established brands in

³The flowmeter is a device that records the flow of liquid moving along the filling line onto a central register, and is supposedly resistant to tampering. According to the Brazilian Association of Soft-Drink Manufacturers (ABIR), such an enforcement system, based on “Normative Instruction” 265 of the Inland Revenue Service of 12/20/2002 – applied to the beer and soft drink industries – is the first of its kind anywhere in the world. Emerson Kapaz, head of one such industry outfit, the “Brazilian Institute for Ethical Competition”, estimates that the enactment into law of the usage of the device in soft drink and beer plants will boost nationwide tax revenues by 240 million *reais* (US\$ 110 million). (<http://www.etco.org.br/reporter.php?Id=1>)

counterpoint to the B brands. One would conjecture that the demand for established brands is less price sensitive than that for B brands, which in equilibrium would push for higher prices for the former relative to the latter. As such, the structural model allows consumer preferences to be informed by the data. On the supply side, in addition to heterogeneous costs, one should allow for different forms of strategic behavior (i.e. conduct) among the firms. For example, while the established firms, each owning multiple “premium” brands, may command market power, setting prices à la Bertrand, the behavior of low-price entrants may approximate price-taking behavior. If this were the case, this would again push for higher prices of established premium brands relative to that of B brands, in line with observed price differences. A structural model of the industry, where the behavior of each agent is appropriately modeled and estimated, should accommodate these different hypotheses, allowing the data to inform in the best way possible the relative weight of each hypothesis in explaining the observed price advantage of the B brands.

The paper finds some support for the low-cost hypothesis, but finds strong support for the demand side hypothesis – the hypothesis which is overlooked in the established industry trade press. The price of premium brands (Coke, say) is considerably higher than that of the B brands in large part because demand for premium brands in equilibrium is not very elastic: the own price elasticity of demand for Coke, for example, is estimated at a low 2.⁴ ⁵ If B brand makers are assumed to be price takers, the market power of the premium brands essentially single-handedly explains the approximate 80% price premium they command over the B brands. The assumption of competitive (price-taking) conduct on the part of B brand makers is perhaps too strong. If B brand makers are assumed to behave strategically, as single-product Bertrand firms over whose brands consumers have symmetric (logit or CES) preferences, the hypothesis that B brands enjoy lower marginal cost than their premium counterparts is consistent with the data, though at a more moderate 10-20% cost advantage over the premium brands. Whether a 40% cost advantage arising from full tax evasion (or more, if one

⁴This low estimated own-price elasticity for the Coke brand falls at the low end of the range of estimates from other demand studies of the soft drink industry and, for that matter, of other differentiated product markets. Gasmi, Laffont and Vuong (1992) also estimate a low own-price elasticity of 1.7, but this corresponds to the firm’s (Coca-Cola Co.), and not the brand’s, elasticity in the “cola market”, obtained through a parsimonious linear demand specification in a duopolistic game against PepsiCo. Dhar et al (2005) also estimate a somewhat aggregated four-brand system – though they adopt a more flexible continuous-choice AIDS specification (similar to the one I use) – to obtain brand-level estimates in the 3 - 4 range. In contrast, Dubé (2005) uses more disaggregated data (at the UPC level observed from individual household purchases) to estimate a multiple discreteness model (Hendel 1999), also finding higher (UPC-level) own-price elasticities in the 3 - 4 range. Employing somewhat similar brand-and-market-level panels to the ACNielsen data I use, and a similar continuous-choice demand specification, Hausman and Leonard (1997) point out that the own-price elasticities they have found for differentiated product industries typically lie between 2 and 5 (e.g. 2 - 3 for breakfast cereal brands in Hausman 1997a, 2 - 4 for paper tissue brands in Hausman and Leonard 2002, and above 4 for beer brands in Hausman, Leonard and Zona 1994). Hausman’s (1997a) low estimates for cereal brands have been at the center of controversial debate surrounding identification of demand (and its implications for the estimation of welfare effects from product introductions) – see the discussion on identification strategy in Section 3. Of note, adopting the discrete-choice approach of Berry, Levinsohn and Pakes (1995), but a somewhat similar identification strategy to that of Hausman (1997a), Nevo (2001) finds similarly low estimates (2 - 3) for the own-price elasticities of cereal brands.

⁵Importantly, my demand identification strategy exploits a large and sudden reduction in the price of Coca-Cola Co.’s brands in July 1999. I argue that this firm’s abrupt decision to lower its prices was motivated on the supply side, taking place around a change in its Brazilian management team and following the period of sharp growth in the aggregate share of B brands.

adds the alleged poor labor and environmental practices), as some representatives of the established firms claim to be widespread, is being offset by potential cost disadvantages owing to lower manufacturing scale, higher cost of procurement (e.g. sugar) and/or higher distribution costs, cannot be determined in the absence of marginal cost data. But this is outside the paper’s scope: the purpose of the exercise is to highlight that the cost-driven accusation is only one side of the story.

The paper makes several contributions. It provides an innovative application of structural IO modeling and estimation within the realms of international business strategy and public finance. It brings the rigorous standards of microeconomics – and the powerful concept of equilibrium strategies in particular – to bear on a highly politicized issue, where the incumbents accuse the entrants of illicit tax evasion, and the former are in turn accused by the latter of seeking disguised protection sponsored by the government⁶. The recent history of the Brazilian soft drink industry should be of interest to the industrial development community. Elements of this story – including (i) high nominal tax rates in developing countries (both a cause and an effect of potentially widespread tax evasion), (ii) heterogeneous business practices across large established firms and small startup ventures in the informal sectors of such countries (potentially including tax evasion, poor labor practices, poor environmental standards, production of counterfeit goods, smuggling etc; see Schneider and Enste 2000), and (iii) growth of low-price unadvertised brands with local appeal and geographic reach at the expense of the traditional advertised nationwide or global brands – suggest that the developments and lessons from the Brazilian soft drink case are reflective of a broader trend.

The balance of the paper is organized as follows. Section 2 reviews the industry and the data. Modeling and estimation of the structural model then takes place in sequence. In Section 3, I specify and estimate the demand system. The supply side is then specified in Section 4, where the structural model is solved out for the marginal cost estimates. Section 5 concludes.

2 Industry and data

The Brazilian carbonated soft drink market is the third largest in the world by volume, following the US and Mexico, with consumption amounting to 14 billion liters in 2002. The leading firm, Coca-Cola Co., commands a nationwide share of 50% by volume and 59% by value. Its flagship brand, (regular) Coca-Cola (Coke hereafter), alone accounts for a 39% value share, with the balance accruing to a handful of other brands, such as Fanta (8%), Diet Coke (5%), Sprite (2%) and a local brand Guaraná Kuat (3%), Coca-Cola Co.’s version of a traditional Brazilian kind of soft drink made from the Amazon berry fruit *guaraná*. (See Figure 2.) As in other countries, Coca-Cola

⁶A somewhat surprising development took place in June 2005 when federal police, acting on orders of the Inland Revenue Service, stormed into the offices of Schincariol, seizing documents and computers, and later arresting members of the controlling family. Schincariol, a beer and soft drink maker, is considered by pundits to be, in light of the dichotomous structure of the industry, a hybrid between established premium brand firms and B brand entrants. Despite being long established, Schincariol’s brands are perceived as lower quality, command lower prices, are distributed regionally rather than nationally, and do not enjoy large advertising budgets. Arresting company executives has (until recently) been a rare event in Brazil – see Figure 1 for a somewhat humorous cartoon from the press. *Experimenta!* (sic) means “Try it!”.

Co. operates a tightly-controlled franchising system by which it nominates franchisees, one per territory, to produce, bottle and distribute its brands in the given territory. In 2002, Coca-Cola Co.'s distribution network was comprised of 17 franchisees, down from around 25 five years earlier (Robarts 2002). Coca-Cola Co. is a minority investor in several franchisees (and in a few cases owns the majority of shares)⁷. Through this network of regional distributors, Coca-Cola Co. appears to strike a balance between centralizing control upstream and exploiting the local market knowledge of its distributors downstream. Industry sources claim that, though disputes periodically break out between the upstream firm and its distributors, the former remains much in command of market positioning⁸, while allowing the latter sufficient autonomy to tailor distribution and promotional efforts to meet local demand variation⁹.

Also operating via a tightly-controlled franchising system, the second largest firm, American Beverages Co. (Ambev), was formed through the merger in 2000 of Coca-Cola Co.'s two largest competitors Antarctica/PepsiCo and Brahma¹⁰. Since 1997, Antarctica had been running PepsiCo's Brazilian operations. In 2002, Ambev's combined shares amounted to 18% by volume and 23% by value. The best-selling brand is Guaraná Antarctica (value share of 13%), Ambev's version of the traditional guaraná soft drink. The Pepsi brand, in its regular and diet versions, commands a 5% value share. (See Figure 2.)

The soft drink businesses of Coca-Cola Co. and of Ambev (and earlier that of its constituent firms) have come under threat during the second half of the 1990s from the fast growth of the so-called "B brands". These brands are referred to somewhat depreciatively as "B" owing to their considerably lower price, smaller scale and limited geographic reach as compared to that of Coca-Cola Co. and of Ambev, and the absence of advertising. The operations of a typical B-brand bottler will cover a limited area, in some instances as limited as a few municipalities¹¹. Despite being individually small,

⁷As a point of comparison, Muris, Scheffman and Spiller (1992) describe how Coca-Cola Co.'s distribution network in the US has evolved since the late 1970s, including consolidation among franchisees and forward integration by Coca-Cola Co. (in the form of the upstream firm acquiring franchisees or entering into joint-ventures with them). They argue that such restructuring has stemmed from increased scale economies and the upstream firm's need to secure control of the vertical chain in response to changes in technology and the competitive environment.

⁸Despite the large extent of outsourcing, Coca-Cola Co. appears to in effect control prices set by franchisees to retailers. In addition to the aforementioned ownership stake in some cases, Coca-Cola Co. relies on several instruments to cure vertical externalities, such as charging for the concentrate and syrup from which its soft drinks are made, paying for distribution and promotion, and sharing the heavy advertising costs of its brands among its franchisees, thus employing a combination of marginal and fixed fees (e.g. the Company may charge franchisees for its syrup based on sales objectives, regardless of whether these are met). Another potential vertical distortion arises from double marginalization between retailer and manufacturer. Though this is a standard concern in empirical studies where retail data is used to make inference about producer supply, in the present case I believe any such distortion is limited given that retail margins on soft drinks are typically low (indeed they are often cited as an example of "loss leaders" among marketing professionals).

⁹This is to be expected considering this is, after all, the owner of what is estimated to be the world's most valuable brand (\$67.5 bi in 2005, according to Interbrand) operating in Brazil, a country of continental dimensions which exhibits stark socio-economic regional differences (see below).

¹⁰This merger was a high profile case in the short history of Brazilian antitrust practice. In addition to producing soft drinks, Antarctica and Brahma were the two leading beer manufacturers, with a combined share of around 70% (in beer). The merger was approved subject to some minor asset-divestiture restrictions. Subsequently, in 2004, Ambev merged with the Belgian brewer Interbrew.

¹¹Brazil is a federation of 27 states, with a population just short of 180 million. Around 5600

the aggregate nationwide share across all B brands grew from a value share of 11% in 1996 to 18% in 2002, or in volume terms from a share of 18% to 33% (see Figures 2 and 3). This corresponds to a large 4.7% volume share gain per year in the three years between 1996 and 1999, and growth has been even more pronounced if only consumption of family-sized bottles is considered, as discussed below. The growth in share follows from the vast number of entrants in recent years; though numbers vary, the number of B-brand producers is said to have grown from around 100 to over 500 in less than a decade. B brands tend to have a higher sugar content and lower “fizz” as compared to the established premium (i.e. Coca-Cola Co. and Ambev’s) brands. They are thus described as having lower quality: indeed, consumer studies find that with a few exceptions, controlling for prices, consumers would pick Coca-Cola Co. or Ambev’s brands over B brands. Consumers report that they tend to favor the former firms’ product flavors to those of the latter¹². On average, B brands sell at a 40% - 50% discount to their premium counterparts. Thus one can say that while Coca-Cola Co. and Ambev’s brands are horizontally differentiated, these firms’ brands are vertically differentiated with respect to the B brands.

What lies behind the entry of B brands? This question naturally begs an explanation as to why this growth happened only from the mid 1990s and not sooner. One explanation that has been put forward relates to an exogenous shift in the cost structure of the industry, reducing barriers to entry. During the course of the 1990s, the fixed cost associated with packaging and distribution dropped significantly with the introduction of one-way (non-returnable) plastic bottles, made from PET. As PET technology improved, it rapidly substituted for the previous glass bottle technology. Glass had required that a bottler maintain an expensive, and thus large-scale, bottle return and reuse operation. In contrast, PET bottles were now disposable after consumption. Thus while the 1-liter returnable family-size bottle made from glass had been the industry norm for many decades, by 1998 the family standard had shifted to the low-cost 2-liter PET bottle. As the industry adopted PET, the fixed cost of entry was sharply reduced, making small-scale operations now affordable. Indeed, most B-brand bottlers offer their soda in the inexpensive 2-liter PET bottle only¹³. Only a few firms can afford to add different sizes such as (single-consumer) 300-ml (milliter) glass bottles or aluminium cans to their offerings. This single offering of a family-sized bottle limits the incursion of B brands into distribution channels where consumption of smaller amounts typically takes place, such as bars and restaurants.

Brazil’s economic stabilization in 1994 may provide a complementary explanation behind the rise in these popular brands. The sharp slowdown in inflation, through the reduction in “inflation tax”, represented a reduction in the transfers from households to the government. In particular, the large mass of consumers among the lower-income groups who previously had no access to instruments of monetary protection, such as

municipalities are distributed across these 27 states, each state comprising on average 200 municipalities. The average population of a municipality is thus 32,000.

¹²Indeed, these studies find that, in a same shopping trip, a lower-income household may well buy both B brands and premium brands: the former for regular consumption (weekdays, say), reserving the latter for special occasions (weekend meals when the family gets together).

¹³In 2002, for example, the 2-l PET bottle accounted for 84% of the total volume consumption of B brands (and 70% of the total volume consumption across all brands). Note, however, that packaging still remains a significant component of marginal cost. ABIR reports that packaging accounts for over half the (plant-level) cost of goods sold (COGS). (http://www.etco.org.br/setoriais_refrigerante.php)

price-indexed savings accounts, saw a significant rise in real incomes. Given their high propensity to consume, this boosted demand across a broad spectrum of goods, such as food, durables and housing. According to ACNielsen, consumption of soft drinks almost doubled from 6 billion liters in 1994 to 11 billion liters in 1997, pulled by consumers with lower purchasing power and higher price sensitivity, with growth slowing thereafter¹⁴. Interestingly, the similarly dramatic consumption growth in other non-durable differentiated-goods industries, such as biscuits, personal hygiene and cleaning products, was also accompanied by entry and growth of low-priced, non-advertised, regional “B brands” (Exame 2002). The observation that the growth in the market share of firms offering B brands – around the same period – was not restricted to soft drinks lends credence to this complementary price-sensitive consumer explanation.

While the exogenous changes on the supply side and on the demand side seem to provide complementary explanations for the rise of the B brands in soft drinks from the mid 1990s, a comment on the different cost structures between the high-price premium brands and their low-price counterparts is in order. While Coca-Cola Co. and Ambev spend heavily to advertise their brands¹⁵, B-brand firms hardly advertise. In terms of marginal costs, it is conceivable that, compared to the premium brands, B brands also enjoy lower costs of labor (both wages and benefits) in manufacturing and sales, possibly offset by higher material costs, which are procured on a lower scale (e.g. sugar, plastic). Of potentially greater significance, makers of B brands stand accused, by the incumbents, of evading taxes. The Brazilian Association of Soft-Drink Manufacturers (ABIR) reports that (in the formal economy) taxes correspond to as much as 40% of the price a consumer pays for a soft drink, with sales taxes amounting to around three-quarters of this total. Coca-Cola Co. and Ambev have claimed, through industry outfits such as ABIR and the “United Front”, that B brands heavily undercut their prices thanks to lower (marginal) costs, chiefly arising from tax evasion. This is a claim whose consistency with respect to the data, in light of the complementary or competing hypotheses, the present study aims to verify.

2.1 Data

This study largely uses data on soft drinks collected and compiled by ACNielsen. This market research firm samples retail outlets located in the coastline states and some neighbouring states, grouping these states into seven (geographic) market areas; those states to the northwest of the centre of the country, which are sparsely populated and mostly covered in jungle, are not audited. In each market, data is aggregated into three classes of distribution channel according to the type of outlet it refers to: (i) supermarkets with checkouts (“self-service” outlets), (ii) over-the-counter stores (“traditional” outlets), and (iii) bars and restaurants (“bars”). Data is available, for each of the three types of outlet, in each of the seven market areas, by brand and by flavor, on average prices and quantities sold (among other variables such as the weighted distribution¹⁶)

¹⁴This translates into a staggering 22% increase per year between 1994 and 1997, with growth slowing to +8% per year in the period 1997 to 2002.

¹⁵Coca-Cola Co. is reported to have spent US\$ 350 million (or 6% of sales) on advertising in 1998, mainly on soft drinks. Ambev is reported to have invested approximately US\$ 100 million. Both firms are among the heaviest advertisers in the country (Gazeta Mercantil 1998).

¹⁶This is the proportion of establishments that carry the brand in stock, weighted by the establishments’ soft drink sales. For example, across markets and time periods, the Coke brand is persistently

over bimonthly/monthly time periods between December 1996 and March 2003¹⁷. Data is also (dis)aggregated according to two sizes of packaging: (i) the standard family-sized 2-liter PET bottle (“family size”), and (ii) single consumption sizes such as the standard 300-ml glass bottle and 350-ml aluminium can (“single size”). To provide an example, one observation would be the average price, total quantity sold, and weighted distribution of family-sized bottles of the Fanta brand, orange flavor, sold through self-service outlets in market 6 (the three southernmost states of Brazil) in July 2000. The rich panel structure of the data thus allows one to explore variation over time and across market areas and across outlet types.

Figure 4 depicts market sizes (in liters and in sales, at constant March 2003 prices¹⁸, across all sizes), among other statistics, by market area broken out by outlet type. The aggregate value share for B brands is highest in the market area with the lowest per capita disposable income: 24% in market 1 (the northeastern states of Brazil). In terms of outlet types, B brands are predominantly sold via self-service or traditional outlets, rather than bars, where single-size packaging is key, as explained above.

Figure 5 depicts the evolution of volume shares and value shares by firm across all markets and outlet types considering *only family-sized bottles*. Shares for each of Ambev’s constituent firms, prior to the merger in March 2000, are shown. The growth in the B brands within the time period for which data is available is striking. At this aggregate level, growth occurs mainly at the expense of Ambev’s market share.

The growth in the B brands’ aggregate market share has come about at different rates across markets areas, as Figure 6 portrays for family-sized bottles sold through self-service outlets. Growth has been higher in the poorer markets of the northeast of the country, albeit starting from a lower base. Constant prices have been declining everywhere, from around R\$ 0.90 per liter to around R\$ 0.55 per liter. Figure 7 portrays the evolution of the family-size version of the Coke brand in self-service outlets. Of relevance to the identification of demand (as I discuss in the next section), Coca-Cola Co. significantly and abruptly lowered Coke’s prices (and also that of its other brands, in their family-size versions; not shown) from around R\$ 1.30 per liter to around R\$ 1.00 per liter around mid 1999. The charts indicate that Coca-Cola Co. managed to stem (and even reverse) the decline in share of its flagship brand in several, though not all, market areas, albeit paying a heavy price in terms of lower unit revenues.

Climatic data in each state capital city (average temperature in degrees Celsius, the amount of sunlight in hours per day, and the amount of rain, in millimeters per day) is available, by month, from the National Institute of Meteorology (INMET). Disposable income in each state is available from the country’s office of national statistics, the Brazilian Institute for Geography and Statistics (IGBE). As for one class of demand-side instruments (see identification discussion below), prices of refined sugar, diesel oil, and

stocked by an average 99.5% of self-service outlets. On the other hand, the proportion of self-service establishments carrying (one or more) B brands increases from 86.5% (averaged across markets and time periods) in the first year of the sample (1997) to 97.5% by the third year (1999), remaining at this level thereafter.

¹⁷Between December 1996 and January 2000, ACNielsen conducted bimonthly audits, modifying the frequency of its readings to a monthly basis from February 2000. The data therefore consists of 57 time periods.

¹⁸I convert observed current prices to constant prices using the widely-used Consumer Price Index (CPI) published by the Fundação Getúlio Vargas (the “IPC-br”).

(high-voltage) electricity are obtained from the Institute for Applied Economic Research (IPEA), the National Agency for Oil (ANP), and the National Agency for Electrical Energy (ANEEL). Manufacturing-sector wages are obtained from the Confederation of National Industry (CNI).

3 Demand

I follow Hausman, Leonard and Zona (1994) and estimate a multi-stage budgeting system à la Gorman (1995)¹⁹. The system is modeled with only two stages since the number of brands is conveniently small. The top-level equation, specified in log-linear form, captures the representative consumer’s allocation decision between consuming the inside good (soft drinks) and the outside good. The bottom-level equation reflects the representative consumer’s allocation among the alternative soft drink brands, conditional on her total expenditure on soft drinks. The bottom-level equation is specified as an AIDS demand function (Deaton and Muellbauer 1980a)²⁰.

3.1 Specification

The AIDS demand function I estimate to capture the bottom stage is:

$$s_{int} = \alpha_{1in} + \alpha_{2in}T_t + \beta_i \log\left(\frac{Y_{nt}}{P_{nt}}\right) + \sum_j \gamma_{ij} \log p_{jnt} + \theta_{in}Z_{int} + \epsilon_{int} \quad (1)$$

for $i = 1, \dots, I$; $n = 1, \dots, N$; $t = 1, \dots, T$

where $s_{int} := \frac{p_{int}q_{int}}{Y_{nt}}$ is brand i ’s value share in geographic market n at time t , p_{int} is the observed average price per liter of brand i in market n at time t , q_{int} is the observed total quantity in liters sold (per month) of brand i in market n at time t , and $Y_{nt} := \sum_i p_{int}q_{int}$ is total expenditure on soft drinks in market n at time t . P_{nt} is an overall soft-drink price index across brands in market n at time t , such as Stone’s (1954) price index²¹, given by $\log P_{nt} := \sum_i s_{int} \log p_{int}$. The econometric error is denoted by ϵ_{int} . The remaining terms capture differences in preferences and demographics across brands and markets, (possibly) including: (i) a brand-market specific fixed effect (through α_{1in}); (ii) a brand-market specific time trend (through an element of $\alpha_{2in}T_t$); (iii) brand specific bi-monthly seasonal effects (through $\alpha_{2i}T_t$, an element of $\alpha_{2in}T_t$); (iv) brand-market specific effects of

¹⁹See, in particular, “Two Stage Budgeting” published therein. See also Blackorby, Primont and Russell (1978).

²⁰I adopt this flexible approach, rather than working with computationally more demanding discrete-choice models à la Berry, Levinsohn and Pakes (1995) or Hendel (1999), since the richness of the data (including my confidence in the “experimental” nature of the identification strategy – see below) allows me to estimate the patterns of substitution *directly*. (In addition, I can avoid having to make potentially *ad hoc* assumptions regarding the consumer’s sequence of choices thanks to the small dimension of her choice set.) The sensible demand estimates I obtain indicate that the choice is appropriate given the purpose of my paper.

²¹The use of a Stone price index represents a linearization of the AIDS demand function that is derived from the consumer’s optimization problem, where the price index is a trans-logarithmic function of prices (see Deaton and Muellbauer 1980a, or the Appendix). Such linearization may introduce inconsistency (through, say, the errors-in-variables problem; see, for example, Pashardes 1993, Alston, Foster and Green 1994, and Buse and Chan 2000) but it buys us a way to deal with non-converging estimation (see Capps, Church and Love 2003).

observed climatic conditions in market n at time t (through $\theta_{in}Z_{nt}$, elements of $\theta_{in}Z_{int}$), such as the average temperature (in degrees Celsius), the amount of sunlight (in hours per day) and the amount of rain (in millimeters per day); and (v) the observed weighted distribution of brand i in market n at time t (through $\theta_i Z_{int}$, an element of $\theta_{in}Z_{int}$). The latter covariate controls for the low initial distribution of B brands in some markets of the sample.

The top stage then corresponds to the overall demand for soft drinks, which is specified as:

$$\log Q_{nt} = \alpha_{1n} + \alpha_{2n}T_t + \beta \log X_{nt} + \gamma \log P_{nt} + \theta_n Z_{nt} + \epsilon_{nt} \quad (2)$$

where $Q_{nt} := Y_{nt}/P_{nt}$ is the overall consumption of soft drinks²² in market n at time t , X_{nt} is total disposable income for market n at time t , and price index P_{nt} is defined as before. ϵ_{nt} denotes the econometric error. The remaining terms similarly capture differences in preferences and demographics across markets, through market-specific fixed effects, market-specific drifts, bi-monthly seasonal effects, and market-specific climatic effects.

Sample characteristics As for the aggregation of data along the different dimensions, there are 57 (monthly or bimonthly) time periods, $T = 57$, and 7 geographic markets, $N = 7$, matching the breakdown provided by ACNielsen to marketing professionals in the industry (see Section 2.1). The base specification considers data for soft drinks sold in family-sized bottles²³ through self-service outlets, in view of the discussion of Section 2.1; in particular, recall that the emergence of B brands is not observed in the “bars” channel. (I can then use data pertaining to sales through traditional outlets as alternative instruments for demand to test robustness; see below.) With a view to striking a balance between dealing with the curse of dimensionality and appropriately capturing competition at the point of sale, I aggregate flavors (and brands) into 9 “brands”, $I = 9$: Coke, Diet Coke, Fanta, Kuat, Other Coca-Cola Co., Guaraná Antarctica, Pepsi, Other Ambev, and B brands. Importantly, the reason why I work with aggregate data for B brands, rather than data at the individual B-brand level, is because these individual B brands are each distributed only within a small geographic area, in addition to there being considerable noise in the disaggregated B brand data (see footnote 38 below). While second best, this is reasonable for my present purpose. As mentioned in Section 2, B brands compete essentially on price, and my primary interest is to estimate substitution patterns across premium brands and between premium brands and B brands, rather than substitution across B brands, which I can safely conjecture to be high, as I later explain. Of note, I later perform several robustness tests around these modeling choices.

Identification strategy To the extent that firms observe demand shocks that the econometrician does not, and these demand shocks are observed by firms in advance of setting prices, prices in (1) and (2) will be endogenous and methods based on ordinary least squares (OLS) will not generate consistent estimates. In spite of controlling to the best of my ability for demand shocks – e.g. through the inclusion of fixed effects

²²Alternatively, one can define $Q_{nt} := \sum_i q_{int}$. See footnote 55 in the Appendix.

²³Alternative specifications, for the sake of testing robustness, allow substitution across family-size (2-l PET bottle) and single-size (300-ml glass bottle and 350-ml aluminium can) packages.

and climatic data, as explained above²⁴ – there may always potentially be a non-trivial component to these shocks which I do not observe.

My identification strategy hinges mainly on Coca-Cola Co.’s abrupt decision in July 1999 to lower the price of the family-size version of its brands by a hefty 25% across all markets (recall Figure 7). Though the dynamics behind this large and sudden price reduction are far from clear (as I discuss later), it is natural to attribute this price change as being motivated on the supply side. The only exogenous shock to the industry that I observe around this time is the downfall of Coca-Cola Co.’s country manager, and this follows the period of sharp growth in the aggregate share of B brands. Indeed, industry sources claim that Coca-Cola Co. was slow to react to the growth of the B brands, and that this price reduction was associated with a change in the Company’s “strategic direction and management”²⁵. The fact that only family-size bottles had their prices reduced, and not single-size packages such as 350-ml cans, lends further support to the notion that Coca-Cola Co. was responding to the growth of B brands, as these were sold largely in family-size bottles. I create a dummy variable which takes on the value 1 for all time periods following July 1999 and interact it with the market fixed effects, thus allowing the effects of this shift in supply to vary by market. (Doing so also conveniently provides $N = 7$ exclusion restrictions.) Of note, the marketing literature has traditionally attempted to identify demand in this manner – observing how demand responds to certain movements (“experiments”) in prices which one argues (or hopes) are exogenous to unobserved demand shocks. Here, the institutional context in which the large and abrupt price reduction is embedded provides strong economic evidence in favor of its exogeneity.

A secondary source of identification borrows from Hausman, Leonard and Zona (1994). They use prices in other (geographic) markets to instrument for prices in a given market, i.e. the price of brand i at time t in market m , p_{imt} , may serve as an instrument for the price of brand i at time t in market $n \neq m$, p_{int} . (In the top-level equation, P_{mt} may analogously serve as an instrument for P_{nt} .) The identifying assumption is that p_{imt} will be correlated with p_{int} (through a common cost structure for a same brand sold in different markets, or through common shifts in the way firms interact strategically, such as Coca-Cola Co.’s decision to reduce prices *across all markets* in July 1999), while not being correlated with ϵ_{int} – the maintained assumption is that the unobserved demand shock is (largely) market specific (i.e. relative to the magnitude of the common supply shocks), once brand-market fixed effects and time trends (among the other controls) have been included in (1). Despite having been used widely in the recent IO literature on the estimation of differentiated-product demand, if only due to the typical lack of alternative instruments, this class of instruments has faced criticism²⁶. In the US cereal

²⁴The inclusion of weighted distribution covariates may also help. The idea here is that weighted distribution may be driven by unobserved consumer demographics and preferences (i.e. successful brands invite greater distribution) in ways not already captured by the brand-market specific fixed effects and time trends.

²⁵Given the size of the market, developments in Brazil had serious repercussions for Coca-Cola Co.’s worldwide business, and were watched closely at company headquarters in Atlanta, GA. In June 1999, the Financial Times (1999) reported: “It is cut-price, regional companies... that are prising sales away from the leading brands in one of the world’s largest soft drinks markets. Coca-Cola blamed difficulties in developing countries such as Brazil when it shocked Wall Street in December by announcing a rare drop in quarterly sales.”

²⁶See, for example, Hausman (1997a, 1997b) and Bresnahan (1997a, 1997b) for an exchange of opposing views regarding the use of such instruments in the estimation of nationally branded products.

industry, for example, where brands are marketed nationally, one might expect the presence of unobserved demand shocks stemming from national advertising or promotional campaigns²⁷. In the present setting, however, there are several reasons why I believe that this class of instruments is appropriate. The first reason relates again to Coca-Cola Co.’s decision to reduce (family-size bottle) prices across its brands in July 1999. There is a sense in which the attempt to capture this change in supply only through a set of time (post July 1999) and market-varying dummies, as explained above, does not fully exploit this unique “natural” experiment. Coca-Cola’s price reduction was synchronized across markets and its effects were brand-specific. Instrumenting for the price of a given brand in a given market with the price of the same brand in another market seems to capture, in a complementary way, what is, in effect, a large brand-specific supply shock. The other reasons for using this class of instruments are institutional. Despite the fact that the established Brazilian soft drink firms are major national advertisers²⁸, there is considerable variation in the way their brands are distributed and promoted within each region. Recall from Section 2 that the established firms employ regional distributors with a view to in effect exploiting their on-the-ground knowledge of local differences in demand. For example, in coordination with upstream firm Coca-Cola Co., regional franchisees downstream tailor promotional strategies to a large degree to better meet region-specific demand opportunities²⁹. In addition, the penetration of national retailers is still limited in Brazil, though it has been growing. Further, while nationwide macro-economic shocks are certainly important, regional variation to exogenous demand in a country as vast as Brazil, with its huge social and economic differences across regions, should not be understated³⁰.

Cost shifters provide a third class of instruments. Given the lack of brand-specific variation, these traditional instruments are particularly relevant in light of the brand-aggregated top-level equation. I observe (brand-common and market-common) factor prices such as wholesale refined sugar prices and (brand-common and market-specific) factor prices such as manufacturing-sector wages and energy (electricity for manufacturing and retailing, and diesel oil for road transportation)³¹. The identifying assumption

²⁷Controlling for advertising expenditures (when these are observed) directly in the demand system can help, but even then one may worry that the econometrician does not observe the *effectiveness* of every dollar spent on advertising, which may vary over time but be correlated across markets. On the other hand, to the extent that a large component of the brand-specific price variation can be attributed to an exogenous promotional calendar, by which manufacturers and retailers jointly mark prices up and down in advance of demand shocks being realized, as opposed to the view that manufacturers and retailers reoptimize prices in response to these demand shocks, prices may be treated as predetermined and OLS estimates will be consistent.

²⁸Unfortunately, I do not observe advertising data. However, advertising campaigns in the soft drink industry are highly seasonal, and thus the seasonal dummy variables (coupled with the brand-market specific climatic effects) should help control for the nationwide component to advertising shocks.

²⁹It is not only in Brazil that major soft drink firms differ from the typical large manufacturer of nationally-branded food products. In the US soft drink industry, for example, Muris, Scheffman and Spiller (1992) document the “importance of promotion via local and regional television, radio, and newspapers” (p.99) and how “promotional pricing has become a major competitive tactic at the bottling (i.e. franchisee) level” (p.88; parentheses added).

³⁰Note, for example, the variation in per capita disposable income across markets in Figure 4. To provide a sense of perspective, market 1 (Brazil’s northeast) alone covers a land area *4.5 times the size of Germany*.

³¹A further plausible cost-shifter is the exchange rate, to the extent that Coca-Cola Co.’s Brazilian operations view imports of syrup and concentrate as marginal cost (i.e. not internalizing the parent company’s transfer revenue).

is that these supply-shifters are uncorrelated with unobserved demand shocks.

Alternative instruments While the base specification does use prices in other markets as a source of identification, I later explore the robustness of this specification by experimenting with two alternative sets of instruments. A first alternative is potentially available by virtue of the channel-specific nature of soft drink distribution and consumption (and the particular panel structure of the data I observe). Writing the prices of family-sized bottles sold through traditional outlets as p^{TRAD} (alternatively, one may use the “bars” channel), and recalling that in the base specification p corresponds to prices of these same family-size bottles sold through self-service outlets, p_{int}^{TRAD} may serve as an instrument for p_{int} . The identifying assumption is that p_{int}^{TRAD} will be correlated with p_{int} but will not be correlated with ϵ_{int} . The maintained hypothesis is that unobserved demand shocks are (largely) channel specific – i.e. $E(\epsilon_{int}\epsilon_{int}^{TRAD}) \approx 0$ – relative to the common supply component to price variation. To the extent that promotional expenditure or other demand shocks are uncorrelated across distribution channels (the more modern self-service supermarkets and hypermarkets, vis-à-vis the traditional over-the-counter outlets), such an identifying assumption is plausible. Say, for example, that the income shocks affecting (or the promotional campaigns targeted at) lower-income households who shop in traditional outlets in rural areas are (largely) orthogonal to income shocks (or promotion) affecting better-off urban households who shop in self-service outlets. Or say that income effects on soft drink consumption inside the home (i.e. sales through self-service and traditional outlets) differ from income effects on soft drink consumption outside the home, on social occasions (i.e. sales in bars). Notice that using prices in other channels (“distribution markets”) as instruments is similar in spirit, though not in terms of the economic rationale, to using prices in other (geographic) markets³².

The second alternative set of instruments hinges on the growing distribution of B brands over the sample period. Recall that (brand-market specific) distribution is included in the base specification (1) of the demand system, on the basis that distribution is driven by *demand* shocks (consumer preferences and demographics) not already accounted for by the fixed effects and time trends (see footnote 24). An alternative interpretation, in the spirit of Berry, Levinsohn and Pakes (1995) and Bresnahan, Stern and Trajtenberg (1997), operates through *supply*, with firms making long-term entry decisions into markets and establishments, and the resulting distribution exhibiting persistence. Given a model of competition, these changes in brand-level distribution over time and across markets should be correlated with prices, yet be exogenous (in an econometric sense) to the unobserved short-term demand shocks. In particular, during the sample period, the distribution of B brands grows at different rates across markets (recall footnote 16). In view of this, I use the market-specific distribution for B brands as an alternative set of instruments, excluding the corresponding covariates from the demand equations.

Cross-equation restrictions and estimation The demand system is comprised by one bottom-level equation for each brand and one top-level equation, i.e. $I + 1$ equations.

³²See Ellison et al (1997) for an application of such a class of instruments to the demand for pharmaceuticals sold through different channels, namely drugstores and hospitals.

In the interest of efficiency, I simultaneously estimate the system of equations using three-stage least squares (3SLS)³³.

Cross-equation restrictions can be applied to further improve efficiency³⁴. Homogeneity (of degree zero with respect to prices and income) implies that $\sum_j \gamma_{ij} = 0$. The symmetry property restricts $\gamma_{ij} = \gamma_{ji}$. To check whether efficiency is being improved at the expense of consistency, likelihood ratio tests can be conducted^{35 36}.

Estimates of the unconditional own and cross price elasticities can be calculated by combining the estimates from the two levels, according to the expression derived in the Appendix. Standard errors can be obtained by the delta method.

3.2 Results

Figure 8 presents the estimated price elasticities of demand for three selected brands – the two leading brands Coke and Guaraná Antarctica, and the aggregation of B brands. The system of $I + 1$ demand equations is estimated under both OLS/SURE (column I, with no cross-equation restrictions imposed; column III where homogeneity and symmetry restrictions are imposed) and 3SLS (columns II and IV respectively). The elasticities under 3SLS tend to be higher (in absolute value) than under OLS (though this difference is not significant in a statistical sense). Own-price elasticities for Coke are in the -2 to -3 range (-2.3 under “restricted 3SLS” in column IV) and between -2.1 and -2.6 for Guaraná Antarctica (-2.6 under restricted 3SLS). This is low relative to own elasticities normally estimated for branded goods (see footnote 4) – I discuss the robustness of this result and its implications below.

The estimated own elasticity for the aggregation of B brands is also low, lying in the -2.6 to -3.1 range (-2.9 under restricted 3SLS). At first glance, this appears odd, given that on average a self-service outlet carries between two and three rival B brands, and differentiation between these tends to be symmetric and limited: consumers view B brands as close substitutes to one another³⁷. Upon further thought, however, this low elasticity owes probably to the fact that the demand for B brands is included in aggregate

³³As a further robustness test, I check that the 3SLS estimation is not improving efficiency at the expense of consistency, by comparing the 3SLS estimates to estimates obtained from (equation-by-equation) 2SLS.

³⁴Homogeneity and (Slutsky) symmetry restrictions for the AIDS system of equations at the individual consumer level follow from consumer theory. (See the Appendix. An additional “adding-up” restriction that may be applied is $\sum_i \beta_i = 0$.) That these should apply at the aggregate representative consumer level, despite their widespread use in applied work, is less clear. See Deaton and Muellbauer (1980b) for a discussion.

³⁵Capps, Church and Love (2003), estimate a multi-stage budgeting system for spaghetti sauce with an AIDS specification at the bottom stage. They conduct LR tests and reject both homogeneity and symmetry restrictions. Unsurprisingly, restricted estimation yields substantially lower estimated standard errors (in addition to reducing the number of cross-price elasticity estimates which are negative).

³⁶Notice that the regressors in the I bottom-level equations (1) are not identical thanks to Z_{int} (i.e. the observed weighted distribution of brand i). Were the regressors identical, one of the bottom-level equations would have to be dropped from the simultaneous estimation due to perfect multicollinearity, and separately estimated by two-stage least squares (2SLS). (To see this, consider the symmetry restriction $\gamma_{ij} = \gamma_{ji}$, and notice that $\sum_i s_{int} = 1$.) An alternative to dropping an equation from the simultaneous estimation is to drop one of the $(I^2 - I)/2$ symmetry conditions.

³⁷Notice that this limited differentiation is consistent with the observation that B-brand makers are essentially single-product, rather than multiple brand, firms.

form: while only 2.9% of the overall quantity demanded of B brands would switch away to the premium brands and to the outside good were the price of *all* B brands raised by 1%, the drop in demand for any specific B brand should be much higher were only its price raised vis-à-vis the prices of other rival B brands, i.e. each individual B brand’s own elasticity should be much higher given this expected close substitution across B brands³⁸.

Most cross-price elasticities are positive, many falling in the 0.2 to 0.5 range, about half of which are significant at the 1% level. For example, under restricted 3SLS, the elasticities of Coke demand with respect to the prices of Diet Coke (cross elasticity 0.40), Fanta (0.18), Kuat (0.17), Other Coca-Cola Co. brands (0.29), Pepsi (0.27) and Other Ambev brands (0.39) are all positive and significant at the 1% level. The elasticity of Coke demand with respect to the price of Guaraná Antarctica (0.10) is positive but not significant, while negative and not significant with respect to the price of B brands (-0.10). According with intuition, these estimates suggest that Coke and Diet Coke are close substitutes, while Coke and B brands are not. By these estimates, Coke is a closer substitute for rival premium brands than it is for B brands, i.e. this accords with the intuitive hypothesis that B brands are located at a distance from premium brands in the space of product characteristics. Still, a 1% increase in the price of Coke (which leads 2.3% of Coke demand to switch away to other brands or the outside good) raises the aggregate demand for B brands by 0.5% (significant at the 1% level), indicating that on raising prices Coke does lose some consumers to the low-end entrants. On the other hand, the cross elasticity of Coke demand with respect to the price of Pepsi seems somewhat low, given that the two brands are global archrivals in the “cola” segment (though note that the 0.27 cross-elasticity should be analyzed in combination with Pepsi’s low market share in Brazil – recall Figure 2).

As one would expect, the estimated standard errors for the elasticities under the restricted systems (either 3SLS or OLS) are about half of their unrestricted counterparts, though in most cases the estimated elasticities do not statistically differ according to whether restrictions are imposed or not. Thus the restrictions appear to be buying us efficiency, but not at the expense of consistency. In any case, the unrestricted estimates seem somewhat inferior: for example, the estimated cross elasticity of Coke demand with respect to the price of Diet Coke, at 1.4, is odd³⁹.

³⁸Data availability does not allow me to estimate substitutability across B brands. Of the approximately 5600 Brazilian municipalities, the area ACNielsen covers includes approximately 4500 municipalities, which makes the average number of municipalities per ACNielsen market equal to $4500/7 \simeq 640$. Recall, however, that the distribution of the “representative” B brand covers only a small fraction of this, around a dozen or two municipalities. This makes the data on individual B brands very noisy and uninformative about the choices consumers make between B brands at the point of sale. Ideally, the econometrician would use store-level data to estimate this choice *among* B brands, thus controlling for the very limited coverage at the individual B brand level. While data on individual B brands is noisy, the overall B brand data (i.e. sum across B brands) that ACNielsen provides contains much more signal, if only because the established firms – who are ACNielsen’s main customers – would be keeping a close eye on their up and coming rivals in this period. That the established firms were mostly tracking the aggregate growth of B brands, rather than particular B brands, is consistent with the view that consumers treat B brands as being symmetrically differentiated from one another (if at all).

³⁹To see this, note that the demand for Coke is on average around eight times the demand for Diet Coke. The unrestricted cross elasticities of other brands’ demands with respect to the price of Diet Coke are also odd (e.g. Guaraná Antarctica’s -1.0 and B brands’ -1.1) relative to their restricted counterparts. It may be that the restrictions reduce distortions arising from the high collinearity between the prices of Coke and Diet Coke: the correlation between the two sets of prices is high at 0.98 (to be contrasted with

Figures 9 and 10 present the entire matrix of estimated elasticities, under restricted OLS and 3SLS respectively⁴⁰.

Robustness As mentioned above, the estimated own-price elasticities are low in comparison to other studies of the demand for soft drinks and of other differentiated product industries. As I show in the next section, these low own-price elasticities, coupled with some high within-firm cross-price elasticities⁴¹, predict very high equilibrium price-cost markups for the premium brands under the assumption of multiproduct Bertrand behavior on the part of the established firms, casting doubt on the validity of this behavioral assumption. While the widespread use of multiproduct Bertrand to model firm behavior in differentiated-product industries obviously does not imply that firms in the industry at hand should be behaving à la multiproduct Bertrand (in fact, many such applications of the model in the literature are maintained rather than tested), it does call for the need to perform robustness tests. I proceed to briefly describing a small fraction of the alternative specifications that I have estimated, in an attempt to ascertain whether my choice of instruments, aggregation or functional form may be biasing the results (downward). As Figure 11 conveys, the low own-price elasticities appear to be robust. These robustness tests confirm the sensible substitution patterns obtained from the base specification, as described above. In Section 4, I take up the question as to why the established multiproduct firms, observing such inelastic demand, do not attempt to raise prices and thus move up along the brand-level demand curves to a point where demand is more elastic.

- Robustness test 1A: Instruments: Prices in other markets. I keep the first and third class of instruments presented above (respectively, market-specific effects of Coca-Cola Co.’s July 1999 price reduction, and factor prices), replacing the second class of instruments (prices in other markets, à la Hausman, Leonard and Zona 1994) by prices in other channels. Estimated elasticities are mostly similar, including the finding of low own-price elasticities (see Figure 11).
- Robustness test 1B: Instruments: Prices in other markets. Again I keep the first and third class of instruments (respectively, the July 1999 price reduction and factor prices), but now replace the second class of instruments (prices in other markets) by the market-specific distribution of B brands (now excluded from the bottom-level equation (1) for B brands). Low own-price elasticities again obtain.

0.91 between the prices of Coke and Fanta). Indeed, interviews with Coca-Cola Co. executives suggest that the company has typically aimed to set the price of Diet Coke at a fixed markup over the price of Coke over time (+2% to 5% conditional on location). Even when estimation is restricted, as Figure 10 shows, some odd elasticities remain, such as $\eta_{DietCoke, BB\ brands} = -1.6$, or $\eta_{Fanta, DietCoke} = -0.41$. In an attempt to control for this multicollinearity and ensure robustness of this paper’s results, one of the robustness tests I present below subsumes Diet Coke into the Coke brand.

⁴⁰Further interesting substitution patterns are obtained. The high cross-elasticity of the demand for Diet Coke with respect to Coke, at 3.3 (again, this should be interpreted in combination with the much higher demand for Coke relative to Diet Coke), again suggests that consumers view the two brands as close substitutes. In contrast, when the price of Coke is raised by 1%, the demand for Fanta increases by only 0.13% (again, this is low considering the much larger demand for Coke relative to Fanta). Similarly, the elasticity of the demand for Guaraná Antarctica with respect to the price of Coke is a low 0.24. At current prices, Coke’s consumers appear to view neither Fanta nor Guaraná Antarctica as a good alternative to Coke.

⁴¹E.g. $\eta_{DietCoke, Coke} = 3.3$, or $\eta_{GuarAntar, OtherAmbev} = 0.79$ – see Figure 10.

- Robustness test 2A: Instruments: The July 1999 price reduction. I keep the second and third class of instruments presented above (respectively, prices in other markets and factor prices) but, rather than using Coca-Cola Co.’s price reduction in July 1999 to instrument for prices as per the first class of instruments, I control for the price reduction directly in the demand equations⁴². By doing this, I am in some sense making the remaining instruments “work harder” at identifying demand, though the supply shift is still operating to some extent (above and beyond the specific functional form taken on by the included controls) through the change in prices in other markets (the second class of instruments). While the estimated price elasticities change somewhat, low own-price elasticities are a robust result (as are their implication for Section 4).
- Robustness test 2B: Instruments: The July 1999 price reduction. An alternative to worrying about the exclusion versus inclusion of variables to account for Coca-Cola Co.’s price reduction is to drop all observations prior to the price reduction⁴³. An added benefit of this specification is that it relies on data only from the later part of the sample, where the established firms managed to stem the (net) entry of B brands and aggregate shares stabilized (see Figures 5, 6 and 7). Identification operates through the second and third classes of instruments (respectively, prices in other markets and factor prices). Again, the estimated elasticities change somewhat (to be expected considering the main element of identification – the July 1999 price reduction – is now absent), but the earlier result of low own-price elasticities remains.
- Robustness test 3: Brand aggregation. In an attempt to deal with potential multicollinearity in the prices of some brands (e.g. Coke and Diet Coke – see footnote 39), I aggregate brands further. One such specification entails $I = 6$ (Coke+Diet Coke, Fanta, Kuat+Other Coca-Cola Co., Guaraná Antarctica, Pepsi+Other Ambev, and B brands). As Figure 11 shows, low own-price elasticities persist.
- Robustness test 4: Substitution across package sizes. While family-size bottles correspond to the lion’s share of soft drinks sold through self-service outlets (on average as high as 80% of the volume sold of Coke, and 90% in the case of Fanta⁴⁴), the base specification, which employs data on family-size sales only, may not be capturing substitution at the point of sale across different consumption sizes, such as between family-size 2-l PET bottles and single-size 350-ml aluminium cans or 300-ml bottles. To control for such potential substitutability⁴⁵, I augment the

⁴²Specifically, in each of the bottom-level brand equations (1) and the top-level equation (2), I allow the market-specific fixed effects to jump, and the market-specific time trends to change, upon Coca-Cola Co.’s price reduction in July 1999. Clearly, including these intercept-and-drift-change covariates improves the goodness of fit of the system of equations by soaking up variation in the left-hand-side variables following July 1999.

⁴³I allow the July 1999 price reduction to take effect over the course of the third quarter of 1999. Thus I actually drop all observations up to and including September 1999.

⁴⁴Of note, the data shows that in March 2001 Ambev abruptly lowers the price of single-size packages of Guaraná Antarctica, sold through self-service outlets, by 40%. This almost doubles single-sized packages’ share of Guaraná Antarctica volume (in proportion to the brand’s total) via this distribution channel.

⁴⁵In the study mentioned in footnote 4, Dubé (2005) finds that, in response to price changes, “consumers tend to substitute primarily between products of the same size” (p.897), rather than stay with a brand and substitute across sizes. In other words, he finds the potential substitutability which this robustness test allows for to be limited.

family-size data with single-size data for some brands, such as the specification with $I = 11$: Coke(+Diet Coke) “family”, Coke(+Diet Coke) “single”, Fanta “family”, Fanta “single”, Other Coke “family”, Guaraná Antarctica “family”, Guaraná Antarctica “single”, Pepsi “family”, Pepsi “single”, Other Ambev “family” and B brands “family”. The matrix of estimated elasticities (under restricted 3SLS) is shown in Figure 12. Interestingly, cross-price elasticities between family and single sizes are significantly positive (in a statistical sense) in most cases (e.g. $\eta_{Coke\ Single, Coke\ Family} = 0.52$). Of further note, own-price elasticities for single sizes are significantly lower than for family sizes in three of the four cases (Coke, Fanta and Guaraná Antarctica). However, the own-price elasticities remain low.

4 Solving the structural model

I now make alternative assumptions regarding the pricing behavior of incumbents and of entrants, analyzing the implications for marginal cost. I begin by assuming that the owners of the premium brands are multiproduct Bertrand oligopolists facing a competitive fringe of B brands. I use the demand estimates of Section 3 to back out the marginal costs of the premium brands and of the B brands that are consistent with this behavioral specification. I then relax the behavioral assumption for each type of firm in a conservative direction for my present purpose, i.e. increasing the backed-out cost advantage enjoyed by B brands over the premium brands. Specifically, I modify the assumption on the part of the established firms to single-product Bertrand, by which each established firm is assumed to price each brand independently, without internalizing the externality on its other brands. As for the B-brand firms, I modify the assumption of price-taking behavior by conservatively assuming that they, too, behave strategically à la single-product Bertrand. Recall, however, that the limited geographic reach of each B brand relative to the geographic disaggregation for which the data is available did not allow me to estimate the own-price elasticity of an individual B brand. So, instead, I *assume* a reasonable range of values.

4.1 Dominant multiproduct Bertrand oligopoly facing a competitive fringe

Label the aggregation of B brands by $i = I$. The $i = 1, \dots, I - 1$ premium brands are owned by $F \leq I - 1$ multiproduct firms. Denoting the set of brands it owns as $\mathcal{O}_f \subseteq \{1, \dots, I - 1\}$, firm f sets prices such that

$$D_i(p) + \sum_{j \in \mathcal{O}_f} (p_j - c_j) \frac{\partial D_j(p)}{\partial p_i} = 0, \text{ where } i \in \mathcal{O}_f, \text{ for } i = 1, \dots, I - 1$$

where $D_i(p)$ and c_i are respectively the demand for and the (flat) marginal cost of brand i . (To simplify notation, market n and time t subscripts are omitted, e.g. given changes in brand ownership over the time period, one should write \mathcal{O}_{ft}) This multiproduct Bertrand FOC may be rewritten as

$$s_i(p) + \sum_{j \in \mathcal{O}_f} s_j(p) \frac{p_j - c_j}{p_j} \eta_{ji}(p) = 0$$

Stacking up the $I - 1$ FOCs one can write

$$s(p) + (\Theta^B \cdot \times \eta(p)') (s(p) \cdot \times L(p; c)) = 0 \quad (3)$$

where $L(p; c)$ is an $(I - 1) \times 1$ vector of Lerner indices with elements $\frac{p_i - c_i}{p_i}$, “ \times ” denotes the element-by-element multiplication operator (Hadamard product), $\eta(p)$ is an $(I - 1)$ -order square matrix of own and cross-price elasticities of demand with elements η_{ij} , and Θ^B is an $(I - 1)$ -order square ownership matrix with (time-varying) elements

$$\Theta_{ij}^B = \begin{cases} 1 & \text{if } \exists f \mid \{i, j\} \subseteq \mathcal{O}_f \\ 0 & \text{otherwise} \end{cases}$$

System (3) can be rearranged to

$$L(p; c) = - \left((\Theta^B \cdot \times \eta(p)')^{-1} s(p) \right) ./ s(p) \quad (4)$$

where “./” denotes the element-by-element division operator. From the demand elasticities estimated in Section 3, $\hat{\eta}_{ij,nt}$, and observed value shares s_{int} , one can use (4) to back out the Lerner indices L_{int} from which marginal cost estimates c_{int} may be calculated⁴⁶.

As for the competitive fringe of B brands, marginal cost may be backed out in light of the price-taking assumption $p = c$ (and the implicit assumption that B brands face upward sloping marginal cost schedules, which is reasonable in view of the limited capacity of each B brand operation)⁴⁷.

4.2 Results

Figure 13 shows predicted marginal cost for the different soft drink brands⁴⁸. Under the base demand specification of Section 3 (recall column (IV) of Figure 8) and the multiproduct Bertrand hypothesis, the backed out marginal cost for the family bottle of the Coke brand is a very low 0.15, corresponding to an equilibrium price-cost markup of 85%. The marginal cost for the other main premium brands in their family-size versions is at most 0.49 R\$/l (Guaraná Antarctica). This is *lower* than the marginal cost of 0.58 (equal to price) implied by price-taking behavior for the B brands!

The marginal cost backed out for Coke appears too low. The even lower, almost zero, cost I back out for Pepsi seems odd, which further suggests that Coke’s inferred

⁴⁶Notice that I specify marginal cost as being flat in quantity (in the relevant range). Alternatively, I could allow for richer specifications of cost (e.g. quadratic cost functions, translog cost functions, or more generally the generalized McFadden 1978 cost function; see Diewert and Wales 1987 and Kumbhakar 1994) or, for that matter, more sophisticated models of behavior. I would then estimate each alternative parametric model of supply and statistically select (using, say, Vuong’s 1989 non-nested LR test) among the alternative models. Given the resulting large demand on the data, I would have to adopt a considerably more parsimonious demand specification (see Gasmi, Laffont and Vuong 1990 for a discussion, and Gasmi, Laffont and Vuong 1992 for an application – to soft drinks, where demand is linear).

⁴⁷Notice that an alternative interpretation of such a pricing specification, other than price-taking behavior, rests on the close substitution across B brands and the observation that at the point of sale a consumer faces a choice between on average two to three rival B brands (i.e. an approximation to homogeneous Bertrand).

⁴⁸Recall that prices and costs are in R\$ per liter at constant March 2003 prices. Variables are taken at their mean values across all geographic markets and over time periods after Coca-Cola Co.’s price reduction in July 1999.

cost, like Pepsi's, may be too low, or the estimated markup may be too high⁴⁹. There are different possibilities to explain this result. The first is that the low estimated own-price elasticities of demand (coupled with some somewhat high cross-price elasticities) are biased downward due to attenuation bias. In view of the discussion of demand identification above, I judge this possibility to be remote.

Another possibility is that the established firms do not behave à la multiproduct Bertrand. In light of my present purpose, I conservatively relax this assumption in two ways. If each established firm sets prices taking into account the externalities across their two main brands only (Coke and Fanta in the case of Coca-Cola Co., and Guaraná Antarctica and Pepsi in the case of Ambev), but not across their other smaller brands (i.e. "Other Coke" and "Other Ambev" brands are priced independently), backed-out marginal cost for the premium brands mostly increases. Marginal cost for Coke is now 0.40, corresponding to a markup of 60%. The second way in which I relax the multiproduct Bertrand assumption for the established firms is by going all the way and assuming that each premium brand is priced independently, i.e. that established firms behave à la single-product Bertrand. Predicted marginal costs for the premium brands are now higher, in the 0.30-0.58 range, with markups falling between 38% and 66%.⁵⁰ In view of the predicted marginal cost for price-taking B brands at 0.58, this would suggest that the average 0.44 R\$/l (or 43%) price discount for B brands (relative to Coke's price of 1.02) does not owe to cost heterogeneity. Rather, the market power of the premium brands single-handedly explains the price premium they command over the B brands.

In this vein, one can conjecture that a reason why price elasticities are so low in equilibrium, leading the (maintained static) multiproduct Bertrand hypothesis to predict such high equilibrium markups for the premium brands, is that the static model may be misspecified. It is possible that the established firms are pricing lower than they would if there were no tomorrow in an attempt to stave off, or slow down, low-end entry. This would explain why the established firms, facing such low (short-run) demand elasticities, do not raise prices and move up their demand curves to a point where demand is more elastic⁵¹: the established firms may believe that this would only invite further entry by B brands. By this limit-price hypothesis, the static marginal revenue under the multiproduct Bertrand hypothesis falls short of, rather than being equal to, marginal cost. Such a conjecture is consistent in view of Coca-Cola Co.'s 25% reduction in the price of the family-size version of its brands in July 1999, following a period of staggering growth in the aggregate share of B brands. How to explain this price reduction lies outside the scope of this paper's static framework. The large, sudden and unilateral price reduction, in the absence of any observed exogenous shock to the industry, suggests that some "tipping point" may have been reached, leading Coca-Cola Co. to switch to a lower-price strategy⁵².

⁴⁹Another odd result is the implied cost of Fanta (0.35) relative to Coke's (0.15).

⁵⁰To provide a point of comparison, despite the usual caveats, in its 2003 financial statements Ambev reports an (accounting) *gross margin* (i.e. net sales minus *cost of goods sold*, before deducting distribution expenses) for its Brazilian soft drink operations of 35%.

⁵¹Unless, of course, the high markups predicted by the multiproduct Bertrand hypothesis are accurate, in which case the established firms do not raise prices since every marginal consumer that would then switch to other firms' brands (or to the outside good) is very lucrative.

⁵²An alternative hypothesis is that in the period leading up to July 1999, the established firms – possibly owing to some form of bounded rationality – had not woken up to the threat posed by the B brands and refused to treat these brands as substitutes for their brands, rather choosing to view

Finally, to check the sensitivity of the estimated cost heterogeneity with respect to the B brands' behavioral assumption, I allow B brands some degree of differentiation and some power over price⁵³. In view of (i) the elasticities typically obtained in differentiated-product demand studies, (ii) that at the point of sale (i.e. self-service outlets) a consumer can typically choose between two or three different B brands, and (iii) that B brands are perceived to be close substitutes, one can conceive that the own-price elasticity of an individual B brand is no less than 6. Applying this lower bound to the true elasticity to the single-product Bertrand pricing equation, this translates into a price-cost markup of 17%, or a marginal cost of (no less than) 0.48. This is still only 0.09 to 0.10 lower than the most conservative (i.e. higher) predicted marginal cost for the premium brands (Coke's 0.57 and Guaraná Antarctica's 0.58 under single-product Bertrand).

5 Concluding remarks

This paper tests the hotly-debated claim that the observed low prices of low-end entrants in the Brazilian soft drink industry are explained by cost advantages over the high-price established brands. It estimates a structural model to disentangle cost heterogeneity from heterogeneity stemming from demand and heterogeneity stemming from firm behavior, letting the data inform on the plausibility of each hypothesis. It finds that the 80% price premium that the established brands command over the fringe of B brands owes mostly to the low price sensitivity of demand for the premium brands in equilibrium.

The paper has limitations. It employs a static rather than a dynamic framework. One benefit of a static framework lies in the rich structure of demand that the researcher can specify. Yet I find suggestive evidence of important dynamic effects in the industry, such as the low estimated own-price elasticities of demand. These are consistent with pricing to deter entry. Another limitation of the paper is that it remains agnostic about the source of marginal cost heterogeneity. It may well be that the hypothesized cost advantages enjoyed by B brands through tax evasion (and poor labor and environmental practices) are being offset by higher procurement costs (sugar, plastic) or higher distribution costs (inefficient scale). But what the exercise points out is that the controversial claim that low-end brands *so considerably undercut Coke's and other premium brands' prices because of tax evasion* misses out on the fundamentally asymmetric nature of consumer demand.

References

- [1] Alston, J. M., K. A. Foster and R. D. Green (1994). Estimating elasticities with the linear approximate Almost Ideal Demand System: Some Monte Carlo results. *Review of Economics and Statistics* 76, 351-356

them as competing in a different market (the outside good). The downfall of Coca-Cola Co.'s country manager in the months shortly before July 1999 suggests this explanation is plausible. In view of this bounded rationality hypothesis, I re-estimate demand eliminating B brands from the dataset and using data from the pre July 1999 period. Estimated own-price elasticities remain low, lending credence to the entry deterrence conjecture.

⁵³One can motivate this through a symmetric demand system, such as the logit or the CES.

- [2] Berry, S., J. Levinsohn and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica* 63, 841-890
- [3] Blackorby, C., D. Primont and R. R. Russell (1978). *Duality, Separability, and Functional Structure: Theory and Economic Applications*. New York: North-Holland
- [4] Bresnahan, T. F. (1997a). Valuation of new goods under perfect and imperfect competition: A Comment. In T. F. Bresnahan and R. Gordon (Eds.), *The Economics of New Goods, Studies in Income and Wealth Vol. 58*. Chicago: National Bureau of Economic Research
- [5] Bresnahan, T. F. (1997b). The Apple Cinamon Cheerios war: Valuing new goods, identifying market power, and economic measurement. Mimeo, Stanford University
- [6] Bresnahan, T. F., S. Stern and M. Trajtenberg (1997). Market segmentation and the sources of rents from innovation: Personal computers in the late 1980s. *RAND Journal of Economics* 28(0), S17-S44
- [7] Buse, A. and W. H. Chan (2000). Invariance, price indices and estimation in Almost Ideal Demand Systems. *Empirical Economics* 25, 519-539
- [8] Capps Jr., O., J. Church and H. A. Love (2003). Specification issues and confidence intervals in unilateral price effects analysis. *Journal of Econometrics* 113, 3-31
- [9] Deaton, A. and J. Muellbauer (1980a). An Almost Ideal Demand System. *American Economic Review* 70, 312-326
- [10] Deaton, A. and J. Muellbauer (1980b). *Economics and Consumer Behavior*. Cambridge University Press
- [11] Dhar, T., J.-P. Chavas, R. W. Cotterill and B. W. Gould (2005). An econometric analysis of brand-level strategic pricing between Coca-Cola Company and PepsiCo. *Journal of Economics & Management Strategy* 14(4), 905-931
- [12] Diewert, W. E. and T. J. Wales (1987). Flexible functional forms and global curvature conditions. *Econometrica* 55, 43-68
- [13] Dubé, J.-P. (2005). Product differentiation and mergers in the Carbonated Soft Drink industry. *Journal of Economics & Management Strategy* 14(4), 879-904
- [14] Ellison, S. F., I. Cockburn, Z. Griliches and J. Hausman (1997). Characteristics of demand for pharmaceutical products: An examination of four cephalosporins. *RAND Journal of Economics* 28(3), 426-446
- [15] Exame (2002). Por que as marcas líderes estão perdendo participação de mercado para produtos populares e baratos. Edition of 09/01/2002
- [16] Financial Times (1999). Brazil's regional drinks makers slake thirst for value: The tax regime and growing demand have penalised leading brands. Edition of 06/16/1999
- [17] Gazeta Mercantil (1998). A indústria de refrigerantes e águas. *Análise Setorial*, 4 volumes. São Paulo

- [18] Gasmi, F., J. J. Laffont and Q. H. Vuong (1990). A structural approach to empirical analysis of collusive behavior. *European Economic Review* 34, 513-523
- [19] Gasmi, F., J. J. Laffont and Q. H. Vuong (1992). Econometric analysis of collusive behaviour in a soft-drink market. *Journal of Economics and Management Strategy* 1(2), 277-311
- [20] Gorman, W. M. (1995). *Separability and Aggregation: Collected Works of W. M. Gorman*. In C. Blackorby and A. F. Shorrocks (Eds.)
- [21] Green, R. and J. Alston (1990). Elasticities in AIDS models. *American Journal of Agricultural Economics* 72, 442-445
- [22] Hausman, J. A., G. K. Leonard and J. D. Zona (1994). Competitive analysis with differentiated products. *Annales D'Economie et de Statistique* 34, 159-80
- [23] Hausman, J. A. (1997a). Valuation of new goods under perfect and imperfect competition. In T. F. Bresnahan and R. Gordon (Eds.), *The Economics of New Goods, Studies in Income and Wealth Vol. 58*. Chicago: National Bureau of Economic Research
- [24] Hausman, J. A. (1997b). Reply to Prof. Bresnahan. Mimeo, MIT
- [25] Hausman, J. A. and G. Leonard (1997). Economic analysis of differentiated product mergers using real world data. *George Mason Law Review* 5(3), 321-344
- [26] Hausman, J. A., and G. K. Leonard (2002). The competitive effects of a new product introduction: A case study. *Journal of Industrial Economics* L (3), 235-261
- [27] Hendel, I. (1999). Estimating multiple-discrete choice models: An application to computerization returns. *Review of Economic Studies* 66, 423-446
- [28] Huse, C. and A. Salvo (2006). Empirical methods in IO and their application to antitrust. In IPEA (Eds.), *Studies in Quantitative Methods Applied to Antitrust and Regulation*. Brasília: SDE (Ministry of Justice)
- [29] Kumbhakar, S. C. (1994). A multiproduct symmetric Generalized McFadden cost function. *Journal of Productivity Analysis* 5, 349-357
- [30] Lewis, W. W. (2004). The power of productivity. *McKinsey Quarterly* 2/04
- [31] McFadden, D. L. (1978). Cost, revenue, and profit functions. In D. L. McFadden and M. Fuss (Eds.), *Production Economics*. Amsterdam: North-Holland
- [32] Muris, T. J., D. T. Scheffman and P. T. Spiller (1992). Strategy and transaction costs: The organization of distribution in the Carbonated Soft Drink industry. *Journal of Economics and Management Strategy* 1(1), 84-128
- [33] Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica* 69, 307-342
- [34] Pashardes, P. (1993). Bias in estimating the Almost Ideal Demand System with the Stone index approximation. *Economic Journal* 103, 908-915

- [35] Robarts, A. (2002). Taste trends in Mexico and Brazil: Changing competitive landscapes. New York: Latin American Equity Research, Santander Central Hispano
- [36] Schneider, F. (2002). Size and measurement of the informal economy in 110 countries around the world. World Bank Working Paper
- [37] Schneider, F. and D. Enste (2000). Informal economies: Size, causes, and consequences. *Journal of Economic Literature* 38, 77-114
- [38] Stone, J. (1954). Linear Expenditure Systems and demand analysis: An application to the pattern of British demand. *Economic Journal* 64, 511-527
- [39] Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypothesis. *Econometrica* 57, 307-333

A Appendix: Derivation of the AIDS demand function, and the elasticity equation

This section derives the AIDS demand function in budget share form, following Deaton and Muellbauer (1980a). (See also Huse and Salvo 2006.) Consider a class of preferences represented by a cost function of the following type

$$\log c(u, p) = (1 - u) \log \{a(p)\} + u \log \{b(p)\}$$

where u denotes utility, p denotes prices, and $a(p)$ and $b(p)$ are homogeneous of degree one in prices, defined as follows⁵⁴. $\log \{a(p)\}$ is quadratic in log prices

$$\log \{a(p)\} = \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \sum_k \sum_j \gamma_{kj}^* \log p_k \log p_j$$

and $\log \{b(p)\} - \log \{a(p)\}$ is given by

$$\log \{b(p)\} - \log \{a(p)\} = \beta_0 \prod_k p_k^{\beta_k}$$

where α_i , β_i and γ_{ij}^* are parameters, such that $\sum_i \alpha_i = 1$ and $\sum_j \gamma_{kj}^* = \sum_k \gamma_{kj}^* = \sum_j \beta_j = 0$. (These restrictions are required for the cost function to be linearly homogeneous in prices.) The (log of the) cost function can then be written

$$\log c(u, p) = \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \sum_k \sum_j \gamma_{kj}^* \log p_k \log p_j + u \beta_0 \prod_k p_k^{\beta_k} \quad (5)$$

By Shephard's Lemma, $\frac{\partial c(u, p)}{\partial p_i} = q_i(u, p)$, the compensated demand for good i , and hence

$$\frac{\partial \log c(u, p)}{\partial \log p_i} = \frac{p_i}{c(u, p)} \frac{\partial c(u, p)}{\partial p_i} = \frac{p_i q_i(u, p)}{c(u, p)} = s_i(u, p) \quad (6)$$

where s_i denotes the budget share of good i . This budget share is then derived by differentiation of (5):

$$s_i(u, p) = \frac{\partial \log c(u, p)}{\partial \log p_i} = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i u \beta_0 \prod_k p_k^{\beta_k} \quad (7)$$

where γ_{ij} denotes the arithmetic mean of γ_{ij}^* and γ_{ji}^*

$$\gamma_{ij} = \frac{1}{2} (\gamma_{ij}^* + \gamma_{ji}^*) \quad (8)$$

and therefore $\gamma_{ij} = \gamma_{ji}$ (symmetry). Utility maximisation implies that $c(u, p)$ equal total expenditure Y . The cost function defined by (5) can then be inverted, yielding:

$$\begin{aligned} u \beta_0 \prod_k p_k^{\beta_k} &= \log Y - \left(\alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \sum_k \sum_j \gamma_{kj}^* \log p_k \log p_j \right) \\ &= \log Y - \left(\alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \sum_k \sum_j \gamma_{kj} \log p_k \log p_j \right) \end{aligned} \quad (9)$$

⁵⁴Note that $c(u, p) = \{a(p)\}^{(1-u)} \{b(p)\}^u$. With some exceptions (see the Appendix in Deaton and Muellbauer 1980a), u lies between 0 and 1 so that $a(p)$ and $b(p)$ can be regarded as the costs of subsistence ($u = 0$) and bliss ($u = 1$), respectively.

where (8) is used in the latter step.

Define a price index P by

$$\log P := \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \sum_k \sum_j \gamma_{kj} \log p_k \log p_j \quad (10)$$

The budget share for good i given in (7) can then be written, using (9) and (10), as a function of prices and expenditure:

$$s_i(u, p) = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log\left(\frac{Y}{P}\right) \quad (11)$$

The restrictions on the parameters of (5) and the symmetry restriction imply

$$\begin{aligned} \sum_i \alpha_i &= 1 & \sum_i \gamma_{ij} &= \sum_i \beta_i = 0 & \text{("adding-up")} \\ \sum_j \gamma_{ij} &= 0 & & & \text{(homogeneity)} \\ \gamma_{ij} &= \gamma_{ji} & & & \text{(symmetry)} \end{aligned}$$

Provided these restrictions hold, (11) characterises a system of demand functions which add up to total expenditure ($\sum_i s_i = 1$), are homogeneous of degree zero in prices and expenditure, and satisfy Slutsky symmetry. Changes in relative prices work through the γ_{ij} parameters: a 1 percent change in the price of good j has an effect γ_{ij} on good i 's budget share, with real expenditure $\frac{Y}{P}$ held constant. Changes in real expenditure work through the β_i parameters. These add to zero and are positive for "luxuries" and negative for "necessities".

In practice (see the empirical application in Deaton and Muellbauer 1980a), the price index P given in (10) may be approximated by a Stone price index P^S (Stone 1954):

$$\log P^S := \sum_i s_i \log p_i$$

Derivation of the elasticity expression corresponding to the two-stage budgeting system From $s_i = \frac{p_i q_i}{Y}$, one can write

$$\log q_i = \log Y - \log p_i + \log s_i$$

Thus the price elasticities of demand are

$$\eta_{ij} = \frac{\partial \log q_i}{\partial \log p_j} = \frac{\partial (\log Y - \log p_i + \log s_i)}{\partial \log p_j} = \frac{\partial \log Y}{\partial \log p_j} - 1[i = j] + \frac{\partial \log s_i}{\partial \log p_j} \quad (12)$$

Now, at the bottom stage, s_i is specified by the AIDS demand function (11), such that

$$\frac{\partial \log s_i}{\partial \log p_j} = \frac{1}{s_i} \frac{\partial s_i}{\partial \log p_j} = \frac{1}{s_i} \left(\beta_i \frac{\partial \log Y}{\partial \log p_j} - \beta_i \frac{\partial \log P}{\partial \log p_j} + \gamma_{ij} \right) \quad (13)$$

Using (13) in (12), it follows that

$$\eta_{ij} = \frac{\partial \log Y}{\partial \log p_j} \left(1 + \frac{\beta_i}{s_i} \right) - 1[i = j] + \frac{1}{s_i} \left(\gamma_{ij} - \beta_i \frac{\partial \log P}{\partial \log p_j} \right) \quad (14)$$

From the trans-logarithmic price index (10), one obtains

$$\frac{\partial \log P}{\partial \log p_j} = \alpha_j + \sum_k \gamma_{jk} \log p_k$$

which, in view of (11), can be rewritten as

$$\frac{\partial \log P}{\partial \log p_j} = s_j - \beta_j \log\left(\frac{Y}{P}\right) \quad (15)$$

Now consider $\frac{\partial \log Y}{\partial \log p_j}$. One can approximate⁵⁵ Y by the product of overall consumption $Q = \sum_i q_i$ and the price index P ; that is

$$Y = \sum_i p_i q_i \simeq P \sum_i q_i = PQ$$

which is equivalent to

$$\log Y = \log P + \log Q$$

where $\log Q$ is given by the top-level equation (2). Therefore,

$$\frac{\partial \log Y}{\partial \log p_j} = \frac{\partial \log P}{\partial \log p_j} + \frac{\partial \log Q}{\partial \log p_j} = \frac{\partial \log P}{\partial \log p_j} \left(1 + \frac{\partial \log Q}{\partial \log P} \right) = \frac{\partial \log P}{\partial \log p_j} (1 + \gamma) \quad (16)$$

Using (15) and (16) in (14), one obtains

$$\eta_{ij} = \left(s_j - \beta_j \log\left(\frac{Y}{P}\right) \right) (1 + \gamma) \left(1 + \frac{\beta_i}{s_i} \right) - 1[i = j] + \frac{1}{s_i} \left(\gamma_{ij} - \beta_i \left(s_j - \beta_j \log\left(\frac{Y}{P}\right) \right) \right) \quad (17)$$

or simply

$$\eta_{ij} = \left(s_j - \beta_j \log\left(\frac{Y}{P}\right) \right) \left(1 + \gamma \left(1 + \frac{\beta_i}{s_i} \right) \right) - 1[i = j] + \frac{\gamma_{ij}}{s_i}$$

Alston, Foster and Green (1994) discuss the several different elasticity expressions that have been employed in the literature based on (slightly) different approximations.

⁵⁵This approximation can be avoided by defining Q in the top-level equation (2) as total industry expenditure Y divided by the overall price index P (i.e. $Q := Y/P$), rather than defining Q as overall consumption (i.e. $Q := \sum_i q_i$). (Indeed, this is what I do in the base specification of Section 3.) In practice, elasticity estimates which follow from either route should be similar.

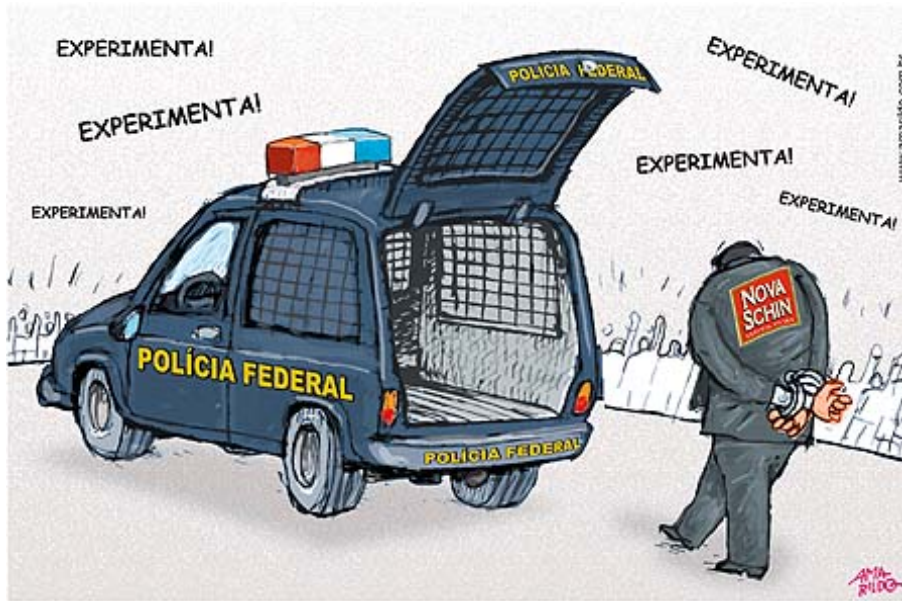


Figure 1: A cartoon from the press following the arrest of Schincariol executives charged with tax evasion in June 2005.

	2002 shares by	
	Value	Volume
Coke	39%	32%
Fanta	8%	7%
Diet Coke	5%	4%
Guaraná Kuat	3%	3%
Sprite	2%	2%
Other Coca-Cola Co.	2%	2%
Total Coca-Cola Co.	59%	50%
Guaraná Antarctica	13%	10%
Pepsi	5%	4%
Other Ambev	5%	3%
Total Ambev	23%	18%
Total Premium Brands	82%	67%
Total B Brands	18%	33%
Grand Total	100%	100%

Figure 2: Shares in the Brazilian carbonated soft drink industry, 2002

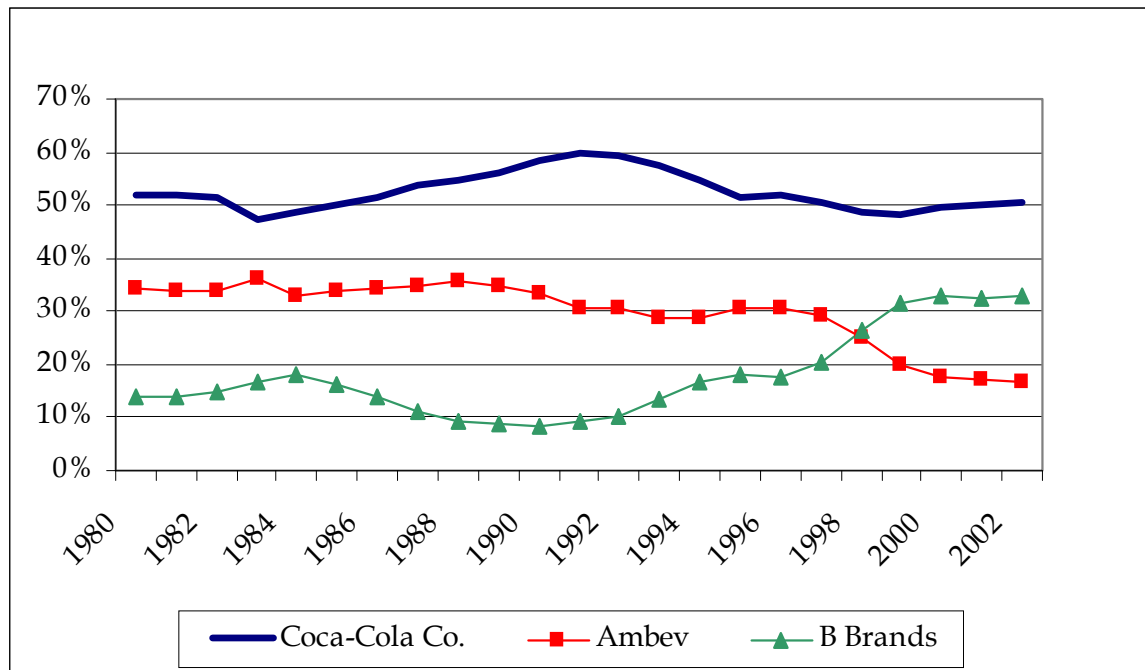


Figure 3: Evolution of volume shares in the Brazilian carbonated soft drink industry

Market	Outlet type	Quantity (million l)	Sales ¹ (R\$ mi)	Avg price ¹ (R\$/l)	Average value shares			Disposable income ²	
					Coke Co.	Ambev	B Brands	Total (\$ bi)	Per capita (\$ k)
1 Northeast	All	1,461	1,948	1.33	51%	25%	24%	73.1	1,918
	Self-Service	565	569	1.01	53%	21%	26%		
	Traditional	498	587	1.18	45%	20%	35%		
	Bar	398	792	1.99	54%	32%	14%		
2 ES, MG, RJ Interior	All	1,587	1,951	1.23	59%	19%	21%	90.4	3,829
	Self-Service	772	686	0.89	58%	17%	25%		
	Traditional	437	505	1.16	58%	14%	28%		
	Bar	378	760	2.01	61%	25%	14%		
3 RJ Metro	All	845	1,185	1.40	65%	21%	14%	60.8	5,816
	Self-Service	390	374	0.96	61%	21%	17%		
	Traditional	229	309	1.35	64%	16%	20%		
	Bar	227	501	2.21	67%	25%	8%		
4 SP Metro	All	1,292	2,034	1.57	62%	28%	10%	101.1	5,834
	Self-Service	646	627	0.97	60%	26%	14%		
	Traditional	277	431	1.56	64%	23%	13%		
	Bar	369	976	2.64	62%	32%	6%		
5 SP Interior	All	1,965	2,381	1.21	59%	21%	20%	107.9	5,834
	Self-Service	1,179	1,090	0.92	58%	20%	22%		
	Traditional	403	502	1.25	59%	17%	24%		
	Bar	383	790	2.06	61%	25%	14%		
6 South	All	1,799	2,217	1.23	59%	23%	18%	109.5	4,480
	Self-Service	1,022	901	0.88	58%	21%	21%		
	Traditional	393	451	1.15	56%	18%	26%		
	Bar	384	866	2.25	62%	27%	11%		
7 DF, GO, MS	All	732	941	1.29	57%	22%	20%	37.5	4,234
	Self-Service	391	391	1.00	53%	22%	25%		
	Traditional	176	219	1.24	60%	17%	24%		
	Bar	165	332	2.02	61%	27%	12%		
All	All	9,681	12,657	1.31	59%	23%	18%	580.2	4,107
	Self-Service	4,963	4,638	0.93	58%	21%	22%		
	Traditional	2,412	3,002	1.24	57%	18%	25%		
	Bar	2,305	5,017	2.18	61%	28%	11%		

¹ At constant March 2003 prices

² In rescaled monetary units. Source: IBGE

Figure 4: Quantities, sales, prices and value shares by ACNielsen market area and outlet type in 2002

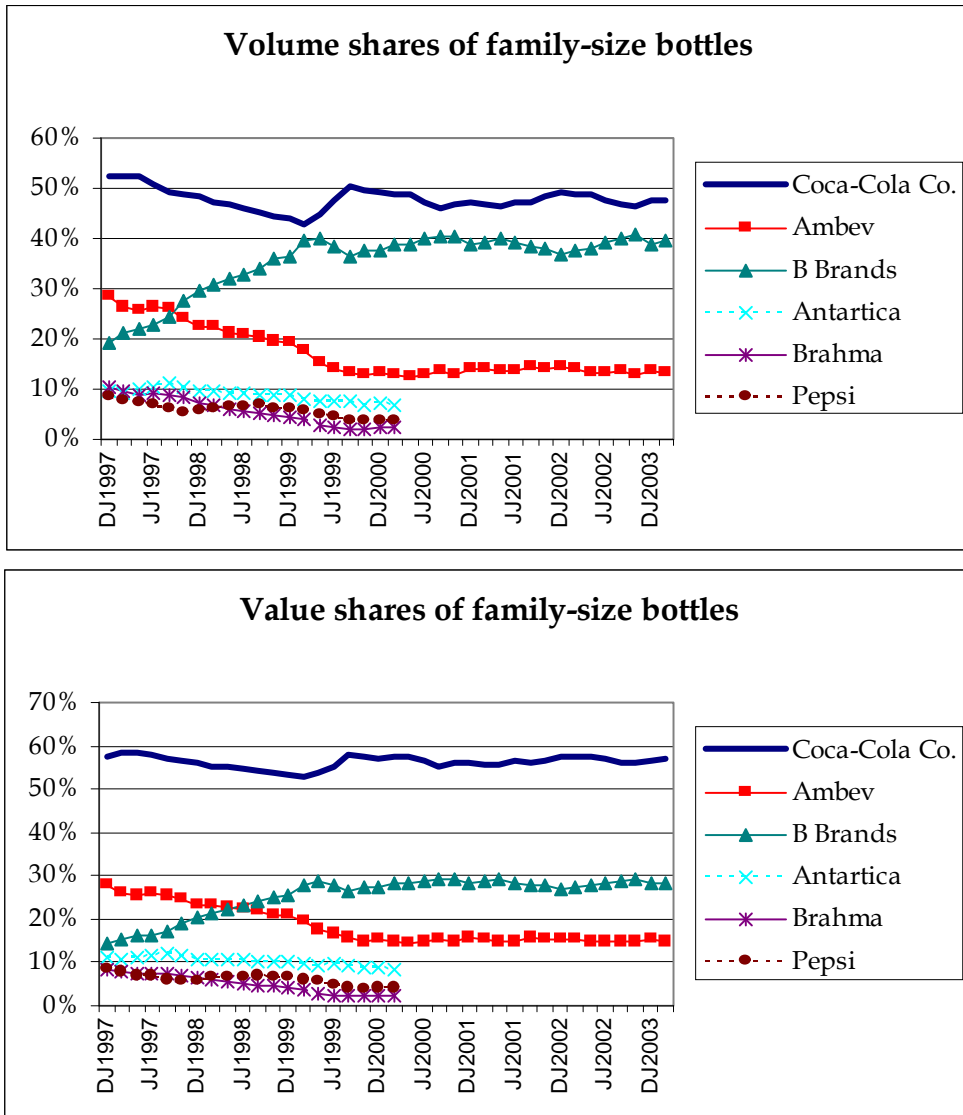


Figure 5: Volume and value shares of family-size bottles across all markets

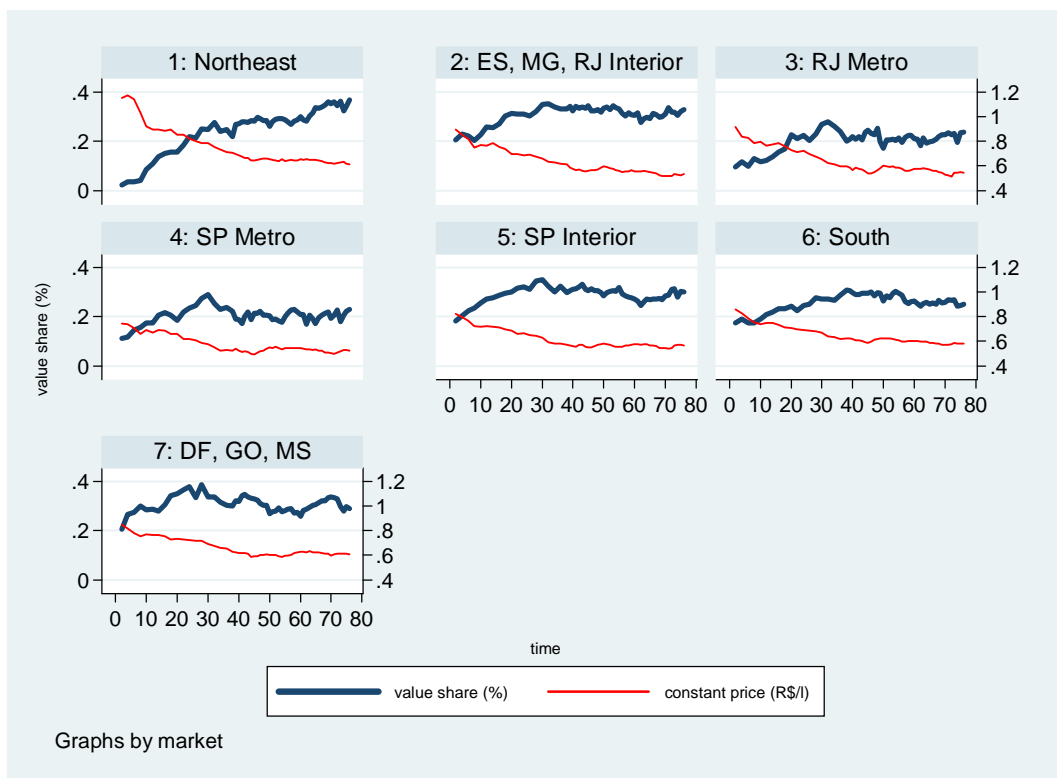


Figure 6: B-brands' value shares and prices by market, for family-sized bottles sold through self-service outlets

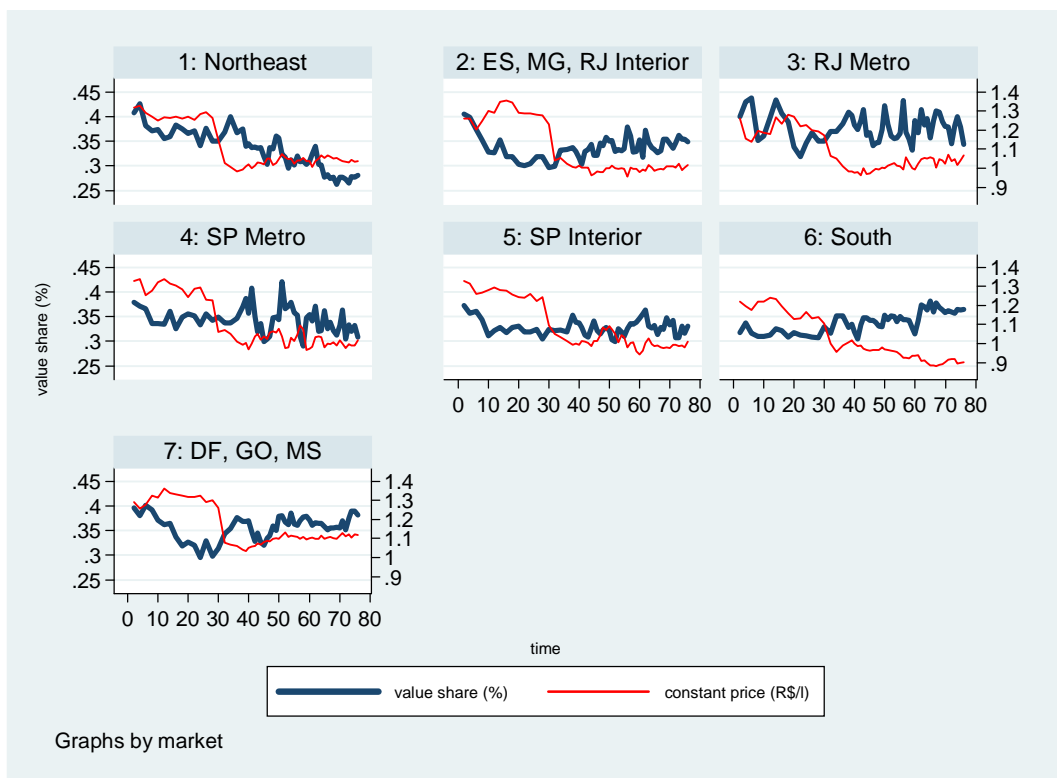


Figure 7: Coke brand's value shares and prices by market, for family-sized bottles sold through self-service outlets

	(I) OLS Unrestricted	(II) 3SLS Unrestricted	(III) OLS Restricted	(IV) 3SLS Restricted
$\eta_{\text{Coke,Coke}}$	-2.224 (0.201)	-3.158 (0.355)	-1.922 (0.114)	-2.252 (0.175)
$\eta_{\text{Coke,Diet Coke}}$	0.651 (0.163)	1.391 (0.276)	0.232 (0.045)	0.401 (0.097)
$\eta_{\text{Coke,Fanta}}$	0.119 (0.081)	0.248 (0.120)	0.139 (0.049)	0.182 (0.069)
$\eta_{\text{Coke,Tai/Kuat}}$	0.137 (0.060)	0.087 (0.086)	0.134 (0.038)	0.165 (0.050)
$\eta_{\text{Coke,Other Coke}}$	0.289 (0.058)	0.431 (0.089)	0.164 (0.029)	0.289 (0.046)
$\eta_{\text{Coke,Guar Antart}}$	0.157 (0.100)	0.083 (0.154)	0.174 (0.051)	0.103 (0.067)
$\eta_{\text{Coke,Pepsi}}$	0.211 (0.093)	0.379 (0.135)	0.271 (0.063)	0.266 (0.088)
$\eta_{\text{Coke,Other Ambev}}$	0.155 (0.076)	0.319 (0.119)	0.327 (0.069)	0.393 (0.108)
$\eta_{\text{Coke,B brands}}$	0.094 (0.120)	-0.171 (0.185)	0.056 (0.109)	-0.098 (0.158)
$\eta_{\text{Guar Antar,Coke}}$	0.336 (0.315)	1.569 (0.577)	0.215 (0.161)	0.241 (0.232)
$\eta_{\text{Guar Antar,Diet Coke}}$	-0.020 (0.265)	-1.040 (0.448)	0.037 (0.076)	-0.091 (0.141)
$\eta_{\text{Guar Antar,Fanta}}$	0.442 (0.126)	0.253 (0.187)	0.490 (0.085)	0.457 (0.113)
$\eta_{\text{Guar Antar,Tai/Kuat}}$	0.035 (0.092)	0.138 (0.133)	-0.074 (0.071)	-0.074 (0.093)
$\eta_{\text{Guar Antar,Other Coke}}$	0.325 (0.091)	0.521 (0.138)	0.230 (0.061)	0.387 (0.089)
$\eta_{\text{Guar Antar,Guar Antart}}$	-2.141 (0.159)	-2.571 (0.240)	-2.135 (0.125)	-2.576 (0.171)
$\eta_{\text{Guar Antar,Pepsi}}$	0.537 (0.139)	0.518 (0.203)	0.307 (0.106)	0.222 (0.144)
$\eta_{\text{Guar Antar,Other Ambev}}$	0.684 (0.110)	0.994 (0.168)	0.520 (0.096)	0.788 (0.144)
$\eta_{\text{Guar Antar,B brands}}$	0.034 (0.156)	-0.125 (0.220)	0.074 (0.147)	0.145 (0.200)
$\eta_{\text{B brands,Coke}}$	0.700 (0.292)	0.773 (0.536)	0.551 (0.092)	0.518 (0.098)
$\eta_{\text{B brands,Diet Coke}}$	-0.566 (0.246)	-1.127 (0.417)	-0.157 (0.028)	-0.220 (0.040)
$\eta_{\text{B brands,Fanta}}$	0.438 (0.115)	0.855 (0.170)	0.189 (0.048)	0.267 (0.063)
$\eta_{\text{B brands,Tai/Kuat}}$	0.036 (0.084)	0.072 (0.119)	0.156 (0.039)	0.156 (0.041)
$\eta_{\text{B brands,Other Coke}}$	-0.168 (0.085)	-0.158 (0.129)	0.065 (0.028)	0.098 (0.041)
$\eta_{\text{B brands,Guar Antart}}$	0.358 (0.146)	0.144 (0.225)	0.268 (0.052)	0.259 (0.051)
$\eta_{\text{B brands,Pepsi}}$	-0.281 (0.131)	-0.387 (0.191)	0.238 (0.066)	0.212 (0.091)
$\eta_{\text{B brands,Other Ambev}}$	1.033 (0.103)	1.465 (0.162)	0.774 (0.077)	0.857 (0.132)
$\eta_{\text{B brands,B brands}}$	-2.599 (0.145)	-3.074 (0.199)	-2.602 (0.127)	-2.898 (0.177)

Note: Standard errors in parentheses. Under 3SLS, instruments for prices are market-specific effects of Coca-Cola Co.'s July 1999 price reduction, prices in other (geographic) markets, and factor prices. Restrictions are homogeneity and symmetry.

Figure 8: Estimated price elasticities of demand for selected brands: Coke brand, Guaraná Antarctica brand and the aggregation of B brands. Family-sized bottles sold through self-service outlets.

Elasticity		With respect to the price of								
		Coke	Diet Coke	Fanta	Tai/Kuat	Other Coke	Guar Antar	Pepsi	Other Ambev	B brands
Family-sized bottles sold through self-service outlets	Coke	-1.922 (0.114)	0.232 (0.045)	0.139 (0.049)	0.134 (0.038)	0.164 (0.029)	0.174 (0.051)	0.271 (0.063)	0.327 (0.069)	0.056 (0.109)
	Diet Coke	1.736 (0.335)	-1.875 (0.285)	-0.255 (0.119)	0.106 (0.099)	0.227 (0.095)	0.172 (0.155)	0.270 (0.157)	0.559 (0.125)	-1.349 (0.166)
	Fanta	0.270 (0.172)	-0.196 (0.071)	-2.253 (0.116)	-0.302 (0.075)	0.087 (0.063)	0.623 (0.096)	0.750 (0.110)	0.653 (0.098)	0.022 (0.161)
	Tai/Kuat	1.102 (0.207)	0.126 (0.088)	-0.336 (0.112)	-2.495 (0.132)	0.206 (0.076)	0.020 (0.122)	0.034 (0.144)	0.299 (0.126)	0.590 (0.193)
	Other Coke	1.319 (0.217)	0.253 (0.111)	0.210 (0.126)	0.219 (0.101)	-3.612 (0.120)	0.619 (0.138)	0.300 (0.155)	0.359 (0.124)	-0.053 (0.185)
	Guar Antar	0.215 (0.161)	0.037 (0.076)	0.490 (0.085)	-0.074 (0.071)	0.230 (0.061)	-2.135 (0.125)	0.307 (0.106)	0.520 (0.096)	0.074 (0.147)
	Pepsi	0.449 (0.267)	0.067 (0.121)	0.813 (0.139)	-0.169 (0.125)	0.090 (0.102)	0.295 (0.155)	-1.636 (0.254)	0.093 (0.150)	-0.178 (0.238)
	Other Ambev	0.133 (0.268)	0.245 (0.107)	0.613 (0.136)	-0.031 (0.122)	0.061 (0.093)	0.522 (0.155)	-0.051 (0.178)	-3.697 (0.198)	2.226 (0.259)
	B brands	0.551 (0.092)	-0.157 (0.028)	0.189 (0.048)	0.156 (0.039)	0.065 (0.028)	0.268 (0.052)	0.238 (0.066)	0.774 (0.077)	-2.602 (0.127)

Figure 9: Matrix of estimated elasticities under restricted OLS (SURE). Standard errors in parentheses. Family-sized bottles sold through self-service outlets.

Elasticity		With respect to the price of								
		Coke	Diet Coke	Fanta	Tai/Kuat	Other Coke	Guar Antar	Pepsi	Other Ambev	B brands
Family-oriented	Coke	-2.252 (0.175)	0.401 (0.097)	0.182 (0.069)	0.165 (0.050)	0.289 (0.046)	0.103 (0.067)	0.266 (0.088)	0.393 (0.108)	-0.098 (0.158)
	Diet Coke	3.331 (0.752)	-3.059 (0.608)	-0.468 (0.208)	0.181 (0.171)	0.343 (0.178)	-0.092 (0.286)	0.038 (0.279)	0.749 (0.225)	-1.638 (0.275)
	Fanta	0.134 (0.248)	-0.405 (0.126)	-2.032 (0.154)	-0.490 (0.099)	0.035 (0.090)	0.416 (0.133)	1.129 (0.149)	0.977 (0.140)	-0.084 (0.226)
	Tai/Kuat	1.347 (0.284)	0.161 (0.155)	-0.538 (0.146)	-2.432 (0.170)	0.359 (0.110)	-0.050 (0.162)	0.135 (0.196)	-0.069 (0.184)	0.482 (0.261)
	Other Coke	1.843 (0.344)	0.273 (0.209)	0.048 (0.180)	0.325 (0.145)	-3.762 (0.184)	0.754 (0.205)	0.374 (0.230)	0.288 (0.179)	-0.433 (0.268)
	Guar Antar	0.241 (0.232)	-0.091 (0.141)	0.457 (0.113)	-0.074 (0.093)	0.387 (0.089)	-2.576 (0.171)	0.222 (0.144)	0.788 (0.144)	0.145 (0.200)
	Pepsi	0.154 (0.394)	-0.190 (0.221)	1.331 (0.190)	-0.120 (0.172)	0.180 (0.153)	0.008 (0.218)	-1.444 (0.365)	0.637 (0.218)	-0.628 (0.337)
	Other Ambev	-0.208 (0.404)	0.282 (0.197)	1.011 (0.197)	-0.533 (0.171)	-0.017 (0.140)	0.741 (0.230)	0.492 (0.264)	-3.280 (0.321)	1.931 (0.421)
	B brands	0.518 (0.098)	-0.220 (0.040)	0.267 (0.063)	0.156 (0.041)	0.098 (0.041)	0.259 (0.051)	0.212 (0.091)	0.857 (0.132)	-2.898 (0.177)

Figure 10: Matrix of estimated elasticities under restricted 3SLS. Standard errors in parentheses. Family-sized bottles sold through self-service outlets.

Specification:		Base	Robust 1A	Robust 1B	Robust 2A	Robust 2B	Robust 3	Robust 4
Number of brands, I		9	9	9	9	9	6	11
Coke	Family	-2.252 (0.175)	-1.942 (0.245)	-1.802 (0.195)	-2.111 (0.315)	-2.563 (0.386)	-1.382 ⁽¹⁾ (0.141)	-1.757 ⁽¹⁾ (0.166)
Diet Coke	Family	-3.059 (0.608)	-3.976 (0.691)	-3.407 (0.565)	-2.111 (0.737)	-2.138 (0.838)		
Fanta	Family	-2.032 (0.154)	-1.984 (0.158)	-1.986 (0.154)	-3.315 (0.292)	-2.427 (0.296)	-1.808 (0.165)	-2.225 (0.175)
Kuat	Family	-2.432 (0.170)	-2.416 (0.203)	-2.425 (0.191)	-2.115 (0.237)	-2.777 (0.319)		
Other Coke	Family	-3.762 (0.184)	-3.576 (0.193)	-3.631 (0.192)	-4.022 (0.227)	-4.101 (0.326)	-2.254 ⁽²⁾ (0.210)	-2.508 ⁽²⁾ (0.197)
Guar Antar	Family	-2.576 (0.171)	-2.681 (0.193)	-2.135 (0.188)	-3.046 (0.267)	-1.843 (0.319)	-2.338 (0.185)	-2.504 (0.189)
Pepsi	Family	-1.444 (0.365)	-1.128 (0.416)	-1.080 (0.388)	-2.682 (0.333)	-2.778 (0.360)		-2.449 (0.345)
Other Ambev	Family	-3.280 (0.321)	-2.991 (0.365)	-2.009 (0.457)	-3.904 (0.274)	-4.923 (0.404)	-1.742 ⁽³⁾ (0.291)	-2.738 (0.272)
B Brands	Family	-2.898 (0.177)	-2.683 (0.339)	-1.909 (0.464)	-1.736 (0.304)	-1.160 (0.330)	-3.385 (0.207)	-3.359 (0.207)
Coke	Single							-1.173 ⁽¹⁾ (0.155)
Fanta	Single							-1.520 (0.186)
Guar Antar	Single							-1.436 (0.066)
Pepsi	Single							-2.580 (0.361)

⁽¹⁾ Includes Diet Coke; ⁽²⁾ Includes Kuat; ⁽³⁾ Includes Pepsi

Figure 11: Estimated own-price elasticities under different specifications. Restricted 3SLS. Standard errors in parentheses. Sales through self-service outlets.

Elasticity	With respect to the price of											
	Coke w/Diet "Family"	Coke w/Diet "Single"	Fanta "Family"	Fanta "Single"	Other Coke "Family"	Guar Antar "Family"	Guar Antar "Single"	Pepsi "Family"	Pepsi "Single"	Other Ambev "Family"	B brands "Family"	
Coke w/Diet "Family"	-1.757 (0.166)	0.800 (0.141)	0.121 (0.073)	0.004 (0.036)	0.364 (0.075)	-0.053 (0.064)	-0.003 (0.057)	0.436 (0.094)	0.087 (0.058)	0.440 (0.089)	-0.551 (0.176)	
Coke w/Diet "Single"	0.521 (0.146)	-1.173 (0.155)	0.173 (0.066)	-0.090 (0.033)	0.041 (0.072)	-0.117 (0.060)	0.275 (0.062)	0.449 (0.083)	0.262 (0.054)	0.181 (0.081)	-0.601 (0.165)	
Fanta "Family"	-0.182 (0.268)	0.564 (0.161)	-2.225 (0.175)	0.200 (0.087)	-0.358 (0.153)	0.318 (0.142)	-0.159 (0.069)	0.972 (0.169)	0.388 (0.115)	0.502 (0.138)	-0.103 (0.230)	
Fanta "Single"	0.073 (0.348)	-0.165 (0.194)	0.660 (0.217)	-1.520 (0.186)	0.231 (0.234)	-0.081 (0.240)	0.089 (0.082)	-0.003 (0.255)	1.086 (0.182)	0.084 (0.201)	-0.565 (0.292)	
Other Coke "Family"	1.324 (0.236)	0.422 (0.161)	-0.211 (0.133)	0.051 (0.081)	-2.508 (0.197)	-0.095 (0.142)	0.182 (0.068)	0.552 (0.165)	0.214 (0.111)	-0.344 (0.138)	0.315 (0.240)	
Guar Antar "Family"	-0.034 (0.215)	0.334 (0.156)	0.447 (0.122)	-0.013 (0.082)	0.028 (0.142)	-2.504 (0.189)	-0.078 (0.063)	0.675 (0.162)	0.208 (0.110)	1.051 (0.136)	-0.232 (0.212)	
Guar Antar "Single"	-0.230 (0.146)	1.300 (0.147)	-0.057 (0.067)	0.022 (0.035)	0.264 (0.073)	-0.199 (0.061)	-1.436 (0.066)	0.001 (0.088)	0.096 (0.054)	-0.116 (0.087)	0.250 (0.174)	
Pepsi "Family"	0.492 (0.349)	0.837 (0.191)	0.940 (0.197)	-0.192 (0.127)	0.361 (0.227)	0.453 (0.222)	-0.397 (0.086)	-2.449 (0.345)	0.743 (0.184)	0.200 (0.204)	-1.004 (0.305)	
Pepsi "Single"	-1.371 (0.490)	1.167 (0.244)	0.712 (0.285)	0.969 (0.190)	0.179 (0.326)	0.043 (0.329)	-0.174 (0.106)	1.531 (0.386)	-2.580 (0.361)	0.305 (0.290)	-0.796 (0.405)	
Other Ambev "Family"	0.687 (0.359)	-0.311 (0.206)	0.376 (0.187)	-0.169 (0.117)	-1.200 (0.222)	1.277 (0.214)	-0.631 (0.095)	0.179 (0.247)	0.151 (0.169)	-2.738 (0.272)	2.378 (0.330)	
B brands "Family"	0.182 (0.147)	0.569 (0.152)	0.311 (0.072)	0.010 (0.036)	0.397 (0.081)	0.105 (0.064)	0.268 (0.057)	0.295 (0.105)	0.169 (0.063)	0.904 (0.099)	-3.359 (0.207)	

Figure 12: (Robustness test 4) Matrix of estimated elasticities under restricted 3SLS for family-size data augmented with single-size data for selected brands (Coke, Fanta, Guaraná Antarctica and Pepsi). Standard errors in parentheses. Sales through self-service outlets.

	p	(p-c)/p	c
Premium brands			
Behavioral assumption: Multi-product Bertrand			
Coke	1.02	85%	0.15
Fanta	0.86	59%	0.35
Guaraná Antarctica	0.93	47%	0.49
Pepsi	0.88	95%	0.04
Behavioral assumption: Multi-product Bertrand with Other Coca-Cola & Other Ambev not internalized			
Coke	1.02	60%	0.40
Fanta	0.86	66%	0.29
Guaraná Antarctica	0.93	38%	0.58
Pepsi	0.88	76%	0.21
Behavioral assumption: Single-product Bertrand			
Coke	1.02	44%	0.57
Fanta	0.86	52%	0.41
Guaraná Antarctica	0.93	38%	0.58
Pepsi	0.88	66%	0.30
B brands			
Behavioral assumption: Price-taking			
B brands	0.58	0%	0.58
Behavioral assumption: Single-product Bertrand, own-price elasticities of 6 (symmetric and limited differentiation)			
B brands	0.58	17%	0.48

Note: Prices in R\$ per liter at constant March 2003 prices. Variables are taken at their mean values across all geographic markets, and over time periods after July 1999. Supply-side estimates correspond to the base demand specification (restricted 3SLS, family-sized bottles sold through self-service outlets).

Figure 13: Inferred marginal cost under alternative behavioral assumptions (and the base demand specification – see Figures 10 and 11)