# Grab them Before they Go Generic: Habit Formation and the Emerging Middle Class*

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**Abstract**

The "emerging middle class" has become a force of great economic importance in consumer markets around the globe. This paper examines the impact of a substantial rise in Brazil's living standards on the development of the country's large soft-drink market, during a six-year period which saw unprecedented growth in the share of generic soda brands. Combining richly varying market and consumer-level data, we estimate a novel structural demand model that identifies a mechanism by which a household develops either a "premium brand habit" or a "frugal habit." We find strong empirical evidence of such persistence in preferences. Our results demonstrate that habit formation plays a crucial role in this emerging market: the arrival of many new consumers, who have not yet developed established habits, allows generic producers to more easily tap into this new demand for soda. Moreover, this persistence in preferences provides strong justification for Coca-Cola Co's decision to abruptly cut prices in July 1999. An estimated variant of our model, that does not account for habit formation, provides much weaker support for this strategic price cut.

**Keywords:** emerging middle class, social mobility, differentiated-product demand, habit formation, generics, competitive fringe, premium brands

**JEL Classification:** L10, D12, O12

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"A study this year by the United Nations Economic Commission for Latin America and the Caribbean concluded that tens of millions of the region's inhabitants have risen into the middle class over the past two decades. That's prompted 'a notable expansion of the consumer market,' ...(thanks to) the prospects of los emergentes—the emerging ones—as marketers call the newly minted middle-class members."

Matt Moffett, *The Wall Street Journal*, November 15, 2011

"Across the developing world millions—perhaps billions—of people are currently forming tastes that will endure for the rest of their lives. Put one of Kraft's Oreos or Cadbury's Flakes in their hands and they may become loyal customers for decades to come."

*The Economist*, November 5, 2009

# 1 Introduction

The "emerging middle class" has become a major economic phenomenon in consumer markets around the globe. Since the mid 1990s, many developing countries, as far-flung and varied as Brazil, China, India, Indonesia and Turkey, are experiencing a socioeconomic transformation, whereby a substantial mass of low-income households emerge from below the poverty line and begin to consume goods and services that they previously could not afford.[1] Bolstering the demand for many consumer goods, these "new consumers" provide a potential engine of growth for the global economy. This new source of demand calls for the development of empirical tools to examine both its nature and the implications for competition in emerging consumer markets.

Our paper examines this demand expansion process via an important test case: the Brazilian market for carbonated soft drinks (or "soda"). We study the evolution of this market from December 1996 through March 2003, a six-year period over which two striking phenomena were evident: a substantial expansion in demand fueled by rising living standards, and the rapid growth of a competitive fringe of soda producers.

Brazil's large soda market trails only the United States and Mexico by volume. Following a successful economic stabilization plan in 1994, aggregate soda consumption doubled by 1997, and continued to grow at an annual rate of about 10% through 1999. As is well documented, this growth was driven by pronounced upward mobility among lower income households, who

[1] The Economist (2011a) states that, using a broad income definition, "(t)he middle classes...trebled in number between 1990 and 2005 in developing Asia to 1.5 billion." Nomura Bank states that by 2014 Indonesia should boast almost 150m "newly affluent Indonesians (who) are certainly spending" (The Economist, 2011b).

were no longer forced to pay an "inflation tax."[2] In 1999, the Financial Times reported that "the increased purchasing power that came with stable prices... allowed about 25m new consumers into the (soft drink) market" (among a total population of 170m at the time). Other markets, ranging from fresh meat to refrigerators to housing, saw similar expansions in demand.

One might have expected that established soda producers, namely the Coca-Cola Company (hereafter Coca-Cola) and Ambev, who in 1996 jointly accounted for almost 90% of Brazilian soda expenditure, were best positioned to tap into this new demand for soda.[3] Instead, between 1996 and 1999, the combined volume share of (ultimately) hundreds of regionally-focused discount brands—which we label "generics"—doubled from 20% to 40%.[4] In contrast to the dominant duopoly's heavy investments in advertising, generic producers focused their marketing efforts on securing shelf space via low prices. With the stiff competition slowing down company growth, "Coca-Cola blamed difficulties in developing countries such as Brazil when it shocked Wall Street in December (1998) by announcing a rare drop in quarterly sales" (Financial Times 1999).

Having kept prices broadly constant during the preceding years of entry and expansion in the fringe, in 1999 Coca-Cola abruptly cut prices across its brands by over 20%, a move that was soon matched by Ambev. Following this price cut, the growth in the market share of the generic fringe was halted. As we discuss below, however, the fringe was able to hold its ground, continuing to command substantial market share even after the premium brands' large price cut.

The goal of this paper is to examine whether—and via which mechanisms— the emerging middle class can provide fertile ground for the growth of a generic fringe.[5] We focus on two possible (and not mutually exclusive) mechanisms that may have been playing a role in the Brazilian soda market. First, emerging middle-class consumers may have been price sensitive, and thus likely to favor cheap generics over expensive brands. To stay with the Financial Times' analysis, "(t)he new (soda) customers...had different priorities...(t)hey were less concerned about expensive TV ads and more interested in value." A price-sensitive, expanding consumer segment may help explain both the growth of generics and the premium sellers' price cut.

Second, it is conceivable that, upon their arrival in the market, the new customers were starting to form consumption habits and tastes in the soda category. The absence of habits may have aided generic entrants in making inroads into this emerging consumer segment. Moreover, if

[2] A substantial mass of households with no access to inflation-indexed bank accounts were the main beneficiaries of the taming of chronically high inflation: "...Jose Benevenuto, a 53-year-old Rio de Janeiro bus driver...still recalls the years in the early 1990s when Brazil's four-digit inflation forced him to rush to the supermarket as soon as he was paid so he could spend his money before it lost all value" (Wall Street Journal 2011). By 1995, inflation was (sustainably) down to single-digit annual levels.

[3] Ambev distributed the Pepsi brand, and is now part of the AB Inbev group.

[4] This pertains to the dominant market segment of family-size bottles sold through the "self-service outlets" distribution channel (supermarkets with checkouts) in urban areas.

[5] Several emerging markets appear to feature a substantial presence of generic producers, underscoring the research question. The China-based appliance manufacturer Galanz cites the National Bureau of Statistics in claiming that there were "nearly 300 brands in (the) Chinese market" in 2008 (Galanz 2008). The Economist (2012) counts 100 "domestic carmakers" in China. Abbott India's brands Digene, Eptoin and Cremaffin face competition from 211, 327 and 242 "regional" generics, respectively (as shared by the company during a corporate presentation in late 2011).

persistence in consumer tastes is important, this second mechanism may have provided a strong incentive for Coca-Cola to cut prices with the goal of defending its future market position.[6]

The extent to which the emerging middle class is price sensitive, as well as the extent to which habit formation plays a role in such markets, are matters for empirical investigation. To this end, we develop and estimate a structural model of demand that allows us to segment consumers according to both their socioeconomic standing and their consumption habits. Our model is well-suited for a fast-changing emerging market setup, and is estimated using a combination of market-level and consumer-level data. Building on the random-coefficient logit framework, our model displays two novel features.

First, we allow consumers to belong in one of three discrete demographic groups: "poor," "established affluent," or "*newly* affluent." Established affluent households are those who were already affluent before the process of upward mobility began, whereas newly affluent households represent the new middle class. In our model, poor households can move up to newly affluent status, while downward mobility is captured by allowing newly affluents to move down to poor status. Such downward mobility is apparent toward the later part of our sample period, when the Brazilian economy was hit by a recession. In addition to upward and downward mobility, our model also accounts for *urbanization*, another pervasive demographic shift.

The second key component of our model is habit formation, of a special kind. In particular, we allow for three habit states: a habit to consume premium soda brands (a "premium habit"), a habit to consume generics (a "generic" or "frugal" habit), or not developing a habit to consume soda. Habits develop according to the choice made by the household in the immediately preceding period.[7] We label this a *Brand Type Persistence* (BTP) mechanism, as it captures a persistence in demand for a certain type of good (i.e., premium or generic). In our model, developing a premium habit in period $t-1$ (by consuming, say, Coke) increases the utility from consuming any premium brand (say, Coke, Fanta or Pepsi) in period $t$. Similarly, recent consumption of a generic brand raises the utility from current consumption of this or any generic brand. This parsimonious modeling approach allows us to capture the key dichotomy between premium versus generic soda products in a rapidly evolving market, where consumers establish shopping patterns that may endure into the future.

A household's type in our model is determined by both its current socioeconomic standing and its current habit state. We extend the empirical literature on discrete-type demand models to our emerging market setup. In particular, we develop an estimation algorithm that tracks the

[6]The role of habit formation in food and beverage has been emphasized in the literature. See Atkin (2011) and Bronnenberg, Dubé and Gentzkow (2012) for recent contributions.

[7]Much of the extant literature on state-dependent preferences assumes that current "habits" were developed in the immediately preceding period. In most papers, periods are captured as shopping trips in household-level retail scanner data. In contrast, a period in our setting lasts one or two months, an interval we view as more appropriate for our habit formation context. A more general model would allow habits to evolve as a function of consumption choices over multiple preceding periods.

population fractions that belong in each type over time. This is accomplished by combining data on aggregate demographic trends with brand choices predicted from our utility framework.

**Findings.** We find that, while newly affluent households are significantly less price sensitive than the poor, their price sensitivity is comparable to that of the established affluents. Our findings do not, therefore, lend support to the notion that the new middle class was especially price sensitive, and that it was via this mechanism that the emerging middle class provided suitable conditions for the growth of the competitive fringe.

Our estimated model does, in contrast, provide strong empirical evidence for the second mechanism hypothesized above: habit formation. This persistence in preferences is shown to be of both statistical and economic significance. Our model allows us to evaluate the *monetary value of habit formation*: for example, a "frugal habit" increases a newly affluent consumer's willingness to pay for a generic product by (Brazilian Real) R$ 2.04 (about US$ 1) per liter relative to displaying no habit. This suggests that habit formation played a prominent role in driving the growth of generic brands. It also explains the sense of urgency with which premium brands acted when they cut prices in mid 1999: had they failed to cut prices, an increasing fraction of new middle-class consumers would have "gone generic." A premium price cut helped ensure that many of these consumers developed a premium habit instead.

We further demonstrate this intuition by employing our model in counterfactual analysis. We find that, had premium brands failed to cut prices in mid 1999, they would have seen their market shares and variable profits suffer substantial declines through 2003. Our estimated BTP model, therefore, provides strong justification for this strategic move. This analysis further indicates that the price cut was more effective with consumers who were yet to form soda-consuming habits, and less effective with consumers who had already developed a generic habit. Finally, and importantly, an estimated model variant that shuts down the habit mechanism provides much weaker support for the premium price cut.

**Identification.** Our empirical approach faces a familiar challenge: how can one separately identify consumer heterogeneity from persistence in tastes? In our analysis, this is accomplished by relying on the rich cross-sectional and time-series data variation in this rapidly changing market. In particular, we exploit region-specific social mobility and pricing variation that is likely exogenous to demand *unobservables*. For example, the magnitude and abruptness of Coca-Cola's nationwide price cut halfway into the sample period strongly suggests that it was unlikely to be correlated with any contemporaneous region-specific shocks to demand, making the price cut itself an effective instrument (Salvo 2009).

Our model allows price sensitivity to vary at the socioeconomic level, identifying it off of the observed co-variation of socioeconomic shifts (i.e., upward and downward mobility), prices and market shares. Identification of the habit mechanism also follows from data variation: for instance, during the recession that set in toward the end of our sample period, households fell back from newly affluent status to the ranks of the poor, yet soda consumption did not fall.

Our framework offers another important insight regarding identification: failing to control for persistence may frustrate the identification of the distribution of consumer price sensitivity. Indeed, the model variant that we estimate shutting down habits biases the price sensitivity of the newly affluent in the direction of that of the poor. Intuitively, this may be explained by the recessionary period, when an increasingly poor population continued to consume stable amounts of soda. A model that does not allow for persistence would have to interpret this as evidence that the poor are "not that price sensitive."

**Literature.** Our study contributes to different lines of research. One line examines competition between branded products and lower cost generics, particularly in pharmaceuticals, including Chaudhuri, Goldberg and Jia (2006) in India, and Hurwitz and Caves (1988) and Scott Morton (2000) in the US. Another line of work examines the relationship between the demographic composition of demand and prices, or inflation moderation (e.g., Frankel and Gould 2001, Bils and Klenow 2004, Nevo and Hatzitaskos 2006, Lach 2007, Calzolari, Ichino and Manaresi 2012).

The empirical literature in economics and marketing has introduced habits or persistence into models of consumer choice, including Eichenbaum, Hansen and Singleton (1988), Erdem (1996), Keane (1997), Shum (2004) and Dubé, Hitsch, Rossi and Vitorino (2008). Our work differs from the extant literature along several dimensions. First, existing studies tend to rely on micro-level panel data, repeatedly observing an individual household's purchasing behavior. When studying an emerging market, repeated observations on a fixed panel of households are less likely to be available. Furthermore, they may miss the demographic shift that lies at the heart of the analysis. Our paper demonstrates that a model with persistent preferences can be estimated with a panel of market-level data (in addition to a single cross-section of household-level data). This is made possible by the rich data variation afforded by the emerging market setup.

Second, the state dependence we model differs from brand loyalty. It is motivated by a desire to address the heterogeneity in business models between premium and generic sellers which plays an important role in some emerging markets.[8] By emphasizing this aspect, our goal is to capture a potentially important mechanism in such settings, rather than to extend the brand loyalty literature. Our focus on emerging markets rather than mature ones marks another departure from the extant literature on persistent preferences. Beyond its economic importance, the emerging market setting provides a unique opportunity to identify and study state-dependent preferences. Finally, this paper wishes to contribute to a better understanding

[8]Executives of a global "fast-moving consumer goods" firm meeting one of us recently in Delhi stated that "as a company in the *A business* we don't naturally understand the *B business*, where the *value* proposition is at the heart of it, putting us at a certain disadvantage when selling to the *Bottom of the Pyramid* in the Indian market." (To be clear, all words—including the terms in italics—are the executives' own, though in slightly rearranged order without modifying context.)

of demand in emerging market settings. Another example is Sancheti and Sudhir (2009), who examine the consumption of education in India. The rapid growth of such markets suggests that studying them offers a promising avenue for applied microeconomic research.

The rest of the paper is organized as follows. Section 2 describes the data and the joint phenomena that motivate our analysis: upward social mobility and the growth of the generic fringe. Section 3 develops our demand model. Section 4 explains our estimation algorithm and provides arguments for identification. Section 5 reports estimation results, as well as counterfactual analysis. Section 6 concludes.

## 2 Market and data

This study brings together data from three main sources. The following subsections describe these data sources, as well as the manner with which they reflect the two striking phenomena discussed above: the emergence of a new middle class and the growth of the generic fringe.

### 2.1 Market-level data

We observe a panel of market-level data from Nielsen, consisting of total quantities and prices for soft drink brands. There are $g = 1, ..., 7$ regions and $t = 1, ..., 57$ time periods, ranging from the December 1996-January 1997 bimonth to the March 2003 month (Nielsen raised the frequency of its bimonthly point-of-sale audits to a monthly basis in 2000). We therefore observe $7 \cdot 57 = 399$ region-period markets.

The seven geographic markets are urban and, as in Salvo (2009), we consider soft drinks sold through the "self-service" channel (supermarkets with checkouts) in the 2-liter family-size bottle. Our focus on this market segment is justified on several counts. First, the focus on urban areas is natural since more than 80% of Brazil's population was urbanized by 1996 and, importantly, our framework allows for rural-to-urban migration. Second, urban households in Brazil perform most of their grocery shopping in supermarkets with checkouts, rather than in traditional behind-the-counter retail stores. Finally, sales of family-size bottles dominate those of "single-serve" (300ml) bottles or cans (mostly sold in bars and restaurants). Moreover, the competitive fringe, whose success we wish to explain, was mostly present in the family-size bottle segment.

Also following Salvo (2009), we aggregate flavors and brands into $j = 1, ..., 9$ brand-groups. These groups include eight "premium brands" (or "A-brands"): five brands of the Coca-Cola Company (Coke, Fanta, the guaraná-flavored Kuat, Diet Coke, and "Other Coca-Cola"), and three brands marketed by Ambev (Guaraná Antarctica, Pepsi, and "Other Ambev"). The ninth brand category is an aggregate of discount brands (or "B-brands") that form the generic fringe.[9]

[9]The data provide limited information on the breakdown of this group into individual discount brands, as they are so numerous.

Table 1 describes the volume shares (of the soda category) for each of the nine brands across the seven Nielsen regions, in the first and last periods in our sample (all statistics pertain to family-size bottles sold in supermarkets with checkouts). Averaged arithmetically across regions, Coca-Cola's brands accounted for a 50% volume share in the first period, with Coke being dominant, whereas Ambev enjoyed a 31% share, with Guaraná Antarctica and Pepsi as its flagship brands. The table reports the stark growth in the generic share, from 19% at the start of the sample to 40% at the end. The table reflects some region-specific tendencies to consume particular brands. Our empirical framework controls for such region-brand effects.

**Defining market size.** We denote the observed quantity and price associated with brand $j$ sold in the region-period market $gt$ by $q_{jgt}$ and $p_{jgt}$, respectively. As is common in discrete-choice applications, we need to define the size of market $gt$, that is, the maximum amount of soft drinks that can potentially be consumed in this market. We define this quantity, denoted $\mathcal{M}_{gt}$, as six liters per week over the duration of period $t$ multiplied by the number of urban households residing in market $gt$ (which we obtain from a fourth data source). One may interpret the six liters per week as three weekly family meals in which a 2-liter family-size bottle of soda might be brought to the table (rather than water, juice, etc). We then compute brand $j$'s share as $s_{jgt} = q_{jgt}/\mathcal{M}_{gt}$. The share of the outside option (that is, the option not to consume soft drinks) is given by $s_{0gt} = 1 - \sum_j s_{jgt}$.[10]

**The growth of the competitive fringe and Coca-Cola's response.** In contrast to the established Coca-Cola/Ambev duopoly, with their heavily advertised brands and nationwide distribution, fringe players ran small-scale operations, in most cases individually covering a fraction of a state, and selling at substantially lower prices. Having hovered around a 15% volume share of the soda category at least since 1980 (Salvo 2009), the fringe began growing strongly in the mid 1990s, as evidenced in Table 1. A shift from the returnable proprietary glass bottle (returned to the bottler for reuse, requiring a certain level of sophistication and scale) to the inexpensive non-returnable 2-liter PET bottle may have lowered barriers to entry (Ambev 2003). No census of fringe operators exists, but industry sources suggest that following three years of substantial entry, the number of firms selling generic soda may have reached 500 by 1999.[11]

Figure 1 reports that both premium and generic brands enjoyed substantial volume growth during the sample period (for illustrative purposes only, the figure aggregates quantities sold over all seven regions, and aggregates all eight premium brands together). Importantly, the generic fringe grew much faster than the premium brands over the first 30 months of the sample—that is, until Coca-Cola's abrupt mid 1999 price cut. The figure also reveals strong seasonality effects,

The aggregate structure of this data is indicative of how Coca-Cola and Ambev—two of Nielsen's largest customers—viewed brand differentiation within the generic fringe.

[10] The appendix reports robustness checks which reassure us that our results are not overly sensitive to the market size definition.

[11] The Financial Times (1999) speaks of over 900 companies in the industry, while Ambev's (2003) financial reports refer to 700 "low-price brands."

for which we control in the empirical application.

The left panel of Figure 2 illustrates the evolution of (mean share-weighted) prices for premium brands and for generics in R$ per liter.[12] Premium brands initially held prices broadly flat, at R$ 1.15. In mid 1999, Coca-Cola cut its prices by more than 20%, a move that was soon matched by Ambev. The figure clearly indicates the sudden nature of this price cut, which we will exploit for identification purposes.

For their part, prices in the fringe declined gradually but relentlessly, from R$ 0.90 in late 1996 to R$ 0.60 in late 2000.[13] Falling generic prices are consistent with substantial entry and capacity expansion in the fringe, as competitive firms passed efficiency gains through to consumers. Fringe prices did not respond to the premium price cut in the sense that they did not deviate from their trend, consistent with competitive behavior.

As the right panel of Figure 2 shows, after 30 months of generics gaining share at the expense of the premium brands, the premium price cut had a clear and immediate impact. It essentially put an end to the staggering generic growth, and led to stable volume shares for premium and generic brands through the end of the sample.

### 2.2 Data on aggregate social mobility

To track the undercurrent of social mobility in the Brazilian economy, we rely on the proprietary LatinPanel survey from IBOPE, a leading (private-sector) provider of data on consumer demographics.[14] The survey, widely used by marketing practitioners, profiles urban households in Brazil's different regions based on their expenditure on durable goods and services (e.g., ownership of a refrigerator, numbers of TVs and bathrooms in a residence, current employment of house maids, education attainment). Adopting an industrywide points scale (ABEP 2003), each household is assigned to a "socioeconomic group." The IBOPE data that we have access to covers the period 1994-2006 (with 1995 missing) and provides the proportion of urban households that belong in either the **AB**, **C** or **DE** groups (respectively with "high," "intermediate" or "low" levels of affluence) in each of seven geographic regions.[15]

The IBOPE data indicate that the demographic composition of urban households: (i) was stable between 1994 and 1996; (ii) displayed strong upward mobility from **DE** to **ABC** (i.e., {AB,C}) status between 1996 and 2000; and (iii) experienced a partial reversal of this upward

[12]Throughout the paper, R$ prices are reported at constant Brazil CPI March 2003 terms (divide by 2 for rough US$ values).

[13]Given that we convert prices to constant R$ (see the appendix), what this means in practice is that nominal prices in the fringe fell 17% compared with the overall price level in the economy (the CPI) growing by 25% over the 45 months to September 2000, i.e., $.6/.9 \simeq (1-.17)\,/\,(1+.25)$.

[14]The company's name is so established among Brazilian households that, as cited in Wikipedia, it is synonymous with research (e.g., see the *Aurélio* Portuguese language dictionary). Coca-Cola kindly shared the data with us for the purpose of this study.

[15]The points scale used to classify each household stays clear of income, there being reasons why income-based measures might less accurately reflect changes in the standard of living (Carvalho Filho and Chamon 2011, Economist 2007). That said, to provide perspective, mean annual incomes in 2000 for **C** and **DE** urban households were respectively US$ 6,100 and US$ 2,600 (ABEP 2003, based on an IBOPE survey, using nominal 2000 R$/US$).

mobility thereafter, consistent with a recession setting in at that time. In aggregate, the proportion of **DE** households fell from 50% in 1996 to 33% in 2000, then rose to 44% by 2003 (conversely, the **AB** proportion rose from 19% in 1996 to 33% in 2000, then fell to 23% by 2003).

These demographic patterns are consistent with media and market research reports. The 1996-1999 upward mobility was fueled by successful economic reforms in the early 1990s, including trade liberalization and, most notably, the taming of very high inflation by the 1994 *Real* stabilization plan. These reforms were followed by strong consumption growth across the Brazilian economy, particularly among lower-income households. Figure 3 reports per capita consumption between the mid 1980s and mid 2000s in two different sectors—beverages (soft drinks) and housing (cement); a similar temporal pattern leading up to 2000 is present.[16]

The Boston Consulting Group (2002), reporting on its own household survey, spoke of the emergence of a middle class with "very strong consumer potential," whereas Fátima Merlin, chief economist for the Brazilian Association of Supermarkets (ABRAS), referencing the same IBOPE data that we use, stated that "following the *Real* Plan, thanks to price stability and real growth in workers' earnings, consumer markets experienced entry by households previously outside such markets, *with upward migration from the 'E' and 'D' segments of the population* to the 'C' segment, *as the IBOPE data indicate*" (SuperHiper 2003; emphasis added).

As for the downward mobility reported by IBOPE over 2001-2003, economic episodes that may have dampened investor and consumer sentiment include the 1997-98 Asian crisis, the 1999 Brazilian currency crisis, and the 2000-01 Argentine crisis.[17]

To analyze the impact of the changing socioeconomic composition, we define three socioeconomic groups: "Established Affluent" (EA), "Newly Affluent" (NA) and "Poor" (P). Using the IBOPE proportions together with urban household counts, we track the number of households who belong in each of these groups, in each region and over time.[18] Our "Established Affluent" group consists of urban households who were already in **ABC** status in 1996, i.e., before the process of upward mobility took off. The number of households in this group, in each of the seven regions, is thus fixed across time at the initial number of **ABC** households in that region. We define the size of the "Poor" group in each region-period market $gt$ by that market's number of urban households who belong to socioeconomic group **DE**.

Finally, we define the size of the "Newly Affluent" group in market $gt$ as the difference between the contemporaneous number of **ABC** households and region $g$'s initial (i.e., 1996) number of **ABC** households. In other words, the number of time-$t$ newly affluents is computed by subtract-

[16]See Carvalho Filho and Chamon (2011) and Salvo (2009, 2010) for further discussion of the consumption effects of reforms in the 1990s. See also Neri (1995).

[17]A similar temporal pattern of prosperity can be detected in earnings data in IBGE's monthly survey of earnings and employment, conducted in 6 large cities, though the turning points in the series tend to occur sooner than 2000. Details are available from the authors upon request.

[18]The appendix details how we interact IBOPE's urban socioeconomic distributions with the number of urban households from IBGE's annual household surveys (PNAD), as well as consistency checks between IBOPE and IBGE survey data.

ing the region's (fixed) number of established affluents from the number of time-$t$ households in **ABC** status.[19]

To illustrate our computations by way of an example from the IBOPE data, in the South region there were: (i) in $t = 1$ (Dec-96/Jan-97), 3149 (thousand urban) **ABC** households and 2116 **DE** households, and (ii) in $t = 2$ (Feb/Mar-97), 3238 **ABC** households and 2045 **DE** households. Between these periods, $3238 - 3149 = 89$ poor households moved up to newly affluent status (and the number of migrants grew by $3238 + 2045 - (3149 + 2116) = 18$). Thus the numbers of established affluents, newly affluents and poor in this region, respectively, are (3149,0,2116) in period 1 and (3149,89,2045) in period 2.

In the data, the number of newly affluent households is strictly positive for all regions and all time periods $t > 1$, and is equal to zero, by definition, for $t = 1$, the initial period of our Nielsen soda market data described above. The zero number of newly affluents in period 1 is justified by the fact that, in the IBOPE data, the process of upward mobility takes off just before our Nielsen sample begins in late 1996. This assumption is also consistent with press and trade articles from the time. For example, our measure of the number of newly affluent households in 1999, summed across the seven Nielsen regions, translates into 20m consumers, a notch below the Financial Times' (June 1999) count of "(Brazil's) 25m new consumers (in the aftermath of an) economic plan" (and noting that our study does not cover rural areas or the northern states).

Figure 4 plots the evolution of the socioeconomic composition by region, i.e., the population fractions of established affluent, newly affluent and poor households. The figure clearly demonstrates the emergence of a new middle class. The increase, toward the end of the sample period, in the fraction of the poor at the expense of the fraction of newly affluents reflects the joint effects of the recession and the urbanization process. There are large regional disparities, with region 1 (states in the Northeast) being the least affluent and region 4 (São Paulo Metro) being the most affluent (65% and 36% of urban households in these regions are initially poor, respectively).

### 2.3 Data on household-level brand choices

Our third main data source allows us to relate household characteristics to soda consumption choices at the beginning of our period of study. We use an urban household expenditure survey conducted between October 1995 and September 1996 by IBGE (a federal agency equivalent to the US Census Bureau and Bureau of Labor Statistics combined). This survey (hereafter HEX 95/96) reports the type of soda brand purchased, as well as the amount spent, for consumption inside the home. Households in the survey are not classified according to the ABCDE system, but we use the detailed information available (e.g., ownership of a refrigerator, numbers of TVs

[19] In addition to upward and downward mobility, another demographic force affecting group sizes is (net) rural-to-urban migration. We capture this process via changes in the urban household population, assuming that households migrating to the city are initially "Poor." See Assumption 2 below.

and bathrooms in the residence, current employment of house maids, education attainment) to assign, like IBOPE does, each household to a socioeconomic group from A to E.

Table 2 reports the relationship between inside-the-home consumption of soft drinks and socioeconomic status. For example, 34.5% of São Paulo Metro's (region 4) **ABC** households in 1996 purchased soda for home consumption whereas only 19.8% of **DE** households did so. Table 2 also shows, for each of the different regions, the share of **ABC** households who consume a premium (generic) brand, and similar figures for **DE** households. These reflect the co-variation between a household's socioeconomic standing and its choice between premium and generic brands. Across all cities, **DE** soda-consuming households were more likely to purchase generics over premium brands (12 : 163) *relative* to **ABC** soda-consuming households (11 : 339). It is worth noting that our modeling of soda-consuming households at each point in time as either premium or generic shoppers, but not "hybrids," is largely consistent with the HEX data.

As we explain below, the fact that the HEX survey was conducted shortly before the beginning of our Nielsen market data allows us to use this information as an "initial condition" for the evolving relationship between socioeconomic standing and consumption choices.

**Additional data sources.** Our analysis draws on additional data: (i) the population of urban households by region from IBGE's expanded annual household surveys (PNAD), (ii) proprietary McCann-Erickson data on advertising intensity at the brand-market level, (iii) proprietary temperature data (another demand shifter) from the National Institute of Meteorology, and (iv) data from various sources on cost shifters such as the prices for sugar, electricity and fuel.

## 3 The model

We develop a model of household demand for soft drinks which accounts for socioeconomic standing and habit formation. Our model accommodates the fundamental features of the data noted above. In particular, we do not observe household-level data over time. We do observe the region-specific, temporal evolution of aggregate brand market shares and prices, and of households' socioeconomic composition. The proposed model allows us to identify consumer demand, and, importantly, the persistence component, given the available data variation.

### 3.1 Household types and the utility framework

In each period $t$, a household belongs in one of three socioeconomic groups $(EA, NA, P)$ (again, established affluent, newly affluent or poor) and, consistent with the data, we allow for region-specific, aggregate mobility across these groups over time.

We denote the eight premium brands (or A-brands) as elements of the set $\mathcal{A}$, and the ninth brand category as the only element of the set of generics (or B-brands) $\mathcal{B}$. A household's current preferences over substitute soft drink brands depend on its current socioeconomic standing as well as on the household's previous-period consumption by virtue of a habit mechanism. We allow for three habit states. Specifically, we differentiate households who, in the preceding period, consumed: (i) a premium brand $j \in \mathcal{A}$, (ii) a generic brand $j \in \mathcal{B}$, or (iii) did not consume soda at all, i.e., chose $j \in \mathcal{O}$, with $\mathcal{O}$ denoting the outside option set. Crossing together the three socioeconomic states and the three habit states, we obtain nine discrete household types, indexed by $r$:

$$r \in \mathcal{R} := \left\{EA^{\mathcal{A}}, EA^{\mathcal{B}}, EA^{\mathcal{O}}, NA^{\mathcal{A}}, NA^{\mathcal{B}}, NA^{\mathcal{O}}, P^{\mathcal{A}}, P^{\mathcal{B}}, P^{\mathcal{O}}\right\} \tag{1}$$

Thus, for example, a time-$t$ newly-affluent household who consumed a generic brand in period $t-1$ is of type $r = NA^{\mathcal{B}}$, whereas an established affluent household who consumed a premium brand in the preceding period is of type $r = EA^{\mathcal{A}}$. Fixing a region-period market $gt$, let $F_{r,gt}$ denote the fraction of that market's household population that belongs to type $r$. We collect these fractions for the nine types in a 9-dimensional vector denoted $\mathcal{F}_{gt}$, to which we refer as market $gt$'s *type-distribution vector*.

The indirect utility of household $i$ of type $r$ in market $gt$ from consuming brand $j$ is given by:

$$u_{i\in r,j,gt} = \delta_{jgt} + \alpha_r \cdot p_{jgt} + \lambda \cdot h_{jr} + \epsilon_{ijgt} \tag{2}$$

We now explain each component of this function. The term $\delta_{jgt}$ denotes a market-specific, household-invariant base utility from brand $j$:

$$\delta_{jgt} = x'_{jgt}\beta + \alpha \cdot p_{jgt} + \xi_{jgt},$$

where $x_{jgt}$ contains brand-region fixed effects, seasonal effects, brand-level advertising, market temperature, and region-specific time trends. These trends allow for region-specific temporal evolution in the utility from the outside option, such as differential rates of expansion in markets for soft-drink alternatives (e.g., juices). The brand's price is $p_{jgt}$, and $\xi_{jgt}$ denotes a (brand-market specific) utility shock observed by firms and consumers, but unobserved to the econometrician, and $(\alpha, \beta)$ are coefficients to be estimated.

The second and third terms in (2) introduce household-type heterogeneity. The parameter $\alpha_r$ shifts the base price sensitivity $\alpha$ in accordance with the household type $r$:

$$\alpha_r := \begin{cases} \alpha_{EA} \text{ if } r \in \left\{EA^{\mathcal{A}}, EA^{\mathcal{B}}, EA^{\mathcal{O}}\right\} \\ \alpha_{NA} \text{ if } r \in \left\{NA^{\mathcal{A}}, NA^{\mathcal{B}}, NA^{\mathcal{O}}\right\} \\ 0 \text{ otherwise} \end{cases}$$

This implies that while $\alpha$ is the price sensitivity of poor households, the sums $(\alpha + \alpha_{EA})$ and $(\alpha + \alpha_{NA})$ are the price sensitivities of the established affluent and the newly affluent, respectively. Note that we allow price sensitivity to vary with a household's socioeconomic standing, but not with its "habit." Below we provide intuition for the role played by this restriction in the identification of the model.

The variable $h_{jr}$ in (2) captures the persistence, or "habit," feature, and is given by:

$$h_{jr} := \begin{cases} 1 \text{ if } r \in \left\{EA^{\mathcal{A}}, NA^{\mathcal{A}}, P^{\mathcal{A}}\right\} \text{ and } j \in \mathcal{A} \\ 1 \text{ if } r \in \left\{EA^{\mathcal{B}}, NA^{\mathcal{B}}, P^{\mathcal{B}}\right\} \text{ and } j \in \mathcal{B} \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

This specification implies that consuming *any premium brand* in the previous period increases one's utility from consuming *any premium brand* in the current period by a magnitude of $\lambda$. Such a household is characterized by a "premium" habit in the current period. Similarly, consuming *any generic brand* in the previous period shifts one's utility from consuming *any generic brand* in the current period by $\lambda$, a situation we refer to as a "frugal" or "generic" habit.

Our modeling of habit formation is parsimonious in a couple of ways. First, habit is formed toward a class of brands—premium or generic— rather than toward an individual brand. This choice is driven by our motivation: to effectively capture a potentially important mechanism in an emerging market setting characterized by rapid growth in discount brands with minimal advertising.[20] Second, our specification implies that both premium and frugal habits boost household utility by the same magnitude of $\lambda$. It is worth noting, however, that a model variant in which we allowed these habits to differ across brand types produced similar magnitudes for the two effects.

The last term in the utility function, $\epsilon_{ijgt}$, represents household and product-specific shocks that follow the Type I Extreme Value distribution and are i.i.d. across households, brands and markets. We complete the utility specification by defining the utility from the outside option, $u_{i\in r,j=0,gt} = \epsilon_{i,0,gt}$. The model's parameters to be estimated are denoted $\theta = \left\{\beta, \alpha, \alpha_{EA}, \alpha_{NA}, \lambda\right\}$. Following familiar terminology from the literature on random-coefficient logit models, we classify these into "linear parameters" $\theta_1 = \left\{\beta, \alpha\right\}$, and "non-linear parameters" $\theta_2 = \left\{\lambda, \alpha_{EA}, \alpha_{NA}\right\}$.

[20] In the appendix we report a robustness check in which we modified our specification to consider brand-loyalty effects. Our findings were qualitatively similar.

We refer to this baseline specification as the *Brand Type Persistence* (BTP) model, and it is on this specification that we base our empirical work. We also estimate a variant of this model which forces $\lambda$ to equal zero, i.e., it shuts down the habit mechanism. This model variant helps us illustrate the importance of allowing for persistence in household preferences.

Two additional aspects of the demand model are worth noting. First, allowing habit to develop as a consequence of choices made in the preceding period only (as opposed to allowing it to form over a longer history of choices) is consistent with the literature of which we are aware (e.g., Dubé, Hitsch and Rossi 2010). Importantly, the time interval between the current and preceding periods is one or two months. This is longer than the typical interval between shopping trips in the scanner data often used in such applications. In that sense, relying on the preceding period is less restrictive in our application.

Second, consumers in this model are not forward-looking, that is, they make static choices that maximize current-period utility and do not internalize the effect of current choices on future utility. Given the nature of soft drinks (non-durable, relatively inexpensive goods), we view this static modeling approach as appropriate, and, once again, it is consistent with the empirical literature on state-dependent preferences.[21] Nonetheless, the demand patterns implied by this model do reflect a dynamic "persistence" feature, and we seek to understand how this feature interacts with the dynamics in demography (i.e., socioeconomic mobility)—and the implications of those dynamics for competition between premium and generic brands.

The share of type-$r$ households consuming brand $j$ in market $gt$ is given by the logit formula:

$$s_{j,r,gt}(\theta) = \frac{exp(\delta_{jgt} + \alpha_r \cdot p_{jgt} + \lambda \cdot h_{jr})}{1 + \sum_{\ell=1}^{J} exp(\delta_{\ell gt} + \alpha_r \cdot p_{\ell gt} + \lambda \cdot h_{\ell r})}, \tag{4}$$

where $J = 9$ is the number of brands sold in each market. The notation $s_{j,r,gt}(\theta)$ reflects the fact that these shares are model predictions and they depend on parameter values. Brand $j$'s predicted aggregate share is the weighted sum of the shares of the nine household types choosing brand $j$, where the weights are the population fractions that belong to these types:

$$s_{jgt}(\theta) = \sum_{r \in \mathcal{R}} F_{r,gt} \cdot s_{j,r,gt}(\theta) \tag{5}$$

Consistent with the literature on estimating demand models with discrete-type heterogeneity (e.g., Berry, Carnall and Spiller 1996, Kalouptsidi 2010), the type-specific shares $s_{j,r,gt}(\theta)$ from (4) are not observed in the data, and our estimation strategy is, therefore, based on matching the aggregate shares $s_{jgt}(\theta)$ predicted from (5) with shares $s_{jgt}$ computed from the Nielsen data (see

[21] An alternative is to follow the dynamic estimation literature and model consumers as maximizing an infinite-horizon utility function, making predictions about the future path of prices. Given the nature of the product, we view this as an unnecessary extension.

Section 2). Our framework adapts this approach to the emerging market setup by incorporating into the estimation procedure a dynamic updating mechanism for the fractions $F_{r,gt}$.

Of particular interest are the household-type specific elasticities. The type-$r$ specific own-price ($j = k$) and cross-price ($j \neq k$) elasticities of demand for brand $j$ are computed from:

$$\eta_{jk,r,gt} = \frac{\partial s_{j,r,gt}}{\partial p_{kgt}} \frac{p_{kgt}}{s_{j,r,gt}},$$

where, for brevity, we omit the argument $\theta$, and,

$$\frac{\partial s_{j,r,gt}}{\partial p_{kgt}} = \begin{cases} (\alpha + \alpha_r)\, s_{j,r,gt} \left(1 - s_{j,r,gt}\right) & \text{if } j = k \\ -\left(\alpha + \alpha_r\right) s_{j,r,gt} s_{k,r,gt} & \text{if } j \neq k \end{cases}$$

### 3.2 Dynamic type evolution

Over time, social mobility (as well as rural-to-urban migration) in a particular urban region $g$ changes the aggregate numbers of households in each socioeconomic standing. In addition, in each period $t$, households make consumption choices that affect the habit state with which they enter period $t+1$. Both of these processes determine the dynamic evolution of the type-distribution vector $\mathcal{F}_{gt}$ over time. We now fully characterize this dynamic updating process.

We begin by computing $\mathcal{F}_{g1}$, i.e., the type-distribution vector for period $t = 1$ in region $g$. These values are computed directly from the household-level survey data (HEX 95/96). Recall that this survey was conducted right before our Nielsen data begins, and that it links a household's socioeconomic class to its consumption choice: premium soda, generic soda, or "no soda." Following the discussion in Section 2, for each region in period $t = 1$ we set the number of newly affluent households to zero. By construction, therefore, we set the $t = 1$ population fractions that belong in the three newly affluent types (that is, newly affluent households with premium, generic and "no-soda" habits) to zero. Population fractions at $t = 1$ for the three established-affluent types are set in proportion to the HEX shares for **ABC** households across premium brands, generics, and no soda. Population fractions at $t = 1$ for the three poor types are set analogously using HEX shares for **DE** households.

Given a particular value for the model's parameters $\theta$, these fractions are updated forward for periods $t = 2, ..., 57$. Fixing region $g$ and period $t$, we explain how to find $\mathcal{F}_{g(t+1)}$ given $\mathcal{F}_{gt}$ and a value for $\theta$. Repeating this updating process for $t = 1, ..., 56$ (and noting that $\mathcal{F}_{g1}$ is known), yields the full trajectory of the distribution of household types over the sample period.

Importantly, a guess of the model's parameters yields a prediction, via (4), of the shares (and masses) of type-$r$ households who consume premium and generic soda in period $t$. Had we not allowed social mobility, the computation of $\mathcal{F}_{g(t+1)}$ would be straightforward by simply summing, across the three types in each socioeconomic group, the number of households who in period $t$ consumed a given brand type (premium or generic), and dividing this sum by the period $(t+1)$ total household population. For example, had the newly affluent population been constant over time, the fraction of households who, in time $(t+1)$, are newly affluent and have the premium habit would be computed by predicting the number of newly affluents who consumed premium soda at time $t$, and dividing by the total population at time $t$.[22]

The social mobility process, however, complicates these computations. For instance, whenever aggregate upward mobility is detected in a given region between periods $t$ and $(t+1)$, it follows that some of period $(t+1)$'s newly affluent households were poor in period $t$; to ascertain their $(t+1)$ habit requires information on poor households' choices at time $t$. Aggregate downward mobility and rural-urban migration between successive periods create similar challenges. To address these challenges and incorporate aggregate data on social mobility and migration to update $\mathcal{F}_{gt}$ into $\mathcal{F}_{g(t+1)}$, we make assumptions on the interaction between social mobility and previous consumption:

**Assumption 1** (Socioeconomic Mobility)**.** *Among those households moving up (down) from Poor to Newly Affluent (Newly Affluent to Poor) status, the previous-period shares of premium versus generic brands equal the previous-period shares of premium versus generic brands among all Poor (Newly Affluent) households.*

Assumption 1 implies that social mobility between period $t$ and $(t+1)$ is independent of consumption choices at time $t$. For example, a household who "moved up" from being poor at $t$ to newly affluent at $(t+1)$ is as likely to have consumed each type of soda at time $t$ as any member in the wider population of poor households at time $t$. Clearly, other assumptions can be made, and we explain in the appendix that our results are robust to alternative mobility assumptions. The appendix also offers numerical examples of the dynamic updating process implied by our assumptions.

We similarly incorporate an assumption regarding rural-urban mobility, inferred from the observed variation in urban populations since household sizes hardly vary over time, as follows (once again, the appendix demonstrates robustness to this assumption):

**Assumption 2** (Migration)**.** *Households moving to urban areas join the Poor socioeconomic group and have a "no-soda" habit. Households moving out of urban areas leave the Poor group, and have premium, generic and no-soda habits in proportion to the shares of those habits among the Poor that remain.*

[22] Recall that there are three types of newly affluent households at time $t$—those with premium, generic and "no-soda" habits—so the number of newly affluents consuming a premium brand in time $t$ is actually the sum of newly affluents across these three habit states who choose premium soda.

## 4 Identification and estimation

We now first describe our estimation algorithm, then proceed with intuitive arguments on identification.

### 4.1 The estimation procedure

The estimation procedure we propose and implement extends the literature on estimating demand models with discrete-type heterogeneity. In that literature, types are often abstract groupings of "similar" consumers, and the population fractions of these types are treated as parameters to be estimated.[23] In our method, in contrast, these population fractions are computed by combining data on aggregate social mobility, and model predictions regarding household choices. The fact that time-$t$ choices determine time-$(t+1)$ habit states requires us to incorporate a dynamic updating routine into each evaluation of the GMM objective function. We now describe the logic of the estimation algorithm, leaving complete technical details to the appendix.

The following steps allow us to construct a GMM objective function and evaluate it at some generic value of the model's parameters $\theta$. Recall that we obtain $\mathcal{F}_{g1}$, i.e., the type-distribution vector for period $t = 1$ in region $g$, from the HEX data source. Conditional on $\mathcal{F}_{g1}$ and $\theta$, we obtain predictions for aggregate brand shares in period $t = 1$ via equation (5). Using the contraction mapping from Berry, Levinsohn and Pakes (1995), we invert the market share equation that equates the predicted aggregate shares to the shares observed in the data, and solve for the unique vector of base utilities $\delta$ for each product that satisfies this equation (noting, as discussed above, that type-specific shares are not observed, and so they cannot be matched).

Using these base utilities, equation (4) now provides us with predictions for type-specific brand choices, from which we can obtain the type-specific fractions of households who, in period $t = 1$, consume premium brands, generic brands, or no soda. This information helps determine habit states for period $t = 2$. Following the discussion in Section 3.2 above, we then use these predicted choices, along with data on region-$g$'s aggregate social mobility between $t = 1$ and $t = 2$, and Assumptions 1 and 2, to compute next period's type-distribution vector $\mathcal{F}_{g2}$.

Repeating this process for periods $t = 2, ..., 56$ (and solving for the base utilities in $t = 57$, the final sample period), and then repeating for each region $g$, we obtain the base utilities for every brand in every region-period market. From $\xi = \delta - x'\beta - \alpha p$, we can now compute the demand unobservables $\xi_{jgt}(\theta)$ for each brand $j$ in each region-period market $gt$. The notation reflects the fact that these demand unobservables are computed conditional on particular parameter values.

We follow a familiar approach from the demand estimation literature and make the identifying assumption that these demand unobservables are mean-independent of a set of instrumental

[23]For example, Nair (2007) models video-game consumers as either "high valuation" or "low valuation" types, and estimates their relative population fractions.

variables $Z$. This assumption gives rise to a GMM objective function that captures the covariance between the instruments and the computed demand unobservables. This approach chooses the parameters which set this covariance as close to zero as possible.

An important feature of this procedure is that inversions of the market share equation cannot be performed independently for different markets over time. One must perform this inversion for period $t$, obtain the population fractions of each type for period $t+1$, and then perform the inversion for period $t+1$. This dynamic process must be performed at every candidate value of $\theta$ considered by the estimation algorithm.

**Choice of instruments.** We adopt three classes of demand instruments used by Salvo (2009).[24] The correlation of these instruments with prices helps alleviate biases associated with price endogeneity. The first class of instruments are cost shifters, a classic choice of demand instruments. In particular, we use prices of sugar, electricity and fuel.

The second class of demand instruments borrows from Hausman, Leonard and Zona (1994). Specifically, we instrument for a brand's price in a given region with the contemporaneous mean price for this brand in the other regions. The identifying assumption is that prices across different regions are correlated through a common cost structure or through common shifts in the way firms strategically interact (for instance, the mid 1999 premium price cut—see below). This approach can be challenged if common demand unobservables are present (see Bresnahan 1997a, 1997b). However, such issues are of a lesser concern in our setting, for the following two reasons: first, we control for region-specific, brand-level advertising intensity, often absent from demand studies. Second, there is considerable regional variation in demand, explaining the very local nature of Brazilian soft drink distribution and promotion.[25]

Finally, a third set of instruments is afforded by the premium brands' abrupt price cut. We argue that this substantial price cut in mid 1999 was exogenous to the brand-region-time specific demand unobservables $\xi_{jgt}$. This argument rests on the notion that this large and sudden price drop was plausibly a response to the demographic shifts and expansion of the fringe that we observe over 1996-1999, and not a response to some sudden unobserved mid-1999 demand shock (noting that we also control for advertising intensity, weather shocks and region-specific drifts). In practice, we generate a dummy variable which takes on the value 1 for all time periods after July 1999, and interact it with brand-region fixed effects, thus allowing the effects of this supply-side shift to vary by brand within each region.

### 4.2 Identification

This section provides intuitive arguments for identification of our model (beyond overcoming

[24] Salvo (2009) estimates an AIDS demand model, a different approach compared to the discrete-choice model we offer in this paper. Just the same, instrumenting for price endogeneity is similarly relevant to both frameworks.

[25] In this context, it is worth noting that the penetration of national retailers in Brazil is still limited relative to the United States.

price endogeneity, as discussed above). In particular, we explain what variation in the data is helpful for identifying our habit mechanism, as well as the heterogeneous price sensitivities across different socioeconomic groups. While the literature often identifies state-dependent preferences from household-level panels of survey data, we explain how the emerging market setup enables identification using rich cross-sectional and temporal variation in *aggregate* data on market shares, prices and social mobility. We emphasize two kinds of data variation: socioeconomic transitions and price changes.

**Socioeconomic transitions.** Shifting demographics play a crucial role in our identification strategy. We observe both the growth of the middle class from 1996/97 on, and the subsequent partial reversion during the recession that started around 2000/01. Importantly, these transitions occurred at differential rates across regions. While our inclusion of brand-region fixed effects controls for *fixed* differences in preferences across regions—stemming, for instance, from cultural or historical reasons—the intra-region temporal variation provides a key source of identification.

To illustrate this point, consider two regions that vary substantially in terms of their dynamic evolution: region 1 (the Northeast) and region 4 (São Paulo Metro). The following tables depict some socioeconomic and product market data for these regions at several points in time:

| **% Urban households** | Dec/Jan 1997 | | Dec/Jan 2000 | | Dec/Jan 2003 | |
|---|---|---|---|---|---|---|
| | Poor | New. Affl. | Poor | New. Affl. | Poor | New. Affl. |
| Region 1 (Northeast) | 65% | – | 44% | 24% | 57% | 15% |
| Region 4 (São Paulo Metro) | 36% | – | 23% | 16% | 23% | 19% |

| **Shares: No Soda & Generics** | Dec/Jan 1997 | | Dec/Jan 2000 | | Dec/Jan 2003 | |
|---|---|---|---|---|---|---|
| | $s_0$ | $s_{gen}$ | $s_0$ | $s_{gen}$ | $s_0$ | $s_{gen}$ |
| Region 1 (Northeast) | 87% | 0.3% | 82% | 5.0% | 80% | 8.4% |
| Region 4 (São Paulo Metro) | 61% | 6.6% | 62% | 12.6% | 59% | 11.9% |

Sources: Nielsen, IBOPE, IBGE (PNAD). Market shares $s_0$ and $s_{gen}$ are for the outside option and for generics, respectively.

At the start of our sample, region 1 is substantially poorer than region 4 (65% of region 1's urban households are poor vis-à-vis 36% for region 4) and, at the same time, exhibits lower soda penetration relative to its wealthier counterpart (87% of region 1's households do not consume soda against 61% for region 4). Notice that this cross-sectional variation can in principle be explained not only by the poor being more price sensitive than the established affluent, but also by region 1 potentially exhibiting a lower preference for soda relative to region 4. Such fixed differences, however, are controlled for with brand-region fixed effects in the utility specification.

From 1997 to 2000, region 1 boasted stronger upward mobility relative to region 4: by 2000, 24% of region 1's households were newly affluent compared with 16% of region 4's households.

Over these same years, region 1's soda penetration $(1 - s_0)$ grew substantially, from 13% to 18%, while soda penetration in region 4 was about flat. Generic brands in region 1 enjoyed a huge gain in share ($s_{gen}$) from 0.3% to 5.0%, while in region 4, the share of generics "only" doubled.

This joint temporal variation in social mobility *and* soda consumption choices helps us identify price sensitivity parameters. Notice that our model allows price sensitivity to vary by socioeconomic standing, i.e., the price sensitivities of the poor, newly affluent and established affluent are given by $\alpha$, $(\alpha + \alpha_{NA})$ and $(\alpha + \alpha_{EA})$, respectively. Intra-regional social mobility of households between poor and newly affluent status thus changes the aggregate price sensitivity in the region. The co-variation of this price sensitivity with aggregate market shares, controlling for prices, identifies the price sensitivity parameters.

The tables above also demonstrate the differential effects of the recessionary period in the two regions. Region 1 saw the proportion of newly affluent households shrink considerably, from 24% in 2000 to 15% by 2003, yet the penetration of soda consumption continued rising, even if at a lower rate, from 18% to 20%. Importantly, the recession was not accompanied by declining soda prices (see Figure 2). This pattern is suggestive of persistence in preferences. Such data variation is quite effective in identifying the parameter $\lambda$. It demonstrates how persistence manifests itself directly in our data, as opposed to being an artifact of an econometric strategy. We provide another example of such variation below.

The stability of soda consumption in the recessionary period can be contrasted with the substantial decline in the sales of cement during those years, as depicted in Figure 3, following years of common growth. This differential pattern is suggestive of stronger persistence in preferences over food and beverage, such as soft drinks, compared to other product categories.

We further argue that controlling for persistence in preferences actually helps us identify the price sensitivity parameters. To see this, imagine that we did not allow for such a persistence feature. Our model would then interpret the data variation in the recessionary period as evidence that the poor are "not that price sensitive," since all one would see through the lens of such a model is an increasingly poor population consuming stable amounts of soda. It would then be difficult to elicit greater price sensitivity among poor households compared to the more affluent groups. This intuition is consistent with estimation results for a model variant in which we shut down the habit mechanism, as we report below. Controlling for persistence, therefore, is not only important in its own right, but plays a key role in identifying other dimensions of household preferences. To our knowledge, this is the first paper that makes this point. It provides another important reason to account for habit formation in the study of demand in emerging markets.

**Price variation.** Another important source of identification stems from price variation which can be viewed as exogenous to unobservable demand shocks. First, consider the gradual but relentless price reduction in the competitive fringe over the period 1996 to 2000, as captured in

Figure 2. The close substitutability among those generic brands suggests that their price should, to a large extent, stay close to their marginal cost of production and distribution. This suggests that the decline in fringe prices was predominantly driven by supply side (cost) considerations. Expanded capacity and scale, learning effects and exit of inefficient producers may all have contributed to declining fringe costs and prices.

Through most of the period of declining fringe prices, generics were able to grow substantially at the expense of the premium brands and the outside good. To stay with the examples from the data (see the table of shares above), between 1997 and 2000: (i) in region 1, the generic share grew by 5 points, with the premium share (i.e., $1 - s_{gen} - s_0$) holding up quite well; and (ii) in region 4, the generic share grew by 6 points, and at the expense of the premium share. Intuitively, the co-movement in prices and shares is picked up by the parameters that govern price sensitivity and habit formation, thus contributing to their identification.

Consider also the abrupt premium price cut in mid 1999. As argued in subsection 4.1, this decision can be viewed as largely exogenous to the demand unobservables $\xi_{jgt}$. Notice that the generic share held up quite well following this premium price cut. This can be seen in the tables above for regions 1 and 4, and in Figure 2 for all regions combined. We view this as further evidence of persistence in preferences. Specifically, it supports our Brand Type Persistence (BTP) mechanism: a habit of "going generic," developed by part of the population prior to the mid 1999 premium price cut, made it very difficult for premium brands to win such households over, even via a drastic price cut. The price cut did, however, help protect premium brands from *further* market share losses, in part by attracting households who, at the time, had a "no-soda" habit. We return to this discussion in the results section.

To sum, largely exogenous variation in both prices and in the socioeconomic composition of households provides us with means to identify both heterogeneous price sensitivities and our habit mechanism. That said, we do treat prices, in general, as endogenous, as explained above.

## 5 Results

We start by reporting estimates obtained from our baseline demand model and comparing these to estimates from a "no habit" model variant. We subsequently employ our estimates to examine, via a counterfactual analysis, the premium sellers' strategic price cut in mid 1999.

### 5.1 Estimates from the demand model

Table 3 reports estimates for our demand model. The price sensitivity of the poor socioeconomic group, $\alpha$, has the expected negative sign and is very precisely estimated. The parameters $\alpha_{NA}$ and $\alpha_{EA}$ are also precisely estimated and are positively signed. Recalling that $(\alpha+\alpha_{NA})$ and $(\alpha+\alpha_{EA})$

capture the price sensitivities of the newly affluent and the established affluent, respectively, we obtain, intuitively, that the affluent groups are less price sensitive than the poor. Also note that both $(\alpha + \alpha_{NA})$ and $(\alpha + \alpha_{EA})$ are estimated to be negative.

Are newly affluent households more price sensitive than established affluent households? As discussed in the introduction, such a finding could help explain the success of generic brands, as well as Coca-Cola's deep price cut. Our estimates, however, do not lend support for such a claim. While the point estimates do reflect that $\hat{\alpha}_{NA} < \hat{\alpha}_{EA}$, the difference is not statistically significant, and is small in terms of economic significance, as we demonstrate below with an analysis of demand elasticities. *We do not, therefore, find evidence that the emerging middle class is more price sensitive than the established middle class.*[26]

In contrast, our findings do provide strong evidence for the second mechanism we study in this paper: habit formation. The coefficient $\lambda$ is estimated to be positive and it is very precisely estimated.[27] To provide a sense of economic significance, notice that $\lambda/|(\alpha + \alpha_{NA})|$ measures the increase in the willingness to pay of a newly affluent household for a liter of generic (premium) soda resulting from previous-period consumption of generic (premium) soda. The implied increase is $5.09/|(-5.25 + 2.75)|$, or R\$ 2.04. Further, the implied increase in willingness to pay for a generic over a premium brand when the newly affluent household has a generic habit *rather than a premium habit* is twice this amount.

These measures indicate a substantial monetary value of habit formation, and a crucial role played by this mechanism in emerging market dynamics. Once a newly affluent household develops a generic habit, "convincing" it to switch to a premium product becomes substantially more difficult. This helps explain the sense of urgency with which premium brands acted in mid 1999, as we argue in the counterfactual analysis below.

Table 3 further reports the effects of several shifters of $\delta_{jgt}$, the base utility of consuming brand $j$ in region-period market $gt$. We control for $9 \times 7 = 63$ brand-region fixed effects, capturing the tendencies of particular regions to consume different brands (e.g., historically, tastes for Pepsi are known to be relatively strong in the South, region 6—see Table 1). We also control for bi-monthly seasonality effects interacted with brand type (i.e., premium versus generic), to allow these effects to differ across product types. Over and above seasonality, market $gt$'s mean temperature has a positive and significant effect on demand.[28]

[26] The appendix reports robustness checks. The finding that newly affluents are not significantly more price sensitive than established affluents holds rather consistently across the bulk of the different specifications we tried.

[27] One possible interpretation for persistence in market shares could be serial correlation in the demand shocks $\xi$. Our inclusion of brand-region fixed effects and region-specific trends makes this possibility less of a concern. Just the same, we have calculated the simple correlation between current-period and previous-period estimated values for $\xi$ for each brand-region combination, yielding 63 such correlations. Most of these correlations are small in absolute value and many of them are negative. In a handful of brand-region combinations, positive correlations as high as 0.5 to 0.7 are observed. Most of those are in region 1, and they do not pertain to the leading brands such as Coke and Diet Coke.

[28] To illustrate within-season variation in temperature, winter temperatures in the southern region 6 averaged $15.1^oC$ in July 2001 against $12.1^oC$ in July 2000.

Our specification also includes region-specific effects of brand-level media advertising.[29] We interact advertising GRP with regional dummy variables, to allow advertising effects to differ across regions (reflecting, for instance, varying levels of ownership of household electronics and exposure to media, and the fact that these measures pertain to only the main cities within each region). The effects of advertising intensity are positive in all seven regions, although in most cases not statistically significant. Finally, coefficients on region-specific time trends are negative and mostly precisely estimated. Such negative effects are consistent with continued improvement in the value of the outside option, which includes beverages other than soda such as juices and (tap or bottled) water, concomitant with the overall trend of economic growth.[30] The trend variables are rescaled to vary from 0 at the start of the sample period to 1 at its end, and thus the effects reported in the table are economically small.

To further explore the economic implications of our demand estimates, Table 4 reports price elasticities. The table lists both aggregate own-price elasticities for the leading brands, and own-price elasticities by household type, computed as means over all region-period markets $gt$. A 1% increase in Coke's price lowers its market share by 1.7%, compared with somewhat larger (in magnitude) elasticities of $-2.1$ for the other premium brands, Guaraná Antarctica, Fanta and Pepsi. The own-price elasticity for generics is $-0.5$. While this value may seem low, note that this is the elasticity of demand for the aggregation of generic brands. The demand for each individual generic brand should be much more elastic, given the limited differentiation and fierce price competition within the fringe.

Examining the nine type-specific elasticities for Coke, and fixing the habit state, we see that demand becomes more elastic the lower is the socioeconomic standing. For instance, considering households with a premium habit, the elasticities are (-1.5,-1.7,-5.0) for the established affluent, newly affluent, and poor groups, respectively. The demand elasticity of the newly affluent is much closer to that of the established affluent than to that of the poor. Further to the discussion above, we find that the difference in price sensitivity between the new and the established middle class is not significant either statistically or economically.

Fixing the socioeconomic standing, the habit state has a strong impact on demand elasticities. Considering, for example, the newly affluent group, demand for Coke is least elastic for households with a premium habit (-1.7). Households with "competing habits"—either generic or "no-soda"—exhibit higher elasticities of demand for Coke (-2.7 and -2.6, respectively).

Further illustrating these findings, Figure 5 plots the evolution of own-price elasticities, by household type, for the Coke brand in region 4. Demand by all groups becomes less elastic

[29] To gain a sense of variation in such measures, the advertising intensity for the Coke brand in São Paulo Metro (region 4) amounted to 2199 Gross Rating Points in December 2000, rising to 3587 GRP in December 2001, while Pepsi's GRP were 351 and 598 respectively in these same periods.

[30] Forbes (2004) reports that the "the juice category grew twenty times over the past decade, albeit from a low base." IBGE's annual household surveys (PNAD) also indicate a sustained increase in access to tap water and piped sewerage in urban Brazil.

halfway through the sample, when premium brands cut prices. The figure separates the nine types into three distinct groups; the least elastic demand for Coke is by established affluent *and* newly affluent households with a premium habit. The most elastic demand is by the three poor types, with the other four types (established affluent and newly affluent with generic or no-soda habits) displaying intermediate price sensitivities. This picture further underscores our point that habit plays a crucial role: conditional on a premium habit, it is hard to tell the difference between the established affluent and the newly affluent, whereas the demand by affluent households with other habits is much more elastic.

Table 5 reports predictions of type-specific consumption choices from the estimated demand model. Overall soda penetration (i.e., the share of households who purchase soda) is 51%, 37% and 3% for the established affluent, the newly affluent and the poor, respectively (these are means computed over all region-period markets). More affluent households are also more likely to favor premium over generic brands: the premium-to-generic consumption ratios are 2.0, 1.5 and 0.6 for the established affluent, newly affluent and poor groups, respectively.

**A "no habit" model variant.** Table 6 presents results from a variant of our demand model which shuts down the habit formation mechanism. To be clear, this model is identical to the baseline model in Table 3 except that the parameter $\lambda$ is constrained to equal zero. Estimates from this model still suggest that established affluent households are less price sensitive than the poor ($\hat{\alpha}_{EA}$ is positive and statistically significantly different from zero) but the price sensitivity difference across these two groups narrows compared to the estimates from the baseline model.

Importantly, the "no habit" model variant does not suggest that the newly affluent are less price sensitive than the poor ($\hat{\alpha}_{NA}$ is negative and statistically insignificant). This result stands in contrast to our baseline model. The fact that the no-habit model variant does not separate the price sensitivities of the newly affluent from that of the poor is consistent with arguments provided in the identification section above: during the recessionary period in the later part of the sample, households moved down from newly affluent to poor status, yet soda consumption remained stable. By not allowing a habit mechanism, the model must interpret this as evidence that the price sensitivity of these two groups is similar.

We view the predictions of the baseline model as more realistic that those of the "no habit" model variant. It is well-documented that Brazil's emerging middle class exhibited lower price sensitivity than the poor, given the demand surge observed across many consumer goods markets, soft drinks being one of them. The predictions of the no-habit model seem to suggest that the emergence of a new middle class did nothing to change the aggregate price sensitivity, since it predicts that the newly affluent are as price sensitive as the poor. This model variant, therefore, entirely misses the phenomenon which is at the heart of our study: an expansion in demand stemming from a socioeconomic transformation.

## 5.2 Counterfactual analysis of the premium price cut

One of the striking features of the data is the premium brands' sharp price cut, led by Coca-Cola, almost halfway through the sample period. As the solid lines in the left panel of Figure 6 indicate for region 5 (this variation is similar for other regions), per-liter premium brand prices stayed broadly flat at about R$ 1.15 until mid 1999, then dropped—abruptly—to R$ 0.90 and stayed at this lower level. Fringe prices, in contrast, experienced a prolonged, gradual decline from R$ 0.80 to R$ 0.55 between late 1996 and mid 2000. The picture reveals that fringe prices did not deviate from their downward trend in response to the premium price cut, consistent with fringe prices closely tracking their producers' marginal costs.

We employ the estimated model to simulate the evolution of market shares had premium sellers *not* cut prices in mid 1999. This counterfactual price path is marked by the dashed line in the left panel of Figure 6. In this analysis, we keep fringe prices equal to the ones observed in the data. This assumption is justified by the fringe's competitive nature and, as discussed, the absence of an apparent pricing response to the premium price cut.

The right panel reports the estimated impact on aggregate premium and generic market shares. Observed shares are marked by solid lines, whereas counterfactual shares are marked by dashed lines (shares in this figure are out of the total market size, which includes the outside option, so that the premium and generic shares do not sum to one). A clear picture emerges: had premium producers failed to cut prices, they would have suffered a deep and substantial market share loss, hitting a rock bottom in the winter of 2000. At that point, the counterfactual premium market share would have been 12%, compared to a share of over 20% in the observed sample.

The counterfactual scenario is marked by the relentless growth of generic brands at the expense of their premium competitors. The analysis suggests that the generic market share would have surpassed the premium share early in 2000. By 2003, generics in region 5 would have enjoyed a market share advantage over premium brands of 10% (24% against 14%).

This analysis provides support for Coca-Cola's price cut, in that it seems to have prevented a substantial drop in market share. An important insight from the analysis is that the premium price cut was especially effective in terms of attracting customers who otherwise would have chosen the outside, "no soda" option. It was less effective in terms of converting consumers of generic brands into premium consumption. For example, inside shares at actual (reduced premium brand) prices over 2001-02 average 46% (28% premium plus 18% generic) to be compared with inside shares of 38% (16% premium plus 22% generic) at (higher) counterfactual prices. This is suggestive of substantial market segmentation, consistent with the habit mechanism that limits the scope for "business stealing" across the types of brand offerings, and with the high monetary value of habit formation. Still, the 4 percentage point growth in the generic share would have represented almost a one-quarter increase (+4.2/17.6) in the fringe's penetration.

**Impact on variable profit.** While the analysis above suggests that Coca-Cola's price cut succeeded in avoiding a deep market share loss, we note that this was achieved at a cost: a deep price cut of over 20%. In other words, premium sellers sacrificed a non-negligible portion of their margins to protect their market shares.[31] To assess the overall impact of the price cut on earnings, we perform a back-of-the-envelope calculation of variable profit both in the observed sample, and under the counterfactual (no price cut) scenario.

Using information gleaned from Ambev's local SEC filings, conversation with industry insiders, among other sources, we estimate that the premium brands' combined variable profits (excluding fixed costs) during the first three years after the price drop amounted to R$ 860 million, to be compared to counterfactual profits of R$ 740 million, had the price cut not occurred.[32] That is, a 14% loss in variable profit over the medium run was avoided by the premium price cut. The evidence supports the notion that the price cut was beneficial in terms of its impact on both market shares and profits.

**A comparison with the "no habit" model variant.** We wish to explore the role played by the habit mechanism in this analysis. To this end, Figure 7 performs the same counterfactual analysis but using estimates from the no-habit model variant discussed above. It is clear from comparing Figure 7 to Figure 6 that the no-habit model is associated with a substantially smaller erosion of market share for premium brands had they failed to cut prices. Further, using the same back-of-the-envelope calculations discussed above, the no-habit model implies that the price cut actually *decreased* premium brands' variable profit, from R$ 1.0 billion (with no price cut) to R$ 860 million (with price cut) over the same three years. This stands in stark contrast to the predictions of the baseline model.

**Discussion.** Though examining the premium brands' pricing policy is the subject of a sequel paper, the counterfactual analysis lends strong justification for Coca-Cola's strategic price cut. Importantly, this conclusion is delivered by the baseline model, but not by the no-habit model variant, highlighting the role played by habit formation in this emerging market. Our discussion of the estimation results above suggested that habit carries a large monetary value. In particular, once a newly affluent household "goes generic," it is significantly less likely to switch into consumption of premium, expensive soda. The counterfactual analysis demonstrated how this feature can wreak havoc on the market share of premium brands: had they not cut prices in mid 1999, the generic fringe would have continued to gain ground, while premium brands would have lost considerable market shares and profit.

Our analysis shows that Coca-Cola's price did not allow it to convert many households with the generic habit into consumption of its premium products. Rather, the main effect was to tap

[31] Protecting market shares, even at a high cost, may be rational insofar as current market share is an "asset," predictive of future profit. See Bronnenberg, Dhar and Dubé (2009) on the persistence of brand market shares.

[32] See the appendix for details on how this calculation was performed.

into the large pool of households with the no-soda habit. By inducing a substantial portion of these households to develop a habit of consuming premium soda, Coca-Cola and Ambev were able to shield themselves against further losses. Our analysis suggests that it is this mechanism that stabilized market shares after mid 1999, as demonstrated in Figure 2.

Our ability to draw such conclusions stems from the richness of our framework, which captures both social mobility and habit formation. In contrast, the more standard "no habit" model variant fails to separately identify the price sensitivities of the newly affluent and the poor. Moreover, it misses the crucial role played by persistent preferences in the dynamics of competition between premium and generic brands in a rapidly changing market.

## 6 Concluding remarks

This paper examines two salient features of the Brazilian soft drink market: the emergence of a new middle class, and the rapid growth of a generic fringe. Using unique data with very rich cross-sectional as well as temporal variation, we estimate a model that highlights two aspects which we view as highly important in such markets: the heterogeneous price sensitivities of different socioeconomic groups, and habit formation in household preferences.

Our brand type persistence (BTP) mechanism captures a world in which premium brands are prompted to cut prices in the wake of an emerging middle class. If they fail to do this, a substantial mass of the "new customers" might be captivated by the generic habit. It may then prove much more difficult to convince these consumers to pay substantially more for a highly advertised premium brand.

While our application focuses on the Brazilian soft drink market, we view the issues tackled in this work as highly pertinent to many consumer goods markets in the developing world, where a tension between advertised branded offerings and discounted generics exists or is developing. Understanding the features of demand and the microeconomics of competition in such markets should be of great interest for policymakers and firms alike.

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# A Appendix

## A.1 Data sources

We refer the reader to Salvo (2009) for further details on Nielsen's soda market panel and McCann-Erickson's media advertising intensity panel. We use regional average monthly temperatures made available by the National Institute of Meteorology (INMET). Wholesale prices of refined sugar (the 'IPA-OG açúcar') and a transport fuel price index (the 'IPA-OG combustíveis e lubrificantes') prepared by the Fundação Getúlio Vargas were obtained from the Institute for Applied Economic Research (IPEA), and regional high-voltage electricity prices ('classe industrial') were provided by the National Agency for Electrical Energy (ANEEL). As with soft drink prices, we inflation-adjust nominal factor prices using a consumer price index (the 'IPC-br') published by the Fundação Getúlio Vargas. The CPI has averaged +7.8% per year over the sample period.

In what follows, we explain how we combine IBOPE's LatinPanel survey with IBGE's annual household surveys (the PNAD, 'Pesquisa Nacional por Amostra de Domicílios') to produce household counts by socioeconomic standing. We then describe how we obtain the type-distribution vector for the first period, $\mathcal{F}_{g1}$, from IBGE's 1995/96 urban household expenditure survey (the POF, 'Pesquisa de Orçamentos Familiares').

**Data on aggregate social mobility.** From IBOPE's LatinPanel we observe the proportion of urban households that belong in either the **ABC** or **DE** socioeconomic groups by year time (see the text) and across regions. IBOPE's regions map directly into Nielsen's 7 regions, with the exception of region 1—states in the Northeast excluding Maranhão and Piauí—for which IBOPE's coverage includes *all* states in the Northeast as well as states in the North. Since Maranhão, Piauí and the North comprise the country's least urbanized and least populated area, we simply take IBOPE's urban distributions for the Northeast/North as representative of urban households in Nielsen's region 1. IBOPE's survey through 2002 was representative of all municipalities with populations of at least 20,000, and their coverage was expanded in 2003 to represent municipalities with populations exceeding 10,000.

We obtain household counts from IBGE's annual household surveys (PNAD). These cover households, both urban and rural, in all 27 states of the country. For perspective, 115,654 households were sampled in 1999. IBGE's household-level weights allow us to expand the representative sample to the universe of households. We consider only households residing in urban areas and in states within each Nielsen region. For example, for region 1, we sum the number of urban households across all states in the Northeast less Maranhão and Piauí.

We then multiply, for each Nielsen region and year, the IBOPE socioeconomic proportions of urban households by the IBGE urban household counts. To increase the frequency of the resulting panel from annual to monthly periods (or bimonthly periods, thus matching the frequency of Nielsen's point-of-sale audits), we linearly interpolate from September of one year to September of the following year, noting that September is the IBGE PNAD's annual "month of reference."

**Data on household-level brand choices.** IBGE's HEX (POF) 95/96 surveyed 16,013 households in 11 large metropolitan areas across the country. Carvalho Filho and Chamon (2011) discuss this survey in detail. Over a reference period of one week falling between October 1995 and September 1996, the soft drink expenditure in R$ for consumption inside the home is recorded for each household, detailed by soda brand(s) purchased. We then classified the following brand descriptions and codes as "premium" brands: *Coca-Cola* (9301), *Pepsi* (9302), *Guaraná* (9303), *Fanta laranja, uva, limão* (9304), *Soda limonada* (9307), *Mirinda* (9308), *Sukita* (9315), *Pop laranja* (9316), and *Refrigerante água tônica* (9349). Examples of coded brand descriptions that we classified as "generic" brands are: *Refrigerante tubaína* (9318), *Refrigerante laranja exceto Fanta, Sukita, Pop, Crush* (9339), *Refrigerante cola exceto Coca-Cola e Pepsi-Cola* (9340), *Refrigerante cajú qualquer marca* (9346), and *Refrigerante Goianinha* (9355). Of the 16,013 households, 10,172 (or 64% of households) were recorded as making no soda purchases, 4,465 households (28%) purchased only brands that we can confidently identify as premium, 310 households (2%) purchased only brands that we identify as generic, and 236 households (only 1%) simultaneously purchased brands that we identify as premium and brands that we identify as generic. This observation justifies our modeling of soda-consuming households at each point in time as either premium or generic shoppers, but not "hybrids."

We deemed four soda descriptions to be ambiguous with regard to brand type: *Refrigerante água natural* (9310), *Refrigerante gasosa* (9319), *Refrigerantes não especificado* (9335) and *Refrigerante dietético* (9360). We need to assign the soda expenditure of the remaining 830 soda-purchasing households (5% of the survey sample) to either premium brands or generic brands. These are households whose soda expenditure we cannot entirely identify by brand type, such as a household purchasing R$ 4 of Coke (9301) and R$ 2 "Soda not specified" (9335). To do this, we first designate as premium the "brand-unidentifiable" soda expenditure portion (R$ 2 in the example) for those households whose identifiable-premium expenditure share of soda exceeds 50% (Coke's 67% share in the example) *and* identifiable-generic expenditure share of soda is less than 10% (0% in the example). Similarly, we assign to generic the unidentifiable soda expenditure portion for those identified-generic-dominant households. Finally, the soda expenditure portion that for a remaining 614 households is still not assigned to a brand type—e.g., a yet to be assigned R$ 2 of "Soda not specified" (9335) purchased by another household—is allocated among premium and generic expenditure: (i) in proportion to the (identified or designated) premium versus generic expenditure shares within the household; or (ii) should none of the household's soda expenditure be identifiable (e.g., a household who purchased R$ 2 of "Soda not specified" (9335) only), the allocation is done in proportion to the premium versus generic expenditure shares across households in the same socioeconomic group and metropolitan area. (We use balance sheet data to classify households according to socioeconomic standing, as described in Section 2, and use IBGE's weights to expand the representative sample to a universe of 12.5 million households across the 11 metropolitan areas.)

To calculate household-level premium and generic quantities, we divide HEX 95/96 expenditures on premium and generic soda by Nielsen's region-specific share-weighted mean prices for premium and generic brands, respectively, on $t = 1$ (December 1996-January 1997). We then aggregate premium (resp., generic) quantities across the universe of households belonging to each socioeconomic segment (**ABC** or **DE**) living in the HEX-surveyed metropolitan areas for each Nielsen region $g$ (e.g., the cities of Recife, Fortaleza and Salvador in the Northeast, $g = 1$). The premium (resp., generic) soda shares among the initial masses of established affluent and poor households are calculated analogously to how we define $s_{jgt} = q_{jgt}/\mathcal{M}_{gt}$ in Section 2, i.e., taking market size (in our base specification) as six liters per household per week times the number of weeks in period $t = 1$. Combining these premium versus generic (versus no soda) shares by socioeconomic group with first-period household counts by socioeconomic group (as per above), yields $F_{EA^{\mathcal{A}},g1}, F_{P^{\mathcal{A}},g1}$ and $F_{EA^{\mathcal{B}},g1}, F_{P^{\mathcal{B}},g1}$ (recall that $F_{NA^{\mathcal{A}},g1} = F_{NA^{\mathcal{B}},g1} = 0$). In our base specification, we consider soda purchases recorded as being for the household's inside-the-home consumption (rather than "individual consumption") and at stores coded as *Supermercado* (1), *Hipermercado* (2), *Padaria* (3), *Lanchonete* (11), and *Mercado & Central de Abastecimento* (26), in view of the mapping to Nielsen's self-service channel (stores with checkouts). Further details can be provided upon request.

Two points are noteworthy. First, the HEX survey suggests that household size does not vary significantly across socioeconomic group. The mean size across **ABC** and **DE** households—all urban—is 3.64 (std. dev. 1.58 across 7,916 households) and 3.76 (s.d. 1.99 across 8,097 households), respectively. Second, while the HEX shares that enter the initial conditions $\mathcal{F}_{g1}$ are calculated following the market share definition of Section 2, one should note that the shares reported in Table 2 are extensive margins of soda consumption, i.e., the proportions of households who purchase any quantity of soda for the home (and which type). For brevity, we do not report "intensive margins"—intensity of soda consumption conditional on positive consumption—but figures are available from the authors upon request. In any event, we note that the modal intensity of consumption, conditional on non-zero, is 2 liters per household per week regardless of the socioeconomic group and the region. One can intuitively interpret this pervasive modal intensive margin as "one 2-liter family-size bottle of soda that is brought to the table every week."

Finally, we performed all manner of "consistency checks," where applicable, to ensure that the data were consistent across the different sources. For example, according to the HEX, among households residing in the three surveyed metropolitan areas in the Northeast, (statistically weighted) premium and generic market shares amount to 12.5% and 0.4%, respectively. (These shares are as defined in Section 2, including the outside option, and grow to 26.6% and 0.7%, respectively, if we condition on the 36% of households who have **ABC** socioeconomic status, comparable to the extensive margins reported in Table 2.) The (unconditional, three-city, 95/96) HEX shares of 12.5% and 0.4% in the example are similar to the Nielsen market shares of 12.3% across premium brands and 0.3% for generics in the Dec-96/Jan-97 bimonth (soda sold in family-size bottles through self-service outlets in the Northeast). By way of another example, the (projected) universe of households for region 3 (the metropolitan area of Rio de Janeiro) is 2.96 million under the HEX 95/96 (see Table 2), to be compared to 2.64 million households under the IBGE PNAD for Dec-96 (noting that Nielsen's region 3, which we adopt for the IBGE household counts, excludes some peripheral villages around the city of Rio de Janeiro). Further, using the HEX 95/96's balance sheet data, as explained in the text, we assigned **ABC** socioeconomic status to 55% of region 3's households (see Table 2), whereas the IBOPE suggest that at that time 57% of region 3's households were **ABC**.

## A.2 Further details

### A.2.1 Dynamic type evolution

We provide examples, from the data, of the dynamic updating process. We consider two transitions, both for region 4 (São Paulo Metro). The first transition, from $t = 1$ to $t = 2$, features upward mobility and, unusually in the data (yet we need to allow for this), a slight flow of residents out of the region ("net urban-to-rural migration"). The second transition, from $t = 10$ to $t = 11$, features upward mobility and the rural-to-urban migration that is prevalent in the data. We illustrate these transitions at the estimated model parameters $\theta^*$. We also comment on the robustness of our estimates to the baseline mobility Assumptions 1 and 2.

**Region 4,** $t = 1$ **to** $t = 2$**.** The initial type-distribution vector is

$$\begin{aligned}\mathcal{F}_{g=4,t=1} &= \left\{F_{EA^{\mathcal{A}},4,1}, F_{EA^{\mathcal{B}},4,1}, F_{EA^{\mathcal{O}},4,1}, F_{NA^{\mathcal{A}},4,1}, F_{NA^{\mathcal{B}},4,1}, F_{NA^{\mathcal{O}},4,1}, F_{P^{\mathcal{A}},4,1}, F_{P^{\mathcal{B}},4,1}, F_{P^{\mathcal{O}},4,1}\right\} \\ &= \{.255, .029, .361, 0, 0, 0, .048, .009, .299\}\end{aligned}$$

As explained, the last element, say, is the product of (region 4's) poor household count in $t = 1$ (observed from IBOPE/IBGE) and the share of the outside option among region 4's **DE** households (calculated from the HEX 95/96), divided by the total household count (IBOPE/IBGE), i.e., $1346585 \times .84093/3789771 \simeq .299$. From $s_{j,r,g=4,t=1}(\theta^*)$ (see (4)), we obtain the mass of households for each of the nine types who choose to consume premium, generic, or no soda. For example, the share of premium soda among established affluent households who have a premium habit, $\sum_{j\in\mathcal{A}} s_{j,EA^{\mathcal{A}},g=4,t=1}(\theta^*) \simeq 97\%$. In contrast, the shares of premium soda among established affluents with generic habits and no-soda habit are 1% and 15%, respectively. Thus, since the established affluent population is constant over time (at 2443186), the number of established affluent households going into $t = 2$ with premium soda habits is (in thousands, hereafter) $3790\,(.255 \times .97 + .029 \times .01 + .361 \times .16) \simeq 1143$.

As for mobility, according to IBOPE/IBGE, the socioeconomic distribution of households evolves from (**ABC**,**DE**) = $(2443, 1347)$ in $t = 1$ to $(2511, 1269)$ in $t = 2$. It follows that, in $t = 2$: (i) $2511 - 2443 = 68$ households are newly affluent; (ii) $(2443 + 1347) - (2511 + 1269) = 10$ households migrated out of the urban area (again, this rarely happens in the data); and (iii) 1269 households are poor. Following Assumption 1 (Socioeconomic Mobility), the 68 upwardly mobile households entering $t = 2$ are endowed with habits in proportion to the choices of poor households in $t = 1$ among premium, generic and no soda (where these proportions are calculated as illustrated for established affluents, for which a proportion $1143/2443 \simeq 47\%$ chose premium rather than generic or no soda). These counts (summing 68) are deducted from the $t = 1$ poor population (1347) that is transitioning to $t = 2$ in proportion to the poor's choices across brand types. Similarly, following Assumption 2 (Migration), the 10 households leaving the city are dropped from the counts of the poor (totaling $1347 - 68$) in proportion to the poor's choices across brand types.

**Region 4,** $t = 10$ **to** $t = 11$**.** We keep this example brief, highlighting mobility. The type-distribution vector following choices made in $t = 9$ and mobility into $t = 10$ is

$$\mathcal{F}_{g=4,t=10} = \{.233, .099, .306, .019, .016, .110, .000, .002, .213\}$$

Having updated from $t = 1$, the history of choices and mobility now determines the distribution of habits across each socioeconomic group. By $t = 10$, the "premium-to-generic ratio" is $.019 : .016 = 1.2$ among newly affluent households, compared to $.233 : .099 = 2.4$ among the established affluent (see Table 5). From IBOPE/IBGE data, the mass of households by socioeconomic group (in thousands) in $t = 10$ is computed as: 2443 established affluent (this stays constant), 560 newly affluent and 826 poor (see Figure 4; $t = 10$ is the Jun-98/Jul-98 bimonth).

The evolution of (**ABC**,**DE**) from $(3003, 826)$ in $t = 10$ to $(3060, 784)$ in $t = 11$ implies that: (i) the newly affluent count grows by 57 (to 617); (ii) 16 migrants arrive at the city and join the ranks of the poor; and (iii) the poor count drops by $57 - 16 = 42$ (to 784). The 57 upwardly mobile households making choices with newly affluent status in $t = 11$ are endowed with habits in proportion to the $t = 10$ choices of the poor they left behind (Assumption 1). The 16 migrants who are new to the city have a no-soda habit (Assumption 2).

**Robustness to Assumptions 1 and 2.** Our results are robust to alternative mobility assumptions, namely: (i) modifying Assumption 1 to endow households moving up from poor to newly affluent status with habits in proportion to the previous-period soda choices of the newly affluents they are joining, rather than the poor they are leaving behind[33] (and analogously with respect to households moving down from newly affluent to poor status, based on the previous-period choices of the poor); and (ii) modifying Assumption 2 to endow households moving to urban areas with habits in proportion to the previous-period soda choices of the city-dwelling poor they are joining. For example, under (ii), $(\alpha_{EA}, \alpha_{NA}, \alpha)$ and $\lambda$ are estimated, respectively, at $(2.98, 2.77, -5.27)$ and $5.09$ (with standard errors of $(1.43, 1.23, 1.45)$ and $.37$), very close to baseline estimates (see Table 3). Full estimates of these model variants are available upon request.

#### A.2.2 The estimation algorithm

In what follows, we explain the structure of the GMM objective, and then detail how this objective function is evaluated at some generic value for the parameters $\theta = (\theta_1, \theta_2)$.

Given any generic value for the non-linear parameters $\theta_2$, steps 1 to 5 of the algorithm below

[33] The exception is the first transition, from $t = 1$ to $t = 2$, in which the newly affluent are a random sample of the poor as, by definition, there are no newly affluents in $t = 1$.

yield an $N \times 1$ vector $\delta(\theta_2)$, containing the base-utility levels for all brands in all regions in all time periods ($N = 9 \cdot 7 \cdot 57$). As noted in Section 4, conditioning on the full parameter vector $\theta$, one obtains an $N \times 1$ vector of base-utility unobservables by subtracting the systematic portion of the base utility from $\delta_{jgt}$, i.e., $\xi_{jgt} = \delta_{jgt} - x'_{jgt}\beta - \alpha \cdot p_{jgt}$. Stacking all these unobservables together, we can write:

$$\xi(\theta) = \delta(\theta_2) - X\theta_1$$

where the $N \times K_1$ matrix $X$ contains the $K_1$ base-utility covariates (including price), and let $K_2$ denote the dimension of $\theta_2$. Now let $Z$ denote a $N \times L$ matrix of instruments containing all covariates in $X$ but price, as well as excluded instruments (e.g., cost shifters), where $L > K_1 + K_2$. Writing $W = (Z'Z)^{-1}$, the GMM objective is defined by:

$$Q_N(\theta) = \xi(\theta)' ZWZ' \xi(\theta)$$

Computation time can be reduced substantially by noting (see BLP 1995, Nevo 2000) that, conditional on a guess for $\theta_2$, there is a closed-form solution for the parameters $\theta_1$ that minimizes the objective:

$$\theta_1^*(\theta_2) = \left(X'ZWZ'X\right)^{-1} X'ZWZ'\delta(\theta_2)$$

This allows us to maximize the objective by searching only over values of the non-linear parameters $\theta_2$.

At every guess $\tilde{\theta}_2$ for the non-linear parameters, the GMM objective is evaluated via the following steps:

1. For every region $g = 1, ..., 7$, and period $t = 1$, given $\tilde{\theta}_2$ and $\mathcal{F}_{g1}$, use the BLP contraction mapping to solve for the unique vector of base utilities that matches observed aggregate market shares with those predicted by the model.

2. For every region $g = 1, ..., 7$ and household type $r = 1, ..., 9$, use equation (4), the base utilities recovered in step 1, and $\tilde{\theta}_2$, to predict the shares of type-$r$ households who consume premium brands, generic brands or no soda in period $t = 1$.

3. For every region $g = 1, ..., 7$, use the shares obtained in step 2, data on aggregate social mobility, and Assumptions 1 and 2, to forward-update the proportion of households in period $t = 2$ who belong to each of the nine types, $\mathcal{F}_{g2}$ (see Section 3.2).

4. Repeat steps 1-3 for periods $t = 2, ..., 57$.

5. Stack the base-utility vectors for all brands, time periods and regions in the $N \times 1$ vector $\delta\left(\tilde{\theta}_2\right)$, and evaluate the GMM objective at the guess $\tilde{\theta}_2$, as explained above.

### A.2.3 Robustness

Given space restrictions, we briefly describe some of the alternative specifications, on top of the alternative mobility assumptions discussed above, that we have estimated to confirm the validity and robustness of our baseline results. Estimates of these model variants are available upon request.

**Market size.** Our baseline model defines market potential as six liters per week, interpreted as 3 meals/week in which a 2-liter family-size bottle of soda might be brought to the table. Estimated price sensitivities and the habit parameter hardly vary as we vary the number of meals per week between 2.6, 2.7, ... , 3.3. Beyond this range, estimated $(\alpha_{EA}, \alpha_{NA}, \alpha)$ vary more, but our estimate for $\lambda$ is very stable about 5 (all the way from 2.0 to 3.6 meals/week).

**Habit formation.** Specifications that we implemented, each addressing alternative mechanisms than the one we wish to highlight, include: (i) allowing habit to form for soda in general, *regardless* of the type of brand (i.e., consuming either heavily advertised premium or discount generic soda in this period shifts the utility from consuming any soda next period by $\lambda$); (ii) allowing loyalties to form for the flagship premium brands Coke (including Diet Coke), Guaraná Antarctica, Fanta, or Pepsi (i.e., consuming Pepsi in this period increases one's utility from consuming Pepsi in the next period—but not another brand—by $\lambda$); and (iii) allowing loyalty to form only for the Coke (including Diet Coke) brand. To illustrate, model (ii) has five habit states which, interacted with 3 socioeconomic groups, implies 15 household types (and we must modify the initial conditions from the HEX accordingly). Brand loyalty is estimated to be strong and significant under alternative models (ii) and (iii), leading to aggregate own-price elasticities that appear too low in magnitude, namely, $-0.7$ and $-0.9$ for Coke under (ii) and (iii), respectively (compared to $-1.7$ in Table 4). In general, estimated habit parameter(s) under these alternative models are large and significant, but do not provide as strong a justification for Coca-Cola's mid 1999 price cut.

**Other specifications.** A more general model allowed the premium habit and the frugal habit to vary in magnitude. Estimated habit parameters $\lambda^{\mathcal{A}}$ and $\lambda^{\mathcal{B}}$, for premium and frugal respectively, are 5.31 (s.e. 0.41) and 4.65 (s.e. 0.50). We also tested robustness with regard to: (i) initial HEX 95/96 shares (namely, expanding the HEX outlet codes that map to Nielsen's stores with checkouts); and (ii) defining market share by the extensive margin once the region-specific intensive margin, as observed in the single cross-section of household-level data (HEX 95/96), is fixed over time.

### A.2.4 Variable profit

Our back-of-the-envelope calculation of variable profit considers the three-year period between April 2000 and March 2003. We assume that the premium sellers' net sales price is 35% of the price Nielsen observes on the shelf, which is paid by the end consumer. (See Ambev 2003 and Salvo 2009 for a discussion of the very high taxes incurred along the formal vertical chain, as well as vertical relations. We also base our calculations on interviews with an executive at a premium seller.) Thus, the observed shelf price of R$ 0.913 / liter (sales weighted across premium brands, averaged over the three years) corresponds to a net sales price for Coca-Cola/Ambev of R$ 0.320 / liter, net of sales tax, retail margin, and distribution costs. Had the premium sellers not cut prices in mid 1999, we assume that this price would have been proportionately higher, at R$ 0.384 / liter. Based on Ambev (2003), we take the "cost of goods sold" as R$ 0.199 / liter. We note that the real prices of sugar, plastic, electricity, labor, and fuel were quite stable between 2000 and 2002 (in general, they began rising at the end of our sample period, in 2003). The variable profit margins for the Coca-Cola/Ambev "systems" are thus R$ 0.120 / liter with the observed price cut and R$ 0.185 / liter under the counterfactual of no price cut. Multiplying by the premium sellers' observed and counterfactual quantities sold over this three-year period (namely, 7.2 billion liters observed; 4.0 bi liters counterfactual under the Brand Type Persistence model; 5.4 bi liters counterfactual under the "no habit" model variant) yields the variable profits stated in the text (respectively, R$ 860 million, R$ 740 million, and R$ 1.0 billion).

# B Tables and Figures

Table 1: Brand Volume Shares of the Soda Category

| Brand | Region 1 | | Region 2 | | Region 3 | | Region 4 | | Region 5 | | Region 6 | | Region 7 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | t=1 | t=57 | t=1 | t=57 | t=1 | t=57 | t=1 | t=57 | t=1 | t=57 | t=1 | t=57 | t=1 | t=57 |
| Coke | 0.40 | 0.21 | 0.37 | 0.26 | 0.36 | 0.26 | 0.32 | 0.24 | 0.31 | 0.25 | 0.28 | 0.31 | 0.34 | 0.29 |
| Fanta | 0.08 | 0.06 | 0.05 | 0.08 | 0.05 | 0.09 | 0.08 | 0.09 | 0.06 | 0.08 | 0.06 | 0.08 | 0.03 | 0.05 |
| Kuat | 0.03 | 0.06 | 0.02 | 0.04 | 0.04 | 0.06 | 0.07 | 0.06 | 0.06 | 0.04 | 0.04 | 0.04 | 0.05 | 0.03 |
| Diet Coke | 0.02 | 0.03 | 0.02 | 0.03 | 0.03 | 0.05 | 0.02 | 0.04 | 0.03 | 0.03 | 0.03 | 0.04 | 0.02 | 0.03 |
| Other Coca-Cola | 0.02 | 0.03 | 0.02 | 0.02 | 0.02 | 0.02 | 0.05 | 0.06 | 0.04 | 0.05 | 0.05 | 0.04 | 0.05 | 0.02 |
| Guarana Antartica | 0.17 | 0.09 | 0.07 | 0.06 | 0.06 | 0.09 | 0.09 | 0.10 | 0.08 | 0.07 | 0.05 | 0.05 | 0.09 | 0.10 |
| Other Ambev | 0.19 | 0.02 | 0.11 | 0.01 | 0.15 | 0.01 | 0.16 | 0.02 | 0.12 | 0.01 | 0.17 | 0.01 | 0.06 | 0.02 |
| Pepsi | 0.06 | 0.03 | 0.08 | 0.03 | 0.19 | 0.07 | 0.05 | 0.05 | 0.06 | 0.04 | 0.11 | 0.09 | 0.09 | 0.05 |
| Generics | 0.03 | 0.47 | 0.26 | 0.47 | 0.12 | 0.36 | 0.17 | 0.34 | 0.25 | 0.41 | 0.21 | 0.33 | 0.27 | 0.41 |

Volume shares of the soda category, by brand in each region in the first and last time periods. Coke, Fanta, Kuat, Diet Coke, and "Other Coca-Cola" are premium brands marketed by the Coca-Cola Company. Guarana Antarctica, Pepsi, and "Other Ambev" are premium brands marketed by Ambev. Source: Nielsen.

Table 2: Soda Consumption by Socioeconomic Group (HEX)

| Region of survey. cities | Socioeconomic group | Households ×1000 Universe | % | Soda purchasing | By brand type Premium | Generic | No soda |
|---|---|---|---|---|---|---|---|
| 1 (Northeast) | ABC | 696 | 36 | 28.0% | 27.0% | 0.9% | 72.0% |
| | DE | 1230 | 64 | 9.1% | 8.3% | 0.8% | 90.9% |
| 2 (MG, ES, | ABC | 529 | 57 | 39.9% | 37.9% | 2.0% | 60.1% |
| RJ interior) | DE | 404 | 43 | 23.2% | 22.1% | 1.2% | 76.8% |
| 3 (RJ Metro) | ABC | 1625 | 55 | 31.9% | 31.6% | 0.3% | 68.1% |
| | DE | 1331 | 45 | 18.3% | 18.3% | 0.0% | 81.7% |
| 4 (SP Metro) | ABC | 2586 | 60 | 34.5% | 33.1% | 1.4% | 65.5% |
| | DE | 1689 | 40 | 19.8% | 17.3% | 2.6% | 80.2% |
| 6 (South) | ABC | 955 | 63 | 43.2% | 42.5% | 0.7% | 56.8% |
| | DE | 559 | 37 | 20.4% | 20.1% | 0.3% | 79.6% |
| 7 (DF, GO | ABC | 428 | 61 | 36.5% | 34.4% | 2.1% | 63.5% |
| MS) | DE | 270 | 39 | 23.6% | 21.1% | 2.5% | 76.4% |
| Total above | ABC | 6819 | 55 | 35.0% | 33.9% | 1.1% | 65.0% |
| | DE | 5482 | 45 | 17.5% | 16.3% | 1.2% | 82.5% |

The extensive margin of soda consumption inside the home by different socioeconomic groups in 1995/96. Socioeconomic groups are defined per the points scale used by IBOPE. Metropolitan areas surveyed were: (Region 1) Recife, Fortaleza and Salvador; (Region 2) Belo Horizonte; (Region 3) Rio de Janeiro Metro; (Region 4) Sao Paulo Metro; (Region 6) Curitiba and Porto Alegre; (Region 7) Brasilia and Goiania. No city was surveyed in Region 5 (state of Sao Paulo excluding Sao Paulo Metro). We do not consider the northern city of Belem as it is located outside the area covered by Nielsen. Source: IBGE HEX (POF) 1995/96.

Table 3: Demand Estimation Results

| | | | | | |
|---|---|---|---|---|---|
| **Price Sensitivity Parameters** | | | | | |
| $\alpha_{EA}$ | 2.96 | (1.42) | | | |
| $\alpha_{NA}$ | 2.75 | (1.22) | | | |
| $\alpha$ | -5.25 | (1.44) | | | |
| **Habit Parameter** | | | | | |
| $\lambda$ | 5.09 | (0.37) | | | |
| **Additional Covariates** | | | | | |
| Constant | -3.24 | 0.30 | | | |
| Temperature | 3.06 | (0.31) | | | |
| Advertising Effects: | | | Region-specific Time Trends: | | |
| Advertising GRPs×Region 1 | 1.06 | (0.46) | Region 1 | -0.45 | (0.18) |
| Advertising GRPs×Region 2 | 0.83 | (0.63) | Region 2 | -0.21 | (0.20) |
| Advertising GRPs×Region 3 | 0.26 | (0.29) | Region 3 | -0.61 | (0.16) |
| Advertising GRPs×Region 4 | 0.41 | (0.45) | Region 4 | -0.88 | (0.12) |
| Advertising GRPs×Region 5 | 0.62 | (0.45) | Region 5 | -0.42 | (0.16) |
| Advertising GRPs×Region 6 | 0.72 | (0.40) | Region 6 | -0.30 | (0.15) |
| Advertising GRPs×Region 7 | 0.50 | (0.35) | Region 7 | -0.52 | (0.16) |
| Seasonality× Brand Type Effects | Yes | | | | |
| Brand-Region Fixed Effects | Yes | | | | |

Standard errors in parentheses. Source: estimated baseline model.

Table 4: Estimated Demand Elasticities

| Aggregate Own-Price Elasticities | | Household-Type Specific Elasticities | | | |
|---|---|---|---|---|---|
| Coke | -1.69 | Coke, $EA^{\mathcal{A}}$ | -1.51 | Generic, $EA^{\mathcal{A}}$ | -1.43 |
| Guaraná Antarctica | -2.13 | Coke, $EA^{\mathcal{B}}$ | -2.46 | Generic, $EA^{\mathcal{B}}$ | -0.19 |
| Fanta | -2.07 | Coke, $EA^{\mathcal{O}}$ | -2.39 | Generic, $EA^{\mathcal{O}}$ | -1.37 |
| Pepsi | -2.07 | Coke, $NA^{\mathcal{A}}$ | -1.70 | Generic, $NA^{\mathcal{A}}$ | -1.56 |
| Generic | -0.51 | Coke, $NA^{\mathcal{B}}$ | -2.69 | Generic, $NA^{\mathcal{B}}$ | -0.23 |
| | | Coke, $NA^{\mathcal{O}}$ | -2.63 | Generic, $NA^{\mathcal{O}}$ | -1.50 |
| | | Coke, $P^{\mathcal{A}}$ | -4.98 | Generic, $P^{\mathcal{A}}$ | -3.29 |
| | | Coke, $P^{\mathcal{B}}$ | -5.66 | Generic, $P^{\mathcal{B}}$ | -1.52 |
| | | Coke, $P^{\mathcal{O}}$ | -5.65 | Generic, $P^{\mathcal{O}}$ | -3.27 |

Reported elasticities are means across region-and-time markets, as predicted by the estimated demand model. Only a few elasticities are shown.

Table 5: Predicted Soda Penetration and Consumption Patterns by Socioeconomic Group

| | Soda Penetration | Premium Share | Generic Share | Premium:Generic Ratio |
|---|---|---|---|---|
| Established Affluent | 0.51 | 0.34 | 0.17 | 2.0 |
| Newly Affluent | 0.37 | 0.22 | 0.15 | 1.5 |
| Poor | 0.03 | 0.01 | 0.02 | 0.6 |

Soda penetration, for the entire category and by type of brand, in each socioeconomic group, as predicted by the estimated demand model. Reported numbers are means across region-and-time markets.

Table 6: Estimates from the "No Habit" Demand Model

| | coeff | (s.e.) |
|---|---|---|
| **Price Sensitivity Parameters** | | |
| $\alpha_{EA}$ | 1.90 | (0.70) |
| $\alpha_{NA}$ | -0.19 | (0.55) |
| $\alpha$ | -3.34 | (0.73) |
| **Additional Covariates** | | |
| Constant | -1.25 | (0.14) |
| Temperature | 1.76 | (0.16) |
| Advertising× Region | Yes | |
| Region-specific time trends | Yes | |
| Seasonality× Brand Type Effects | Yes | |
| Brand-Region Fixed Effects | Yes | |

Source: the no-habit model variant.

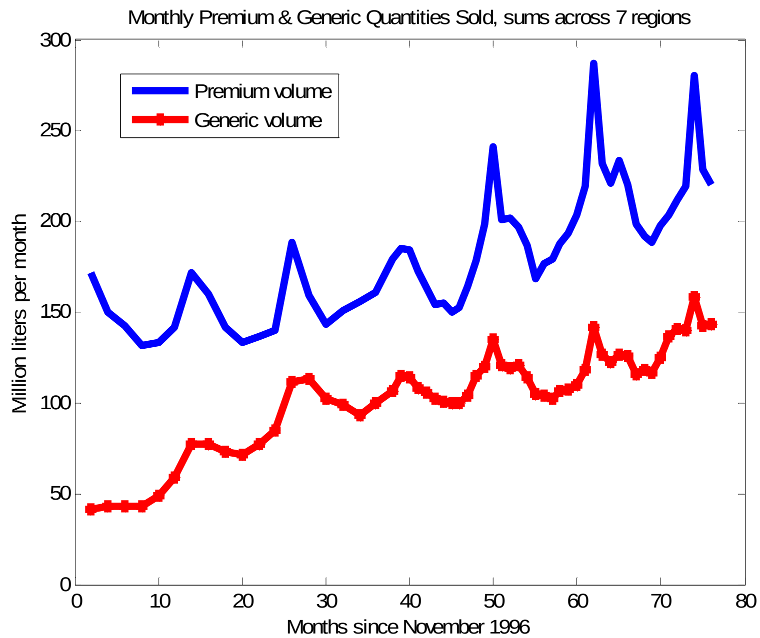


Figure 1: The evolution of quantities (in million liters/month) by type of brand (Premium versus Generic), for soda sold in family-size bottles through the self-service channel across the seven Nielsen regions, in the period Dec-96 to Mar-03. Source: Nielsen.

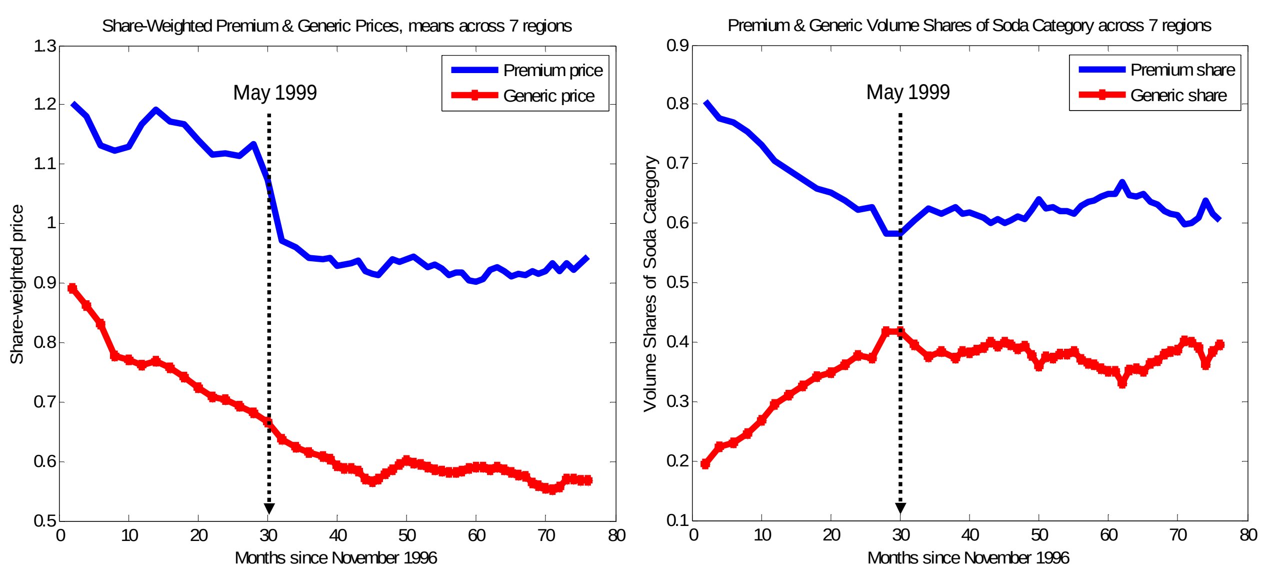


Figure 2: The evolution of prices (in constant Brazilian R$/liter) and category volume shares (in percent, summing to one) by type of brand (Premium versus Generic), for soda sold in family-size bottles through the self-service channel across the seven Nielsen regions, in the period Dec-96 to Mar-03. Source: Nielsen.

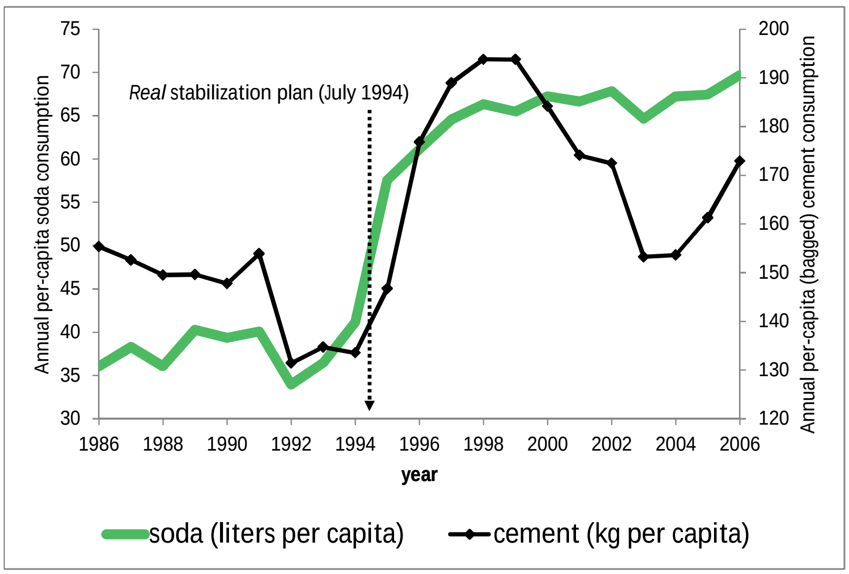


Figure 3: Annual aggregate per capita consumption of soft drinks (in liters per person) and of bagged cement (in kilograms per person). (Cement sold in bags, as opposed to sales in bulk, filter out any large-scale construction activity, such as government spending on infrastructure.) Source: Brazilian trade associations for soft drink makers and for cement producers, ABIR and SNIC respectively.

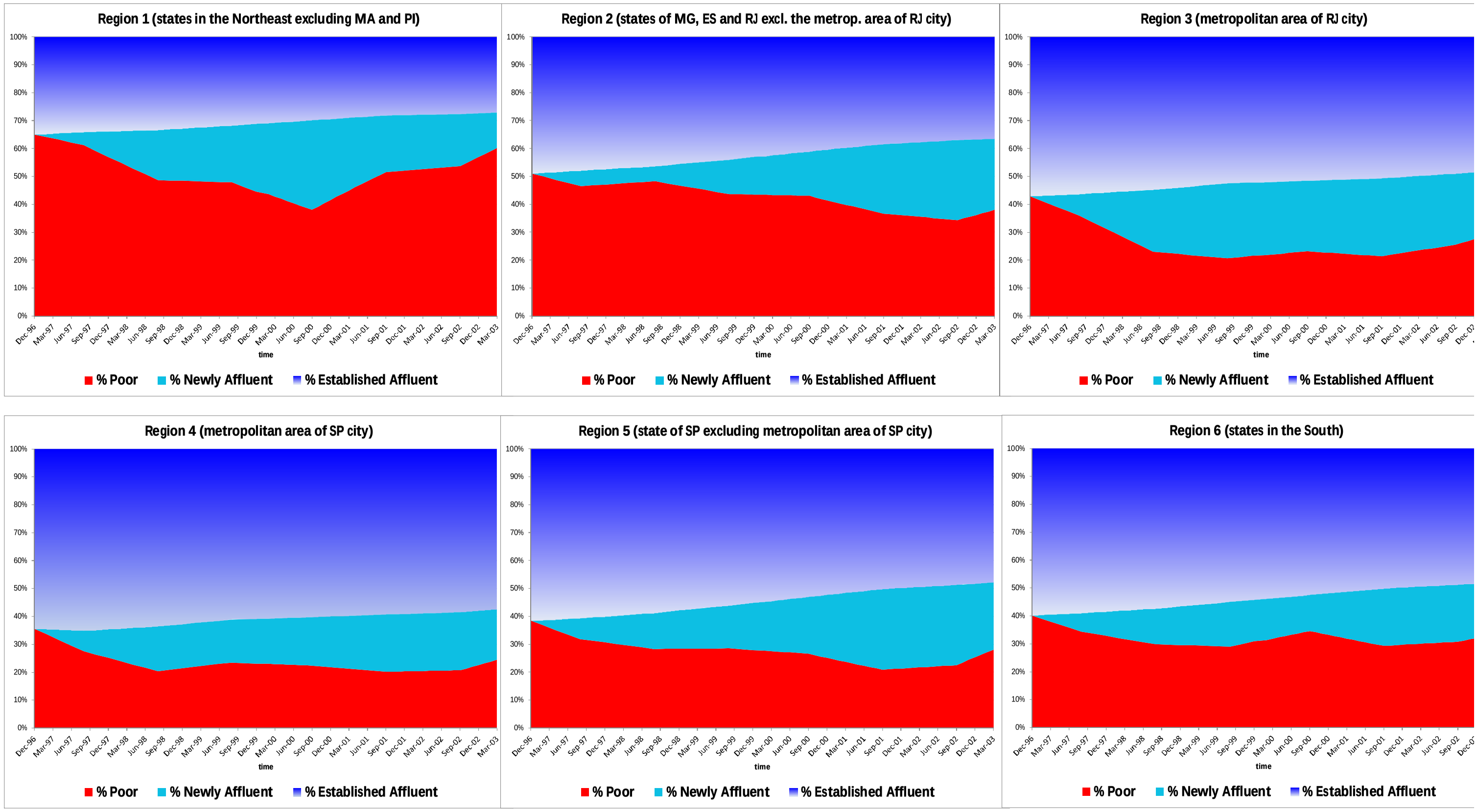


Figure 4: The rise of "newly affluent" households: Proportion of urban households in each of three constructed socioeconomic groups ("Established Affluent," "Newly Affluent" and "Poor"), as defined in the text, by region in the period Dec-96 to Mar-03. The smallest region by number of households, region 7 (Federal District and states of GO and MS), is not shown for lack of space (the pattern is similar to region 2). Source: IBOPE LatinPanel and IBGE PNAD.

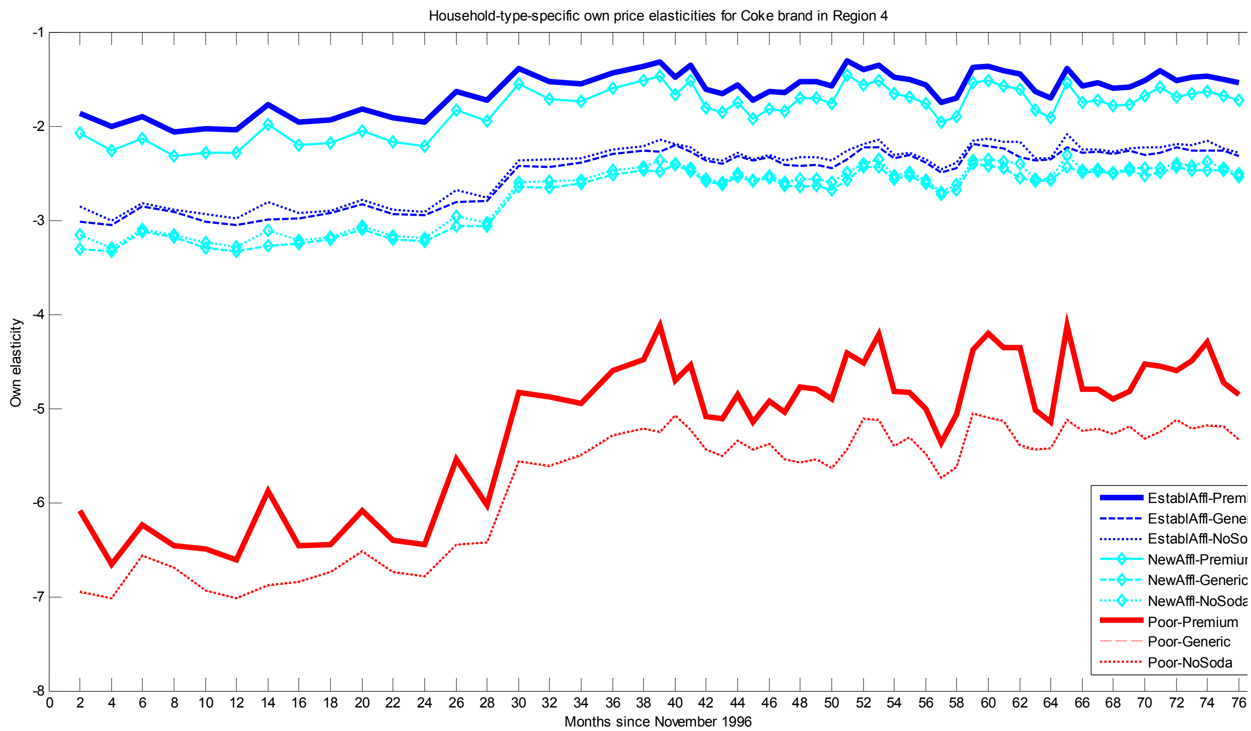


Figure 5: Evolution of own-price elasticities for Coke brand, by household type, in region 4 (São Paulo Metro). Source: Baseline model (Brand Type Persistence). Source: baseline model.

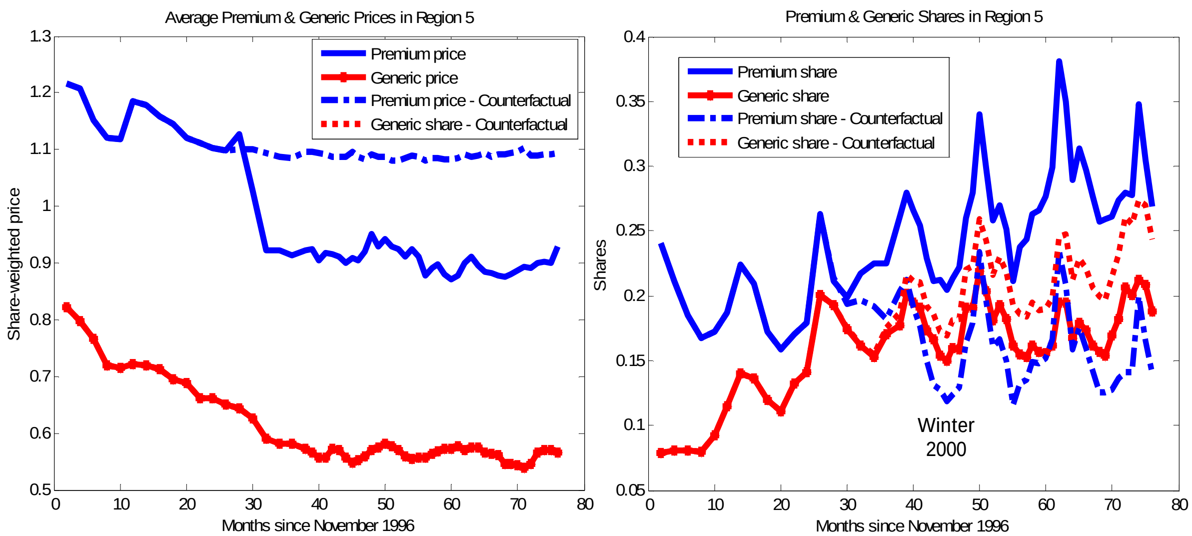


Figure 6: Actual against counterfactual price and share paths for premium brands and generic brands in region 5 (São Paulo Interior). Prices in the left panel and shares in the right panel. The counterfactual scenario considers premium brands not cutting prices in mid 1999. Source: Baseline model (Brand Type Persistence).

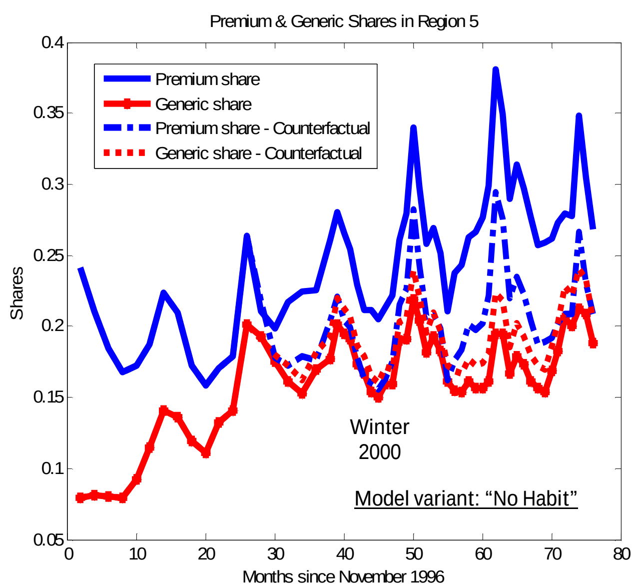


Figure 7: Share paths for premium brands and generic brands, in region 5, for the same counterfactual experiment of the earlier figure (premium brands not cutting prices in 1999), but employing the "No Habit" model variant.