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Evidence on search costs under hyperinflation in Brazil: the effect of *Plano Real*

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Keywords: Hyperinflation; Search costs; Price dispersion; Structural estimation

JEL Codes: C14; D4; D83; E31

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1 Introduction

Plano Real put an end to hyperinflation in 1994 and significantly altered price-setting behavior in Brazil.[1] This paper highlights the impact of the plan on consumers' search costs. Both inflation and search costs affect relative price distribution and the informational content embedded in prices. I document a new empirical finding connecting these two features: when inflation is high – particularly during hyperinflation – consumers' search costs of finding the lowest-priced firm are higher than when inflation is low and prices are more stable.

I estimate a nonsequential search model for homogeneous goods, as in Moraga-González and Wildenbeest (2008), to retrieve consumers' search costs. The empirical identification strategy consists of using *Plano Real* as a structural breakpoint in the data. The plan was implemented on July 1, 1994 and its effect on monthly inflation was immediate. In 1994, consumer inflation went from 50.8% in June to 7.0% in July and then to 2.0% in August.

I split my dataset into two inflationary periods, one before and one after *Plano Real*: January 1993 to June 1994 (hyperinflation) and August 1994 to December 1995 (low inflation). I compare the cumulative search-cost distribution during both estimation periods using the criterion of first-order stochastic dominance (FOSD).

I find evidence of FOSD of the distribution before the implementation of *Plano Real*; that is, search costs are higher during hyperinflation than during lower rates of inflation. I estimate the model using store-level price quotes collected by *Fundção Instituto de Pesquisas Econômicas* (FIPE) in the city of São Paulo. My dataset comprises 11,673 price quotes. Stores are quoted every month by FIPE to compute their Consumer Price Index (CPI).

I analyze 15 brands:[2] 7 food items, 4 industrial goods, and 4 services.[3] All brands are homogeneous in terms of physical characteristics. To quantify the extension of search costs, I focus only on geographically isolated markets, defined as all stores quoted by FIPE that sell a certain brand within a radius of 6 km. I restrict the sample to stores that are close to each other.

In both inflationary environments, Brazilian consumers exhibit fairly high search costs. The majority of consumers search only once or twice before buying an item, but this share is marginally higher during hyperinflation. Before *Plano Real*, 84% of all consumers on average quote prices in one or two stores, whereas 79% do so after the plan. In addition, after *Plano Real* a larger share of consumers is willing to quote prices in all stores before committing to a purchase. I also document evidence of the effect of the plan on shrinking price-cost margins. When searching is less costly, stores lose market power.

The pattern of consumers exhibiting fairly high search costs is a common feature in the literature. Moraga-González and Wildenbeest (2008), Wildenbeest (2011), and González and Miles-touya (2018) document the same behavior. The novelty of this paper is its extension of

[1] Araujo (2018b) and Araujo (2018a).

[2] Section 5 presents the selection criteria.

[3] The brands are: (i) food items – *chicken, Antarctica beer, Coca-Cola, top sirloin, mozzarella, pork loin, and mortadella*; (ii) industrial goods – *shampoo, deodorant, shaving cream, and steel sponge*; (iii) services – *coffee, meal, doctor's appointment, and haircut*.

the search-cost approach to different inflationary environments in a developing economy. By focusing on the same stores selling the same homogeneous product, I highlight the impact of *Plano Real* on the decrease in consumers' search costs. By assuming that this was the major event behind consumer behavior during my 3-year sample, which it arguably was, I focus on how the transition form hyperinflation to price stability impacts search frictions.

Hoomissen (1988) presents a theoretical framework connecting inflation and search costs: when inflation is high, consumers buy less information because information is costly to acquire and its value decreases significantly over time (mainly because prices are increasing and relative prices are changing). Here, I use a structural model to estimate and compare search costs during two very distinct inflationary scenarios. I provide empirical evidence of higher search costs during a hyperinflationary episode. To the best of the author's knowledge, this is the first study to empirically assess the connection between inflation and search costs through a structural estimation of the latter.

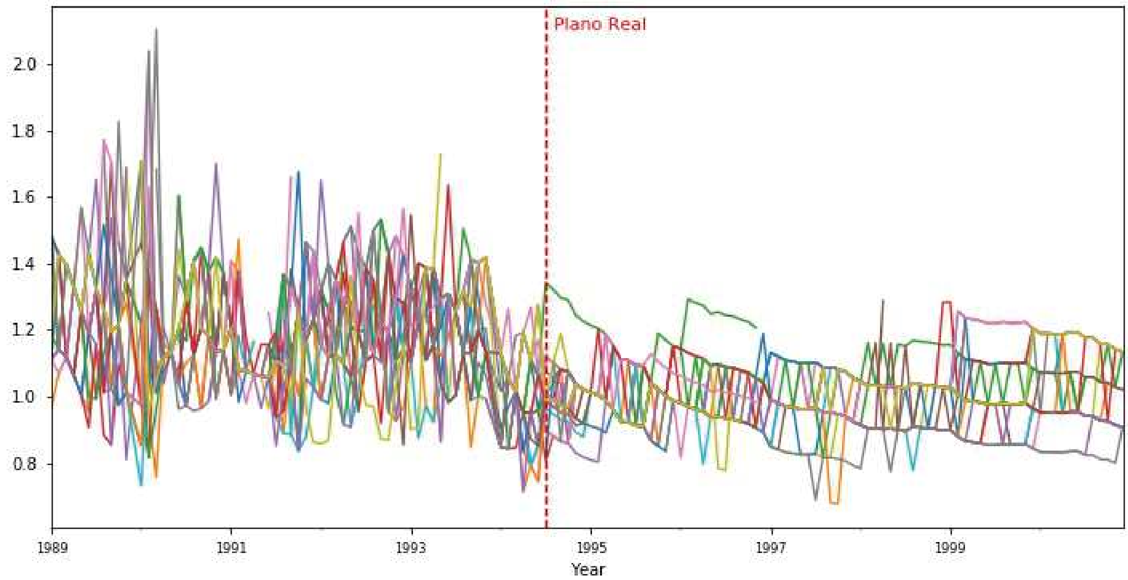


Figure 1: Relative prices for 290-ml bottle of Coca-Cola

Figure 1 illustrates the empirical motivation behind the idea of investigating the periods before and after *Plano Real*. The figure plots the relative price (ratio of the price in a particular store to the average price in all stores) of a 290-ml bottle of Coca-Cola in 25 different stores. During hyperinflation, the price ranking of different stores constantly changes over time. Stores do not change their prices in lockstep.

In any given month, consumers cannot properly distinguish cheap and expensive stores. Prices also change more often. Yet, there is a clear shift in the data immediately after *Plano Real*. The price ranking becomes clearer, and some firms consistently charge higher prices, whereas others are consistently cheaper. At this point, consumers can learn from prices, which directly impacts their search costs.

Search costs translate into an unequal distribution of price information across consumers. They cannot always correctly identify stores that charge low prices, thus it is likely that differences in observed prices will persist. Varian (1980) recognizes that the *law of one price* can be no law, because most retail markets exhibit a large degree of price dispersion. In fact, price dispersion seems rather the norm than an exception in most markets.[4] Some of the theoretical studies regarding price dispersion include Diamond (1971), Burdett and Judd (1983), and Stahl (1989). See Baye et al. (2006) for a literature review.

Inflation also increases price dispersion – see Hoomissen (1988), Lach and Tsiddon (1992), Konieczny and Skrzypacz (2005), Caglayan and Filiztekin (2003), and Baglan et al. (2016). During periods of high inflation, consumers cannot learn from relative prices. Inflation distorts the informational content of nominal prices. Both inflation and search costs constitute sources of welfare losses for consumers. Nevertheless, there is still a lack of empirical studies connecting the two. This paper contributes to the literature by documenting differences in search-cost distributions depending on the inflationary environment.

This article relates to the Industrial Organization literature on estimating consumers' search costs using only price data in markets for homogeneous goods. The first empirical study to use prices to recover search costs is Hong and Shum (2006). The authors exploit the equilibrium restrictions imposed by price-search models, such as Burdett and Judd (1983). They propose an empirical maximum likelihood estimation procedure to retrieve unknown search-costs parameters using price data alone. They demonstrate that optimal consumer and firm behavior impose enough structure for such estimation.

Moraga-González and Wildenbeest (2008) extend the approach of Hong and Shum (2006) to the case of oligopoly and propose a new estimation method. They derive a maximum likelihood estimator that allows for standard asymptotic theory implications. This is the estimation procedure on which the present paper is based. Sanches et al. (2018) propose a minimum distance estimator approach. All these methodologies are especially useful, since price data is widely available, while quantities supplied or demanded are not.[5]

Despite the relevance of search-costs heterogeneity, a great deal of room remains for estimations of real-life markets, especially in developing countries. González and Miles-touya (2018) analyze data on the Spanish food retail market and investigate the impact of search costs and vertical product differentiation on price dispersion. The authors find evidence of fairly high search costs in the market. They calculate that more than two-thirds of consumers do not compare prices and buy at the first and only store they visit. Moraga-González and Wildenbeest (2008) estimate search costs for computer memory chips and also find evidence of low search intensity for a large share of consumers.

[4]Price dispersion may also arise due to store differentiation and quality-related characteristics of products – see Wildenbeest (2011) and Gorodnichenko et al. (2018) – and due to menu costs – see Sheshinski and Weiss (1977) and Benabou (1988).

[5]Hortaçsu and Syverson (2004) extend this approach by including data on quantities. By doing so, they also incorporate the possibility of quality differences across searched products.

Richards et al. (2016) analyze online grocery pricing data in the UK. The authors estimate search costs by accounting for differences regarding the purchasing behavior for a single product and a basket of products. They emphasize the importance of considering the *variety effect* when searching. Consumers usually look for more than one product at the same time, and this affects the welfare losses of price searching. The authors also document a lower search intensity across consumers. Nishida and Remer (2018) investigate consumer search costs in retail gasoline markets using US price data. The authors emphasize the importance of considering geographically isolated markets when assessing searching behavior, which closely relates to my spatial criteria for selecting stores.

Stigler (1961) presents a pioneering approach regarding the rationale behind price dispersion through search models. Moraga-González et al. (2017a) investigate the impact of the number of firms in a market on price dispersion and consumer surplus. The authors argue that this relationship depends on the nature of search-cost dispersion. When search costs are relatively dispersed, an increase in the number of acting firms may translate into higher mean prices and lower welfare. This result is not trivial. The authors provide evidence for the importance of considering search-cost heterogeneities. Here I consider two heterogeneity dimensions: across consumers and across inflationary scenarios. See Konieczny and Skrzypacz (2004) for methods of connecting searching and price-setting behavior.[6]

The literature on models of price dispersion covers a wide range of markets in different countries, such as groceries [Caglayan et al. (2008) in Turkey, Richards et al. (2016) in the UK, and González and Miles-touya (2018) in Spain], electronics [Baye et al. (2006) for online sales in the US and abroad and Gatti and Kattuman (2003) for several Europeans countries], books [Hong and Shum (2006) in the US and Ancarani and Shankar (2004) in Italy] and airlines [Borenstein and Rose (1994) in the US]. See also Hortaçsu and Syverson (2004) for data on mutual funds. Regarding high-inflation economies, Lach (2002) focuses on price dispersion and its persistence over time in Israel. Nevertheless, there is still a lack of empirical estimations for developing countries, especially Brazil.

The remainder of the paper proceeds as follows. Section 2 documents the inflation environment and relevance of *Plano Real*. Section 3 presents the theoretical model, followed by a description of the estimation procedure in Section 4. Section 5 presents the dataset. Section 7 documents the estimation results, and Section 8 concludes the paper.

[6]Some studies also investigate how consumer characteristics may affect their willingness to search among stores. De Los Santos (2018) finds a negative correlation between income and searching. Richer consumers search with less intensity.

2 *Plano Real* and inflation

Since the late 1970s, Brazil experienced a chronic inflation process, which turned into hyperinflation in the beginning of the 1980s. Monthly inflation peaked at 79.1% in March 1990, and annual inflation peaked at 2,490.9% in 1993.[7] Figure 2 plots the monthly inflation from 1970 to 2018. *Plano Real* was implemented on July 1, 1994. Its effect on monthly inflation was immediate. The monthly CPI-FIPE was 50.8% in June 1994, 7.0% in July 1994, and 2.0% in August 1994. After more than a decade of excruciating levels of inflation, hyperinflation was finally tamed.

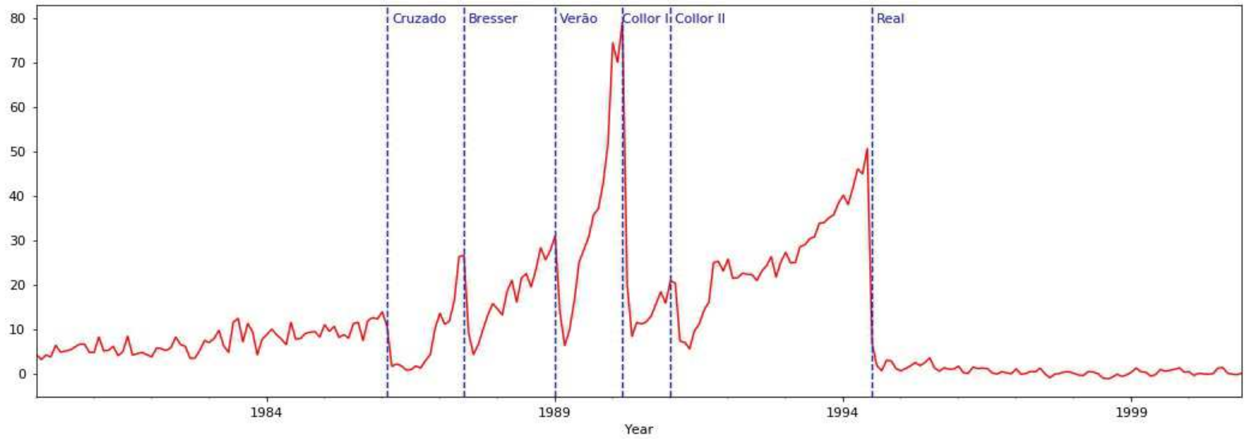


Figure 2: Monthly inflation and economic plans

Several economic plans failed to put an end to hyperinflation since the late 1980s. Each plan was followed by some degree of euphoria and another round of inflation, often with even higher peaks than before. The first civilian government after the 20-year military regime (José Sarney 1986–1989) implemented three plans – *Plano Cruzado*, *Plano Bresser*, and *Plano Verão* – all of which contained measures to halt inflation that were heterodox to some degree.

Next, under President Collor, two stabilization plan were enforced: *Plano Collor I* and *Plano Collor II*. Figure 2 displays vertical lines indicating the adoption month of each plan. For an extensive description of the Brazilian economy during these two decades, see Dornbusch and Cline (1997), Giambiagi et al. (2010), and Garcia et al. (2014).

During hyperinflation, shop owners would adjust price tags more than once per day. Daily inflation in Brazil reached roughly 2% per day. The economy was in a severe trap created by indexation. Wages, rents, bank deposits, and other prices were continuously adjusted according to past inflation. The common interpretation at that time was that the inertial component of inflation was prevalent. Orthodox measures to control inflation would then fail. Restrictive

[7]All inflation statistics in this paper refer to the CPI collected by FIPE. In contrast to most countries, several agencies calculate price indexes relative to consumers' and producers' expenditures in Brazil. The official CPI is collected by *Instituto Brasileiro de Geografia e Estatística* (IBGE) and is the reference index for the inflation target regime. Although under different methodologies and products, indexes are strongly correlated.

monetary policy could not promote disinflation when inertia ruled inflation's behavior. As part of this diagnosis, many failed attempts involving the freezing of prices and wages were implemented.

The country also adopted several short-lived currencies (the *Cruzado*, *Cruzado Novo*, *Cruzeiro*, and *Cruzeiro Real*) during those years. Fiscal and balance-of-payments crises also contributed to the fragile economic situation of the country. Inflation eroded the purchasing power of families at the same time that a recession shrank per capita GDP. It was only during the administration of President Itamar Franco that *Plano Real* was conceived. *Plano Real* had 3 essential pillars: (i) fiscal balance, (ii) the creation of the units of real value (*Unidade Real de Valor* - URV) to prevent continuous automatic indexation, (iii) the adoption of a new currency called the *Real* (R$).

First, beginning in early 1993, the government adopted several measures to restrict expenses and amplify revenues. A series of contracting fiscal as well as monetary policies were enacted. The Brazilian state demanded a great deal of resources to stay functional, which was an important source of money printing and inflation. See Garcia et al. (2014) for an extensive investigation of the fiscal adjustment in Brazil during this period and how it relates to the country's inflation environment.

Second, and probably the most important reason behind the success of the plan, was the creation of the URVs. Since March 1994, most contracts were converted to URVs. During hyperinflation, the *Cruzeiro Real* (CR$), the currency at that time, lost its value as a unit of account. The idea behind the creation of the URV was to establish a noncurrency (or fake currency) to prevent uncontrolled price adjustments. Prices in CR$ were adjusted to URVs on a daily basis. The conversion rate from CR$ to URV was pegged the US dollar. The URV was far more stable than the *Cruzeiro Real*, serving as an anchor to the domestic currency in nominal terms.

It is important to emphasize the public support for the plan. In the wake of many failed attempts, the success of *Plano Real* was closely related to the social pact behind its implementation. Brazilian society embraced the innings of the plan. Finally, three months after the URV, the new currency was adopted at the exchange rate of CR$ 2,750.00 to R$ 1.00. Since *Plano Real*, there has been no return to anything similar to pre-1994 inflation. In 1999, Brazil adopted an inflation target regime, and *Plano Real* remains a textbook case of success. The *Real* (R$) is still the official currency of the country.

3 Model

The model is broadly based on Hong and Shum (2006), Moraga-González and Wildenbeest (2008), Sanches et al. (2018), and Moraga-González et al. (2017a). All of these authors propose a similar base model following the theoretical work of Burdett and Judd (1983) in order to structurally estimate search costs in markets of homogeneous goods using only observed price distribution data.[8]

3.1 Demand side

There is a continuum of imperfectly informed consumers in this economy. Consumer search costs are associated with discovering a given store's price. They adopt a nonsequential search strategy and buy from the cheapest store after looking through a random sample of $k \geq 1$ prices. Nonsequential search strategies are based on a fixed sample size, and consumers commit to a number of searches prior to entering the market.

There are homogeneous sampling probabilities over each store. Define the marginal expected savings from searching k places rather than $k+1$ as

$$\Delta_k = E(p_{1k}) - E(p_{1k+1}) \tag{1}$$

Where p_{1k} is the lowest price out of k search trips; that is, $E(p_{1k}) = E[min(p : k\ draws)]$. Consumers draw prices from the same $i.i.d.$ continuous cumulative distribution function of prices $F_p(p)$, to be determined in equilibrium. It follows that

$$Prob(p_{1k} \leq p \in \Re) = Prob[min(p : k \text{ draws}) \leq p]$$
$$Prob(p_{1k} \leq p \in \Re) = 1 - [1 - F_p(p)]^k$$

Therefore,

$$E(\mathrm{p}_{1k}) = \int_{\underline{p}}^{\overline{p}} pk[1 - F_p(p)]^{k-1} f_p(p)dp \tag{2}$$

Where $\underline{p}$ and $\overline{p}$ denote the lower and upper bound in the support of $F_p(p)$, respectively. Moreover, $f_p(p)$ is the price density function and $0 < \underline{p} < \overline{p} < \infty$. Integrating by parts

$$\int_{\underline{p}}^{\overline{p}} pk[1 - F_p(p)]^{k-1} f_p(p)dp = [-(1 - F_p(p))^k p]\Big|_{\underline{p}}^{\overline{p}} + \int_{\underline{p}}^{\overline{p}} [1 - F_p(p)]^k dp$$

[8]See Wildenbeest (2011) for a discussion of search cost with vertically differentiated products. Hortaçsu and Syverson (2004) present a similar approach.

Note that $\overline{p}$ can be seen as the consumer valuation (v) of the good, that is, the maximum amount she is willing to pay for it. Because $[1 - F_p(\overline{p})] = 0$ and $[1 - F_p(\underline{p})] = 1$, the first part reduces to only $\underline{p}$

$$E(\mathrm{p}_{1k}) = \underline{p} + \textstyle\int_{\underline{p}}^{\overline{p}}[1 - F_p(p)]^k dp \tag{3}$$

Where $\underline{p}$ is the lowest market price and $\int_{\underline{p}}^{\overline{p}}[1 - F_p(p)]^k dp$ is the markup charged above it, a nonnegative and nonincreasing convex function of k. Consumer's i demand is inelastic for a single unit of the good. All consumers enter the market for search. See Rauh (2004) and Moraga-González et al. (2017b) for investigations of endogenous decisions to participate in the market. Her utility (U_{ik}) from sampling through k stores is set as

$$\mathrm{U}_{ik} = -E(p_{1k}) - c_i(k - 1) \tag{4}$$

Where c_i is the individual-specific search cost. This is the source of heterogeneity in searching behavior. There is a positive cost of obtaining each additional price quote. This is the so-called *"shoe-leather cost"*, which accounts for the consumer's opportunity cost of searching between stores. The cost c_i is observed only by the consumer, and the first price quote is obtained at no cost (all consumer search leads to a transaction). The econometrician supposes $c_i \overset{iid}{\sim} G_c(c)$, with support $]0, \infty[$, and positive density $g_c(c)$. An individual search cost is assigned by a random draw from this distribution.

The consumer seeks to maximize her utility based on an optimal search behavior. Consumers weigh the cost of searching an additional store against the expected benefit of doing so. An individual searches k times if her expected utility is higher than searching $k-1$ or $k+1$ times. If k solves the consumer's problem, then

$$U_{ik} \geq U_{ik+1} \text{ and } U_{ik} \geq U_{ik-1}$$
$$c_i \geq E(p_{1k}) - E(p_{1k+1}) = \Delta_k \text{ and } c_i \leq E(p_{1k-1}) - E(p_{1k}) = \Delta_{k-1}$$

The consumer searches k times if her cost lies between $\Delta_k \leq c_i \leq \Delta_{k-1}$. Consumers cannot distinguish stores in terms of expected prices. They search among them randomly, choosing the optimal sample size to do so. Notice that Δ_k can also be interpreted as the search cost of the consumer indifferent between quoting $k+1$ or k stores. The share $q_k \in [0, 1]$ of consumers sampling through k stores, or, alternatively, the probability that a consumer will search exactly k stores is set as

$$\text{Prob[consumer } i \text{ searches } k \text{ times]} = q_k = Prob[\Delta_k \leq c_i \leq \Delta_{k-1}] = G_c(\Delta_{k-1}) - G_c(\Delta_k) \tag{5}$$

Expanding for each q_k

$$q_1 = 1 - G_c(\Delta_1) \text{ - share of consumers searching only one price}$$

$$q_2 = G_c(\Delta_1) - G_c(\Delta_2) \text{ - share of consumers searching two prices}$$

$$q_3 = G_c(\Delta_2) - G_c(\Delta_3) \text{ - share of consumers searching three prices}$$

$$...$$

$$q_N = G_c(\Delta_{N-1}) \text{ - share of consumers searching N prices}$$

The cutoff Δ_l generates partitions of the search-cost distribution $G_c(c)$. I retrieve search costs as the share of consumers who compare prices when shopping for a product. Figure 3 illustrates the regions limiting each partition of the set of consumers into their optimal sampling behavior. The highlighted areas measure the fraction of agents who obtain one, two, three, or four different price quotes before deciding on the purchase. This parametrization will be essential to recovering the quantiles associated with the consumer's search-cost distribution.

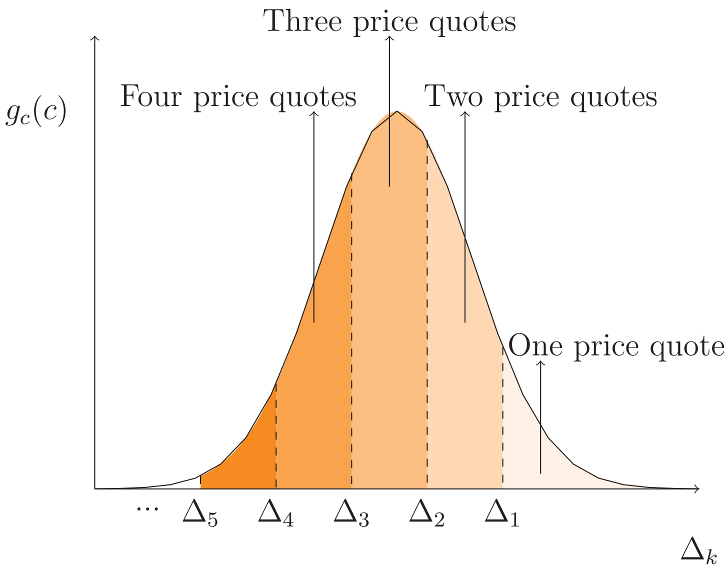


Figure 3: Identification scheme for search-cost distribution

The partition of the space regarding the search trips made by every consumer, q_k, ensures a strictly positive fraction of all sampling possibilities; that is, $q_k > 0$, with k being an integer. Given optimal behavior of stores, the number of price quotes k a consumer obtains, constrained by her search cost of c_i per visited store, must be optimal

$$k^*(c) = \arg\min_{k>1} c(k-1) + \int_{\underline{p}}^{\bar{p}} pk[1 - F_p(p)]^{k-1} f_p(p)dp$$

3.2 Supply side

The supply side is an oligopoly of N retailers supplying the same homogeneous good, as in Moraga-González and Wildenbeest (2008). They operate under the same marginal cost r, which is common knowledge. All stores are ex ante identical in terms of expected price. Given q_k, profits are set as

$$\pi(p; F_p(p), r) = (p - r) \left\{ \prod_{k=1}^{N} \frac{q_k k}{N} [1 - F_p(p)]^{k-1} \right\} \tag{6}$$

This must hold for all $p \in [\underline{p}; \overline{p}]$. Note that the profit function has a straightforward interpretation: $(p - r)$ is the markup, and the remainder of the expression refers to the expected quantities sold considering all $k \in [1; N]$ possibilities of search. Sellers differ only by the price they set ex post.

3.3 Equilibrium

The equilibrium is set in mixed strategies played at the price dimension. All sellers choose a price that maximizes their expected profit given consumers' behavior and their beliefs regarding their opponent's moves. If consumers search only once (q_1), stores set their prices at the upper bound $\overline{p}$, thus charging exactly how much the consumer appreciates the good (v). If consumers search through all N stores, prices are set at the lower bound $\underline{p}$. Stores are indifferent between payoffs generated by choosing any $p \in [\underline{p}; \overline{p}]$. In particular, they are indifferent between $\underline{p}$ and $\overline{p}$. Therefore, the symmetric Nash mixed strategy equilibrium must satisfy

$$(p - r) \sum_{k=1}^{N} \frac{q_k k}{N} [1 - F_p(p)]^{k-1} = (\overline{p} - r) \frac{q_1}{N}, \quad \text{for any } p \in [\underline{p}; \overline{p}] \tag{7}$$

The minimum price $\underline{p}$ and marginal cost r are given by

$$\underline{\text{p}} = \frac{q_1(\overline{p} - r)}{\sum_{k=1}^{N} k q_k} + r \tag{8}$$

$$r = \frac{\underline{p} \sum_{k=1}^{N} k q_k - q_1 \overline{p}}{\sum_{k=2}^{N} k q_k} \tag{9}$$

4 Estimation procedure

Equations (1), (5), (7), (8), and (9) ensure that is possible to retrieve $G_c(c)$ using only a sample of random prices drawn from the empirical distribution of F_p. I follow the estimation procedure of Moraga-González and Wildenbeest (2008). The authors propose a maximum likelihood (ML) estimator to retrieve search costs.[9] The focus is on recovering $\{\Delta_k, q_k\}$ for $k \in [1, N]$. There are N stores in this economy in t sampling periods of time. They play a stationary repeated game of finite horizon, and the data on all periods reflect this equilibrium. Mixed strategies ensure the cross-sectional dispersion of prices and its persistence over time.[10]

The procedure begins by estimating the parameters of the price distribution through ML using the equilibrium constancy-of-profits condition of Equation (7) and the observed prices drawn from the empirical $F_p(p)$ distribution. These estimations are used to recover the cut-off points Δ_k and shares q_k of the search-cost distribution (Equations (1) and (5)) through ML using the invariance property condition. Therefore, based only on a sample of random prices, it is possible to retrieve all relevant quantiles of the consumer search-cost distribution. By spline approximation $G_c(c)$ is recovered.

Note that there are $N-1$ restrictions in the optimization problem; because $q_k \in [0,1]$ and $\sum_{i=1}^{N} q_k = 1$, only $N-1$ fractions need to be estimated. Consider the sequence of prices $p_1, p_2, \ldots, p_N$ ordered as $p_1 \leq p_2 \leq \ldots \leq p_N$ without loss of generality. In this ascending order, the minimum observed price p_1 can consistently estimate $\underline{p}$ and p_N can consistently estimate $\overline{p}$. They super-consistently converge to the true values of the edges of the price distribution support

$$\widehat{\underline{p}} = p_1 \leq p_2 \leq ... \leq p_{N-1} \leq p_N = \widehat{\overline{p}}$$

The problem then reduces to the following maximum likelihood estimation problem

$$\max_{\{q_k\}} \sum_{l=2}^{N-1} log f_p(p_l; q_1; , q_2, ..., q_N)$$

Where $F_p(p_l)$ solves the profit indifference condition of all stores in a symmetric Nash mixed strategy equilibrium

$$(\mathrm{p}_l - r) \sum_{k=1}^{N} \frac{q_k k}{N} [1 - F_p(p_l)]^{k-1} = (\overline{p} - r)\frac{q_1}{N}, \qquad \text{for all } l = 2, 3, ..., N-1 \tag{10}$$

Differentiating Equation (10) and solving for f_p by applying the implicit function theorem yields

$$f_p(p) = \frac{\sum_{k=1}^{N} k q_k (1 - F_p(p))^{k-1}}{(p - r)\sum_{k=1}^{N} k(k-1) q_k (1 - F_p(p))^{k-2}}$$

[9] See also Hong and Shum (2006) for an empirical likelihood estimation (MEL) and Sanches et al. (2018) for a minimum distance (MD) estimation approach.

[10] See Moraga-González et al. (2017a) for a discussion of the existence and uniqueness properties of the equilibrium.

4.1 Inflation and search costs

This subsection briefly discusses the relationship between inflation and search costs in the context of this paper's empirical strategy. The first question is: Why should consumers change their search habits depending on the inflationary environment? The theoretical framework for this question is addressed in Hoomissen (1988). The author compares the act of searching for the lowest price to buying information through prices. When inflation is high, consumers buy less information, because information is costly to acquire and its value is significantly decreasing over time since prices are increasing and relative prices are changing.

During hyperinflation, a consumer quotes prices in many stores in time t, but her newly acquired knowledge on relative prices has diminished value at time $t+1$, because stores will not change their prices in lockstep. During very high levels of inflation, the parameters of the price distribution and store price ranking are constantly changing – Hoomissen (1988). Even fully rational individuals may find it optimal to hold only a small share of price information during this period. Because searching is costly and has limited future value, many consumers may even choose not to search at all during hyperinflation. They buy at the first store to ensure a certain price.[11]

Nevertheless, once inflation is low and stable relative prices reclaim their role as the efficient allocative mechanism for resources. Consumers may learn from prices, which turns searching into a less costly action. Thus, the inflationary environment may change consumers' willingness to search. Searching is only valuable when relative price teaches consumers something about how cheap or expensive a certain store is, which arguably was not the case during hyperinflation (as seen in Figure 1 in Section 1).

My empirical strategy consists of estimating the model presented in Section 3 using periods immediately before and after *Plano Real*. I use the plan as an exogenous event affecting search behavior in Brazil (because the plan aimed for price stability, not search costs). I assume that during my 3-year sample period, the only relevant change was inflation stabilization. Consumers and stores are assumed to be the same, thus allowing for a comparison between the two inflationary environments. Section 5 presents my dataset, and Section 7 presents my empirical results.

[11] Although my model does not allow for a store to change prices during the same period of time, during hyperinflation it is completely plausible for a consumer to quote a price in a store only to find that the price has already increased when she returns to buy the product. This is another rhetorical argument for low search activity during hyperinflation.

5 Data

The data contribution of this paper is to incorporate microdata into the analysis of search costs in Brazil. The dataset consists of store-level price quotes collected by FIPE to calculate the CPI in the city of São Paulo. The CPI-FIPE dates back to 1939 and is one of the most traditional price indexes in Brazil. Researchers visit a list of selected outlets every month to collect price quotes. There is no price imputation or sales flag in the dataset. When an item is out of stock or a certain store is not visited in a particular month, a missing value is assigned to that data point.

The CPI-FIPE index is published at the product level. A product is a good or service defined by an aggregation of one or more brands. A brand is my unit of interest in the data. It comprises the highest degree of information on defining a good/service, such as name, model number, packing, size, weight, and so on. A brand may fully describe an item, such as a 600-ml bottle of Brahma beer, or it may be a generic description of a nonhomogeneous good, such as a dentist appointment. In this paper, I focus only on homogeneous goods to ensure full comparability across stores. To estimate the model outlined in Section 3, I choose transaction prices on 15 different brands. See Table 1 for a description.

Table 1: Selected brands

Brand	Description	Sector
Chicken	1 kg of chicken	Food at home
Antarctica beer	Antarctica beer bottle 600 ml	Food at home
Coca-Cola	Coca-Cola bottle 290 ml	Food at home
Top sirloin	1 kg top sirloin (contrafilé)	Food at home
Mozzarella	1 kg sliced mozzarela	Food at home
Pork loin	1 kg pork loin with bone	Food at home
Mortadella	1 kg sliced mortadella	Food at home
Shampoo	Colorama clássico 500 ml	Industrial good
Deodorant	Impulse spray 90 ml	Industrial good
Shaving cream	Shaving cream Bozzano mint 65 gr	Industrial good
Steel sponge	Bombril 60 gr 8 units	Industrial good
Coffee	1 cup of coffee	Service
Meal	1 meal (prato comercial)	Service
Doctor's appointment	Doctor's appointment (scheduled)	Service
Haircut	Men's haircut at a barber shop	Service

I select the brands based on number of price quotes available, degree of homogeneity, and sectoral relevance. First, following the classification provided by the Brazilian Central Bank (BCB), I aggregate products into four sectors: *Food at home*, *Services*, *Industrial goods*, and *Regulated prices*. Since Regulated prices are mainly controlled by the government and do not respond to market dynamics of price adjustment, I do not consider any brand from this category. This study focuses only on nonregulated prices.

It is important to consider a representative set of brands in order to assess the relevance of search frictions. Different types of goods or services may offer different insights on how search costs change depending on the inflationary environment. I ordered all brands from January 1993 to December 1995 by the number of their of available price quotes during this period. I choose 7 brands from *Food at home*, 4 brands from *Industrial goods*, and 4 brands from *Services*.

This roughly replicates their weight in the consumer basket in the CPI-FIPE. that is, *Services* and *Industrial goods* are almost equally weighted, whereas *Food at home* has approximately double their weight. Appendix A presents a list of all brands ordered by sector and number of price quotes. I choose brands with the highest number of price quotes that are somewhat different from each other. For example, in *Food at home*, meat products are the most quoted product, but I focus on ensuring a higher degree of variety through my investigation of search costs.

From *Food at home*, I consider the prices of 3 kinds of meat (chicken, top sirloin [*contrafilé*], and pork loin with bone), 2 types of beverages (Coca-Cola and Antarctica beer), and 2 delicatessen items (sliced mozzarela and mortadella). During the sample years, food products represent the absolute majority of price quotations. From *Industrial goods*, I focus on 3 beauty care items (Colorama clássico shampoo, Impulse deodorant, and Bozzano shaving cream) and 1 cleaning product (Bombril steel sponge). I do not consider any durable good, because FIPE only incorporated products such as TVs and cars after a methodology revision in January 1994. Finally, from services, I investigate 2 brands from eating away from home (a cup of coffee and a meal [*prato comercial*], a doctor's appointment, and a men's haircut.

When collecting prices to compute the CPI index, a surveyor must ensure complete homogeneity at the brand level across stores and time. This particular concern makes this type of data uniquely suitable for the investigation of search costs for homogeneous items. Once the brands are chosen, it is time to investigate the relevant stores for consumer quotation. Each selected brand is quoted in stores throughout São Paulo. The next section narrows comparable quotations by spatial criteria.

5.1 Spatial criteria

This section describes the spatial criteria for narrowing relevant stores. The city of São Paulo has an extension of 1,521 square kilometers according to the Brazilian Institute of Geography and Statistics (IBGE). To quantify the magnitude of search costs, I focus on geographically isolated markets, as in Nishida and Remer (2018). I define a geographically isolated market by all stores quoted by FIPE that sell a certain brand within a radius of 6 km (approximately 3.73 miles). The center of the circle is defined in order to maximize the number of quoted stores around it.

Figure 4 displays a map of São Paulo. The blue dots represent the stores quoted for the respective brands. Each store has a code in the dataset. I plot the locations of stores on the map by connecting their addresses to latitude–longitude locations. I focus only on stores located inside the red circle that represents the 6-km radius. By restricting the search to a pre-fixed delimited area, I try to control for the opportunity cost of time. A consumer may not be willing to search through an area as big as São Paulo just to buy 1 kg of chicken or some other low-value product. I impose a geographic restriction in which searching makes sense.

Table 2: Summary statistics: stores

	Jan 1993–Jun 1994				Aug 1994–Dec 1995			
Brands	No. of obs.	Mean no. of stores	Min.	Max.	No. of obs.	Mean no. of stores	Min.	Max.
Chicken	588	33	30	35	565	33	31	35
Antarctica beer	767	43	37	45	736	43	40	45
Coca-Cola	436	24	22	25	416	24	23	25
Top sirloin	563	31	29	32	533	31	30	32
Mozzarella	524	29	27	30	502	30	28	30
Pork loin	472	26	22	28	451	27	24	28
Mortadella	440	24	19	27	445	26	23	27
Shampoo	254	14	8	15	248	15	14	15
Deodorant	232	13	9	18	286	17	13	20
Shaving cream	328	18	15	23	330	19	16	22
Steel sponge	442	25	22	26	434	26	23	26
Coffee	265	15	13	15	253	15	14	15
Meal	166	9	8	10	168	10	9	10
Doctor's appointment	214	12	11	12	203	12	11	12
Haircut	212	12	11	12	200	12	9	12

Table 2 presents statistics regarding all stores within the 6-km radius where prices were quoted from 1993 to 1995. I divide the sample between periods before and after *Plano Real*. The former period ranges from January 1993 to June 1994, and the latter ranges from August 1994 to December 1995. I exclude data on July 1994, the month *Plano Real* was implemented. Hereafter I will refer to each sample period as *before* and *after*.

My dataset comprises 11,673 price quotes. To ensure comparability, it is important to have a balanced number of stores between the two samples. All stores in the dataset are active throughout the 3-year sample period. Some may not have a price quotation in a particular month, but on average the sample periods are quite similar.

Wildenbeest (2011) discusses unbalanced panels for store-level data and concludes that no significant bias emerges from this type of missing data. Since the stores are the same, I control for all sources of heterogeneity derived from store-related effects. I assume that the active consumer population is the same between the two periods, so the main source of variability between the sample periods is the inflationary environment.

Prices of food goods are quoted in the largest number of stores. In contrast, fewer stores are searched by FIPE for price quotes on services. There are 25 stores in the sample selling Coca-Cola bottles. From January 1993 to June 1994, there are at least 22 stores with price data on the soda each month. From August 1994 to December 1995, there are at least 23 stores with such price data. An average of 24 stores is quoted every month during both sample periods.

The Antarctica beer presents the largest amount of price quotes available for search-cost estimation. The hyperinflation sample contains 767 observations, whereas the lower-inflation sample contains 736 observations. A total of 45 stores can be searched for this brand within the 6-km radius, and at least 37 are available every month for quotation.

Top sirloin and cheese have a rather similar number of observations in the dataset. Each brand can be searched in approximately 30 different stores each month. Pork loin and mortadella, on the other hand, are available for quotation in a smaller set of stores. Considering *Industrial goods*, the steel sponge is quoted in 26 stores during the sample, while the shaving cream is quoted in 22 and shampoo and deodorant are quoted in 15 and 20, respectively.

The smallest set of observations comes from *Services*, probably because it is quite difficult to collect this type of price data. Rather than just looking at a price tag, the surveyor often has to ask for a specific kind of service. A cup of coffee is quoted, on average, in 15 different stores each month, whereas a meal is quoted in 10. Both a doctor's appointment and a men's haircut are quoted in 12, also on average.

(a) Chicken (b) Antarctica beer (c) Coca-Cola

(d) Top sirloin (e) Mozzarella (f) Pork loin

(g) Mortadella (h) Shampoo (i) Deodorant

(j) Shaving cream (k) Steel sponge (l) Coffee

(m) Meal (n) Doctor's appointment (o) Haircut

Figure 4: Spatial outlet selection: 6-km radius

6 Price dispersion

This section documents price dispersion on the 15 selected brands. Because the sample comprises data during very high levels of inflation, each nominal price quotation was transformed into real prices by fixing the *numeraire* index in January 1995. Henceforth, all prices are in terms of January 1995 R$. Lach (2002) also adopts the same data transformation when documenting price dispersion in Israel during high inflation. Table 3 presents simple mean and variability measures of the real-price data.

Table 3: Summary statistics: real prices

	Jan 1993 - Jun 1994						Aug 1994 - Dec 1995					
Brands	Mean	Median	Std. dev.	Min.	Max.	CV (%)	Mean	Median	Std. dev.	Min.	Max.	CV (%)
Chicken	1.26	1.25	0.19	0.78	2.21	15.3	1.29	1.24	0.27	0.80	2.42	21.2
Antarctica beer	0.86	0.84	0.27	0.35	1.53	31.0	0.98	0.85	0.25	0.53	1.47	25.8
Coca-Cola	0.45	0.45	0.05	0.33	0.59	11.3	0.49	0.49	0.04	0.41	0.65	8.0
Top sirloin	3.50	3.49	0.57	2.17	5.34	16.2	4.51	4.44	0.81	2.69	6.99	18.0
Mozzarella	5.32	5.29	1.86	1.29	11.86	34.9	6.88	6.62	2.21	2.75	15.77	32.1
Pork loin	3.21	3.20	0.63	1.86	6.02	19.7	4.25	4.20	0.88	2.43	7.35	20.7
Mortadella	3.58	3.06	1.56	1.42	9.74	43.5	3.71	3.26	1.23	1.63	7.23	33.0
Shampoo	1.27	1.22	0.32	0.65	2.26	25.5	1.35	1.32	0.25	0.94	2.40	18.6
Deodorant	1.00	0.98	0.27	0.35	1.93	27.4	0.99	0.99	0.24	0.49	1.86	23.9
Shaving cream	1.26	1.23	0.31	0.70	3.52	24.6	1.41	1.37	0.22	0.81	2.59	15.4
Steel sponge	0.36	0.35	0.07	0.16	0.70	18.8	0.38	0.38	0.05	0.24	0.59	12.5
Coffee	0.24	0.23	0.05	0.16	0.41	19.8	0.31	0.30	0.05	0.24	0.49	17.3
Meal	1.75	1.73	0.28	1.22	2.81	15.9	2.54	2.50	0.37	1.89	4.25	14.4
Doctor's appointment	27.51	23.51	14.96	9.48	75.04	54.4	45.31	36.05	25.05	20.16	124.25	55.3
Haircut	2.96	2.68	1.12	1.14	6.50	37.8	6.10	5.69	2.23	2.73	12.85	36.5

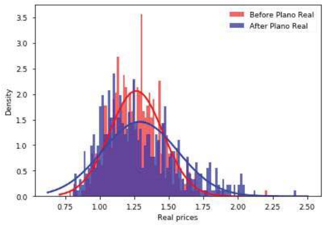
Prices exhibit substantial dispersion during the sample period. The *law of one price* does not hold during hyperinflation or during lower rates of inflation. Figure 5 presents the price histograms for each brand pooled over stores and months during both sample periods. I fit a normal distribution in each histogram. Real prices tend to be more dispersed during hyperinflation, which is captured by a higher kurtosis in the normal distribution.

Averaging stores and months from 1993 to June 1994, the mean and median price of the Coca-Cola bottle is 0.45, with a standard deviation of 0.05. Prices range from 0.33 to 0.59. The coefficient of variation (CV), defined as the ratio of the standard deviation to the mean price, is 11.3%. The mean and median price of the soda in the sample from August 1994 to 1995 is quite similar to those in the previous period. However, the coefficient of variation is smaller, at 8.0%.

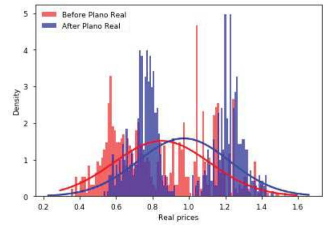
Among the food goods, mortadella presents the greatest coefficient of variation in both sample periods. The range between the minimum and maximum price of the brand is also quite large. During hyperinflation, 1 kg of sliced mortadella costs from 1.42 to 9.74, and it costs from 1.63 to 7.23 during the subsequent year and a half. Regarding the meat brands, an interesting fact emerges. The coefficient of variation is smaller before *Plano Real* than after it. For chicken, the CV goes from 15.3% to 21.2%, for top sirloin it goes from 16.2% to 18.0%, and for pork loin it goes from 19.7% to 20.7%.

The 4 industrial goods brands present a roughly similar coefficient of variation of around 20%

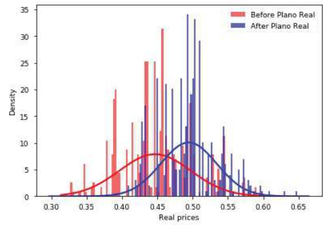
before *Plano Real*. The CV is 25.5% for the shampoo brand, 27.4% for the deodorant brand, 24.6% for the shaving cream brand, and 18.8% for the steel sponge brand. This measure of dispersion decreases for all of them after the plan, but the movement is larger for the shampoo. Finally, prices of services present the highest CV (55.3% for a doctor's appointment from August 1994 to December 1995).



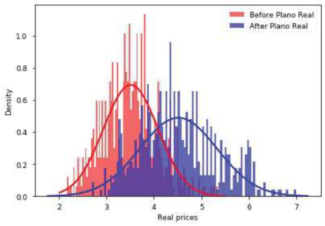
(a) Chicken



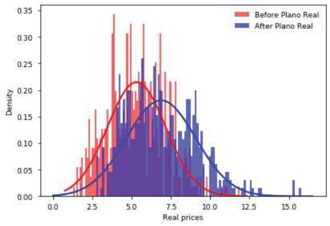
(b) Antarctica beer



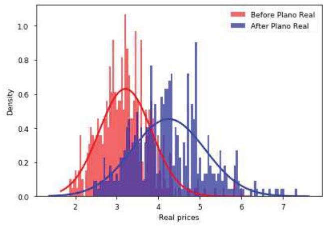
(c) Coca-Cola



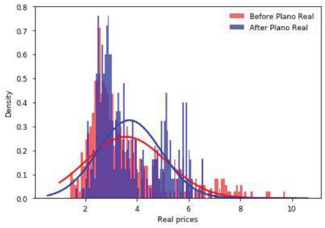
(d) Top sirloin



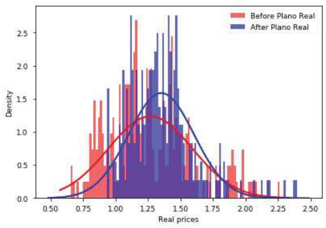
(e) Mozzarella



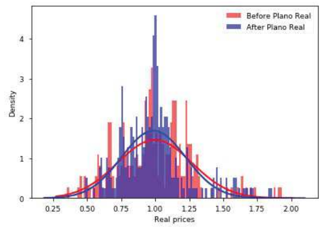
(f) Pork loin



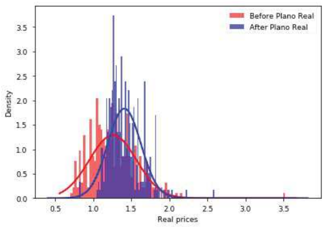
(g) Mortadella



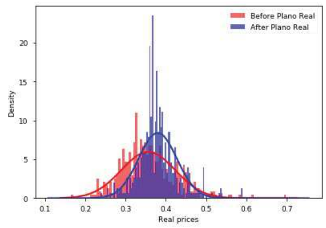
(h) Shampoo



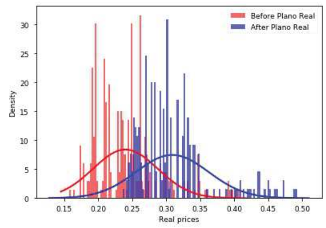
(i) Deodorant



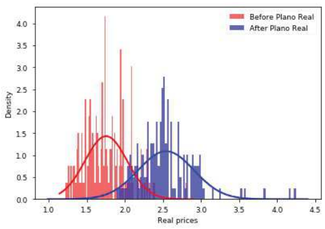
(j) Shaving cream



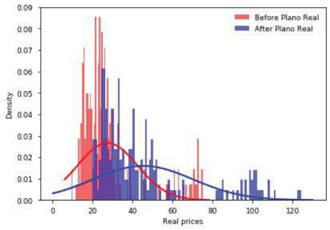
(k) Steel sponge



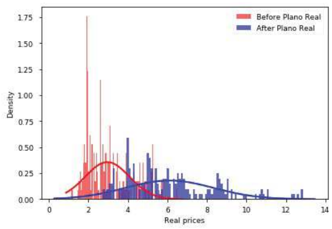
(l) Coffee



(m) Meal



(n) Doctor's appointment



(o) Haircut

Figure 5: Real-price histograms

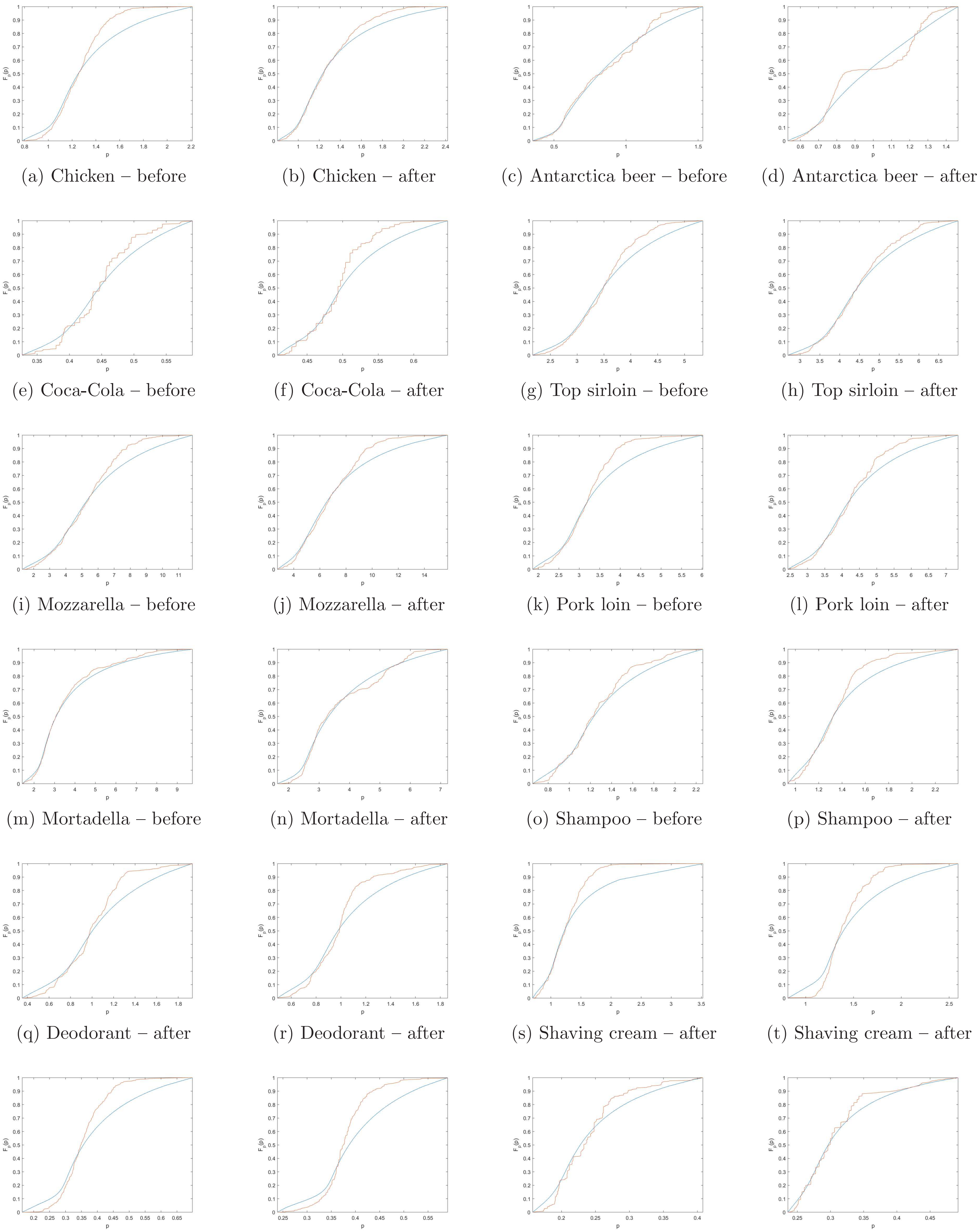
7 Empirical results

In this section, I present estimates of the-search cost distribution implied by the theoretical model outlined in Section 3. The estimation closely follows the procedure presented in Moraga-González and Wildenbeest (2008). The search-cost distribution is fully characterized by the cutoff points Δ_k and quantiles q_k. My empirical identification strategy consists of estimating the model using data before and after the *Plano Real*. The impact of hyperinflation is assessed by contrasting estimations of Δ_k and q_k between the two periods using the criterion of FOSD. Evidence on FOSD suggests higher search costs in the corresponding inflationary environment.

First, I assess the goodness of fit of the model during both sample periods. In order to retrieve all relevant quantiles of the search-cost distribution $G_c(c)$, I start by estimating the theoretical cumulative distribution function (cdf) of prices $F_p(p)$ predicted by the model. I then compare the theoretical estimation to the empirical price distribution observed in the data. Figure 6 presents the goodness of fit of the model during both sample periods. It displays the empirical cdf (red line) and the estimated cdf (blue line). Despite being a demand-side asymmetry, search costs help to explain firms' decisions during both inflation periods.

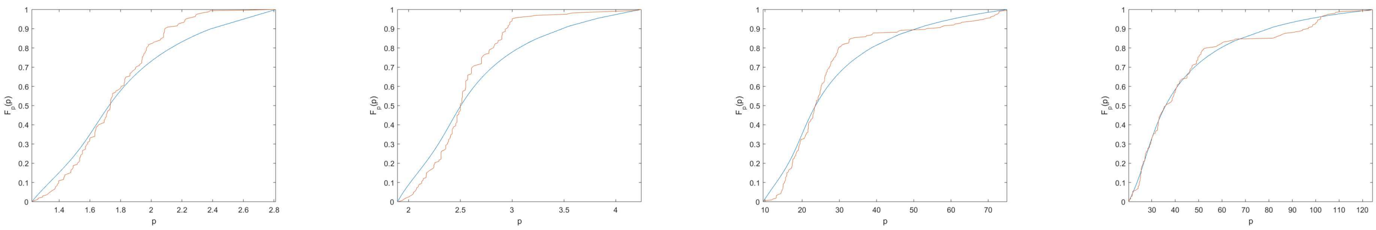
The best fitting of the actual price distribution to the fitted distribution is obtained using prices of mortadella (Figure 6m and Figure 6n). The worst fitting comes from shaving cream prices (Figure 6s and Figure 6t). Following Moraga-González and Wildenbeest (2008), I also test the goodness of fit of the model through a Kolmogorov–Smirnov test. The test basically investigates whether the observed prices may have been drawn from the estimated price distribution obtained within the theoretical model and its equilibrium restrictions. I do not reject the null hypothesis that they have the same distribution under 10% confidence for all brands. The model performs well in the face of empirically observed data.

Table 4 presents the estimation results for the 15 different brands. Standard errors are shown in parentheses. The first row reports the estimated proportion of consumers searching only once (q_1). They have very high search costs and buy at the first and only visited store. This share is above 10% for all brands, both before and after *Plano Real*. Roughly one out of every 10 consumers does not search at all and ends up paying the monopoly price. Considering the period before *Plano Real*, the Coca-Cola bottle presents the largest share of q_1. From 1993 until July 1994, 43% of all consumers do not conduct a price search before buying this soda. The smallest q_1 during hyperinflation is for shaving cream.



(a) Chicken – before
(b) Chicken – after
(c) Antarctica beer – before
(d) Antarctica beer – after
(e) Coca-Cola – before
(f) Coca-Cola – after
(g) Top sirloin – before
(h) Top sirloin – after
(i) Mozzarella – before
(j) Mozzarella – after
(k) Pork loin – before
(l) Pork loin – after
(m) Mortadella – before
(n) Mortadella – after
(o) Shampoo – before
(p) Shampoo – after
(q) Deodorant – after
(r) Deodorant – after
(s) Shaving cream – after
(t) Shaving cream – after
(u) Steel sponge – after
(v) Steel sponge – after
(w) Coffee – after
(x) Coffee – after

Figure 6: Fitting of the model

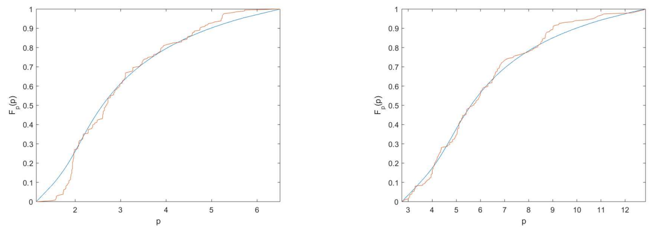


(y) Meal - before

(z) Meal - after

(aa) Doctor's appointment - before

(ab) Doctor's appointment - after



(ac) Haircut - before

(ad) Haircut - after

Figure 6: Fitting of the model

The second row reports estimations on consumers who search only two stores. Considering all brands, the share q_2 ranges from 38% to 68% during the period before *Plano Real* and from 23% to 73% during the period after its implementation. Adding the share of consumers who look once or twice before committing on a purchase results in roughly 80% of all consumers.

Before *Plano Real*, 84% of all consumers on average quote prices in one or two stores, while 79% do so after the plan. This empirical finding is quite common in the literature on search-cost estimations. There is evidence of fairly high search costs in real life. González and Miles-touya (2018) calculate a share of 90% of consumers who search for one or two firms, and Moraga-González and Wildenbeest (2008) calculate a share ranging from 60% to 90%. De Los Santos (2018) also reports that consumers visit relatively few firms before buying a product.

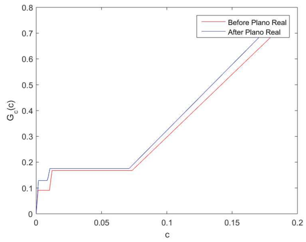
For most brands, consumers also search in three stores (q_3). For a smaller group of brands, searching also takes place into four stores (q_4). The last row presents estimates on the share of consumers searching all stores (q_N). This proportion is relevant for all brands. A small group of consumers is willing to search all available stores for the best price. This group exhibits very low search costs. They pay the lowest possible price when buying the item. Before the plan,q_N ranges from 6% to 18%, and it ranges from 4% to 23% afterwards. After *Plano Real*, a larger share of consumers is willing to search prices in all available stores; that is, search costs have lowered.

Figure 7 displays the estimation of the cumulative distribution of search costs $G_c(c)$ both before and after *Plano Real*. The figure illustrates the numerical results presented above. The sampling quotes probabilities have a similar pattern across brands and inflation scenarios. Search costs are initially high, which translates into sampling at only a few stores (one, two, three, or four). Then, costs become quite low, which translates into quoting prices in all available places within the selected 6-km radius.

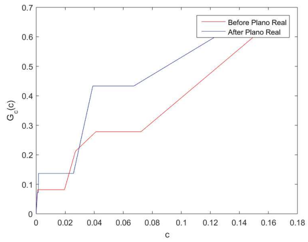
Following Moraga-González et al. (2017b), I compare the cumulative search-cost distribution during the two inflationary scenarios. I find evidence on FOSD regarding 11 of the 15 brands: chicken, Coca-Cola, top sirloin, pork loin, shampoo, deodorant, shaving cream, steel sponge, coffee, meal, and doctor's appointment. The cdf of search costs before *Plano Real* presents FOSD on the cdf after the plan. This implies that search costs are higher during hyperinflation. For the remaining 4 brands (beer, cheese, mortadella, and haircut), the result is inconclusive. I do not find any evidence on FOSD of the distribution after the plan.

Table 4: Estimation results

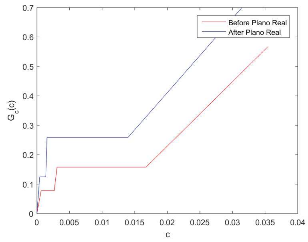
	Chicken		Antarctica beer		Coca-Cola	
	Before	After	Before	After	Before	After
q_1	0.25 (0.03)	0.30 (0.04)	0.34 (0.09)	0.34 (0.01)	0.43 (0.08)	0.30 (0.04)
q_2	0.58 (0.04)	0.53 (0.04)	0.38 (0.07)	0.23 (0.04)	0.41 (0.03)	0.44 (0.04)
q_3	0.08 (0.03)	0.03 (0.37)	0.07 (0.24)	0.30 (0.04)	0.08 (0.04)	0.13 (0.04)
q_4	-	0.01 (0.38)	0.13 (0.27)	-	-	-
...	-	-	-	-	-	-
q_{N-1}	-	-	-	-	-	-
q_N	0.09 (0.04)	0.13 (0.07)	0.08 (0.09)	0.13(0.08)	0.08 (0.06)	0.13 (0.08)
	Top sirloin		Mozzarella		Pork loin	
	Before	After	Before	After	Before	After
q_1	0.40 (0.07)	0.37 (0.05)	0.33 (0.06)	0.26 (0.05)	0.32 (0.07)	0.27 (0.02)
q_2	0.46 (0.03)	0.44 (0.03)	0.47 (0.04)	0.53 (0.06)	0.49 (0.05)	0.50 (0.03)
q_3	0.07 (1.84)	0.09 (0.04)	0.10 (0.05)	0.08 (0.98)	0.09 (2.44)	0.07 (0.61)
q_4	-	-	-	0.03 (1.07)	-	0.01 (0.65)
...	-	-	-	-	-	-
q_{N-1}	-	-	-	-	-	-
q_N	0.07 (0.59)	0.10 (0.06)	0.10 (0.07)	0.10 (0.74)	0.10 (0.78)	0.15 (0.05)
	Mortadella		Shampoo		Deodorant	
	Before	After	Before	After	Before	After
q_1	0.21 (0.05)	0.38 (0.05)	0.37 (0.08)	0.23 (0.05)	0.38 (0.10)	0.33 (0.07)
q_2	0.68 (0.08)	0.58 (0.03)	0.49 (0.02)	0.53 (0.06)	0.44 (0.04)	0.49 (0.05)
q_3	0.01 (0.70)	0.00 (0.00)	-	0.05 (0.10)	0.07 (0.07)	0.04 (0.06)
q_4	-	-	-	-	-	-
...	-	-	-	-	-	-
q_{N-1}	-	-	-	-	-	-
q_N	0.10 (0.16)	0.04 (0.02)	0.14 (0.09)	0.19 (0.14)	0.11 (0.09)	0.14 (0.09)
	Shaving cream		Steel sponge		Coffee	
	Before	After	Before	After	Before	After
q_1	0.16 (0.03)	0.11 (0.05)	0.33 (0.05)	0.35 (0.06)	0.34 (0.05)	0.25 (0.06)
q_2	0.60 (0.07)	0.50 (0.03)	0.50 (0.02)	0.43 (0.04)	0.58 (0.03)	0.60 (0.05)
q_3	0.06 (0.05)	0.10 (0.02)	-	-	-	0.06 (0.07)
q_4	-	0.06 (0.01)	-	-	-	-
...	-	-	-	-	-	-
q_{N-1}	-	-	-	-	-	-
q_N	0.18 (0.08)	0.23 (0.08)	0.17	0.22	0.08 (0.03)	0.09 (0.07)
	Meal		Doctor's appointment		Haircut	
	Before	After	Before	After	Before	After
q_1	0.33 (0.08)	0.24 (0.06)	0.24 (0.04)	0.18 (0.04)	0.37 (0.06)	0.33 (0.08)
q_2	0.50 (0.03)	0.54 (0.04)	0.62 (0.03)	0.73 (0.02)	0.57 (0.04)	0.56 (0.04)
q_3	-	-	-	-	-	0.02 (0.06)
q_4	-	-	-	-	-	-
...	-	-	-	-	-	-
q_{N-1}	-	-	-	-	-	-
q_N	0.17 (0.10)	0.22 (0.09)	0.14 (0.06)	0.09 (0.02)	0.06 (0.03)	0.09 (0.09)



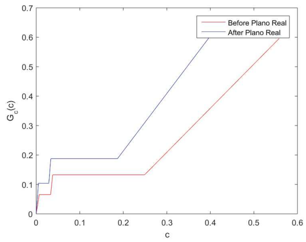
(a) Chicken



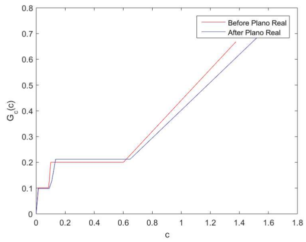
(b) Antarctica beer



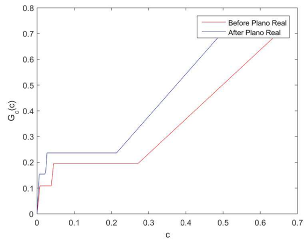
(c) Coca-Cola



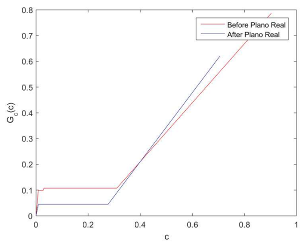
(d) Top sirloin



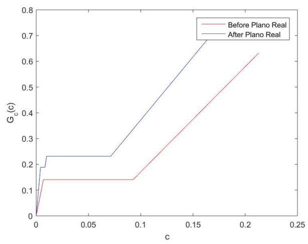
(e) Mozzarella



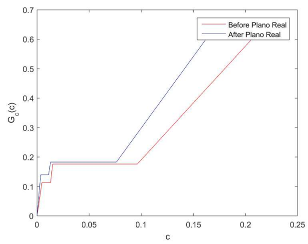
(f) Pork loin



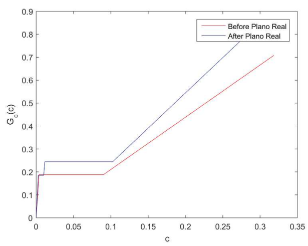
(g) Mortadella



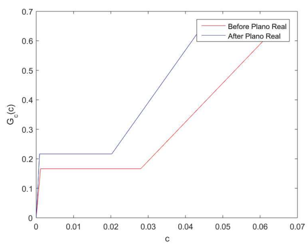
(h) Shampoo



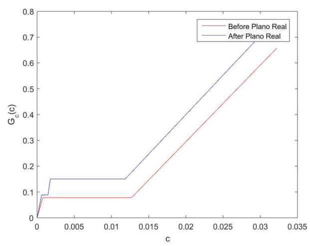
(i) Deodorant



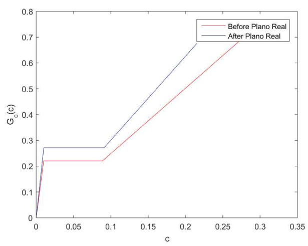
(j) Shaving cream



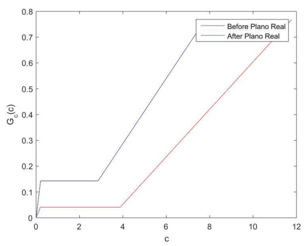
(k) Steel sponge



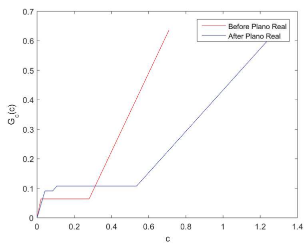
(l) Coffee



(m) Meal



(n) Doctor's appointment



(o) Haircut

Figure 7: Search-cost distributions

Figure 7 illustrates search-cost estimations associated with the same brand being sold in the same stores. I also assume that the active consumer population is the same between the two periods.[12] Here, my hypothesis is that different search costs do not trigger the entry of new consumers into market. I focus only on the intensive margin of searching, that is, the decision on how many stores to visit.[13] The only dimension in which my two samples are potentially different is the inflationary environment in which each search takes place. It is important to emphasize that no causal mechanism is assumed. After *Plano Real*, search costs are endogenously different. Figure 7 confirms and illustrates this pattern.

I also present estimations on the marginal cost of each brand during both inflation environments. Table 5 presents the statistics regarding $\underline{p}$ (the lowest price in the sample, which is the one paid by the share q_N of consumers), v (the consumer valuation of the brand, or the highest price in the sample, which is the one paid by the share q_1 of consumers), and r (the marginal cost). The standard error of the marginal cost estimation is shown in parentheses. I also calculate the Lerner Index of price-cost margin (in %) considering both the lowest and highest price in the sample in each sample period.

The Lerner Index considering the lowest price in the sample is given by $(\underline{p} - v)/\underline{p}$, whereas the index considering the highest price is $(v - r)/v$. Considering the search process for 1 kg of chicken, the Lerner Index for the lowest price drops from 8.1% to 4.1% after *Plano Real*. The index for the highest price also drops, going from 72.9% to 71.1%. I observe the same pattern in all 15 brands in my sample. When inflation is at skyrocketing values, consumers cannot properly distinguish cheap and expensive stores, which translates into more market power to charge prices well above their marginal costs.

During hyperinflation, the price ranking of different stores changes constantly over time. It is very costly for consumers to identify which store charges the lowest price. Although many factors may lie behind price dispersion, such as market concentration and product differentiation, I focus on the costly acquisition of price information and its relationship to inflation. A key aspect of public policy is to correctly identify sources of price dispersion. Some of the welfare losses related to inflation may be explained by the search-cost channel.

[12] See Moraga-González et al. (2017b) for an investigation of lower search costs allowing new consumers to enter the market and how this affects equilibrium results.

[13] I do not consider decisions regarding the extensive margin (to search or not to search). See Moraga-González et al. (2017b) for a discussion of this approach.

Table 5: Prices and margins

	Chicken		Antarctica beer		Coca-Cola	
	Before	After	Before	After	Before	After
$\underline{p}$	0.78	0.80	0.35	0.53	0.33	0.41
v	2.21	2.42	1.53	1.47	0.59	0.65
r	0.60 (0.01)	0.72 (0.01)	0.28 (0.02)	0.49 (0.01)	0.29 (0.01)	0.40 (0.00)
$(\underline{p}-r)/\underline{p}$	8.1	4.1	9.8	8.8	22.0	1.5
$(v-r)/v$	72.9	71.1	86.9	72.8	66.1	38.5
	Top sirloin		Mozzarella		Pork loin	
	Before	After	Before	After	Before	After
$\underline{p}$	2.17	2.69	1.29	2.75	1.86	2.43
v	5.34	6.99	11.86	15.77	6.02	7.35
r	1.93 (0.03)	2.52 (0.48)	0.57 (0.14)	2.05 (0.72)	1.68 (0.03)	2.21 (0.42)
$(\underline{p}-r)/\underline{p}$	5.1	2.7	6.7	4.8	4.3	3.1
$(v-r)/v$	64.4	64.2	95.8	87.3	73.4	70.1
	Mortadella		Shampoo		Deodorant	
	Before	After	Before	After	Before	After
$\underline{p}$	1.42	1.63	0.65	0.94	0.35	0.49
v	9.74	7.23	2.26	2.40	1.93	1.86
r	0.99 (0.10)	1.43 (0.13)	0.46 (0.04)	0.86 (0.02)	0.19 (0.04)	0.38 (0.02)
$(\underline{p}-r)/\underline{p}$	5.3	3.2	11.1	5.8	13.0	10.2
$(v-r)/v$	90.8	80.6	82.3	66.7	94.8	83.9
	Shaving cream		Steel sponge		Coffee	
	Before	After	Before	After	Before	After
$\underline{p}$	0.70	0.81	0.16	0.24	0.16	0.24
v	3.52	2.59	0.70	0.59	0.41	0.49
r	0.63 (0.01)	0.80 (0.01)	0.13 (0.00)	0.22 (0.00)	0.12 (0.01)	0.21 (0.01)
$(\underline{p}-r)/\underline{p}$	2.8	0.4	8.6	6.8	14.6	8.2
$(v-r)/v$	83.0	69.1	85.7	66.1	75.6	59.2
	Meal		Doctor's appointment		Haircut	
	Before	After	Before	After	Before	After
$\underline{p}$	1.22	1.89	9.48	20.16	1.14	2.73
v	2.81	4.25	75.04	124.25	6.50	12.85
r	1.03 (0.04)	1.72 (0.04)	4.31 (0.86)	18.76 (2.18)	0.13 (0.21)	1.28 (0.37)
$(\underline{p}-r)/\underline{p}$	7.8	4.5	6.9	1.7	16.0	11.9
$(v-r)/v$	64.4	60.0	94.3	85.5	98.5	90.7

8 Concluding remarks

Plano Real put an end to hyperinflation and significantly altered price-setting behavior in Brazil. The plan was implemented on July, 1994, and its impact on monthly inflation was immediate. This paper investigates the effect of the plan on consumers' search costs. Both inflation and search costs impact price dispersion and decrease welfare in equilibrium. Here, I propose a link connecting both features.

I use a nonsequential search model for homogeneous goods to retrieve search patterns among Brazilian consumers using a store-level dataset on 15 different brands from 1993 to 1995. The dataset is collected by FIPE to construct the CPI-FIPE. The empirical identification strategy is to compare the cumulative distribution function of search costs between the two periods, one before and one after *Plano Real* (from January 1993 to June 1994 and from August 1994 to December 1995). I follow the estimation procedure presented in Moraga-González and Wildenbeest (2008).

In both inflationary environments, Brazilian consumers exhibit fairly high search costs. The majority of consumers search only once or twice before buying an item, but this share is marginally higher during hyperinflation (84% *vs.* 79%). In addition, after *Plano Real*, a larger share of consumers is willing to quote prices in all stores before committing to a purchase. The pattern of consumers exhibiting fairly high search costs is a common feature in the literature,[14] but the difference observed between the two inflationary environments is a new contribution.

I find evidence on FOSD of the distribution of search costs before *Plano Real*; that is, search costs are higher during hyperinflation. For some brands, the comparison is inconclusive, but I do not find evidence in the opposite direction. When inflation is high, consumers' search costs are higher than when inflation is low and stable. When consumers are able to learn from prices, their search costs decrease. *Plano Real* had a direct impact on relieving search frictions. I also document evidence of the effect of the plan on shrinking price-cost margins. When searching is less costly, stores lose market power.

Both inflation and search costs have a negative impact on welfare. This paper identifies a mechanism by which these two features interact. Inflation – and especially hyperinflation – erodes the informational content embedded in prices, thus turning searching into an even more costly action. Further progress in this research stream requires a formal modeling of the channel by which inflation affects the magnitude of search frictions. Nevertheless, the empirical evidence suggests that hyperinflation shuffles the price ranking of firms and that this directly impacts searching for the lowest price.

[14]See, for instance, Moraga-González and Wildenbeest (2008), Wildenbeest (2011), and González and Milestouya (2018).

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APPENDIX A

Table 6: Brands in the sample – ordered by # of observations and sectors

# of observations	Brand	Description	Sector
7,927	Chicken	1 kg chicken	Food at home
6,719	Antarctica beer	Antarctica beer bottle 600 ml	Food at home
6,412	Brahma beer	Brahma beer bottle 600 ml	Food at home
6,229	Coca-Cola	Coca-Cola bottle 290 ml	Food at home
6,209	Guaraná	Guaraná bottle 290 ml	Food at home
5,737	Topside	1 kg topside	Food at home
5,730	Outside flat	1 kg outside flat	Food at home
5,703	Top sirloin	1 kg top sirloin (contrafilé)	Food at home
5,701	Knuckle	1 kg knuckle	Food at home
5,691	Rump steak	1 kg rump steak	Food at home
5,656	Eyeround	1 kg eyeround	Food at home
5,594	Shank	1 kg shank	Food at home
5,586	Chuck	1 kg chuck	Food at home
5,550	Mozzarella	1 kg sliced mozzarela	Food at home
5,310	Neck steak	1 kg neck steak	Food at home
5,183	Liver	1 kg liver	Food at home
5,176	Tenderloin	1 kg tenderloin	Food at home
5,113	Pork loin	1 kg pork loin with bone	Food at home
4,984	Pork rib	1 kg pork rib	Food at home
4,799	Cheese plate	1 kg cheese plate	Food at home
4,641	Mortadella	1 kg sliced mortadella	Food at home
...	...	...	...
5,120	Shampoo	Colorama clássico 500 ml	Industrial good
4,973	Deodorant	Impulse spray 90 ml	Industrial good
4,472	Shaving cream	Shaving cream Bozzano mint 65 gr	Industrial good
4,396	Deodorant	Rexona spray 90 ml - powder	Industrial good
4,303	Shampoo	Seda 500 ml	Industrial good
4,049	Conditioner	Neutrox 230 gr	Industrial good
3,654	Conditioner	Colorama Garnier 500 ml	Industrial good
3,542	Steel sponge	Bombril 60 gr 8 units	Industrial good
...	...	...	...
3,305	Coffee	1 cup of coffee	Service
2,687	Sandwich	Misto quente (unit)	Service
2,629	Sandwich	Bauru (unit)	Service
2,236	Meal	Prato comercial	Service
1,937	Pastel	Meat pastel (unit)	Service
1,888	Pastel	Cheese pastel (unit)	Service
1,776	Coxinha	Coxinha (unit)	Service
1,676	Doctor's appointment	Doctor's appointment (prescheduled)	Service
1,675	Sandwich	Cheeseburguer (unit)	Service
1,673	Doctor's appointment	Doctor's appointment	Service
1,451	Esfiha	Esfiha (unit)	Service
1,393	Haircut	Men's haircut at a barber shop	Service