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PRICE SETTING IN BRAZIL FROM 1989 TO 2007
DINÂMICAS DE PREÇOS NO BRASIL DE 1989 A 2007

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PRICE SETTING IN BRAZIL FROM 1989 TO 2007

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To my family.

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So I urge everyone – all women and men of goodwill – to dare the difference and bet on women. I promise you this: you will not be disappointed. For when women shine like the sun, their radiance will be forever undimmed.

Christine Lagarde
Tokyo, September 12, 2014

ABSTRACT

This doctoral dissertation documents price-setting behavior in Brazil using a unique dataset of store-level price quotes collected by the *Fundação Instituto de Pesquisas Econômicas* (FIPE) to construct the Consumer Price Index (CPI-FIPE) from 1989 to 2007. The dataset is extensive in terms of time (222 months), inflation variability (from hyperinflation to monthly deflation), and basket of goods and services (almost 11 million price quotes on 8,294 brands). The first chapter documents new evidence on the frequency and absolute size of price changes during the sample period. I find evidence of marked differences between hyperinflation (1989–1993) and low inflation (1995–2007) periods. During hyperinflation, the frequency and magnitude of price movements are remarkably higher. Once *Plano Real* took place, both statistics immediately shifted to a much lower and stable level, as did inflation. Price increases are more frequent during hyperinflation, although a small share of prices (mostly food items) drops every month. During low inflation, price decreases are almost as likely as price increases. I also document heterogeneities across different classifications of products. The second chapter investigates the relationship between inflation and relative price variability (RPV). The intramarket RPV significantly increases with the rate of inflation, but I find marked differences between the two inflationary scenarios. During hyperinflation, the relationship is roughly 70% of the magnitude of the relationship during low inflation. Higher levels of inflation are associated with higher degrees of inflation variability, yet the link is somewhat looser during the hyperinflation period. The impact of deflation (in absolute terms) is smaller than the impact of positive inflation during hyperinflation, yet stronger during low inflation. Finally, the third chapter documents the importance of *Plano Real* on consumers' search costs. I estimate a nonsequential search model for homogeneous goods to structurally retrieve search costs using price data on 15 different brands of goods and services. The empirical strategy consists of using the *Plano Real* as a structural breakpoint in the data. I estimate the model splitting the data into before (January 1993 to June 1994) and after (August 1994 to December 1995) the plan, and I find evidence on first-order stochastic dominance of the search cost distribution of the former into the latter; that is, search costs are higher during hyperinflation. I also document evidence of the effect of the plan on shrinking price-cost margins. When searching is less costly, stores lose market power.

RESUMO

Esta tese de doutorado documenta comportamentos de fixação de preços no Brasil através de uma base de dados única de cotações ao nível da loja coletadas pela Fundação Instituto de Pesquisas Econômicas (FIPE) para a construção do Índice de Preços ao Consumidor (IPC-FIPE) de 1989 a 2007. Minha base de dados é extensa em tempo (222 meses), variabilidade da inflação (de hiperinflação à deflação mensal) e cesta de bens e serviços (quase 11 milhões de cotações sobre 8.294 marcas). O primeiro capítulo documenta novas evidências sobre a frequência e o tamanho absoluto das mudanças de preços durante o período da amostra. Eu encontro diferenças marcantes entre os períodos de hiperinflação (1989-1993) e baixa inflação (1995-2007). Durante a hiperinflação, a frequência e a magnitude dos movimentos de preços são notavelmente maiores. Após o Plano Real, ambas as estatísticas imediatamente mudam para um nível significativamente mais baixo e estável, seguindo o movimento da inflação. Aumentos de preços são mais frequentes durante a hiperinflação, embora uma pequena parcela de preços (principalmente de alimentos) ainda se reduza a cada mês. Sob inflação baixa, reduções de preços são quase tão prováveis quanto aumentos de preços. Eu também documento heterogeneidades presentes em diferentes classificações de produtos. O segundo capítulo investiga a relação entre inflação e variabilidade de preços relativos (VPR). A VPR intra-mercado aumenta significativamente com a taxa de inflação, mas eu encontro diferenças marcantes entre os dois cenários inflacionários. Durante a hiperinflação, a relação é aproximadamente 70% menor do que a estimada sob inflação mais baixa. Níveis mais altos de inflação estão associados à maior variabilidade desta, mas a ligação é um pouco mais fraca durante o período de hiperinflação. O impacto de uma deflação (em termos absolutos) é menor do que o impacto de um aumento de preço durante a hiperinflação, porém mais forte durante níveis mais baixos de inflação. Finalmente, o terceiro capítulo documenta a importância do Plano Real sobre os custos de busca (*search costs*) dos consumidores. Eu estimo um modelo de busca não sequencial por bens homogêneos para recuperar estruturalmente os custos de busca dos consumidores utilizando dados de preços sobre 15 marcas diferentes de bens e serviços. A estratégia empírica consiste em usar o Plano Real como um ponto de quebra estrutural nos dados. Eu estimo o modelo dividindo os dados entre antes (de janeiro de 1993 a junho de 1994) e depois (de agosto de 1994 a dezembro de 1995) do plano e encontro evidências de dominância estocástica de primeira ordem da distribuição do custo de busca do primeiro sobre o segundo período, ou seja, os custos de busca são maiores durante a hiperinflação. Eu também encontro evidências do efeito do plano na redução da margem de preço (*markup*) das empresas. Quando buscar preços é menos custoso, firmas perdem poder de mercado.

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INTRODUCTION

This doctoral dissertation documents price-setting behavior in Brazil using a unique dataset of store-level price quotes collected by the *Fundação Instituto de Pesquisas Econômicas* (FIPE) to construct the Consumer Price Index (CPI-FIPE).

The first chapter documents new evidence on price-setting behavior using Brazilian microdata from 1989 to 2007. The dataset is extensive in terms of time (222 months), inflation variability (from hyperinflation to monthly deflation), and basket of goods and services (almost 11 million store-level price quotes on 8,294 brands). I find evidence of marked differences between frequency and absolute size of price changes immediately after *Plano Real*. The plan put an end to hyperinflation and substantially altered price-setting behavior in Brazil. The main empirical findings can be summarized as follows: (i) during hyperinflation, an average of 78.7% of all prices change every month (*vs.* 36.8% after *Plano Real*), (ii) price increases are more frequent during hyperinflation, although a small share of prices (mostly food items) drops every month, (iii) once inflation reaches lower levels, price decreases are almost as likely as price increases, (iv) the absolute size of nonzero price changes during hyperinflation is 34.1%, whereas monthly inflation averages 25.3%, (v) the intensive margin (size) explains most of the inflation variation from 1989 to 1993, (vi) in contrast, the extensive margin (frequency) gains importance during the 1995–2007 period, (vii) price changes are less frequent on *Services* items, but this stands out only during lower inflation, (viii) in the hyperinflation period, price changes have a similar frequency and size across different products, which suggests that hyperinflation nearly eliminates the role of idiosyncratic shocks.

The second chapter investigates the relationship between inflation and relative price variability (RPV) using store-level data on prices in Brazil from 1989 to 2007. In brief, the linkage grows stronger during periods of lower inflation rates. I divide the sample into two subsamples: from 1989 to 1993 (hyperinflation) and from 1995 to 2007 (low inflation). I study the distribution of inflation at the most disaggregated level (brands), and I find strong evidence that *Plano Real* decreased inflation variability almost immediately after its implementation. The size and frequency of price changes also decreased immediately after the plan took place. The intramarket RPV significantly increased with the rate of inflation, but I find marked differences between the two inflationary scenarios. During hyperinflation, the relationship is roughly 70% of the magnitude of the relationship during lower inflation; that is, the link is looser during hyperinflation. The impact of deflation (in absolute terms) is weaker than the impact of positive inflation during hyperinflation, yet stronger during lower inflation. I also document similar patterns aggregating brands into sectors and groups of products. This chapter highlights the

importance of considering different inflation scenarios when assessing inflation-related effects.

The third chapter highlights the impact of *Plano Real* on search frictions. I estimate a nonsequential search model for homogeneous goods to structurally retrieve consumers' search costs. The estimation is performed by Maximum Likelihood using price data alone. The dataset comprises 11,673 price quotes from 1993 to 1995. I choose 15 brands to analyze: 7 food items, 4 industrial goods, and 4 services. 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. The empirical strategy consists of using *Plano Real* as a structural breakpoint in the data. I estimate the model splitting the data into before (January 1993 to June 1994) and after (August 1994 to December 1995) the plan, and I find evidence on first-order stochastic dominance of the search-cost distribution of the former into the latter; that is, search costs are higher during hyperinflation. 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 are 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.

1 PRICE SETTING IN BRAZIL FROM 1989 TO 2007: EVIDENCE ON HYPERINFLATION AND STABLE PRICES

1.1 Introduction

Price-setting behavior has crucial macroeconomic implications. When prices exhibit patterns of stickiness, both demand shocks and monetary policy have real economic effects. Indeed, sticky prices constitute a common microfoundation in many models, such as those developed by Taylor (1980), Calvo (1983), Reis (2006), Nakamura and Zerom (2010), Midrigan (2011), Alvarez and Lippi (2014), and Golosov and Lucas (2016). The speed at which an economy responds to a shock is directly related to the speed at which each firm reacts to it. Understanding price-setting dynamics is an essential tool for macroeconomists.

This chapter documents new evidence on price-setting behavior using Brazilian microdata from 1989 to 2007. The dataset is provided by *Fundação Instituto de Pesquisas Econômicas* (FIPE). The sample comprises information on price quotes for a wide range of consumer goods and services at the establishment level used to construct the CPI-FIPE in the city of São Paulo. The dataset includes five years of hyperinflation, from January 1989 to June 1994. During these years, prices rose 472,894,862%.

The period of hyperinflation ended with the successful implementation of *Plano Real* in July 1994. My dataset is extensive in terms of time (222 months), inflation variability (from hyperinflation to monthly deflation), and basket of goods and services (almost 11 million store-level price quotes on 8,294 brands). On the basis of this unprecedented dataset, I document and contrast estimations on the frequency and size of price changes under hyperinflation and under lower inflation rates.

I find striking differences between price-setting behavior during hyperinflation (1989–1993) and during lower inflation (1995–2007).[1] The average frequency of price changes was 78.7% during the former period and dropped to 36.8% during the latter. I find no evidence of a transition period. After the implementation of *Plano Real*, the frequency of adjustments markedly shifted to a much lower and stable level, as did inflation. The plan substantially altered price-setting behavior in Brazil. After *Plano Real*, price decreases also became almost as likely as price

[1] In this chapter, I refer to 1995–2007 as the lower-inflation period. It should be borne in mind that Brazil exhibits higher and more volatile inflation levels than developed economies. The reference emphasizes only the difference from the hyperinflation years.

increases. From 1989 to 1993, only 7.5% of all prices changes were decreases, whereas, from 1995 to 2007, this share rose to 42.3%. I do not find robust evidence in favor of nominal downward price rigidity: even during hyperinflation, some prices (mostly food items) drop every month.

The size of price changes strongly correlates with inflation. During hyperinflation, the monthly average size of a price change was 34.1%. In this period, prices changed frequently and in sizeable amounts. In contrast, from 1995 to 2007, the average size of price changes was 11.4%. The size of price increases dropped from 35.1% to 11.5%. The absolute magnitude of decreases was quite similar between the two periods: 6.9% during hyperinflation and 9.9% afterward.

I also investigate the impacts of the extensive and intensive margins on inflation. The former relates to how often prices change and the latter to how much they change. I find evidence of a more central role of the magnitude of price adjustments during the years of hyperinflation. When inflation is skyrocketing, prices change frequently, but the size of price changes is the predominant force in overall inflation. Following the successful implementation of *Plano Real*, the extensive margin gains importance. In this period, the variation in the frequency of price changes explains most of the variation in inflation.

Finally, I provide evidence on heterogeneities and asymmetries across different classifications of products and services into sector and groups of items. I find substantial heterogeneity in price stickiness across different sectors and groups of products, but this stands out only under lower levels of inflation. When inflation was high, during 1989–1993, all sectors changed prices at a similar frequency, ranging from 70% to 80% a month.

This suggests that when price pressures are higher, readjustments are faster and synchronized since they depend on a common factor. The effect of an aggregate shock dominates idiosyncratic shocks. When inflation levels are lower, producers of *Food* and *Industrial goods* adjust prices more often than producers in other sectors. Prices of *Services* exhibit more rigidity, as is widely documented in the literature. The size of downward adjustments is also smaller in this sector.

Although there is substantial evidence on price adjustments in-low inflation countries, lots of room remain to understand pricing decisions during hyperinflationary episodes. Few countries experienced hyperinflation of the magnitude that Brazil did in the 80s and mid-90s, and even fewer have reliable microdata on prices that would allow the study of this phenomenon.

This chapter contributes to the literature by documenting price-adjustment patterns under both hyperinflation and lower rates of inflation. The inflation variability range is wide, thus providing valuable evidence regarding price rigidity. The implementation of *Plano Real* also

provides insights into the transition between two different inflation scenarios and how price-setting behavior almost immediately adapts to a new reality.

The remainder of this chapter is organized as follows. Section 1.2 presents a brief review of the literature. Section 1.3 describes the macroeconomic environment in Brazil from 1989 to 2007. Section 1.4 presents a description of the dataset. Section 1.5 defines the statistics computed in this chapter and Section 1.6 presents the chapter's main results. Section 1.7 concludes the chapter.

1.2 Literature review

The growing availability of microdata on prices has led to the emergence of several studies regarding price-setting behavior. Since the publication ofBils and Klenow (2004), many empirical works have documented patterns and degrees of price stickiness for a large set of countries. The interest lies in how often and how much prices of individual goods and services change. Alvarez and Julián (2008) and Klenow and Malin (2010) provide an extensive literature review. For an overview connecting empirical findings to macroeconomic models with price rigidity, see Nakamura and Steinsson (2013).

The literature on price setting is generally based on two types of datasets: quantitative data on prices compiled by national statistical offices to measure the Consumer Price Index (CPI) and the Producer Price Index (PPI), and qualitative surveys on firms' pricing behavior, which are conducted mostly by local Central Banks. The first type, on which this chapter is based, contains millions of establishment-level monthly price quotes over several years for a diverse set of goods and services. The latter is restricted to a sample of firms. Such data is also available in the form of scanner data (Eichenbaum et al. (2011) and through online price scraping (Cavallo (2018).

Most studies focus on developed countries during periods of low and stable inflation. In particular, most of them draw on data for the United States and the euro area. Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008) use micro-level US consumer price data collected by the Bureau of Labor Statistics (BLS). These studies have the disadvantage of spanning only the post-1987 period of the US economy, when annual inflation was close to 3%. An important exception is Nakamura et al. (2018), who extend the BLS dataset back to 1977, thereby also including the years of the Great Inflation, when annual inflation peaked at roughly 12% at the beginning of the 80s.

The Inflation Persistence Network at the European Central Bank accounts for most of the studies using microdata on euro countries. Álvarez et al. (2006) summarize evidence on consumer and producer prices, from both micro-level and survey data, for 10 euro countries.[2] Dhyne et al. (2006) also review the main stylized facts for price changes in Europe. In general, studies find that prices change at a lower frequency in Europe than in the United States. Evidence suggests frequencies close to twice a year in the United States and once a year in the euro area, as reported in Klenow and Malin (2010).

Large inflation variability reveals interesting features of how price adjustments occur and how

[2] Austria, Belgium, Finland, France, Germany, Italy, Luxembourg, the Netherlands, Portugal, and Spain.

they correlate with different levels of inflation. Nevertheless, studies of high-inflation economies account for only a small portion of the literature. Papers analyzing periods of high inflation include Lach and Tsiddon (1992) for Israel (1978–1984),[3] Konieczny and Skrzypacz (2005) for Poland (1990–1996), Gagnon (2009) for Mexico (1994–2002), Alvarez et al. (2011) for Argentina (1988–1997), and Wulfsberg (2016) for Norway (1975–2004). See Figure 1 for a comparison of 12-month inflation (%) among the cited countries and Brazil. Data is displayed in log scale to make the differences visible. See also Gagnon (2009) and Alvarez et al. (2011) for a detailed comparison of high-inflation studies.[4]

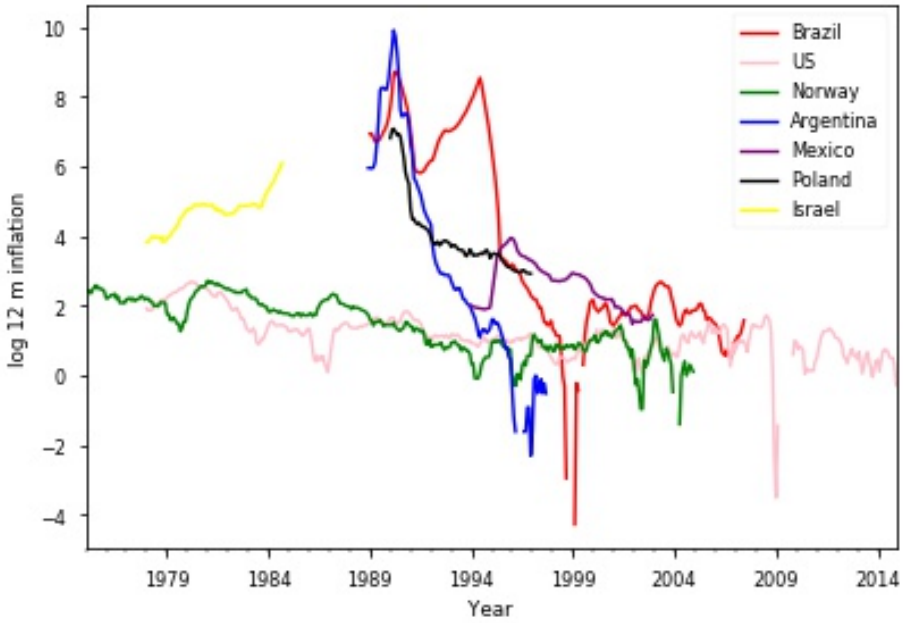


Figure 1: Inflation and time coverage across high-inflation studies

As Figure 1 indicates, Argentina is the only country with a hyperinflation episode comparable to Brazil's. In the late 80s, the country experienced a hyperinflationary scenario in which 12-month inflation reached 20,263% in March 1990. Table 1 presents a comparison across studies of high-inflation economies and the present chapter. My dataset is extensive in terms of time span and products covered. The inflationary scenario is also rich in variability (from hyperinflation to monthly deflation) and the basket of goods and services (8,294 brands).[5] I present new evidence on price-setting behavior during periods of hyperinflation and evidence on the transition between this inflationary scenario to a stable price environment.

[3] Eden (2001) and Baharad and Eden (2004) also draw on data for Israel during periods of high inflation.

[4] Studies of price setting in other countries include Medina et al. (2007) for Chile, Creamer and Rankin (2008) for South Africa, Julio and Zárate (2008) for Colombia, and Gabriel and Reiff (2010) for Hungary.

[5] See Section 1.4.1 for comparison across datasets.

Table 1: Comparison across high-inflation studies

High-inflation study	Country	Sample	Inflation (peak at 12 m)
This chapter	Brazil	Jan 89 - Jun 07	6,239% in 1990
Nakamura et al. (2018)	United States	Jan 78–Dec 14	12.0% in 1980
Wulfsberg (2016)	Norway	Jan 75–Dec 04	15.1% in 1981
Alvarez et al. (2011)	Argentina	Dec 88–Sep 97	20,263% in 1990
Gagnon (2009)	Mexico	Jan 94–Jun 02	52.0% in 1995
Konieczny and Skrzypacz (2005)	Poland	Jan 90–Dec 96	1,200% in 1990
Lach and Tsiddon (1992)	Israel	Jan78–Sep84	450.0% in 1984

Regarding price setting in Brazil, Barros et al. (2009) and Gouvea (2007) analyze microdata from the *Instituto Brasileiro de Estatísticas* for the *Fundação Getulio Vargas* (IBRE-FGV). Both samples start in March 1996, when the CPI dataset became electronic, and they run until 2008 and 2006, respectively. They focus on the period shortly after the disinflationary process. Lopes (2008) and Angelis (2012), like the present chapter, use the CPI dataset provided by FIPE. In particular, Angelis (2012) also focus on the hyperinflationary period, analyzing the correlation between price dispersion and inflation from 1989 to 2000. For a qualitative price survey on Brazilian firms, see Correa et al. (2016).

The empirical findings presented in this chapter regarding the lower-inflation sample are remarkably close to those of previous studies. This common pattern is interesting, because it confirms similar behaviors using very different datasets of countries, methodologies, and inflationary environments. The chapter's results regarding a hyperinflationary scenario are somewhat new, and its detailed evidence on price-setting behavior after a stabilization plan of the magnitude and relevance of *Plano Real* is a genuine contribution to the literature.

The frequency of price adjustments during the Brazilian hyperinflation episode is close to 80%. Almost all prices were changing every month; that is, prices were near the complete flexibility benchmark. This result is similar to Alvarez et al. (2011). The authors find a frequency ranging from 16% to 99% during the country's hyperinflation episode. In contrast to Alvarez et al. (2011), I do not find evidence of the frequency of price decreases converging to zero during hyperinflation. Even under four-digit annual inflation, I still observe price decreases in my dataset (mostly for food items).

Regarding the international evidence on high-inflation episodes, Konieczny and Skrzypacz (2005) document frequencies ranging from 30% to 59% in Poland, and Gagnon (2009) documents an interval from 27% to 45% in Mexico. Neither of these two countries experienced an

inflationary environment as extreme as Brazil's, so their findings are close to mine using the full sample period (49.6% from 1989 to 2007).

The frequency of price changes during the 1995–2007 period (36.8%) is close to findings in Barros et al. (2009) for the Brazilian economy. The authors use another source of microdata (CPI-FGV) for the 1996–2008 period and find an average of 37.4% for the frequency of price changes in their sample. Gouvea (2007) also uses the CPI-FGV and finds a weighted average of 37% during the 1996–2006 period. The results lie well above estimations for the United States and euro area, confirming different pricing dynamics in high-inflation developing countries. For example, regarding the United States, Nakamura and Steinsson (2008) calculate a frequency of 21.1%, and Dhyne et al. (2006) calculate a frequency of 15.1% for the euro area.

Hyperinflation eliminates the effect of idiosyncratic shocks and eliminates almost all variability in the frequency and size of price changes among different products. This result is in line with Alvarez et al. (2011). The authors find the same pattern in Argentina. When inflation is very high, almost all producers adjust prices every month. The frequency of price changes is close to 80% across all sectors and groups of products in Brazil during this period.

Once inflation is running at lower levels, common patterns in the literature emerge, such as a lower frequency for *Services* and a higher frequency for *Food*. Dhyne et al. (2006), Nakamura and Steinsson (2008), and Gagnon (2009) provide similar findings. Regarding the relevance of the extensive and intensive margin in overall inflation, this chaper reaches a new conclusion: the intensive margin (size) explains most of the inflation variation from 1989 to 1993, whereas the extensive margin (frequency) gains importance during the 1995–2007 period. Wulfsberg (2016) highlights the relevance of the extensive margin in Norway, whereas Klenow and Kryvtsov (2008) and Gagnon (2009) discuss the relevance of the intensive margin.

1.3 Macroeconomic environment and *Plano Real*

To contextualize the macroeconomic environment of the sample period, this section presents the main aspects of the Brazilian economy during the covered years. For a more comprehensive description of the Brazilian economy, see Giambiagi et al. (2010). Alongside many South American countries, Brazil underwent a difficult economic period between the 80s and 90s. The 80s are commonly painted as "the lost decade" for the country's economy. From recession to hyperinflation, Brazil experienced the entire spectrum of economic crises. Anemic growth associated with very high levels of inflation rapidly eroded the purchasing power of Brazilian families during these years.

Since the beginning of the 70s, the Brazilian economy witnessed increases in inflation to ever-higher levels. Between 1980 and 1985, the rise in the CPI escalated from 84.8% to 228.2% in annual terms.[6] During these years, several stabilization plans failed to constrain price pressures. Table 2 presents a brief description of each plan. 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 some degree of unorthodox measures for controlling inflation, such as freezing prices and wages.

Table 2: Economic plans from 1986 to 1991

Plan	Date	Description
Cruzado	02/28/1986	Freezing of prices New currency called the *Cruzado* (Cz$) New trigger to wages: once inflation reaches 20% a month, wages are automatically adjusted
Bresser	06/16/1987	Freezing of prices (3 months)
Verão	01/16/1989	Freezing of prices New currency called the *Cruzado Novo* (NCz$) Raising of interest rates
Collor I	03/16/1990	Freezing of prices Confiscation of savings and other financial investments New currency called the *Cruzeiros* (Cr$)
Collor II	01/31/1991	Freezing of prices

Subsequently, under President Collor, two more stabilization plans were implemented. *Plano*

[6] For consistency, Brazilian inflation statistics are always from CPI-FIPE.

Collor I confiscated financial investments above a threshold value, in a misguided attempt to slow down demand pressures on inflation, and *Plano Collor II* also tried to freeze prices. During these years, Brazil also changed currencies four times under different economic plans. Table 3 presents currencies, periods, and conversion rates. Because my dataset goes from January 1989 to June 2007, I adjust prices to a common currency in order to make them comparable. I convert all prices to the current *Real* (R$).

Plano Cruzado introduced a new currency, the *Cruzado* (Cz$) in 1986. Three years later, under the same presidential regime, the *Cruzado Novo* ("New Cruzado" - NCz$) was implemented. These were years of very high inflation, and the currency's purchasing power was rapidly eroding. Almost a year later, the *Cruzeiro* was adopted by *Plano Collor*. The new currency was simply a new name, because it was set at the parity of 1 NCz$= 1 Cr$. Next, the *Cruzeiro Real* also eliminated three zeros from prices. This was the shortest-lived currency in Brazil. Finally, since July 1, 1994, Real (R$) has been the official currency in Brazil.

Table 3: Currencies from 1989 to 2007

Date	Period	Currency	Symbol	Conversion rate
02/28/86 - 01/15/89	34 months	*Cruzado*	Cz$	-
01/16/89 - 03/15/90	13 months	*Cruzado Novo*	NCz$	1,000 Cz$/NCz$
03/16/90 - 07/31/93	40 months	*Cruzeiro*	Cr$	1 Cr$/NCz$
08/01/93 - 06/30/94	10 months	*Cruzeiro Real*	CR$	1,000 Cr$/CR$
07/01/94 - now	-	Real	R$	2,750 CR$/R$

Annual inflation in Brazil reached four digits in all years from 1989 to 1993, except for 1991, when it reached 458.6%. In 1993, annual inflation peaked at 2,491.0%. Monthly inflation peaked at 79.1% in March 1990. The hyperinflation spiral was only terminated under the successful implementation of *Plano Real* in July 1994. Figure 2 presents the monthly CPI from 1986 to 2007. Vertical lines indicate the implementation of each stabilization plan. The impact of *Plano Real* was immediate: monthly CPI went from 50.8% in June 1994 to 7.0% in July 1994, and finally to 2.0% in August 1994.

The successful implementation of *Plano Real* was based on three fundamental pillars: (i) fiscal consolidation; (ii) creation of the units of real value (*Unidade Real de Valor* - URV) to prevent continuous automatic indexation; (iii) adoption of the *Real* (R$). The first pillar was a guideline rather than an actual, fully implemented, public policy. The diagnosis was that hyperinflations are always associated with some degree of fiscal imbalance. In order to prevent prices from rising uncontrollably, some measures of fiscal tightening were necessary. See Garcia et al. (2014) for

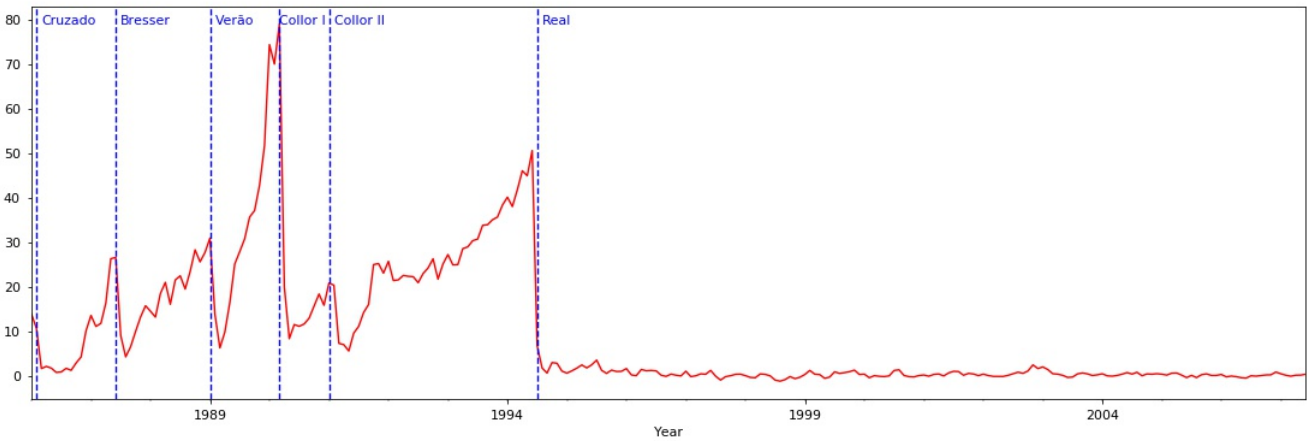


Figure 2: Monthly inflation and economic plans

an extensive description of Brazil's fiscal situation during the 90s and how it relates to the success of *Plano Real*.

Second, and probably the most important reason behind the success of the plan, was the creation of the units of real value (URV). Since March of 1994, most contracts were converted to URVs. During hyperinflation, the *Cruzeiro Real* (CR$), the currency at that time, lost its value as a unit of account. Indexation of contracts made it possible for the country to cope with hyperinflation, but the cycle needed to end. The idea behind the creation of the URVs was to establish a noncurrency (or fake currency) to prevent uncontrolled price adjustments. Prices in CR$ were daily adjusted to URVs. The exchange rate was linked to movements in the US dollar.

The URV was far more stable than the *Cruzeiro Real*, serving as an anchor to the domestic currency in nominal terms. In the meantime, measures to prevent prices from being automatically adjusted according to past inflation (the inertial component of inflation) were also implemented. Finally, three months after the URV implementation, the new currency was adopted at the exchange rate of CR$ 2,750.0 to R$ 1.0.

It is worth emphasizing that although *Plano Real* unquestionably ended the hyperinflation spiral in Brazil, it would be inaccurate to claim that inflation has been low and stable ever since. The annual CPI was 23.2% in 1995 and 10% in 1996, for instance. Whereas 1998 was a year of deflation (-1.8%) under an artificially fixed exchange rate, in 1999, prices rose almost 9%, still a sizeable magnitude. These years were also marked by macroeconomic instabilities and economic downturns. The hyperinflation was tamed, but the absence of shocks is far from

being the norm for the Brazilian economy. The environment thus provides a unique dataset regarding inflationary variability.

1.4 Data

The dataset is provided by the *Fundação Instituto de Pesquisas Econômicas* (FIPE). The sample comprises information on price quotes for a wide range of consumer goods and services at the establishment level used to construct the CPI-FIPE. The data covers almost 19 years, from January 1989 to June 2007.[7] The data was collected in the city of São Paulo, which is by far the most important and prosperous area of the country. The data is weekly based, but a specific store is quoted only once a month. The dataset is restructured to monthly price quotes. The data does not contain a sales indicator.

In contrast to most countries, in Brazil several institutions have calculated price indexes using various methodologies up to the present day. The main statistical office in the country is *Instituto Brasileiro de Geografia e Estatística* (IBGE), which collects the national Consumer Price Index (*Índice Nacional de Preços ao Consumidor Amplo* [IPCA]). The IPCA dates back to 1980 and has been the reference index for inflation targeting by the Brazilian Central Bank (BCB) since the regime was adopted in 1999. There is no microdata available from the IPCA dating back to the hyperinflation period.[8]

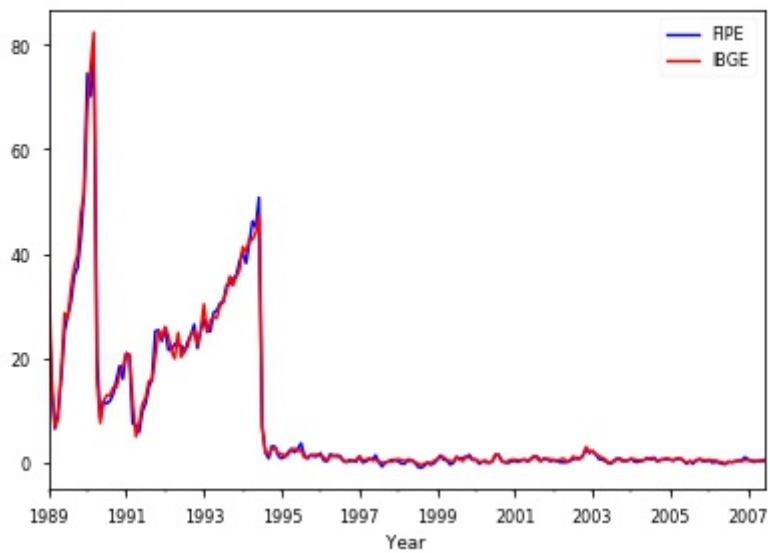


Figure 3: Monthly CPI inflation: FIPE and IBGE

[7] I extend the period covered by Gouvea (2007), Lopes (2008), and Barros et al. (2009) by also including five years of data under hyperinflation. I also extended the sample covered in Angelis (2012).

[8] The CPI index of *Fundação Getulio Vargas* (CPI-FGV) is another example of an index for the Brazilian economy. There is no microdata available for the CPI-FGV during hyperinflation as well. Gouvea (2007) and Barros et al. (2009) use this dataset to compute price setting statistics.

The CPI-FIPE, although collected only in the city of São Paulo, has a methodology and weighting structure similar to that of the IPCA. The two indexes have consistently mimicked each other over the years, even under very different inflation scenarios. Both also reproduce the significant drop in monthly inflation after *Plano Real*. This can be seen in Figure 3. The correlation coefficient between the two indexes is 0.996.

The original dataset contains a total of 12,921,795 price quotes covering 100% of the CPI-FIPE. Prices are quoted in 22,705 different outlets. Outlets are divided into 350 different types, such as supermarkets, butcher shops, malls, and electronic stores. Almost half of the dataset comes from supermarkets. The original dataset contains price quotes for 578 different products and 9,532 brands. There are different degrees of precision in defining a brand in my dataset, such as size, material, model, packing, and weight. An aggregation of brands defines a product.

The dataset comprises specific information regarding the brand of the good/service. For non-homogeneous goods, this can be a generic characteristic, such as "1 kg of tomatoes," "a male shirt," or "a dentist appointment." For homogeneous goods, it comes with detailed information, such as "1 bottle of Coca-Cola 350 ml" or "1 pack of 24 x 22 cm napkins from Santapel." A product is a combination of one or more brands. The product "carrot," for instance, aggregates only one brand ("1 kg of carrot"). The product "mobile phone" comprises over 200 brands in the sample. The CPI-FIPE is published at the product level, which is the equivalent of the Entry Level Items (ELIs) in the United States.

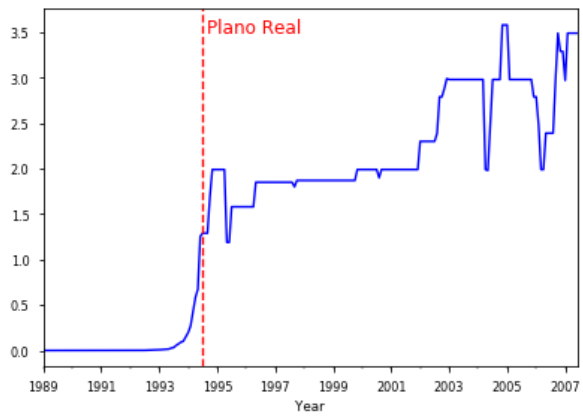
In my dataset, all brands are assigned a different code number. The number completely describes the brand, and if there is the slightest change in its characteristics, a new code is created. There is no product substitution. A particular good/service not found to quote in a certain store receives a missing value. This is a fundamental property, because item substitution interferes with the way price-setting statistics are computed. Here, neither this nor price imputation is a concern.[9]

The relevant unit of analysis in the dataset is an observation through time of a specific brand of good/service sold in a particular store.[10] I refer to this most disaggregated level as an *item*. There are 559,161 items in the original dataset. The sample items change over time as new products are introduced, and old ones are dropped. The temporal sequence of each item's price quote is called price trajectory, or quote line. See Figure 4 for an illustration of typical price trajectories, in both level (R$) and log terms, for two items: 1 kg of chicken (*Food*) and a

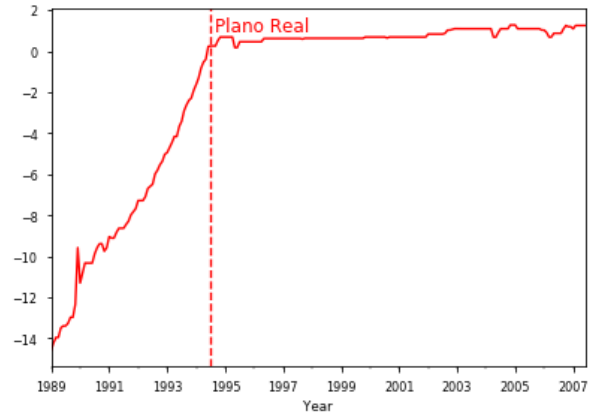
[9]Many studies deal with these problems, see for instance Klenow and Kryvtsov (2008) and Gagnon (2009).

[10]The dataset contains information about the brand and its price. Quotes are also described by a code indicating the store and a code for the type of store. Besides from that, only the week, month, and year of the price quotation are available.

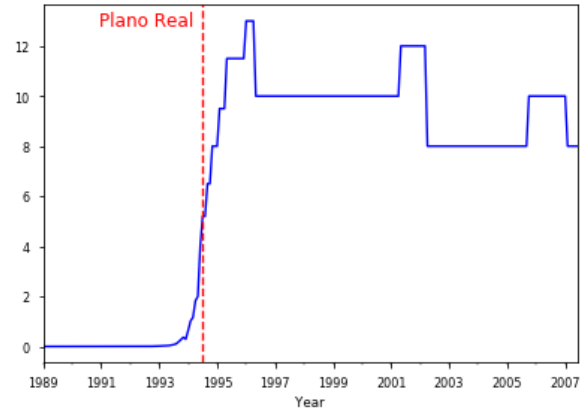
car wash for a small vehicle (*Service*). Here, some early patterns emerge: food prices seem to change more frequently than service prices.



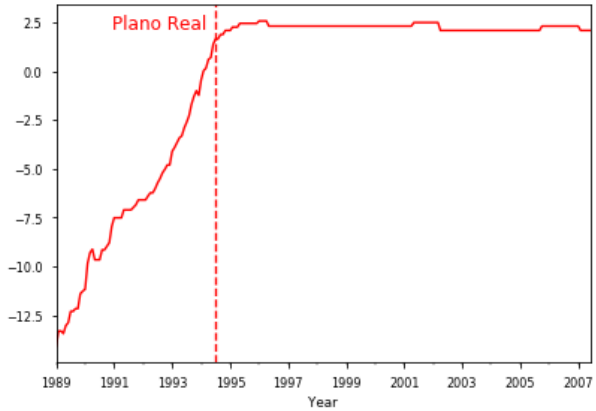
(a) Chicken (R$)



(b) Chicken (log R$)



(c) Car wash (R$)



(d) Car wash (log R$)

Figure 4: Examples of price trajectories

Note: Vertical line marks the implementation of *Plano Real*.

FIPE regularly conducts Household Budget Surveys (*Pesquisa de Orçamento Familiar* [POF]) on the average consumption basket of a typical family in São Paulo earning up to 20 minimum wages of income. Weights are recalibrated through new surveys that incorporate new habits and new products, and drop old ones. During the sample period, the CPI-FIPE changed weights under three different surveys. Table 4 presents the evolution of the three methodologies during my sample period.

Table 4: CPI weights

	Weights		
Sectors	POF 81/82 1989–1994	POF 90/91 1994–2000	POF 98/99 2000–2007
Housing	18.35	26.51	32.79
Food	37.67	30.81	22.73
Transportation	10.54	12.97	16.03
Personal expenses	19.56	12.52	12.30
Healthcare	3.78	4.58	7.08
Apparel	8.06	8.66	5.29
Education	2.04	3.95	3.78

The FIPE-CPI basket is divided into seven different groups of products: (i) *Housing*, (ii) *Food*, (iii) *Transportation*; (iv) *Personal expenses*, (v) *Healthcare*, (vi) *Apparel*, (vii) *Education*. The heaviest group in the CPI is *Housing*. The weight of the group almost doubled since POF 81/82. It includes products such as TVs, lamps, showers, and housing repairs. The *Food* group is the second in weight, followed by *Transportation*. The *Education* group includes prices of tuition and school supplies and has a weight of only 3.78% in the total CPI.

I also follow the classification provided by the BCB to aggregate products into four different sectors: (i) *Food at home*,[11] (ii) *Industrial goods*,[12] (iii) *Services*, (iv) *Regulated prices*. This aggregation is straightforward in the literature as well; see Klenow and Malin (2010) and Gagnon (2009). Table 5 presents three examples of items' classification and aggregation in the dataset.

Table 5: Example of aggregation

	Example 1	Example 2	Example 3
Brand	1 kg of tomatoes	Brastemp duplex frost free (84 L)	Replacement of brake light bulb (unit)
Product	Tomatoes	Fridge	Motor vehicle repair
Group	Food	Housing	Transportation
Sector	Food at home	Industrial good	Service

To produce aggregate measures across all years, this chapter weights all products according to

[11]The sector *Food at home* differs from the group *Food* by not including prices of food goods consumed away from home, such as coffee and meals in restaurants or bars, which all belong to the *Services* sector classification.

[12]This sector is the equivalent of the *Non-energy industrial goods* of Álvarez et al. (2006), for instance, since energy items such as electricity and fuel are *Regulated prices* in Brazil.

the last POF survey in our sample, which was carried out in 1999–1998 and used to calculate the index since January 2000. Because not all products are quoted in all months, weights vary through time. In all statistics regarding the frequency and size of price changes, I focus on weighted means across products. I aggregate brands through simple averages within the product level.

1.4.1 Sample treatment

I refine the original dataset to ensure consistency. First, I eliminate all *Regulated prices* from the sample. Prices of goods and services such as medicines, gasoline, electricity, and water utilities, for instance, are all dropped out. These prices are controlled mainly by the government and respond to a somewhat different dynamic regarding price adjustment. They account for 502,463 price quotes (3.9% of the original dataset). In CPI weight, regulated prices correspond to 27.3% on average during the sample period. Thus, this chapter accounts only for price setting of nonregulated prices.

I also exclude prices with a frequency of quotation higher than 1. This is the case for some *Apparel*[13] and *Transportation* goods. When an item is not homogeneous, a basket of items is collected and grouped by the average price, thus bringing the frequency of quotation above 1. I also exclude prices of *rent*, *condo fee*, and *housekeeping services*. The methodology of price collection for these items changed many times during the sample period, so I drop them to keep the data comparable through time.

Table 6: Sample treatment

	Original data	Treated data
Price quotes	12,921,795	10,721,683
Items	559,161	511,668
Brands	9,532	8,294
Products	578	527
Outlets	22,705	15,541

I also ensure that the data is consistent with my unit of interest: same brand, same store, and same period of time. I do not assign missing values to any outlier. Because this is a period of hyperinflation, the definition of an outlier may exclude valuable information. FIPE

[13] Gagnon (2009) also does not include some products in the *Apparel* group.

already has a system for detecting and excluding wrongly collected prices.[14] Table 6 presents the comparison between the original and treated dataset.

The products in the treated dataset represent 60.7% in weight of the CPI-FIPE and 83.0% share of the original dataset's number of price quotes. It is worth noting that the length of a price quote is quite small. See Figure 5 and Table 7. The average length of a price trajectory is 21.0 months (the dataset comprises 222 months). The number may seem low, but this is due to the lack of product substitution. The methodology ensures consistency regarding the same brand and outlet to define an item. This will lead to frequently censored and relatively small price trajectories.

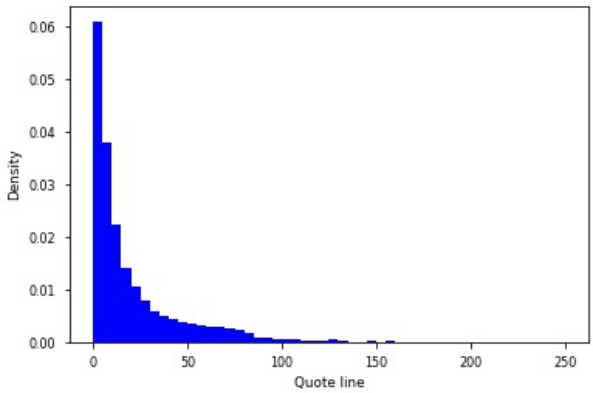


Figure 5: Density of quote lines

Quote line	Months
Min.	1
Max.	222
Mean length	21.0
Std. dev.	27.8
p25	3
p50	10
p75	27

Table 7: Statistics of quote lines

The apparently short length is typical for datasets without brand substitution. For instance, Wulfsberg (2016) analyzes data for Norway from January 1975 to December 2004 with an average of 33.1 observations per price trajectory. Klenow and Kryvtsov (2008) have 43 observations on average in their BLS dataset for the United States from January 1988 to January 2005.

Table 8 presents a comparison between the dataset of this chapter and those of other high-inflation studies regarding product coverage, percentage of CPI expenditure weight, number of items, number of observations per month, and total number of observations. I extend the table in Alvarez et al. (2011). My dataset covers a period of significantly high inflation and is also extensive regarding products, CPI weight, and number of price quotes.

[14] I do not exclude sales prices, because they are not flagged in my dataset. I also do not exclude observations with excessive missing values.

Table 8: Comparison of datasets across high-inflation studies

High-inflation study	Product coverage	CPI %	Items	Obs. per month	Price quotes
This chapter	527	60.7	511,668	45,567 on average	10,721,683
Nakamura et al. (2018)	351	-	-	80,00 to 100,000	-
Wulfsberg (2016)	1,124	73.9	433,666	39,900 on average	14,363,828
Alvarez et al. (2011)	506	84.0	-	81,305 on average	8,618,345
Gagnon (2009)	227	54.1	44,272	31,470 on average	3,209,947
Konieczny and Skrzypacz (2005)	52	-	-	up to 2,400	-
Lach and Tsiddon (1992)	26	-	-	250	-

1.5 Inflation accounting

This section presents the definitions of price-setting statistics explored throughout the chapter, which are close to those in Gagnon (2009). First, let p_{it} be the price of an item i at time $t = 1, 2, ..., T$. Note that an item i is a combination of brand and outlet. Define an indicator function of price change as

$$I_{it} = \begin{cases} 1, & if \quad p_{it} \neq p_{it-1} \\ 0, & if \quad p_{it} = p_{it-1} \end{cases}$$

I_{it} is defined only when both price quotes in t and in $t-1$ are nonmissing. The frequency f_{jt} of price changes at time t for a product j is set as the combination of price changes among all observed prices[15]

$$f_{jt} = \frac{1}{S_{jt}} \sum_{i \in s_{jt}} I_{it}$$

Where s_{jt} is the set of nonmissing prices of items i within the definition of a product j and $S_{jt} \equiv card(s_{jt})$; that is, the number of elements in s_{jt}. The frequency of price changes for a product j is set as the fraction of all nonzero price changes between two months to all price observations (zero and nonzero price changes). In other words, f_{jt} is the simple average among changes in all items defining a product j.

The aggregate measure of price change is computed by weighting frequencies by their corresponding product-specific CPI weight in the FIPE index

$$f_t = \sum_{j=1}^{J} \omega_{jt} f_{jt}$$

The weights ω_{jt} are not constant over time, because the composition of products in the CPI changes and not all products are always quoted in the sample. Weights are provided by FIPE and are recalibrated to sum one all months ($\sum_{j=1}^{J} \omega_{jt} = 1$ for *all* t). All else being equal, the greater f_t is, the more flexible prices are. It is also possible to split the frequency of price changes between increases and decreases. Define the aggregate frequency of increases as

[15] I assume that the occurrence of a missing value does not relate to any difference in price decisions, i.e., it is a random phenomenon.

$$f_t^+ = \sum_{j=1}^{J} \omega_{jt} \frac{1}{S_{jt}} \sum_{i \in s_{jt}} I_{it}^+$$

Where I_{it}^+ is an indicator function of a positive price change ($p_{it} > p_{it-1}$). Analogously, I_{it}^- is an indicator function of a negative price change ($p_{it} < p_{it-1}$). The aggregate frequency of prices decreases is set as

$$f_t^- = \sum_{j=1}^{J} \omega_{jt} \frac{1}{S_{jt}} \sum_{i \in s_{jt}} I_{it}^-$$

Note that: $f_t = f_t^+ + f_t^-$.

Not only the occurrence but also the magnitude of a price change is of interest. Define $\Delta p_{it} = \frac{|p_{it} - p_{it-1}|}{p_{it-1}}$ as the absolute size of price change of an item i at time t. It follows that an aggregate measure of the average magnitude of nonzero price changes is set by

$$\Delta p_t = \sum_{j=1}^{J} \omega_{jt} \frac{1}{S_{jt}^*} \sum_{i \in s_{jt}^*} \Delta p_{it}$$

Where s_{jt}^* is the set of nonzero price changes at product j level and $S_{jt}^* \equiv card(s_{jt}^*)$. The weight ω_{jt} also refers to the importance of each product in consumer expenditures. This is the intensive margin; that is, how much prices change – on average and in absolute value – when they do change. Note that the set s_{jt} includes s_{jt}^*.

Additionally, the absolute size of positive (Δp_t^+) and negative (Δp_t^-) price changes are, respectively, defined as

$$\Delta p_t^+ = \sum_{j=1}^{J} \omega_{jt} \frac{1}{S_{jt}^{+*}} \sum_{i \in s_{jt}^{+*}} \Delta p_{it}$$

$$\Delta p_t^- = \sum_{j=1}^{J} \omega_{jt} \frac{1}{S_{jt}^{-*}} \sum_{i \in s_{jt}^{-*}} \Delta p_{it}$$

Where $S_{jt}^{+*} \equiv card(s_{jt}^{+*})$, the number of positive price changes in a period of time, and $S_{jt}^{-*} \equiv card(s_{jt}^{-*})$ is the analogous for negative price movements. By computing the frequency and size of price adjustments, it is possible to decompose total inflation in two margins: extensive (the share of firms recalibrating prices) and intensive (the magnitude with which they do it). Section 1.6.3 focuses this decomposition.

Note that $\Delta p_t = \frac{f_t^+}{f_t}\Delta p_t^+ + \frac{f_t^-}{f_t}\Delta p_t^-$, where $\frac{f_t^+}{f_t}$ refers to the share of positive price changes and $\frac{f_t^-}{f_t}$ to the share of negative price changes.

1.6 Main empirical results

This section presents a set of summary statistics on the frequency and size of price changes. I split the sample into two subsamples: one from January 1989 to December 1993 (hyperinflation) and the other from January 1995 to June 2007 (lower inflation). I exclude the year 1994, because *Plano Real* was implemented in July. By doing so, I emphasize the main differences between these two very distinct inflationary scenarios and highlight the relevance of *Plano Real*. I also provide evidence on the importance of the extensive and intensive margins in the variation of inflation and document heterogeneities and asymmetries in price setting across different types of products and services.

1.6.1 Frequency of price changes

I begin by estimating the frequency of price changes.[16] I first compute the occurrence of a price change for each item each month. I compute the frequency of price changes by product using a simple average among items. I then construct a measure of aggregate frequency using FIPE's product-specific weights. All price changes are computed, including zero ones. The frequency f_t yields information on the degree of price stickiness in the economy. A value close to 100% means that almost all prices are changing at that moment (prices are almost completely flexible).

Figure 6 illustrates the positive relationship between frequency and contemporaneous inflation. The correlation coefficient is 0.89 during the entire sample period, and it is driven mainly by the hyperinflation years. It is worth noting here that, because the data is monthly based, there is an inherent underestimation of the actual share of price changes. It is not possible to recover prices that change more than once a month. The frequency estimator is censored to a maximum of 100%. It may be the case in which at least almost all prices are changing, but some may have changed more than once a month.

The frequency of price changes covaries strongly with inflation, although there are sharp differences between hyperinflation and lower-inflation periods. Note the marked fall in July 1994, precisely when *Plano Real* was implemented. Both frequency and inflation instantaneously collapsed. The frequency of price changes was 93.5% in June 1994 and dropped to 41.4% in August of the same year. The movement was synchronized with monthly inflation: 50.8% in June and 2.0% in August 1994. When inflation peaked at 79.1% in March 1990, 95.6% of all

[16] I follow Bils and Klenow (2004), Dhyne et al. (2006), Nakamura and Steinsson (2008), and Gagnon (2009) and do not focus on estimating the duration of prices. The presence of censored price spells and heterogeneous products may lead to biased estimations. Therefore, This chapter focuses only on frequencies of adjustments.

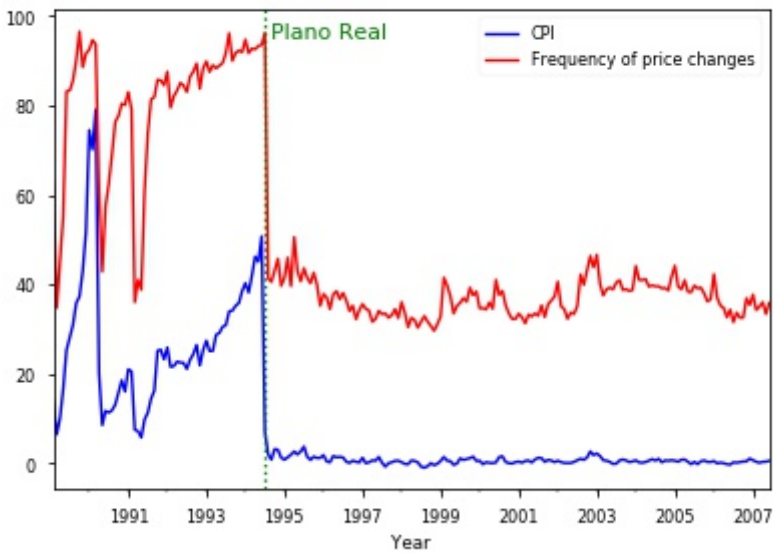


Figure 6: CPI-FIPE and frequency of price changes

prices were changing. The frequency of price changes peaked in October 1989, when a share close to 97% of all prices changed.

I find no evidence of a transition period from hyperinflation to lower levels of inflation. As *Plano Real* succeeded in reanchoring inflation under one digit per month, the frequency of price changes also shifted to a new lower level. There are significant differences between the hyperinflation and lower inflation periods. Prices went from almost entirely flexible to a share of roughly one-third of changes per month. On average, almost half of all prices changed every month from 1989 to 2007, although the behavior is quite heterogeneous before and after *Plano Real*. The frequency of price changes is systematically higher during hyperinflation. Prices are continuously changing.

Table 9: Frequency of price changes (%)

Year	IPC-FIPE	Frequency of price changes	Increases	Decreases
1989–1993	25.3	78.7	72.8	5.9
1995–2007	0.6	36.8	21.2	15.5
Full sample	8.3	49.6	36.9	12.7

To emphasize the marked difference between the hyperinflation and lower-inflation periods, Table 9 reports estimates of the frequency of price changes during both inflation periods, 1989 to 1993 and 1995 to 2007. I also split the changes between upward and downward adjustments.

During the years of hyperinflation, the frequency of price changes drops significantly from 78.7% to 36.8%.[17] The frequency of price increases drops from 72.8% to 21.1%, whereas the frequency of price decreases rises from 5.9% to 15.5%. See Figure 7 for an illustration of this behavior.

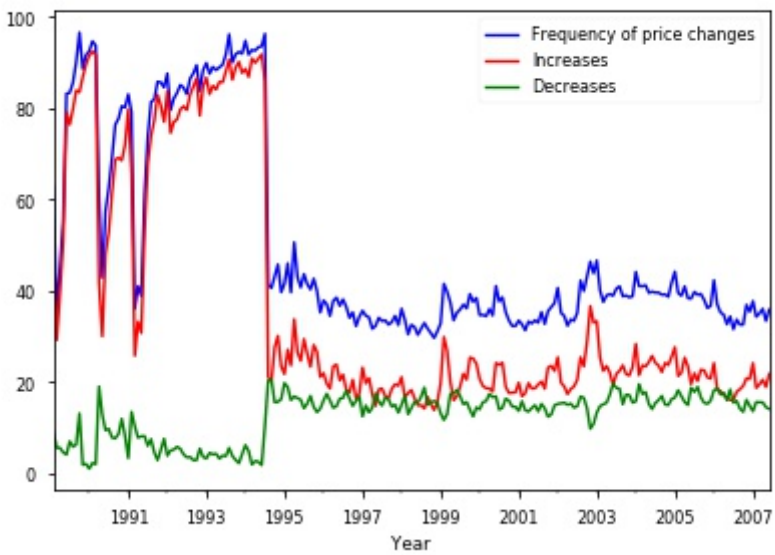


Figure 7: Frequency of price increases and decreases

Not only did the frequency of price changes decline remarkably shortly after hyperinflation ended, but price decreases also became more likely. From 1989 to 1993, only 7.5% of all price changes were for a smaller final value. In contrast, during the lower-inflation period, price increases and decreases were almost balanced: 57.7% of all price changes were increases, whereas the remaining 42.3% were decreases. See Figure 8 for the evolution of the share of price increases and decreases during the sample years. Note also the relevance of *Plano Real*.

As inflation declined, so did the episodes of an upward revision on prices. I do not find robust evidence favoring nominal downward price rigidity, because even during hyperinflation some prices were dropping every month. Price decreases are not uncommon between 1989 and 1993, although they are less frequent during this period. Nevertheless, this behavior is quite heterogeneous across aggregations of products in groups and sectors (see Section 1.6.4 for a detailed discussion).

[17] Using the median frequency of price changes ensures a very similar result.

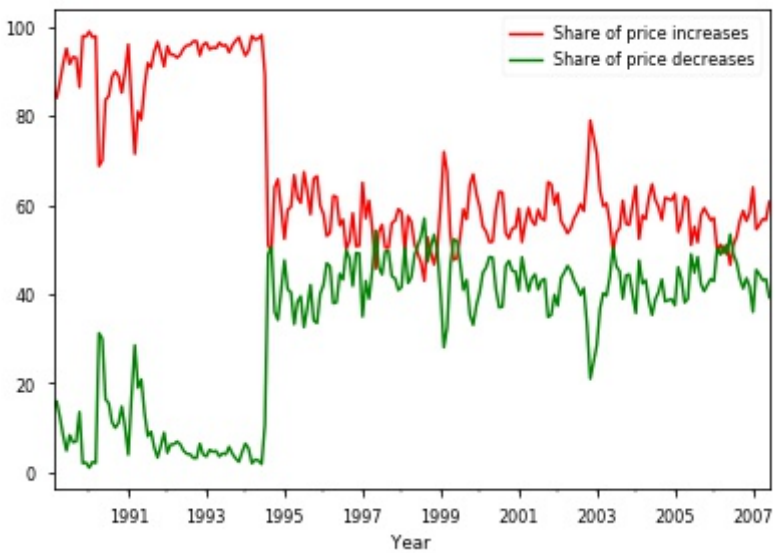


Figure 8: Share of price increases and decreases

1.6.2 Size of price changes

I now document the magnitude of price movements (always in absolute terms) conditional on the occurrence of a price change. Figure 9 presents the time series of the average absolute size of price changes in the sample and the monthly CPI-FIPE. The coefficient of correlation is 0.97 in the hyperinflation subsample and 0.49 in the lower-inflation subsample. The correlation between inflation and the size of price changes is somewhat looser during lower levels of inflation, as shown in Gagnon (2009).

When monthly inflation peaked at 79.1% in March 1990, the size also peaked, reaching a magnitude of 88.4%. When monthly inflation dropped to 8.5% in May 1990, the size dropped to 19.2%, half of the amount registered in the previous month. Note that, like the frequency, the size of price changes instantaneously dropped after *Plano Real*. The plan induced less frequent and smaller price changes.

Despite a high correlation, the size of price changes is often larger than required to keep up with aggregate inflation. As Klenow and Malin (2010) demonstrate, this feature commonly emerges because idiosyncratic shocks affect the size of transitory price adjustments. Consequently, some relative price changes are temporary, and prices may go up and down within a year. This seems to be the case for a sizeable portion of price changes. Moreover, market failures, such as imperfect information or menu costs, might prevent firms from fully adjusting their prices. Thus, micro price changes are, on average, commonly larger than aggregate CPI.

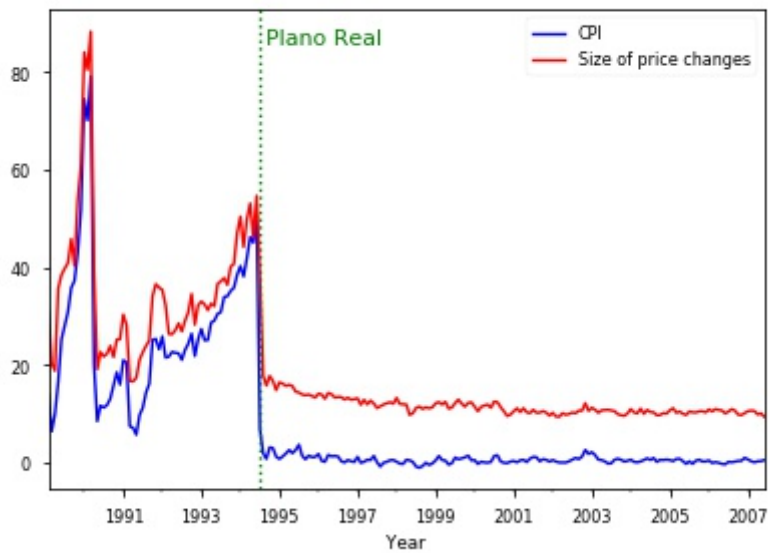


Figure 9: CPI-FIPE and size of price changes

During hyperinflation, the average size of price changes is 34.1%, while monthly inflation averages 25.3%. The magnitude of the movement is driven mainly by price increases, which have a total size of 35.1% on average, against 6.9% of price decreases. During hyperinflation, price increases are more frequent and larger. The magnitude of price changes is noticeably higher during hyperinflation. Table 10 reports the weighted average of price increases and decreases during the years covered by the sample, which I also split into the two inflationary periods.

Table 10: Size of price changes (%)

Year	IPC-FIPE	Size of price changes	Increases	Decreases
1989–1993	25.3	34.1	35.1	6.9
1995–2007	0.6	11.4	11.5	9.9
Full sample	8.3	18.6	19.0	9.1

Under low inflation rates, while monthly inflation averages 0.6%, the average size of price changes is 11.4%. The absolute size of price movements is almost symmetric for upward changes (11.5%) and downward changes (9.9%) in prices, as in Alvarez et al. (2011).[18] The frequency with which they occur seems to be the predominant factor behind positive inflation. In addition, the absolute size of price decreases is surprisingly similar during hyperinflation and

[18] Gouvea (2007) documents an average absolute size of 16% for price increases and 12.6% for price decreases. Barros et al. (2009) calculate 12.0% for increases and 14.0% for decreases.

lower inflation (6.9% and 9.9%, respectively). Conditional on a decrease, the magnitude of the movement is quite large during both periods.

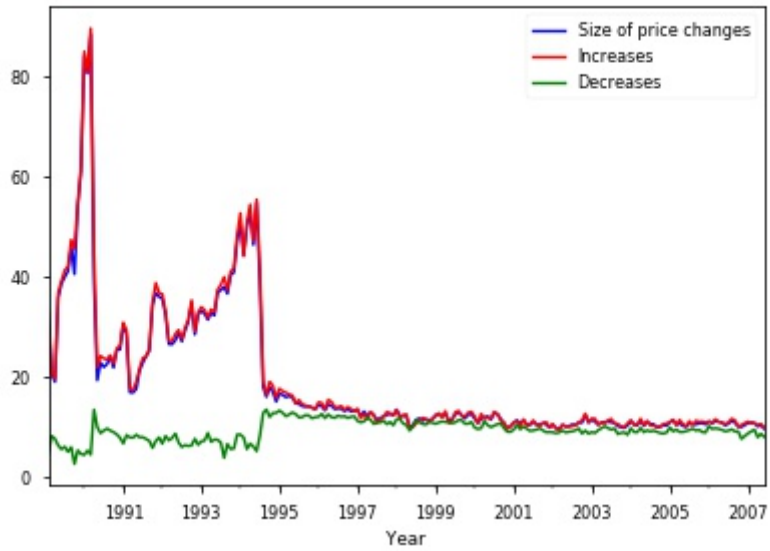


Figure 10: Size of price increases and decreases

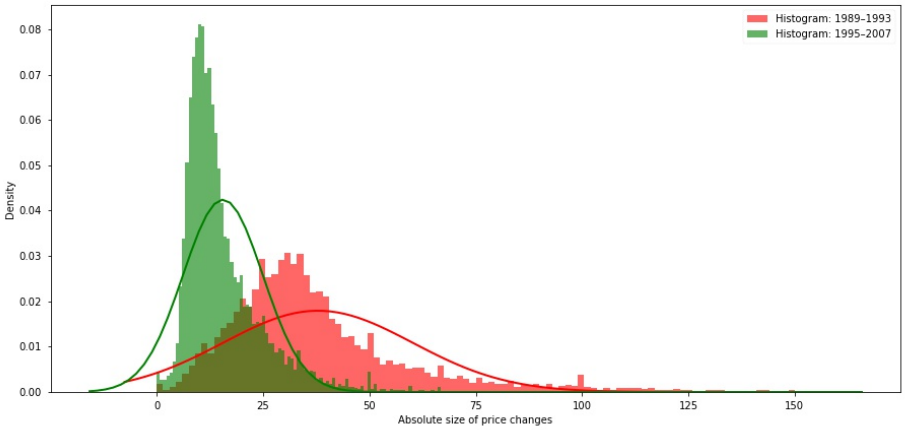
Figure 10 plots the time series of Δ_t, Δ_t^+, and Δ_t^-. The *Plano Real* effect is clear. The distribution of the absolute size of nonzero price changes is remarkably different during hyperinflation and during lower inflation. Figure 11a plots the histogram of the absolute size of price changes for both periods, as well as a Gaussian distribution fitting the mean and standard deviation from each period. Figure 11b plots the histogram for positive price changes, and Figure 11c plots the histogram for negative price changes. A common pattern emerges from all the graphs: distributions have more mass around their means than implied by a Gaussian distribution. Table 11 presents the main quantiles.

Table 11: Distribution of the size of price changes

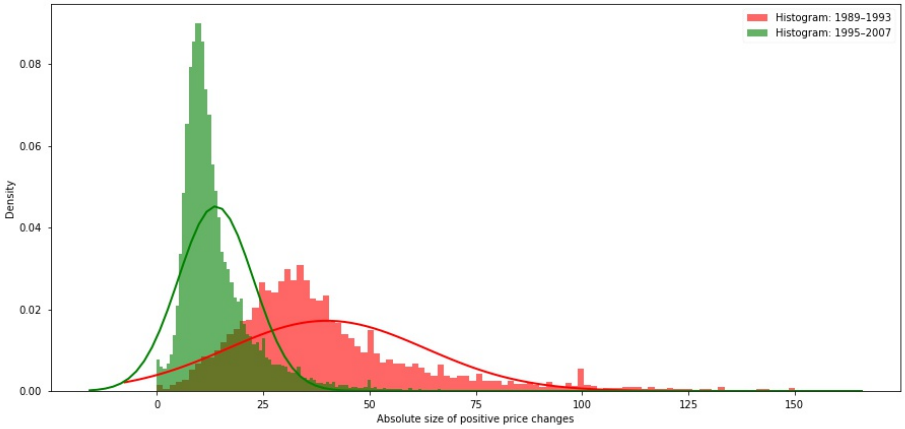
Increases	p25	p50	p75
1989–1993	25.3	34.7	48.9
1995–2007	8.6	11.5	16.5
Decreases			
1989–1993	8.2	10.9	14.9
1995–2007	7.5	12.5	18.3

The distribution of price changes during hyperinflation is more dispersed than during low

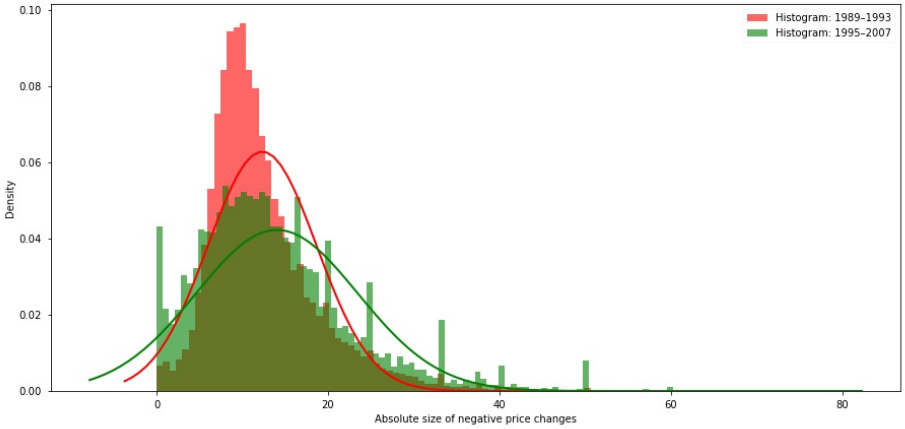
inflation. Small price changes are also present during hyperinflation, although they are less frequent. The distribution of the size of positive price changes resembles the distribution of absolute price changes (Figure 11a *vs.* Figure 11b). Furthermore, the distribution of the absolute size of price decreases is remarkably similar during both periods. Small price decreases are common, although the distribution during hyperinflation is leptokurtic, with more mass around smaller and bigger price decreases. Regarding price decreases, the relevant margin is how often prices drop, because the size of the movement does not change under different inflation scenarios.



(a) Price changes



(b) Increases



(c) Decreases

Figure 11: Histogram of the absolute size of price changes

1.6.3 Extensive and intensive margin

After quantifying the share of price changes and their size, I compute the fraction of the influence of these two components on aggregate inflation. Two margins are relevant: the extensive margin and the intensive margin. The former refers to the frequency of price adjustments, and the latter represents the magnitude with which they occur.

First, following Wulfsberg (2016), I estimate the importance of each margin to the level of inflation. I then examine their impact on the variance of inflation, as in Klenow and Kryvtsov (2008) and Gagnon (2009). Both views confirm a sizeable share of influence on the intensive margin during the hyperinflation period. The extensive margin becomes more relevant once inflation is running at lower levels.

Following Wulfsberg (2016), this subsection measures the relative contribution of the extensive and intensive margins to the inflation rate. To do so, I first calculate the counterfactual inflation ($\widehat{\pi}_t$) using the treated dataset. I define $\widehat{\pi}_t$ as the weighted average of all products' (j) price changes:

$$\widehat{\pi}_t = \sum_{j=1}^{J} \omega_{jt} f_{jt} \Delta p_{jt}$$

Where ω_{jt} is the CPI weight, f_{jt} is the frequency of price changes, and Δp_{jt} is the average size of a price adjustment conditional on nonzero changes. Figure 12 shows the adherence of $\widehat{\pi}_t$ to the observed π_t from FIPE. The counterfactual estimate tracks the official CPI-FIPE extremely well. The correlation coefficient is 0.98 for the entire duration of the sample. The main difference between the two series comes from the exclusion of *Regulated prices*. Note that $\widehat{\pi}_t$ also precisely replicates the drop in monthly inflation that followed *Plano Real*.

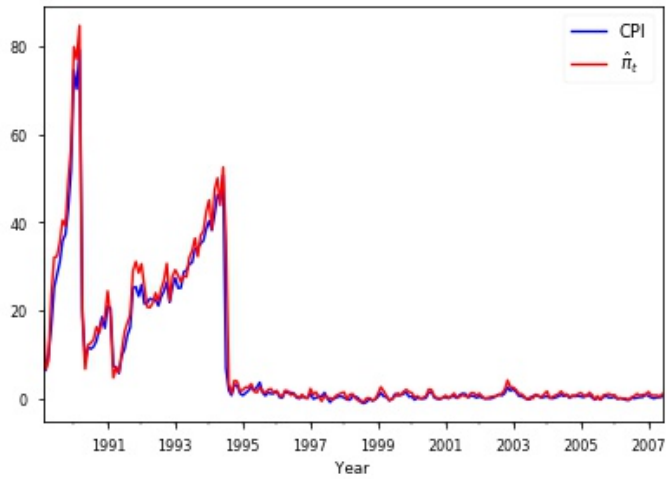
Each margin is isolated by constructing two counterfactuals. The extensive margin is estimated by holding the size of price changes for each product in their mean sample values ($\overline{\Delta} p_j^+, \overline{\Delta} p_j^-$), while allowing for frequencies to vary over time. Analogously, the intensive margin considers time-varying magnitudes of price changes while frequencies are held constant in their product-level means ($\overline{f}_j^+, \overline{f}_j^-$). The extensive margin $\widehat{\pi}_{f,t}$ is set as

$$\widehat{\pi}_{f,t} = \widehat{\pi}_t(f_{jt}^+, f_{jt}^- | \overline{\Delta} p_j^+, \overline{\Delta} p_j^-) = \sum_{j=1}^{J} \omega_{jt}(f_{jt}^+ \overline{\Delta} p_j^+ + f_{jt}^- \overline{\Delta} p_j^-)$$

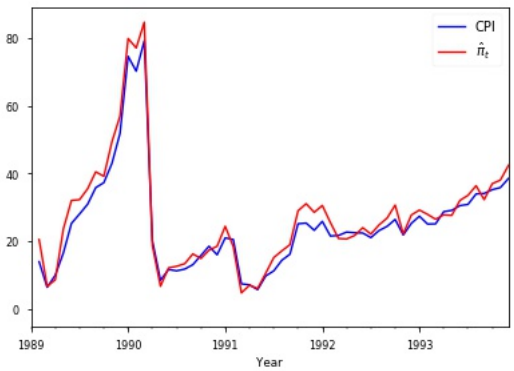
The intensive margin $\widehat{\pi}_{\Delta,t}$ is

$$\widehat{\pi}_{\Delta,t} = \widehat{\pi}_t(\Delta p_{jt}^{+}, \Delta p_{jt}^{-} | \overline{f}_j^{+}, \overline{f}_j^{-}) = \sum_{j=1}^{J} \omega_{jt}(\overline{f}_j^{+} \Delta p_{jt}^{+} + \overline{f}_j^{-} \Delta p_{jt}^{-})$$

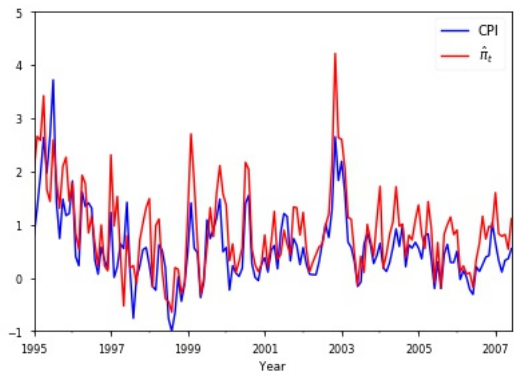
Here, I also split the sample into hyperinflation (1989–1993) and lower-inflation (1995–2007). While computing each margin, values are held constant in their respective average in both sample periods. Figure 13 presents the two counterfactuals, $\widehat{\pi}_{f,t}$ and $\widehat{\pi}_{\Delta,t}$. The correlation coefficient for the extensive margin and inflation is 0.70 during hyperinflation, whereas this value is 0.96 for the intensive margin. This implies that, during hyperinflationary years, the magnitude of price adjustments is the main reason behind such high levels of variation in inflation.



(a) 1989–2007



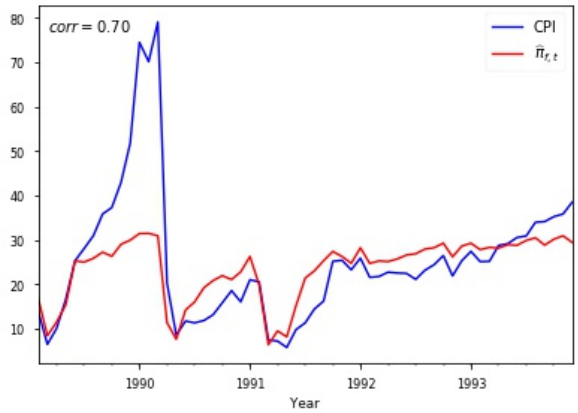
(b) 1989–1993



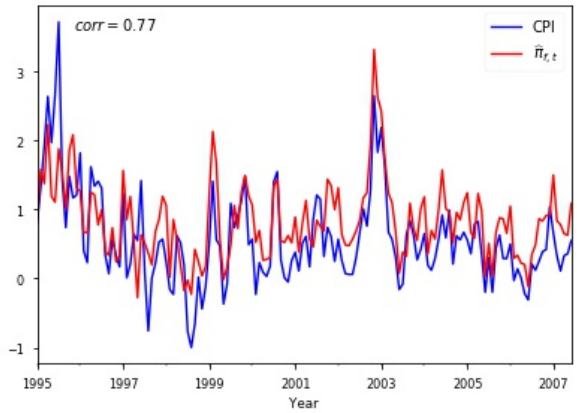
(c) 1995–2007

Figure 12: CPI-FIPE and $\hat{\pi}_t$ (Wulfsberg (2016))

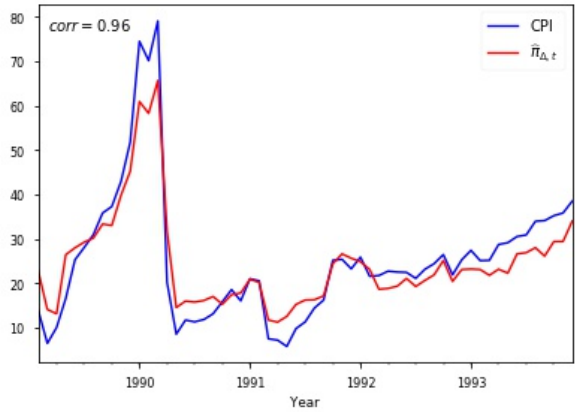
Following the successful implementation of *Plano Real*, the extensive margin climbs to play a much more critical role in the inflation rate. The correlation between the two series goes



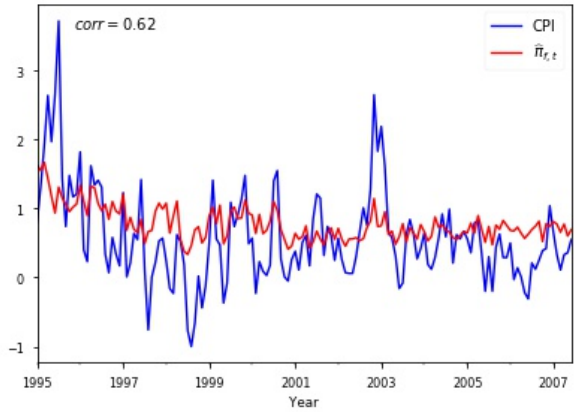
(a) 1989–1993: Extensive margin



(b) 1995–2007: Extensive margin



(c) 1989–1993: Intensive margin



(d) 1995–2007: Intensive margin

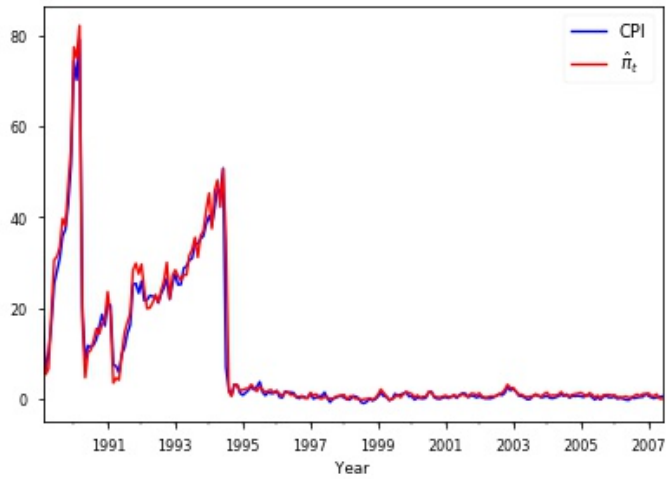
Figure 13: CPI-FIPE and conditional estimates of $\widehat{\pi}_{,t}$

from 0.70 during hyperinflation to 0.77 afterward. Simultaneously, the intensive margin loses its significant role, with correlation down from 0.96 to 0.62. Thus, the size of price changes seems to play a stronger role in determining the path of inflation during years of extraordinarily high inflation. During calmer periods, by contrast, the frequency of the readjustments gains greater importance. In a nutshell, for Brazilian data, what mattered during hyperinflation was how much prices changed, whereas what mattered during lower inflation was how often they changed.[19].

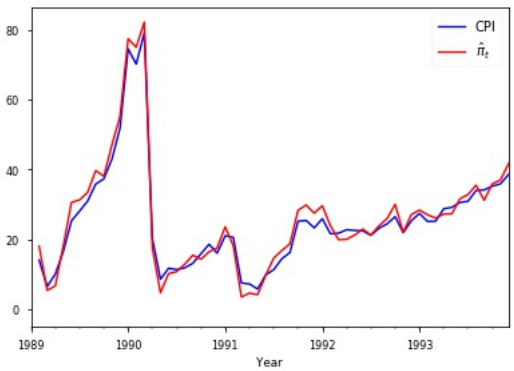
The results differ in some respects from those of Wulfsberg (2016), who finds a more relevant role for the frequency than the for size of price changes in the variation of inflation in Norway.

[19]The weights ω_{jt} also affect both margins. Estimating the two counterfactuals with time-constant weights does not change the results significantly.

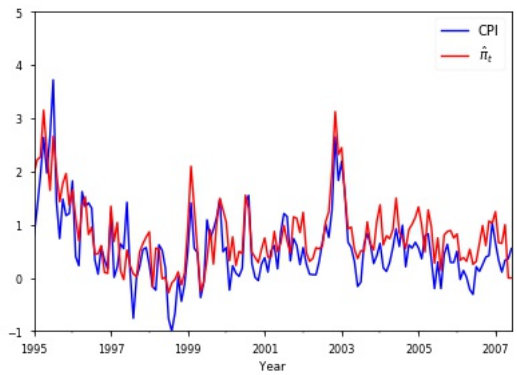
He even finds a negative correlation of -0.24 between $\widehat{\pi}_{\Delta,t}$ and the official CPI. He thus concludes that size-related inflation does not play a central role in overall inflation in Norway, even during a period when annual inflation peaked above 15%. The frequency of price changes is more important than their size: prices adjust frequently and in small steps when inflation is high. Here, I find a much more relevant role for the size of price changes under a hyperinflationary period. When inflation was as high as 2% a day in Brazil, the size of price readjustments was indeed relevant to overall inflation.



(a) 1989–2007



(b) 1989–1993



(c) 1995–2007

Figure 14: CPI-FIPE and $\hat{\pi}_t$ (Klenow and Kryvtsov (2008) and Gagnon (2009))

I now follow the methodology presented in Klenow and Kryvtsov (2008). Gagnon (2009) applies the same method. The authors decompose monthly inflation into the frequency of price changes and the weighted average size of those price changes: $\widehat{\pi}_t = f_t \Delta_t$, where: $\Delta_t = \dfrac{p_{it} - p_{it-1}}{p_{it-1}}$.

Figure 14 plots the counterfactual $\widehat{\pi}_t$ and the actual CPI-FIPE. The correlation coefficient is 0.96.

To quantify the relevance of each margin, I take the first-order Taylor series expansion, which yields

$$\widehat{\pi}_t = \overline{f}\,\overline{\Delta p} + \overline{f}(\Delta p_t - \overline{\Delta p}) + \overline{\Delta p}(f_t - \overline{f}) + (\Delta p_t - \overline{\Delta p})(f_t - \overline{f})$$

Where $\overline{f}$ and $\overline{\Delta p}$ are the mean values of the frequency and size of price changes, respectively. By calculating the variance of $\widehat{\pi}_t$ one obtains:

$$var(\widehat{\pi}_t) = var(\Delta p_t)\overline{f}^2 + var(f_t)\overline{\Delta p}^2 + 2\overline{f}\,\overline{\Delta p}\,cov(f_t, \Delta p_t) + O_t$$

Where O_t accounts for higher-order terms. Note that $var(\Delta p_t)\overline{f}^2$ depends only on the variance of the magnitude of price adjustments. This term refers to the intensive margin, the time-dependent component of the variance. The remaining part of the expression refers to the extensive margin, the state-dependent contribution. Table 12 shows the contribution (in %) of each margin to the variance of inflation in both sample periods.

Table 12: Inflation variance decomposition

	Intensive margin	Extensive margin
1989–1993	0.59	0.41
1995–2007	0.17	0.83
Full sample	0.29	0.71

The results reinforce the importance of the intensive margin during the years of hyperinflation. Almost 60% of the inflation variance observed from 1989 to 1993 results from fluctuations in the magnitude of price changes. The frequency of price changes also plays an important role, because 40% of the total variance is attributed to the extensive margin. However, the primary driver during hyperinflation is the size of the price movements. Prices change fast, but the magnitude of their changes matters the most.

An opposite scenario emerges after *Plano Real*. During the 1995–2007 sample period, the extensive margin gains importance; its contribution climbs to 83% of the total variance in inflation. The share of the intensive margin drops from 59% to only 17%. In a nutshell, the

results presented above confirm the common finding in the literature that the extensive margin explains most of the variance in inflation during years of low and relatively high inflation. However, once the economy is under hyperinflation, the picture changes. Prices may change fast, but once they begin to do so, the size of the movement explains a larger share of the overall variance in inflation.

1.6.4 Sector and group heterogeneity

As Klenow and Malin (2010) note, the literature broadly emphasizes that products exhibit marked differences regarding the frequency and the absolute size of their price changes through time and under different inflation scenarios. Heterogeneity and asymmetries are common. This subsection focuses on the differences across sectors and groups of products.

Table 13 illustrates the heterogeneity in the frequency of price changes across the three sectors, namely *Food at home*, *Industrial goods*, and *Services*. When inflation is high, all sectors exhibit a similar frequency of price changes, ranging roughly from 70% to 80%. The variability of sectors' price-change frequencies diminishes as inflation grows. It is not possible to infer any particular behavior. The frequency observed for *Services* is surprisingly the highest of all sectors (81.5%).

During hyperinflation, the cross-industry dispersion vanishes and the effect of an aggregate shock dominates idiosyncratic shocks that affect each sector individually. Price decreases are less likely but still present in all sectors, although they are more frequent in food items. From 1989 to 1993, the frequency of price decreases is 7.8% in the *Food at home* sector, but only 2.1% for *Services*.

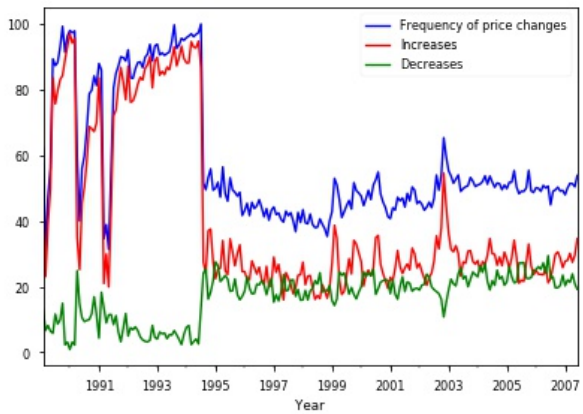
Table 13: Frequency of price changes: sector heterogeneity (%)

Sector	Frequency of price changes	Increases	Decreases
Food at home			
1989–1993	80.9	73.2	7.8
1995–2007	47.5	26.5	21.0
Full sample	57.9	40.9	17.1
Industrial goods			
1989–1993	78.6	73.2	5.4
1995–2007	39.1	22.9	16.2
Full sample	51.1	38.1	13.0
Services			
1989–1993	81.5	79.4	2.1
1995–2007	23.8	15.4	8.3
Full sample	41.4	34.8	6.6

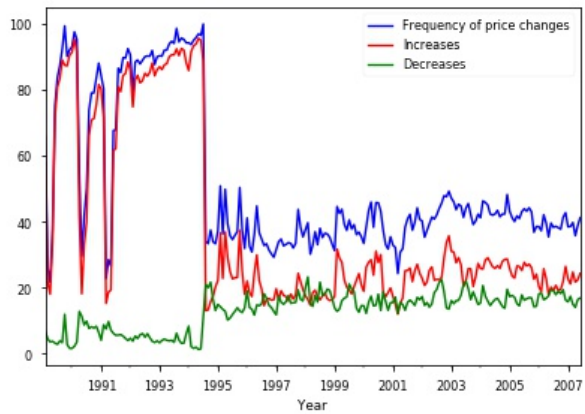
The results regarding the Brazilian economy during 1995–2007 are in accordance with the international evidence. There is substantial heterogeneity in price stickiness across sectors.

See Figure 15 for an illustration of each sector's dynamics. During the lower-inflation sample, *Food at home* exhibits the highest share of price adjustments every month, averaging 47.5%. The monthly frequency of *Industrial goods* is 39.1%. *Services*, exhibits the lowest price-change frequency, only 23.8% on average.

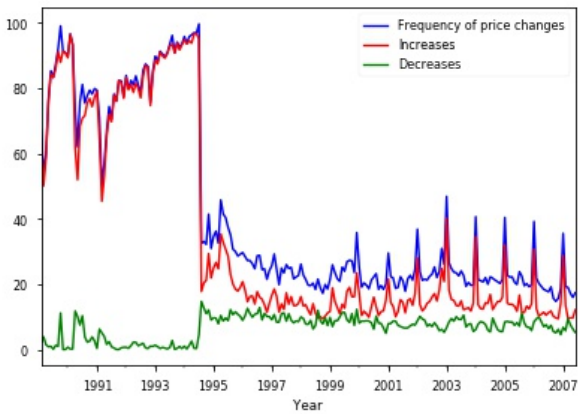
The same ranking of frequencies across sectors is also found in the euro area and the United States, Álvarez et al. (2006). In all sectors, price decreases are more frequent under low inflation rates, although less frequent for *Services*. Dhyne et al. (2006) highlights the fact that a higher degree of price rigidity in *Services* may lie behind a large share of inflation persistence at the aggregate level.



(a) Food at home



(b) Industrial goods



(c) Services

Figure 15: Frequency of price changes according to sector

Firms providing services are more labor intensive than those providing goods. Thus *Services*

prices and wages tend to follow similar paths. Álvarez et al. (2006) document that one of the most important factors behind price movements is labor costs. Different cost structures also help to explain various degrees of price flexibility. Besides wage stickiness, seasonal factors and specific demand components associated with *Services* affect the speed at which nominal prices adjust in this sector. Price adjustments in *Services* are less frequent as well as less uniformly distributed throughout the year. Note the seasonal pattern in *Services* that results from readjustments of fees and tuitions every January.

Table 14: Frequency of price changes: group heterogeneity (%)

Group	Frequency of price changes	Increases	Decreases
Housing			
1989–1993	88.1	85.2	3.0
1995–2007	40.5	23.5	17.0
Full sample	54.8	41.8	13.0
Food			
1989–1993	81.1	73.8	7.3
1995–2007	45.1	25.2	19.9
Full sample	56.3	40.2	16.1
Transportation			
1989–1993	77.8	72.7	5.1
1995–2007	47.1	30.1	17.1
Full sample	56.4	43.0	13.5
Personal expenses			
1989–1993	77.4	72.8	4.6
1995–2007	29.3	17.9	11.4
Full sample	44.0	34.6	9.4
Healthcare			
1989–1993	67.8	67.1	0.7
1995–2007	13.5	9.0	4.5
Full sample	30.4	27.1	3.4
Apparel			
1989–1993	80.0	69.2	10.8
1995–2007	34.0	17.7	16.3
Full sample	48.2	33.6	14.6
Education			
1989–1993	67.0	65.8	1.3
1995–2007	14.9	10.2	4.7
Full sample	31.3	27.4	3.9

In addition, I document aggregate data by major group classification in the CPI. Table 14 presents information on the frequency of price changes for each of the 7 CPI groups. See also Figure 16. The pattern of high frequencies during hyperinflation emerges in all groups, as does the significant drop after *Plano Real*. This confirms the importance of aggregate shocks on price setting under extremely high inflation. In contrast, the degree of nominal price stickiness

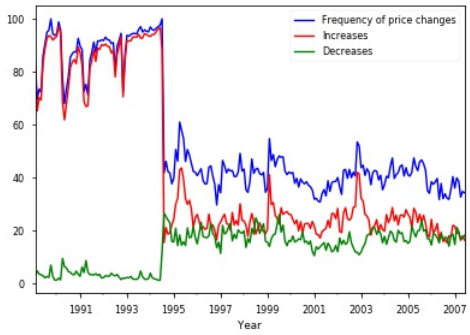
varies considerably across all groups of products in the lower-inflation sample.

From 1989 to 1993, a share of 81.1% of all *Food* prices changed every month. The *Housing* goods group presents the highest frequency of price changes during hyperinflation (88.1%), whereas *Education* presents the lowest (67%). *Healthcare* also presents a exhibits lower-frequency price changes (67.8%). During hyperinflation, no seasonal pattern is observed, and for almost all groups the frequency of price changes is close to 80%.

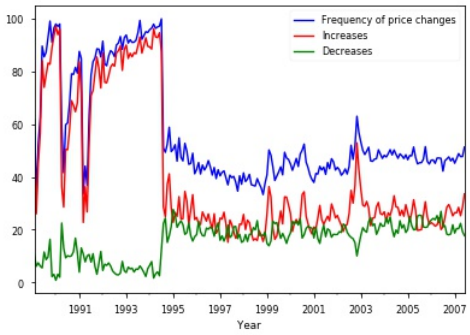
A clearer pattern of heterogeneity emerges when considering only the lower-inflation sample. Prices of *Transportation* present the highest frequency of adjustment from 1995 to 2007. On average, 47.1% of all prices change every month. The high frequency in this group is closely related to durable goods, such as cars and motorcycles (which entered the FIPE dataset only after the methodology revision of 1994). The prices of such products are continually changing from month to month in my sample, thus influencing the overall behavior of the group. In addition, Dhyne et al. (2006) observe that volatility in input prices may be one of the explanations behind higher frequencies at the retail level of such items. Excluding this type of products would grant a frequency of 36.3% for the *Transportation* group during the 1995–2007 sample period.

The frequency of adjustments in *Food* also exhibits an interesting pattern. During the lower inflation period, 45.1% of all prices in this group are changing every month. The group presents the highest occurrence of price decreases: 19.9% of all prices change to a smaller final price. This highlights the importance of supply shocks. Food items are more likely to present price decreases than any other item in the sample. This is especially true for unprocessed food products.

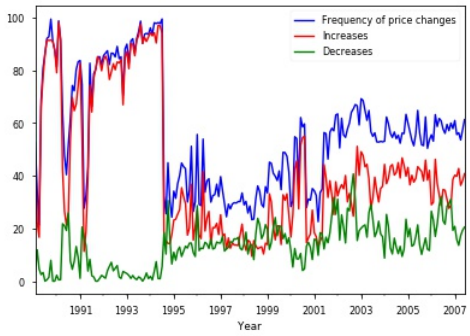
Housing goods present the highest expenditure share in the FIPE-CPI, and on average, 40.5% of their prices change during the lower-inflation period. The frequency is also high (34.0%) for *Apparel*, likely connected to seasonal winter and summer sales as well as a strong cyclical component. It is unclear, though, whether cyclicality generates price flexibility (prices are flexible and then exhibit a more cyclical behavior) or both features are induced by a third driving force. Note the clear seasonal pattern in *Education* readjustments.



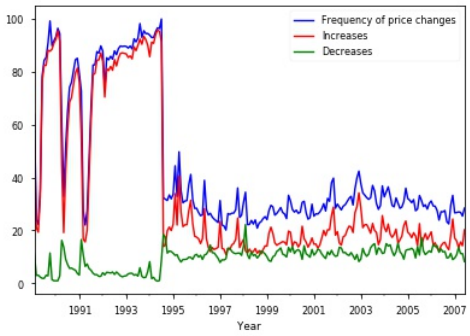
(a) Housing



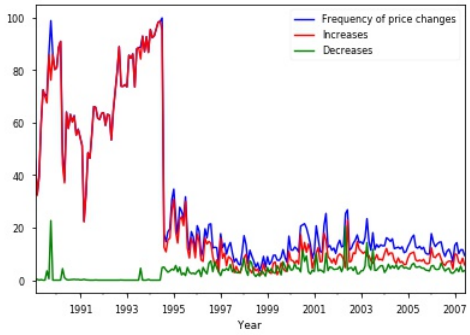
(b) Food



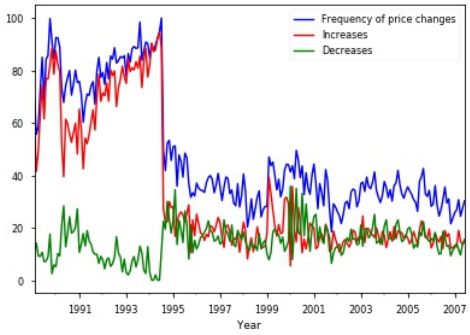
(c) Transportation



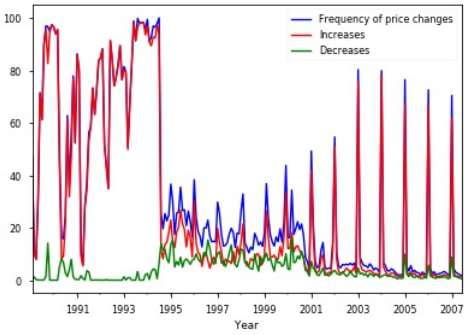
(d) Personal expenses



(e) Healthcare



(f) Apparel



(g) Education

Figure 16: Frequency of price changes according to group

Table 15 documents the absolute size of price changes for all three groups during both sample periods. Under hyperinflation, all sectors present a similar size of roughly 30%. Prices increases are also relatively close to each other values. The only difference emerges in the absolute size of price decreases. *Food at home* and *Industrial goods* present a close magnitude for price decreases, 8.1% in the former and 7.7% in the latter. The size of price decreases in *Services* is remarkably smaller, averaging only 3.4% during hyperinflation.

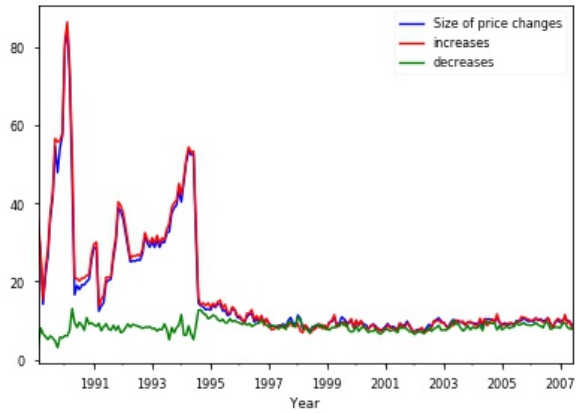
Table 15: Size of price changes: sector heterogeneity (%)

Sector	Size of price changes	Increases	Decreases
Food at home			
1989–1993	34.6	35.5	8.1
1995–2007	13.6	14.0	12.0
Full sample	20.4	21.0	10.9
Industrial goods			
1989–1993	32.1	33.7	7.7
1995–2007	9.6	9.5	8.5
Full sample	16.7	17.1	8.3
Services			
1989–1993	35.2	35.9	3.4
1995–2007	11.0	11.2	9.2
Full sample	18.7	19.0	7.6

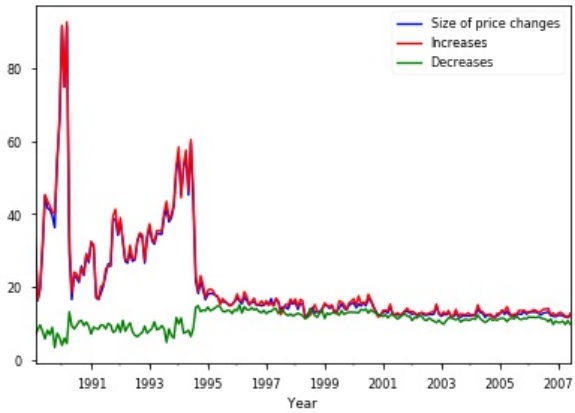
During hyperinflation, prices of *Services* not only decrease with a lower frequency (2.1% of all price changes in *Services* are decreases, as opposed to 7.8% for products in the *Food at home* sector, for instance), but when they do, the size of the movement is also smaller than observed in the other two sectors. This illustrates the nominal downward rigidity observed in *Services*, especially during hyperinflation. Figure 17 illustrates the behavior of all sectors during the sample period. The level shift after *Plano Real* is once again observed.

Under low inflation rates, sector heterogeneity in the size of price changes also becomes clear. Table 16 presents the size of price changes for each of the 7 CPI groups. During hyperinflation, the largest price movements are observed in *Healthcare* items. When prices in this group change, the average absolute size is 40.9%. This behavior is influenced mainly by the size of price increases (41.2%), whereas the size of price decreases is remarkably smaller (0.4%). Price changes in *Education* and *Transportation* are also quite large, 38.0% and 37.5%, respectively.

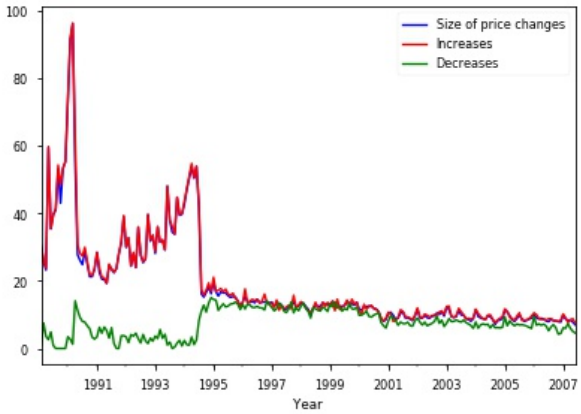
Apparel items exhibit the smallest price variation during hyperinflation. Prices in this group



(a) Industrial goods



(b) Food at home



(c) Services

Figure 17: Size of price changes according to sector

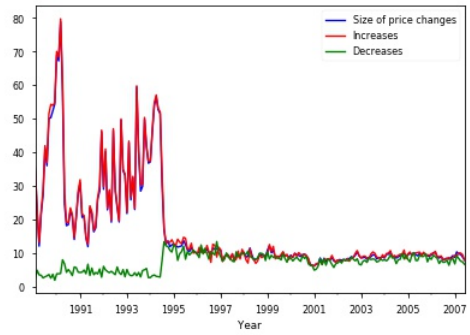
present the third largest frequency of price changes during this period (lagging behind only *Housing* and *Food*), but when prices do change, the magnitude of the movement is not quite as sizeable as it is in other groups of items. Prices in *Apparel* change very often, but they do so by a limited amount each time.

In the lower inflation sample, I once again observe large discrepancies across groups. The *Healthcare* group still presents the most prominent price movements. The absolute value of the group's price changes is 16.0%, although the absolute value of its price decreases is also sizeable (10.2%). Regarding the absolute size of negative price movements, the *Food at home* group stands out, exhibiting the largest magnitude of downward revisions in prices (12.2%).

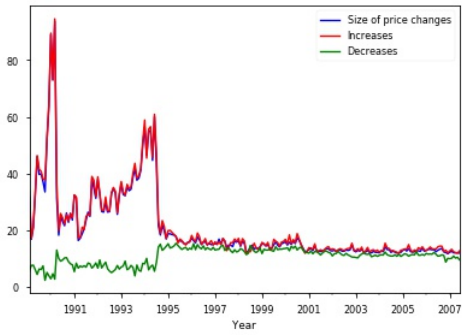
Table 16: Size of price changes: group heterogeneity (%)

Group	Size of price changes	Increases	Decreases
Housing			
1989–1993	32.7	33.6	4.2
1995–2007	9.3	9.4	8.5
Full sample	16.7	17.1	7.3
Food			
1989–1993	34.3	35.2	6.9
1995–2007	13.9	14.3	12.2
Full sample	20.6	21.1	10.7
Transportation			
1989–1993	37.5	38.9	8.0
1995–2007	8.6	8.9	7.4
Full sample	17.4	18.0	7.6
Personal expenses			
1989–1993	36.1	37.3	8.1
1995–2007	10.6	10.5	9.0
Full sample	18.5	18.9	8.8
Healthcare			
1989–1993	40.9	41.2	0.4
1995–2007	16.0	15.9	10.2
Full sample	23.7	23.7	7.4
Apparel			
1989–1993	26.9	28.8	6.1
1995–2007	11.1	11.0	9.8
Full sample	16.3	16.7	8.8
Education			
1989–1993	38.0	38.7	2.6
1995–2007	9.3	9.3	7.2
Full sample	18.2	18.5	6.1

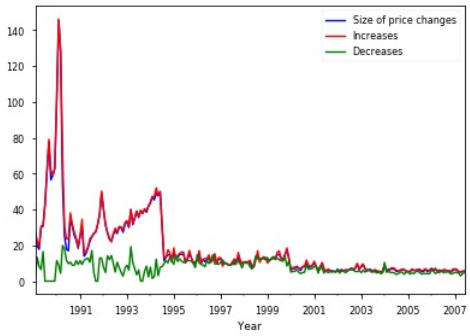
Lastly, Figure 18 illustrates the behavior of the size of all nonzero price changes in every group during the sample period. *Healthcare* adjustments present the highest variability in size, which is probably due to heterogeneities within nonhomogeneous groups, such as a dentist or a doctor appointment. *Education* presents some seasonal patterns, although they are not as clear as the pattern observed in the frequency of adjustments in this group.



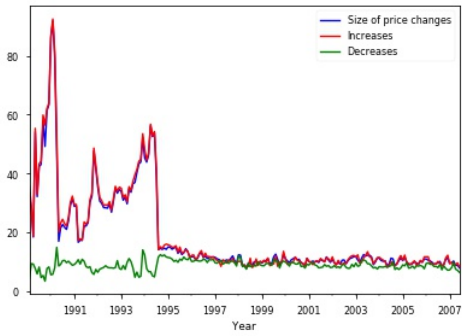
(a) Housing



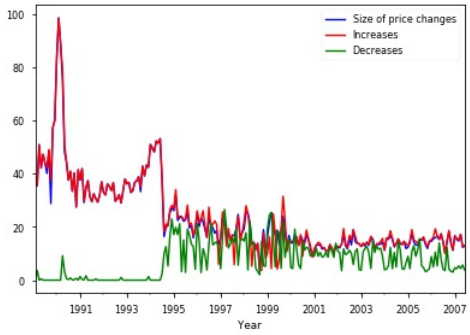
(b) Food



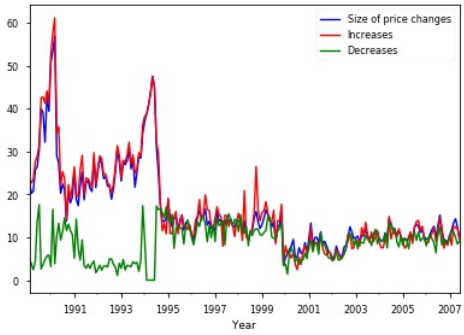
(c) Transportation



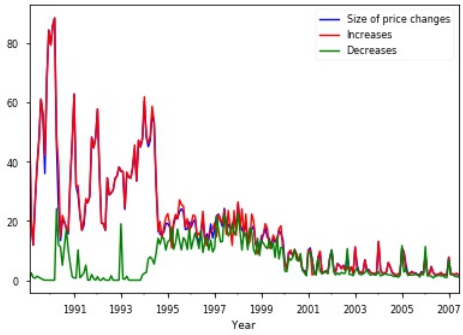
(d) Personal expenses



(e) Healthcare



(f) Apparel



(g) Education

Figure 18: Frequency of price changes according to group

1.7 Concluding remarks

A better understanding of individual price-setting behavior is crucial to improving the design of monetary policy. I document new evidence on price-setting behavior in the Brazilian economy using microdata from 1989 to 2007. The sample includes 5 years of hyperinflation (January 1989 to June 1994) and 14 years of lower rates of inflation (July 1994 to June 2007). The dataset contains almost 11 million monthly price quotes collected by FIPE in the city of São Paulo. Although there is substantial evidence on price adjustments in low-inflation countries,[20] much remains to be understood regarding pricing decisions under hyperinflationary episodes.

I find evidence of sharp differences between the frequency and size of price changes shortly after *Plano Real*. The plan ended the period of hyperinflation and substantially altered price-setting behavior in Brazil. During hyperinflation (1989–1993), the frequency of price changes was 78.7% on average. From 1995 to 2007, the average frequency was 36.8%. I find no evidence of a transition period: once *Plano Real* successfully put an end to hyperinflation, the frequency of price changes drastically dropped. Once inflation reached lower levels, price decreases became almost as likely as price increases.

The size of price changes also dropped immediately after the implementation of *Plano Real*. During hyperinflation, the monthly average absolute size of a price change was 34.1%, while monthly inflation averaged 25.3%. From 1995 to 2007, under one-digit monthly inflation, the average size dropped down to 11.4%. This is explained mainly by the size of price increases, which decreased from 35.1% to 11.5% between the two inflationary scenarios. The absolute size of price decreases was somewhat similar during hyperinflation (6.9%) and the period of lower inflation rates (9.9%). The intensive margin (size) was responsible for most of the inflation variation from 1989–1993, whereas the extensive margin (frequency) gained importance during the 1995–2007 period.

I also investigate patterns of cross-industry heterogeneity. During hyperinflation, prices of *Food at home*, *Industrial goods*, and *Services* exhibited a similar frequency of price changes of roughly 80% per month. Price increases were more frequent, although a small share of prices (mostly for food items) dropped every month. By contrast, in the 1995–2007 sample, clearer patterns emerge. Prices of *Services* present a higher degree of rigidity, whereas prices of *Food at home* and *Industrial goods* are fairly more flexible. The results under lower inflation confirm common findings in the literature, but this chapter's detailed results for a hyperinflation period and for the transition after a stabilization plan are new.

[20] See Bils and Klenow (2004), Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) for the United States and Dhyne et al. (2006) for the euro area.

2 INFLATION AND RELATIVE PRICE VARIABILITY IN BRAZIL FROM 1989 TO 2007

2.1 Introduction

Homogeneous goods are often sold at different prices across various stores. Firms also adjust their prices in different amounts over time. When prices do not rise in tandem, demand shocks and monetary policy have real economic effects. Understanding the sources of price rigidities and unsynchronized price adjustments is central to assessing welfare losses and designing effective public policies.

Despite widespread evidence of a positive relationship between inflation and relative price variability (RPV), there is still room for studies regarding developing economies, especially studies that address hyperinflationary episodes. This article addresses the issue through an examination of microdata from Brazil using almost 19 years of data including 5 years of hyperinflation.

The main question of this chapter is as follows: Do inflation and intramarket inflation variability have the same relationship during periods of hyperinflation and periods of low inflation? Using store-level price quotes collected by the *Fundação Instituto de Pesquisas Econômicas* (FIPE) in the city of São Paulo, I find compelling evidence of marked differences between these two scenarios.

The dataset comprises more than 6 million price quotes for 1,272 brands sold in 10,490 different stores from January 1989 to June 2007. I divide the sample into two very different inflationary regimes: (i) 1989–1993, when monthly inflation averaged 25.3% (hyperinflation), and (ii) 1995–2007, when monthly inflation averaged 0.6% (low inflation[21]).

I document the shape and structure of brand-level intramarket inflation for these two time periods. The distribution of price changes is far from uniform or even symmetric. I find evidence of persistent inflation dispersion among firms selling the same brand of good or service. The kernel estimation function drastically collapses after the hyperinflation ended.

I find strong support that *Plano Real* decreased inflation dispersion immediately after its implementation. The size and frequency of price changes also decrease right after the plan was

[21] I refer to the period between 1995–2007 as the low-inflation period. Keep in mind that Brazil exhibits higher and more volatile inflation levels than do developed economies. I use the term "low-inflation period" only to emphasize the difference between this period and the hyperinflation years.

put into practice. There is no evidence of a transition path. The lower the level of aggregate inflation, the lower the dispersion of price changes at the store level.

In both sample periods, inflation (in absolute terms) has a positive impact on intramarket inflation variability. I perform fixed effects panel estimations considering two measures of RPV: the standard deviation (SDP) of price changes across stores and the coefficient of variation (CV) of price levels across stores.

The magnitude of the impact of inflation on RPV is stronger when measured by the SDP than when measured by the CV. Both measures indicate the presence of a positive and significant linkage, although the magnitude is roughly 70% weaker during hyperinflation. Higher levels of inflation are normally associated with higher degrees of inflation variability, yet the link is somewhat looser during the hyperinflation period.

During hyperinflation, the weaker impact of inflation on its variability results from the frequency of price increases. When inflation is very high, most price changes are increases, thus narrowing the observed inflation dispersion among all items. On the other hand, when inflation is low and more stable, price decreases and price increases are almost equally likely, thus widening inflation dispersion. This translates into a relatively higher impact of inflation on its dispersion in my low-inflation sample.

Note that inflation dispersion is, in fact, higher during hyperinflation. My results indicate only that the correlation between inflation and inflation dispersion is weaker during hyperinflation. When inflation is extremely high, inflation dispersion is also high, but not as high as predicted by their relationship during low inflation.

I also investigate the presence of asymmetric effects from negative and positive price movements on RPV. The impact of deflation (in absolute terms) is weaker than the impact of positive inflation during hyperinflation. In contrast, from 1995 to 2007, price decreases have a more significant impact on RPV than price increases. I also document the same pattern when analyzing different sectors and groups of brands.

A higher frequency of price decreases also helps to explain the greater impact of negative price movements on inflation dispersion during the 1995–2007 period for each sector/group of product. I find robust evidence of a structural change in the relationship between inflation and RPV, depending on the inflationary regime. Although the effect is significant, I do not assume any causal mechanism.

This chapter contributes to a vast literature on tracking the relationship between inflation

and inflation variability. The novelty of this study's empirical contribution is its rich and unprecedented dataset on store-level prices in Brazil, encompassing years of hyperinflation as well as years of low inflation. I analyze more than 6 million price quotes taken from a period spanning almost 19 years. The data included here is also extensive in terms of products (1,272 brands of goods and services). I analyze a much larger dataset than Angelis (2012).

This chapter closely relates to studies by Lach and Tsiddon (1992), Caglayan and Filiztekin (2003), and Konieczny and Skrzypacz (2005). Lach and Tsiddon (1992) is one of the first empirical works based on microdata to investigate the relationship between inflation and RPV.[22] The authors use data on 26 food items in Israel, at a time when inflation peaked at roughly 60% a year.

Lach and Tsiddon (1992) find a positive association, mainly driven by the expected component of inflation. The authors also find evidence of unsynchronized price setting among firms, and therefore advocate for some staggering in the way prices are set. They document that whenever inflation is high, the distribution of real prices is not uniform or symmetric. My study strongly supports their findings. I also document a positive relationship between RPV and inflation, as well as an asymmetric inflation distribution during the years of hyperinflation in Brazil.

Caglayan and Filiztekin (2003) employ a similar approach, using price data on 22 food products in Turkey. They emphasize the importance of considering structural changes in inflation.[23] Their main conclusion is that the association between inflation and RPV is significantly weaker during higher levels of inflation. I reach the same conclusion here.

The impact of inflation on its variability is stronger in the sample taken from 1995 to 2007 (low inflation) in Brazil than in the sample taken from 1989 to 1993 (hyperinflation). When inflation is low, price decreases are more likely, which widens the inflation distribution and translates into a greater correlation between the level of inflation and its dispersion.

Konieczny and Skrzypacz (2005) investigate price-setting behavior in Poland after the dissolution of the Soviet Union. This was a period of high inflation in the country (from 250% in 1990 to 18% in 1996). The authors highlight a positive relationship between RPV and the frequency, size, and dispersion of price changes. They document a stronger effect of inflation on RPV when the latter is measured by the SDP than when it is measured by the CV. I reach the same conclusion using Brazilian data.

[22] Hoomissen (1988) also investigates the impact of inflation on price dispersion. She highlights the role of inflation in reducing the information content of prices, which translates into greater price dispersion.

[23] Caraballo et al. (2006) analyze data on Spain and Argentina and document significant changes in the relationship between inflation and RPV depending on the inflationary regime.

Price dispersion is a salient feature in both theoretical and empirical macroeconomic models. The phenomenon is often associated with three nonexclusive sources: (i) differences in costs and quality-related characteristics of products, (ii) menu costs, and (iii) imperfectly informed consumers. The first relates to inherent differences in the location where a product is sold. Stores may differ in terms of location, facilities, and other dimensions, a situation that results in different prices for the same commodity – see Stigler (1961) and Gorodnichenko et al. (2018).

Moreover, when price readjustments are costly, unsynchronized price setting may arise across firms – see Sheshinski and Weiss (1977) and Benabou (1988). Finally, search costs associated with discovering the lowest-priced firm may also lead to price dispersion in equilibrium – see Burdett and Judd (1983), Benabou (1992), and Rauh (2007).

As inflation increases, the range of prices for the same homogeneous good spreads, and the informational content of nominal prices decreases. Higher inflation is thus often associated with higher degrees of price-change variability, which is one of the social costs of inflation. There is a relatively broad consensus regarding the presence of a positive link between inflation and inflation variability. Nevertheless, some studies document an effect in the opposite direction, leaving room for further investigation on the direction of the final impact.

Reinsdorf (1994) uses data from the US Bureau of Labor Statistics from 1980 to 1982 (Volcker disinflation period) and finds that inflation and price dispersion may be negatively correlated. Sheremirov (2015) also finds a negative relationship between price dispersion and inflation, but the effect is driven entirely by the presence of temporary sales. The author finds a positive relation for regular prices. Silver and Ioannidis (2001) find a similar negative relationship based on intermarket data for 9 European countries.

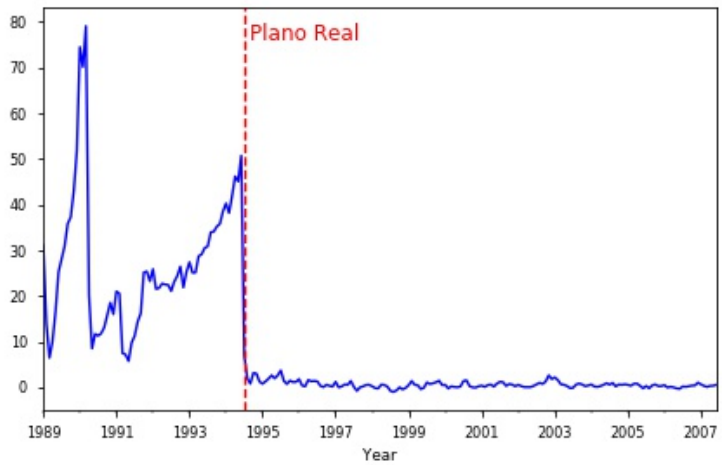
The literature that investigates links between prices and their dispersion during high-inflation scenarios includes Hoomissen (1988) and Lach and Tsiddon (1992) for Israel; Tommasi (1992) for Argentina; Caglayan and Filiztekin (2003), Caglayan et al. (2008), and Baglan et al. (2016) for Turkey; and Konieczny and Skrzypacz (2005) for Poland. Among these countries, only Argentina experienced hyperinflation similar to that experienced by Brazil from the 80s until mid-90s. My dataset reflects considerably higher inflation variation than other studies.

The chapter is organized as follows. Section 2.2 discusses the inflation environment in Brazil from 1989 to 2007. Section 2.3 presents the dataset and summarizes information on the frequency and size of price adjustments during the covered period. Section 2.4 documents patterns of inflation behavior at the brand level in different inflationary scenarios. Section 2.5 presents the econometric estimation of the relationship between inflation and intramarket inflation variability. Finally, Section 2.6 offers a conclusion.

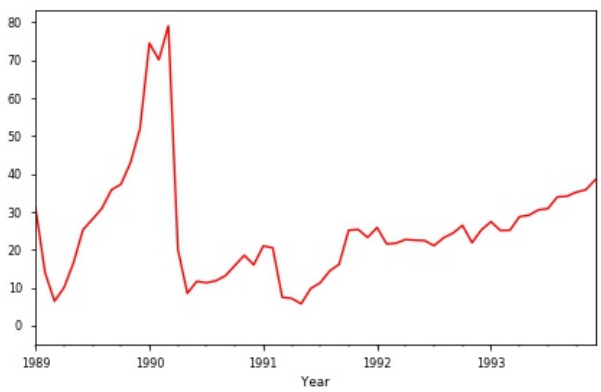
2.2 Inflation environment

The data comprises two very different inflation scenarios in the Brazilian economy. From January 1989 to June 1994, the Consumer Price Index (CPI) measured by FIPE rose 472,894,862%. Annual inflation reached three digits, peaking at 2,490% in 1993. Monthly inflation peaked at 79.1% in March 1990. At a certain point, prices in Brazil rose close to 2% a day. A series of economics plans attempted halt the chronic hyperinflation process.

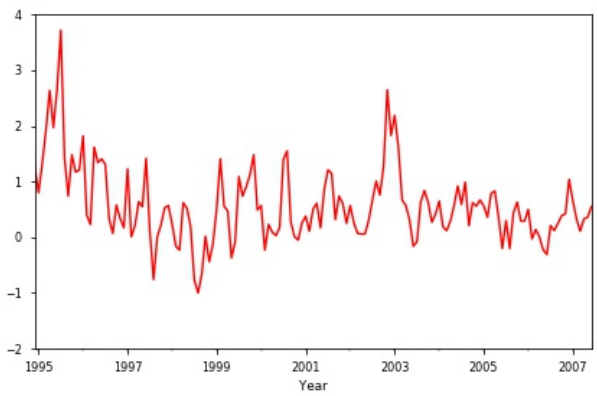
An extensive set of unorthodox policies were tested, such as freezing prices and wages adjustments by law and confiscating personal savings to prevent demand pressures on prices. From 1989 to 1993 all the plans failed. Brazil also changed currency four times during those years. See Giambiagi et al. (2010) for an extensive description of the Brazilian economy.



(a) 1989–2007



(b) 1989–1993



(c) 1995–2007

Figure 19: Monthly CPI-FIPE

It was only under the successful implementation of *Plano Real* in July 1994 that hyperinflation was finally tamed in Brazil. The plan significantly altered inflation dynamics in the country, finally controlling the explosive CPI path. The impact of *Plano Real* was immediate. Monthly inflation went from 50.8% in June 1994 to 6.9% in July and 1.9% in August of the same year.

Figure 19 illustrates the behavior of the monthly CPI-FIPE during the sample years, as well as the subsamples in Figure 19b (hyperinflation) and Figure 19c (low inflation rates). The vertical line in Figure 19a marks the implementation of *Plano Real* in July 1994. My subsample division excludes 1994.

Brazil underwent two very distinct inflation regimes during the sample period. From 1989 to 1993 annual inflation averaged 1,470%, whereas from 1995 to 2007 it averaged 7.1%.[24] Monthly inflation averages 25.3% from 1989 to 1993 and 0.6% from 1995 to 2007. In this chapter, I explore the differences inherent in each scenario.

I split the sample into two subsamples: hyperinflation (1989–1993) and low inflation (1995–2007). This pragmatic division is possible only because Brazil has undergone two distinct inflationary regimes. There is a clear structural break in the data. Because the range of data is significantly large, the Brazilian case is especially suitable for analyzing inflation and inflation variability.

Brazil underwent one of the most prolonged periods of hyperinflation ever witnessed by a country, and to a certain extent this was due to the fact that the economy was severely indexed. Indexation was probably the central component of Brazilian inflation. Almost all contracts were automatically adjusted according to past inflation.

Through a spiral of adjustments, high past inflation contributed to even higher future inflation. The key to taming escalating price increases was then to stop this cycle. *Plano Real* succeeded by introducing a temporary index into the economy, the units of real value (*Unidade Real de Valor* - URV).

The most crucial aspect of the plan was the creation of the URV. Prices were quoted in *Cruzeiros Reais* (CR$) at that time, and by March 1994 the new index was introduced. The index had daily fluctuations pegged to the US dollar. The URV acted as a unit of account for transactions. All agents were encouraged to quote prices in CR$ and URV's. Prices would rise in CR$, but prices in URV's would be much better behaved, because they were connected to a stable currency.

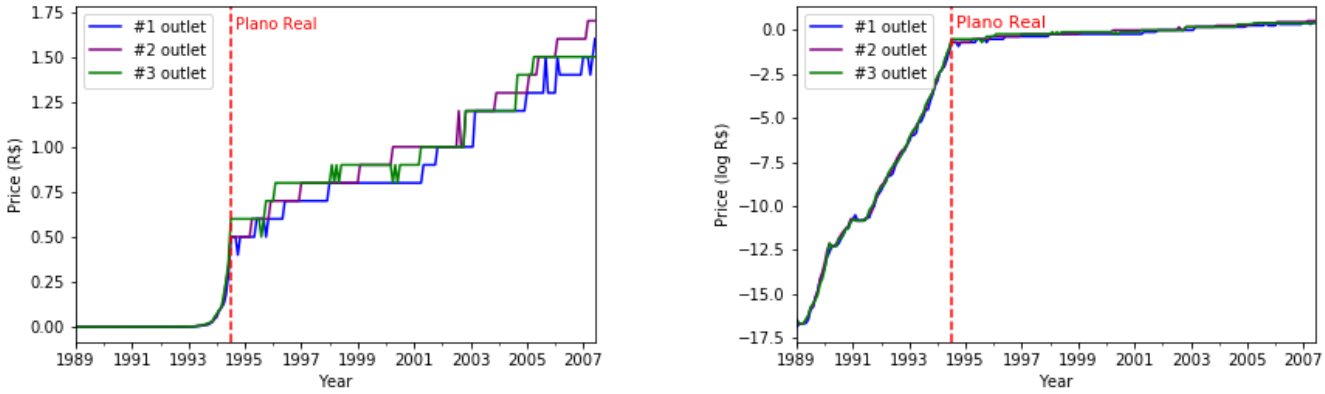
[24]Note that, although significantly lower, inflation in Brazil runs at higher levels than that in developed economies.

Consumers and sellers had three months to adapt to the new indexing and pricing processes. Once prices in URV's were stable, the new currency (*Real* - R$) was introduced. On July 1, 1994, all prices in *Cruzeiros Reais* were converted to *Reais* at the rate of R$ 1 to CR$ 2,750. This mechanism made it possible to break once and for all the hyperinflation in Brazil. The *Real* is still the official currency in the country until today.

2.3 Data

This chapter uses the dataset for the CPI collected by FIPE. The data consists of monthly price quotes at the store level for a variety of goods and services (100% in CPI weight). The original dataset comprises 12,921,795 price quotations from January 1989 to June 2007. The dataset covers the geographical area of the city of São Paulo, which corresponds to roughly 11% of the total national GDP.[25] Tracking the same good/service in the same store through time yields a price trajectory. The cross-section dimension tracks the dispersion among different brands and outlets.

The unit of interest is defined as a particular brand. Brands are set in the sample as a summary of the product's main characteristics, such as size, packing, material, etc. An aggregation of one or more brands comprises the product definition in the CPI. For example, many brands of soda, such as Coca-Cola, Guaraná, Fanta Uva, aggregate into the product level *Soda*, a part of the group *Foods and Beverages*, with a weight of 1.2% in the total CPI. The CPI-FIPE is published at the product level, which is the equivalent of the entry level items (ELIs) in the United States. There is no brand substitution or sales flag in the sample.



(a) Frequency (b) Size

Figure 20: Example of price trajectory: 3 outlets selling one 290-ml bottle of Guaraná

Figure 20 illustrates the price trajectory of three different outlets selling the same brands of soda, a one 290-ml bottle of Guaraná Antártica, a common soda in Brazil. The vertical line indicates the implementation of *Plano Real*. Figure 20a illustrates the evolution of prices in R$ and Figure 20b presents the evolution of prices in log scale. These two figures show how *Plano Real* affected individual price setting and inflation. They also illustrate how price dispersion is

[25] 2015 data, according to the national official statistic office, the *Instituto Brasileiro de Geografia e Estatística* (IBGE).

a common feature in the data. Although the brand is completely homogeneous, its price differs across stores in a given period of time.

The original dataset was treated to eliminate prices not in accordance with this chapter's purpose. First, I drop all prices regulated by the government, because they obey particular rules of readjustment. Products in this sector include water and sewer utilities, electricity, gasoline, and prescription drugs, for instance. Regulated goods and services account for 502,463 price quotes in the dataset, which correspond to 27.3% in CPI weight on average. This chapter focuses only on nonregulated prices.

I also exclude prices of *rent*, *condo fee*, and *housekeeping services*, because their methodology of price quoting changed many times during the sample period. I also drop brands with fewer than 10 price quotes per month, that is, fewer less than 10 stores selling the brand each month. Because the focus is on price variability, I ensure a minimal threshold of quotations per brand. The treated dataset corresponds to 51.9% of the original number of price quotes and 45.6% in CPI weight. Table 17 presents the comparison between the original and treated dataset.

Table 17: Sample treatment

	Original data	Treated data
Price quotes	12,921,795	6,708,165
Items	559,161	216,944
Brands	9,532	1,272
Products	578	386
Outlets	22,705	10,490

The treated sample encompasses 6,708,165 individual price quotes. A combination of brand and outlet defines an item. Brands are sold in 10,490 different stores, which results in 216,944 different items. Each item has its own price trajectory. The treated dataset comprises information about 1,272 brands. Most of the literature on inflation variability analyzes only a subset of products, mostly food. For instance, Hoomissen (1988) considers only 13 goods, Lach and Tsiddon (1992) analyze 26 food products, Reinsdorf (1994) addresses 65 food items, Konieczny and Skrzypacz (2005) examine 52 goods, and Baglan et al. (2016) investigate 128 goods.

The dataset is also representative in terms of groups of products considered. The FIPE-CPI basket is divided into 7 groups of products: (i) *Housing*, (ii) *Food*, (iii) *Transportation*, (iv) *Personal expenses*, (v) *Healthcare*, (vi) *Apparel*, (vii) *Education*. All 7 groups are represented in my dataset, which is a somewhat unique feature of this study. Figure 21 presents the

comparison between the CPI weight (year 2000)[26] and the sample weight. The groups *Food* and *Personal expenses* gained importance, whereas *Housing* and *Transportation* lost a certain share. Regulated prices and *rent* explain most of the effect. Regulated prices in *Transportation* were also dropped.

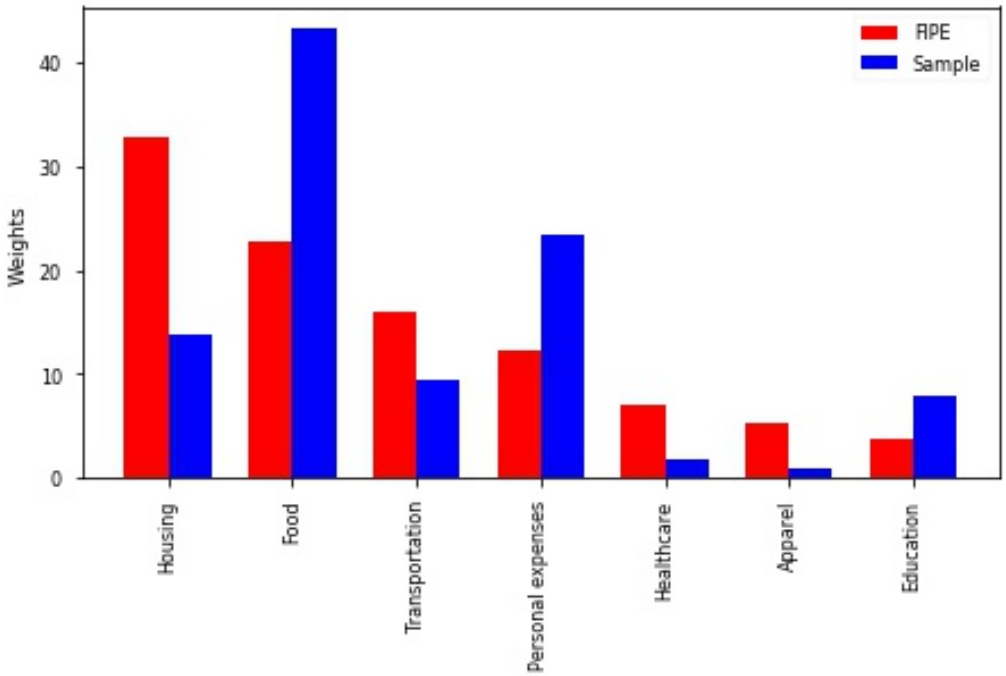


Figure 21: Sample and FIPE-CPI weights

2.3.1 Summary statistics

In this subsection, I summarize the information on the probability and size of price changes for the 1,272 brands in the sample. Let P_{ijt} be the price of a brand i sold in outlet j at time t. I first compute the average monthly frequency of price changes for each brand as the fraction of the total number of $p_{ijt} \neq p_{ijt-1}$ to all nonmissing price observations between two periods t and $t-1$ (including zero price changes).

I combine data from items to products by a simple average. I then use the product-specific FIPE-CPI weights to construct a measure of aggregate frequency f_t. It is also possible to decompose f_t into the frequency of price increases (f_t^+) and decreases (f_t^-). It follows that:

[26] Weights in the CPI-FIPE are determined by Household Budget Surveys (*Pesquisa de Orçamento Familiar* [POF]). FIPE conducts the survey regularly to analyze the average consumption basket of a typical family in São Paulo earning up to 20 minimum wages of income. I use the weights calculated by the POF 98/99 in this study.

$f_t = f_t^+ + f_t^-$.

I also investigate the size of price nonzero price changes Δp_t. I compute the absolute size of price changes at the store level level by $\Delta p_{ijt} = \frac{|p_{it} - p_{it-1}|}{p_{it-1}}$, whenever $p_{ijt} \neq p_{ijt-1}$. Items are again aggregated into brands and products by a simple average and then weighted using product-specific FIPE-CPI weights. Finally, I compute the size of price increases (Δp_t^+) and price decreases (Δp_t^-). Note that: $\Delta p_t = \frac{f_t^+}{f_t}\Delta p_t^+ + \frac{f_t^-}{f_t}\Delta p_t^-$.

Table 18: Frequency and size of price changes (%)

Year	$\pi_t^{(*)}$	f_t	f_t^+	f_t^-	Δ_t	Δ_t^+	Δ_t^-
1989	27.2	75.1	69.6	5.5	39.7	41.2	5.9
1990	29.2	74.7	65.8	8.9	41.0	42.7	8.9
1991	15.6	69.2	62.9	6.3	26.8	27.7	7.6
1992	23.3	88.3	84.6	3.7	29.4	30.1	6.7
1993	31.2	93.9	90.7	3.2	36.2	36.9	6.6
1994	23.3	74.6	65.0	9.6	34.4	35.6	8.6
1995	1.8	42.0	26.3	15.8	13.7	14.2	11.7
1996	0.8	35.4	19.5	16.0	12.6	13.1	11.4
1997	0.4	35.1	19.4	15.8	11.9	11.9	11.1
1998	-0.1	32.8	16.9	15.9	11.2	11.1	10.7
1999	0.7	40.1	24.0	16.1	12.1	12.2	10.9
2000	0.4	38.4	21.3	17.0	12.0	12.1	10.7
2001	0.6	36.0	21.0	15.0	11.1	11.2	10.0
2002	0.8	38.5	24.6	13.9	11.1	11.2	9.4
2003	0.7	40.5	24.1	16.4	11.0	11.2	9.4
2004	0.5	39.3	23.3	16.0	10.7	10.9	9.1
2005	0.4	37.9	20.8	17.1	11.1	11.3	9.4
2006	0.2	36.4	19.4	17.0	11.0	11.3	9.3
2007	0.4	37.4	22.2	15.1	10.8	11.1	8.9
Mean 1989–1993	25.3	80.3	74.6	5.7	27.8	28.2	8.2
Mean 1995–2007	0.6	37.5	21.6	15.9	10.6	9.9	10.2

Note: $(*)$ Monthly average inflation

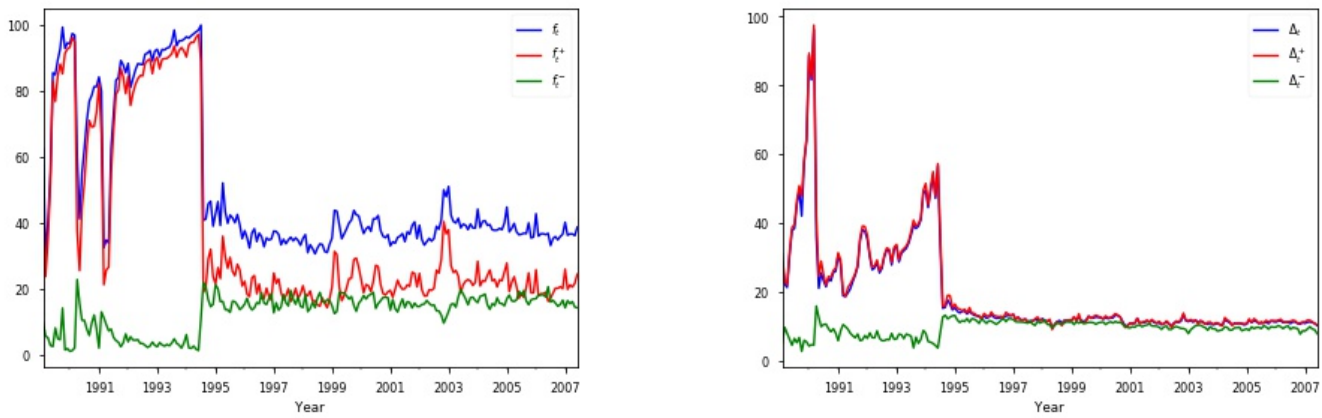
The two inflationary scenarios in my sample display marked differences regarding the frequency and size of price adjustments. Table 18 summarizes the information on the frequency and size of price changes. The average inflation rate from 1989 to 1993 is 25.3%. During hyperinflation

(1989 to 1993), an average of 80.3% of all prices changes every month. The frequency peaks at 93.9% in 1993; that is, prices are almost entirely flexible. Prices also may change more than once per month, but my monthly dataset prevents me from observing such movements. It may be the case that some stores changed prices more than once per month.

From 1989 to 1993, the majority of price movements are increases. The frequency of increases is 74.6%, whereas the frequency of decreases is only 5.7%. Price decreases are no more than 7% of all price changes during hyperinflation. Although it is less frequent, some prices drop each month during hyperinflation.

I do not find evidence of the frequency of price decreases converging to zero. Even during hyperinflation, some prices are dropping every month in Brazil. Nevertheless, this behavior is mainly observed in prices of food items, whereas prices of services present more rigidity (see Araujo (2018b) for a detailed discussion).

The monthly frequency of price changes drops drastically after *Plano Real*. During the lower-inflation period (1995–2007), the average frequency of price changes is 37.5%. Not only do prices change less often, but price decreases become more likely. From 1995 to 2007, price decreases correspond to a share of roughly 43% of all price movements. The shift in the frequency of price change occurs immediately after *Plano Real*. Figure 22a plots the monthly series of f_t, f_t^+, and f_t^-. I find no evidence of a transition period after the plan. *Plano Real* significantly changed price setting in Brazil.



(a) Frequency

(b) Size

Figure 22: Frequency and size of price changes

Figure 22b plots the time series for the absolute size of nonzero price changes. From 1989 to 1993, the average size is 27.8%, above the average inflation of 25.3%. The size of price increases

is 28.2% on average, whereas the size of price decreases is 8.2%. During hyperinflation, prices often undergo changes – and changes of large magnitude. On the other hand, from 1995 to 2007, the average size of price changes is 10.6%. The magnitude is larger than the average monthly inflation in this period (0.6%). This gap results from the higher frequency of price decreases, because the size of price increases and decreases are somewhat similar (8.2% *vs.* 10.2%).

2.4 The morphology of inflation

In this section, I focus on the shape and structure of the distribution of price changes (inflation dispersion). This approach, rather than directly examining price level dispersion, has the advantage of differencing out store-level effects, controlling for possible nonstationarities in price levels, and facilitating aggregation of different products. See Lach and Tsiddon (1992). I focus on heterogeneities in the rate of inflation across sellers of the same brand.

Define p_{ijt} as the price of a brand i in store j at time t. The rate of change in prices between t and $t-1$ is set as: $\pi_{ijt} \equiv \ln p_{ijt} - \ln p_{ijt-1}$. The in-sample rate of inflation of a brand i among all sellers is set by a simple average: $\pi_{it} = \frac{1}{S_{it}} \sum_j \pi_{ijt}$. Where S_{it} is the number of stores in which prices are observed (the number of two consecutive nonmissing observations).

In order to address the comprehensiveness of the sample, Figure 23 plots the comparison between the official FIPE-CPI and a measure of aggregate inflation constructed using the sample brands ($\widehat{\pi}_t$). Brands are aggregated into n products using a simple average. A measure of aggregate inflation is then obtained by weighting products by their correspondent FIPE weight

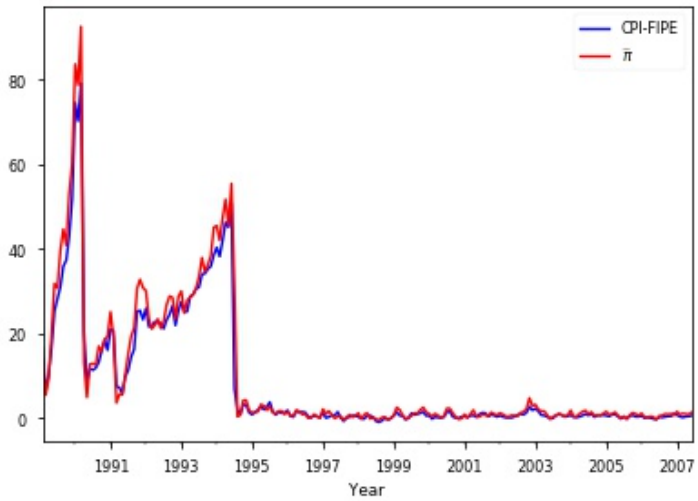
$$\widehat{\pi}_t = \sum_{n=1}^{N} \omega_{nt} \frac{1}{S_{nt}} \sum_i \pi_{it}$$

Where S_{nt} is the set of brands defining a product n in a month t (number of nonmissing observations). Weights (ω_{nt}) are calculated by the Household Budget Survey (POF) conducted by FIPE. I choose weights relative to the year 2000 POF and recalibrate them to always sum 1 every month. The counterfactual ($\widehat{\pi}_t$) presented in Figures 23b and 23c correctly replicates CPI patterns in both sample periods.

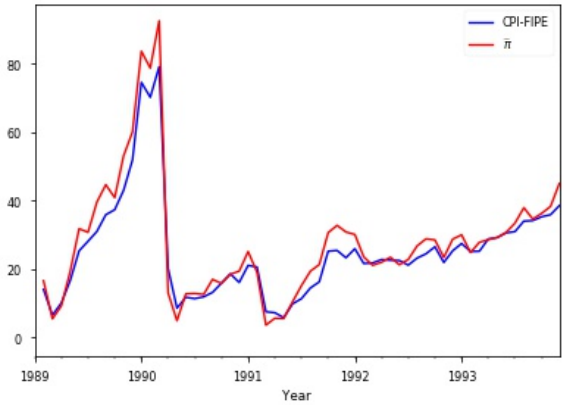
Although using different methodologies[27] and different products, $\widehat{\pi}_t$ properly reproduces the behavior of the official CPI. The correlation coefficient is 0.99 from 1989 to 2007. In the low-inflation sample, $\widehat{\pi}_t$ is more volatile due to a larger contribution of food items. The counterfactual inflation also replicates the drastic decrease in inflation immediately after *Plano Real*.

I now focus on the morphology of inflation variability. Firms adjust prices in different amounts each period, and this pattern is consistently present. Figure 24 displays the kernel estimates of the inflation rate distribution pooled over brands (π_{it}). I split the sample into years and inflation

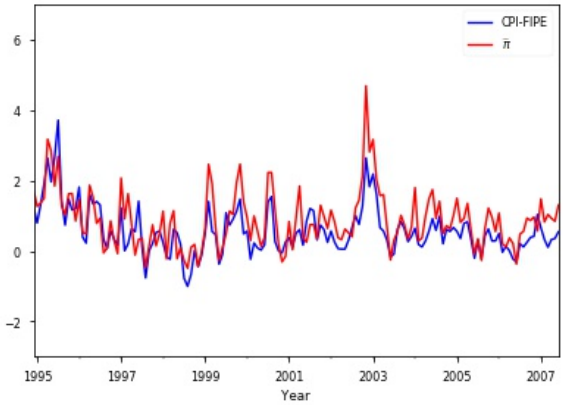
[27] FIPE-CPI is calculated as a geometric mean based on a Cobb-Douglas utility.



(a) 1989–2007



(b) 1989–1993



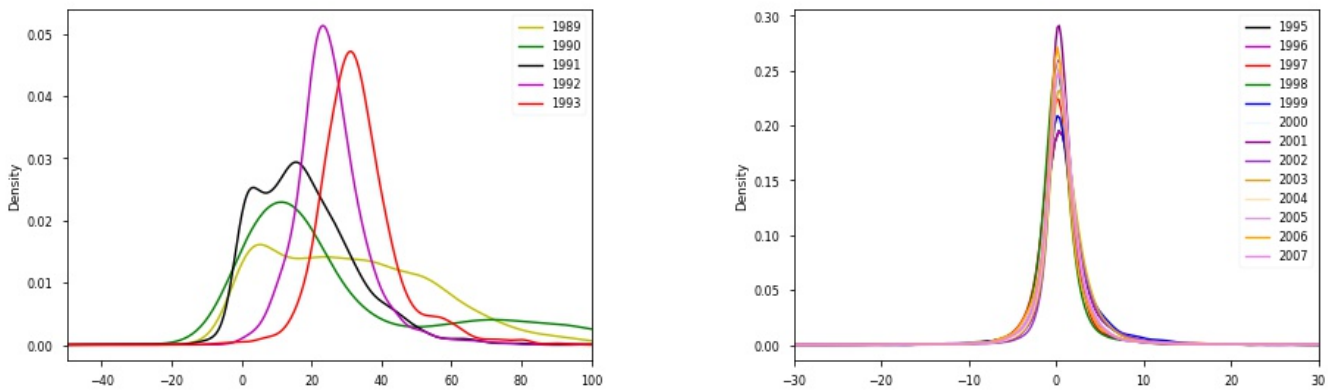
(c) 1995–2007

Figure 23: FIPE-CPI and aggregate in-sample inflation ($\widehat{\pi}$)

scenarios. The data clearly shows that the hypothesis of synchronized price adjustments does not hold. Each market for a specific brand adjusts prices by a certain amount.

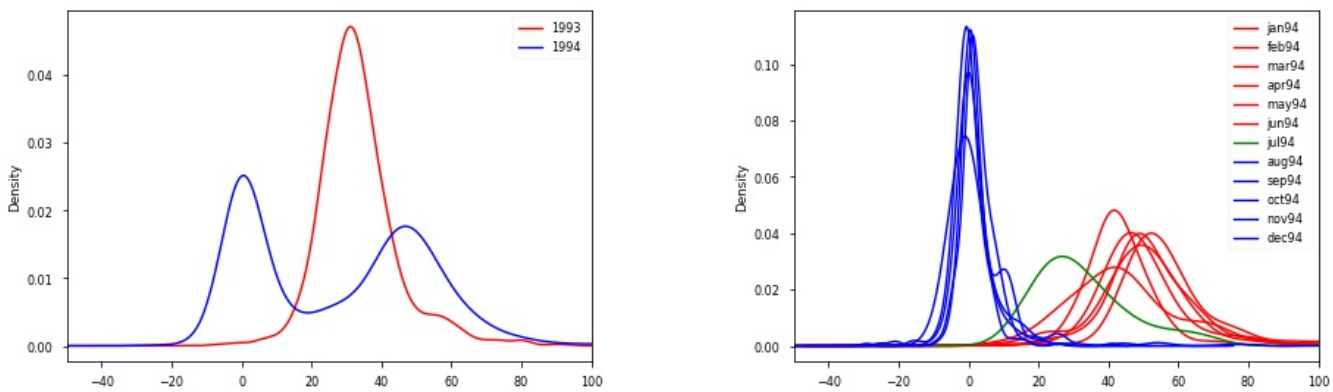
The link between inflation and the inflationary environment is also interesting. Figure 24a presents the kernel estimates for the hyperinflation years, and Figure 24b presents the estimation for the low rates of inflation years. During the 1989–1993 period, the kernel estimate exhibits a higher degree of dispersion. The distribution is also leptokurtic and asymmetric. The size of price adjustments is approximately 30% of monthly price increases. I find no evidence of unified price adjustments during hyperinflation.

In contrast, during the 1995–2007 sample period, the kernel estimation is consistently more symmetric around zero and exhibits noticeably less dispersion. The kernel distributions for all years from 1995 to 2007 are surprisingly similar.



(a) 1989–1993 (b) 1995–2007

Figure 24: Inflation density: 1989–2007



(a) 1993–1994 (b) 1994 (monthly)

Figure 25: Inflation density: 1993–1994

In order to illustrate the remarkable impact of *Plano Real* on the distribution of price adjustments, Figure 25 illustrates the density function for the years 1993 and 1994. Note the concentration around 30% of price changes during 1993 in Figure 25a. The distribution of inflation is mildly asymmetric to higher adjustment values.

Interestingly, the 1994 distribution is bimodal. This pattern results from the implementation of *Plano Real* in the middle of the year, in July 1994. Figure 25b illustrates the monthly kernel

estimates of intramarket inflation for the year 1994. Note the bimodal pattern in the data, with a transition month (July 1994), precisely when the plan was implemented.

Figures 24 and 25 illustrate the importance of *Plano Real* in controlling inflation and its dispersion among the most individual-level price observations in the sample (brands). The plan not only ended hyperinflation but significantly altered price-setting behavior as well. Once inflation is lower, producers adjust prices less often and less dispersed in time. There is less dispersion in inflation both between sellers of the same good and between sellers of different goods.

2.5 Inflation and relative price variability

This section investigates the impact of inflation on the dispersion of price adjustments among all firms selling the same brand of good/service (intramarket RPV). The interest lies in how the first moment of inflation affects the second moment of its distribution, that is, how inflation is linked to inflation variability. Following Konieczny and Skrzypacz (2005), I focus on two measures of inflation variability: the standard deviation of price changes and the coefficient of variation of price levels. Define the standard deviation (SDP_{it}) of price changes across stores as

$$SDP_{it} = \left[\frac{1}{S_{it}} \sum_j (\pi_{ijt} - \pi_{it})^2 \right]^{1/2}$$

Where S_{it} is the number of two consecutive nonmissing price-change observations and π_{ijt} and π_{it} are in-sample inflation at the store and brand level, respectively. SDP_{it} yields the evolution of the rates of price change around the average inflation rate across all sellers of a particular brand, the cross-sectional variance of inflation.

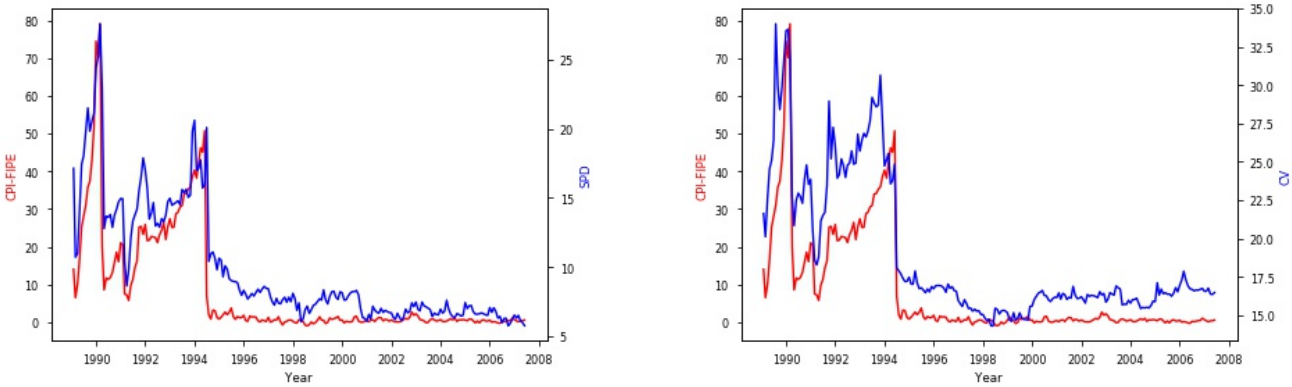
In addition, define the coefficient of variation (CV_{it}) of price levels across stores as

$$CV_{it} = \left[\frac{1}{S_{it}} \sum_j \left(\frac{p_{ijt} - P_{it}}{p_{it}} \right)^2 \right]^{1/2}$$

Where p_{it} is the average price level of a brand i across stores at time t. The coefficient (CV_{it}) accounts for contemporaneous discrepancies between the price of the same brand across all of its sellers. Following Konieczny and Skrzypacz (2005), I work with both measures of price variability.

One imperfect aggregate measure of price-change dispersion is set by combining brands into products by a simple average and then using CPI weights to compute an aggregate index for both measures of variability (SPD and CV). Following Alvarez et al. (2011), Figure 26 plots the aggregate measures alongside monthly CPI-FIPE. The correlation coefficient is 0.94 for SPD and 0.87 for CV. Note that during the hyperinflation period in Brazil, RPV was significantly higher. Higher levels of inflation widen the inflation variability range under both measures.

As an initial guideline, Figure 27 present a visual inspection of the relationship between inflation

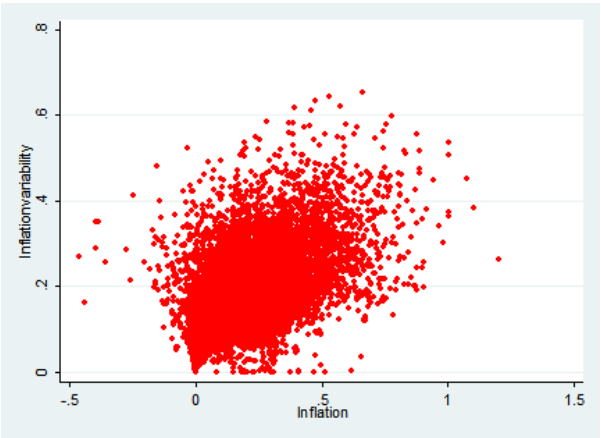


(a) Standard deviation of price changes (SPD)

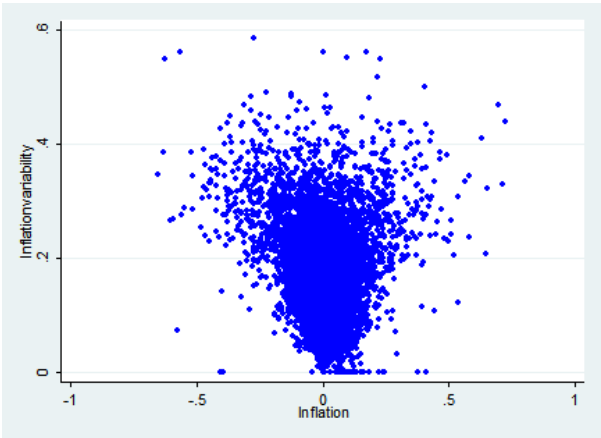
(b) Coefficient of variation of price levels (CV)

Figure 26: Inflation and relative price variability

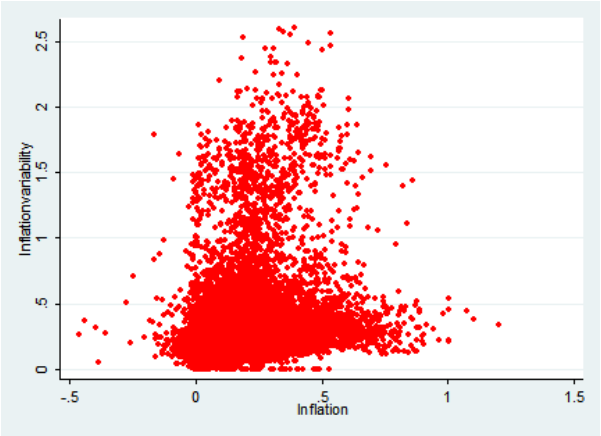
and inflation variability during both sample periods. Figures 27a and 27b present scatter plots of the standard deviation of price changes, and Figures 27c and 27d for the coefficient of variation of price levels. The distribution of inflation variability is quite different between the two inflationary scenarios. For both measures, the relationship does not appear to be symmetric around zero.



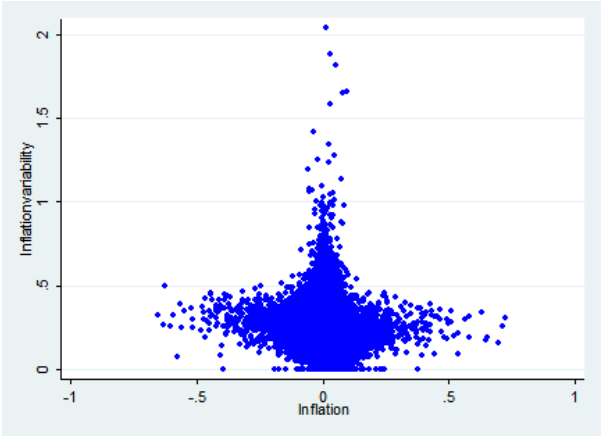
(a) SDP: 1989–1993



(b) SDP: 1995–2007



(c) CV: 1989–1993



(d) CV: 1995–2007

Figure 27: Scatter plots of inflation and inflation variability

2.5.1 Fixed effects panel

To estimate the effect of inflation on inflation variability, I run fixed effects panels regressions with both measures of dispersion (SPD and CV) as dependent variables. I use two different approaches: I estimate the impact of the absolute value of inflation and I also split inflation into the absolute value of positive and negative movements to highlight the importance of asymmetric impacts. The estimation procedure is defined as

$$\text{SDP}_{it} = \lambda_i + \sum_{t'}^{T'} \tau_t + \sum_s^S D_s + \beta \left|\pi_{it}\right| + \epsilon_{it} \tag{1}$$

$$\text{SDP}_{it} = \lambda_i + \sum_{t'}^{T'} \tau_t + \sum_s^S D_s + \beta_1 \pi_{it}^+ + \beta_2 \left|\pi_{it}^-\right| + \epsilon_{it} \tag{2}$$

$$CV_{it} = \lambda_i + \sum_{t'}^{T'} \tau_t + \sum_s^S D_s + \beta \left|\pi_{it}\right| + \epsilon_{it} \tag{3}$$

$$CV_{it} = \lambda_i + \sum_{t'}^{T'} \tau_t + \sum_s^S D_s + \beta_1 \pi_{it}^+ + \beta_2 \left|\pi_{it}^-\right| + \epsilon_{it} \tag{4}$$

Where λ_i is the brand specific effect, τ_t are year dummies, and D_s are month dummies controlling for seasonal effects. The idiosyncratic error term is ϵ_{it}. I follow the procedure presented in Konieczny and Skrzypacz (2005). The coefficient β refers to the impact of absolute inflation on inflation variability. The coefficient β_1 refers to the impact of positive price movements and the coefficient β_2 to the impact of the absolute value of negative price movements. Table 19 presents the estimation results for the hyperinflation period (1989–1993), the low-inflation period (1995–2007), and the entire sample period

Table 19: Fixed effects panel results

	SDP as dependent variable			*CV as dependent variable*		
	$\lvert\pi\rvert$	π^+	$\lvert\pi^-\rvert$	$\lvert\pi\rvert$	π^+	$\lvert\pi^-\rvert$
1989–1993	0.314**	0.355***	0.301***	0.221***	0.327***	0.204***
1995–2007	0.448**	0.389***	0.518***	0.304***	0.345***	0.462***
1989–2007	0.345***	0.294***	0.489***	0.306***	0.313***	0.363**

a Note: $***p < 0.01, **p < 0.05, *p < 0.1$

The hypothesis of a positive relationship between inflation and inflation variability finds strong support in the Brazilian data. I find evidence of a significant and positive correlation between inflation and inflation variability captured by the linear coefficient. Considering all 19 years of the sample, the linear coefficient on the absolute value of inflation indicates an effect of 0.345 in magnitude for SPD and 0.306 in magnitude for CV. The magnitude of the impact of inflation on RPV is stronger when measured by SDP than when measured by CV. Konieczny and Skrzypacz (2005) reach the same conclusion.

The overall degree of association between inflation and RPV is weaker during the hyperinflation years. The interstore inflation variability significantly increases with the rate of inflation, but the relationship is somewhat looser during hyperinflation. Considering Equation (1), the coefficient β is 0.314 from 1989 to 1993 and 0.448 from 1995 to 2007. The strength of the linear relationship is roughly 70% weaker during the years hyperinflation in Brazil (or, equivalently, 40% stronger during the low-inflation sample).

A similar conclusion is reached in Equation (3), where the coefficient β is also roughly 70% weaker comparing hyperinflation to low inflation (0.221 *vs.* 0.304). Both results are statistically significant at the 5% confidence level. The inflationary regime thus impacts the strength of the relationship. This result is in line with Caglayan and Filiztekin (2003), who also report evidence on a significantly lower association between inflation and inflation variability during high-inflation years in Turkey.

The looser link between inflation and RPV during hyperinflation is explained by the higher frequency of price increases during that period. When inflation is high, most price changes are price increases, which narrows inflation dispersion at the brand level. Thus, the relationship between inflation and its dispersion is weaker during these years.

Nevertheless, after *Plano Real*, price decreases are almost as likely as price increases, which widens price-change dispersion in the data and increases the impact of inflation on it. Note that price changes dispersion is higher during hyperinflation than during low inflation. The point is that the impact of inflation on RPV is relatively higher during low inflation because for low inflation levels, there is higher inflation dispersion due to the presence of price decreases.

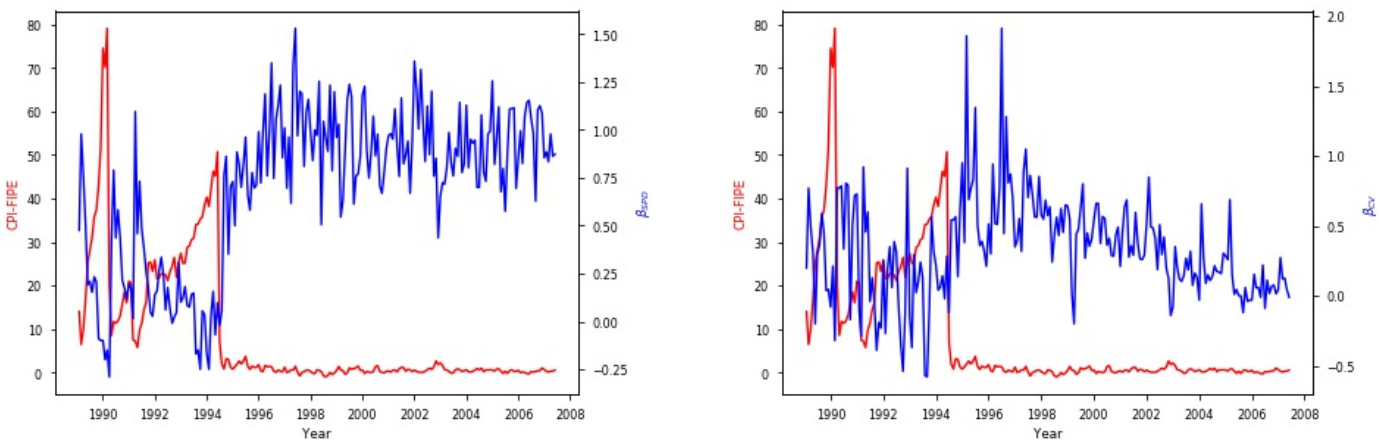
I also find evidence of asymmetric effects. Deflation, in absolute terms, has a higher impact on RPV considering both RPV measures during the 1995–2007 sample. During lower levels of inflation in Brazil, price decreases contribute marginally more to price dispersion than do price increases. From Equation (2) 1995–2007 sample period, the impact of $\left|\pi_{it}^{-}\right|$ is 0.518 against 0.389 of π_{it}^{+}. From Equation (4), during the same low-inflation sample period, the impacts are, respectively, 0.462 and 0.345.

In contrast, during hyperinflation, because price decreases are less frequent, the effect of $\left|\pi_{it}^{-}\right|$ is weaker than the effect of π_{it}^{+}, yet positive and significant. Even during hyperinflation, some prices (mostly for food items) drop every month and this impacts overall inflation variability. Tommasi (1992) reaches the same conclusion.

To gain further insight into the importance of inflation in price adjustment variability, I perform a simple least squared estimation on intramarket data individually for each of the 221 months in the sample. Table 19 presents evidence on a structural change in the relationship between inflation and RPV. During hyperinflationary episodes, the relationship is significantly lower. The additional exercise enables for time-varying effects without imposing any timing for breakpoints in the sample, thus allowing for an investigation of the structural change. The estimation procedure is set as

$$\mathrm{SPD}_{it} = \lambda_{it} + \beta_t \left|\pi_{it}\right| + \epsilon_{it}, \qquad \textit{for each } t = 2, 3, ..., 222 \tag{5}$$

$$\mathrm{CV}_{it} = \lambda_{it} + \beta_t \left|\pi_{it}\right| + \epsilon_{it}, \qquad \textit{for each } t = 2, 3, ..., 222 \tag{6}$$



(a) β_{SPD} (b) β_{CV}

Figure 28: Rolling regression results for β_{SPD} and β_{CV}

Where λ_{it} is the intercept of the regression for each month. I focus on the time evolution of β_t. Figure 28 plots the OLS results for all months in the sample. A major structural change is clearly evident in July 1994, precisely when *Plano Real* was implemented. The shift is clear, and both coefficients – considering SDP and CV as the dependent variable – display a similar timing of breakpoints.

Once the hyperinflation spiral was tamed, the structure of the relationship between inflation and inflation variability changed. I confirm a higher impact of inflation on RPV for both SDP and CV during low inflation. The link between inflation and inflation variability was looser during the hyperinflation years. Once again, I find no evidence of a transition period.

I also document the estimation results of β, β_1, and β_2 based on sectors and groups of brands. The estimation results are displayed in Table 20. I aggregate products into three sectors: *Services*, *Industrial goods*, and *Food at home*. I follow the methodology of the Brazilian Central Bank (BCB) to aggregate products. This aggregation is common in the literature as well. I also present the estimation for products in each of the 7 groups of products in the CPI-FIPE, namely *Housing*, *Food*, *Transportation*, *Personal expenses*, *Healthcare*, *Apparel*, and *Education*.

All sectors and groups associated with the 1,272 brands confirm the same aggregate empirical result: inflation and inflation variability present a significant positive relationship, and this link is stronger during low inflation than during hyperinflation. I also document asymmetries for upward and downward price movements.

Table 20: Fixed effects panel results by sector and group

	SDP as dependent variable			*CV as dependent variable*		
	$\lvert\pi\rvert$	π^+	$\lvert\pi^-\rvert$	$\lvert\pi\rvert$	π^+	$\lvert\pi^-\rvert$
Categories						
Food at home						
1989–1993	0.260***	0.260***	0.205***	0.212***	0.232***	0.167***
1995–2007	0.352***	0.287***	0.421***	0.269**	0.245**	0.265***
1989–2007	0.270***	0.257***	0.383***	0.257***	0.243***	0.234***
Industrial goods						
1989–1993	0.364***	0.365***	0.591***	0.199***	0.153***	0.281**
1995–2007	0.749***	0.646***	0.931***	0.377***	0.379***	0.676*
1989–2007	0.370***	0.362***	0.804***	0.353***	0.352***	0.411***
Services						
1989–1993	0.356***	0.358***	0.083	0.185***	0.154**	-0.062
1995–2007	1.344***	1.269***	1.070**	0.405***	0.404***	0.194**
1989–2007	0.327***	0.325***	1.367**	0.300***	0.300***	0.491**
Groups						
Housing						
1989–1993	0.420***	0.422***	0.421***	0.179***	0.120***	0.227
1995–2007	0.713***	0.614***	0.843***	0.430***	0.429***	0.255***
1989–2007	0.408***	0.394***	0.780***	0.386***	0.389***	0.300**
Food						
1989–1993	0.254***	0.254***	0.206***	0.218***	0.217***	0.211***
1995–2007	0.350***	0.285***	0.417***	0.436***	0.345**	0.482**
1989–2007	0.266***	0.251***	0.406***	0.292***	0.286***	0.454***
Transportation						
1989–1993	0.285***	0.291***	0.141	0.211*	0.126**	-0.026
1995–2007	0.497***	0.460***	0.633***	0.392**	0.394***	0.827
1989–2007	0.279***	0.272***	0.577***	0.324***	0.318***	0.540***
Personal expenses						
1989–1993	0.351***	0.353***	0.258***	0.285***	0.272***	0.311**
1995–2007	0.767***	0.678***	0.953***	0.387***	0.390***	0.866*
1989–2007	0.341***	0.337***	0.789***	0.385***	0.385**	0.462***
Healthcare						
1989–1993	0.351***	0.351***	–	0.0415	0.0415	–
1995–2007	1.204***	1.616***	0.964*	0.165***	0.387**	0.0895
1989–2007	0.361***	0.354***	1.085*	0.0537*	0.0522	0.299
Apparel						
1989–1993	0.318***	0.318***	0.286**	0.106*	0.143*	0.245**
1995–2007	1.104***	1.049***	1.757***	0.246***	0.250***	0.681**
1989–2007	0.318***	0.320***	0.499***	0.238***	0.243**	0.747***
Education						
1989–1993	0.339***	0.340***	0.694	0.341***	0.338***	0.357
1995–2007	0.996***	0.873***	1.535***	0.401***	0.403***	0.394*
1989–2007	0.353***	0.345***	1.285***	0.372***	0.372***	0.456***

Note: $***p < 0.01, **p < 0.05, *p < 0.1$ Note2: – not enough observations for estimation

It may not be the case that all goods and services will be affected to the same degree by variations in inflation. It is possible that, due to the purchase frequency or relative expensiveness of brands, price adjustments dispersion will vary across brands. Although different categories of brands are similar in terms of the impact's significance and direction, some differences appear across these categories. The magnitude of the impact of inflation is stronger for *Services*.

Food at home items, on the other hand, present a weaker relationship, which is probably due to a higher incidence of supply shocks (price decreases). Regarding the division of products in groups, the RPV of *Healthcare* and *Education* brands are strongly correlated to inflation. Prices are stickier in both groups, so unsynchronized timing of adjustments also affects the link. The coefficient is also high in *Apparel*.

In short, the empirical evidence suggests a looser link between inflation and inflation variability during the Brazilian hyperinflation years. Inflation drives a wedge into the informational content of nominal prices, causing persistent distorting impacts on relative price adjustments. Nonetheless, when inflation is at skyrocketing levels, as in the Brazilian economy in the mid-80s and mid-90s, firms will change prices according to sources of information other than price movements among their competitors. High inflation distorts the channel through which inflation affects relative price variability.

2.6 Concluding remarks

This chapter investigates patterns of price-change variability across firms selling the same homogeneous brand using Brazilian microdata from 1989 to 2007. I find evidence of a different relationship between relative price variability and inflation during hyperinflation and lower levels of inflation at the microeconomic level. The link (in magnitude) during hyperinflation is roughly 70% of the magnitude during low inflation. I also find asymmetric impacts from deflation and positive inflation.

I document the morphology of inflation variability at the brand level across time. I find evidence of an asymmetric and leptokurtic kernel density function during the years of hyperinflation. The distribution is more symmetric and concentrated around lower values of inflation during the 1995–2007 period. I find no evidence of a transitional period. The density function on inflation instantaneously adjusted to a new pattern once *Plano Real* was implemented in July 1994. I also provide a set of summary statistics regarding the frequency and size of price adjustments, which also highlight the substantial impact of the plan on price-setting behavior in Brazil.

The empirical results obtained in this chapter indicate a positive relationship between inflation and intramarket inflation variability. Through a fixed effects panel estimation, I find compelling evidence of a significantly weaker association between inflation and RPV during hyperinflation. Higher levels of inflation are associated with higher inflation variability, but the relationship is somewhat looser during hyperinflation, which relates to the higher frequency of price increases during this period.

The impact of deflation (in absolute terms) is weaker than the impact of positive inflation during hyperinflation, yet stronger during low inflation. The magnitude of the impact of inflation on RPV is stronger when measured by SDP than when measured by CV. The empirical evidence indicates different inflation-RPV links depending on the inflationary environment.

Despite the extensive empirical evidence on the relationship between inflation and inflation variability, there is still room for research on developing countries, especially during hyperinflation. This chapter contributes to the literature by analyzing a unique dataset on more than 6 million store-level prices encompassing 5 years of hyperinflation in Brazil. The data is also extensive in terms of products. I analyze data on 1,272 brands of goods and services from 1989 to 2007 (almost 19 years). The chapter provides further evidence highlighting the importance of considering different inflation scenarios when assessing inflation-related effects.

3 EVIDENCE ON SEARCH COSTS UNDER HYPERINFLATION IN BRAZIL: THE EFFECT OF *PLANO REAL*

3.1 Introduction

Plano Real put an end to hyperinflation in 1994 and significantly altered price-setting behavior in Brazil.[28] 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:[29] 7 food items, 4 industrial goods, and 4 services.[30] All brands are homogeneous in terms of physical characteristics. To quantify the extension of search costs, I

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

[29] Section 3.5 presents the selection criteria.

[30] 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.*

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 chapter is its extension of 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 29 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.

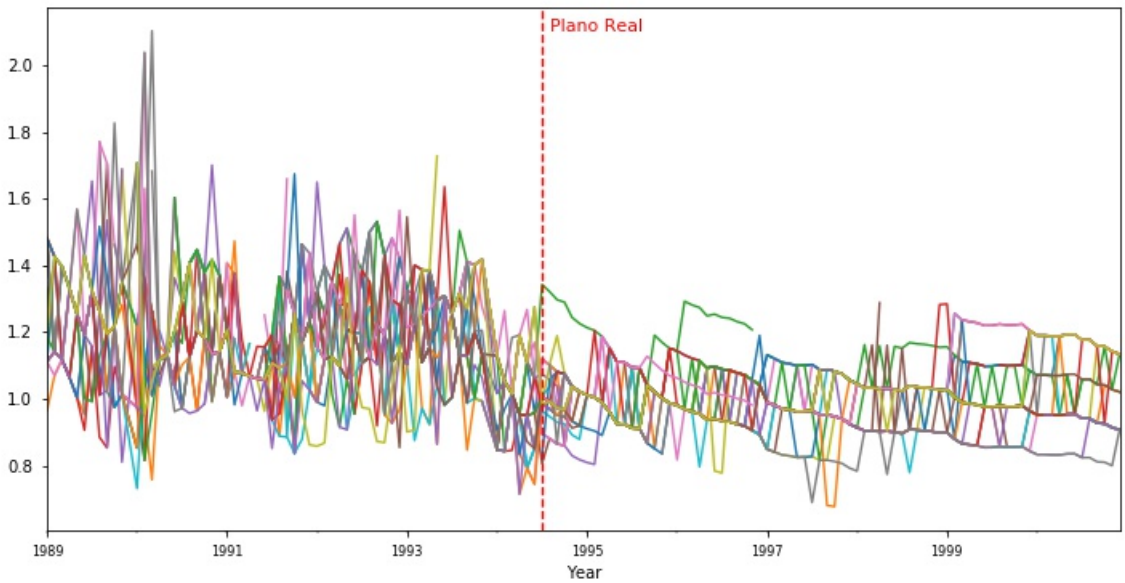


Figure 29: Relative prices for 290-ml bottle of Coca-Cola

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.[31] 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 chapter contributes to the literature by documenting differences in search-cost

[31] 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).

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 chapter 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.[32]

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.

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

[32] 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.

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.[33]

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 chapter proceeds as follows. Section 3.2 documents the inflation environment and relevance of *Plano Real*. Section 3.3 presents the theoretical model, followed by a description of the estimation procedure in Section 3.4. Section 3.5 presents the dataset. Section 3.7 documents the estimation results, and Section 3.8 concludes the chapter.

[33]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.

3.2 *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.[34] Figure 30 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.

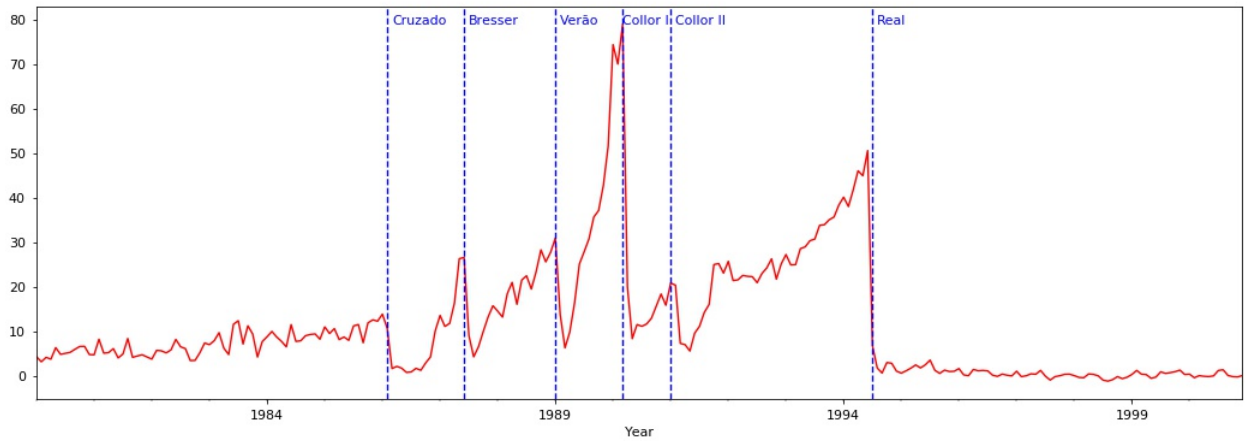


Figure 30: Monthly inflation and economic plans

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 30 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).

[34] All inflation statistics in this chapter 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.

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 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.

3.3 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.[35]

3.3.1 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

$$\Delta_k = E(p_{1k}) - E(p_{1k+1}) \tag{7}$$

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,

$$E(\mathrm{p}_{1k}) = \int_{\underline{p}}^{\overline{p}} pk[1 - F_p(p)]^{k-1} f_p(p)dp \tag{8}$$

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

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

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

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 $\underline{p}$

$$E(\mathrm{p}_{1k}) = \underline{p} + \int_{\underline{p}}^{\overline{p}} [1 - F_p(p)]^k dp \tag{9}$$

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

$$\mathrm{U}_{ik} = -E(p_{1k}) - c_i(k - 1) \tag{10}$$

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

$$\text{Prob[consumer } i \text{ searches } k \text{ times]} = q_k = Prob[\Delta_k \leq c_i \leq \Delta_{k-1}] = G_c(\Delta_{k-1}) - G_c(\Delta_k) \tag{11}$$

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 31 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.

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

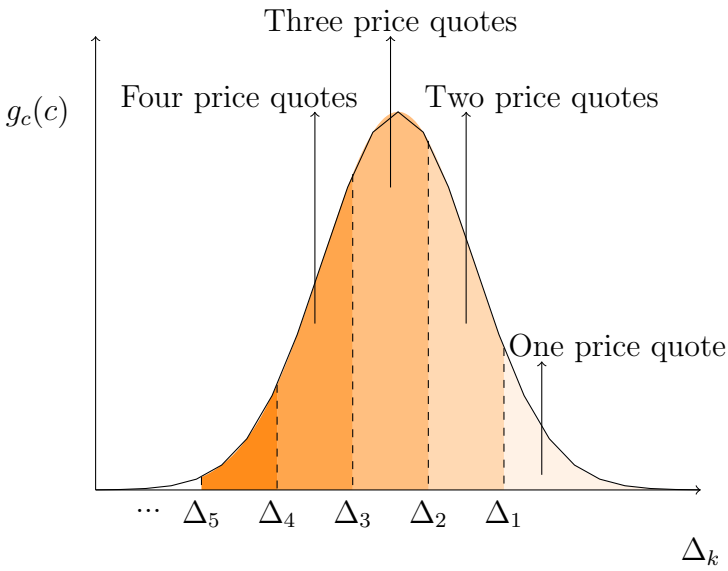


Figure 31: Identification scheme for search-cost distribution

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

3.3.2 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

$$\pi(p; F_p(p), r) = (p-r)\left\{\prod_{k=1}^{N} \frac{q_k k}{N}[1-F_p(p)]^{k-1}\right\} \tag{12}$$

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.

3.3.3 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 p and $\overline{p}$. Therefore, the symmetric Nash mixed strategy equilibrium must satisfy

$$(p - r) \sum_{k=1}^{N} \frac{q_k k}{N} [1 - F_p(p)]^{k-1} = (\overline{p} - r) \frac{q_1}{N}, \quad \text{for any } p \in [\underline{p}; \overline{p}] \tag{13}$$

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

$$\underline{\text{p}} = \frac{q_1(\overline{p} - r)}{\sum_{k=1}^{N} k q_k} + r \tag{14}$$

$$r = \frac{\underline{p} \sum_{k=1}^{N} k q_k - q_1 \overline{p}}{\sum_{k=2}^{N} k q_k} \tag{15}$$

3.4 Estimation procedure

Equations (7), (11), (13), (14), and (15) 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.[36] 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.[37]

The procedure begins by estimating the parameters of the price distribution through ML using the equilibrium constancy-of-profits condition of Equation (13) 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 (7) and (11)) 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

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

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

$$(\mathrm{p}_l - r)\sum_{k=1}^{N}\frac{q_k k}{N}[1-F_p(p_l)]^{k-1} = (\overline{p}-r)\frac{q_1}{N}, \quad \text{for all } l = 2,3,...,N-1 \tag{16}$$

Differentiating Equation (16) and solving for f_p by applying the implicit function theorem yields

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

3.4.1 Inflation and search costs

This subsection briefly discusses the relationship between inflation and search costs in the context of this chapter'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.[38]

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 29 in Section 3.1).

[38] 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.

My empirical strategy consists of estimating the model presented in Section 3.3 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 3.5 presents my dataset, and Section 3.7 presents my empirical results.

3.5 Data

The data contribution of this chapter 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 chapter, I focus only on homogeneous goods to ensure full comparability across stores. To estimate the model outlined in Section 3.3, I choose transaction prices on 15 different brands. See Table 21 for a description.

Table 21: 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.

3.5.1 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 32 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 22: 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 22 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.

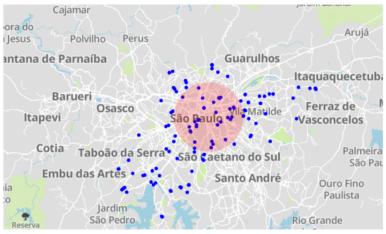
Wildenbeest (2011) discusses unbalanced panels for store-level data and concludes that no significant bias emerges from this type of missing data. Since the stores are the same, I control for all sources of heterogeneity derived from store-related effects. I assume that the active consumer population 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.

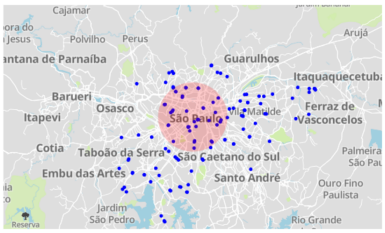
The Antarctica beer presents the largest amount of price quotes available for search-cost estimation. The hyperinflation sample contains 767 observations, whereas the lower-inflation sample contains 736 observations. A total of 45 stores can be searched for this brand within the 6-km radius, and at least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

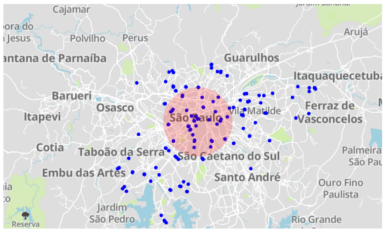
The smallest set of observations comes from *Services*, probably because it is quite difficult to collect this type of price data. Rather than just looking at a price tag, the surveyor often has to ask for a specific kind of service. A cup of coffee is quoted, on average, in 15 different stores each 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.



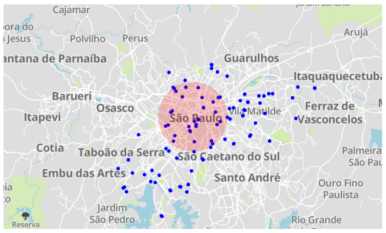
(a) Chicken



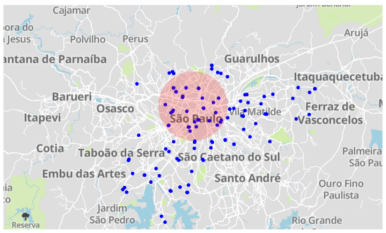
(b) Antarctica beer



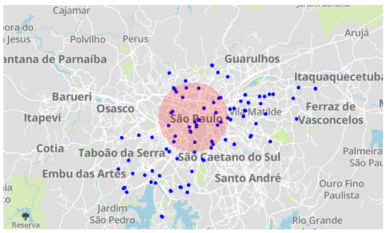
(c) Coca-Cola



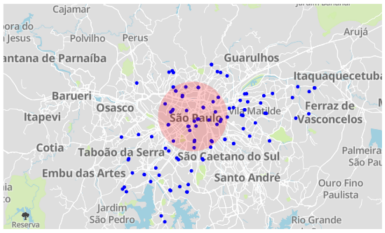
(d) Top sirloin



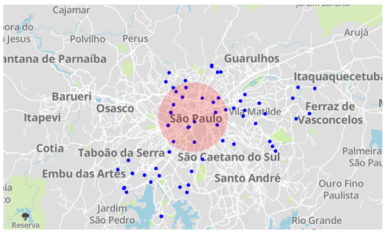
(e) Mozzarella



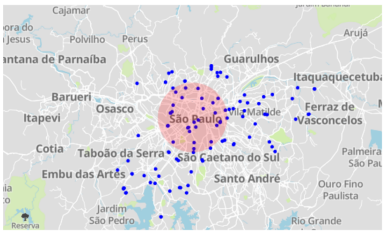
(f) Pork loin



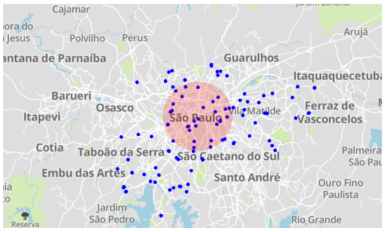
(g) Mortadella



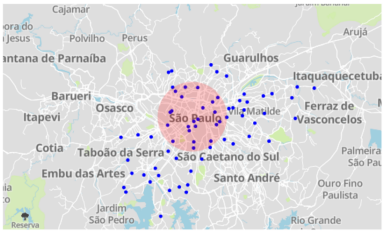
(h) Shampoo



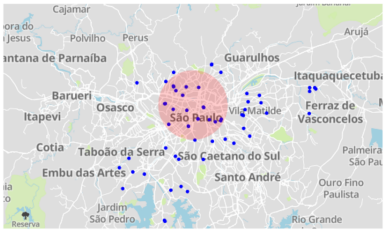
(i) Deodorant



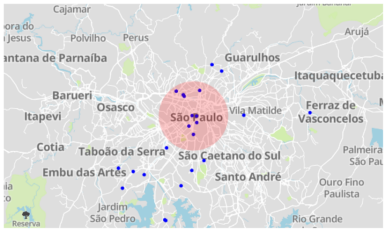
(j) Shaving cream



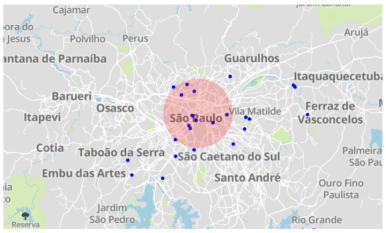
(k) Steel sponge



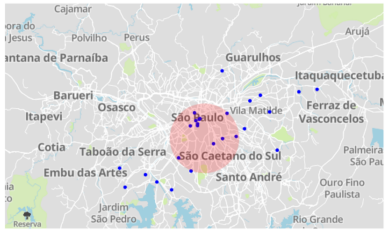
(l) Coffee



(m) Meal



(n) Doctor's appointment



(o) Haircut

Figure 32: Spatial outlet selection: 6-km radius

3.6 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. Figure 23 presents simple mean and variability measures of the real-price data.

Table 23: Summary statistics: real prices

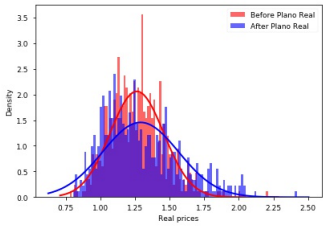
	Jan 1993 - Jun 1994						Aug 1994 - Dec 1995					
Brands	Mean	Median	Std. dev.	Min.	Max.	CV (%)	Mean	Median	Std. dev.	Min.	Max.	CV (%)
Chicken	1.26	1.25	0.19	0.78	2.21	15.3	1.29	1.24	0.27	0.80	2.42	21.2
Antarctica beer	0.86	0.84	0.27	0.35	1.53	31.0	0.98	0.85	0.25	0.53	1.47	25.8
Coca-Cola	0.45	0.45	0.05	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 33 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.

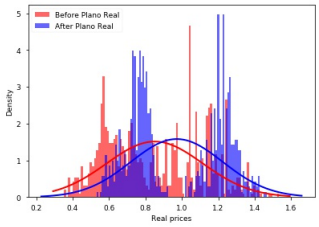
Averaging stores and months from 1993 to June 1994, the mean and median price of the Coca-Cola bottle is 0.45, with a standard deviation of 0.05. Prices range from 0.33 to 0.59. The coefficient of variation (CV), defined as the ratio of the standard deviation to the mean price, is 11.3%. The mean and 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%.

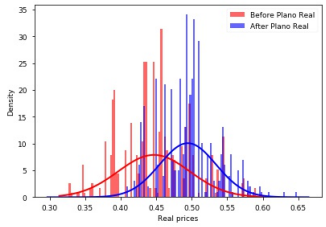
The 4 industrial goods brands present a roughly similar coefficient of variation of around 20% before *Plano Real*. The CV is 25.5% for the shampoo brand, 27.4% for the deodorant brand, 24.6% for the shaving cream brand, and 18.8% for the steel sponge brand. This measure of dispersion decreases for all 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).



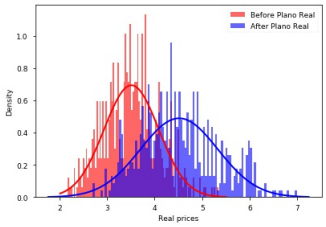
(a) Chicken



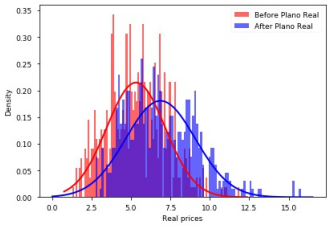
(b) Antarctica beer



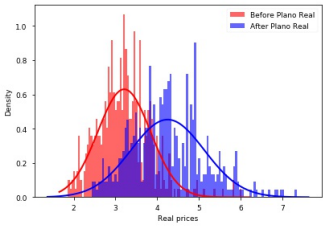
(c) Coca-Cola



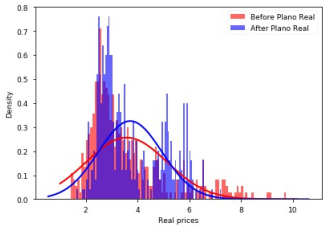
(d) Top sirloin



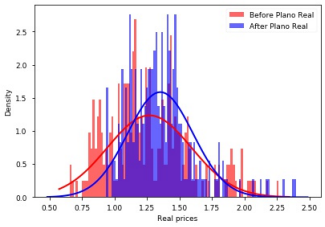
(e) Mozzarella



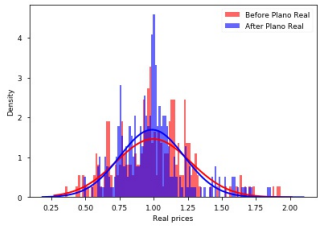
(f) Pork loin



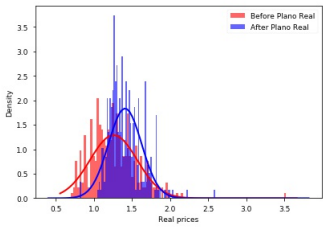
(g) Mortadella



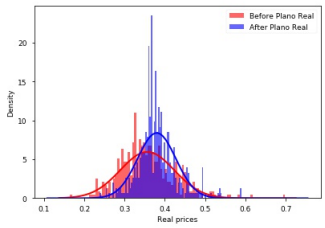
(h) Shampoo



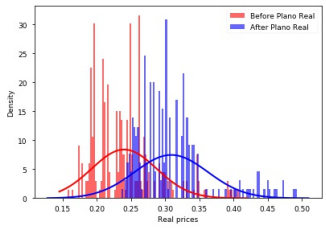
(i) Deodorant



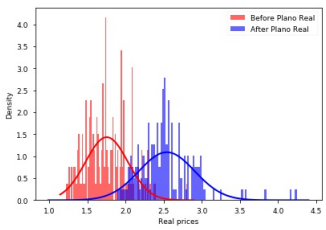
(j) Shaving cream



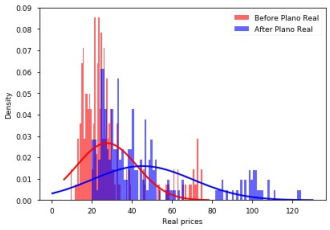
(k) Steel sponge



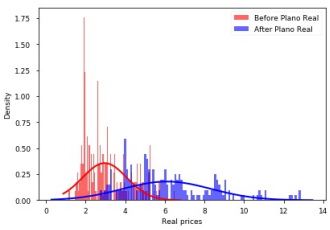
(l) Coffee



(m) Meal



(n) Doctor's appointment



(o) Haircut

Figure 33: Real-price histograms

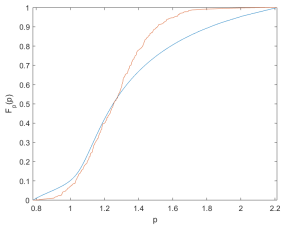
3.7 Empirical results

In this section, I present estimates of the-search cost distribution implied by the theoretical model outlined in Section 3.3. 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.

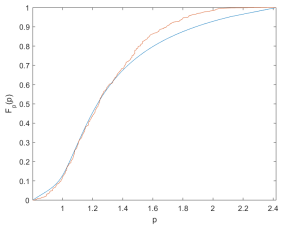
First, I assess the goodness of fit of the model during both sample periods. In order to retrieve all relevant quantiles of the search-cost distribution $G_c(c)$, I start by estimating the theoretical cumulative distribution function (cdf) of prices $F_p(p)$ predicted by the model. I then compare the theoretical estimation to the empirical price distribution observed in the data. Figure 34 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 34m and Figure 34n). The worst fitting comes from shaving cream prices (Figure 34s and Figure 34t). 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.

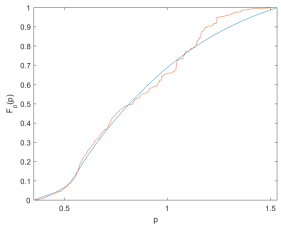
Table 24 presents the estimation results for the 15 different brands. Standard errors are shown in parentheses. The first row reports the estimated proportion of consumers searching only once (q_1). They have very high search costs and buy at the first and only visited store. This share is above 10% 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.



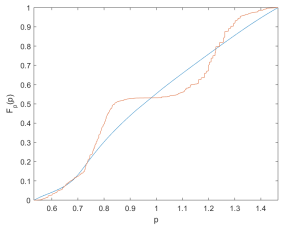
(a) Chicken – before



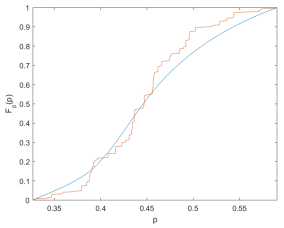
(b) Chicken – after



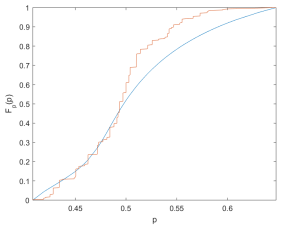
(c) Antarctica beer – before



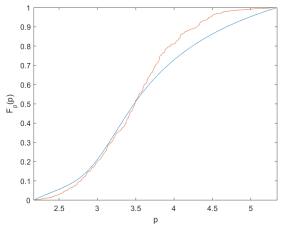
(d) Antarctica beer – after



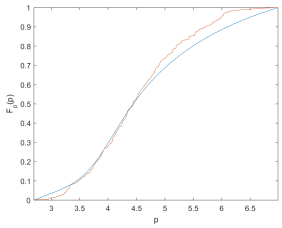
(e) Coca-Cola – before



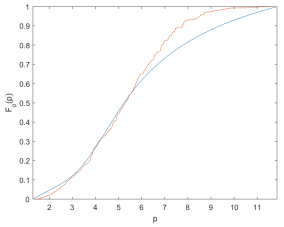
(f) Coca-Cola – after



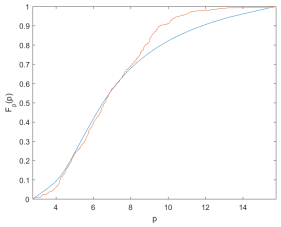
(g) Top sirloin – before



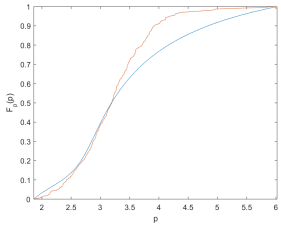
(h) Top sirloin – after



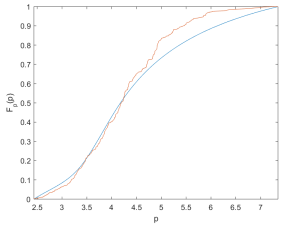
(i) Mozzarella – before



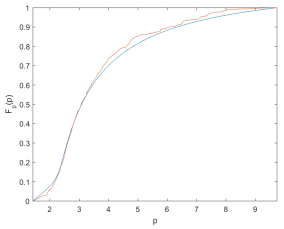
(j) Mozzarella – after



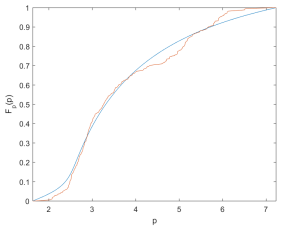
(k) Pork loin – before



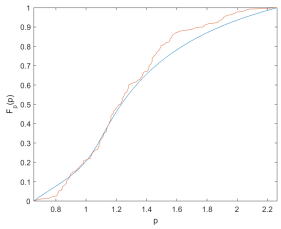
(l) Pork loin – after



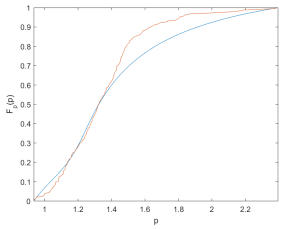
(m) Mortadella – before



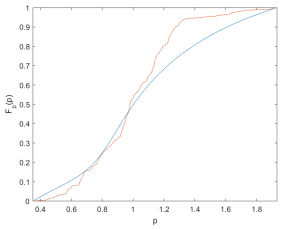
(n) Mortadella – after



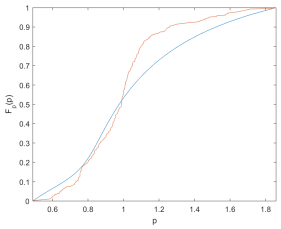
(o) Shampoo – before



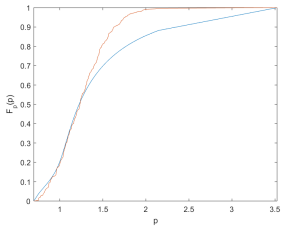
(p) Shampoo – after



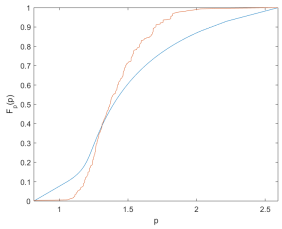
(q) Deodorant – after



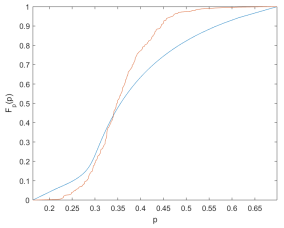
(r) Deodorant – after



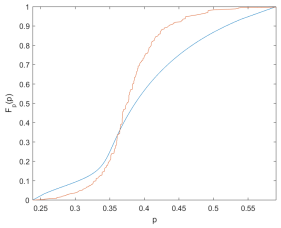
(s) Shaving cream – after



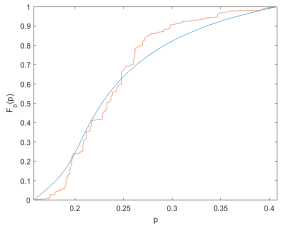
(t) Shaving cream – after



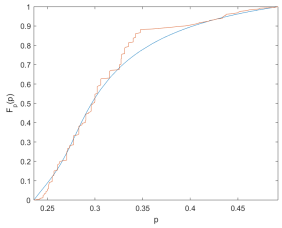
(u) Steel sponge – after



(v) Steel sponge – after

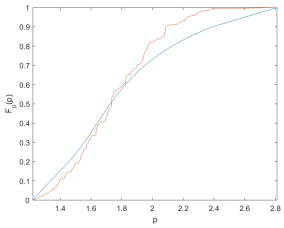


(w) Coffee – after

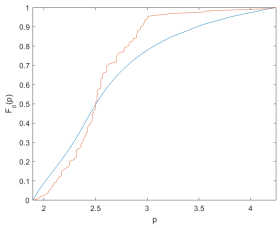


(x) Coffee – after

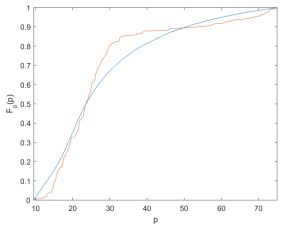
Figure 34: Fitting of the model



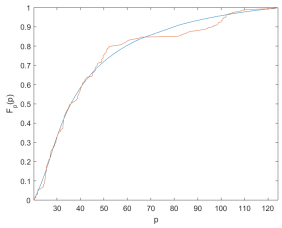
(y) Meal - before



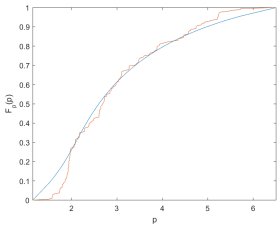
(z) Meal - after



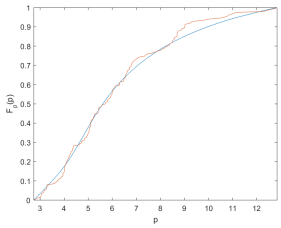
(aa) Doctor's appointment - before



(ab) Doctor's appointment - after



(ac) Haircut - before



(ad) Haircut - after

Figure 34: 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.

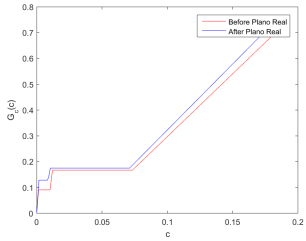
For most brands, consumers also search in three stores (q_3). For a smaller group of brands, searching also takes place into four stores (q_4). The last row presents estimates on the share of consumers searching all stores (q_N). This proportion is relevant for all brands. A small group of consumers 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 35 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.

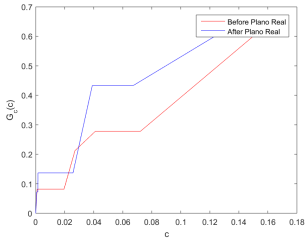
Following Moraga-González et al. (2017b), I compare the cumulative search-cost distribution during the two inflationary scenarios. I find evidence on FOSD regarding 11 of the 15 brands: chicken, Coca-Cola, top sirloin, pork loin, shampoo, deodorant, shaving cream, steel sponge, coffee, meal, and doctor's 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 24: Estimation results

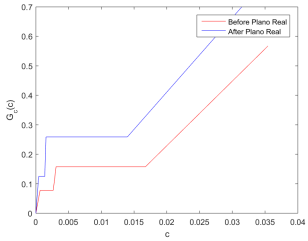
	Chicken		Antarctica beer		Coca-Cola	
	Before	After	Before	After	Before	After
q_1	0.25 (0.03)	0.30 (0.04)	0.34 (0.09)	0.34 (0.01)	0.43 (0.08)	0.30 (0.04)
q_2	0.58 (0.04)	0.53 (0.04)	0.38 (0.07)	0.23 (0.04)	0.41 (0.03)	0.44 (0.04)
q_3	0.08 (0.03)	0.03 (0.37)	0.07 (0.24)	0.30 (0.04)	0.08 (0.04)	0.13 (0.04)
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)



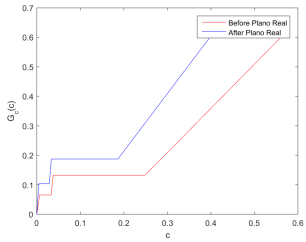
(a) Chicken



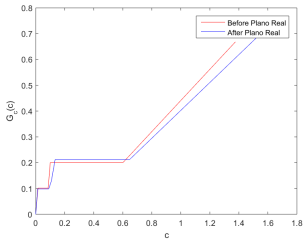
(b) Antarctica beer



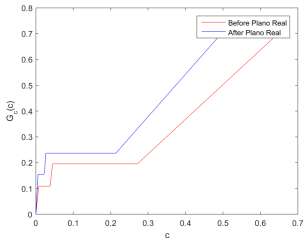
(c) Coca-Cola



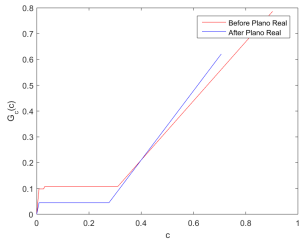
(d) Top sirloin



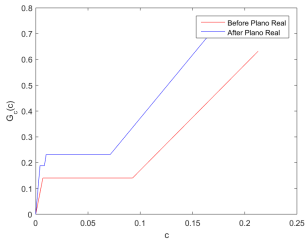
(e) Mozzarella



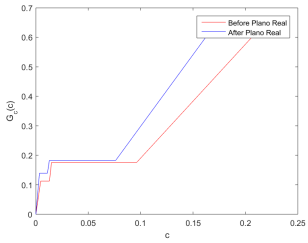
(f) Pork loin



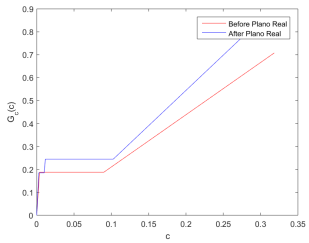
(g) Mortadella



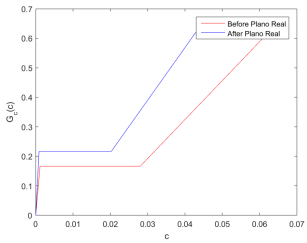
(h) Shampoo



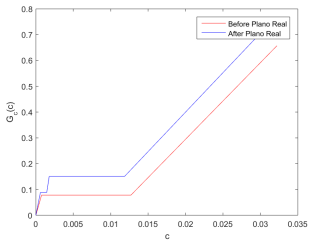
(i) Deodorant



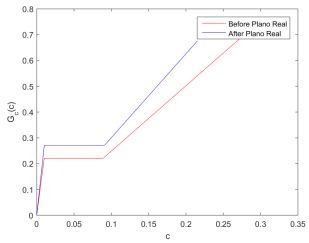
(j) Shaving cream



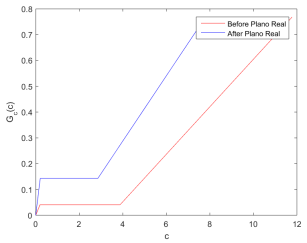
(k) Steel sponge



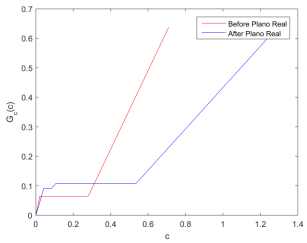
(l) Coffee



(m) Meal



(n) Doctor's appointment



(o) Haircut

Figure 35: Search-cost distributions

Figure 35 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.[39] 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.[40] 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 35 confirms and illustrates this pattern.

I also present estimations on the marginal cost of each brand during both inflation environments. Table 25 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.

[39] 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.

[40] 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 25: 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
$\overline{v}$	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
$(\overline{v}-r)/\overline{v}$	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
$\overline{v}$	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
$(\overline{v}-r)/\overline{v}$	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
$\overline{v}$	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
$(\overline{v}-r)/\overline{v}$	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
$\overline{v}$	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
$(\overline{v}-r)/\overline{v}$	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
$\overline{v}$	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
$(\overline{v}-r)/\overline{v}$	64.4	60.0	94.3	85.5	98.5	90.7

3.8 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 chapter 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,[41] 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 chapter 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

[41] See, for instance, Moraga-González and Wildenbeest (2008), Wildenbeest (2011), and González and Miles-touya (2018).

evidence suggests that hyperinflation shuffles the price ranking of firms and that this directly impacts searching for the lowest price.

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APPENDIX A

Table 26: 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