Price Setting in a Variable Macroeconomic Environment: Evidence from Brazilian CPI*

(Incomplete / Work in progress / Comments welcome)

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Abstract

We study price setting in a variable macroeconomic environment using a unique data set from the Brazilian CPI index of Fundação Getulio Vargas. Our primary data consist of a panel of individual prices for goods and services covering 100% of the CPI for the 1996-2008 period. During this period a number of important events produced substantial macroeconomic variability in Brazil: two emerging market crises, a change of exchange rate and monetary regimes, blackouts and energy rationing, an election crisis, and a regular disinflation. As a consequence, inflation, macroeconomic uncertainty, exchange rates, and output exhibit important variation in our sample. We construct time series of price-setting statistics and relate them to macroeconomic variables using regression analyses. As an illustration of our results, we find that price increases are less frequent after a period of exchange rate appreciation, and more frequent: i) when inflation is higher; after a period of exchange rate depreciation (with an asymmetry relative to appreciations); in periods of high economic activity; and when macroeconomic uncertainty is higher.

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1 Introduction

In the past few years, access to vast amounts of micro price data has generated renewed interest in research on price setting among macroeconomists. Starting with Bils and Klenow (2004), the use of disaggregated data from stable economies has produced hard evidence on various aspects on price setting, including the frequency and size of price changes, for a very wide range of goods and services in several countries. We learned that prices change more frequently than previously thought, and that the size of a large fraction of price changes is much larger than what is implied by models that feature only plausible aggregate shocks. However, in most of the studies, the small time-series dimension of the sample and/or the macroeconomic stability during the sample period did not allow a detailed investigation of the relation between price setting and the macroeconomic environment.[1] In this paper, we use the last thirteen years of individual price data from a Brazilian consumer price index to study this issue.

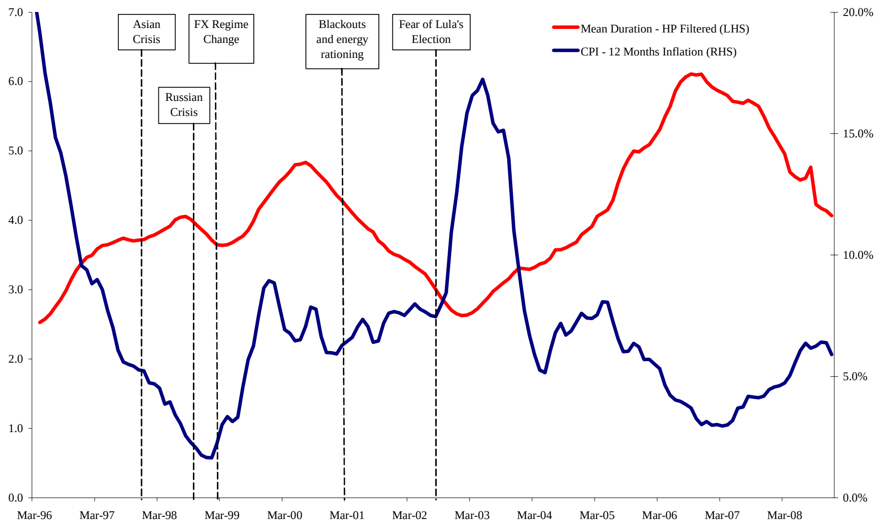
During our sample period, Brazil experienced important macroeconomic variability. Our sample starts in 1996, towards the end of one of the most extraordinary disinflationary processes experienced by a large economy in many decades. In 1997 and 1998 Brazil suffered significant spillovers from the Asian and Russian crises, and in the beginning of 1999 the country moved from a crawling peg exchange rate regime to a floating exchange rate coupled with inflation targeting. After experiencing blackouts and energy rationing in 2001, in the middle of 2002 the prospects of a left-wing presidential candidate victory generated a huge confidence crisis, brought about by uncertainty with respect to the management of future fiscal and monetary policies. The ensuing implementation of an orthodox stabilization policy by the elected government resulted in another important reduction of inflation and macroeconomic uncertainty in 2003. All those episodes produced sizeable variation in inflation, macroeconomic uncertainty, the exchange rate, and output.

As Figure 1 illustrates, price-setting behavior appears to have changed in significant ways in response to changes in the macroeconomic environment. It depicts a measure of the average duration of individual price spells and the inflation rate, and also highlights the main macroeconomic episodes during the period of our sample. At the beginning of the period, in April 1996, prices were fixed on average for around 2.5 months, and annual inflation was about 20%. As inflation fell due to the consolidation of Brazil's macroeconomic stabilization program launched two years earlier, the average duration of price spells kept increasing, and reached roughly 5 months in the Fall of 2000. Towards the end of 2002, inflation had a spike during the confidence crisis that preceded president Lula's election, and the average

[1] An exception is Gagnon (2009), who explores the inflation variation in Mexico during 1994-2002 to analyze price-setting practices under different inflationary environments.

degree of price rigidity decreased to just short of 3 months at the end of 2002. As the new government announced the intention to follow orthodox economic policies and conquered credibility, inflation receded and the duration of price spells started to increase towards a peak of just above 6 months around March 2007. Since then, price rigidity has been falling in parallel with an increase in inflation.

Figure 1: Mean duration of price spells and inflation



In addition to the duration of individual price spells, every other price-setting statistic that we construct shows strong evidence of varying with the macroeconomic environment: the frequency of positive and negative price adjustments, the size of price adjustments, measures of heterogeneity in the extent of price rigidity, and the average dispersion of prices. We relate those price-setting statistics with a small set of macroeconomic variables. Although common wisdom takes aggregate inflation to be the most important macroeconomic determinant of individual price-setting behavior, we find that other macroeconomic variables are also extremely important. These include proxies for macroeconomic uncertainty, changes in the exchange rate, and the level of economic activity.

We explore a large panel of individual prices from the CPI-FGV electronic data set.[2] It contains "store-level" information about goods and services covering 100% of the CPI-FGV - the oldest consumer price index in Brazil, produced since 1944. This unique data set covers a wide variety of products during a relatively long period of time. Available since 1996, it includes monthly observations on approximately 326,000 items, amounting to approximately 22 million price observations. Another nice feature of the data set is that it keeps the exact

[2]FGV stands for Fundação Getulio Vargas.

same item along a quote line as long as it exists, and never uses a similar item's price in place of the original item. Those features are key for achieving quote lines that have an average length in excess of 80 months for the same item, after our data treatments.

We start by constructing common statistics of price setting based on averages across products and time. These include various measures of the frequency and size of price changes. The commonly used measure of the average duration of price spells based on inverting the aggregate frequency of price changes leads to an implied duration of roughly two months. The calculation that computes implied durations at a level of disaggregation that is comparable to the one analyzed by Bils and Klenow (2004), Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008), and only then takes a cross-sectional average, leads to an average implied duration of price spells of approximately 4.0 months.

Having long quote lines for each individual item allows us to take an extra step, and provide measures of the average duration of price spells that are less subject to the downward biases due to cross-sectional heterogeneity that affect most of the available measures. We compute a frequency of price adjustments at the individual item level, and invert it to obtain an implied (average) duration of price spells at the most disaggregated level. We then aggregate the item-level measures to obtain an aggregate measure that fully accounts for cross-sectional heterogeneity. It produces an average duration of price spells of 5.7 months. The importance of working with the data at its most disaggregated level for the purpose of computing less biased measures of price stickiness also becomes evident in a formal analysis-of-variance exercise. We decompose the cross-sectional variance of the frequency of price changes across items as the sum of the variance across items within products, and the variance of the frequency of price changes between products. We find that the heterogeneity in the frequency of price changes within products (i.e., across items in the same product) account for about 32% of all the cross-sectional variance in the frequency of price changes.

The average frequency of price increases is 24%, and exceeds the frequency of price decreases of 13%. The average size of price change is quite large at 13%. The size of negative adjustments exceeds that of positive adjustments: 14.6% versus 12%. However, these averages are influenced by some very large adjustments. The median adjustment size is smaller, at 8.3%, and the proportion of small adjustments ($< 5\%$ in absolute value) is large, at around 34%. These findings are in line with the results documented in the recent empirical literature on price setting that makes use of broad micro price data sets.

Finally, we study the macroeconomic determinants of price-setting. First, we draw time-series plots of inflation and price-setting statistics of interest: frequency and mean size of positive and negative adjustments, and the positive and negative components of inflation implied by a simple decomposition. These price-setting variables appear to be related to inflation to different extents. Moreover, it is also apparent that some price-setting statistics exhibit important systematic variation that appears to be unrelated to the level of aggregate inflation. This suggests that other aggregate factors might be important determinants of price setting behavior.

This conjecture is confirmed in the second part of our time-series investigation, in which we study the macroeconomic determinants of price-setting by running a series of regressions of our constructed price-setting statistics on selected macroeconomic variables. Relying on both panel and single-equation regressions, we relate each price-setting statistic to aggregate inflation, measures of macroeconomic uncertainty, changes in nominal exchange rates, and measures of economic activity. As an illustration of our results, we find that price increases are less frequent after a period of exchange rate appreciation, and more frequent: i) when inflation is higher; after a period of exchange rate depreciation (with an asymmetry relative to appreciations); in periods of high economic activity; and when macroeconomic uncertainty is higher.

Overall, the macroeconomic variables that we analyze explain an important fraction of the time-series variation of our price-setting statistics. Our results confirm that inflation is an important determinant of the frequency and size of price adjustments. However, we find that other explanatory variables, in particular one that proxies for macroeconomic uncertainty, are extremely important.

The plan for the remaining of the paper is as follows. In the next section we describe the data set. In the third section we report results for various measures of price-setting across items, products and time. Section 4 relates the time series of price-setting statistics to macroeconomic variables; we also present various robustness analyses. The last section concludes.

2 Data

In contrast to most countries, price indices in Brazil are produced by several institutions. The governmental statistical agency (IBGE), responsible for the price index based on which the government's inflation target is defined, started calculating price indices in 1979. Prior to that, price indices were produced by private non-profit organizations. The oldest such index is a consumer price index produced by FGV (CPI-FGV) since 1944. The data that we analyze were extracted from the CPI-FGV electronic data set, which stores the primary data used in the construction of the index since 1996.

2.1 The data set

The data set contains detailed price information covering 100% of the CPI-FGV, all collected by FGV employees. We refer to the most disaggregated level of the data as an *item*. Items are identified with a set of characteristics (when applicable), including brand, size, model, packaging, neighborhood, city, store etc. Each item in the data set is surveyed at least once a month, with Food, Cleaning Materials and Personal Care items being surveyed every 10 days. Each record also includes the exact date of information collection.

Each item is associated with a given *product*. In the construction of the CPI-FGV, this is the level at which the data are weighted. Weights come from a household survey conducted by FGV (Pesquisa de Orçamento Familiar), which we refer to as the "Household Budget Survey." Later in the paper we relate price-setting statistics to some sectoral variables, and thus we also aggregate products in a way that allows us to map them into industry sectors, as defined by FGV's "Survey of Industrial Conditions" (described later in Section 4).

The structure of the data set and of our aggregation scheme is illustrated in Table 1.

Table 1: Data structure

	Definition
Item	Individual-level goods and services for which prices are collected. Each item is identified with a set of characteristics: brand, size, model, packaging, neighborhood, city, store. Example: Coke, 355 ml, aluminium can, supermarket A, City Z.
Product (ELI equivalent)	Set of items for which CPI sub-indices are calculated. Weights come from the Household Budget Survey. Example: soft drinks.
Sector	Industry classification of economic activities for which IBRE/FGV's Survey of Industrial Conditions provides statistics. Example: Industrial Food and Beverage Production.

Our data set runs from March 1996 - when the CPI data set became electronic - to December 2008. It results from the merging of the (active) data set currently used in the calculation of the CPI with an inactive data set. The latter is composed of items discontinued from the current data set, which belonged to the CPI during some time period after March 1996. An item may be deemed inactive if its price has been missing for a long enough period of time.[3] The active data set comprises around 8.7 million price quotes and 117 thousand items. Our merged data set has around 22 million price quotes and 326 thousand items.

The geographic coverage of the survey changed during our sample period. As shown in Table 2, up to December 2000 it comprised only the metropolitan regions of the two largest

[3] In fact, this length of time depends on the type of product to which the item belongs. For a non-seasonal product, six months is usually the adopted limit. Items belonging to seasonal products have a higher limit.

cities in Brazil - São Paulo and Rio de Janeiro. After January 2001, ten other cities were included, and since April 2005 the survey ceased to include the five smallest cities among these.[4] It currently covers the seven largest cities in Brazil.

Table 2: Geographic Coverage

Period	Number of cities	Cities
Mar/96 - Dec/00	2	Rio de Janeiro, São Paulo
Jan/01 - Mar/05	12	Belém, Belo Horizonte, Brasília, Curitiba, Fortaleza, Goiânia, Porto Alegre, Recife, Rio de Janeiro, Salvador, São Paulo
Apr/05 - Dec/08	7	Belo Horizonte, Brasília, Porto Alegre, Recife, Rio de Janeiro, Salvador, São Paulo

A particular feature of this data set is that there is never a substitution of an item by another similar item belonging to the same product category. In the Bureau of Labor Statistics (BLS) data set used in the calculation of the CPI for the U.S. economy, if a price is not found it is substituted by the price of a similar item. In the CPI-FGV data set, if a price is not found the quote line continues with missing values. As a consequence one can be assured that each price change registered for an item was an actual price change. On the other hand, if price substitutions are in fact disguised price changes, as suggested by Klenow and Kryvtsov (2008), it is not possible to recover those changes from our sample. Additionally, in the BLS data set, after some time each item is purposedly substituted by a similar item, while in our sample this type of rotation is not done; instead, new items are introduced.

2.2 Data treatment

In order to eliminate the effects of the change in the geographical coverage of the survey and ensure homogeneity in the longest time span available, we choose to keep only observations from the metropolitan regions of Rio de Janeiro and São Paulo. This reduces the number of price quotes to 12,356,714, and of items to 137,780. For the product categories that have prices collected every ten days (Food, Cleaning Materials and Personal Care), we choose to keep the last price quote of the items in each month. This produces a sample with monthly price quotes for all items.

[4] The ten cities added in 2001 are Belo Horizonte, Brasília, Porto Alegre, Recife, Salvador, Belém, Curitiba, Florianópolis, Fortaleza, and Goiânia. The latter five cities were dropped in 2005.

We assign missing values to outliers and sales prices. We define as outliers all prices that are higher than 10 times or lower than 0.1 times the preceding price in the item's quote line. This aims at eliminating common typing errors. We define a sales price as one that results from a reduction of at least 5% from the price in the month before, and increases in the following month by at least the percentage by which it has been reduced.[5]

We further refine our sample by eliminating items with too many or too many consecutive missing prices. We drop items with more than 30% of missing prices, as well as items with more than 12 consecutive missing observations. This results in a final sample with an average number of 98,194 items per month, and a total number of 5,345,270 price quotes.

The prices of some goods are regulated by either the executive government or a regulatory agency. Their weight in the CPI-FGV amounts to about 30%. Unless regulated prices are explicitly mentioned, we report price-setting statistics with only *non-regulated prices*.

In Figure 2 below we show the distribution of the length of quote lines in our final sample. Having substantial mass on long quote lines is somewhat important given our interest in constructing time series of price-setting statistics. The distribution is truncated at the shortest span admissible after treatment (12 months). There is one big spike at the maximum length, corresponding to items that have quote lines from the beginning to the end of our sample (154 months). The typical item in this bucket is an homogenous good that does not undergo any important innovation (e.g. rice).

Figure 2: Distribution of the length of quote lines

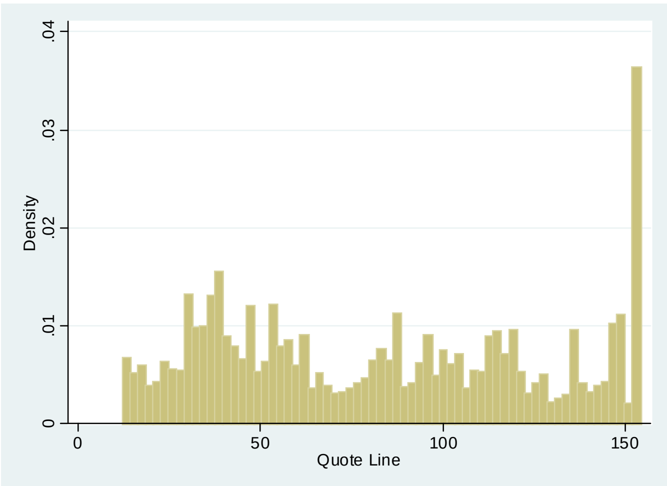


Table 3 below compares our data set with the BLS data used in Klenow and Kryvtsov (2008), and the Mexican data set explored by Gagnon (2009). The top part of the table refers to the primary data sets. The CPI-FGV data set has broad coverage of the CPI for

[5] Formally p_t is a sales price if $\frac{p_{t-1}-p_t}{p_{t-1}} \geq 5\%$ and $p_{t+1} \geq p_t \left(1 + \frac{p_{t-1}-p_t}{p_{t-1}}\right)$.

a longer period of time - more than 12 years. As in the BLS data set, the primary data consist of actual individual prices, in contrast to the mean price available in the data set of Gagnon (2009). With more than 22 million price quotes and more than 300 thousand items, it has a much larger number of observations. Additionally, it is the only one with no item substitutions nor price imputation.

The bottom part of Table 3 reports some sample statistics from our final sample and compares them to those of the BLS sample of Klenow and Kryvtsov (2008) and of the Mexican sample of Gagnon (2009). The average length of quote lines in our final sample is 82.8 months - about twice the one in the final BLS sample used by Klenow and Kryvtsov (2008). In addition, our final sample still has close to 100 thousand items, which, again, is a large number compared to those of the two other samples.

Table 3: Data set comparison

	Brazil - BBCM (2009)	**USA - KK (2008)**	**Mexico - Gagnon (2009)**
Primary data set			
Period	Mar/96 - Dec/08	Jan/88 - Jan/05 (with breaks)	Jan/94 - Jun/02
Data source	IBRE/FGV	Bureau of Labor Statistics	Bank of Mexico
CPI coverage(%)	100%	70%	100%
Nature of price data	Individual price data	Individual price data	Mean of monthly price
Item substitution ?	No	Yes	Yes
Price imputation ?	No	Yes	Yes
Total # price quotes	22,080,598	NA	4,700,000
Total # items	328,984	85,000	nearly 50,000
Sample statistics			
Quote-line			
Average # items (per month)	98,194	13,000 -14,000	44,272 (non regulated)
Average quote-line length (in months)	82.8	43	
p25	42	24	
p50	81	45	
p75	119	60	
Total # price quotes	**5,345,270 (34,710/month)**		**3,209,947(31,470/month)**

3 Price-setting statistics

In this section we calculate various statistics on price setting at both sectoral and aggregate levels, including frequency of price changes, duration of price spells, and size of price adjustments. We start by presenting the definitions of the price-setting variables that we use in this section and Section 4.

3.1 Definitions

Let p_{it} be the log of the price of item i at time $t = 1, ..., T$. We define I_{it} to be the price change indicator:

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

defined only when there are non-missing price quotes in both time t and $t-1$. We define S_i as the set of non-missing times for item i:

$$S_i = \{0 \leq t \leq T, I_{it} \in \{0, 1\}\}.$$

The frequency of price changes for item i is calculated as the proportion of price changes in the total of non-missing observations in the quote line:

$$f_i = \frac{\sum\limits_{t \in S_i} I_{it}}{N_i},$$

where $N_i \equiv card\,(S_i)$ denotes the number of elements in set S_i (its cardinality).

Let N_y be the number of items that belong to product category $y = 1, ..., Y$. The frequency of price changes for product y, f_y, is the average frequency across items belonging to that product category:

$$f_y = \frac{1}{N_y} \sum_{i=1}^{N_y} f_i.$$

The measure of the aggregate frequency of price changes in our sample is obtained by computing the weighted average of the Y product frequencies, with the weights used in the CPI-FGV:[6]

$$f = \sum_{y=1}^{Y} \omega_y f_y.$$

The frequency of positive price adjustments is given by

$$f^+ = \sum_{y=1}^{Y} \frac{\omega_y}{N_y} \sum_{i=1}^{N_y} \left(\sum_{t \in S_i} \frac{I_{it}^+}{N_i} \right).$$

[6] The weights are from the last available Household Budget Survey, carried out in 2002-2003, which has been used to calculate the CPI-FGV since January 2004.

where $I_{it}^{+} = 1$ if $p_{it} > p_{it-1}$. Similarly, we define

$$f^{-} = \sum_{y=1}^{Y} \frac{\omega_y}{N_y} \sum_{i=1}^{N_y} \left(\sum_{t \in S_i} \frac{I_{it}^{-}}{N_i} \right),$$

where $I_{it}^{-} = 1$ if $p_{it} < p_{it-1}$. It follows that $f = f^{+} + f^{-}$.

We define the frequency of positive adjustments at time t, f_t^{+}, as

$$f_t^{+} = \sum_{y=1}^{Y} \omega_{yt} \sum_{i \in S_{yt}} \frac{I_{it}^{+}}{N_{yt}},$$

where S_{yt} is the set of items of product y with non-missing observations in t and $t-1$, $N_{yt} \equiv card\,(S_{yt})$ is its number of elements, and ω_{yt} is the weight of product y at time t. The latter may differ from the fixed product weights ω_y, because some of the products do not exist since the beginning of the sample (our data set consists of an unbalanced panel). The possibly time-varying weights ω_{yt} obtain from a renormalization of the fixed weights ω_y given the set of products that exist in the panel at time t, so that they sum to unity at all times. The frequency of negative adjustments at time t, f_t^{-}, is defined analogously, and the frequency of adjustments at t, f_t, is obtained as $f_t = f_t^{+} + f_t^{-}$.

The average size of positive price adjustments at a given time t, Δp_t^{+}, is obtained according to

$$\begin{aligned} \Delta p_t^{+} &= \sum_{y=1}^{Y} \omega_{yt} \Delta p_{yt}^{+} \\ &= \sum_{y=1}^{Y} \omega_{yt} \left(\frac{1}{N_{yt}^{+}} \sum_{i \in S_{yt}^{+}} \Delta p_{it} \right), \end{aligned}$$

where Δp_{ty}^{+} is the average size of positive price changes for product y, S_{yt}^{+} is the set of items belonging to product y that had a positive price change at time t, $N_{yt}^{+} \equiv card\left(S_{yt}^{+}\right)$ is its number of elements, and $\Delta p_{it} = \log p_{it} - \log p_{it-1}$. The corresponding expression for the average size of price decreases, $\left|\Delta p_t^{-}\right|$, is

$$\left|\Delta p_t^{-}\right| = \sum_{y=1}^{Y} \omega_{yt} \left(\frac{1}{N_{yt}^{-}} \sum_{i \in S_{yt}^{-}} \left|\Delta p_{it}\right| \right).$$

The average size of adjustments at time t is computed by averaging the absolute value of positive and negative adjustments for each product, and then averaging across products according to their weight:

$$|\Delta p_t| = \sum_{y=1}^{Y} \frac{\omega_{yt}}{N_{yt}^{+} + N_{yt}^{-}} \left(\sum_{i \in S_{yt}^{+}} \Delta p_{it} + \sum_{i \in S_{yt}^{-}} |\Delta p_{it}| \right).$$

Statistics for the whole sample are constructed by averaging each of them across time. Thus, the average size of price adjustments in the sample is given by:

$$\begin{aligned} |\Delta p| &= \sum_{t=1}^{T} \frac{|\Delta p_t|}{T} \\ &= \sum_{t=1}^{T} \sum_{y=1}^{Y} \frac{\omega_{yt}}{T\left(N_{yt}^{+} + N_{yt}^{-}\right)} \left(\sum_{i \in S_{yt}^{+}} \Delta p_{it} + \sum_{i \in S_{yt}^{-}} |\Delta p_{it}| \right). \end{aligned}$$

Using the notation defined above, we can construct a measure of inflation by weighting the price changes that we observe in our data set:

$$\widehat{\pi}_t \equiv \sum_{y=1}^{Y} \omega_{yt} \left(\frac{1}{N_{yt}} \sum_{i \in S_{yt}} \Delta p_{it} \right).$$

Then, for use later in the paper, we follow Gagnon (2009) and decompose this measure of inflation into its positive and negative components, as:

$$\widehat{\pi}_t = f_t^{+} \Delta p_t^{+} - f_t^{-} |\Delta p_t^{-}|. \tag{1}$$

3.2 Frequency and size of price changes

Table 4 reports the mean frequency (f) and size ($|\Delta p|$) of price changes. On average, 37.4% of prices change every month, and conditional on a price change the average magnitude of the change is 13% of the initial price. This is large compared to the average monthly (log) inflation rate of roughly 0.5% in our sample. When we condition on the sign of the adjustment, we find that positive adjustments occur more often (64% of all adjustments) and are smaller on average (12%, versus 14.6% for the average size of price decreases).

Table 5 reports some statistics of the distribution of the size of price adjustments. More than a third of all price adjustments are smaller than 5% and more than half are below 10%. The fraction of adjustments below 2.5% is larger for price increases than for price decreases.

Figure 3 shows that the distribution of the magnitude of price adjustments departs from normality because of a larger proportion of small and large adjustments, and a smaller fraction of medium-size adjustments. There is also an asymmetry between the size of price

Table 4: Frequency and size of price changes

	Mean	Median	Up	Down
Frequency of Price Changes	37.2%	40.6%	23.8%	13.4%
Size of Price Changes	13.0%	8.3%	12.0%	14.6%

Sample runs from March 1996 through December 2008. The statistics reported use weights from the Household Budget Survey used to calculate the CPI-FGV from January 2004 on. Size of price changes are reported in absolute values.

Table 5: Distribution of the size of price changes

Price Changes	Fraction Below 2.5%	Fraction Below 5%	Fraction Below 10%
Total	19.91%	34.20%	55.20%
Positive	19.94%	34.20%	56.20%
Negative	12.59%	34.10%	53.50%

Sample runs from March 1996 through December 2008. The statistics reported use weights from the Household Budget Survey used to calculate the CPI-FGV from January 2004 on. Size of price changes are reported in absolute values.

increases and decreases, which becomes clear when we plot the two distributions in the same graph, in Figure 4. The higher proportion of very small positive adjustments as compared to the negative ones is apparent.

Figure 3: Distribution of the size of price changes

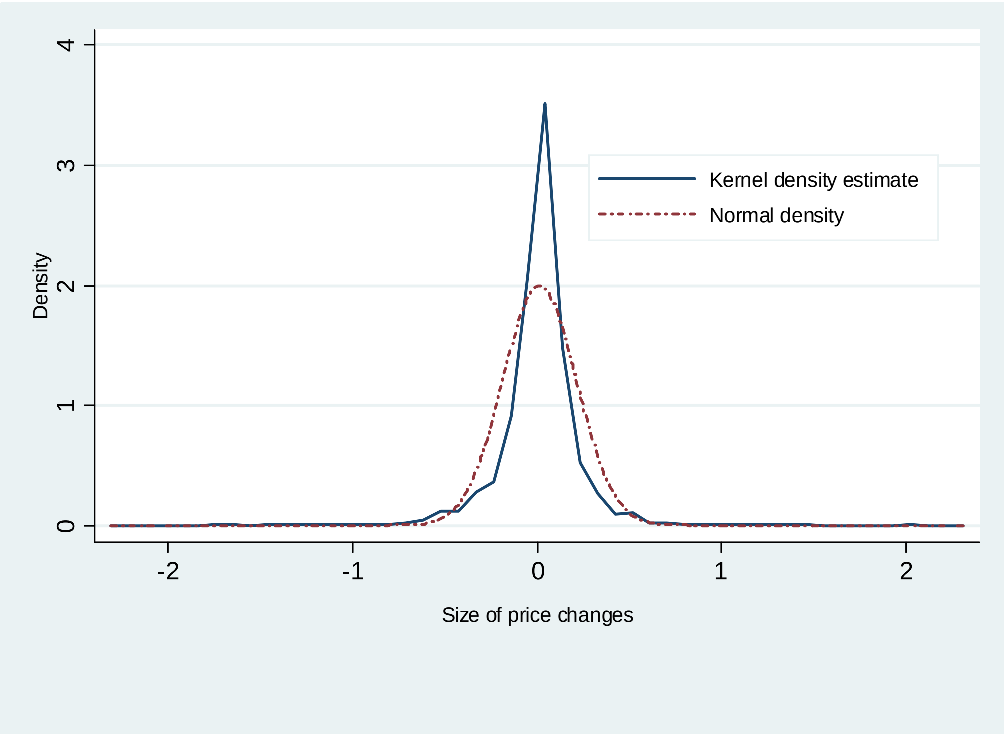
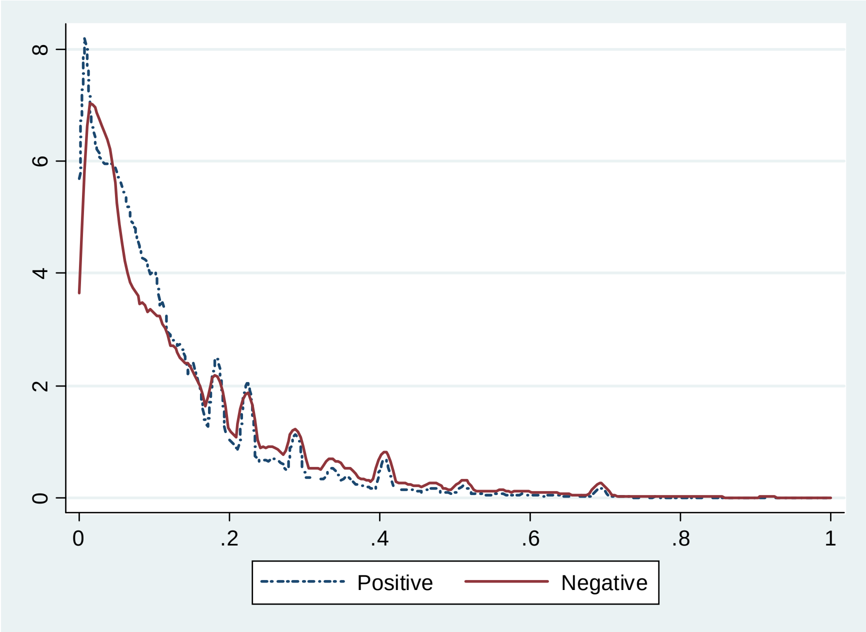


Figure 4: Size of positive and negative price changes



The type of "asymmetry in the small" apparent in Table 5 and in Figure 4 is extensively documented by Levy et al. (2009) in supermarket scanner data. We also find it to be a feature of our broader data set.

3.3 Heterogeneity in frequencies and implied duration of price spells

We stick to the literature's tradition of calculating the duration of price spells from measures of the frequency of price changes.[7] An *implied duration* is defined as the expected duration of price spells under the assumption that these last until a random terminal date that arrives according to a Poisson process with a constant hazard. Following most of the recent literature, we report results based on the assumption of a constant continuous-time hazard rate. The measures of implied duration are then calculated by "inverting" the relevant frequency of price adjustments.[8]

We define the aggregate implied duration of price spells, d_{agg}, as the implied duration based on the aggregate frequency of price changes. The aggregate implied duration is then calculated as

$$d_{agg} = \frac{-1}{\ln(1-f)}.$$

[7] In the Appendix we provide estimates of the average duration of price spells based on direct measurement.

[8] Then, given a frequency of price changes f, the implied duration is $d = \frac{-1}{\ln(1-f)}$. Under the discrete-time assumption, implied duration is instead given by $1/f$. This measure is upward biased if spells can in fact last less than the sampling interval (or alternatively, if price changes can occur more than once per period).

The average frequency of price changes is a natural summary measure of price stickiness in the context of the most popular macroeconomic models with sticky prices, in which all prices are equally sticky. However, because such frequency is a broad average, in the presence of important heterogeneity in the frequency of price adjustments across products or items, the aggregate implied duration is a downward biased measure of the average of implied durations calculated at more disaggregated levels, due to Jensen's inequality. In light of the ample evidence of heterogeneity in the degree of price stickiness in modern economies, recent theoretical work emphasizes the importance of the average duration of price spells - and of higher moments of the distribution of durations of price spells - in shaping aggregate dynamics.[9] While we analyze such type of heterogeneity in more detail in Subsection 3.4, here we also report measures of implied duration that (partially) account for it.

To circumvent the bias in the measure of implied duration based on the aggregate frequency of price changes, the usual practice is to calculate the implied duration for each product, which should correct for heterogeneity under the assumption that the frequency of price changes is the same for items within each product (more on this below) - and then aggregate. We evaluate the implied duration at the product level d_{prod} according to:

$$d_{prod} = \sum_{y=1}^{Y} \omega_y d_y = \sum_{y=1}^{Y} \omega_y \frac{-1}{\ln(1-f_y)}.$$

The long quote lines of our sample allow us to, in addition, calculate the average frequency of price changes *for each item*, and invert it to find a measure of implied duration at the item level. We then take the average over all items of each product to find an average s(implied) duration at the product level. Finally, we aggregate these product-level durations using the CPI weights to find an alternative aggregate measure of duration of price spells d:

$$\begin{aligned} d &= \sum_{y=1}^{Y} \omega_y \left(\frac{1}{N_y} \sum_{i=1}^{N_y} d_i \right) \\ &= \sum_{y=1}^{Y} \frac{\omega_y}{N_y} \sum_{i=1}^{N_y} \frac{-1}{\ln(1-f_i)}. \end{aligned}$$

Table 6 reports measures of duration according to the three calculations described above. We also report the median under each of the three concepts. Panels 1 and 2 differ with respect to the treatment of sales. Panel 1 reports results where missing values were attributed to the periods classified as sales, while in Panel 2 the last regular price was repeated in those periods (a process that we refer to as *price imputation*). Since sales are not so frequent in

[9] See Carvalho (2006), and Carvalho and Schwartzman (2008).

Brazil, the numbers in Panels 1 and 2, corresponding to each aggregation level, are close to each other.

The measures of duration differ significantly by the level of aggregation. While the aggregate implied duration is 1.8 months (without price imputation), the weighted average of product-level implied durations is 3.9 months. Most strikingly, the measure derived from implied durations computed at the item level is 5.7 months.

Table 6: Implied duration measures, in months

	Mean	**Median**
Panel 1: without price imputation		
by item (d)	5.7	2.9
by product (d_{prod})	3.9	1.7
Aggregate (d_{agg})	1.8	1.8
Panel 2: with price imputation		
by item (d)	5.8	3.1
by product (d_{prod})	4.1	1.9
Aggregate (d_{agg})	2.0	2.0

Sample runs from March 1996 through December 2008. The statistics reported use weights from the Household Budget Survey used to calculate the CPI-FGV from January 2004 on.

The important difference between implied durations calculated by inverting the frequency of price changes at the item and product levels suggests the existence of important within-product heterogeneity. In order to investigate this issue, we decompose the total cross-sectional weighted variance of the frequency of price changes, $var_i(f_i)$, into the sum of the variance *between* products and variance *within* products:[10]

$$\begin{aligned} var_i(f_i) &= \sum_{i=1}^{N} \omega_i (f_i - f)^2 \\ &= \sum_{y=1}^{Y} \sum_{i=1}^{N_y} \frac{\omega_y}{N_y} (f_i - f_y)^2 + \sum_{y=1}^{Y} \omega_y (f_y - f)^2 , \end{aligned}$$

where ω_i is the item weight, and N is the total number of items. The first term on the right-hand side is the variance of the frequency of price changes *within* products and the second term is the variance *between* products. If the products are homogenous groups in terms of the frequency of price changes, 100% of the variance is accounted for by the variance between products.

[10] Actually, Andrea Tambalotti correctly argues that under the assumption that all firms exhibit the same degree of price rigidity, the right measure would obtain from pooling all price changes when computing the average frequency of price changes. In other words, using "observation weights" instead of CPI weights. To keep oru results comparable to the existing literature, we focus on the weighted aggregate frequency of price changes.

Applying this decomposition to our data set we find that about 32% of the total variance can be attributed to the heterogeneity of items included in the same product group. Thus, in face of Jensen's inequality in the relationship between frequency of price changes and implied duration of price spells, it is not surprising that the duration measure calculated by inverting the frequency at the item level is higher than the one evaluated by inverting the average frequency by product. Our results indicate that even measures of implied duration constructed at the level of disaggregation corresponding to BLS's ELI may still underestimate the average duration of price spells in a quantitatively important way.

All measures used above rely on taking a time average at some level of aggregation. As we document below in Section 4, the frequency of price changes appears to be strongly related to the macroeconomic environment, and varies significantly over time. This should result in an additional downward bias in all of the above measures of average duration. Unfortunately, there is no easy way around all of the possible biases. In order to calculate frequencies one needs to average adjustments either over time for a given item, or across items at a given time, and heterogeneity is present in both dimensions.

3.4 Sectoral heterogeneity

In this section we construct price-setting statistics for various aggregation schemes. We start by partitioning our sample into three groups: goods, services and regulated products (goods and services).

Table 7 reports the results for item-level implied durations, while Table 8 presents statistics on the frequency and size for all, positive and negative price changes. Prices of goods are the most flexible, changing more often - every 3.3 months on average - and by larger magnitudes - 13.4% of the base price, on average. Services are less flexible, with somewhat longer average price spells (10.9 months), and slightly smaller price adjustments than goods (12.1% on average). Finally, prices of regulated products remain fixed for almost as long as services, 9.6 months on average, and then change by a smaller amount - about 7.3% of the base price. The median size of price changes is much smaller than the mean for all groups, indicating an important proportion of small price adjustments. It is striking that the average size of adjustments for services, whose prices change very infrequently, is lower than the one for goods, whose prices change more than three times as often. This may indicate that the prices of goods have much more idiosyncratic variation, while the trend inflation component is relatively more important for services.

The pattern of the asymmetries in the frequency and size of price adjustment across these three groups is the same obtained in the aggregate statistics. Positive adjustments happen more often and are smaller. The main eye-catching feature at this level of aggregation is the pronounced frequency asymmetry for services. The frequency of positive adjustments is about five times the frequency of negative adjustments, while in the goods categories this ratio is approximately 1.4. The asymmetry in the magnitude of price adjustments is also higher for services. Both asymmetries, in frequency and size of price adjustments, reinforce our conjecture that trend inflation is a more important determinant of price adjustments for services than for goods.

Table 7: Item-level implied duration, in months

	Mean	**Median**
Goods	3.30	2.5
Services	10.93	12.2
Regulated	9.60	10.1

Sample runs from March 1996 through December 2008. The statistics reported use products weights from the Family Budget Survey used to calculate the CPI-FGV from January 2004 on. Within each product items are equally weighted.

Table 8: Frequency and size of price changes

	Mean	**Median**	**Up**	**Down**
Frequency of Price Changes				
Goods	43.0%	44.8%	25.1%	17.9%
Services	25.3%	11.6%	21.1%	4.2%
Regulated	22.3%	12.6%	13.7%	8.6%
Size of Price Changes				
Goods	13.4%	8.5%	12.3%	14.1%
Services	12.1%	8.0%	11.2%	16.3%
Regulated	7.3%	4.7%	7.3%	7.0%

Sample runs from March 1996 through December 2008. The statistics reported use weights from the Household Budget Survey used to calculate the CPI-FGV from January 2004 on. Size of price changes are reported in absolute values.

We proceed to a finer division of the sample into 17 groups: 9 groups of goods, 6 groups of services, and 2 groups of goods with regulated prices. Table 9 displays our item-level implied duration measure for each group, while Table 10 presents the mean absolute size and the frequency and average size for positive and negative adjustments. The degree of heterogeneity is substantial, entailing a whole range of pricing practices. On one extreme we have in Raw Food a very flexible group with a lot of price variation: average duration of 2.5 months and mean adjustment size of 23.5%. On the other end of the spectrum we find Medical Care Services, with prices that are fixed on average for almost two years (21.8 months), and with somewhat smaller but still large price adjustments (21.1%). As in the previous partition, it seems that the most flexible types of products are subject to relatively more idiosyncratic variation.

The groups with more rigdid prices tend to have more asymmetric frequency and size of adjustments. Service groups tend to have a larger difference between the frequency of positive and negative adjustments and also between the size of negative and positive adjustments. Figure 5 relates the two asymmetries by plotting the difference between the size of negative and positive adjustments against the difference between the frequency of positive and negative adjustments (both as a fraction of the mean frequency of price changes) for our 15 groups of goods and services.

Table 9: Item-level implied duration, in months

	Mean	**Median**
Goods	**3.3**	**2.5**
Raw Food	2.5	2.2
Processed Food	2.9	2.4
House Maintenance Goods	4.0	3.0
Apparel	2.2	2.1
Educational and Recreational Goods	5.7	3.3
Vehicles and Equipments	2.1	1.1
Other Goods	7.9	9.6
Personal Care Goods	3.4	2.7
Fuel	3.4	3.4
Services	**10.9**	**12.2**
Food Away From Home	9.6	7.3
House Maintenance Services	6.4	4.5
Transportation	12.3	14.9
Medical Care Services	21.8	21.0
Personal and Recreation Services	16.6	15.8
Educational Services	12.0	12.2
Regulated Prices	**9.6**	**10.1**
Federal Regulated Goods and Utilities	7.9	6.3
State Reg. Utilities and Public Transp.	13.5	14.6

Sample runs from March 1996 through December 2008. The statistics reported use products weights from the Household Budget Survey used to calculate the CPI-FGV from January 2004 on. Within each product items are equally weighted.

Figure 5: Asymmetry in size vs. asymmetry in frequency

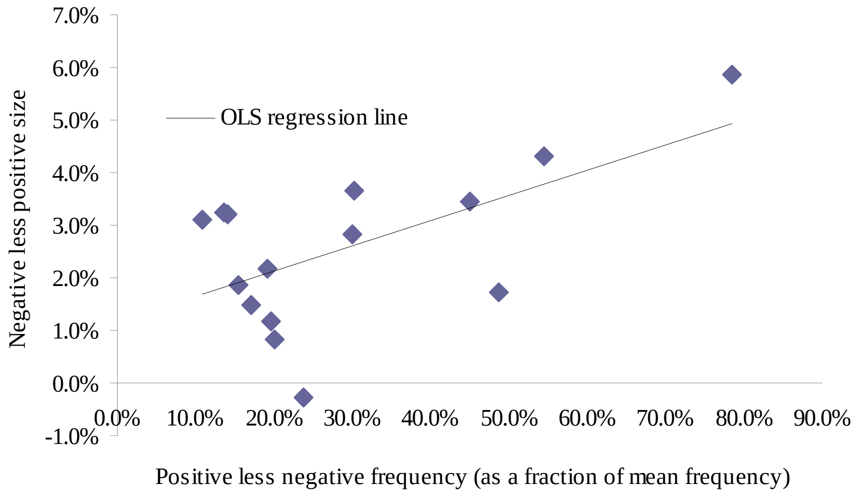


Table 10: Frequency and size of price changes by main groups

	Mean	Median	Up	Down
Frequency of Price Changes				
Goods	**43.0%**	**44.8%**	**25.1%**	**17.9%**
Raw Food	51.1%	52.1%	29.1%	22.1%
Processed Food	46.1%	47.4%	27.0%	19.1%
House Maintenance Goods	38.2%	40.7%	22.1%	16.2%
Apparel	46.3%	47.7%	25.7%	20.6%
Educational and Recreational Goods	32.4%	36.8%	18.5%	13.9%
Vehicles and Equipments	54.6%	65.5%	32.7%	21.9%
Other Goods	18.8%	11.9%	14.0%	4.8%
Personal Care Goods	39.8%	44.7%	23.7%	16.1%
Fuel	37.4%	37.3%	23.1%	14.3%
Services	**25.3%**	**11.6%**	**21.1%**	**4.2%**
Food Away From Home	14.9%	17.0%	10.8%	4.1%
House Maintenance Services	45.2%	37.6%	40.4%	4.9%
Transportation	26.3%	14.8%	15.8%	10.5%
Medical Care Services	6.1%	5.7%	4.0%	2.1%
Personal and Recreation Services	11.5%	9.2%	7.5%	4.0%
Educational Services	10.2%	9.4%	7.9%	2.3%
Regulated Prices	**22.3%**	**12.6%**	**13.7%**	**8.6%**
Federal Regulated Goods and Utilities	27.7%	20.3%	15.9%	11.9%
State Reg. Utilities and Public Transp.	9.6%	8.2%	8.6%	0.9%
Size of Price Changes				
Goods	**13.4%**	**8.5%**	**12.3%**	**14.1%**
Raw Food	23.5%	18.2%	20.6%	23.9%
Processed Food	11.2%	7.8%	10.3%	11.8%
House Maintenance Goods	12.3%	7.7%	11.6%	13.4%
Apparel	24.5%	18.4%	23.0%	26.1%
Educational and Recreational Goods	17.1%	11.0%	15.6%	18.9%
Vehicles and Equipments	7.2%	4.2%	6.6%	7.8%
Other Goods	10.5%	8.4%	9.9%	11.6%
Personal Care Goods	11.3%	7.5%	10.4%	12.6%
Fuel	4.9%	3.1%	4.5%	4.3%
Services	**12.1%**	**8.0%**	**11.2%**	**16.3%**
Food Away From Home	13.2%	9.1%	12.1%	15.5%
House Maintenance Services	6.9%	2.4%	6.5%	12.4%
Transportation	15.0%	10.5%	14.0%	14.8%
Medical Care Services	21.1%	18.2%	19.9%	22.7%
Personal and Recreation Services	19.6%	15.4%	18.4%	22.0%
Educational Services	14.8%	9.5%	13.2%	17.5%
Regulated Prices	**7.3%**	**4.7%**	**7.3%**	**7.0%**
Federal Regulated Goods and Utilities	7.1%	4.1%	6.9%	7.1%
State Reg. Utilities and Public Transp.	8.1%	6.5%	8.0%	6.2%

Sample runs from March 1996 through December 2008. The statistics reported use weights from the Household Budget Survey used to calculate the calculate the CPI-FGV from January 2004 on. Size of price changes are reported in absolute values.

4 Time-series analysis

As detailed in Subsection 3.1, we construct time series of various price-setting statistics, including the frequency and size of positive and negative price changes. We start by illustrating how some of these measures evolve over time in connection with the changing macroeconomic environment. Then, we use a series of regressions to relate the price-setting variables to a small set of aggregate (and sectoral) time series, chosen for their potential importance for pricing decisions.

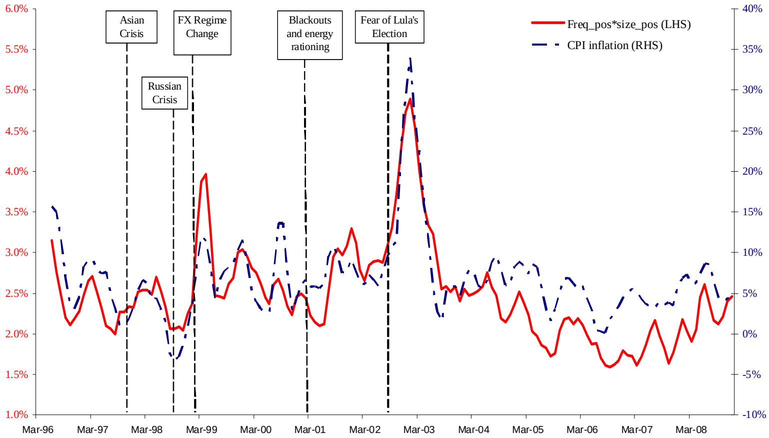
4.1 The evolution of price setting statistics

We start by illustrating the behavior of our main price-setting statistics over time. Following up on the decomposition of inflation in (1), Figures 6 and 7 show the evolution of, respectively, the 3-month moving average of the positive ($f_t^+ \cdot \Delta p_t^+$) and negative ($f_t^- \cdot |\Delta p_t^-|$) components of inflation constructed from our micro data. For comparison, it also plots the 3-month moving average of annualized inflation as measured by the official consumer price index used for inflation targeting (IPCA),[11] and indicates the timing of important events that produced macroeconomic variability in Brazil, such as the Asian and Russian crises, the abandonment of the exchange rate crawling peg regime in January 1999, the occurrence of blackouts and energy rationing in 2001, and the electoral period that preceded President Lula's election. In Figures 8-11 we further decompose the positive and negative components of inflation into their frequency and size terms.

From Figures 6-11 it is apparent that the various components of our decomposition comove with aggregate inflation to different extents. While the frequency of positive price changes (Figure 8) is strongly positively correlated with aggregate inflation, the size of positive price changes (Figure 10) is moderately so. The effect of the frequency of positive price changes appears to dominate the positive component of inflation (Figure 6), which also has a very high positive correlation with inflation. In contrast, the frequency of negative price changes (Figure 9) has only a small negative correlation with aggregate inflation, and, perhaps surprisingly, the size of negative price changes (Figure 11) has a small positive correlation with inflation. As a result, the negative component of inflation (Figure 7) is essentially uncorrelated with aggregate inflation.

[11] This index is computed by the Brazilian Institute of Geography and Statistics, IBGE.

Figures 6-11: The positive and negative components of inflation, and its frequency and size terms



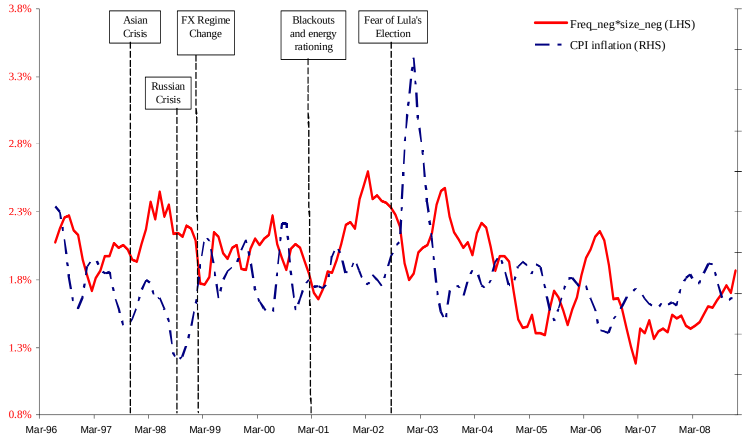
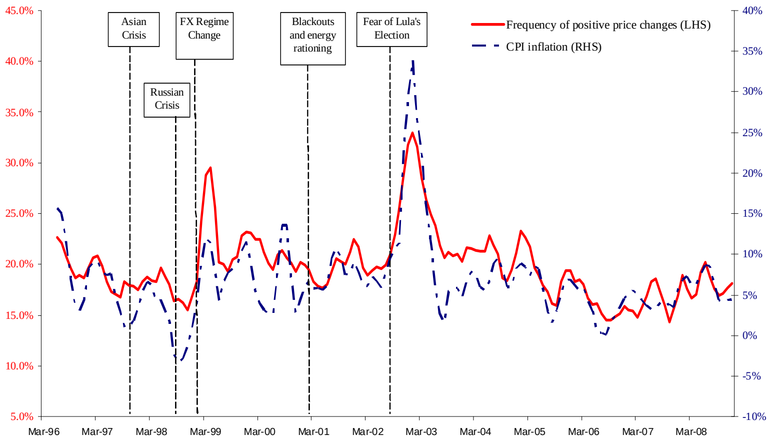


Figure 6

Figure 7



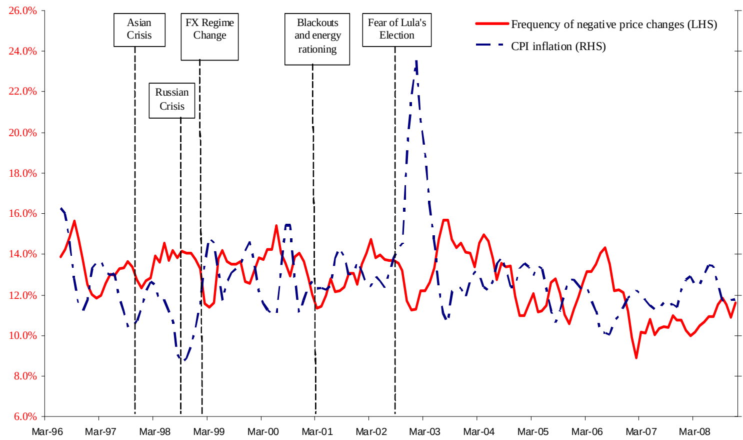
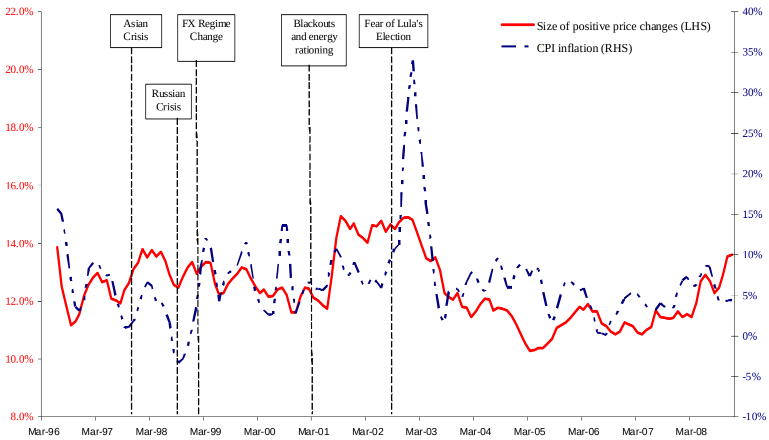


Figure 8

Figure 9



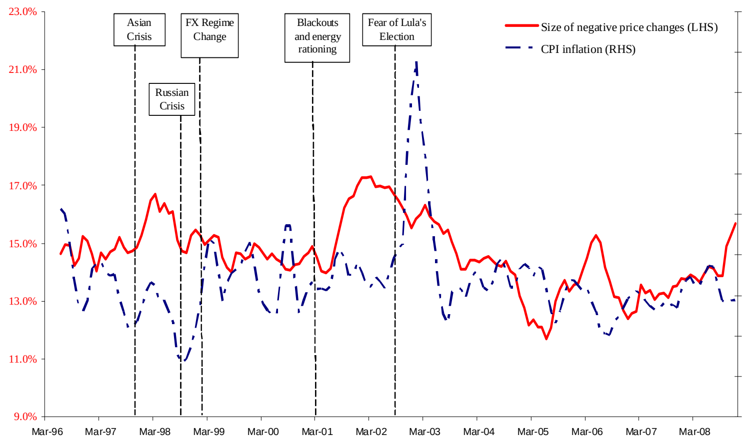


Figure 10

Figure 11

It is also apparent that some price-setting statistics exhibit important variation that appears to be unrelated to the level of aggregate inflation. For example, the size of both price increases and decreases goes up significantly in the period right after the occurrence of blackouts and energy rationing in March 2001, a period during which inflation exhibited very little variation. This result suggests that other aggregate factors might be important determinants of price setting behavior. For example, the positive correlation between the size of positive and negative price changes might be due to clustering of large positive and negative shocks, or time variation in the degree of macroeconomic uncertainty.

In the next subsections we document in a more systematic way the relationship between our time series of price-setting statistics and a small set of sectoral and macroeconomic variables. We start with a description of the aggregate and sectoral data that we use in our regressions.

4.2 Time-series data

Price-setting behavior can be thought of as depending on the process of the firm's desired ("frictionless optimal") price, and on the frictions that prevent continuous and/or fully informed price adjustments. Thus, for our empirical analysis we choose macroeconomic variables that we believe capture important aggregate determinants of firms' desired prices. The most obvious macroeconomic variable in this respect, and one that is used in most studies, is the aggregate inflation rate.

In addition to inflation, in an open economy the exchange rate may be an important determinant of costs, through imported inputs, and may also affect the market power of price-setting firms. Both of these channels suggest that, say, an exchange rate depreciation should increase domestic firms' desired prices. To account for this possibility we include changes in the exchange rate, allowing for different effects of depreciations and appreciations.

The level of economic activity should also affect firms' desired prices. In standard models of price setting, the smaller the degree of "slack" in the economy, the higher firms' desired prices. In this context the natural measure of economic activity would be the output gap. But broad measures of output, such as GDP, are not available on a monthly basis, and potential output is not observable. Moreover, in our regression analyzes we would like to make use of some sectoral measures of economic activity, to explore the panel structure of our data set. As a result, we use measures of activity from the "Survey of Industrial Conditions,"[12] produced by IBRE/FGV, to which we have access at a monthly frequency, and which allow a clear mapping between (a subset of) the products in our CPI price data set and sectoral measures of economic activity. We pick the index that combines six indicators collected in the survey, as a weighted average of: current level of demand, current level of inventories, current business conditions, forecast of production, forecast of employment, and forecast of business conditions.

[12] Sondagem Conjuntural da Indústria de Transformação.

Finally, uncertainty about the macroeconomic environment should also matter for price setting. Higher uncertainty, if realized, should be associated with larger shocks. Moreover, in the presence of information frictions that preclude the continuous monitoring of macroeconomic conditions, higher uncertainty should lead firms to revisit their pricing decisions more frequently and/or devote more resources to tracking the aggregate state of the economy. We try to capture the effects of macroeconomic uncertainty by including the spread of Brazilian external debt over U.S. Treasuries, as measured by JP Morgan's Emerging Market Bond Index (EMBI), as a regressor.

To sum up, all of the above reasoning leads us to choose the following explanatory variables in our baseline regressions: inflation, changes in the nominal exchange rate (separating appreciation from depreciation),[13] economic activity as measured by IBRE's Survey of Industrial Conditions, and macroeconomic uncertainty as measure by the EMBI spread of Brazilian external debt. The exact measures that we use for these variables are listed in Table 6.[14]

Table 6: Measures of macroeconomic variables

Variable	Measure	Notation
Aggregate inflation	Annualized 1-month log-percentage change of the official CPI index (IPCA)	π_t
Exchange rate		
Appreciation	Annualized 3-month log-percentage change of the exchange rate, if negative	$de^{-}_{3,t}$
Depreciation	Annualized 3-month log-percentage change of the exchange rate, if positive	$de^{+}_{3,t}$
Economic activity	3-month log-percentage change of the Industrial Confidence Indices (ICIs)	$ici_{3,t}$ for aggregate $ici^{k}_{3,t}$, for sector k
Aggregate uncertainty	EMBI spread of Brazilian external debt over U.S. Treasuries	$embi_t$

Although our micro data sample starts in March 1996, Brazil experienced a change of monetary and exchange rate regime in January 1999, when it moved from a crawling peg to a regime of explicit inflation targeting coupled with a floating exchange rate. After extensive analysis, the spirit of which we illustrate in the Appendix, we concluded that this regime shift produced important changes in price-setting behavior, even after controlling for the set

[13]We define the nominal exchange rate in terms of Brazilian Reais per U.S. dollar, so that an increase in the exchange rate implies a depreciation of the Brazilian Real.

[14]In Subsection **??** we explore alternative measures of these variables.

of macroeconomic variables that we use in our analysis. As a result, we restrict our sample to the period January 1999 - December 2008.[15]

4.3 Baseline panel regressions

Driven by our desire to incorporate sectoral measures of economic activity in our analysis, our baseline specifications are based on panel regressions, specified in terms of *products*. The right-hand-side variables are the ones detailed in Table 6, with *sectoral* measures of the ICIs. The latter are available at a coarser level of disaggregation relative to the level of our products. Thus, all products in the panel that belong to sector k, say, have the same $ici^k_{3,t}$ index.[16] The panel comprises 234 products grouped into 13 sectors.

More specifically, we run a series of (unbalanced) panel regressions with product fixed effects of the form:

$$s_{kj,t} = \alpha_i + \beta_1 \pi_t + \beta_2 de^-_{3,t} + \beta_3 de^+_{3,t} + \beta_4 ici^k_{3,t} + \beta_5 embi_t + \sum_{m=1}^{11} \gamma_m D_{m,t} + u_{kjt}, \qquad (2)$$

where the left-hand-side variable s_{kj} is a price-setting series for product j from sector k, $D_{m,t} \equiv \mathbb{1}_{\{month(t)=m\}}$ is a seasonal dummy for month m, and u_{kjt} is the error term. For each product i in sector k, $s_{kj,t}$ is one of six price-setting variables: the positive $(f^+_{kj,t} \cdot \Delta p^+_{kj,t})$ and negative $(f^-_{kj,t} \cdot |\Delta p^-_{kj,t}|)$ components of inflation , the monthly frequency $(f^+_{kj,t})$ and size $(\Delta p^+_{kj,t})$ of positive price changes, and the monthly frequency $(f^-_{kj,t})$ and size $(|\Delta p^-_{kj,t}|)$ of negative price changes.

The results are reported in Table 7. Each price-setting variable corresponds to a column. We report the point estimates of the coefficients corresponding to the variables listed on the first column, with p-values based on "clustered" standard errors in parentheses.[17] The sample period is January 1999 - December 2008.

4.3.1 Positive and negative components of inflation

Higher aggregate inflation is, not surprisingly, associated with a larger positive component $(f^+ \cdot \Delta p^+)$ and a smaller negative component $(f^- \cdot \Delta p^-)$ of inflation as measured in our

[15] In future work we plan to document and investigate in detail the nature of the changes produced by the adoption of the new monetary regime.

[16] The cost of this specification is that we have to drop all products from sectors for which there is no specific measure of economic activity. This essentially restricts the panel to tradable goods. In Subsection **??** we explore specifications that do not make use of sectoral variables, and for which we can use series of price-setting satistics that also include services.

[17] We use Stata, and apply cluster() at the level of individual panel units (that is, at the product level). Thus, the standard errors on which the p-values are based are robust to heteroskedasticity and serial correlation, but do not account for any cross-sectional dependence in the error terms. In Subsection **??** we report standard errors under alternative assumptions about cross-sectional dependence.

Table 7: Baseline panel regressions

	$f_{kj,t}^{+} \cdot \Delta p_{kj,t}^{+}$	$f_{kj,t}^{-} \cdot \lvert\Delta p_{kj,t}^{-}\rvert$	$f_{kj,t}^{+}$	$f_{kj,t}^{-}$	$\Delta p_{kj,t}^{+}$	$\lvert\Delta p_{kj,t}^{-}\rvert$
π_t	0.072^{***}	-0.030^{***}	0.522^{***}	-0.175^{***}	0.037^{***}	-0.022
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.116)
$de_{3,t}^{-}$	-0.006^{***}	0.001	-0.044^{***}	0.004	-0.001	0.003
	(0.000)	(0.224)	(0.000)	(0.438)	(0.557)	(0.304)
$de_{3,t}^{+}$	0.002^{***}	-0.003^{***}	0.014^{***}	-0.023^{***}	0.001	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.723)	(0.466)
$ici_{3,t}^{k}$	0.001^{***}	-0.002^{***}	0.007^{***}	-0.012^{***}	0.001	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.168)	(0.601)
$embi_t$	0.061^{***}	0.061^{***}	0.177^{***}	0.191^{***}	0.154^{***}	0.149^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_1	-0.002^{***}	0.001^{**}	-0.010^{**}	0.009^{**}	-0.004^{***}	0.000
	(0.001)	(0.044)	(0.013)	(0.011)	(0.005)	(0.980)
D_2	-0.002^{**}	0.002^{*}	-0.003	0.009^{*}	-0.006^{***}	-0.001
	(0.011)	(0.061)	(0.474)	(0.053)	(0.000)	(0.648)
D_3	-0.001	0.002^{**}	0.000	0.009^{*}	-0.003^{**}	0.002
	(0.282)	(0.022)	(0.966)	(0.053)	(0.020)	(0.257)
D_4	0.001	0.002^{***}	0.006	0.013^{***}	-0.001	0.002
	(0.372)	(0.008)	(0.256)	(0.007)	(0.521)	(0.387)
D_5	0.000	0.001	0.007	0.007	-0.001	0.002
	(0.534)	(0.165)	(0.145)	(0.128)	(0.528)	(0.447)
D_6	0.000	-0.000	0.009^{*}	0.001	-0.002	-0.002
	(0.831)	(0.690)	(0.050)	(0.833)	(0.136)	(0.490)
D_7	-0.003^{***}	0.002^{**}	-0.015^{***}	0.010^{**}	-0.003^{*}	0.001
	(0.000)	(0.024)	(0.001)	(0.048)	(0.059)	(0.618)
D_8	-0.000	0.002^{*}	0.005	0.007	-0.002	0.003
	(0.512)	(0.055)	(0.245)	(0.143)	(0.268)	(0.115)
D_9	0.000	-0.001	0.015^{***}	-0.007	-0.006^{***}	-0.005^{**}
	(0.704)	(0.199)	(0.001)	(0.169)	(0.000)	(0.019)
D_{10}	0.000	-0.001	0.015^{***}	0.001	-0.004^{***}	-0.002
	(0.543)	(0.499)	(0.004)	(0.821)	(0.006)	(0.268)
D_{11}	0.001^{*}	0.000	0.007	-0.001	-0.001	0.002
	(0.082)	(0.952)	(0.127)	(0.765)	(0.347)	(0.334)
# *Obs*	25,371	25,046	26,108	25,371	26,108	25,046

Note: P-values in parentheses are based on (heteroskedasticity and serial correlation) robust standard errors ("clustered" at the product level). Superscripts *,**, and *** denote statistical significance at, respectively, 10%, 5% and 1% levels.

micro price data. These relationships are statistically significant at a less than 1% level. An exchange rate appreciation has a highly statistically significant *negative* association with the positive component of inflation, but no statistically significant association with the negative component. In contrast, an exchange rate depreciation has a highly statistically significant *positive* association with the positive component of inflation, and also a highly statistically significant *negative* association with the negative component of inflation. A higher level of economic activity as measured by the ICIs has a highly statistically significant *positive* association with the positive component of inflation, and a highly statistically significant *negative* association with the negative component of inflation. Finally, aggregate uncertainty as measured by the EMBI spread has a symmetric, highly statistically significant *positive* association with both components of inflation.

We move on to decompose the relationship between our set of macroeconomic variables and the positive and negative components of inflation by their frequency and size terms. We defer a discussion of the magnitude of the estimated coefficients to Section 4.5.

4.3.2 Frequency of price increases and decreases

Aggregate inflation has a positive relationship with the frequency of price increases, and a negative relationship with the frequency of price decreases. Both relationships are statistically significant at less than 1%. In accordance with its connection to the positive and negative components of inflation, an exchange rate appreciation has a highly statistically significant *negative* association with the frequency of price increases, but no statistically significant association with the frequency of price cuts. In contrast, and just like with the positive and negative components of inflation, an exchange rate depreciation has a highly statistically significant *positive* association with the frequency of price increases, and also a highly statistically significant *negative* association with the frequency of price decreases. Likewise, a higher level of economic activity as measured by the ICIs has a highly statistically significant *positive* association with the frequency of price increases, and a highly statistically significant *negative* association with the frequency of price cuts. Finally, aggregate uncertainty has, once again, a symmetric, highly statistically significant *positive* association with the frequency of both price increases and decreases.

4.3.3 Size of price increases and decreases

The results for the size of price increases and decreases are somewhat different from those for the frequencies of price changes. Aggregate inflation has a positive relationship with the size of price increases, but there is only weak evidence of a negative association with the size of price decreases (p-value of 0.116). The coefficients on exchange rate appreciation, depreciation, and the level of economic activity all have signs that accord with economic intuition, but are not statistically significant at the usual levels. Aggregate uncertainty as measured by the EMBI spread, however, has once again a symmetric, highly statistically significant *positive* association with the size of both price increases and decreases.

4.4 Alternative regression specifications

In this subsection we provide additional results based on alternative regression specifications. We estimate product-by-product regressions in the spirit of (2), explore an alternative specification for the panel, and provide results based on single regressions using only aggregate variables.

4.4.1 Product-by-product OLS regressions

In the spirit of our baseline panel specification, we estimate the following product-by-product OLS regressions:

$$s_{kj,t} = \alpha_{kj} + \beta_{1kj}\pi_t + \beta_{2kj}de^{-}_{3,t} + \beta_{3kj}de^{+}_{3,t} + \beta_{4kj}ici^{k}_{3,t} + \beta_{5kj}embi_t + \sum_{m=1}^{11}\gamma_{mkj}D_{m,t} + \upsilon_{kjt},$$

where the notation is self-explanatory. Given a left-hand-side price-setting variable, this produces a cross-section of 229 point estimates for each coefficient.[18] We compute unweighted means of these cross-sectional distributions, and report them in Table 8 for the left-hand-side variables f^{+}, Δp^{+}, f^{-}, and $|\Delta p^{-}|$.[19] To facilitate the comparison we reproduce the point estimates from our baseline panel specification from Table 7, including the indicators of statistical significance.

The bottom line is that, with few exceptions, the cross-sectional averages of OLS estimates are quite similar to the point estimates obtained with our baseline panel specification. We conclude that the latter adequately captures the central tendency of the various relationships between the small set of macroeconomic variables included in the regressions and the left-hand-side price-setting variables.

4.4.2 An alternative panel specification

We explore an alternative panel specification that comprises a sector instead of a product as its primary unit. The price-setting series for the 234 products included in the sample used

[18] The number is smaller than the 234 units of the baseline panel because irregularities in the time-series of five products made OLS infeasible.

[19] We omit the the results for the positive and negative components of inflation for brevity. The results for the unweighted medians of the cross-sectional distribution of OLS coefficients are quite similar.

Table 8: Results based on product-by-product OLS

	$f^{+}_{kj,t}$		$f^{-}_{kj,t}$		$\Delta p^{+}_{kj,t}$		$\lvert\Delta p^{-}_{kj,t}\rvert$	
	Baseline Panel	Mean Ols	Baseline Panel	Mean Ols	Baseline Panel	Mean Ols	Baseline Panel	Mean Ols
π_t	0.522***	0.512	−0.175***	−0.139	0.037***	0.034	−0.022	−0.034
$de^{-}_{3,t}$	−0.044***	−0.044	0.004	0.006	−0.001	0.001	0.003	0.006
$de^{+}_{3,t}$	0.014***	0.012	−0.023***	−0.019	0.001	−0.000	−0.001	0.003
$ici^{k}_{3,t}$	0.007***	0.001	−0.012***	−0.013	0.001	0.001	−0.001	0.000
$embi_t$	0.177***	0.270	0.191***	0.169	0.154***	0.177	0.149***	0.258

Note: Superscripts *,**, and *** denote statistical significance at, respectively, 10%, 5% and 1% levels.

in the baseline panel are aggregated into sectoral price-setting series corresponding to the 13 sectors of the Survey of Industrial Conditions with which the products can be associated. With this sectoral data set, we run the following panel regressions:

$$s_{k,t} = \alpha_k + \beta_1 \pi_t + \beta_2 de^{-}_{3,t} + \beta_3 de^{+}_{3,t} + \beta_4 ici^{k}_{3,t} + \beta_5 embi_t + \sum_{m=1}^{11} \gamma_m D_{m,t} + \varepsilon_{kt}, \tag{3}$$

where the notation is self-explanatory.

The results are reported in Table 9. There is only one statistically significant coefficient with a sign that contradicts that of the corresponding coefficient in the baseline panel. The coefficient of $de^{-}_{3,t}$ in the panel for $f^{-}_{k,t} \cdot |\Delta p^{-}_{k,t}|$ is negative and statistically significant at a 10% value. In contrast the same coefficient in the baseline panel is positive, but not statistically significant at the usual levels. Other than that, there are a few discrepancies in terms of statistical significance, but the signs of all other coefficients in both panel specifications coincide. And the majority of statistically significant associations in the baseline panel remain so in the sectoral panel, with magnitudes that are quite comparable. We conclude that the lessons that we draw from the baseline panel are robust to this alternative specification.

4.4.3 Time-series regressions with aggregate variables

In this subsection we consider single-equation OLS versions of our regressions that only use aggregate series. We run two specifications: an aggregate version of our baseline panel (and sectoral panel as well, for that matter), and a version that uses aggregate price-setting statistics computed from all unregulated products.

In the aggregate versions that build on the sample used in the panels, the left-hand-side variables are the aggregate (weighted average) versions of the panel units. With these

Table 9: Sectoral panel regressions

	$f^+_{k,t} \cdot \Delta p^+_{k,t}$	$f^-_{k,t} \cdot \lvert\Delta p^-_{k,t}\rvert$	$f^+_{k,t}$	$f^-_{k,t}$	$\Delta p^+_{k,t}$	$\lvert\Delta p^-_{k,t}\rvert$
π_t	0.045^{***}	-0.015^{*}	0.370^{***}	-0.150^{***}	0.040	0.008
	(0.003)	(0.062)	(0.002)	(0.001)	(0.466)	(0.818)
$de^-_{3,t}$	-0.009^{***}	-0.004^{*}	-0.049^{***}	-0.014	-0.011	-0.004
	(0.000)	(0.069)	(0.000)	(0.137)	(0.225)	(0.682)
$de^+_{3,t}$	0.001	-0.003^{***}	-0.000	-0.020^{***}	0.000	-0.001
	(0.503)	(0.009)	(0.974)	(0.000)	(0.976)	(0.796)
$ici^k_{3,t}$	0.001^{*}	-0.001	0.005	-0.008^{***}	0.001	0.000
	(0.093)	(0.224)	(0.189)	(0.006)	(0.702)	(0.956)
$embi_t$	0.136^{***}	0.112^{***}	0.423^{***}	0.384^{***}	0.291^{***}	0.300^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
D_1	-0.003^{***}	-0.001	-0.006	0.009^{*}	-0.011^{***}	-0.012^{*}
	(0.001)	(0.724)	(0.473)	(0.078)	(0.000)	(0.078)
D_2	-0.002^{*}	-0.000	-0.001	0.011	-0.005	-0.012
	(0.079)	(0.926)	(0.917)	(0.123)	(0.238)	(0.114)
D_3	0.000	-0.001	0.012	0.003	-0.006	-0.007
	(0.871)	(0.698)	(0.310)	(0.675)	(0.129)	(0.295)
D_4	0.003^{***}	-0.000	0.032^{**}	0.007	-0.001	-0.008
	(0.002)	(0.921)	(0.012)	(0.407)	(0.736)	(0.385)
D_5	-0.000	-0.000	0.011	0.009	-0.007	-0.008
	(0.784)	(0.919)	(0.317)	(0.127)	(0.132)	(0.233)
D_6	-0.002	-0.003^{*}	0.002	0.001	-0.009^{**}	-0.012^{**}
	(0.136)	(0.093)	(0.803)	(0.922)	(0.013)	(0.033)
D_7	-0.003^{***}	-0.001	-0.012	0.008	-0.007	-0.010
	(0.010)	(0.646)	(0.111)	(0.140)	(0.226)	(0.153)
D_8	-0.001	0.001	-0.005	0.016^{**}	0.003	-0.003
	(0.496)	(0.456)	(0.555)	(0.010)	(0.849)	(0.721)
D_9	-0.002	-0.003	-0.002	0.002	-0.008	-0.017^{*}
	(0.287)	(0.170)	(0.868)	(0.764)	(0.169)	(0.083)
D_{10}	-0.002	0.000	0.004	0.009^{*}	-0.007^{*}	-0.006
	(0.189)	(0.975)	(0.642)	(0.089)	(0.072)	(0.374)
D_{11}	-0.001	-0.001	-0.002	-0.001	-0.004	-0.002
	(0.607)	(0.611)	(0.845)	(0.821)	(0.312)	(0.716)
# *Obs*	$1,502$	$1,502$	$1,503$	$1,503$	$1,502$	$1,502$

Note: P-values in parentheses are based on (heteroskedasticity and serial correlation) robust standard errors ("clustered" at the sector level). Superscripts *,**, and *** denote statistical significance at, respectively, 10%, 5% and 1% levels.

variables, we run the following regressions:

$$s_t = \alpha + \beta_1 \pi_t + \beta_2 de_{3,t}^{-} + \beta_3 de_{3,t}^{+} + \beta_4 \overline{ici}_{3,t} + \beta_5 embi_t + \sum_{m=1}^{11} \gamma_m D_{m,t} + w_t,$$

where $\overline{ici}_{3,t}$ denotes the weighted average of the $ici_{3,t}^k$'s, and the rest of the notation is self-explanatory. The results are reported in Table 10, with p-values based on Newey-West robust standard errors in parentheses.

In the versions with aggregate price-setting variables, which make use of all of our working sample as described in Sections 2 and 3, the specification is analogous, but the right-hand-side variable for the level of activity is $ici_{3,t}$, the official aggregate index of the Survey of Industrial Conditions. The results are reported in Table 11, with p-values based on Newey-West robust standard errors in parentheses.

The bottom line is that our main conclusions are robust to these alternative specifications, and, more importantly, that they are not only a feature of the subset of products (sectors) that we included in our baseline (sectoral) panel, and which consisted essentially of industrial, tradable goods. They also hold for our aggregate measures of price-setting statistics, which include services (essentially all the non-tradable products).

4.5 Discussion

4.5.1 Assessing the magnitude of the estimated coefficients

Using the estimates of our baseline panel regression, we infer that a percentage point increase in inflation is associated with a 0.52 percentage point rise in the frequency of price increases and a 0.17 percentage point decrease in the frequency of price reductions. The same asymmetry of responses appear also in Nakamura and Steinson (2008) Gagnon (2009)'s studies for US and Mexico, respectively. In the latter work, Gagnon estimated a smaller effect of inflation than what we found on the frequency of price increases, and a larger effect on the frequency of price decreases at zero inflation (0.35 and 0.22, respectively). However, he obtained magnitudes which are similar to ours at 15% inflation rate (0.56 and 0.13)[20]. Although average inflation in our sample is about 7%, and the effects seem aproximately linear in our sample (more on this in section 4.6 below).

Inflation has a much smaller effect on the magnitude of price changes. A percentage point increase in inflation amplify price increases by 0.04 percentage points, while the effect on price decreases is not statistically different from zero at 10% significance level. This is

[20]Since in Gagnon (2009)'s regression there are non-linear inflation terms, this estimate depends on the inflation level.

Table 10: Aggregate regressions using composites of 13 sectors

	$f_t^+ \cdot \Delta p_t^+$	$f_t^- \cdot \lvert\Delta p_t^-\rvert$	f_t^+	f_t^-	Δp_t^+	$\lvert\Delta p_t^-\rvert$
π_t	0.093*** (0.000)	−0.029*** (0.003)	0.737*** (0.000)	−0.284*** (0.000)	0.058*** (0.004)	−0.018 (0.491)
$de_{3,t}^-$	−0.008** (0.025)	−0.001 (0.658)	−0.038* (0.087)	−0.014 (0.449)	−0.010 (0.190)	−0.006 (0.451)
$de_{3,t}^+$	0.004** (0.021)	−0.004** (0.012)	0.021 (0.341)	−0.032*** (0.000)	0.004 (0.405)	−0.001 (0.901)
$\overline{ici}_{3,t}$	0.001 (0.638)	−0.005* (0.053)	0.009 (0.500)	−0.016 (0.278)	−0.005 (0.226)	−0.012*** (0.002)
$embi_t$	0.050*** (0.004)	0.060*** (0.000)	0.118 (0.406)	0.264*** (0.005)	0.137*** (0.002)	0.151*** (0.004)
D_1	−0.004** (0.013)	0.003 (0.113)	−0.019 (0.111)	0.017* (0.086)	−0.007*** (0.009)	0.000 (0.953)
D_2	−0.002* (0.096)	0.003* (0.080)	−0.003 (0.804)	0.016 (0.116)	−0.005 (0.117)	0.003 (0.523)
D_3	−0.001 (0.761)	0.003* (0.097)	0.006 (0.640)	0.016 (0.181)	−0.001 (0.717)	0.007 (0.122)
D_4	0.002 (0.304)	0.004* (0.095)	0.013 (0.342)	0.021* (0.078)	0.004 (0.418)	0.008 (0.214)
D_5	0.002 (0.402)	0.003 (0.220)	0.011 (0.433)	0.018 (0.122)	0.001 (0.905)	0.006 (0.356)
D_6	0.001 (0.608)	0.002 (0.416)	0.012 (0.511)	0.014 (0.267)	−0.000 (0.943)	0.004 (0.562)
D_7	−0.001 (0.537)	0.004* (0.059)	−0.007 (0.613)	0.023** (0.046)	−0.000 (0.957)	0.003 (0.491)
D_8	−0.001 (0.591)	0.005** (0.015)	−0.004 (0.800)	0.032** (0.014)	−0.000 (0.990)	0.010** (0.047)
D_9	0.000 (0.985)	0.002 (0.231)	0.004 (0.779)	0.012 (0.275)	−0.001 (0.894)	0.002 (0.649)
D_{10}	−0.001 (0.587)	0.004** (0.013)	0.000 (0.989)	0.020** (0.044)	−0.002 (0.688)	0.007* (0.086)
D_{11}	0.011 (0.570)	0.001 (0.236)	0.003 (0.800)	0.008 (0.257)	0.000 (0.871)	0.002 (0.542)
# *Obs*	120	120	120	120	120	120
R^2	0.771	0.283	0.730	0.405	0.501	0.306

Note: P-values in parentheses are based on Newey-West robust standard errors. Superscripts *,**, and *** denote statistical significance at, respectively, 10%, 5% and 1% levels.

Table 11: Aggregate regressions

	$f_t^+ \cdot \Delta p_t^+$	$f_t^- \cdot \lvert\Delta p_t^-\rvert$	f_t^+	f_t^-	Δp_t^+	$\lvert\Delta p_t^-\rvert$
π_t	0.074***	−0.024***	0.531***	−0.186***	0.048**	−0.018
	(0.000)	(0.001)	(0.000)	(0.000)	(0.011)	(0.413)
$de_{3,t}^-$	−0.008***	−0.001	−0.049**	−0.007	−0.006	−0.005
	(0.007)	(0.618)	(0.013)	(0.640)	(0.317)	(0.491)
$de_{3,t}^+$	0.004**	−0.003***	0.021	−0.025***	0.004	−0.000
	(0.026)	(0.008)	(0.217)	(0.000)	(0.327)	(0.945)
$ici_{3,t}$	0.002	−0.007	0.023	−0.039	−0.013	−0.015
	(0.653)	(0.310)	(0.540)	(0.326)	(0.394)	(0.375)
$embi_t$	0.050***	0.054***	0.217*	0.300***	0.145***	0.187***
	(0.002)	(0.000)	(0.088)	(0.001)	(0.000)	(0.000)
D_1	−0.002	0.002**	0.003	0.013**	−0.005*	0.003
	(0.169)	(0.014)	(0.801)	(0.045)	(0.066)	(0.453)
D_2	−0.001	0.002	−0.005	0.008	−0.001	0.001
	(0.243)	(0.212)	(0.619)	(0.328)	(0.706)	(0.756)
D_3	−0.001	0.002	−0.000	0.009	−0.002	0.005
	(0.701)	(0.271)	(0.996)	(0.343)	(0.686)	(0.414)
D_4	0.001	0.002	−0.000	0.013	0.002	0.003
	(0.684)	(0.196)	(0.986)	(0.140)	(0.677)	(0.664)
D_5	0.001	0.002	0.002	0.009	−0.000	0.002
	(0.701)	(0.244)	(0.864)	(0.269)	(0.947)	(0.693)
D_6	−0.000	0.000	0.003	0.004	−0.002	−0.004
	(0.823)	(0.982)	(0.804)	(0.640)	(0.646)	(0.515)
D_7	−0.003*	0.001	−0.014	0.010	−0.003	−0.003
	(0.067)	(0.453)	(0.175)	(0.226)	(0.479)	(0.478)
D_8	−0.002	0.002**	−0.010	0.017**	0.001	0.003
	(0.269)	(0.038)	(0.295)	(0.044)	(0.855)	(0.456)
D_9	−0.001	0.000	−0.009	0.004	−0.001	−0.002
	(0.370)	(0.762)	(0.262)	(0.583)	(0.887)	(0.655)
D_{10}	−0.001	0.002**	−0.010	0.009	−0.001	0.002
	(0.208)	(0.041)	(0.298)	(0.112)	(0.814)	(0.687)
D_{11}	0.000	0.001	−0.005	0.006	0.001	−0.001
	(0.842)	(0.405)	(0.572)	(0.388)	(0.716)	(0.802)
# *Obs*	120	120	120	120	120	120
R^2	0.787	0.316	0.728	0.338	0.540	0.433

Note: P-values in parentheses are based on Newey-West robust standard errors. Superscripts *,**, and *** denote statistical significance at, respectively, 10%, 5% and 1% levels.

similar to the results obtained by Gagnon (2009) for inflation rates in the range of 0 to10%, who atribute the sensitivity of the average size of price changes to inflation to a composition effect.

Exchange rate variations, the level of economic activity and economic uncertainty all affect significantly price-setting statistic, as described above, but have no counterpart in other studies. In order to help assess the relevance of the effects, Table 12 reports the sample standard deviation of the regressors and its product with each coefficient in the panel regressions for $f^{+}_{kj,t}$, $f^{-}_{kj,t}$, $\Delta p^{+}_{kj,t}$ and $|\Delta p^{-}_{kj,t}|$.[21] For the measure of economic activity we report the cross-sectional average of the sample standard deviations.

A one-standard-deviation increase in aggregate inflation is associated with an increase in the frequency of positive price changes of 2.82 percentage points, and a reduction in the frequency of price decreases of roughly 0.95 percentage point. Absent a well-defined benchmark, there is no formal sense in which these effects are large or small. However, for comparison purposes, recall that the average frequency of price increases in our sample is roughly 24%, whereas the average frequency of price decreases is 13%.

Regarding the size of price changes, a one-standard-deviation increase in aggregate inflation is associated with an increase in the size of price increases of 0.20 percentage point. The relationship with the size of price increases, of -0.12 percentage point, is not statistically significant at the usual levels. For reference, recall that the average size of positive adjustments is 12%, whereas the average size of price decreases is 14.6%.

Overall, we are able to identify more significant and relevant effects on the (positive and negative) frequencies than on the magnitude of price adjustments. In particular, the size of price cuts are not strongly related with our chosen macroeconomic variables, with exception of the EMBI.

Table 12: Interpreting the regression coefficients

	$st\ dev \cdot 100$	$f^{+}_{kj,t}$	$f^{-}_{kj,t}$	$\Delta p^{+}_{kj,t}$	$\|\Delta p^{-}_{kj,t}\|$
π_t	5.4	2.819	−0.945	0.200	-0.119
$de^{-}_{3,t}$	16.2	−0.713	0.065	-0.016	0.049
$de^{+}_{3,t}$	44.5	0.623	−1.024	0.045	-0.045
$ici^{k}_{3,t}$	55.3	0.387	−0.664	0.055	-0.055
$embi_t$	4.4	0.779	0.840	0.678	0.656

[21] We use faded (grey) fonts for the coefficients whose p-value exceeds 10%.

4.6 Non-linearities in inflation: a comparison with Gagnon's (2009) results

Gagnon (2009) runs regressions of the form:

$$s_t = \alpha + \beta_1 \pi_t + \beta_2 \pi_t^2 + \beta_3 \pi_t^3 + \sum_{y=2000}^{2008} \gamma_y D_{y,t} + w_t,$$

where the left-hand-side price-setting variables refer to aggregates of nonregulated *goods*, and $D_{y,t} \equiv \mathbb{1}_{\{year(t)=y\}}$ is a dummy variable for year y.

Our specifications differ from his in two aspects: we do not include non-linear inflation terms, and we include macroeconomic variables, instead of year dummies, in order to capture aspects of the macroeconomic environment other than inflation.

Non-linear inflation terms do not seem to be important in our specification and/or sample. For example, when we include non-linear inflation terms in our aggregate specifications they are not statistically significant at the usual levels (see Table 13 below). The reason could be the smaller inflation range in our sample: although inflation varies a lot, it only exceeds 15% for about one quarter - at the end of 2002.

On the other hand, by not using yearly dummies we are able to capture the influence of the macroeconomic environment through aggregate variables that should affect firms' optimal prices. Furthermore, the addition of non-linear terms has only small effects on the magnitude and statistical significance of our estimated coefficients, as is evident from the comparison between Tables 10 and 13.

For a complete comparison, we also run Gagnon's (2009) specification in our sample. The results are presented in Table 14, with p-values based on Newey-West robust standard errors in parentheses. The sample period is January 1999 - December 2008.

We also illustrate the fit of the regressions by plotting the results for one specification. In the spirit of Figure IV in Gagnon (2009), Figure 12 shows the scatter plot of the frequency of price increases as a function of inflation, and includes the fitted values of the corresponding regression.

Table 13: Aggregate regressions with non-linear inflation terms - composites of 13 sectors

	$f_t^+ \cdot \Delta p_t^+$	$f_t^- \cdot \lvert\Delta p_t^-\rvert$	f_t^+	f_t^-	Δp_t^+	$\lvert\Delta p_t^-\rvert$
π_t	0.083^{***} (0.000)	-0.070^{**} (0.030)	0.655^{**} (0.020)	-0.581^{***} (0.001)	0.051 (0.501)	-0.017 (0.860)
π_t^2	0.009 (0.964)	0.264 (0.319)	1.485 (0.455)	1.931 (0.154)	-0.025 (0.964)	-0.191 (0.812)
π_t^3	0.098 (0.804)	-0.401 (0.446)	-4.217 (0.280)	-2.975 (0.270)	0.180 (0.861)	0.666 (0.673)
$de_{3,t}^-$	-0.008^{**} (0.027)	-0.001 (0.728)	-0.037^{*} (0.076)	-0.012 (0.519)	-0.009 (0.204)	-0.006 (0.462)
$de_{3,t}^+$	0.004^{**} (0.025)	-0.004^{**} (0.013)	0.021 (0.346)	-0.031^{***} (0.000)	0.004 (0.401)	-0.000 (0.932)
$\overline{ici}_{3,t}$	0.001 (0.640)	-0.005^{**} (0.049)	0.007 (0.577)	-0.017 (0.238)	-0.005 (0.248)	-0.011^{***} (0.005)
$embi_t$	0.051^{***} (0.005)	0.060^{***} (0.000)	0.110 (0.441)	0.262^{***} (0.002)	0.137^{***} (0.003)	0.152^{***} (0.005)
D_1	-0.004^{**} (0.013)	0.003^{*} (0.089)	-0.018 (0.121)	0.018^{*} (0.063)	-0.008^{**} (0.010)	0.000 (0.967)
D_2	-0.002^{*} (0.097)	0.003^{*} (0.083)	-0.003 (0.838)	0.016 (0.102)	-0.005 (0.117)	0.003 (0.545)
D_3	-0.001 (0.760)	0.004^{*} (0.090)	0.007 (0.600)	0.017 (0.151)	-0.002 (0.714)	0.007 (0.135)
D_4	0.002 (0.315)	0.004^{*} (0.090)	0.015 (0.297)	0.023^{*} (0.054)	0.004 (0.429)	0.007 (0.244)
D_5	0.001 (0.458)	0.003 (0.257)	0.013 (0.359)	0.017 (0.146)	0.000 (0.936)	0.005 (0.402)
D_6	0.001 (0.718)	0.001 (0.549)	0.014 (0.485)	0.010 (0.414)	-0.001 (0.894)	0.003 (0.609)
D_7	-0.001 (0.540)	0.004^{*} (0.071)	-0.008 (0.589)	0.023^{*} (0.050)	-0.000 (0.964)	0.003 (0.458)
D_8	-0.001 (0.570)	0.005^{**} (0.019)	-0.002 (0.884)	0.032^{**} (0.015)	-0.000 (0.974)	0.010^{*} (0.057)
D_9	-0.000 (0.924)	0.002 (0.269)	0.006 (0.635)	0.011 (0.320)	-0.001 (0.859)	0.002 (0.734)
D_{10}	-0.001 (0.573)	0.004^{**} (0.016)	0.001 (0.949)	0.020^{**} (0.044)	-0.002 (0.687)	0.007^{*} (0.096)
D_{11}	0.001 (0.722)	0.001 (0.338)	0.007 (0.527)	0.007 (0.352)	0.000 (0.971)	0.001 (0.785)
# *Obs*	120	120	120	120	120	120
R^2	0.773	0.298	0.735	0.424	0.502	0.310

Note: P-values in parentheses are based on Newey-West robust standard errors. Superscripts *,**, and *** denote statistical significance at, respectively, 10%, 5% and 1% levels.

Table 14: Aggregate regressions with non-linear inflation terms - Gagnon (2009) specification

	f_t	f_t^+	f_t^-	Δp_t	Δp_t^+	$\|\Delta p_t^-\|$
$\widehat{\pi}_t$	-0.022	0.261^{***}	-0.283^{***}	0.146^{***}	0.020	-0.067^{***}
	(0.757)	(0.000)	(0.000)	(0.000)	(0.211)	(0.000)
$\widehat{\pi}_t^2$	1.474^{***}	0.925^{***}	0.549^{**}	0.051	0.255^{*}	0.335^{**}
	(0.001)	(0.004)	(0.011)	(0.375)	(0.092)	(0.049)
$\widehat{\pi}_t^3$	-1.779^{***}	-1.218^{**}	-0.561	-0.182^{**}	-0.457^{*}	-0.538^{*}
	(0.006)	(0.009)	(0.113)	(0.035)	(0.081)	(0.069)
D_{2000}	0.001	-0.002	0.003	0.002	-0.003	-0.007^{**}
	(0.874)	(0.719)	(0.520)	(0.314)	(0.142)	(0.020)
D_{2001}	-0.016	-0.016^{*}	-0.001	0.005^{***}	0.009	0.007
	(0.230)	(0.074)	(0.894)	(0.002)	(0.166)	(0.339)
D_{2002}	0.017^{**}	0.003	0.014^{**}	0.004^{**}	0.020^{***}	0.022^{***}
	(0.047)	(0.441)	(0.011)	(0.019)	(0.000)	(0.000)
D_{2003}	0.045^{***}	0.019^{***}	0.025^{***}	0.002	0.007^{***}	0.007
	(0.001)	(0.003)	(0.000)	(0.154)	(0.010)	(0.123)
D_{2004}	0.039^{***}	0.027^{***}	0.013^{*}	0.002	-0.003^{***}	-0.005^{*}
	(0.000)	(0.000)	(0.067)	(0.345)	(0.269)	(0.091)
D_{2005}	-0.004	-0.002	-0.002	0.001	-0.015^{***}	-0.017^{***}
	(0.715)	(0.774)	(0.717)	(0.508)	(0.000)	(0.000)
D_{2006}	-0.038^{***}	-0.022^{**}	-0.015^{***}	0.002	-0.009^{***}	-0.017^{***}
	(0.002)	(0.034)	(0.003)	(0.165)	(0.000)	(0.000)
D_{2007}	-0.049^{***}	-0.027^{***}	-0.022^{***}	0.003^{*}	-0.009^{***}	-0.016^{***}
	(0.000)	(0.000)	(0.000)	(0.074)	(0.000)	(0.000)
D_{2008}	-0.038^{***}	-0.023^{***}	-0.016^{**}	0.003^{**}	0.006	0.001
	(0.000)	(0.000)	(0.014)	(0.038)	(0.189)	(0.908)
# *Obs*	120	120	120	120	120	120
R^2	0.722	0.855	0.715	0.941	0.748	0.629

Note: P-values in parentheses are based on Newey-West robust standard errors. Superscripts *,**, and *** denote statistical significance at, respectively, 10%, 5% and 1% levels.

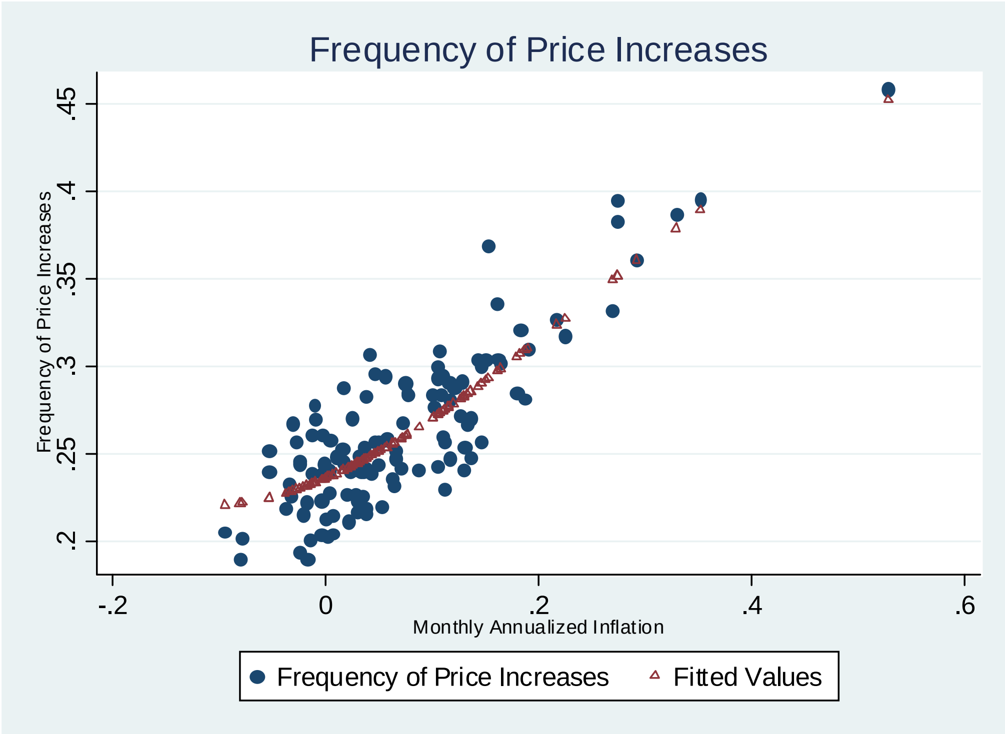


Figure 12: Frequency of price increases and fitted values as a function of inflation

The results of our regressions are qualitatively consistent with those of Gagnon (2009), in that they suggest a role for non-linear inflation terms. These were found to be statistically significant in most regressions.[22] However, the quantitative importance of these non-linearities appears to be small, as Figure 12 illustrates. Despite the coefficients on π_t^2 and π_t^3 being statistically significant in the regression for the frequency of price increases, and similar in magnitude to the estimates found by Gagnon (2009), the non-linearity appears to be mild.

These results might still be consistent with Gagnon's (2009) findings on the quantitative importance of inflation non-linearities. As we mentioned above, inflation only exceeded 15% in the last quarter of 2002. This implies that the non-linearities that Gagnon (2009) argues become important when annualized inflation is above 10-15% should be hard to detect in our sample. It remains to be seen whether these non-linear effects were more important in the Brazilian experience pre-1994, when annualized inflation reached three (and sometimes four) digits for prolonged periods of time. This requires micro price data for a period that is not available in our data set.

[22] In this regression we follow Gagnon in using the inflation internal to the sample ($\widehat{\pi}_t$), instead of the official aggregate inflation. This increases the importance of the non-linearities.

4.7 The differential effect of the change of exchange rate regime on tradables price-setting statistics

The exchange rate regime changed from a crawling peg to a floating regime in January 1999. We investigate if the change had a differential effect on the price setting statistics of tradable goods, relative to non-tradable goods. Let s_t^T be a price-setting statistic of the tradable sector and s_t^{NT} be the same statistic for the non-tradable sector. We define the statistic differential as $\Delta(s_t) \equiv s_t^T - s_t^{NT}$ and run the following regressions for the frequency of positive and negative adjustments and for size of positive and negative adjustments:

$$\Delta(s_t) = \alpha + \beta_1 \pi_t + \beta_2 de_{3,t} + \beta_3 embi_t + \beta_4 ici_{3,t} + \beta_5 D_{99-2008} + e_t,$$

where $D_{99-2008}$ is a dummy variable that has value 1 after 1999. The regression relates the difference between tradable and nontradable price-setting statistics to macroeconomic variables, and allows for the difference to be affected by the change in regime. The results are reported in Table 15 below:[23]

Table 15: Differential effect of change in FX regime

	$\Delta(f_t^+)$	$\Delta(\Delta p_t^+)$	$\Delta(f_t^-)$	$\Delta(\lvert\Delta p_t^-\rvert)$
π_t	0.320^{***} (0.000)	0.017 (0.417)	-0.188^{***} (0.000)	-0.077^{***} (0.005)
$de_{3,t}$	0.009 (0.429)	-0.002 (0.424)	-0.009 (0.204)	0.001 (0.854)
$ici_{3,t}$	0.010 (0.788)	0.011 (0.350)	-0.012 (0.642)	0.003 (0.864)
$embi_t$	-0.255^{**} (0.017)	-0.012 (0.689)	-0.096 (0.145)	-0.052 (0.268)
$D_{99-2008}$	0.017^{*} (0.099)	0.011^{***} (0.000)	0.034^{***} (0.000)	0.016^{***} (0.000)
$const$	0.065^{***} (0.000)	-0.001 (0.797)	0.069^{***} (0.000)	0.006 (0.184)
# Obs	153	153	153	153
R^2	0.199	0.128	0.417	0.150

Note: P-values in parentheses are based on Newey-West robust standard errors. Superscripts *,**, and *** denote statistical significance at, respectively, 10%, 5% and 1% levels.

Inflation is positively related with the difference of frequency and size of price increases, and negatively to the difference of frequency and size of price decreases. The EMBI is negatively related to all differences but, only significant for the difference in the frequency of price increases. The constant is positive and significant for all differences of price-setting statistics, implying that controlling for other macroeconomic determinants, tradable goods

[23] Significance levels based on Newey-West robust standard errors.

are adjusted more often than nontradables, both upwards and downwards, and that, with the same controls, the average size of adjustments is larger (again, both upwards and downwards). Furthermore, this difference is mainly due to the floating exchange rate regime, since dummy coefficients are all positive and significant in all four regressions, and unreported results show that when the dummy is added the constant decreases in size and looses statistical significance.Cross-sectional analysis

5 Conclusion

[To be included]

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6 Appendix

6.1 Direct measures of duration

It is well known that direct measures of duration of spells that rely on averages of observed spells are subject to a downward bias due to selection effects. Biases may be introduced because of two related issues. First, each quote line starts and finishes during the occurrence of a spell. Censored spells tend to be larger than uncensored spells. If we evaluate the duration including incomplete spells we produce a downward bias because we have interrupted spells. But if we exclude the incomplete spells we may also introduce a downward bias because the spells excluded tend to be larger than average. In principle, those biases should be smaller the longer the quote lines. Given the relatively long length of the latter in our data set, we also compute duration of price spells directly.

For each quote line, we average the time interval between price adjustments, and then take cross-sectional averages. Table 20 presents the results of our direct measures of duration with and without censored prices. Despite our long quote lines, this bias still appears to be substantial in our sample. Our direct measures of duration are significantly smaller than our preferred indirect duration measure obtained by computing implied durations at the item level and then aggregating.

Table 20: Direct measures of duration

	Mean	Median
Censored prices		
with price imputation	5.28	3.27
without price imputation	4.59	2.73
No censored prices		
with price imputation	4.27	2.64
without price imputation	3.81	2.44

Samples runs from March 1996 through December 2008. The statistics reported use weights from the Household Budget Survey used to calculate the CPI-FGV from January 2004 on. Direct duration is calculated by first computing the arithmetic mean of the lenght of each price spell per item, and then aggregating. In no-censored-prices statistics the durations are calculated only between the first and last price variation of each item.

6.2 A comparison with Klenow and Kryvtsov's results

6.2.1 Decomposing the variance of inflation

We follow Klenow and Kryvtsov (2008) in doing the following decomposition of the time-series variance of our internal inflation measure, $var\left(\widehat{\pi}_t\right)$:

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

where $\overline{f}$ is the average frequency of price changes, f_t is the mean (across items) frequency of price changes in month t, $\overline{\Delta p}$ is the average price adjustment, and Δp_t is the mean (across items) price adjustment at time t. The first term in the right-hand side is the part of the variance attributed to time variation in the size of adjustment, the second term is due to time variation in the frequency of price adjustments, while the third-term is due to the covariance of the mean (across items) size of price adjustments and frequency of price changes.

Table 21 reports our results. The first row shows that almost 90% of the variance of inflation for the whole sample can be attributed to variation over time in the size of adjustments, and only 0.4% to variation of the aggregate frequency of price changes. In the other two rows we report the decomposition for two sub-periods. The first one, from January 2000 to December 2003, was a period with a lot of macroeconomic instability, and the second one, which starts in January 2004, is the most stable period in our sample.[24] While in the decomposition for the instable sub-period the first term has the lowest share - 88%, it is still only slightly lower than that for the entire sample. In the last sub-period, this shares increase to 96%. The difference in share of the first term is not reflected in the term of pure variance of the frequency, which remains very low between 0.3 and 0.4%, but to the term of covariance between frequency and adjustment sizes, which reaches almost 7% during the unstable period.

Table 21: Inflation variance decomposition

March 1996 - December 2008					
Mean Inflation	Inflation Variance	t1	t2	t3	error
5.90%	0.004%	86.6%	0.6%	6.3%	6.5%
January 2000 - December 2003					
Mean Inflation	Inflation Variance	t1	t2	t3	error
8.80%	0.008%	82.6%	0.7%	9.6%	7.0%
January 2004 - December 2008					
Mean Inflation	Inflation Variance	t1	t2	t3	error
5.20%	0.003%	96.5%	0.6%	1.9%	0.8%

[24]Perhaps surprisingly, the ongoing global financial crisis produced only a small amount of macroeconomic variability in Brazil from a historical perspective.