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Retail Price Setting in Uruguay

In recent years there has been a large increase in the empirical literature on price behavior. As new and detailed data sets become available, we observe a number of important studies on the microeconomic fundamentals of price setting by firms—mainly retailers—and their impact on inflation. This analysis allows a better understanding of the behavior, dispersion, and volatility of prices.

In this paper, we use a rich and unique data set of 30 million daily prices in grocery stores and supermarkets across Uruguay to analyze stylized facts about consumer price behavior. Our findings are as follows:

—The median duration of prices is two and one-half months. Therefore, retail prices in Uruguay are less sticky than in the United States and Brazil but stickier than in Chile and the United Kingdom.

—We do not find evidence of a seasonal pattern in the likelihood of price adjustments.

—The frequency of price adjustment is correlated with expected inflation only for the personal care product category. For the food category we find that supermarkets change the percentage points of the adjustment but not their frequency.

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—The probability of price change on the first day of the month is nine times higher than on any other day.
—The probability of a price change is not constant over time.
—There exists a high synchronization of price changes in our database, either at the city level or chain level. Overall, our analysis seems to be consistent with time-dependent models, although the high synchronization of price changes on the first day of the month awaits a better theoretical explanation.

A Brief Review of the Empirical Literature

Although there are different theoretical models in the literature that explain the microeconomic behavior of prices—such as menu cost models, sticky price and sticky information models, and time- or state-dependent pricing strategies—the stylized facts still avoid a unique theoretical explanation. Klenow and Malin (2010), which provides an up-to-date and concise overview of the empirical evidence, confronts the data with different theoretical models. The authors stress ten facts of the microeconomic behavior of prices. The primary facts are that prices do change at least once a year; that the main instrument for downward price adjustment is sales; that most markets have a stickier reference price; that goods prices differ in frequency of adjustment and the changes are asynchronous for different types of goods; that microeconomic forces explain the behavior of prices that differ from aggregate inflation; and that prices adjust mainly when wages change.

Gopinath and Rigobon (2008) studies the stickiness of traded goods using microdata on U.S. import and export prices at the dock for the period 1994–2005. The authors find long price duration for traded goods—10.6 months for imports and 12.8 months for exports; great heterogeneity in price stickiness across goods at the disaggregated level; a declining probability of price adjustment over time for imports; and a rather low exchange rate pass-through into U.S. import prices.

Nakamura and Steinsson (2008) uses the consumer price index (CPI) and the producer price index (PPI) from the U.S. Bureau of Labor Statistics (BLS) for the period 1988–2005 to study price stickiness. The results show that there is a duration of regular prices of between eight and eleven months, after excluding sale prices; that temporary sales are an important source of price flexibility—mainly downward price flexibility; that roughly one-third of price changes, excluding sales, are price decreases; that price increases strongly covary with inflation, but price decreases do not; and that price changes are highly seasonal, mainly in the first quarter. Finally, the study finds that the hazard function of price changes, which estimates the probability of a price change after *t* periods without changing, is slightly downward sloping, which implies that the probability of a price change occurring decreases the longer the time span since the last change.

Some of these conclusions are relativized in Klenow and Kryvtsov (2008). Using monthly price information from the BLS for the period 1988–2004, the authors find that prices change quite frequently, every 3.7 months if sales are included and up to 7.2 months if excluded. They compare their results with those of other papers for the United States and conclude that the estimated rigidity of prices changes depending on how different methodologies include or do not include sales and on how they take into account prices of substituted goods. Price changes are quite large, up to an average of 10 percent a year in their sample. Also, they find a large number of small price changes: nearly 44 percent of price changes are smaller than 5 percent in absolute value, and 12 percent of those changes are smaller than 1 percent. The distribution of the size of price changes is similar for price increases and decreases. Hazard rate estimates for a given item are quite flat after the mix of heterogeneous hazard rates for different goods—that is, survival bias—is taken into account.

Ellis (2009) studies the behavior of prices using weekly data for the United Kingdom. The author finds low price rigidities in the U.K. retail industry. Prices change frequently (the mean duration is about two weeks) even after promotions and sales are excluded. When analyzing the sign of the price change in price reversals—that is, price changes that later reverted to the original price—he finds that price decreases, which are consistent with sales, are prevalent. Also, the range of price changes is very wide: some products display large changes in prices and a large number show small changes. Last, he finds, as does Nakamura and Steinnson (2008), that all products have declining hazard functions.

Studies for Latin America are scarce due to the lack of available scan data, and they have concentrated on micro CPI data. Barros and others (2009) and Medina, Rappoport, and Soto (2007) analyze price formation in Brazil and Chile, respectively. These studies show that the frequency of adjustment is different from that obtained using macrodata. They estimate median duration of four and three months for Brazil and Chile, respectively. Because they use monthly data, they cannot capture price changes within a month. Also, CPI data must deal with higher measurement error than do scan data. Chaumont and others (2010) studies price-setting behavior in Chile using weekly scan data. The authors find significant heterogeneity in price behavior by supermarkets. One salient finding is the relative price flexibility of Chilean supermarkets in their database; price duration is about 1.3 weeks, even lower than in the United Kingdom (see Ellis 2009). In contrast to Nakamura (2008), they find that nearly 35 percent of price changes are idiosyncratic to product or chain shocks and that 65 percent of price changes are common shocks that affect all products in a category and all stores in the country at the same time. The only paper that compares price rigidities across Latin American countries is Cavallo (2010). Using scraped online data from Argentina, Brazil, Chile, and Colombia, the author finds price stickiness in Chile and relative price flexibility in Brazil.

To the best of our knowledge, our paper is the first to analyze the price behavior of retailers in a small open economy using daily price data from across all country regions. Our objective is to describe stylized facts of price formation in Uruguay and to compare them with those in the existing literature. We first provide a detailed description of the database and then present the main findings of our analysis and offer a brief comparison of our findings with the available evidence. Next we discuss the implications of our findings for existing theory; that discussion is then followed by the study's main conclusions.

Data

We analyze a set of microdata with a daily frequency compiled by the General Directorate of Commerce (DGC, for its Spanish acronym), which includes more than 300 grocery stores all over Uruguay and 155 products (see appendix A for a map of the cities included in the data set). The product brands, which were chosen to be the most representative of the product being described, were selected as the best-selling brands in each category. The products in the sample represent at least 12.6 percent of the goods and services in the CPI basket (see appendix B).

The DGC, in the Ministry of Economy and Finance, is the authority responsible for the enforcement of the Consumer Protection Law. In 2006 a new tax law was passed that changed the tax base and rates of the value-added tax (VAT). The basic rate of the VAT was reduced from 23 percent to 22 percent, and its minimum rate (for staple foods, hotel rooms during high season, and certain health-related services) was reduced from 14 percent to 10 percent. In addition, exemptions were eliminated (for example, for the health sector, passenger transport, and sales of new homes). A 3 percent tax on intermediate consumption of goods (COFIS) was eliminated. The tax reform also reduced the asymmetries between economic sectors regarding the employer contribution to social security and introduced a personal income tax.

Because the Ministry of Economy and Finance is concerned about incomplete pass-through of reductions in taxes to consumer prices, it publishes an open public data set of prices in different grocery stores and supermarkets in order to inform consumers. Resolution 061/006 mandates that grocery stores and supermarkets must report the daily prices for a list of products if the businesses meet the following two conditions: they sell more than 70 percent of the products listed in annex 2 of the resolution, and they have more than four grocery stores under the same name or more than three cashiers in a store. Because each price report is a sworn statement, the businesses are subject to penalties if they misreport their prices.

The DGC makes the information public through a web page that publishes the average monthly prices of each product for each store in the defined basket (see www.precios.gub.uy/publico). This information is available within the first ten days of the next month. It should be noted that the government makes no further use of the information; for example, there are no price controls, and no further policies are implemented to control supermarkets or producers. The idea is to give consumers adequate information about prices so that they can shop at the cheapest store if they choose to.

The products to be reported to the DGC were initially chosen on the basis of the results of a survey distributed to the main supermarket chains inquiring about their annual sales for each item and brand. After supermarkets' own brands were eliminated, the three highest-selling brands for each item were chosen to be reported. Most items had to be homogenized in order to be comparable, and each supermarket must always report the same item. For example, bottled sparkling water of the SALUS brand is reported in its 2.25 liter size by all stores. If that specific size is not available at a store, then no price is reported.

Each item is defined by its universal product code (UPC), with the exception of beef, eggs, ham, some types of cheese, and bread. In some instances, as in the case of meat and various types of cheese, general definitions were set, but because of the nature of the products, the items could not be homogenized. In the case of bread, most grocery stores buy frozen bread and bake it rather than produce it at the store. Grocery stores sell different sizes of bread, so in some cases the reported size does not coincide with the definition and grocery stores prorate the price submitted to the DGC—that is, if the store sells bread that is 450 grams per unit and the requested unit is 225 grams, it submits half the price of its bread.

Each month, the DGC issues a brief report with general details on the price evolution. This report counts the number of products that increase or decrease in price; the prices used for the calculations are the simple average market prices for each product.

The database records begin in March 2007, and the new tax system went into effect in July 2007. A few months later, new products were added to the database, after a push of inflation in basic consumer products in 2008. The government made "voluntary sectoral price agreements" with producers in the salad oil, rice, and meat markets. In addition, in the second semester of 2010, newer goods were added to increase the representativeness of the data set.

Within four working days of the end of the month, each supermarket uploads its price information to the DGC database. After that, the DGC begins a process of "price consistency checking" by calculating the average price for each item in the basket. Each price 50 percent greater or less than the average price is selected. Then, the supermarket is contacted in order to check whether the submitted price is right. If there is no answer from the supermarket, or if the supermarket confirms the price submitted, the price is posted online as reported. If the supermarket corrects the price, which is the exception, the price is corrected in the database and posted online.

Our final database contains daily prices from April 2007 to December 2010 on 155 items. From the database, we eliminated those items that were not correctly categorized (marked as "XXX" and "0") and some products that mistakenly share the same UPC. The complete list of products can be found in appendix B. We also eliminated March 2007 observations because they were preliminary and had not been posted online. Finally, we eliminated those products—and supermarkets—for which there were no observations for more than half of the period.

We ended up with data for 117 products in 303 grocery stores from 45 cities in the 19 Uruguayan departments (see appendix A). These cities represent 80 percent of the total population of Uruguay. The capital city, Montevideo, has 40 percent of the population and 57 percent of the supermarkets in the sample.

Table 1 summarizes the total number of price observations (30 million), in four product categories: food, soft drinks, alcohol, and personal care and cleaning items (named personal products). Food is the main category, followed by personal products and beverages.

TABLE 1. Number of Daily Price Observations, by Product Category, April 2007–December 2010

Category	*Number*	*Percent of total*
Food	20,380,541	66
Soft drinks	1,814,628	6
Alcohol	1,486,176	5
Personal products	7,038,089	23
Total	30,719,434	100

Source: Authors' calculations based on data from the Uruguayan Ministry of Economy and Finance.

Finally, as our results could be driven by differences in the overall inflation in the sample, we plot the monthly variation of prices (see figure 1). This period is characterized by inflation pushes (the median monthly inflation rate is 0.56 percent), as the government was worried that inflation would reach a high level in the medium term.

Results

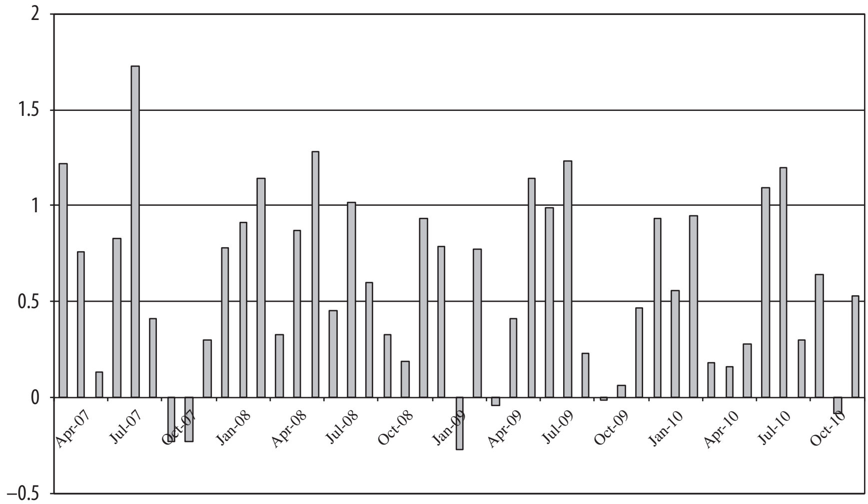
Here we review the frequency of price adjustments by supermarkets and examine seasonality in price adjustments and the nexus between individual price changes and expected overall inflation. We also analyze price changes by day of the month, which is new in the literature. We then compute the joint hazard rate of price changes and examine the synchronization of prices at the chain and city level.

Frequency of Price Adjustments

As is standard in the literature, we first study the rigidity of prices by computing the median probability of daily price changes and the median duration of prices in months and by contrasting the results of price increases and decreases. It should be noted that we study the whole sample and do not differentiate between sales and the absence of sales. From a theoretical point of view, a price decrease because of a sale shows evidence of price flexibility, and we do not want to eliminate such an observation (see Klenow and Kryvtsov 2008).

The median daily price change for the whole sample is a nontrivial 1.3 percent. That implies a medium price change every 75 days, or every 2.5 months, on average, which is considerably lower than the estimates in Nakamura and Steinsson (2008) and Nakamura (2008) but higher than the results in Chaumont and others (2010) for Chile and those in Ellis (2009). This result

FIGURE 1. Monthly Inflation Rate (Percent)



Source: National Institute of Statistics

is slightly less than the median durations of three and four months found in Barros and others (2009) and Medina, Rappoport, and Soto (2007) for Brazil and Chile, respectively.

We offer two explanations for our result. First, this is a period of relatively high inflation, so one could expect prices to change more quickly: the median monthly inflation during the period in Uruguay was 0.56 percent. Second, because our database has daily prices, we can calculate price changes more accurately than in previous studies that use weekly or monthly data. In this case, we can detect earlier price changes and our measure of price rigidity would be more sensitive to them. That would result in less price stickiness for our database.

In line with Nakamura and Steinsson (2008), 40 percent of the price changes are price decreases. Table 2 presents the median probability of price changes, the percentage of price decreases, and the median monthly duration by product category. Our results show that prices change most frequently in the personal products category and least frequently in the alcohol category. There is significant variation in price stickiness across product categories, ranging from 1.9 months for personal products to 3.5 months for alcohol.

TABLE 2. Price Variation and Duration, by Product Category

Category	*Median probability of daily variation*	*Percent decrease*	*Monthly duration*
Food	0.013	40.6	2.5
Soft drinks	0.010	33.3	3.2
Alcohol	0.009	30.0	3.5
Personal products	0.017	42.0	1.9
Total	0.013	40.4	2.5

Source: Authors' calculations based on data from the Uruguayan Ministry of Economy and Finance.

Appendix C presents a detailed analysis of the results for each product in the sample. There is a high variability of results across products. For example, we find products that change prices quite frequently, such as cheese of the "Disnapt" and "Cerros del Este" brands, for which prices change five and two times a month, respectively. Prices of other products change more slowly, like "El Ecologito" brand brown eggs and "Torrevieja" brand salt, whose prices can remain the same up to five months.

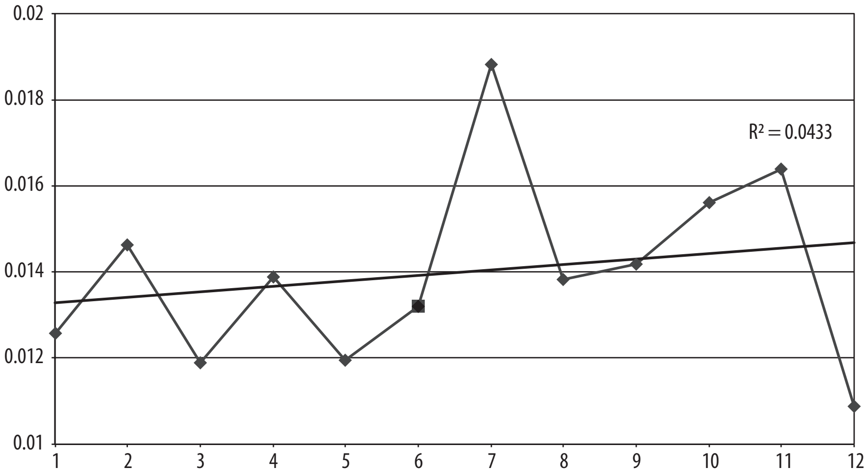
Seasonality of Price Changes

Second, we study seasonal adjustment patterns of prices. Nakamura and Steinsson (2008) finds that price changes in the United States are highly seasonal; they are concentrated in the first quarter and then decrease. This finding is consistent with the authors' price rigidity calculation of about eight months. In contrast, Ellis (2009) finds no monthly seasonality, a result in line with the author's finding of just two weeks of price rigidity. As we find a price duration of 2.5 months, we should expect to find no seasonality in the data.

Figure 2 shows that there is not a clear pattern of seasonality in the price adjustments. In addition, we do not find a seasonal pattern in price changes when we look at quarterly data. The percentage of daily price changes in the first quarter is 1.28, 1.29 in the second, 1.58 in the third, and 1.49 in the fourth. The greatest price change seems to be concentrated in the third quarter. Table 3 shows that all categories but personal products have the greatest number of price changes in the third quarter, although there is no clear tendency in the data. Therefore, we cannot conclude that seasonality exists in the frequency of price adjustments.

Nor do we observe a clear pattern of seasonality in the *level* of price adjustments. Figure 3 shows the rate of price growth conditional on price change by month. It should be stated that in Uruguay workers receive an extra half-month's wages in June and December. Also, during December's New Year

FIGURE 2. Probability of Price Change, by Month



Source: Authors' calculations based on data from the Ministry of Economy and Finance.

festivities, supermarket sales generally receive a boost.[1] In summary, we do not find demand-driven seasonal price changes in the data.

Individual Price Changes and Inflation Expectations

One interesting issue is whether price changes and inflation expectations move together. Ellis suggests a positive relationship between the frequency of price changes in his sample and respondents' expectations of inflation in a survey conducted by the Bank of England (Ellis 2009). Table 4 shows the result of an ordinary least squares (OLS) regression estimation in which the dependent variable is the median probability of price change and the exploratory variables

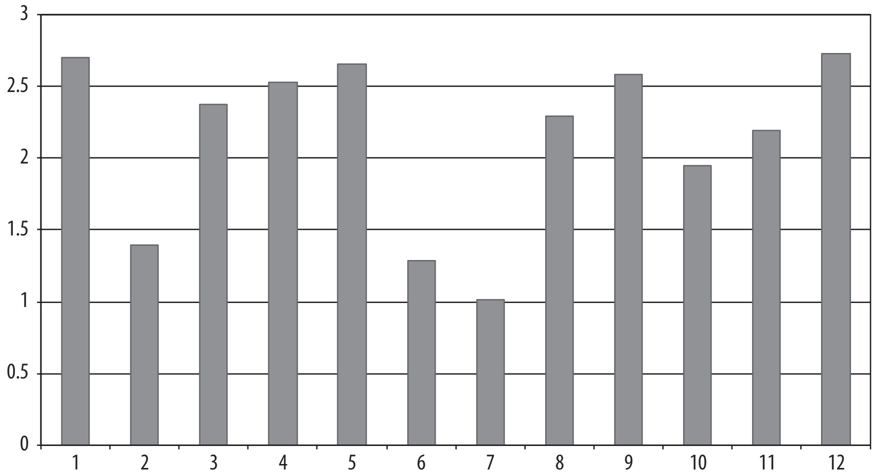
TABLE 3. Seasonal Probability of Price Change, by Product Category

Quarter	*Food*	*Soft drinks*	*Alcohol*	*Personal products*
1	0.013	0.008	0.006	0.013
2	0.012	0.009	0.008	0.017
3	0.016	0.012	0.010	0.018
4	0.015	0.010	0.009	0.019

Source: Authors' calculations based on data from the Uruguayan Ministry of Economy and Finance.

1. In Uruguay, sales usually soar the day before supermarkets close for a holiday. January 1 and 6, May 1, and December 25 are usually the days when supermarkets do not open.

FIGURE 3. Price Growth Rate Giving Price Change, by Month (Percent)



Source: Authors' calculations based on data from the Ministry of Economy and Finance.

TABLE 4. Individual Price Changes and Inflation Perceptions: OLS Regression
April 2007–December 2010[a]

	Dependent variable			
		Price change (percent)		
Variable	*Probability of price change*	*All*	*Increases*	*Decreases*
Expected yearly inflation	0.001	−0.024	0.449	−0.640***
	(0.001)	(0.412)	(0.369)	(0.194)
Tax reform indicator variable				
May 2007	0.008*	3.052*	3.659**	−1.043
	(0.004)	(1.792)	(1.604)	(0.844)
June 2007	0.012**	−4.102**	2.500	−0.288
	(0.004)	(1.790)	(1.602)	(0.843)
July 2007	0.011**	−1.371	−4.849***	2.740***
	(0.004)	(1.789)	(1.602)	(0.843)
August 2007	−0.018***	3.396*	−0.550	−1.401
	(0.004)	(1.793)	(1.605)	(0.845)
September 2007	−0.009***	−0.390	0.183	0.479
	(0.003)	(1.293)	(1.158)	(0.609)
Constant	−0.001	1.520	5.090**	−4.304***
	(0.007)	(2.780)	(2.488)	(1.309)
Observations	45	45	45	45
R^2	0.733	0.229	0.405	0.399

Source: Authors' calculations based on data from the Uruguayan Ministry of Economy and Finance and the Central Bank of Uruguay.
a. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 5. Individual Price Changes and Inflation Expectations: OLS Regression by Product Category
April 2007–December 2010[a]

	Dependent variable			
		Price change (percent)		
Category	*Probability of price change*	*All*	*Increases*	*Decreases*
Food	0.001	−0.168	0.700	−0.771***
	(0.001)	(0.522)	(0.456)	(0.221)
Soft drinks	−0.001	−1.644*	−1.678	0.393
	(0.001)	(0.924)	(1.997)	(0.513)
Alcohol	0.003	0.298	0.256	−0.064
	(0.002)	(0.790)	(0.781)	(0.552)
Personal products	0.003**	0.839	0.195	−0.602
	(0.001)	(0.527)	(0.477)	(0.361)
Observations	45	45	45	45

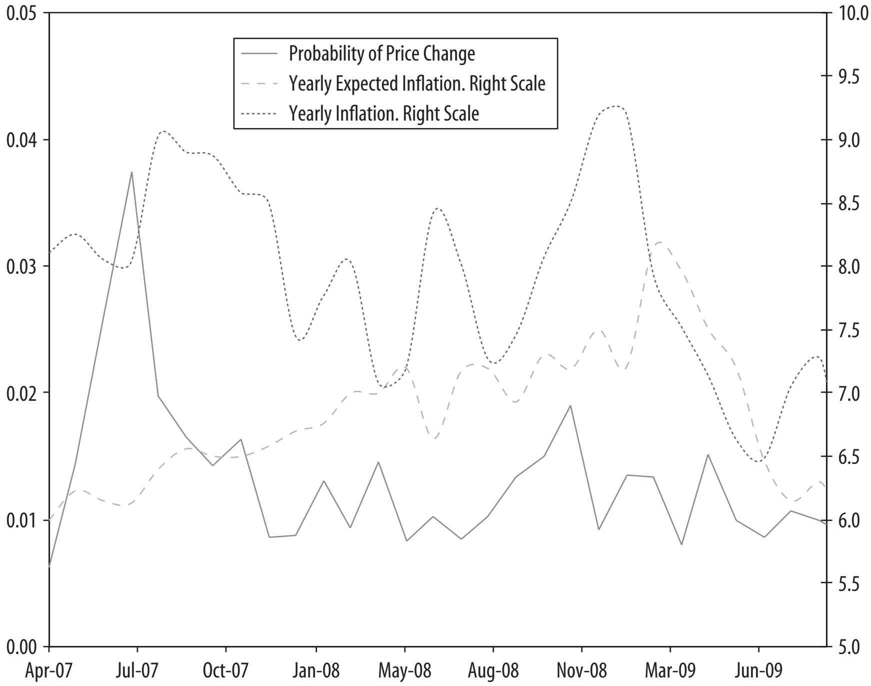
Source: Authors' calculations based on data from the Uruguayan Ministry of Economy and Finance and the Central Bank of Uruguay.
a. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

are expected inflation and indicator variables for the July 2007 tax reform. The expected inflation variable is the median forecast from a survey of experts conducted by the Central Bank of Uruguay. We include an indicator variable before and after the tax reform to capture anticipated effects of the reform.

The regression shows no correlation between changes in prices and inflation perceptions. If prices tended to be stickier, then inflation should not be expected to accelerate. It is interesting to point out that we observe a correlation between inflation and the percent variation in individual prices only when considering price decreases. The tax reform indicator variables suggest that supermarkets anticipated the reform and changed prices before the implementation of the reform in July 2007.

For a better understanding of the relationship between individual daily prices and inflation, we estimate the previous equation by product category. Table 5 shows the results of the coefficient on expected inflation. Interestingly, results indicate that there is a positive association between probability of price changes and expected inflation only for the personal product category. For the other product categories, the correlation is zero. That means that expectations about future inflation do not influence the price strategies of supermarkets in those markets. We do find an association between changes in prices and the average rate of price decreases in the food product category. To provide more evidence for this topic, figure 4 plots the probability of price adjustment (left

FIGURE 4. Probability of Price Change, Inflation, and Expected Inflation



Source: Authors' calculations base on data from the Ministry of Economy and Finance and the Central Bank of Uruguay.

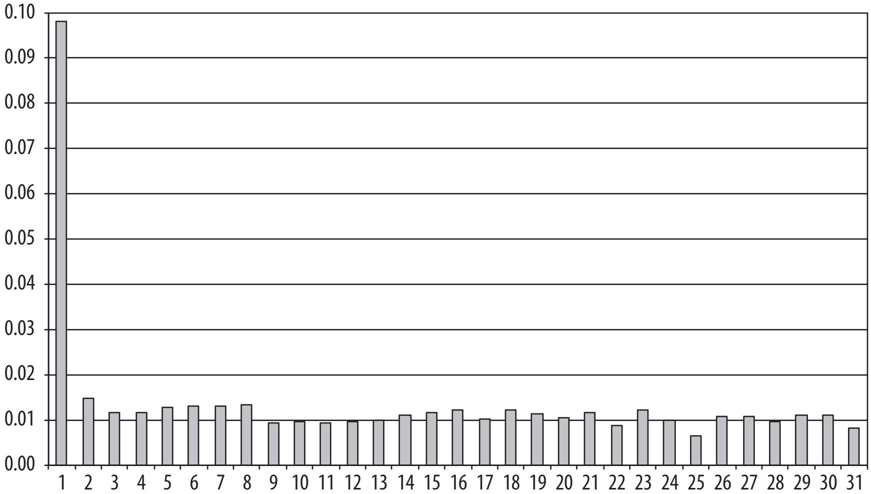
scale) and the inflation and expected inflation rates (right scale). We observe no association between price changes and inflation perceptions.

Price Changes by Day of the Month

Given that we have daily data, we can analyze the pricing decisions of supermarkets by day of the month. Figure 5a shows the probability of a price change by day of the month. Interestingly, the probability of price change is nine times higher on the first day of the month than on any other day. Figure 5b plots the daily probability of a price change from the second day to the last day of the month. In this case, we do not observe a clear pattern in the data.

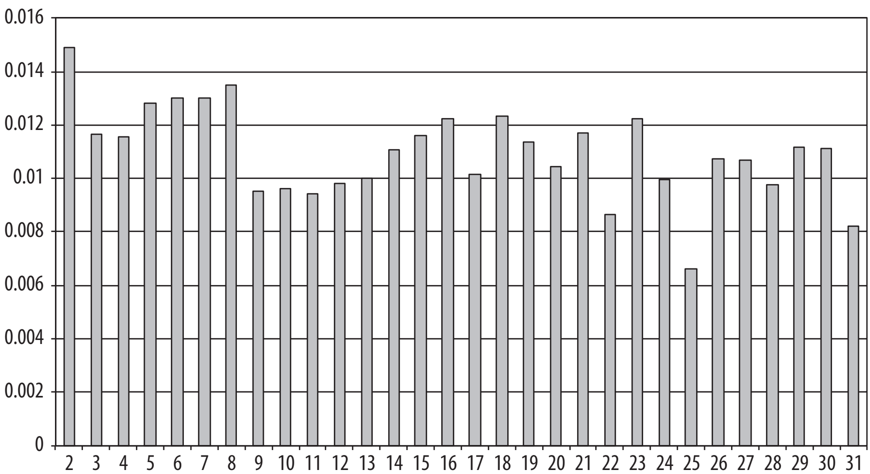
Figure 6 shows that price increases and decreases also are concentrated on the first day of the month. In addition, figure 7 shows that the finding that price changes are concentrated on the first day of the month is a general result, valid for all product categories. This is one of the most remarkable findings

FIGURE 5A. Probability of Price Change, by Day of Month



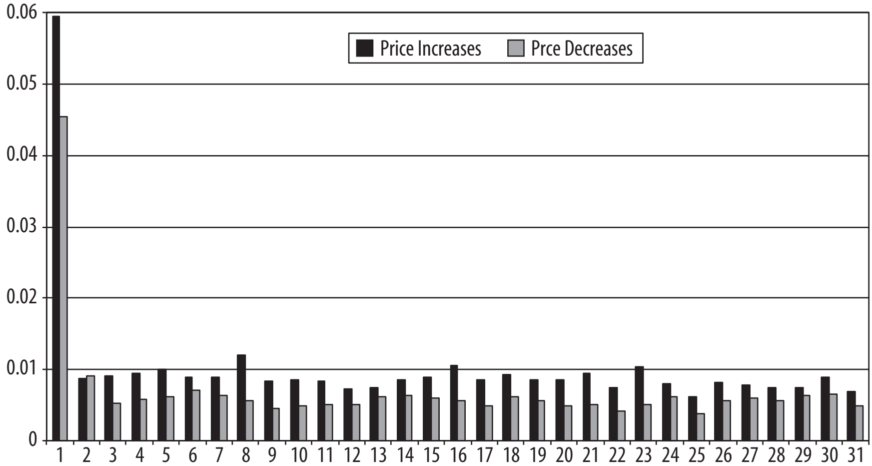
Source: Authors' calculations based on data from the Ministry of Economy and Finance.

FIGURE 5B. Probability of Price Change, by Day 2 to Day 31



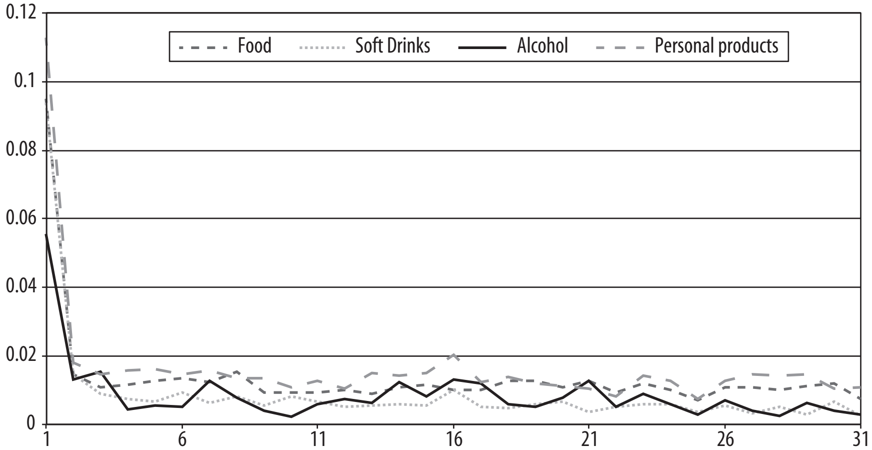
Source: Authors' calculations based on data from the Ministry of Economy and Finance.

FIGURE 6. Probability of Price Increases and Decreases, by Day of Month



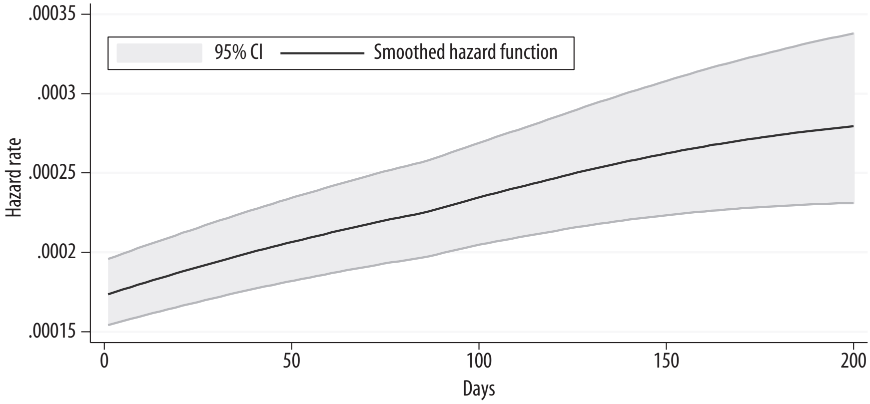
Source: Authors' calculations based on data from the Ministry of Economy and Finance.

FIGURE 7. Daily Probability of Price Change, by Product Category



Source: Authors' calculations based on data from the Ministry of Econonomy and Finance and the Central Bank of Uruguay.

FIGURE 8. Smoothed Hazard Estimate



Source: Authors' calculations based on data from the Ministry of Economy and Finance.

of our study, since to the best of our knowledge no other study analyzes the distribution of price changes by day of the month. One supermarket manager told us that this pricing behavior is related to producers, who tend to adjust their prices the first day of the month. In this case, the observed behavior could be a response to cost increases by supermarkets. The pattern is the same for price increases and price decreases. As price decreases are associated with sales, this implies that supermarkets tend to follow a pattern of price changes that concentrates most of them in one day, which may indicate the existence of menu costs associated with price change for supermarkets or some other rigidity that prevents the supermarkets from changing prices.

Hazard Rate Estimates

In order to study whether price changes are time dependent, we estimate the hazard rate. The hazard rate at moment *t* is calculated as the quotient of the number of prices that change at *t*, given that they do not change until that moment, over the number of prices that have not changed until moment *t.* As the greatest price duration is half a year (see appendix C) we calculate the hazard function up to 200 days. Figure 8 shows the smoothed hazard rates. We observe a hazard rate that is not constant over time. This result is consistent with results in Nakamura (2008) and Ellis (2009), although the authors find hazard rates to be decreasing and we find them to be increasing. The upward-sloping hazard rate is consistent with state-dependent pricing. This fact invalidates the modeling of a constant probability of price change and implies that

TABLE 6. Price Synchronization across Stores That Belong to the Same Chain

Chain	*Fisher and Konieczny indicator*
Devoto	0.94
Tienda Inglesa	0.92
Macromercado Mayorista	0.96
El Dorado	0.92
Multiahorro	0.91
Disco	0.96
Ta Ta	0.84

Source: Authors' calculations based on data from the Uruguayan Ministry of Economy and Finance.

supermarkets do not follow a time-dependent strategy for price setting. In turn, this result is in line with our finding of no seasonality in price changes.

Price Synchronization

We estimate price synchronization in two ways: across stores that belong to the same chain and across stores in each city. To estimate price synchronization we calculate the Fisher and Konieczny (2000) estimator (FK). Table 6 indicates that price changes across supermarkets of the same chain are highly synchronized.[2] For this result, two remarks are in order. First, our database consists of daily observations, and we find that prices change on average after about 2.5 months. Second, we also find that price changes are concentrated on the first day of the month. Therefore, our database has a great deal of synchronized "*no* price changes" and consequently a high FK. To control for this effect, we also estimate the FK synchronization indicator, conditional on price change (see table 7).

In this case, the synchronization estimates are lower than before, but the main result of high synchronization of price adjustments in supermarkets that belong to the same chain remains. This result is in contrast to that in Chaumont and others (2010), which finds much lower price synchronization for Chile. In addition, we estimate the FK synchronization indicator across the cities in our sample. Figure 9 shows the FK estimator for each city. As can be seen, synchronization is by itself large, with a minimum of 0.63 for Montevideo—which has the greatest number of supermarkets—and 1 for a large number of cities that have few supermarkets.

2. We estimate the FK indicator just for the major chains: those that have more than five stores and more than three cashiers per store on average.

TABLE 7. Adjusted Price Synchronization across Stores That Belong to the Same Chain, Conditional on Price Change

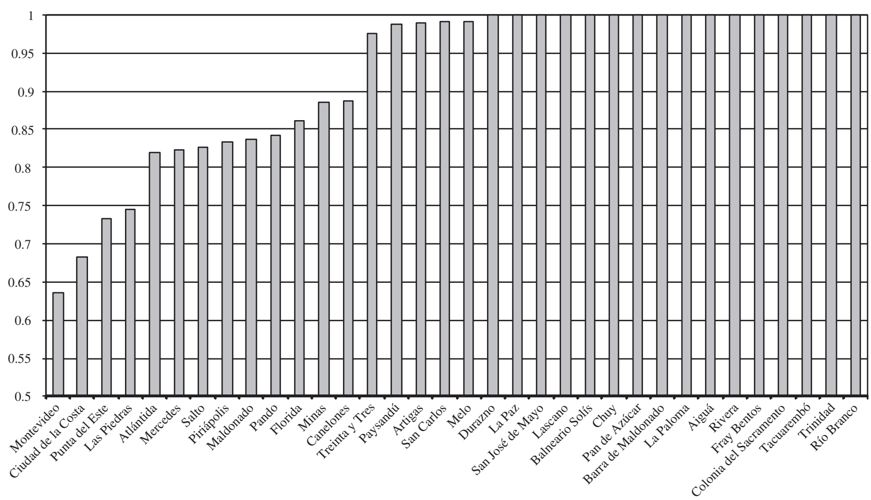
Chain	*Synchronization indicator*
Devoto	0.54
Tienda Inglesa	0.56
Macromercado Mayorista	0.75
El Dorado	0.51
Multiahorro	0.56
Disco	0.61
Ta Ta	0.36

Source: Authors' calculations based on data from the Ministry of Economy and Finance.

Comparing Results with Theory

Here we compare the results of the analysis with the main theoretical predictions of menu costs and time-dependent and state-dependent theories, discussing each stylized fact in the analysis and how it fits the theoretical explanations. Table 8 presents a brief summary of the analysis, in a vein similar to that of table 14 in Klenow and Malin (2010). As can be seen in the table, the empirical evidence seems to point to state-dependent models

FIGURE 9. Fisher and Konieczny Synchronization Indicator, by City



Source: Authors' calculations based on data from the Ministry of Economy and Finance

TABLE 8. Stylized Facts and Model Features

Fact	*Consistent Features*	*Inconsistent Features*
Price changes are somewhat flexible	Small menu costs	Large menu costs
No seasonality of price changes	State-dependent models	Time-dependent models
Price changes are mainly on the first day of the month	Time-dependent models	State-dependent models/ common shocks
Upward-sloping hazard rates	State-dependent models	Time-dependent models
Price changes are highly synchronized	State-dependent models/common shocks/strategic complementarities	Big idiosyncratic shocks

Source: Authors' elaboration.

as the main explanation for the inflation phenomena in Uruguay. The flexibility of prices remains a disputed issue in the empirical literature; as we have considered sales in our database, the relative flexibility could be less if we take them out.

Our results, unlike those in the empirical literature, found high synchronization of prices even at the chain and city level. That result could be driven by the particularity of our database, which consists of daily observations. In the same vein, we discovered that prices tend to change on the first day of the month. This result suggests that common shocks may be an important part of price adjustment policies of supermarkets.

We think that this result could not be explained in full using macro models. As all the items in our database are the highest-selling brands and most markets are oligopolies—even in the supermarket industry—price-setting behavior needs to be analyzed using micro modeling. As for the matter of prices changing mostly on the first day of the month, we think that this could serve as a reference point for price setting by supermarkets. Setting prices on this particular day, in turn, could reduce menu costs in the event of price changes.

Conclusions

This paper presents evidence on price formation at the retail level in Uruguay, drawn from a rich and unique data set of 30 million daily prices in grocery stores and supermarkets across the country, to analyze the behavior of consumer prices. We find that retail prices in Uruguay change frequently. Prices are less sticky than in the United States and Brazil but stickier than in the United Kingdom and Chile. The median duration of prices in Uruguay is 2.5 months.

We do not find evidence of a seasonal pattern in the adjustment of prices. The probability of price changes varies positively with expected inflation only for the personal products category. However, for the food category we find an association between price changes and the percentage rate of price decreases. In addition, we find that the probability of price changes on the first day of the month is nine times higher than on any other day of the month and the probability of price adjustments is not constant over time. Finally, we find very high synchronization of price changes.

This evidence seems to point to a state-dependent model of price changes. Nonetheless, the high synchronization of price changes is a newer element in the empirical literature, which could be the result of analyzing daily data. Last, the high concentration of price changes on the first day of the month needs further theoretical analysis, as one possible interpretation could be that this day serves as a reference point for price adjustment.

Appendix A. Plot of Cities Whose Data Were Included in the Study, Located in All *Departamentos* of Uruguay

Appendix B. List of Products[a]

Product	*Brand*	*Specification*	*Share in CPI (percent)*	*Category*
Beer	Patricia	0.96 L	0.3	Alcohol
Beer	Pilsen	0.96 L	0.3	Alcohol
Wine	Roses	1 L	0.34	Alcohol
Wine	Santa Teresa Clasico	1 L	0.34	Alcohol
Wine	Tango	1 L	0.34	Alcohol
Beef (*peceto*)	No brand	1 Kg	0.9	Food
Beef (*nalga*)	Boneless, no brand	1 Kg	0.43	Food
Beef (*nalga*)	With bone, no brand	1 Kg	0.43	Food
Beef (*aguja*)	Boneless, no brand	1 Kg	0.86	Food
Beef (*aguja*)	With bone, no brand	1 Kg	0.86	Food
Beef (*paleta*)	With bone, no brand	1 Kg	n/i	Food
Beef (*rueda*)	With bone, no brand	1 Kg	n/i	Food
Ground beef	Up to 20 percent fat	1 Kg	0.29	Food
Ground beef	Up to 5% fat	1 Kg	0.29	Food
Bread	No brand	1 unit (≈ 0.215 Kg)	1.21	Food
Brown eggs	El Ecologito	1/2 dozen	0.34	Food
Brown eggs	El Jefe	1/2 dozen	0.34	Food
Brown eggs	Prodhin	1/2 dozen	0.34	Food
Butter	Calcar	0.2 Kg	0.15	Food
Butter	Conaprole sin sal	0.2 Kg	0.15	Food
Butter	Lacterma	0.2 Kg	0.15	Food
Cacao	Copacabana	0.5 Kg	0.04	Food
Cacao	Vascolet	0.5 Kg	0.04	Food
Cheese	Cerros del Este	1 Kg	0.23	Food
Cheese	Dispnat	1 Kg	0.23	Food
Chicken	Avicola del Oeste	1 Kg	0.64	Food
Chicken	Tenent	1 Kg	0.64	Food
Coffee	Aguila	0.25 Kg	0.1	Food
Coffee	Chana	0.25 Kg	0.1	Food
Dulce de leche	Conaprole	1 Kg	0.14	Food
Dulce de leche	Los Nietitos	1 Kg	0.14	Food
Dulce de leche	Manjar	1 Kg	0.14	Food
Flour	Canuelas	1 Kg	0.16	Food
Flour	Cololo	1 Kg	0.16	Food
Flour	Puritas	1 Kg	0.16	Food
Frankfurters	Cattivelli	8 units (≈0.340 Kg)	0.26	Food
Frankfurters	Ottonello	8 units (≈0.330 Kg)	0.26	Food
Frankfurters	Schneck	8 units (≈0.330 Kg)	0.26	Food
Grated cheese	Conaprole	0.08 Kg	0.15	Food
Grated cheese	El Trebol	0.08 Kg	0.15	Food
Grated cheese	Milky	0.08 Kg	0.15	Food

(*continued*)

Product	Brand	Specification	Share in CPI (percent)	Category
Semolina noodles	Adria	0.5 Kg	N/I[b]	Food
Semolina noodles	Las Acacias	0.5 Kg	N/I[b]	Food
Ham	Centenario	1 Kg	0.21	Food
Ham	La Constancia	1 Kg	0.21	Food
Ham	Schneck	1 Kg	0.21	Food
Margarine	Danica dorada	0.2 Kg	0.02	Food
Margarine	Doriana nueva	0.25 Kg	0.02	Food
Margarine	Primor	0.25 Kg	0.02	Food
Mayonnaise	Fanacoa	0.5 Kg	0.09	Food
Mayonnaise	Hellmans	0.5 Kg	0.09	Food
Mayonnaise	Uruguay	0.5 Kg	0.09	Food
Noodles	Cololo	0.5 Kg	0.3	Food
Peach jam	Dulciora	0.5 Kg	0.17	Food
Peach jam	Limay	0.5 Kg	0.17	Food
Peach jam	Los Nietitos	0.5 Kg	0.17	Food
Peas	Arcor	0.35 Kg	0.05	Food
Peas	El Hogar	0.35 Kg	0.05	Food
Peas	Trofeo	0.35 Kg	0.05	Food
Quince jam	Los Nietitos	0.4 Kg	n/i	Food
Rice	Aruba tipo Patna	1 Kg	0.2	Food
Rice	Blue Patna	1 Kg	0.2	Food
Rice	Green Chef	1 Kg	0.2	Food
Rice	Pony	1 Kg	0.2	Food
Rice	Vidarroz	1 Kg	0.2	Food
Crackers	El Trigal	0.15 Kg	0.17	Food
Crackers	Famosa	0.14 Kg	0.17	Food
Crackers	Maestro Cubano	0.12 Kg	0.17	Food
Salt	Sek	0.5 Kg	0.05	Food
Salt	Torrevieja	0.5 Kg	0.05	Food
Salt	Urusal	0.5 Kg	0.05	Food
Semolina pasta	Adria	0.5 Kg	n/i	Food
Semolina pasta	Las Acacias—franja celeste	0.5 Kg	n/i	Food
Soybean oil	Condesa	0.9 L	n/i	Food
Sugar	Azucarlito	1 Kg	0.25	Food
Sugar	Bella Union	1 Kg	0.25	Food
Sunflower oil	Optimo	0.9 L	0.25	Food
Sunflower oil	Uruguay	0.9 L	0.25	Food
Tea	Hornimans	Box (10 units)	0.09	Food
Tea	La Virginia	Box (10 units)	0.09	Food
Tea	Lipton	Box (10 units)	0.09	Food

(*continued*)

Product	*Brand*	*Specification*	*Share in CPI (percent)*	*Category*
Tomato paste	Conaprole	1 L	0.08	Food
Tomato paste	De Ley	1 L	0.08	Food
Tomato paste	Qualitas	1 L	0.08	Food
Yerba	Canarias	1 Kg	0.34	Food
Yerba	Del Cebador	1 Kg	0.34	Food
Yerba	Sara	1 Kg	0.34	Food
Yogurt	Conaprole	0.5 Kg	0.06	Food
Yogurt	Parmalat (Skim)	0.5 Kg	0.06	Food
Bleach	Agua Jane	1 L	0.08	Personal
Bleach	Sello Rojo	1 L	0.08	Personal
Bleach	Solucion Cristal	1 L	0.08	Personal
Dishwashing detergent	Deterjane	1.25 L	0.2	Personal
Dishwashing detergent	Hurra Nevex Limon	1.25 L	0.2	Personal
Laundry soap	Drive	0.8 Kg	N/I[b]	Personal
Laundry soap	Nevex	0.8 Kg	N/I[b]	Personal
Laundry soap	Skip, Paquete azul	0.8 Kg	n/i	Personal
Laundry soap, in bar	Bull Dog	0.3 Kg (1 unit)	0.45	Personal
Laundry soap, in bar	Nevex	0.2 Kg (1 unit)	0.45	Personal
Shampoo	Fructis	0.35 L	n/i	Personal
Shampoo	Sedal	0.35 L	n/i	Personal
Shampoo	Suave	0.93 L	n/i	Personal
Soap	Astral	0.125 Kg	0.16	Personal
Soap	Palmolive	0.125 Kg	0.16	Personal
Soap	Suave	0.125 Kg	0.16	Personal
Toilet paper	Higienol Export	4 units (25 M each)	0.24	Personal
Toilet paper	Personal	4 units (25 M each)	0.24	Personal
Toilet paper	Sin Fin	4 units (25 M each)	0.24	Personal
Toothpaste	Closeup Triple	0.09 Kg	0.49	Personal
Toothpaste	Colgate Total	0.09 Kg	0.49	Personal
Toothpaste	Kolynos	0.09 Kg	0.49	Personal
Cola	Coca Cola	1.5 L	1.94	Soft drinks
Cola	Nix	1.5 L	1.94	Soft drinks
Cola	Pepsi	1.5 L	1.94	Soft drinks
Sparkling water	Matutina	2 L	0.7	Soft drinks
Sparkling water	Nativa	2 L	0.7	Soft drinks
Sparkling water	Salus	2.25 L	0.7	Soft drinks

Source: Authors' elaboration based on data from Ministry of Economy and Finance.

a. Kg = kilograms; L = liters; M = meters.

b. N/I = not included in the CPI.

Appendix C. Detailed Price Changes and Duration, by Product

Product	*Brand*	*Probability of daily variation*	*Monthly price duration*	*Percentage decrease*
Beer	Patricia	0.008	3.9	20.4
Beer	Pilsen	0.009	3.5	23.2
Wine	Roses	0.008	4.0	22.1
Wine	Santa Teresa Clasico	0.012	2.7	38.3
Wine	Tango	0.011	2.9	39.4
Beef (*peceto*)	No brand	0.026	1.2	40.3
Beef (*nalga*)	Boneless, no brand	0.027	1.2	43.1
Beef (*nalga*)	With bone, no brand	0.015	2.2	34.2
Beef (*aguja*)	Boneless, no brand	0.018	1.8	34.7
Beef (*aguja*)	With bone, no brand	0.027	1.2	40.1
Beef (*paleta*)	With bone, no brand	0.028	1.2	39.9
Beef (*rueda*)	With bone, no brand	0.013	2.5	34.2
Ground beef	Up to 20 percent fat	0.022	1.5	37.5
Ground beef	Up to 5 percent fat	0.019	1.7	36.6
Bread	No brand	0.011	2.9	28.6
Brown eggs	El Ecologito	0.007	5.0	24.7
Brown eggs	El Jefe	0.008	4.2	29.5
Brown eggs	Prodhin	0.012	2.8	33.8
Butter	Calcar	0.018	1.8	41.8
Butter	Conaprole sin sal	0.016	2.0	32.3
Butter	Lacterma	0.007	4.7	43.2
Cacao	Copacabana	0.011	2.9	34.4
Cacao	Vascolet	0.019	1.7	40.7
Cheese	Cerros del Este	0.068	0.5	45.0
Cheese	Dispnat	0.145	0.2	48.4
Chicken	Avicola del Oeste	0.041	0.8	42.8
Chicken	Tenent	0.039	0.8	44.6
Coffee	Aguila	0.009	3.7	34.0
Coffee	Chana	0.007	4.6	42.6
Dulce de leche	Conaprole	0.013	2.5	33.3
Dulce de leche	Los Nietitos	0.013	2.6	40.0
Dulce de leche	Manjar	0.013	2.6	31.4
Flour	Canuelas	0.027	1.2	43.7
Flour	Cololo	0.024	1.4	39.6
Flour	Puritas	0.015	2.2	36.3
Frankfurters	Cattivelli	0.010	3.2	45.7
Frankfurters	Ottonello	0.012	2.7	42.4
Frankfurters	Schneck	0.015	2.1	36.1
Grated cheese	Conaprole	0.009	3.8	25.1
Grated cheese	El Trebol	0.009	3.5	36.9
Grated cheese	Milky	0.007	4.4	30.0

(*continued*)

Product	Brand	Probability of daily variation	Monthly price duration	Percentage decrease
Semolina noodles	Adria	0.015	2.2	36.6
Semolina noodles	Las Acacias	0.019	1.7	40.2
Ham	Centenario	0.008	4.2	29.0
Ham	La Constancia	0.034	1.0	46.1
Ham	Schneck	0.015	2.2	35.8
Margarine	Danica dorada	0.012	2.7	39.0
Margarine	Doriana nueva	0.013	2.6	42.6
Margarine	Primor	0.016	2.1	41.2
Mayonnaise	Fanacoa	0.011	3.0	39.5
Mayonnaise	Hellmans	0.021	1.5	41.9
Mayonnaise	Uruguay	0.024	1.3	42.3
Noodles	Cololo	0.017	1.9	38.8
Peach jam	Dulciora	0.012	2.6	35.9
Peach jam	Limay	0.008	4.1	30.4
Peach jam	Los Nietitos	0.011	3.0	37.9
Peas	Arcor	0.010	3.3	42.9
Peas	El Hogar	0.009	3.5	25.3
Peas	Trofeo	0.017	1.9	44.4
Quince jam	Los Nietitos	0.011	2.9	38.6
Rice	Aruba tipo Patna	0.018	1.8	43.4
Rice	Blue Patna	0.024	1.4	41.4
Rice	Green Chef	0.027	1.2	42.6
Rice	Pony	0.009	3.5	41.1
Rice	Vidarroz	0.012	2.7	49.3
Crackers	El Trigal	0.009	3.6	32.4
Crackers	Famosa	0.010	3.2	29.5
Crackers	Maestro Cubano	0.012	2.6	41.1
Salt	Sek	0.011	3.1	41.9
Salt	Torrevieja	0.007	4.7	30.4
Salt	Urusal	0.012	2.7	41.7
Semolina pasta	Adria	0.015	2.2	35.6
Semolina pasta	Las Acacias	0.018	1.9	41.1
Soybean oil	Condesa	0.029	1.1	56.2
Sugar	Azucarlito	0.017	1.9	35.3
Sugar	Bella Union	0.017	2.0	34.7
Sunflower oil	Optimo	0.033	1.0	42.1
Sunflower oil	Uruguay	0.032	1.0	40.9
Tea	Hornimans	0.009	3.5	46.5
Tea	La Virginia	0.010	3.2	46.8
Tea	Lipton	0.009	3.8	40.6

(*continued*)

Product	*Brand*	*Probability of daily variation*	*Monthly price duration*	*Percentage decrease*
Tomato paste	Conaprole	0.017	1.9	36.3
Tomato paste	De Ley	0.012	2.7	34.4
Tomato paste	Qualitas	0.012	2.8	45.8
Yerba	Canarias	0.013	2.5	38.1
Yerba	Del Cebador	0.013	2.5	36.4
Yerba	Sara	0.015	2.2	40.4
Yogurt	Conaprole	0.013	2.6	29.5
Yogurt	Parmalat (Skim)	0.012	2.8	34.1
Bleach	Agua Jane	0.018	1.8	37.7
Bleach	Sello Rojo	0.015	2.2	33.6
Bleach	Solucion Cristal	0.018	1.8	43.3
Dishwashing detergent	Deterjane	0.024	1.3	44.1
Dishwashing detergent	Hurra Nevex Limon	0.024	1.4	43.3
Laundry soap	Drive	0.015	2.2	43.1
Laundry soap	Nevex	0.023	1.4	44.8
Laundry soap	Skip, paquete azul	0.018	1.8	45.3
Laundry soap, in bar	Bull Dog	0.016	2.0	39.6
Laundry soap, in bar	Nevex	0.015	2.2	39.8
Shampoo	Fructis	0.022	1.5	44.5
Shampoo	Sedal	0.016	2.1	47.3
Shampoo	Suave	0.011	3.0	45.0
Soap	Astral	0.018	1.8	46.3
Soap	Palmolive	0.023	1.4	50.0
Soap	Suave	0.013	2.5	46.6
Toilet paper	Higienol Export	0.016	2.1	32.7
Toilet paper	Personal	0.013	2.5	31.8
Toilet paper	Sin Fin	0.021	1.6	41.8
Toothpaste	Closeup Triple	0.009	3.7	38.1
Toothpaste	Colgate Total	0.023	1.4	39.1
Toothpaste	Kolynos	0.013	2.5	34.6
Cola	Coca Cola	0.010	3.3	25.5
Cola	Nix	0.008	4.0	34.6
Cola	Pepsi	0.010	3.2	31.7
Sparkling Water	Matutina	0.011	3.0	43.0
Sparkling Water	Nativa	0.007	4.6	27.0
Sparkling Water	Salus	0.013	2.6	35.0

Source: Authors' elaboration based on data from the Ministry of Economy and Finance.