Fundação Getúlio Vargas
Escola de Pós-Graduação em Economia - EPGE

The Behavior of Temporary Sales in a Macroeconomic Context

Dissertação submetida à Escola de Pós-Graduação em Economia
da Fundação Getúlio Vargas como requisito de obtenção do título de
Mestre em Economia

Aluno: João Luiz Ayres Queiroz da Silva
Orientador: Marco Antonio Bonomo
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Rio de Janeiro
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Resumo

Nós investigamos promoções temporárias usando uma base de dados detalhada de 13 anos sobre preços ao consumidor no Brasil, com cotações de preços coletadas decendialmente. Nós encontramos forte evidências da existência de relação entre a frequência e tamanho de promoções e as variáveis macroeconômicas. A crença comum na literatura de que promoções não reagem a mudanças nas variáveis macroeconômicas pode ser devido a baixa volatilidade do cenário macroeconômico nos países analisados até o presente momento.

Abstract

We investigate temporary sales using a very detailed data set for 13 years of retail prices in the Brazilian economy, with price quotes collected every 10-days. We find strong evidence of co-movement between frequency and size of sales and the macroeconomic varibles. The common belief in the literature that sales do not react to changes in macroeconomic variables may be due to little macro volatility in the analysed countries so far.

Palavras-Chave: Consumer Prices, Micro-Data, Temporary Sales, Variable Macroeconomic Enviroment.

1 Introduction

In recent years economists have obtained access to new data sets containing micro data information about prices. These recent studies have provided new information on price setting behavior creating new challenges for macroeconomic models of monetary economics to match the new empirical evidences. Models of sticky information[1] and sticky prices, both time-dependent[2] and state-dependent[3], can now be evaluated according to these new stylized facts on price dynamics. However, one of these new stylized facts has been a teaser for these macroeconomic models: the significant presence of temporary sales.

Instead of choosing just the regular price, it was verified that a typical retail firm often deals with the choice of two additional variables: the size and the frequency of temporary sales. According to Klenow and Kryvtsov (2008) temporary sales represent 11% of price quotes and 20% of price changes for consumer prices in the United States (US). In our data set from Brazilian Consumer Price Index (CPI) of Fundação Getúlio Vargas (FGV) sales represent $4.7-7.8\%$ of total price quotes and $16.7-24.6\%$ of the frequency of total price changes.[4] If we consider the hypothesis that higher quantities of products are sold during temporary sales than during regular prices, then we must conclude that sales represent an important feature of price setting in the economy. Even so, there is still a great discussion if sales reflect macroeconomic conditions or not.[5] International empirical evidence indicates a weak relationship between macro variables and temporary sales[6], and this may be the reason why most macroeconomic studies have ignored it so far.[7] Our estimates, however, do not support this view, since we verify a strong co-movement between the size and frequency of temporary sales and a group of selected macroeconomic variables in Brazil.

The micro data studies also show that price setting statistics drastically change depending on how sale price quotes are treated in their respective samples, with important implications for actual monetary policies followed by central banks. If sales are considered as ordinary price changes, then prices are highly flexible and monetary shocks has small real effects. In contrast, when excluding sales from the sample, prices seem to be very sticky and monetary shocks present larger real effects. For example, Nakamura and Steinsson (2008) find that the median frequency of price changes may vary from 8.7% to 19.4% depending on the treatment given to sale price quotes, resulting in implied durations of 11 months and 4.6 months, respectively.[8]

In addition, the average size of price changes is also affected by the treatment given to sale price quotes, since the size of price changes involving sales seem to be much larger than the regular price ones. Nakamura and Steinsson (2008) show that the median size of price changes may vary from 8.5% to 10.7%. Therefore, as the frequency of price changes and their size are key statistics when calibrating either sticky information or sticky price models, these different estimates on price

[1] See Mankiw and Reis (2002) for an example of sticky information model.

[2] See Bonomo and Carvalho (2004) for an example of time-dependent model.

[3] See Golosov and Lucas (2007) for an example of state-dependent model.

[4] The estimates differ according to the sales definition we use and weightening. See section 4.1.

[5] See Nakamura and Steinsson (2008) and Klenow and Willis (2007).

[6] See Nakamura and Steinsson (2008). We discuss their results in the next Section.

[7] Exception for Guimaraes and Sheedy (2008).

[8] Here we consider NS estimates excluding substitutions. The implied duration is calculated as $\frac{-1}{\ln(1-f)}$, where f is the median frequency of price changes.

setting statistics gave rise to the discussion about how these models should be calibrated.[9]

Kehoe and Midrigan (2008) suggest that standard time-dependent and state-dependent models, that do not contain sales explicitly, overestimate the real effects of monetary shocks when calibrated with the frequency of price changes excluding sales; and that they underestimate these effects when calibrated with the frequency of price changes including sales. Golosov and Lucas (2007), on the other hand, suggest two options to deal with this problem: keeping sales out of the model and using the frequency of price changes excluding sales; or adding sales to the model and using the frequency of price changes including all prices[10]. It is important to notice, though, that there is an implicit hypothesis when choosing the first option: that the frequency and size of sales do not react to changes in the macroeconomic environment. We show that this hypothesis does not reflect the behavior of temporary sales for the Brazilian economy.

Using both Ordinary Least Squares (OLS) and Fixed Effects Panel estimations, we show that the evidences for the Brazilian economy suggest that the frequency and size of sales strongly co-moves with inflation, economic activity, macroeconomic uncertainty and variations of the exchange rate, meaning that there is a relationship between sales and macroeconomic variables that should not be neglected. We claim that the lack of evidence of other empirical studies are due to the relative stable macroeconomic environment and little price setting variability. During the period covered by our data set (1996-2009) Brazil experienced changes of exchange rate and monetary regimes, two emerging market crises, energy rationing and an election crisis, all contributing for a large macroeconomic variability.

We also provide some useful statistics about sales for the Brazilian economy that can be used as a comparison to the estimates of KK and NS. Similarly to them, we find high heterogeneity among temporary sales statistics among different economic groups of products.

This paper is organized as follows: In the next section we present an overview of the literature, both empirical and theoretical, about sales. In section 3 we describe the data set and how we treated it. The main empirical evidence about sales in Brazil is presented in section 4. Section 5 we provide evidence on how sales statistics co-moves with macroeconomic variables. The last section concludes.

2 What do we know about temporary sales ?

As stated before, microdata studies have verified that temporary sales play a significant role in retail pricing. These statistics are mostly based on studies involving the Bureau of Labor Statistics (BLS) data set used to calculate the US CPI. Here we mention three of these works that together comprise most of the empirical evidence on temporary sales from micro data:[11] Hosken and Reiffen (2004a), Klenow and Kryvtsov (2008) (henceforth KK) and Nakamura and Steinsson (2008) (henceforth NS). Hosken and Reiffen (2004a) verify that sales are responsible for $20\%-50\%$ of annual variation in retail prices for popular product categories and represent roughly 8% of price quotes in their

[9] See Golosov and Lucas (2007) for an example of calibration using price setting statistics from micro data studies.

[10] Both models, NS and Golosov and Lucas (2008), do not contain sales and they calibrate them using the frequency of price changes without sales.

[11] Althoug they all use the data set from BLS, there are significant differences between their samples. See Hosken and Reiffen (2004), Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) for a full description of their samples.

sample. KK verify that sales represent roughly 11% of price quotes and 20% of price changes in their sample and, finally, NS verify that sales represent 21.5% of price changes in their sample.[12] Based on these facts, we can only conclude that sales represent an important feature of retailer behavior. However, it has been a challenge for Industrial Organization (IO) researchers to develop theoretical models able to explain their existence while matching the empirical evidence. In this section we discuss some of these models.

Some models explain sales as a feature of equilibrium in static price competition models, usually considering heterogeneous consumers. For example, Salop and Stiglitz (1977) analyze a static model where firms producing a single product compete in prices in a market with heterogeneous consumers, differing in respect to their costs for acquiring full information about prices. They show that there will be an equilibrium with price dispersion (a lower price being the competitive price and a higher price being the monopolistic price) where the consumers with lower cost to acquire information will choose to get informed and the others will not. The fact that the same product is charged by a lower price should characterize the sales behavior. Varian (1980) also consider the case where there are informed and uninformed consumers in the market, but firms have the possibility to adopt random pricing strategies, creating a dynamic aspect, and faces a declining average cost curve[13]. Therefore, these random pricing strategies in equilibrium are interpreted as sales behavior. Braido (2009) analyze the case of a Bertrand model of price competition with multiproduct firms where the firms face fixed costs. The author shows that the presence of fixed costs, even with homogeneous consumers, is enough to make the symmetric random strategy equilibrium the only possible one.

Sales are also explained as an output of dynamic models, such as Salop and Stiglitz (1982), Conlisk *et. al.* (1984) and Sobel (1984). Salop and Stiglitz (1982) consider a dynamic model of a single product economy where each consumer lives for two periods and demands one unit of the product per period if its price is below the consumer reservation price. Hence, each consumer has the possibility of buying two units of the product in the first period and saving one unit for consumption in the second period. Considering the existence of a storage cost and a cost for re-entering the market in the second period, the authors show the existence of an equilibrium with price dispersion between two prices, where the lower price should represent a sale. Conlinsk et. al. (1984) and Sobel (1984), on the other hand, explain sales as an intertemporal price discrimination strategy adopted by firms. The first consider a single product economy with a single monopolistic firm, where a new cohort of consumers enters the market each period willing to make a once-and-for-all purchase of this product. The consumers within each cohort differ in respect to their reservation prices and, consequently, the firm will choose to charge the higher price most of the time for those consumers with higher reservation prices, but there will be times when the firm will choose to lower its price to capture all those consumers with low reservation price waiting to make their purchase. Sobel (1984) extend this model to the case with many firms competing in an oligopolistic market and verify that the motivation for the sales behavior remains.

The models cited above are based only on single product firms. Hosken and Reiffen (2004b),

[12] It is important to mention that NS and KK use the sale flag presented in the BLS data set to analyze sales, while Hosken and Reiffen (2004) use a sale filter similar to the one used in our analysis. See section 4.1.

[13] The hypothesis of declining average cost curves and price competition rules out the possibility of a pure strategy equilibrium.

however, show that when retailers sell many products, there is an incentive to advertise sales for specific products because the retailer expects to sell a bundle of products, and not just one. Therefore, the authors argue that the most popular products are usually advertised on sale by firms in order to attract the consumers to their stores and save advertisement costs. Finally, we also have to consider the models that attribute sales to inventory management strategies. Lazear (1986), for example, develop a model where firms selling a durable good have the opportunity to reprice its product each period. Therefore, the firm may lower its price if the good remains too long on the shelf or goes out of fashion. These models gave rise to the definition of *clearance sales*, where a firm lower the price of its product before it leaves the market.

As we may notice, there is still a lot of divergence between models trying to explain the sales behavior. Moreover, Hosken and Reiffen (2004b) show that none of these models are able to match the empirical evidences on temporary sales presented in the microdata studies.

2.1 Temporary Sales and Macroeconomic Variables

If it remains a puzzle for the IO literature to explain the existence of sales, the incorporation of sales by macroeconomic models of monetary economics becomes a very difficult task. As we could see, none of these models involving sales give us an idea about how the price setting variables (regular price, sale price, and the probability of having a sale) would react when firms face either cost or demand shocks To our knowledge, there is just one study that explicitly added sales to a macroeconomic model; the work of Guimaraes and Sheedy (2008).

The authors develop a time-dependent model with heterogeneous consumers differing in their price elasticities. Each firm faces two types of consumers: those with high price elasticity and those with low price elasticity. In equilibrium, firms will choose to charge a higher price some periods, but will often lower its price to capture the consumers that have higher price elasticity. This behavior, therefore, should represent a sale. The firm will choose the sale price, the regular price, and the fraction of time that the product will be on sale. In this case it is not optimal for the firms to charge just the higher price, because a firm that lower its price would capture all those consumers that are very price sensitive and would increase its profits. Similarly, if all firms charged the lower price, it would be optimal for a firm to raise its price in order to focus just on those consumers that are not very price sensitive.

Hence, considering the case where the firm optimally sets its regular price, its sale price and the probability of having a temporary sale, their results are quite similar to the ones obtained by standard macroeconomic models that do not contain sales explicitly, suggesting that this microeconomic variability in prices do not affect aggregate price rigidity. In our results, we find a significant relationship between macroeconomic variables and sales statistics, but all of small magnitudes, which does not contradict the implications of their model.

2.1.1 Previous Empirical Studies

Moreover, there are just few empirical studies that tried to explore the question of how sales react to macroeconomic shocks. NS regress a panel of the frequency and size of sales on the

CPI, a time trend and Entry Level Item (henceforth ELI) fixed effects.[14] Their results suggest a *negative* relationship between the macroeconomic variable and the frequency of temporary sales and a *positive* relationship between the macroeconomic variable and the size of sales, but both estimates are not statistically significant. The authors point to the fact that there was not too much variability in the inflation rate during the covered period to capture it. Our results, on the other hand, indicate a statistically significant *positive* relationship between the inflation rate and the frequency of sales and a *negative* but not statistically significant relationship regarding the size of sales. Finally, Klenow and Willis (2007) regress the size of price changes due to sales on their estimate of predicted price changes due to new information on aggregate prices and conclude that the size of price changes involving sales does react in response to new macro information.[15] Again, in contrast to our results, they point to a *positive* relationship between the size of sales and recent inflation.

Despite these results, we consider that there is one drawback when using the CPI Research Database to analyze temporary sales: the price quotes are collected either monthly or bimonthly, while empirical evidence from higher frequency data sets suggest that sales last less than a month.[16] This makes their estimates less accurate for the size and frequency of sales, and downward biased for the frequency of sales, so we should be cautious when interpreting their results. We will see that our data set contains price quotes collected in every 10 days and that the macroeconomic variables present much more variability.

3 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. Our data base was extracted from the CPI-FGV electronic data set, which stores the primary data used in the construction of the index since 1996. This data set was used previously in Barros *et. al.* (2009) (henceforth BBCM (2009)), but here we work with 10 days interval prices.

3.1 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.

[14] See Nakamura and Steinsson (2008) for the definition of ELI.
[15] They also use the CPI Research Database. See Klenow and Willis (2007) for more detail.
[16] See Pesendorfer (2002).

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 5).

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 June 2009. 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.[17] 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 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.[18] 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 - Jun/09	7	Belo Horizonte, Brasília, Porto Alegre, Recife, Rio de Janeiro, Salvador, São Paulo

[17] 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.

[18] 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.

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 purposively substituted by a similar item, while in our sample this type of rotation is not done; instead, new items are introduced.

3.2 Data treatment

Since we are analyzing sales, which in general have short length, we have decided to work only with those items whose prices were collected in every 10-days. In order to keep the same city coverage during the whole sample, we only use the price records from Rio de Janeiro and São Paulo, which together represent 63% of the sample. We also discard the regulated goods since they are not relevant to our analyses of sales[19]. Their weight in the CPI-FGV amounts to about 30%.

We start from the full sample with approximately 23 million quotations. Keeping only the non-regulated products and product categories that have prices collected every 10-days the sample is reduced to 16.3 million observations. When excluding price quotes from cities other than Rio de Janeiro and São Paulo, we reach 10, 216, 189 price quotes.

To avoid the problem of mistaken item inclusions in the base, that often happens, we exclude items whose quote lines are shorter than 12 months (36 10-days intervals). Finally, we attribute missing values to outliers. We define as outliers all prices that are larger than 10 times or smaller than 0.1 times their preceding prices[20]. We achieve, then, our final sample comprising 10, 185, 585 of price quotes (roughly 44.3% of our initial data set).

4 Sales statistics

In this section we calculate statistics on sales at both sectorial and aggregate levels, for their various definitions. We start by presenting the definitions of sales that we use in this study.

4.1 Sales Definitions

The identification of sales was not straightforward in our analysis. As we do not observe the sale flag indicator[21] and as we are dealing with price quotes collected every 10-days, we decided to create different definitions of sales in comparison to other studies. In fact, we adopted four definitions of sales (Sale-1,Sale-2, Sale-3 and Sale-4), differing just on their maximum length. Sale-1 represents one-period asymmetric V-shape sales; Sale-2 represents two-periods asymmetric V-shape sales; Sale-3 represents three-periods asymmetric V-shape sales; and Sale-4 represents four-periods asymmetric V-shape sales.

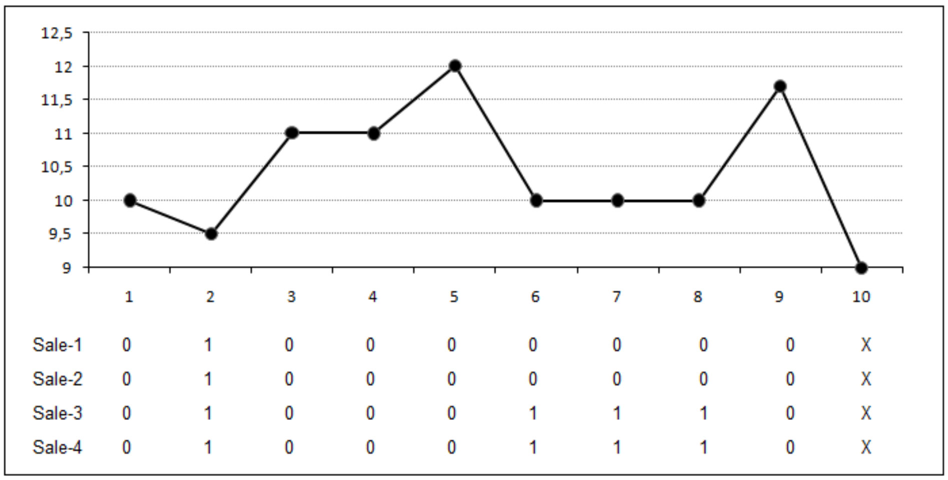
A z-periods ($z = 1, 2, 3, 4$) sale in t is identified by a price decrease of at least 5%, 10% or 20%,[22] in t, followed by a price increase of at least $\left(1 - \frac{p_t}{p_{t-1}}\right)$% up to z periods[23]. During the period between the price decrease and increase, we do not allow any other price changes, even if they are very small. As we can see, they are called asymmetric V-shape sales because the price after-sale does not need to return exactly to its pre-sale price. In fact, we even allow an after-sale price a bit lower than the pre-sale price. Finally, note that if a price quote has a sale indicator equal to one according to Sale-1, it must have a sale indicator equal to one for Sale-2, Sale-3 and Sale-4 and henceforth.

In Figure 1 we show an example of a hypothetical price series during ten periods where there are no missing values. Here, we will be considering the minimum size of 5% as an example. Despite the fact that we do not observe the price quote before period 1, we can conclude that the price quote in the first period does not represent a sale,

[19] Regulated goods do not have sales by definition.
[20] This aims at eliminating common typing errors.
[21] Our data set does contain the variable indicating sale prices, but depending on the period and location, it was not reported. Therefore, it does not represent reliable information.
[22] Here we follow Hosken and Heifen (2004a) and set a minimum price decrease to characterize a sale. We have results using these different sizes, but we will use 10% as our benchmark.
[23] Following these definitions, we do not identify *clearance sales*.

regardless of which definition of sales we use, because it is followed by a price decrease between periods 1 and 2. In period 2 we observe a price decrease of 5% followed by a price increase of more than 5%. Therefore, regardless of the definition of sales we use, the price quote in period 2 does represent a temporary sale. The price quotes in periods 3, 5 and 9 exhibit the sale indicator equal to zero because they represent price increases. The price quote in period 4 do not represent a sale price because it is equal to its preceding price quote that has a sale indicator equal to zero. The price quotes in periods 6, 7 and 8 will exhibit the sale indicator equal to one for Sale-3 and Sale-4, but not for Sale-1 and Sale-2, since it lasts more than two periods. In this case, note that the after-sale price is a bit lower than the pre-sale price. Finally, we are not able to conclude if the price quote in period 10 represents a sale price or not, since there is a price decrease of more than 5% between periods 9 and 10 and we do not observe the price quote after that period. Therefore, the sale indicator will be missing in period 10 for all definitions.

Figure 1: Construction of Sales Indicators



In order to analyze the effects of missing price quotes in our sample, in Figure 2 we consider the same price series as before, but now we do not observe the price quotes in periods 3 and 9. Therefore, regardless of which definition of sales we use, the sale price indicator in periods 2, 3 and 4 will be missing. For the sale price indicators in periods 6, 7 and 8, the impact of a missing price in period 9 will differ according to which definition of sales we use. Following Sale-1 or Sale-2, the sale price indicator will be zero in periods 6, 7 and 8. However, according to Sale-3 and Sale-4, the sale price indicator will be missing for periods 6, 7 and 8. The reason becomes clear when we compare both pictures because, depending on the value of the price quote in period 9, we could have a sale price or not under Sale-3 and Sale-4 definitions. The sale indicator in period 9 will be missing for all definitions.

Considering the minimum size of 10%, sale price quotes represent 4.7%, 6.2%, 7.3% and 7.8% of total price quotes in our sample according to Sale-1, Sale-2, Sale-3 and Sale-4, respectively. In fact, the different definitions presented above will not make much difference when reporting aggregate sales statistics because, as we show in Table 3, they are highly correlated.

4.2 Frequency and size of sales - Definitions

In order to define the frequency of sales for a particular product in a given period, we consider the sale indicator for each of the three definitions of sales specified above: $Isale\_z_d^{yi}$, where z denotes the definition of sales we are considering ($z = 1, 2, 3, 4$), subscript i refers to the specific item, y represents the product associated to this specific item and t denotes the period. Note that we are considering each period as a 10 days interval, so we have 479 periods in our sample.

We define S_i as the set items for time d:

$$S_d = \left\{ 0 \leq i \leq \bar{i}, Isale\_z_d^{yi} \in \{0, 1\} \right\}.$$

Figure 2: Construction of Sales Indicators - Missing Values

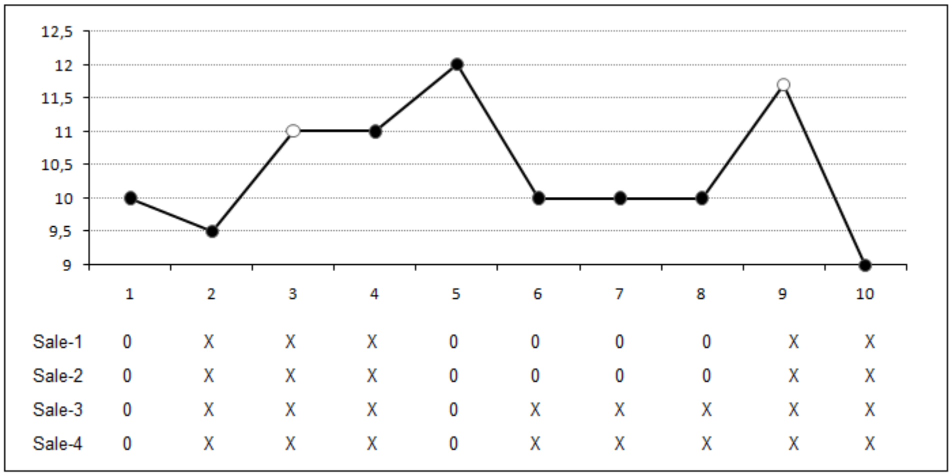


Table 3: Correlations Between Sales Definitions

Correlations	Sale-1	Sale-2	Sale-3	Sale-4
Sale-1	1	0.9396	0.8528	0.8205
Sale-2	0.9396	1	0.9183	0.8866
Sale-3	0.8528	0.9183	1	0.9631
Sale-4	0.8205	0.8866	0.9631	1

The statistics reported refer to the correlations between the different sales definitions we used. Here, we used the minimum size of 10%.

Therefore, we formally define the frequency of sales of each product in each period as:

$$freq\_sale\_z_d^y = \frac{\sum_{i=1}^{N_{yd}} Isale\_z_d^{yi}}{N_{yd}}$$

Where $N_{yd} \equiv card\,(S_d)$ denotes the number of elements in set S_d (its cardinality) representing the number of items associated with product y that have a non-missing sale indicator according to definition z in period d.

The definition for the size of sales depends on whether we observe a sale or not. We define R_i as the set items for time d:

$$R_d = \left\{0 \leq i \leq \bar{i}, Isale\_z_d^{yi} = 1 \text{ } and \text{ } Isale\_z_{d-1}^{yi} \neq 1\right\}.$$

In the case where the item does not present the sale indicator equal to one, the sale size will be missing. Therefore, we define the size of a sale for product y in period t according to definition z, as:

$$sz\_sale\_z_d^y = \frac{\sum_{i=1}^{M_{yd}} \ln\left(\frac{p_{d-1}}{p_d}\right)}{M_{yd}}$$

In this case, $M_{yd} = card(R_d)$ represent the number of items associated with product y that has the sale indicator (according to definition z) equal to 1 in period d and equal to 0 in period $d-1$. Therefore, the size of a sale for product j in period d represents the arithmetic average of the log price changes of those items associated to product

j that had a sale in period d. Note that we are considering just the first sale price after the price decrease in the sale size definition. Otherwise, we would have sales with size equal to zero. See Figure 1, for example. Using Sale-3, we would have a sale size equal to zero between periods 7 and 8.

4.3 Sales Aggregated Statistics

In this section we calculate aggregate statistics on the frequency and size of sales. The frequency of sales of each product is defined as the arithmetic average of the variable $freq\_sale\_z_d^y$ across time[24]. Unless otherwise specified, we will be considering $z = 2$ and minimum size of 10% as our benchmark.

The measure of the aggregate frequency of temporary sales in our sample is obtained by computing the weighted average of the Y product frequencies, with the weights used in the CPI-FGV[25]:

$$freq\_sale = \sum_{y=1}^{Y} \omega_y freq\_sale\_z^y.$$

The aggregate frequency of price adjustment is 47.6% (weighted mean). We may compare this statistic with the result of 37.2% that was found for monthly data in BBCM (2009). The frequency of positive variations is 25.5% and exceeds the frequency of price decreases of 22.2%. If we replace the previous price as sales occurs, and define this price as a regular one, the frequency of total price variation reduces to 43.1%.for Sale−2, for example. The frequency of regular prices defined according to the other three definitions of sales does not seen to differ significantly, which should be expected since the four measures of sales are strongly correlated.

Table 4: Frequency of price changes

Frequency of Price Changes (Weighted)	Mean	Up	Down
All - Aggregated	47.6%	25.5%	22.2%
Regular: Excluding Sale-1	43.6%	23.8%	19.8%
Regular: Excluding Sale-2	43.1%	23.6%	19.5%
Regular: Excluding Sale-3	43.0%	23.6%	19.4%
Regular: Excluding Sale-4	42.9%	23.5%	19.3%

Sample runs from March 1996 through June 2009. The statistics reported use weights from the Family Budget Survey used on CPI-FGV from January on.

As can be seen in Table 5, in Brazil sales occurs in $3.9 - 7.8\%$ of price quotes, depending on the definition of sales and weightening. We can also see that the largest fraction of these temporary price decreases (sales) is symmetric, that is, the price returns to its previous level. In NS(2008), where the sale flag indicator was used to identify sales, the authors found this same pattern.

In Table 6 we report the fraction of price changes involving price quotes with sale indicator equal to one, i. e., price changes that are sales related. We can see that sales represent $16.7 - 24.6\%$ of total price changes.

The unconditional average size of a price adjustment was computed in a similar way, where the absolute size of variation was averaged whenever the respective indicator was 1. The absolute size of sales variation for Sale-2 is quite large, 25.1%, and exceed the regular price change of 11.7% as can be seen from Table 8 and Table **??**. The results for the other sales definitions are almost the same. It is important to notice that since we are selecting as sales those temporary price decreases larger than 10%, in this case, we could already expect higher values for the size of sales, unless there were many large price changes lasting more than 4 periods and few price changes smaller than 10%.

An important point is that, since we do not use the sale flag indicator, we may be considering normal price changes as sales, especially for those items whose price volatility is very high. The use of different minimum sizes

[24] In Table **??** in appendix we report the frequency of sales for each product.

[25] 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.

Table 5: Aggregated Frequency of Temporary Sales

Frequency of Sales (% of Total)	Mean	Symmetric	Up	Down	Mean (Non-Weighted)
Sale-1	3.9%	2.0%	1.4%	0.5%	4.7%
Sale-2	5.1%	2.6%	1.8%	0.7%	6.2%
Sale-3	6.0%	3.1%	2.1%	0.8%	7.3%
Sale-4	6.3%	3.3%	2.3%	0.8%	7.8%

The statistics reported refers to the percentage of price quotes with the sale indicator equal to one over the full sample of price quotes. We use the minimum size of 10%. Symmetric means that the price returns to its previous level. Up means that the price returns to a higher level, and Down means that the price returns to a lower level. These statistics were calculated using the weights from CPI-FGV.

Table 6: Fraction of Price Changes Due to Sales

Fraction of Price Changes due to Sales	Mean	Symmetric	Up	Down	Mean (Non-Weighted)
Sale-1	16.7%	8.9%	5.6%	2.2%	19.4%
Sale-2	19.4%	10.3%	6.6%	2.6%	22.7%
Sale-3	20.7%	11.1%	6.9%	2.7%	24.2%
Sale-4	21.0%	11.3%	7.0%	2.7%	24.6%

The statistics reported refers to the percentage of price price changes involving price quotes with sale indicator equal to one. We use the minimum size of 10%. These statistics were calculated using the weights from CPI-FGV.

for sales (5%, 10% and 20%) and considering just symmetric temporary price changes should serve as a robustness check. We also divided the items into 12 groups of price stickiness to check how the frequency and size of sales are affected. The statistics of the fraction of price changes due to sales and its size are reported in Table 9. To separate into these 12 groups, we use the concept of implied duration [26]. We did not report the frequency of sales, because the number of price quotes with sale indicator equal to zero would increase as the implied duration (frequency of price changes) gets higher (lower) and would make it difficult to interpret them. From now on, the statistics reported will be related to the Sale-2 definition with minimum size of 10%, unless otherwise stated. We can notice that the fraction of price changes that are sales related do not change too much between groups, that most sales are symmetric, and that the fraction of symmetric temporary price decreases is larger for the groups with higher implied duration.

4.4 Sectorial heterogeneity

We proceed to a finer division of the sample in 13 groups: four groups of non-tradable goods and services and 9 groups of tradable goods. Table 10 displays the frequency of price variation (total, regular and sales related) for each group. The heterogeneity is substantial, entailing a whole range of sales practices. On one extreme we have Apparel and Raw Food, two sectors with a very high frequency of variation (59.7% and 58.4%) as well the higher fraction of sales related price changes, 28, 2% and 32.2% respectively. On the opposite side we have Fuel, Transportation and Vehicles and Equipments, with the fraction of price changes that are sales related equal to 0.5%, 2.7% and 7.2%.

Table 11 presents the weighted mean absolute size of price adjustments. There is considerable sectorial heterogeneity according to our economically meaningful classification. We obtain a very wide range of absolute size of price changes for regular prices: from 2.5% for Fuels[27], to 26% for Apparel. The size of sales also present high

[26] $implied\ duration = -\frac{1}{\ln(1-f)}$, where f is the frequency of price changes of each item.

[27] Retail fuels in Brazil are not regullated, but wholesale are, so prices are significantly more sticky than in other countries.

Table 7: Aggregated Absolute Size of Price Changes

Absolute Size of Price Changes (Weighted)	Mean	Up	Down
All - Aggregated	14.6%	14.4%	15.2%
Regular: Excluding Sale-1	12.1%	11.6%	12.8%
Regular: Excluding Sale-2	11.7%	11.1%	12.4%
Regular: Excluding Sale-3	11.5%	10.9%	12.2%
Regular: Excluding Sale-4	11.4%	10.8%	12.1%

Sample runs from March 1996 through June 2009. Size of price changes are reported in absolute values.
Regular size of price changes mean average size of price changes excluding the ones that are sales related.

Table 8: Aggregated Absolute Size of Price Decreases

Absolute Size of Temporary Sales	Mean (weighted)
Sale-1	25.5%
Sale-2	25.1%
Sale-3	24.9%
Sale-4	24.9%

Sample runs from March 1996 through June 2009. Size of price changes are reported in absolute values.

heterogeneity among groups, running from 14% to 37.3% for Fuel and Apparel respectively. It seems to exist a positive relationship between the size of regular price changes and the size of price changes that are sales related.

5 Time-series analysis

As detailed in Subsection 4.1, we construct time series for the frequency and size of sale prices. We begin by illustrating how 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 sectorial) time series, chosen for their potential importance for pricing decisions. As we only have monthly data for these variables, we need to define the monthly frequency and size of price changes.

Consider the definition $freq\_sale\_z_d^y$ used before. Note that each month t contains three 10 days intervals, i. e., there are three values of d related to it. Therefore, we can interpret each t as a set containing three values of d ($d = 1, 2, 3$). The frequency of sales for product y in month t is defined by:

$$freq\_sale\_z_t^y = \frac{\sum\limits_d freq\_sale\_z_d^y}{N_{yt}}$$

Where N_{yt} represents the number of 10 days interval contained in month t for which $freq\_sale\_z_d^y$ is defined.

For the definition of the monthly size of sales, consider again the definition $sz\_sale\_z_d^y$. The size of sales for product y in month t is defined by:

$$sz\_sale\_z_t^y = \frac{\sum\limits_d sz\_sale\_z_d^y}{M_{yt}}$$

Now, M_{yt} represents the number of 10 days interval contained in month t for which $sz\_sale\_z_t^y$ is defined.

Table 9: Fraction of Price Changes Due to Sales by Stickiness Group

		Fraction of Price Changes Due to Sales				Size
Stickiness Group	Implied Duration (months)	Mean	Symmetric	Up	Down	Mean
1	< 1	22.4%	7.1%	10.9%	4.3%	29.5%
2	1 to 1.5	23.2%	12.3%	8.0%	2.9%	25.8%
3	1.5 to 2	24.0%	15.3%	6.4%	2.3%	26.0%
4	2 to 2.5	23.6%	16.6%	5.1%	1.9%	27.1%
5	2.5 to 3	22.6%	16.8%	4.2%	1.6%	28.2%
6	3 to 4	21.4%	16.9%	3.3%	1.2%	28.6%
7	4 to 5.5	22.5%	18.8%	2.7%	1.0%	31.6%
8	5.5 to 7	22.8%	19.9%	2.1%	0.8%	33.5%
9	7 to 10	21.2%	19.0%	1.8%	0.4%	33.4%
10	10 to 13	25.0%	22.1%	2.4%	0.4%	33.0%
11	13 to 16	19.0%	17.3%	1.4%	0.4%	31.8%
12	> 16	17.4%	12.1%	3.6%	1.7%	32.5%

The statistics reported refers to the percentage of price price changes involving price quotes with sale indicator equal to one by stickiness group. The groups were defined according to their implied duration, givem by dur= -(1/ln(1-f)), where f is the frequency of price change.

5.1 The evolution of price setting statistics

We start by illustrating the behavior of our sales statistics over time. Figures 3 and 4 show the evolution of, respectively, the size and frequency of temporary sales 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),[28] 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 and the electoral period that preceded President Lula's election.

5.2 Time-series data

One important question that we are investigating is that if the frequency and size of sales respond to macroeconomic shocks or not, so in this section we present results from our regressions of sales statistics on a set of macroeconomic variables. As there is a lack of theoretical models trying to investigate this possible relationship between sales behavior and macroeconomic variables, we had to choose as regressors those variables that we believe may have some relationship to them. In order to do that, we decided to choose variables that have already been shown to have some relationship to price setting decisions by firms, such as: aggregate inflation, economic activity, exchange rate and aggregate uncertainty.

For those readers that are familiar to standard sticky price and sticky information models of monetary economics, the inclusion of aggregate inflation and economic activity should already be expected. The exchange rate, on the other hand, could be expected to affect the costs and the market power of firms, with direct impact on their pricing decisions. In order to investigate this relationship closer, we decided to separate the exchange rate effect into appreciation effect and depreciation effect. Finally, we may consider that aggregate uncertainty reflects the expectation of large shocks and should also affect the price decision process of firms.

The ideal measure of aggregate economic activity should be the output gap, but a series of potential output is not available for Brazil. As an alternative, we could use the GDP series for Brazil, but it is not available on a monthly basis. Therefore, we decided to use the "Survey of Industrial Conditions" series (ICI), published by IBRE/FGV on a monthly basis, and also the unemployment rate, published by IBGE (governmental statistical

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

Table 10: Frequency of Price Changes by Major Group

Frequency of Price Changes	Mean	Regular	Sale *	Symmetric Sale *
Non-Tradables				
Food Away From Home	26.8%	25.1%	11.7%	9.4%
House Maintenance Services	49.4%	47.3%	10.4%	5.6%
Transportation	55.6%	54.6%	2.7%	2.7%
Personal and Recreation Services	22.5%	18.5%	25.8%	17.6%
Tradables				
Raw Food	58.4%	49.1%	32.2%	14.8%
Processed Food	49.2%	44.7%	19.7%	10.3%
House Maintenance Goods	45.6%	41.3%	19.2%	10.8%
Apparel	59.7%	52.1%	28.2%	15.2%
Educational and Recreational Goods	39.9%	34.9%	22.4%	13.9%
Vehicles and Equipments	45.4%	43.4%	7.2%	3.4%
Other Goods	31.5%	29.4%	13.8%	8.7%
Personal Care Goods	45.5%	40.9%	19.9%	10.7%
Fuel	28.6%	28.5%	0.5%	0.4%

* For these statistics we report the fraction of price changes due to Sales/Symetric Sales.
Samples runs from March 1996 through December 2008. The statistics reported use weights from the Family Budget Survey used on CPI-FGV from January 2004 on.

Figure 3: Size of temporary sales and CPI inflation

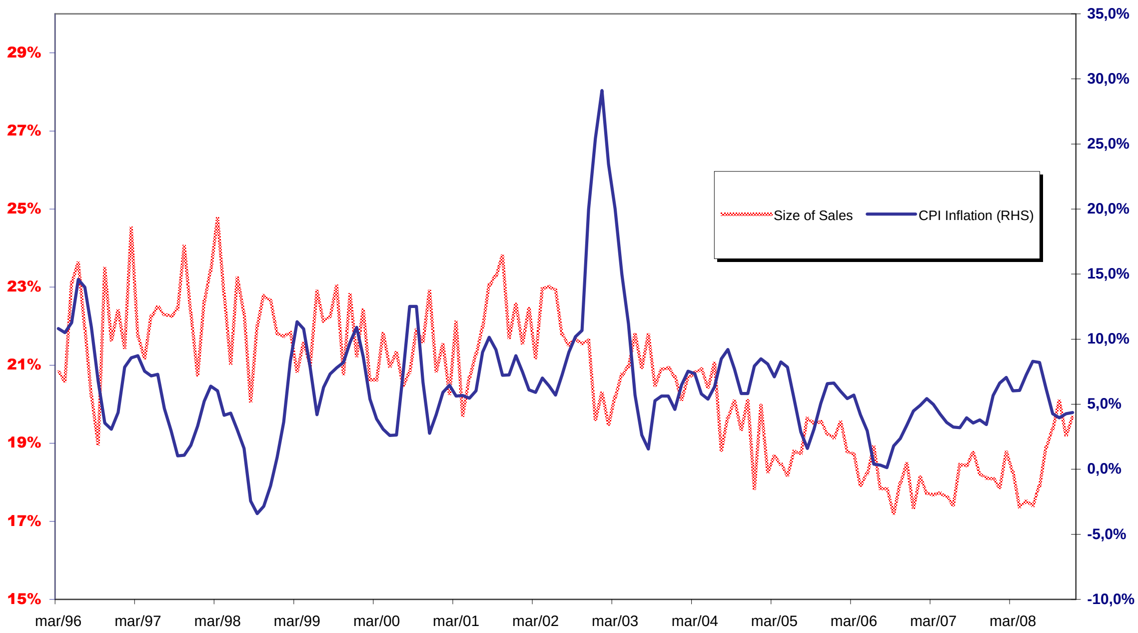


Figure 4: Frequency of temporary sales and CPI inflation

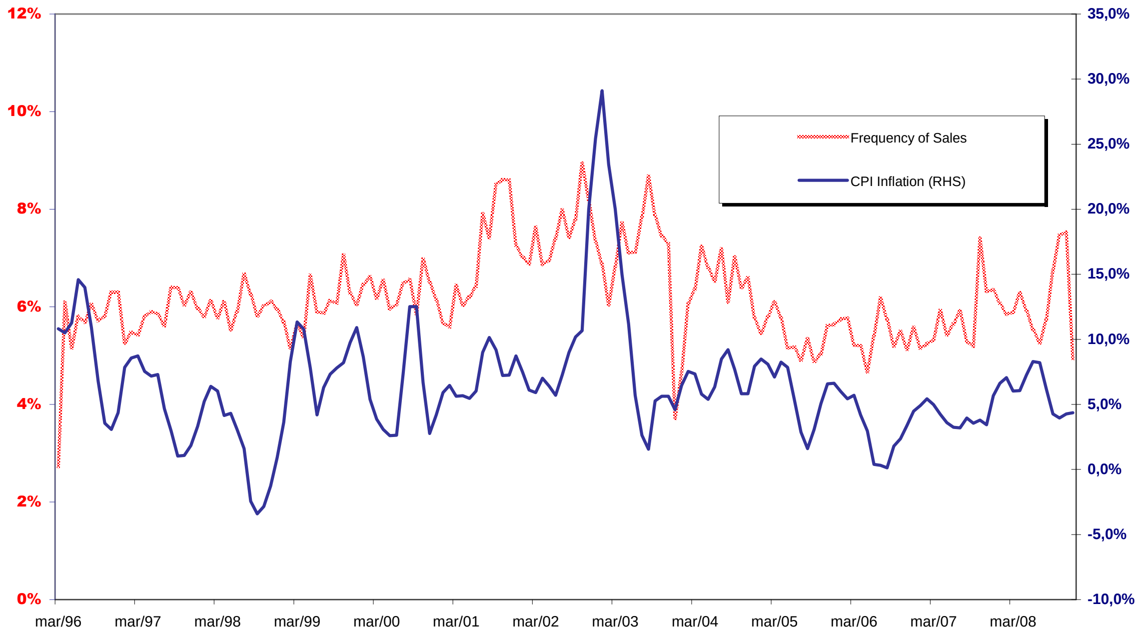


Table 11: Absolute Size of Price Change by Major Group

Size of Price Changes	Mean	Regular	Sale
Non-Tradables			
Food Away From Home	11.6%	10.1%	20.2%
House Maintenance Services	7.2%	5.7%	22.6%
Transportation	22.4%	22.6%	14.0%
Personal and Recreation Services	29.5%	27.3%	37.3%
Tradables			
Raw Food	26.8%	21.0%	34.5%
Processed Food	13.9%	11.0%	23.5%
House Maintenance Goods	14.1%	11.4%	23.4%
Apparel	29.0%	26.0%	34.0%
Educational and Recreational Goods	22.0%	19.0%	30.5%
Vehicles and Equipments	7.1%	5.8%	21.4%
Other Goods	11.8%	10.0%	22.7%
Personal Care Goods	13.7%	10.7%	24.0%
Fuel	2.6%	2.5%	20.5%

Samples runs from March 1996 through December 2008. The statistics reported use weights from the Family Budget Survey used on CPI-FGV from January 2004 on.

agency). An advantage of using the "Survey of Industrial Conditions" series is that it make it possible to explore the panel structure of our data set, since it also publishes indexes by sector of economic activity. It does not give us a measure of economic activity by product, but it allows us a clear mapping between a subset of products in our data set and sectorial measures of economic activity (160 products are divided into 13 sectors). This index comprises six indicators: current level of demand, current level of inventories, current business conditions, forecast of production, forecast of employment, and forecast of business conditions. We use both the log of the level for this index and its log change in three months as regressors.

As a measure of aggregate uncertainty we chose the IPCA, published by IBGE, that is also used by the Central Bank of Brazil for the inflation target regime. We use its annualized log change in 1 month. Finally, as a measure of aggregate uncertainty, we utilized the spread of Brazilian external debt over U.S. Treasures, as measured by JP Morgan's Emerging Market Bond Index (EMBI). The exact measures that we use for these variables are listed in Table 12.

We need to emphasize that since some of these variables present seasonal behavior, we decided to make an seasonality adjustment. We run Ordinary Least Squares (OLS) regressions of unemployment rate, aggregate inflation and the Industrial Confidence Index on monthly dummies and used their residuals as regressors in our analysis. Finally, as Brazil experienced a change of monetary and exchange rate regime in January 1999, when it adopted a regime of inflation targeting together with a floating exchange rate, we decided to restrict our sample to the period January 1999 - June 2009.[29]

5.3 Baseline panel regressions

Driven by our desire to incorporate sectorial 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

[29] 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.

Table 12: Measures of macroeconomic variables

Variable	Measure	Notation
Aggregate inflation	Annualized 1-month log-percentage change of the official CPI index (IPCA)	π_t
Economic activity	log of the Industrial Confidence Indices (ICIs) 3-month log-percentage change	$\ln ici_t$ for aggregate $\ln ici_t^k$, for sector k $\Delta \ln ici_{3,t}^k$, for sector k
Unemployment rate	Level of unemployment rate	ur_t
Exchange rate appreciation	Annualized 3-month log-percentage change of the exchange rate, if negative	$de_{3,t}^-$
Exchange rate depreciation	Annualized 3-month log-percentage change of the exchange rate, if positive	$de_{3,t}^+$
Aggregate uncertainty	EMBI spread of Brazilian external debt over U.S. Treasuries	$embi_t$

Table 12, with *sectorial* 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 $\ln ici_t^k$ index.[30] The panel comprises 160 products grouped into 13 sectors[31].

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

$$s_{j,k,t} = \alpha_j + \beta_1 \pi_t + \beta_2 Activity_t^k + \beta_3 embi_t + \beta_4 de_{3,t}^- + \beta_5 de_{3,t}^+ + \sum_{m=1}^{11} \gamma_m D_{m,t} + u_{jt}, \tag{1}$$

where the left-hand-side variable $s_{j,k}$ is a 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_{jt} is the error term. For each product y in sector k, $s_{j,k,t}$ is the monthly frequency ($freq\_sale\_z_t^y$) and size ($sz\_sale\_z_t^y$) of temporary sales.

The results are reported in Table 13. We report just the results for Sale-2 definition with minimum size of 10%[32].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.[33]

Frequency of sales From Table 13, we can see that higher inflation rates are associated with higher frequency of sales, but this *positive* association is not statistically significant at 10% level. Aggregate uncertainty shows a strong *positive* association, statistically significant at a 10% level. The frequency of sales has a strong statistically significant *positive* association with unemployment rate. The 3-month log-percentage change in ICI shows a *positive* association, statistically significant at 1% level. The log of ICI also shows a *positive* association with the frequency of sales, statistically significant at a 1% level, but with small magnitude. The results regarding the variations of the exchange rate, indicate that the frequency of sales has a *negative* association with both the depreciation and appreciation of exchange rate, statistically significant at a 1% level. Note, however, that the coefficient on appreciation is much larger in absolute value. The results regarding the monthly dummies indicate that the frequency of sales is lower in December and much larger in January.

Size of sales The results for the size of sales are somewhat different from those for the frequencies of price changes. The inflation rate shows a *negative* association with the size of sales and this relationship is significant at

[30] 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.

[31] See Appendix for the definitions of sectors and products classifications.

[32] The other results are avaiable upon request.(jayres@fgvmail.br).

[33] 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.

Table 13: Baseline panel regressions

	Size of Sales			Frequency of Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
π_t	-0.048^{***} (0.000)	-0.040^{***} (0.006)	-0.020^{***} (0.169)	0.008 (0.390)	0.007 (0.442)	0.025 (0.006)
$embi_t$	0.039^{***} (0.000)	0.038^{***} (0.000)	0.024^{***} (0.013)	0.016^{***} (0.000)	0.019^{***} (0.000)	0.011^{***} (0.000)
$de^{+}_{3,t}$	0.015^{***} (0.000)	0.016^{***} (0.000)	0.013^{***} (0.001)	-0.014^{***} (0.000)	-0.015^{***} (0.000)	-0.015^{***} (0.000)
$de^{-}_{3,t}$	-0.014^{***} (0.000)	-0.015^{***} (0.000)	-0.006^{**} (0.037)	-0.002^{**} (0.034)	-0.003^{***} (0.002)	-0.002^{***} (0.076)
$\Delta \ln ici^{k}_{3,t}$	0.002 (0.383)			0.011^{***} (0.000)		
$\ln ici_t$		-0.000^{***} (0.026)			0.000^{***} (0.000)	
ur_t			0.501^{***} (0.000)			0.167^{***} (0.000)
D_1	-0.000 (0.879)	-0.001 (0.808)	0.005 (0.118)	0.134^{***} (0.000)	0.135^{***} (0.000)	0.136 (0.000)
D_2	0.001 (0.764)	0.001 (0.852)	0.003 (0.286)	0.011^{***} (0.000)	0.011^{***} (0.000)	0.012^{***} (0.000)
D_3	0.005 (0.141)	0.005 (0.144)	0.008^{***} (0.009)	0.011^{***} (0.000)	0.011^{***} (0.000)	0.013^{***} (0.000)
D_4	-0.000 (0.961)	0.000 (0.986)	0.005 (0.168)	0.009^{***} (0.000)	0.009^{***} (0.000)	0.011^{***} (0.000)
D_5	-0.002 (0.502)	-0.003 (0.467)	0.001 (0.706)	0.013^{***} (0.000)	0.013^{***} (0.000)	0.014^{***} (0.000)
D_6	0.002 (0.630)	0.002 (0.615)	0.007^{***} (0.027)	0.009^{***} (0.000)	0.009^{***} (0.000)	0.011^{***} (0.000)
D_7	0.003 (0.342)	0.003 (0.306)	0.007^{***} (0.048)	0.015^{***} (0.000)	0.015^{***} (0.000)	0.016^{***} (0.000)
D_8	0.005^{*} (0.097)	0.005^{*} (0.097)	0.010^{***} (0.001)	0.017^{***} (0.000)	0.017^{***} (0.000)	0.018^{***} (0.000)
D_9	0.002 (0.519)	0.002 (0.574)	0.011^{***} (0.001)	0.018^{***} (0.000)	0.018^{***} (0.000)	0.021^{***} (0.000)
D_{10}	0.003 (0.304)	0.002 (0.668)	0.005 (0.170)	0.005^{***} (0.000)	0.005^{***} (0.000)	0.006^{***} (0.000)
D_{11}	0.008^{**} (0.022)	0.003 (0.408)	0.008^{***} (0.036)	0.007^{***} (0.000)	0.007^{***} (0.000)	0.007^{***} (0.000)
# *Obs*	18,991	18,991	18,991	21,750	21,750	21,750
R^2	0.152	0.152	0.156	0.371	0.370	0.369

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

a 1% level. In contrast, the size of sales shows a highly statistically significant *positive* association with aggregate uncertainty, also significant at a 1% level. The 3-month log-percentage change in ICI shows a *positive* association, but it is not statistically significant at a 10% level. Again, the log of ICI also shows a *positive* association with the frequency of sales, statistically significant at a 1% level, but with small magnitude. The results regarding the variations of the exchange rate, indicate that the frequency of sales has a *negative* association with the depreciation of exchange rate, and a *positive* association with the appreciation of exchange rate, all these relationships being statistically significant at a 1% level. The results regarding the monthly dummies do not indicate a seasonality behavior for the size of sales.

In Appendix, we show the results regarding the different definitions of sales and their minimum size. From Tables 15, 16, 17 and 17, we can see that our results are not much sensitive to these changes.

5.3.1 Time-series regressions with aggregate variables

In this subsection we consider single-equation Ordinary Least Squares (OLS) versions of our baseline regression that only use aggregate series.

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 variables, we run the following regressions:

$$s_t = \alpha + \beta_1 \pi_t + \beta_2 Activity_t + \beta_3 embi_t + \beta_4 de^{-}_{3,t} + \beta_5 de^{+}_{3,t} + \sum_{m=1}^{11} \gamma_m D_{m,t} + u_t$$

where the ICI variable is (that was sectorial), was now replaced by the aggregate measure of the ICI.

Frequency of Sales From Table 14, we can see that the results present some similarity to the ones obtained before. The coefficients on the inflation rate are not statistically significant at a 10% level, but now two of them are negative. The coefficients on our proxy for aggregate uncertainty keeps showing a *positive* relationship to the frequency of sales, statistically significant at a 1% level. The coefficient on unemployment rate is *positive*, but no longer statistically significant at a 10% level. The frequency of sales has a strong statistically significant *positive* association with unemployment rate. The 3-month log-percentage change in ICI is now *positive* and statistically significant at a 1% level. The log of ICI also shows a *positive* association with the frequency of sales and with small magnitude, but no longer statistically significant at a 10% level. The coefficients on the exchange rate variation now show a *negative* association between its appreciation and depreciation in relation to the frequency of sales.

Size of Sales The results for the size of sales keeps indicating a *negative* relationship between the size of sales and aggregate inflation, but not statistically significant at a 10% level in regression (3). Again, the size of sales shows a highly statistically significant *positive* association with aggregate uncertainty, significant at a 1% level. The 3-month log-percentage change in ICI shows a *positive* association, but it is not statistically significant at a 10% level. The log of ICI shows a *negative* association with the size of sales, but not statistically significant at a 10% level. The results regarding the appreciation and depreciation of the exchange rate shows a *positive* and *negative* association to the size of sales, respectively. Both are statistically significant at a 10% level for regressions (1) and (2), but not for regression (3). The results regarding the monthly dummies do not indicate any seasonality behavior for the size of sales.

6 Conclusion

In this work we investigate the behavior temporary sales, both its size and frequency, based on a very detailed data set for 13 years of retail prices in the Brazilian economy, with price quotes collected every 10-days. We verify that temporary sales, as in the US, also play an important role in retail price for Brazil, representing $4.7 - 7.8\%$ of total price quotes and $16.7 - 24.6\%$ of the frequency of total price changes. We also find a strong heterogeneity of both the size and frequency of sales among different sectors of the economy.

Our main finding from our panel regressions is that the common belief that temporary sales do not reflect macroeconomic conditions does not find support in our results. The size of sales present a negative relationship to aggregate inflation, exchange rate depreciation and economic activity, and a positive relationship to aggregate uncertainty, exchange rate appreciation and unemployment rate. The frequency of sales, on the other hand, shows

Table 14: Aggregate regressions

	Size of Sales			Frequency of Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
π_t	-0.056^{*}	-0.053	-0.034	-0.009	-0.008	0.014
	(0.088)	(0.128)	(0.271)	(0.824)	(0.843)	(0.737)
$embi_t$	0.035^{***}	0.036^{***}	0.024^{***}	0.021^{**}	0.025^{***}	0.017^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)
$de^{+}_{3,t}$	0.012	0.011	0.009	-0.015	-0.021	-0.019
	(0.118)	(0.137)	(0.232)	(0.265)	(0.177)	(0.240)
$de^{-}_{3,t}$	-0.009^{***}	-0.011^{***}	-0.004	-0.001	-0.003	-0.003
	(0.009)	(0.009)	(0.275)	(0.782)	(0.512)	(0.359)
$\Delta \ln ici^{k}_{3,t}$	0.005			0.025^{**}		
	(0.156)			(0.011)		
$\ln ici_t$		-0.002			0.031	
		(0.897)			(0.211)	
ur_t			0.388^{***}			0.183
			(0.003)			(0.203)
D_1	0.001	0.001	0.005	0.118^{***}	0.118^{***}	0.120^{***}
	(0.858)	(0.872)	(0.298)	(0.000)	(0.000)	(0.000)
D_2	-0.002	-0.002	0.000	0.011^{***}	0.011^{***}	0.011^{***}
	(0.638)	(0.608)	(0.995)	(0.004)	(0.001)	(0.000)
D_3	-0.003	-0.003	0.000	0.011^{***}	0.011^{***}	0.013^{***}
	(0.537)	(0.530)	(0.973)	(0.000)	(0.000)	(0.000)
D_4	-0.003	-0.003	0.000	0.011^{***}	0.011^{***}	0.013^{***}
	(0.486)	(0.491)	(0.948)	(0.018)	(0.009)	(0.001)
D_5	-0.004	-0.004	-0.001	0.012^{***}	0.013^{***}	0.014^{***}
	(0.405)	(0.402)	(0.894)	(0.000)	(0.000)	(0.000)
D_6	-0.003	-0.003	0.002	0.010^{**}	0.009^{**}	0.012^{***}
	(0.598)	(0.597)	(0.699)	(0.015)	(0.018)	(0.004)
D_7	-0.001	-0.000	0.003	0.014^{***}	0.015^{***}	0.018^{***}
	(0.908)	(0.985)	(0.579)	(0.000)	(0.000)	(0.000)
D_8	0.001	0.002	0.005	0.016^{***}	0.016^{***}	0.018^{***}
	(0.761)	(0.738)	(0.271)	(0.000)	(0.000)	(0.000)
D_9	0.002	0.002	0.009	0.020^{***}	0.020^{***}	0.024^{***}
	(0.749)	(0.740)	(0.134)	(0.000)	(0.000)	(0.000)
D_{10}	0.005	0.005	0.006	0.007^{**}	0.007^{**}	0.008^{**}
	(0.378)	(0.361)	(0.300)	(0.010)	(0.010)	(0.012)
D_{11}	0.007^{**}	0.007^{**}	0.006^{**}	0.007^{***}	0.007^{***}	0.007^{***}
	(0.023)	(0.018)	(0.031)	(0.002)	(0.002)	(0.005)
# Obs	126	126	126	126	126	126
R^2	0.590	0.586	0.645	0.806	0.790	0.787

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.

a positive relationship to aggregate uncertainty and acceleration of economic activity, but we do not find evidence of its relation to aggregate inflation, exchange rate variations, economic activity and unemployment rate.

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7 Appendix

Table 15: Baseline Panel Regressions - 1 period, 10 p.c.

	Size of Sales			Frequency of Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
π_t	-0.067^{***} (0.000)	-0.063^{***} (0.000)	-0.038^{**} (0.012)	0.019^{***} (0.036)	0.009 (0.306)	0.036^{***} (0.000)
$embi_t$	0.042^{***} (0.000)	0.042^{***} (0.000)	0.027^{***} (0.000)	0.013^{***} (0.000)	0.018^{***} (0.000)	0.008^{***} (0.000)
$de^{+}_{3,t}$	0.016^{***} (0.000)	0.016^{***} (0.000)	0.014^{***} (0.001)	-0.017^{***} (0.000)	-0.021^{***} (0.000)	-0.018^{***} (0.000)
$de^{-}_{3,t}$	-0.015^{***} (0.000)	-0.015^{***} (0.000)	-0.007^{**} (0.011)	-0.001 (0.109)	0.001 (0.365)	-0.001 (0.308)
$\Delta \ln ici^{k}_{3,t}$	0.003 (0.120)			0.012^{***} (0.000)		
$\ln ici_t$		-0.003 (0.691)			0.042^{***} (0.000)	
ur_t			0.500^{***} (0.000)			0.174^{***} (0.000)
D_1	-0.002 (0.499)	-0.002 (0.486)	0.003 (0.330)	0.133^{***} (0.000)	0.133^{***} (0.000)	0.135^{***} (0.000)
D_2	0.001 (0.697)	0.001 (0.730)	0.004 (0.273)	0.006^{***} (0.000)	0.006^{***} (0.000)	0.007^{***} (0.000)
D_3	0.006^{**} (0.048)	0.006^{**} (0.048)	0.010^{***} (0.002)	0.008^{***} (0.000)	0.007^{***} (0.000)	0.009^{***} (0.000)
D_4	0.001 (0.838)	0.001 (0.827)	0.005 (0.123)	0.006^{***} (0.000)	0.006^{***} (0.000)	0.008^{***} (0.000)
D_5	-0.001 (0.705)	-0.001 (0.688)	0.002 (0.502)	0.007^{***} (0.000)	0.008^{***} (0.000)	0.009^{***} (0.000)
D_6	0.003 (0.448)	0.003 (0.446)	0.009^{**} (0.018)	0.005^{***} (0.000)	0.005^{***} (0.000)	0.007^{***} (0.000)
D_7	0.004 (0.217)	0.004 (0.206)	0.008^{**} (0.026)	0.010^{***} (0.000)	0.008^{***} (0.000)	0.011^{***} (0.000)
D_8	0.008^{**} (0.014)	0.008^{**} (0.014)	0.012^{***} (0.000)	0.012^{***} (0.000)	0.011^{***} (0.000)	0.014^{***} (0.000)
D_9	0.004 (0.160)	0.004 (0.167)	0.013^{***} (0.000)	0.012^{***} (0.000)	0.012^{***} (0.000)	0.015^{***} (0.000)
D_{10}	0.006 (0.101)	0.006 (0.102)	0.007^{**} (0.049)	0.004^{***} (0.000)	0.004^{***} (0.000)	0.005^{***} (0.000)
D_{11}	0.009^{***} (0.010)	0.009^{**} (0.010)	0.008^{**} (0.018)	0.006^{***} (0.000)	0.006^{***} (0.000)	0.006^{***} (0.000)
# *Obs*	18,729	18,729	18,729	21,767	21,767	21,767
R^2	0.145	0.145	0.148	0.412	0.412	0.409

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

Table 16: Baseline Panel Regressions - 4 periods, 10 p.c.

	Size of Sales			Frequency of Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
π_t	-0.043^{***} (0.002)	-0.041^{***} (0.004)	-0.017 (0.252)	-0.001 (0.907)	-0.014 (0.157)	0.014 (0.161)
$embi_t$	0.038^{***} (0.000)	0.038^{***} (0.000)	0.023^{***} (0.000)	0.017^{***} (0.000)	0.022^{***} (0.000)	0.012^{***} (0.000)
$de^{+}_{3,t}$	0.013^{***} (0.000)	0.014^{***} (0.000)	0.011^{***} (0.001)	-0.014^{***} (0.000)	-0.019^{***} (0.000)	-0.015^{***} (0.000)
$de^{-}_{3,t}$	-0.012^{***} (0.000)	-0.013^{***} (0.000)	-0.005^{**} (0.078)	-0.004^{***} (0.004)	-0.001 (0.439)	-0.004^{***} (0.006)
$\Delta \ln ici^{k}_{3,t}$	0.001 (0.653)			0.011^{***} (0.000)		
$\ln ici_t$		-0.003 (0.651)			0.048^{***} (0.000)	
ur_t			0.485^{***} (0.000)			0.147^{***} (0.000)
D_1	0.001 (0.747)	0.001 (0.754)	0.006^{**} (0.040)	0.118^{***} (0.000)	0.118^{***} (0.000)	0.120^{***} (0.000)
D_2	0.001 (0.748)	0.001 (0.765)	0.003 (0.284)	-0.003 (0.210)	-0.003 (0.230)	-0.002 (0.299)
D_3	0.005^{*} (0.092)	0.005^{*} (0.091)	0.009^{***} (0.005)	-0.004 (0.108)	-0.004^{*} (0.066)	-0.002 (0.268)
D_4	-0.001 (0.822)	-0.001 (0.828)	0.004 (0.227)	-0.005^{**} (0.049)	-0.005^{*} (0.055)	-0.003 (0.218)
D_5	-0.002 (0.655)	-0.002 (0.647)	0.002 (0.560)	-0.002 (0.234)	-0.002 (0.263)	-0.001 (0.528)
D_6	0.002 (0.543)	0.002 (0.535)	0.008^{**} (0.017)	-0.006^{***} (0.004)	-0.007^{***} (0.001)	-0.004^{**} (0.049)
D_7	0.004 (0.234)	0.004 (0.221)	0.007^{**} (0.028)	0.001 (0.655)	-0.001 (0.814)	0.002 (0.289)
D_8	0.004 (0.163)	0.004 (0.160)	0.008^{***} (0.000)	0.002 (0.342)	0.002 (0.470)	0.004^{*} (0.098)
D_9	0.003 (0.340)	0.003 (0.343)	0.012^{***} (0.001)	0.006^{***} (0.006)	0.005^{***} (0.008)	0.008^{***} (0.000)
D_{10}	0.003 (0.284)	0.003 (0.283)	0.005 (0.150)	-0.002 (0.176)	-0.003 (0.120)	-0.002 (0.256)
D_{11}	0.007^{**} (0.045)	0.007^{**} (0.045)	0.006^{*} (0.069)	0.010^{***} (0.000)	0.010^{***} (0.000)	0.010^{***} (0.000)
# *Obs*	19,146	19,146	19,146	21,744	21,744	21,744
R^2	0.158	0.158	0.162	0.277	0.279	0.276

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

Table 17: Baseline Panel Regressions - 2 periods, 20 p.c.

	Size of Sales			Frequency of Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
π_t	-0.057^{***} (0.004)	-0.056^{***} (0.006)	-0.025 (0.232)	-0.003 (0.680)	-0.007 (0.382)	0.008 (0.300)
$embi_t$	0.039^{***} (0.000)	0.039^{***} (0.000)	0.021^{***} (0.000)	0.013^{***} (0.000)	0.015^{***} (0.000)	0.009^{***} (0.000)
$de^{+}_{3,t}$	0.013^{***} (0.005)	0.013^{***} (0.007)	0.010^{***} (0.029)	-0.007^{***} (0.000)	-0.008^{***} (0.000)	-0.007^{***} (0.000)
$de^{-}_{3,t}$	-0.015^{***} (0.000)	-0.015^{***} (0.000)	-0.006 (0.192)	-0.001 (0.288)	-0.000 (0.827)	0.000 (0.849)
$\Delta \ln ici^{k}_{3,t}$	0.002 (0.359)			0.006^{***} (0.000)		
$\ln ici_t$		0.001 (0.859)			0.017^{***} (0.000)	
ur_t			0.594^{***} (0.000)			0.136^{***} (0.000)
D_1	-0.008^{*} (0.069)	-0.008^{*} (0.067)	0.001 (0.793)	0.063^{***} (0.000)	0.063^{***} (0.000)	0.065^{***} (0.000)
D_2	-0.009^{**} (0.021)	-0.009^{**} (0.019)	-0.007^{*} (0.097)	0.005^{***} (0.000)	0.005^{***} (0.000)	0.006^{***} (0.000)
D_3	-0.009^{**} (0.041)	-0.009^{**} (0.039)	-0.005 (0.283)	0.006^{***} (0.000)	0.005^{***} (0.000)	0.007^{***} (0.000)
D_4	-0.008^{*} (0.054)	-0.008^{*} (0.054)	-0.003 (0.496)	0.004^{***} (0.000)	0.004^{***} (0.000)	0.005^{***} (0.000)
D_5	-0.015^{***} (0.000)	-0.015^{***} (0.000)	-0.011^{***} (0.004)	0.005^{***} (0.000)	0.006^{***} (0.000)	0.006^{***} (0.000)
D_6	-0.010^{**} (0.027)	-0.010^{**} (0.025)	-0.003 (0.480)	0.005^{***} (0.000)	0.004^{***} (0.000)	0.006^{***} (0.000)
D_7	-0.009^{**} (0.032)	-0.009^{**} (0.031)	-0.005 (0.238)	0.007^{***} (0.000)	0.006^{***} (0.000)	0.008^{***} (0.000)
D_8	-0.009^{**} (0.020)	-0.009^{**} (0.019)	-0.004 (0.352)	0.008^{***} (0.000)	0.008^{***} (0.000)	0.009^{***} (0.000)
D_9	-0.010^{**} (0.014)	-0.010^{**} (0.013)	0.001 (0.788)	0.009^{***} (0.000)	0.009^{***} (0.000)	0.011^{***} (0.000)
D_{10}	0.000 (0.984)	0.000 (0.993)	0.001 (0.737)	0.003^{***} (0.000)	0.002^{***} (0.000)	0.003^{***} (0.000)
D_{11}	0.002 (0.747)	0.001 (0.766)	0.000 (0.947)	0.004^{***} (0.000)	0.004^{***} (0.000)	0.003^{***} (0.000)
# *Obs*	16,832	16,832	16,832	21,753	21,753	21,753
R^2	0.120	0.120	0.123	0.239	0.238	0.238

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

Table 18: Baseline Panel Regressions - 2 periods, 5 p.c.

	Size of Sales			Frequency of Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
π_t	-0.043^{***}	-0.040^{***}	-0.016	0.015	-0.001	0.033^{***}
	(0.001)	(0.002)	(0.232)	(0.137)	(0.882)	(0.001)
$embi_t$	0.036^{***}	0.036^{***}	0.023^{***}	0.014^{***}	0.020^{***}	0.009^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$de^{+}_{3,t}$	0.012^{***}	0.012^{***}	0.010^{***}	-0.015^{***}	-0.020^{***}	-0.016^{***}
	(0.001)	(0.001)	(0.005)	(0.000)	(0.000)	(0.000)
$de^{-}_{3,t}$	-0.012^{***}	-0.012^{***}	-0.005^{*}	-0.004^{***}	0.000	-0.003^{**}
	(0.000)	(0.000)	(0.050)	(0.007)	(0.780)	(0.020)
$\Delta \ln ici^{k}_{3,t}$	0.004^{**}			0.012^{***}		
	(0.018)			(0.000)		
$\ln ici_t$		0.000			0.058^{***}	
		(0.981)			(0.000)	
ur_t			0.452^{***}			0.185^{***}
			(0.000)			(0.000)
D_1	0.009^{***}	0.009^{***}	0.014^{***}	0.177^{***}	0.177^{***}	0.179^{***}
	(0.003)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
D_2	0.004	0.004	0.006^{**}	0.014^{***}	0.015^{***}	0.015^{***}
	(0.117)	(0.132)	(0.019)	(0.000)	(0.000)	(0.000)
D_3	0.005^{*}	0.005^{*}	0.008^{***}	0.015^{***}	0.014^{***}	0.016^{***}
	(0.075)	(0.077)	(0.003)	(0.000)	(0.000)	(0.000)
D_4	0.002	0.002	0.006^{**}	0.013^{***}	0.013^{***}	0.015^{***}
	(0.537)	(0.523)	(0.037)	(0.000)	(0.000)	(0.000)
D_5	0.003	0.003	0.007^{**}	0.015^{***}	0.016^{***}	0.017^{***}
	(0.320)	(0.333)	(0.040)	(0.000)	(0.000)	(0.000)
D_6	0.006^{*}	0.006^{*}	0.011^{***}	0.012^{***}	0.011^{***}	0.014^{***}
	(0.069)	(0.071)	(0.000)	(0.000)	(0.000)	(0.000)
D_7	0.006^{**}	0.006^{**}	0.009^{***}	0.020^{***}	0.018^{***}	0.021^{***}
	(0.037)	(0.037)	(0.002)	(0.000)	(0.000)	(0.000)
D_8	0.010^{***}	0.010^{***}	0.014^{***}	0.020^{***}	0.020^{***}	0.022^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_9	0.006^{**}	0.005^{**}	0.014^{***}	0.024^{***}	0.024^{***}	0.027^{***}
	(0.038)	(0.042)	(0.000)	(0.000)	(0.000)	(0.000)
D_{10}	0.006^{**}	0.006^{**}	0.007^{**}	0.006^{***}	0.006^{***}	0.007^{***}
	(0.039)	(0.041)	(0.013)	(0.000)	(0.000)	(0.000)
D_{11}	0.010	0.010^{***}	0.009^{***}	0.009^{***}	0.008^{***}	0.008^{***}
	(0.002)	(0.002)	(0.004)	(0.000)	(0.000)	(0.000)
# *Obs*	19,550	19,550	19,550	21,749	21,749	21,749
R^2	0.171	0.171	0.175	0.437	0.439	0.436

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