

FUNDAÇÃO GETULIO VARGAS  
ESCOLA DE ECONOMIA DE SÃO PAULO

CELIO FELTRIN JUNIOR

**TIME-DEPENDENT OR STATE-DEPENDENT PRICING?  
EVIDENCE FROM A LARGE CURRENCY DEVALUATION  
EPISODE**

São Paulo

2014

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Dissertação apresentada à Escola de  
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Getulio Vargas, como requisito para  
obtenção do título de Mestre em  
Economia

Campo de Conhecimento:  
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Orientador: Prof. PhD. Bernardo Gui-  
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# ABSTRACT

Two classes of models seek to explain the pattern of price adjustment of firms: models time-dependent and state-dependent. The objective of this work is to raise some empirical evidence in order to distinguishing between the models , i.e. identifying in the way firms actually change price. For this reason, we chose the large devaluation of 1999 as the main tool and analytical environment. The fundamental hypothesis is that the exchange rate shock significantly impacts the cost of some industries, in some cases inducing them to change price after the shock. From a vast base of micro data formed by prices that make up the CPI, some important estimates as the probability and average magnitude of price changes were raised. The magnitude is given by a simple average, while the probability is estimated by the method of maximum likelihood. In the end, the results indicate a behavior of pricing similar to ones proposed by state-dependent models.

Keywords: Price setting; Micro data; Exchange rate devaluation; Monetary economics.

## RESUMO

Duas classes de modelos buscam explicar o padrão de ajustamento de preço das firmas: modelos tempo-dependente e estado-dependente. O objetivo deste trabalho é levantar algumas evidências empíricas de modo a distinguir os modelos, ou seja, identificar de que maneira as firmas realmente precificam. Para isso, escolheu-se a grande desvalorização cambial de 1999 como principal ferramenta e ambiente de análise. A hipótese fundamental é que o choque cambial impacta significativamente o custo de algumas indústrias, em alguns casos induzindo-as a alterarem seus preços após o choque. A partir de uma imensa base de micro dados formada por preços que compõem o CPI, algumas estimações importantes como a probabilidade e a magnitude média das trocas foram levantadas. A magnitude é dada por uma média simples, enquanto a probabilidade é estimada pelo método da máxima verossimilhança. Os resultados indicam um comportamento de precificação similar ao proposto por modelos estado-dependente.

Palavras-Chave: Ajustamento de preço; Micro dados; Desvalorização cambial; Economia monetária.

# Contents

	<b>Introduction</b> . . . . .	<b>8</b>
<b>1</b>	<b>Literature</b> . . . . .	<b>12</b>
1.1	Theoretical Literature . . . . .	12
1.2	Empirical Literature . . . . .	14
<b>2</b>	<b>Data Base</b> . . . . .	<b>16</b>
2.1	Aggregation and Some Stats . . . . .	16
<b>3</b>	<b>Methodology</b> . . . . .	<b>19</b>
3.1	Data Treatment . . . . .	19
3.2	Estimation: Probability of a Price Change and Mean Magnitude . . . . .	20
<b>4</b>	<b>Results</b> . . . . .	<b>24</b>
	<b>Concluding Remarks</b> . . . . .	<b>28</b>
<b>A</b>	<b>Appendix - Results for 2002</b> . . . . .	<b>29</b>
<b>B</b>	<b>Appendix - Data Base Statistics</b> . . . . .	<b>32</b>
<b>C</b>	<b>Appendix - Tests</b> . . . . .	<b>33</b>
	<b>Bibliography</b> . . . . .	<b>38</b>

# Introduction

An important question in macroeconomics is: what are the patterns of price adjustment? Are they closer to time-dependent models or state dependent models? These models try to explain patterns of price setting in a different way. Time-dependent models state the optimal price is chosen considering that prices will remain unchanged for a predetermined period. That is, the pattern by which prices change over time depends on the time itself. State-dependent models assume that prices are set according to the developments of the economy, regardless of the time over which the developments occur. It is important to differentiate these models because monetary policy has different implications on both, having greater effect on real output in time-dependent models. In other words, state-dependent models characterize the response to shocks as fully efficient, making the impact of monetary shocks in the real product practically null. However, identifying these extreme models is not an easy task.

This paper tries to distinguish between the models, the idea is the following. Suppose that in a certain short period of time there are some large positive shocks affecting some industries' costs. In a state-dependent model firms adjust their prices whenever their current price gets some distance from their optimal price. With all firms reacting fast, prices change more frequently. In other words, the probability of a price change would increase following the shock. In time-dependent models, as prices remain fixed for a certain period of time, firms would not react during the shock period, but would factor in the shocks in the next opportunity of changing prices, which would lead to a larger price changes. Thus, time-dependent models are closer to scenarios of less frequently pricing changes with larger magnitudes.

To test this proposition this dissertation uses the large exchange rate devaluation of 1999 that occurred in Brazil. Figure 1 illustrates the daily exchange rate from January 1995 till May 2013. From this graph we can notice three big devaluation episodes. The first one, in January of 1999, is the most dramatic among them and is the one I focus in this study. It happened when the Central Bank decided to switch from a fixed exchange rate regime to a floating exchange rate regime. The other devaluations are not that extreme, but the 2002 one will be examined, given the data base covers this period.

Figure 2 shows the exchange rate in the beginning of 1999 and highlights the relevance of this event for this paper. The first month presents a faster devaluation: the exchange rate value jumps from 1.2 to around 2 dollars. The whole point of using these currency shocks is that we are assuming they represent a considerable cost shock for some industries. This can



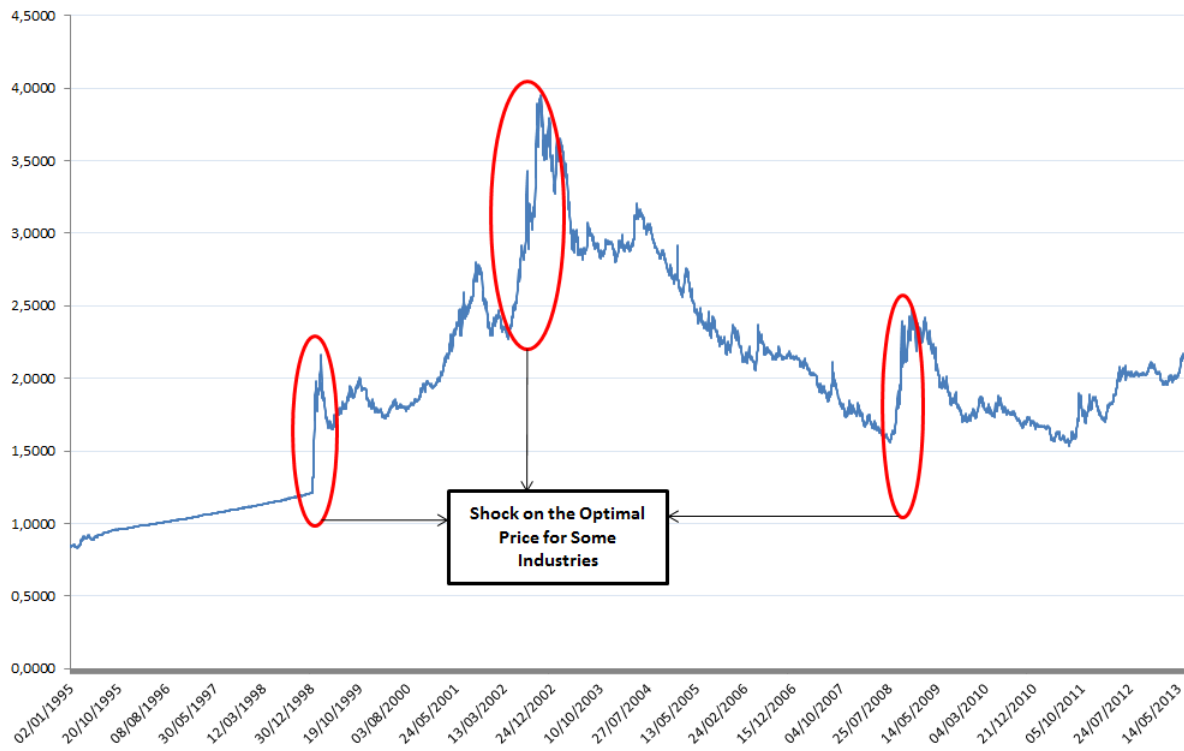


Figure 1 – Large Exchange Rate Devaluations

be seen as an advantage, as it provides different price responses depending on what sector we are looking at. By this way this paper connects exchange rate shocks to price changes.

Combining the devaluation episode with a significant data base of micro prices for Brazil, we have a favorable environment for studying pricing behavior from different groups of items. The objective of this study is to generate stylized facts about pricing given a positive shock on the exchange rate that can be used to evaluate theoretical models. The idea is to confront results brought from micro data with the two main classes of models related to the literature of price rigidity. In addition, it allow us to understand the patterns of price adjustment in scenarios of large devaluations.

To this purpose, estimations of the probability of a price change and mean size of price changes were carried out. Using micro data on pricing it was possible to aggregate items in different ways in order to understand if, for example, goods classified as tradables (the ones that suffer certain competition from imported items) tend to adjust prices more quickly than non-tradables (mostly services). Are services less sensitive to exchange rate shocks? Do commodities respond immediately?

The first step was to classify the items in the data base into three major groups: (i) non-tradables; (ii) tradables non-commodities; (iii) commodities. Then, the estimation of the hazard rate employed the maximum likelihood method. A total of twenty four monthly

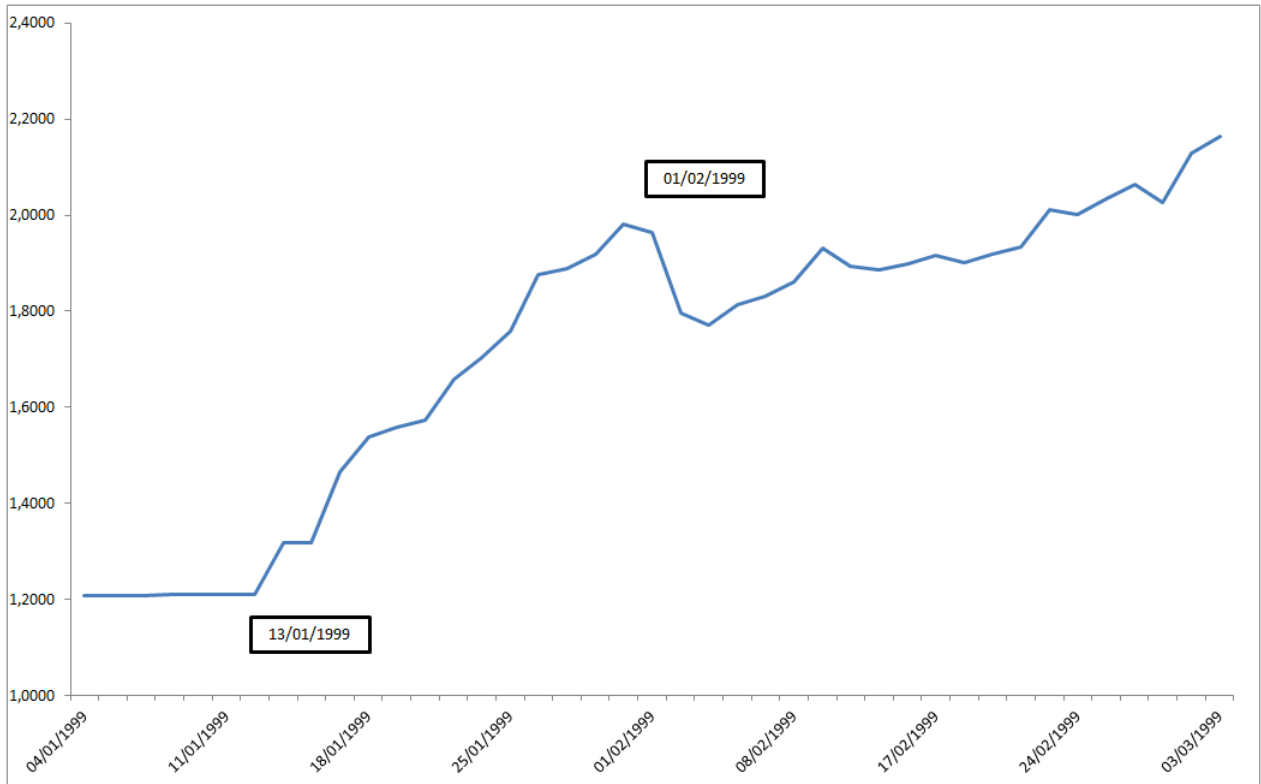


Figure 2 – Exchange Rate: Beginning of 1999

estimates in a two year period show the difference between pricing before and after the exchange rate shock. The magnitude of those changes was estimated by taking the average size of price changes in a predefined period. After that, some hypothesis tests were conducted.

The impacts of the large devaluation on the probability of a price change and mean magnitude are very different and give us some insights about pricing models. The main effect is over the probability of a price change. It clearly jumps after the shock when looking to commodities and tradables non-commodities, being this movement not that evident for non-tradables. This frame is even more significant when looking to the probability of a positive price change. Importantly, the mean size of those changes does not seem to vary that much. The results of probability and magnitude corroborate state-dependent models.

In fact, this is a case in which state-dependent pricing makes more sense. It is related to menu costs. In other words, firms incur only in a changing price cost. These are in general small and firms affected by the shock should decide to pay it for changing their prices in face of a cost raise. Because the exchange rate devaluation is a shock known to every one, the informational cost should be low and that does not match with time-dependent pricing, where firms keep their prices rigid restricted by informational costs. Therefore, it would be expected to obtain results pointing to state-dependent models rather than time-dependent

models. This is a very relevant evidence but can not be extended to other circumstances.

The structure of this paper is the following: the next section presents the theoretical and empirical literature. Chapter 2 gives an idea of the data base discussing some descriptive statistics. Chapter 3 shows the methodology employed in the estimation of the mean size of price changes and hazard rates. Chapter 4 presents the results. And at last, the conclusion.

# 1 Literature

Part of the empirical literature in macroeconomics has raised some evidence that monetary shocks can result in real effects in the product of the economy. One of the main challenges is to justify such facts. The main hypothesis, arguing that there are real effects, is that it takes a while to adjust prices given aggregate variations. Models found in the theoretical literature that are built from this premise propose that the sluggish price adjustment at the microeconomic level is the reason for the change of the real product. On state-dependent models the effect is the opposite. The main message of these models is that the effect of monetary policy on real product is practically none. In this context, evaluating the pricing pattern of firms is essential to assist in the formulation of economic policy.

Empirical works have been stimulated lately from access to large quantities of micro data, usually taken from the consumer price index. Some features of price adjustment patterns such as the frequency and size of price changes are appellants in these studies. Bils and Klenow (2004) performed one of the first works using a large amount of data from the Bureau of Labor and Statistics (BLS). Since then several other studies were conducted with similar data from other countries. Concerns about the influence of sales price, heterogeneity and replacement of products also appear among these works. Many of these question the price rigidity in different inflationary states, in which the higher inflation faster the adjustments. Both theoretical and empirical literature are briefly described in the next two subsections.

## 1.1 Theoretical Literature

The theoretical literature is important not only for understanding the models that deal with pricing under nominal frictions, but also, and mainly, for comparison with the results from an empirical analysis. The models are based on the assumption that nominal variations are not completely irrelevant, even though they have little significance at the microeconomic level. Based on the New - Keynesian view, these models bring the fact that small nominal barriers result, in some way, in significant macroeconomic changes. Most of them follow a specific framework: (i) imperfect competition; (ii) pricing under nominal price rigidity; (iii) currency existence.

Nominal rigidity is understood as the time it takes to certain price reacts to a shock, both in the micro environment, or in the aggregate. For example, an idiosyncratic shock may face resistance in affecting the price of a firm. As well as a monetary expansion can affect

aggregate variables in smaller or larger scale. The latter case is of the utmost importance for economic policy. Thus, it is crucial to identify the validity of the models developed so far, since the choice of a particular policy may be based on results of inappropriate models.

In this sense, there are two groups of dynamic models that address the topic, time-dependent models and state-dependent models. The basic difference between them is the way firms decide to price its products. In time-dependent models firms chose their prices to be stabled in a predetermined period of time (exogenously chosen), as mentioned before. In this case, the main cost involved is informational. Two examples frequently saw in the literature are the works of Taylor (1980) and Calvo (1983). In the first one, prices are set in advance for “contracts” and remain fixed for a given time. In the second, the pricing of the firm for some periods ahead depends on a probability distribution. In addition, the price changes are done only when the firm receives a signal, what characterizes the stiffness of the model.

An interesting extension of the time-dependent models is to consider the period for which prices are adjusted as endogenous. Bonomo and Carvalho (2004) worked with this assumption. In addition, their model considered the possibility of firms reassess the time when prices remain the same given exogenous shocks. In fact, it is reasonable to imagine that a significant change in economic policy could influence the size of the period in which prices of a particular firm remain fixed. According to the authors the endogeneity proposed alters significantly the results of a time-dependent model.

The second class of models are the state-dependent models. In this case, the price setting depends on the state of the economy. The adjustment cost of firms is what characterizes the microeconomic friction. In general, these are known as menu cost, and give the idea of operating costs involved in price changes. The model developed by Caplin and Spulber (1987) is a benchmark among the state-dependent models. The main contribution of their study is that monetary shocks do not produce real effects on product, something not shared by time-dependent models.

A sophistication of the state-dependent models can be found at Gertler and Leahy (2008). The authors build a structural model for inflation in which prices chosen by firms impact the aggregate variables and thus a new Phillips curve is formed. The model increment takes place in the inclusion of real rigidity and an idiosyncratic shock. In addition, the article assesses the economy in a steady state with low and stable inflation, being this, one of the limitations of the model. In the same track Golosov and Junior (2007) also include an idiosyncratic shock, besides to calibrate a model  $S_s$ .

## 1.2 Empirical Literature

The empirical literature brings interesting results about the importance of nominal rigidity in business cycles. Most of the work is related to micro price data from Europe and USA, being a small portion related to studies in emerging countries. The contribution is not only by the confrontation of several results with the models mentioned, but also by the comparison between their empirical works. The various empirical evidence found in this literature are typically directed to explain how rigid is the general price level given an aggregate shock. Perhaps the greatest contribution of the literature of micro data is to detail the characteristics of price friction on the less aggregated level, to consequently understand macro variations in response to certain shocks.

Klenow and Malin (2010) raised ten stylized facts from other works. It would be interesting to understand whether some results fit to the data.<sup>1</sup> The fourth fact shows one of the expected results in this work. Refers to how different is the rate of price changes between goods and services. Not surprisingly items classified as commodities tend to change prices more frequently. On the other hand, services present greater rigidity.

Nakamura and Steinsson (2013) reviewed the empirical literature in order to illustrate how the different “barriers” to price adjustment (micro-level) affect the response of the price index in an aggregate shock scenario. Using micro data (CPI), the authors found an average frequency of price change of 27% for a month. It is important to note that this percentage includes variations related to sales price. Some price changes do not necessarily reflect the pattern of price adjustment (they are only temporary changes). Price promotions are an example. However, several studies minimize the importance of treating these promotions, justifying that its influence is insignificant to impact the real rigidity level.

Another aspect about the average frequency of a price change is that given the frequency of price collection of different products, the use of average frequency could underestimate average nominal rigidity (heterogeneity of products leads to an asymmetric distribution of frequencies). The replacement of products also seems to influence the price change. According to the authors, a significant number of firms update their prices only in replacement of products.

The frequency of price changes in different inflation scenarios is also in their work. Nakamura and Steinsson (2013) mention two papers with similar results. Gagnon (2007) studied the behavior of prices for Mexico in the period 1994-2002. The author finds evidence that the frequency of price changes in an environment of low inflation is close to zero, since the chances of positive and negative movements cancel each other out. In a high-inflation sce-

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<sup>1</sup> See Klenow and Malin (2010).

nario, the probability of prices to rise is considerably greater than the estimated frequency for negative changes. Alvarez et al. (2011) is quite close to those results, but analyzing the Argentina economy.

The literature that uses micro Brazilian data is still relatively new, but some results can be helpful to this paper. The study of Barros et al. (2009) seeks to understand how some pricing-related statistics (probability and magnitude) change in front of macroeconomic variables over the period 1996-2008. According to the authors, price increases are less frequent after a currency appreciation, and more frequent after currency devaluation. In addition, firms seem to change price faster in periods of high inflation (reinforcing the state-dependent character). In addition to the estimates of the average frequency (and median) and the size of price changes, BBCM compute the duration of prices, i.e. the average time that prices in a given aggregation remain fixed. At the beginning of the period (April 1996) concerned, prices remained fixed, on average, 2.5 months. With the stabilization of the price level this value almost double in 2000 (5 months).

Gouvea (2007) investigates the pricing adjustment patterns in Brazil, based on micro data from 1996-2006. She brings some statistics as the average frequency of price changes, average duration, consequences of heterogeneity and pricing against current and expected inflation. The results indicate that prices remain unchanged, on average, 2.7 to 3.8 months (depending on the method used). Moreover, according to the author, there is a great diversity in the way prices are set. Another finding is the strong symmetry between the proportions of positive and negative changes.

## 2 Data Base

The database is composed by products and services prices collected by IBRE/FGV and used to compute the consumer price index (CPI). The indexes items are divided in seven major expenditure classes (food, housing, clothing, health and personal care, education, reading and Recreation, transport and miscellaneous expenditure). The collections of prices are made in 12 cities of the country and differ between the items regarding the periodicity. For some items the collection occurs on average from thirteen to thirteen days. For others, the prices are cataloged on a monthly basis.

It is important to understand some definitions about the items included in the base before any data manipulation. We call it “a product category” the product (or service) in its more aggregated level and “informed item” the product (or service) on their level more unpinned. Thus, an informed item refers to a particular product with precise characteristics, priced in a specific reseller. An example of an informed item would be the **Soda cola, brand Guaraná, 2L, sold in a resale number 1155**. In this case, the product category would be **Soda cola**. It is the price of the informed item that we are interested in. With the most disaggregated data level it is feasible to understand price rigidity in the firm level.<sup>1</sup>

The initial sample contains around seven million observations starting in 1996 and extending until 2005, with significant representation of the consumer price index. An observation is the price of an item on a certain date. In total there are approximately 120 thousand items divided into different categories.

### 2.1 Aggregation and Some Stats

Before the estimation the data was managed in a way of classifying the products into different groups. In this context, all items were classified as tradables or non-tradables. The aggregation was based on an official division from the Brazilian Central Bank. Figure 3 gives an idea of the items included in this data base.

Items classified as non - tradable are goods and services produced and consumed domestically that are not close substitutes to import or export goods and services. Examples of non-tradables are rents, education, food away from home and so on. In the same way, tradables are known as products that compete with foreign goods and so should suffer from exchange rate volatility.

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<sup>1</sup> From here on an informed item will be called simply as an item.



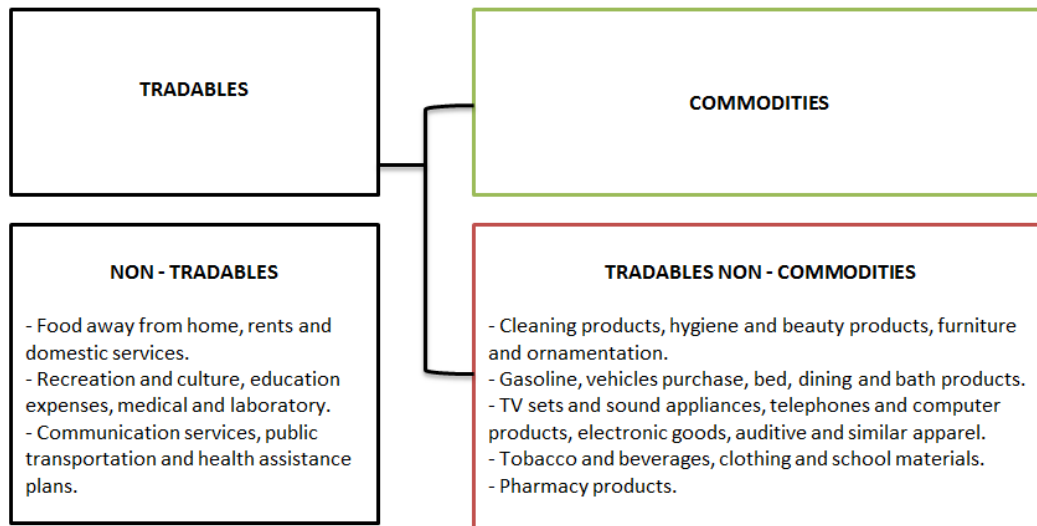


Figure 3 – Items Aggregation

After this first division, tradables were divided into commodities and tradables non-commodities. The second group includes products that should be strongly influenced by movements on the exchange rate. The greatest example of an item in this category would be electronic goods. Most of these items are heavily dependent on imported supplies, which affect directly their final costs. The group of commodities is composed mostly by foods in general. These item are also dependent from currency volatility but maybe because their prices are "formed" in the international market.

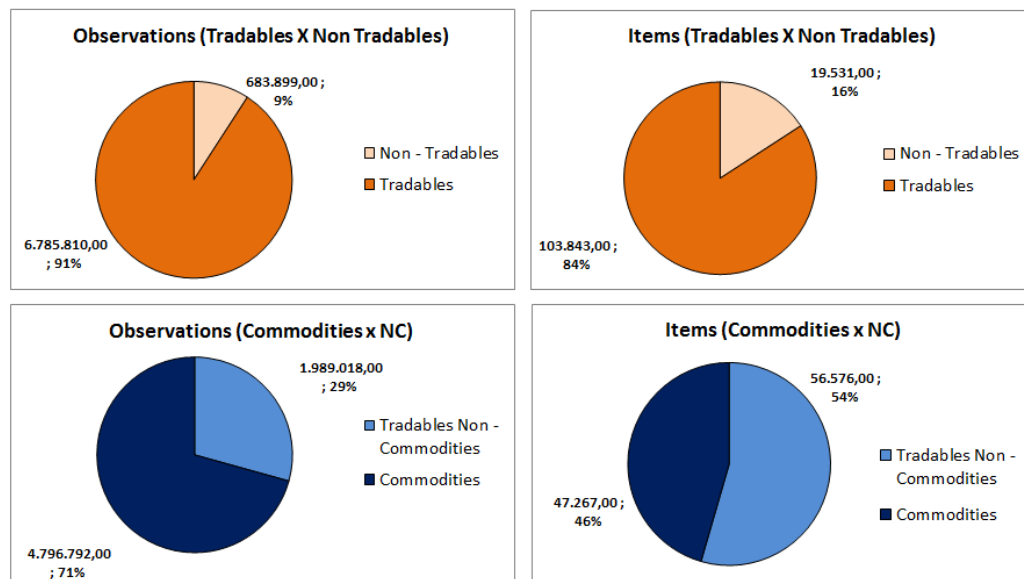


Figure 4 – Data Composition

In terms of number of observations, it is evident the predominance of the items classified as tradables. These represent more than 90% of the role sample when compared to non-tradables goods. Inside the tradables the majority of items when looking to observations are commodities. The pie charts in Figure 4 give a clear idea of the sample composition.

Comparing the total items of commodities against non-tradables could give us the impression this is the reason the first has the most observations in the sample. However, it keeps showing more observations than tradables non-commodities even having fewer items than those. This fact might be explained by the higher frequency of commodities price collection. From Figure 5 we can see that even for different periods of sample the mean time of collecting prices remain very similar for all groups.

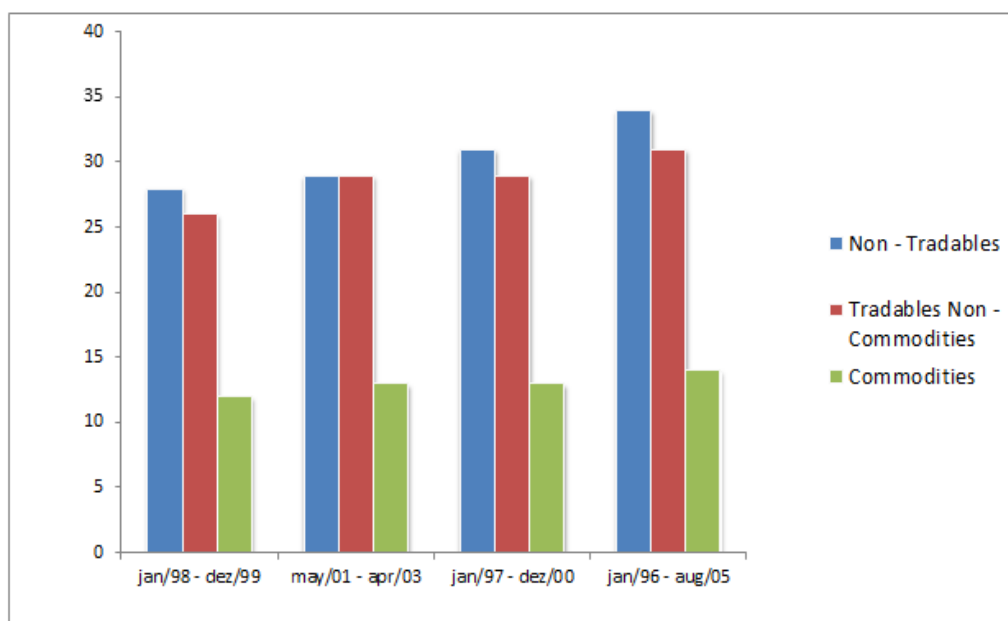


Figure 5 – Mean Frequency of Price Collection

As we can see, commodities have its price collected in average every thirteen days, that is about twice faster than tradables non-commodities and non-tradables that have their price collected in average every 30 days. A complete table with informations about the data sample is contained in Appendix B.

## 3 Methodology

In the empirical literature some statistics are brought to characterize some evidences about certain patterns of price adjustment. As mentioned previously, the prices considered on these statistics are in its most disaggregated level. One idea is to reduce the possible effect of heterogeneity between the items. Whether a more aggregated group of products changes its prices on average, does not bring any relevant information concerning the nominal rigidity of individual firms (and consequently in the aggregate). Besides that, having individual collected prices allow us to rearrange items and group them according to our interest. These are the reasons of working with this type of data base.

### 3.1 Data Treatment

The data treatment will be quite simple. After aggregating items into different classifications, a price collected time series was created for each item in the sample. These individual time series does not have to be necessarily the same in terms of collection dates. For example, an item may have its price collected each seven days starting in December of 2001 till August 2003, while others each fifteen days ranging from 1999 till 2000. Besides that, a single item may not present a pattern of pricing collection. In other words, the collection may be done in different time spaces.

Given the considerable size of the data base a second step was to resize our time series in short periods. In this context, the two moments in the sample that presented large exchange rate devaluation were taken into consideration. The first period range from January 1998 till the end of 1999, i.e. practically one year forward and one year ago from the large devaluation of January 1999. The second period attempts to capture the exchange devaluation happened in 2002. It goes from May 2001 till April 2003, being the devaluation moment also in the center of the period.<sup>1</sup> As mentioned before, the first devaluation is expected to have a greater impact on pricing change, given its faster jump in the exchange rate.

To guarantee that some items have at least a minimum of significance in the sample, a restriction of a minimum of observations per item was imposed. In the next section it is presented the results considering the minimum of ten observations by item. Before deciding moving on with this lower bound, 6, 10, 14, 22, 40 and 80 required minimum observations were “tested” to note how sensible the data set is in exchanging this minimum. For example

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<sup>1</sup> The definition, or the identification of the exact devaluation shock moment is not that clear for this period. This brought some uncertainty when looking the results.

defining a minimum of 80 observations in a two year period left us a few observations in average, which was already expected. The number of items left for the other values are very close to the one found for ten observations, not considerably influencing the size of the sample. For that reason, it was decided to keep ten observations as a minimum.

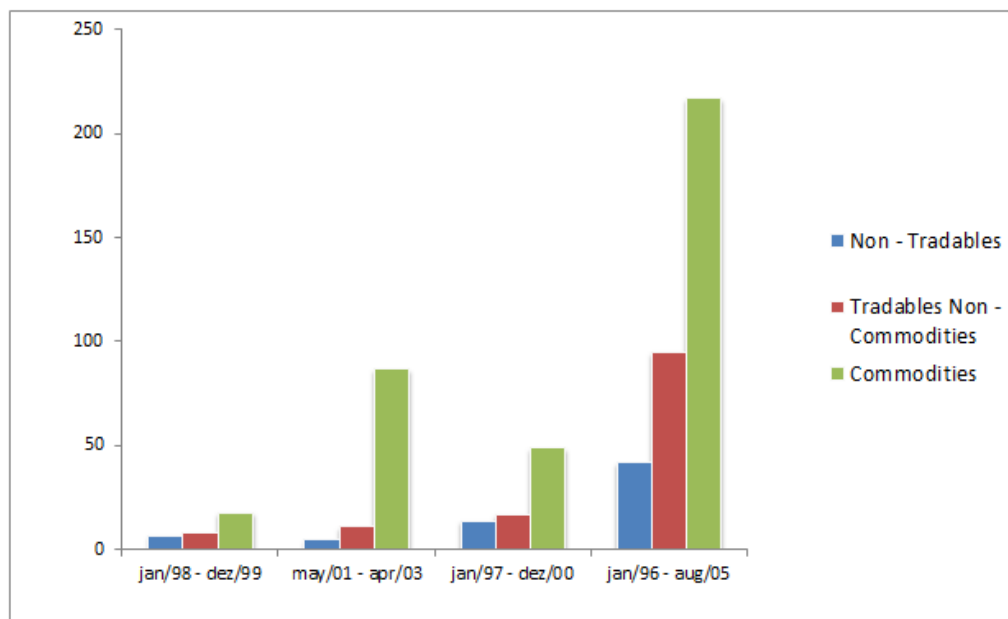


Figure 6 – Outliers

After defining a minimum number of observations by item, some outliers were excluded. A prior consultation of the data indicated that some values are extremely disproportionate. The outliers were defined as prices changes greater or equal than 900% or minor or equal than negative 90%. The idea is to capture some typing mistakes when cataloging prices. Just for curiosity, Figure 6 shows the number of price changes considered outliers for each aggregation in different periods. As we can see, most of outliers appears in commodities price changes. Maybe because these items have a higher price collection frequency, raising the probability of some kind of errors.

### 3.2 Estimation: Probability of a Price Change and Mean Magnitude

The estimation of the probability of a price change was constructed using the maximum likelihood estimation method. The idea behind it is to find an estimator that for a fixed set of data and an underlying statistical distribution maximizes a likelihood function. In other words, it maximizes the probability of the sample used in the estimation be the closest one to the populations' aspects of interest. The maximum likelihood can be applied to an

extremely wide variety of models and it generally yields estimators with a lot of excellent asymptotic properties. The parameters to be estimated in our case are the probabilities of a price change, called *lambda*. It is important to highlight that estimating lambda give us the chance to make some tests after the estimation itself. That is not really common in empirical studies of price setting using micro data.

Before getting into more details, or, to be more specific how the likelihood function was built and maximized, it is necessary to explain the concept defined here as a price spell. A price spell is the period of time in days that comprehends two collection dates (have the items' price changed or not). So the number of spells for a specific item is the number of observations for that item minus one. Figure 7 helps to understand the concept of a spell and why it is important in this paper.

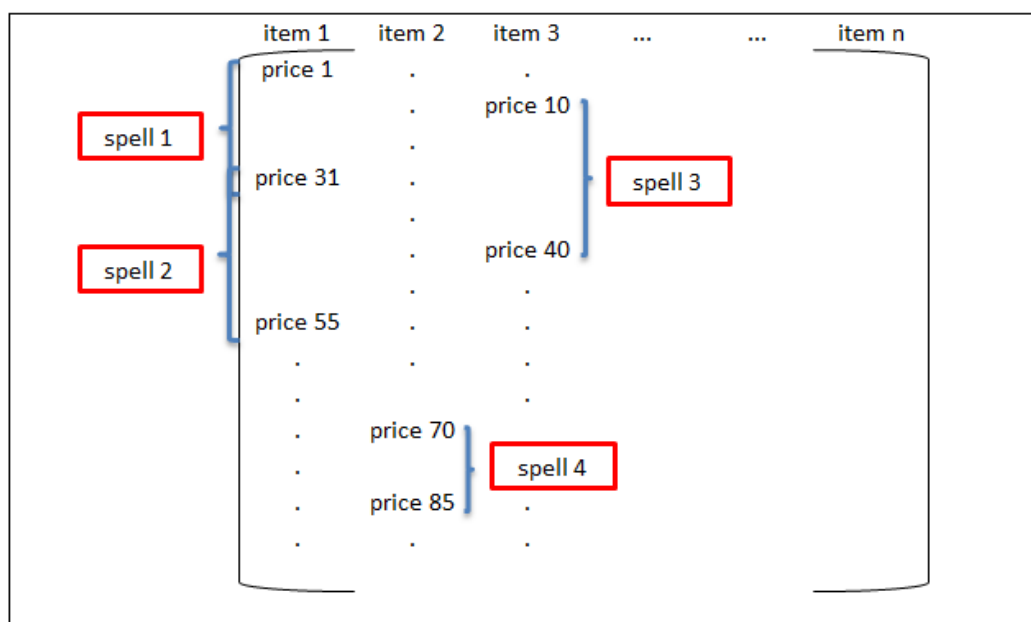


Figure 7 – Example of Spells

Each spell brings a probability function related to the fact that a price change was observed or not. The length of the spell depends on how many days there is no information about prices between two collection dates. Therefore the probability function of a price change for each spell is given by:

$$f(y_k, \lambda) = (1 - y_k)g(X, \lambda) + y_k[1 - g(X, \lambda)] \quad (3.1)$$

where  $y$  is a binary variable that assumes either the value 1 or 0 ( $y = 0$  when there is no price change and  $y = 1$  when there is a price change),  $k$  is the position (in terms of time

series) of an specific spell for a given item, and  $X$  is a set of information (as collection dates and its respective prices). In this sense:

$$g(X, \lambda) = \prod_{t=1}^n (1 - \lambda_t) \quad (3.2)$$

is a function that represents the probability that there is no price change for spell  $k$ , where  $n$  is the number of days contained in the spell. Thus, from one day after the first date of collection till the last day of a spell, the probability that the item have not changed its price during that spell is defined. The likelihood function for each item can be written as:

$$L(\lambda, y_k) = \prod_{k=1}^m f(\lambda, y_k) \quad (3.3)$$

where  $m$  is the total number of spells for an item. Thus, the likelihood function is just the product of the spell probability function for each item. For simplicity and optimization, it was decided to work with the loglikelihood function, which is basically:

$$l(\lambda, y_k) = \sum_{k=1}^m f(\lambda, y_k) \quad (3.4)$$

Summing up all the loglikelihood function values (for all items) we have the final value of the loglikelihood function. In this context, we are interested in finding a vector of lambdas (could be daily, monthly, yearly) that maximizes our loglikelihood function. The procedure was done using Matlab and in the next section the results are presented with a confidence interval of two standard deviations.

In this optimization problem there would be a choice finding the probability of a price change for each day according to our sample selection. That would take us a long period of estimation, given the huge size of the data sample. By that reason it was decided to work with monthly estimations. When considering the first and the second period mentioned before, we end up with a total of 24 monthly estimates, being the moment of the exchange rate shock right in the middle of that.

It is clear that the probability of price changes could tell us a lot of patterns of price adjustment, but another statistic can help us to improve these signs. The mean size of price changes is important in a way to know how big the changes are in average. That could be a indication to time-dependent models. A daily mean magnitude of price changes was calculated by the average of prices changes each day of the sample. It's relevant notice that there is no information about prices every day. Therefore, there is no way to know when exactly an item has its price changed in a spell that tells us there had been a change. Thus, whenever there is a change, that value is attributed to all day in that spell, keeping a constant percentage change value through time.

Just to recall that either the probability of price changes or the mean size of those changes were calculated not only for all changes “together”, but mainly for positive changes. That is extremely relevant to realize weather firms are adjusting its price due to a cost pressuring or they are simply changing up from time to time.

Some comments on the construction of the series and the estimation: (i) on the choice of the time period. Such a definition not only influences the number of observations per item, but also the inclusion or not of each item. Depending on the dates of collection, it is possible that an item is simply discontinued, not influencing the calculation of statistics; (ii) some items had double dates of collection. The prices were the same so we have just excluded one of them, not altering the data base significantly.

## 4 Results

The application of the methodology was done on different aggregations focusing on the period January 1998 - December 1999. Results for the period May 2001 - April 2003 are not that clear and can be found on Appendix A. It is important to understand how the results differ between items classified as tradables and the ones classified as non-tradables. As mentioned previously, it is expected that goods considered non-tradables react slowly, or even do not present a significantly move in their prices, differing from the others. Items classified as tradables non-commodities, for example, are expected to change prices more frequently after the exchange rate shock.

First of all it is interesting taking a look at the group that would not be expected to suffer from a cost rise immediately, given the devaluation moment: the non-tradables. An intuitive thought relative to non-tradables price setting would be low probability with high magnitude, something close to time-dependent models. The Figures 8 and 9 show the mean size and the probability of a positive price change from January 1998 till December 1999, respectively.<sup>1</sup>

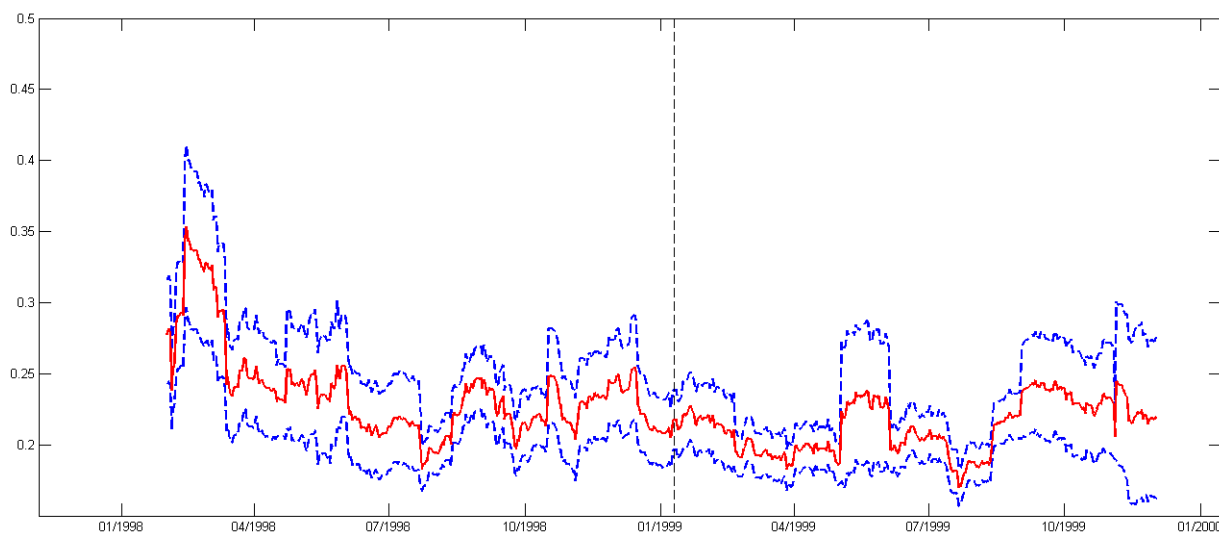


Figure 8 – Mean Size of Positive Price Changes: Non-Tradables

From Figure 8, after the shock the mean magnitude of positive price changes decreases

<sup>1</sup> From Figure 8 to Figure 19 the vertical dot line represents the devaluation moment. In 1999 the shock was set in 01/13/1999 while in 2002 in 05/01/2002. The colored dot lines are plus and minus two estimated standard errors, considering a 5% confidence level. The mean magnitude is presented daily while the probability monthly.



a little, or by the deviations, it does not seem to change that much. Actually, it is not so clear what really happens. In Figure 9 the probability of a positive price change gives the idea that something could be happening in January, or February of 1999, but the results are not that clear again. It seems to have some seasonality in the beginning of the year, which cannot be enforced by the LR tests<sup>2</sup>. Thus, we can not precise the way non-tradables firms are pricing after the shock.

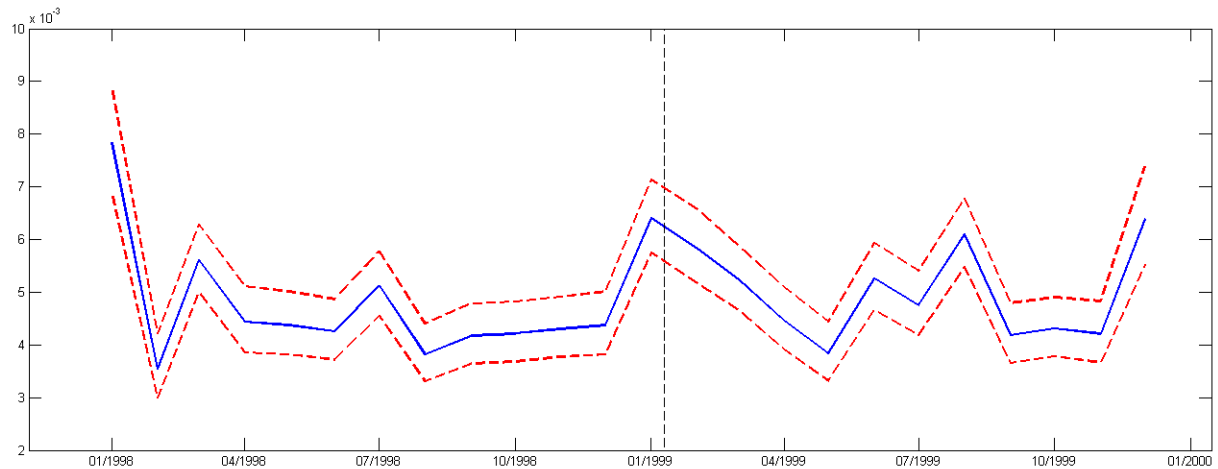


Figure 9 – Probability of a Positive Price Change: Non-Tradables

The results for tradables non-commodities have the most valuable information in this paper. Figure 10 shows the impact of the devaluation on the mean magnitude of all price changes for these items.

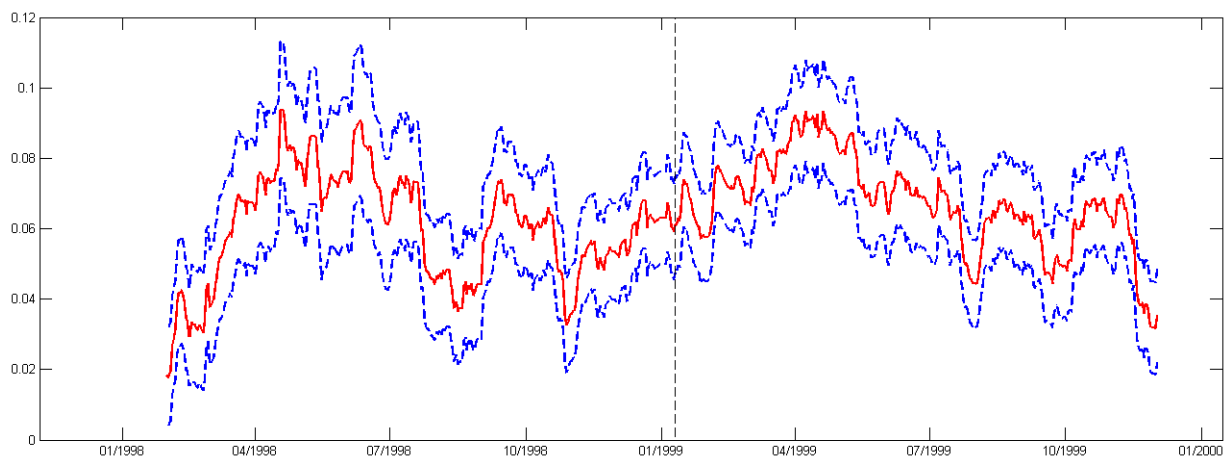


Figure 10 – Mean Size of Price Changes: Tradables Non-Commodities

<sup>2</sup> The hypothesis test are found in Appendix C

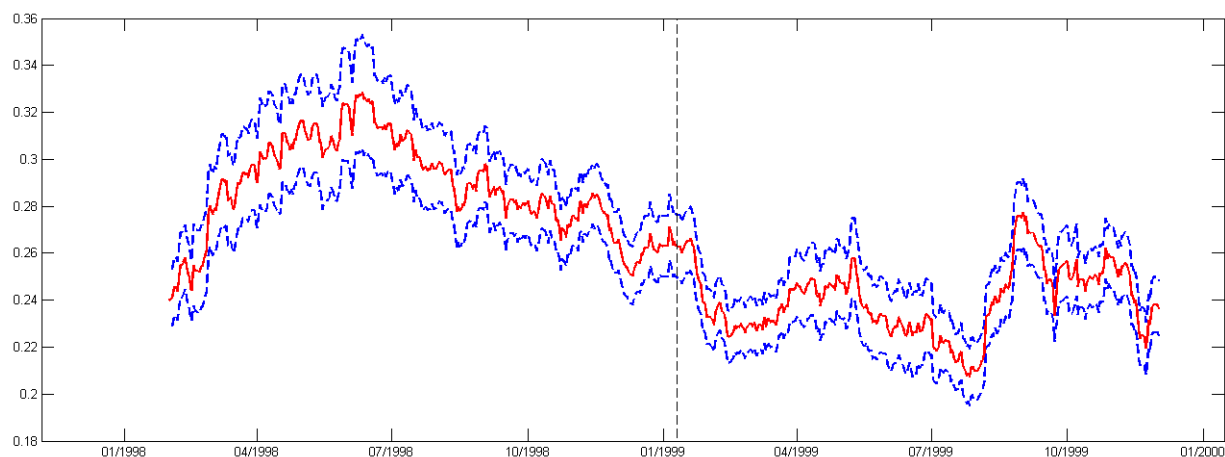


Figure 11 – Mean Size of Positive Price Changes: Tradables Non-Commodities

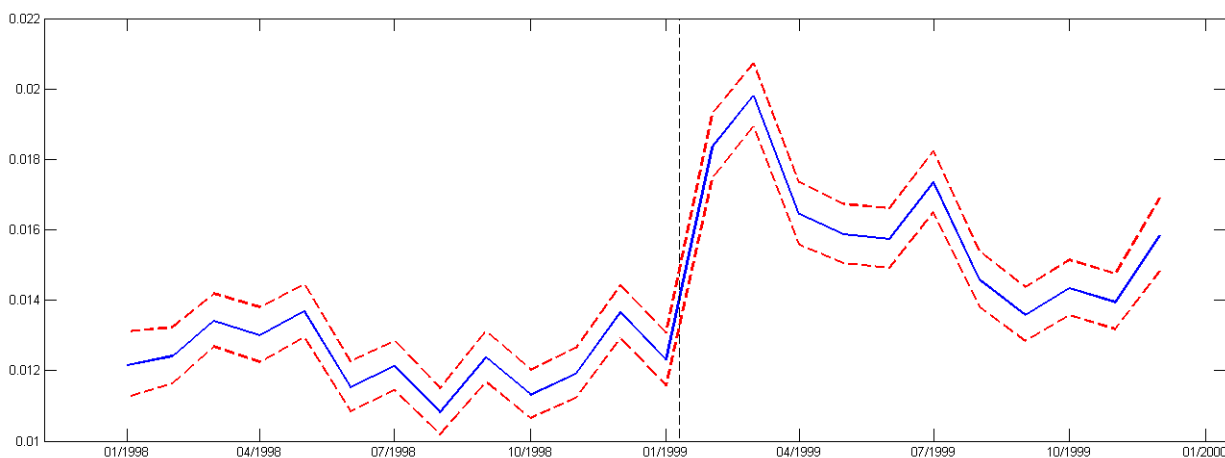


Figure 12 – Probability of a Positive Price Change: Tradables Non-Commodities

The mean magnitude mostly stays between 4 and 9 percentage changes. Given the shock, the mean size of price changes increases a little reaching the highest level (after the devaluation) in April 1999. A first guess would be that firms are raising prices in a higher magnitude, but that does not seem the case. Figure 11 illustrates why.

After the devaluation, the mean size of positive price changes falls and therefore it is not positively influencing the magnitude for all changes. The whole point here is that what is driving the mean magnitude up is the probability of a positive price change.

Figure 12 shows the probability of a positive price change for tradables non-commodities. By this figure it gets clear that tradables non-commodities firms are pricing up right after the shock, giving the idea that they are aware of the devaluation. The probability of a positive change does not show any strong variation before January 1999. It swings between 1.1% and

1.4% the whole year of 1998. The spike appears only right after the shock.

Just to clarify what we are looking at: the probability of a price change presented is the daily mean probability of a random sorted item had its price changed. Thus, the probability of a positive price change in a month is considerably high (specially in the tradables non-commodities case). Importantly, after the shock this probability almost double. That seems a lot more significant than the change in the magnitude (around 10%). In Figure 13 a similar frame can be seeing for commodities but with a smaller leap.

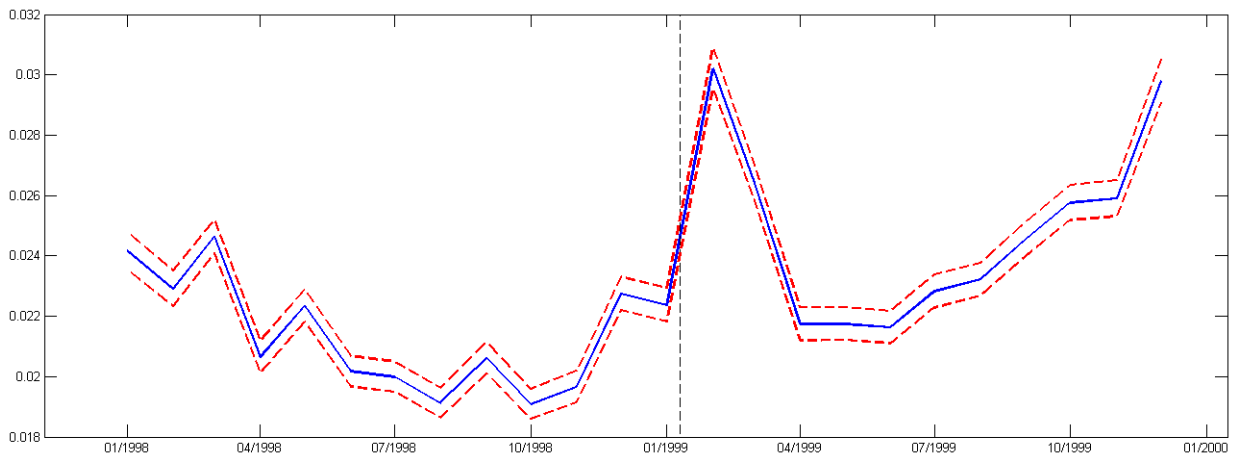


Figure 13 – Probability of a Positive Price Change: Commodities

The figure above shows the probability of a positive price change for commodities. Before January it varies above tradables non-commodities, between 2% and 2.5%. After the shock it raises to approximately 3%. The thing is commodities appears to change price a lot (not just after the shock). Therefore, the results for this group are less expressive, but still important.

## Concluding Remarks

This dissertation explored a clearly positive exchange rate shock which affects mainly some specific industries. This fact allowed us to distinguish between state-dependent and time-dependent models, depending on the estimations for our different aggregations. The main conclusion we can take is the effects in the mean magnitude and probability of a price change are consistent with state-dependent and not time-dependent pricing. Besides that, the estimation method can be seen as a gain for this type of work. It is not common papers using maximum likelihood to estimate hazard rates in the price adjustment literature.

It is important to note that there are some caveats to this conclusion. The evidence is based on the reaction to one specific exchange rate shock that is easily observed. It is quite possible that firms pricing exhibit a different behavior in other circumstances. Nevertheless, it is a relevant piece of evidence in favor of state-dependent pricing.

## A Appendix - Results for 2002

The results for the period defined from may/2001 - april/2003 are not that clear in terms of how are firms responding after the exchange rate devaluation. The next figures present the mean size and the probability of a price change just as before.

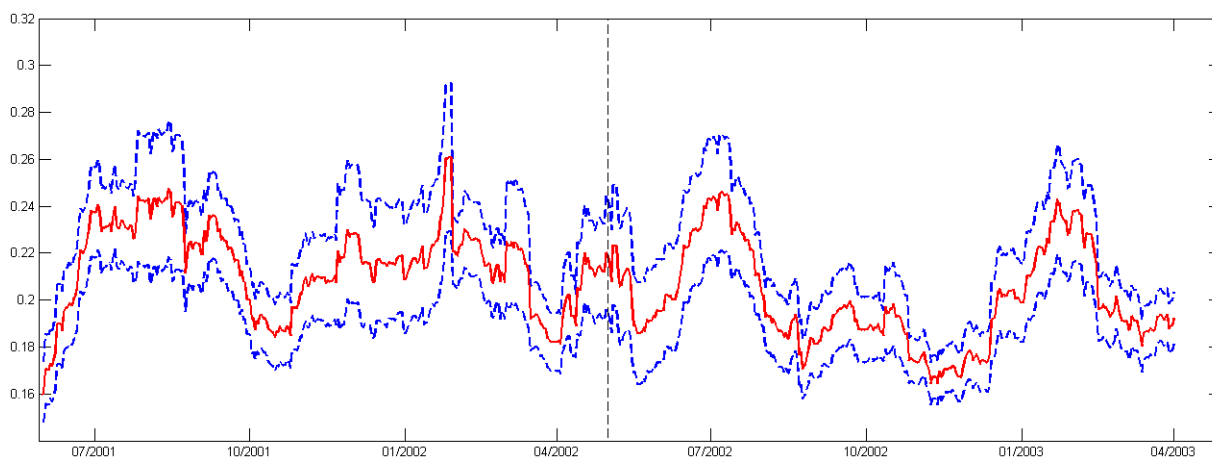


Figure 14 – Mean Size of Positive Price Changes: Non-Tradables

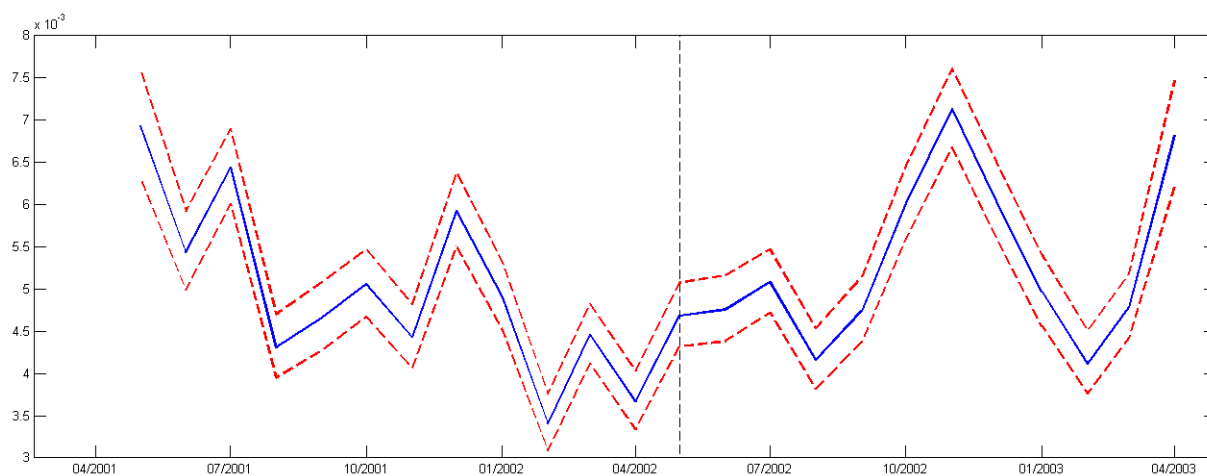


Figure 15 – Probability of a Positive Price Change: Non-Tradables

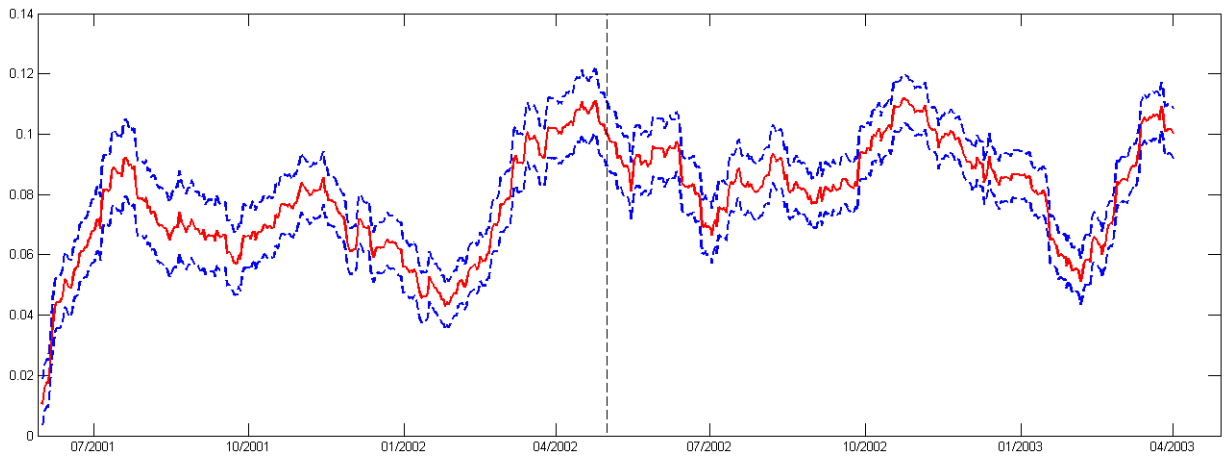


Figure 16 – Mean Size of Price Changes: Tradables Non-Commodities

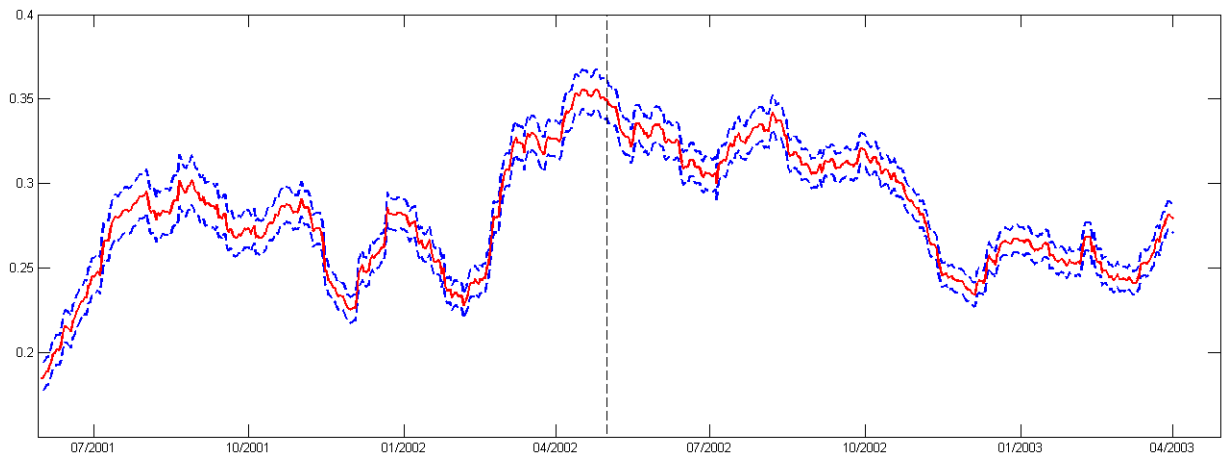


Figure 17 – Mean Size of Positive Price Changes: Tradables Non-Commodities

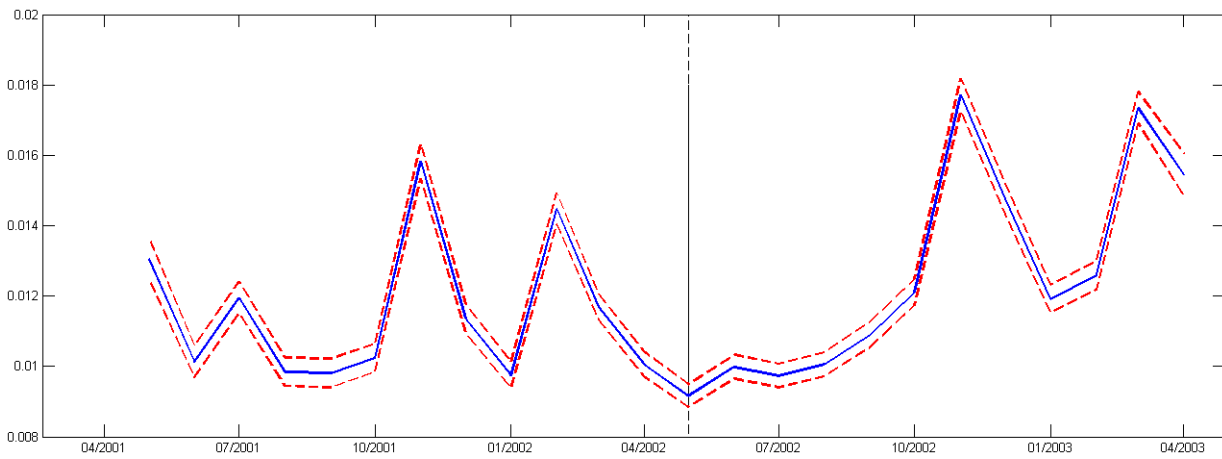


Figure 18 – Probability of a Positive Price Change: Tradables Non-Commodities

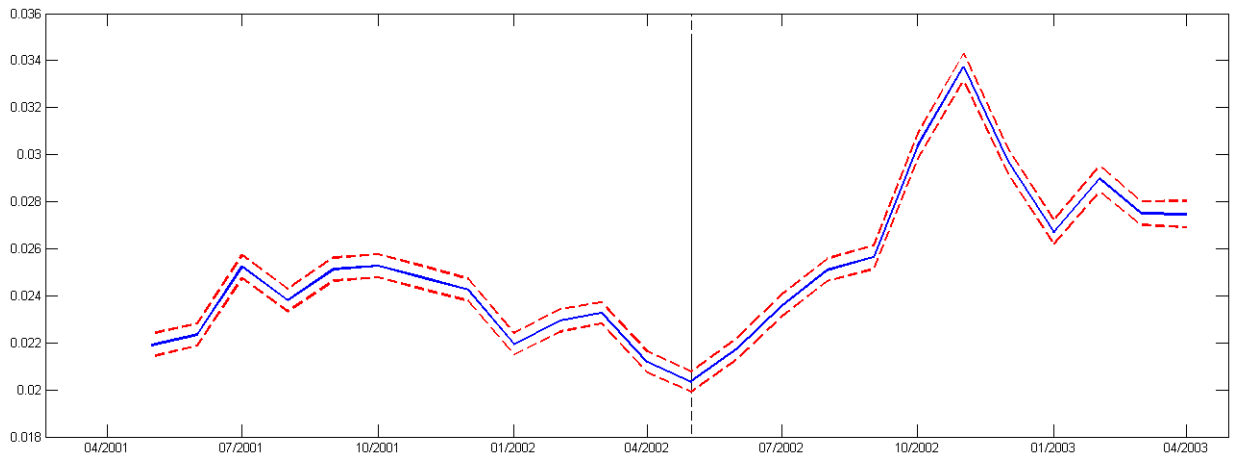


Figure 19 – Probability of a Positive Price Change: Commodities

## B Appendix - Data Base Statistics

Aggregation	Period	Files	Total Observations	Items	Observations (Setting a minimum of 10 by item)	Items (Setting a minimum of 10 obs by item)	Mean Time of Price Collection	Outliers
Non - Tradables	jan/98 - dez/99	51	78.870	3.987	74.996	2.859	28	7
	may/01 - apr/03		190.620	10.548	177.262	7.440	29	5
	jan/97 - dez/00		165.485	7.663	155.468	3.800	31	14
Tradables Non - Commodities	jan/96 - aug/05	76	683.899	19.531	660.247	13.835	34	42
	jan/98 - dez/99		194.597	8.825	180.444	5.715	26	8
	may/01 - apr/03		569.493	36.466	522.394	21.515	29	11
Commodities	jan/97 - dez/00	115	401.167	17.486	371.190	7.955	29	17
	jan/96 - aug/05		1.989.018	56.575	1.885.905	43.003	31	95
	jan/98 - dez/99		821.060	16.478	816.296	15.443	12	18
Tradables	may/01 - apr/03	191	1.157.757	24.262	1.143.509	21.075	13	87
	jan/97 - dez/00		1.665.302	26.123	1.633.135	17.500	13	49
	jan/96 - aug/05		4.796.792	47.267	4.722.835	40.408	14	217
TOTAL ; Mean (for Collection Time)	jan/98 - dez/99	242	1.015.657	25.303	996.740	21.158	19	26
	may/01 - apr/03		1.727.250	60.728	1.665.903	42.590	21	98
	jan/97 - dez/00		2.066.469	43.609	2.004.325	25.455	21	66
TOTAL ; Mean (for Collection Time)	jan/96 - aug/05	242	6.785.810	103.842	6.608.740	83.411	23	312
	jan/98 - dez/99		1.094.527	29.290	1.071.736	24.027	24	33
	may/01 - apr/03		1.917.870	71.276	1.843.165	50.030	25	103
TOTAL ; Mean (for Collection Time)	jan/97 - dez/00	242	2.231.954	51.272	2.159.793	29.255	26	80
	jan/96 - aug/05		7.469.709	123.373	7.268.987	97.246	28	354

Figure 20 – Descriptive Statistics



## C Appendix - Tests

The following three Wald tests were done to verify the rejection of  $H_0 : X_i = X_j$ , where  $X_i$  and  $X_j$  are the probabilities of a positive price change for month  $i$  and  $j$ , respectively. The matrices provide as an output zeros or ones. One means rejection of the null hypothesis, while zero the opposite.

Figure 24 presents the Likelihood Ratio Test for all aggregations. In this case, the restriction imposes that the probability of a price change in January 1998 equals the probability of a price change in the the same month one year forward, for all months. These restrictions are considered together. The results are the following:

	jan/98	feb/98	mar/98	abr/98	mai/98	jun/98	jul/98	ago/98	set/98	out/98	nov/98	dez/98	jan/99	feb/99	mar/99	abr/99	mai/99	jun/99	jul/99	ago/99	set/99	out/99	nov/99	dez/99	
jan/98	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
feb/98	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
mar/98	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
abr/98	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
mai/98	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
jun/98	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
jul/98	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ago/98	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
set/98	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
out/98	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
nov/98	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1
dez/98	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1
jan/99	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1
feb/99	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1
mar/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1
abr/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1
mai/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1
jun/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1
jul/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1
ago/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1
set/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1
out/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1
nov/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1
dez/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1

Figure 21 – Wald Test for Non-Tradables

	jan/98	fev/98	mar/98	abr/98	mai/98	jun/98	jul/98	ago/98	set/98	out/98	nov/98	dez/98	jan/99	fev/99	mar/99	abr/99	mai/99	jun/99	jul/99	ago/99	set/99	out/99	nov/99	dez/99
jan/98	NaN	0	1	0	1	0	0	1	0	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1
fev/98	0	NaN	0	0	1	0	0	1	0	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1
mar/98	1	0	NaN	0	0	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
abr/98	0	0	0	NaN	0	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
mai/98	1	1	0	0	0	NaN	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
jun/98	0	0	1	1	1	1	NaN	0	0	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1
jul/98	0	0	1	1	1	1	0	1	NaN	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
ago/98	1	1	1	1	1	1	0	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
set/98	0	0	0	0	0	1	0	1	NaN	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
out/98	0	1	1	1	1	1	0	0	0	NaN	1	1	0	1	1	1	1	1	1	1	1	1	1	1
nov/98	0	0	1	1	1	1	0	1	0	0	NaN	1	0	1	1	1	1	1	1	1	1	1	1	1
dez/98	1	1	0	0	0	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1
jan/99	0	0	1	1	0	1	0	1	0	0	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1
fev/99	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1
mar/99	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1
abr/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1
mai/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1
jun/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	NaN	1	1	1	1	1	1	1
jul/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1
ago/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1
set/99	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	NaN	1	1	1	1
out/99	1	1	0	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	NaN	1	1	1
nov/99	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	NaN	1	1
dez/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN

Figure 22 – Wald Test for Tradables Non-Commodities

	jan/98	feb/98	mar/98	abr/98	mai/98	jun/98	jul/98	ago/98	set/98	out/98	nov/98	dez/98	jan/99	feb/99	mar/99	abr/99	mai/99	jun/99	jul/99	ago/99	set/99	out/99	nov/99	dez/99	
jan/98	NaN	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
feb/98	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
mar/98	0	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
abr/98	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
mai/98	1	0	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
jun/98	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
jul/98	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ago/98	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
set/98	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
out/98	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
nov/98	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	1	1	1	1
dez/98	1	0	1	1	1	1	1	1	1	1	1	NaN	0	1	1	1	1	1	1	1	1	1	1	1	1
jan/99	1	0	1	1	1	1	1	1	1	1	1	1	NaN	0	1	1	1	1	1	1	1	1	1	1	1
feb/99	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1	0
mar/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	1	1	1	1	1	1	1	1	1	1
abr/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	0	0	0	0	0	0	0	0	0
mai/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	0	0	0	0	0	0	0	0
jun/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	0	0	0	0	0	0	0
jul/99	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	0	0	0	0	0	0
ago/99	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	0	0	0	0	0
set/99	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	0	0	0	0
out/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	0	0	0
nov/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN	0	0
dez/99	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	NaN

Figure 23 – Wald Test for Commodities

Aggregation	pValue	H0 rejected?		
		1%	5%	10%
Non - Tradables	3,3112E-07	Yes	Yes	Yes
Tradables Non-Commodities	0	Yes	Yes	Yes
Commodities	0	Yes	Yes	Yes

Figure 24 – LR Test

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