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PRICE STICKINESS IN EMERGING ECONOMIES: EMPIRICAL EVIDENCE FOR FOUR LATIN-AMERICAN COUNTRIES

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Price Stickiness in Emerging Economies: Empirical Evidence for Four Latin-American Countries

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Abstract

In spite of vast theoretical developments on the issue of price stickiness in the context of macroeconomic models, papers assessing the empirical validity of such hypothesis using micro-data are scarce. Most of these few attempts have been done for developed economies. The few papers that focus on developing countries, in particular, on Latin America utilize different methodologies and data sets, making it difficult to compare and generalize the results. Thus, in an effort to fill this gap, the aim of this paper is to study price stickiness using more homogenous methodologies and data by estimating the duration of prices (and the frequency of price adjustments) and the price setting rule that is most relevant for four emerging Latin American economies: Brazil, Chile, Colombia, and Mexico. The results reveal that Chile and Colombia exhibit a greater degree of nominal rigidity and that there is a substantial amount of heterogeneity in the duration of prices across the different product categories comprising the CPI basket. Furthermore, it was found that state-dependent price setting rules tend to better explain the behavior of the data in the case of all four countries analyzed.

JEL Classification: C41, D21, D40, E31, L11

Key Words: Consumer price index, sticky prices, frequency of price changes, duration of price spells, hazard functions.

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1 Introduction

As emphasized in the literature, for example in Romer (2005), one of the most important factors explaining the resurgence of the interest on how monetary policy is conducted, is the considerable improvement in the theoretical frameworks used in policy analysis. In particular, and as noted by Clarida et al. (1999), the incorporation of the techniques of dynamic general equilibrium theory, pioneer in the study of real business cycles, along with the explicit inclusion of frictions such as nominal price rigidity, made this framework an adequate tool for the evaluation of monetary policy and its impact on the economy in the short run. In this context, many theoretical models of price stickiness have been developed (for example, Rotemberg, 1982, Calvo, 1983 and Taylor, 1999) and incorporated in empirical and theoretical macroeconomic models. In this literature, the typical distinction made when characterizing price stickiness is that between *time-dependent* and *state-dependent* price setting behavior of the firms (Kovanen, 2006). Choosing one rule or the other for the analysis of the implications of monetary policy on real output and inflation is not trivial, since the predictions of these can differ dramatically.

In time-dependent sticky price models, it is assumed that firms adjust their prices using a time contingent mechanism and that the timing of such price changes is exogenously determined. In particular, a firm can either adjust its prices after a determined number of periods (Taylor, 1999) or do so randomly (Calvo, 1983). Both these models feature exogenous staggering of price changes and, as a result, the fraction of firms that adjust their prices is constant from one period to another (Klenow and Kryvtsov, 2005). These models allow for an easy aggregation of the firms' price setting policies and provide a relatively simple solution of dynamic aggregate responses to monetary shocks. However, and as emphasized in the literature (Bils and Klenow, 2004, Klenow y Kryvtsov, 2005, Kovanen, 2006), time-dependent sticky price models tend to lack microeconomic foundations.

Contrary to time-dependent models, in state-dependent sticky price models, firms are assumed to endogenously choose the timing of price changes, which are subject to menu costs. This implies that firms will choose to adjust their prices when specific events occur. As a result, the timing and the magnitude of the firms' price changes will depend on the state of the economy, assuming that the costs associated to price changes, or menu costs, are fixed (Dotsey et al., 1999).

Given the discussion above, two questions immediately come to mind: Are prices really sticky? What type of price setting rule is used in the economy? Even though the theoretical literature on the issue has been vast, papers that have tried to respond to these questions using micro-level data are scarce and are primarily focused on industrialized economies[1]. The literature is even sparser for developing economies, particularly for those in Latin America. Hence, the objective of this paper is to contribute to the scarce existing literature using micro-level data to respond the two questions above for four Latin American economies, namely, Brazil, Chile, Colombia, and Mexico. For these countries taken individually, Espinosa et al. (2001), Medina, et al. (2007), Gouvea (2007) and Gagnon (2007) have tried to measure the duration of prices and in some cases have attempted to identify the relevant price setting rule. However, each of these papers utilizes distinct methodological instruments and data making it difficult to compare and generalize the results. Hence, this paper also seeks to contribute with results that, on one hand, are robust to distinct methodologies proposed in the literature and, on the other hand, allow comparisons and generalizations based on more homogenous methodologies and data.

These four Latin American countries were chosen based on the monetary policy framework currently being applied - inflation targeting and a floating exchange rate – and because disaggregated price data are publicly available (at least to the product level). As highlighted by Batini, et al. (2005), it is widely known that the use of a full fledged inflation targeting strategy requires a profound knowledge of the structure of the economy in order to be able to model and forecast inflation. These countries have been mostly successful in achieving price stability, particularly Chile and Mexico. While Brazil and Colombia still have a (short) way to go in this matter, their inflation rates are in the one-single digit area and decreasing. To keep price stability or low inflation rates, it is important to have a good grasp on the price formation processes prevailing in the real economy. Consequently, answering the questions above is vital for the central banks of these four countries[2].

Results in our paper reveal that Chile and Colombia exhibit a greater degree of nominal rigidity. Prices in these economies were maintained fixed for a period of approximately three months. On the other hand, prices change more frequently in Brazil and Mexico. The average duration in each of these cases was approximately a month and a half. Furthermore, results indicate that there is substantial heterogeneity in the duration of prices across the different product categories defined in the construction of

[1] See Baumgartner, et al. (2004) for an extensive literature review.

[2] See for example Corbo (2002) and Mishkin and Schmidt-Hebbel (2002).

the CPI basket in all four countries. In each case, less-processed goods, such as food items, tend to show more frequent price changes[3]. Finally, it was found that state-dependent price setting rules tend to better explain the behavior of the data for all four countries analyzed.

The paper is organized as follows. Section 2 presents a brief data description. In Section 3, the average duration of price spells for the four countries is estimated using two different approaches: survival analysis and frequency analysis. Section 4 analyzes the type of price setting rule that best describes the behavior of the data in all four countries using determinants of the probability of price adjustments. Finally, Section 5 concludes.

2 Background and Data

2.1 Some background on the chosen countries

The central banks of Brazil, Colombia and Mexico adopted the inflation targeting framework to conduct monetary policy in 1999. Chile, on the other hand, implemented a crude version much earlier in the 1990s and by 1999, when inflation had declined sufficiently – up to 3% annually - it decided to move to a full fledged inflation targeting scheme after abandoning an exchange rate band and allowing the currency to float freely (Morandé, 2002). At the moment of adopting the scheme, the target in each of the four countries was defined using the variation over twelve months of the consumer price index (CPI) and the relevant time horizon for the prevalence of the target was set in one year. In all cases, the inflation target itself was gradually reduced as a means to abate inflation in the medium term. In 1999, when the central bank of Chile moved to a full fledged scheme, the target was set at 3% annually to be reached permanently on average – around a +/- 1% band – as it has not been changed until now. The Bank of Mexico also made a similar decision in 2002, when its monetary policy horizon became indefinite and the target was set at 3% annually.

In terms of results, during the post-adoption period of the inflation targeting scheme the inflation rate in all four countries converged to low and stable figures with the exception of Brazil (Figure 1). In this latter case, the uncertainty associated to the 2002 presidential elections and the substantial increase in the sovereign risk placed strong

[3] The results are qualitatively similar to those found by Espinosa et al. (2001), Medina, et al. (2007), Gouvea (2007) and Gagnon (2007).

pressure on the country's currency and brought higher inflation, beyond the central bank target range. This forced an upward change in the target range itself around 2003 but in more recent years inflation has been reduced after an aggressive monetary policy. Nevertheless, in all four cases current inflation rate falls within the targeting range defined in each country. In this context, the sample periods utilized in the analysis cover precisely the phase during which the inflation rates were converging towards low and stable levels (the dark section in Figure 1). Hence, the results obtained from the analysis should not be contaminated by periods of high macroeconomic instability (with the exception of what occurred in Brazil).

On the other hand, it is observed in Figure 1 that during the sample periods all four countries have experienced phases of low economic growth (including even absolute falls in output), as well as periods during which economic activity was substantially more dynamic. Thus, in all four cases the databases contain information associated to a complete business cycle (and in some cases, more than one) and, hence, the conclusions of the paper should not be associated to a specific period[4].

2.2 Description of the database

We use a longitudinal dataset of prices, which was collected on a monthly basis for the construction of the Consumer Price Index (CPI) in each of the four countries: Brazil, Chile, Colombia, and Mexico. The cross-section dimension of the panel is represented by the individual products (sub items) of the CPI basket. In each country, individual products are categorized into distinct groups of goods according to its type. Therefore, the basic observation in each sample is the price of the individual product at a given point in time (month and year of the record). The choice of the time period of the analysis depended on the last methodological revision made for the calculation of the CPI by the statistical offices in each country. As a result, the sample period differs with each country. Table 1 presents a summary of the main features of the database used for each of the four countries.

In the case of Brazil, the data were obtained from the *Brazilian Institute of Geography and Statistics (IBGE)* and corresponds to the Extended Consumer Price Index (ECPI). The sample is composed of 42,496 prices and contains monthly records for almost 7 years (August 1999 to June 2006) for 512 products, which are categorized into

[4]An important aspect that needs to be emphasized is the external vulnerability of these four economies, which was evident during and after the Asian crisis.

9 distinct groups (see Table 1). It is important to note that since the price records published by the Brazilian statistical office were expressed in monthly growth rates, it was necessary to harmonize the data with that of the other three countries. Hence, the price records were transformed to index numbers.

In the case of Colombia, the database of the Consumer Price Index (CPI) at the product level was obtained from the *National Administrative Department of Statistics (DANE)*. The sample spans over the time period from January 1999 to October 2006 and contains a total of 176 individual products that are grouped into 8 categories (see Table 1). Thus, the entire sample is comprised of 16,544 price records, which, unlike the previous case, were published in terms of index numbers.

For Chile, the disaggregated information of the Consumer Price Index (CPI) was provided by the *National Statistical Institute (INE)*. In this case, the CPI basket contains 482 products and comprises a total of 45,790 observations. The period covered by the analysis starts in December 1998 and ends in October 2006. As in the previous case, the products are categorized into 8 groups according to the type of product (see Table 1). In this case, prices are expressed in Chilean pesos and correspond to the individual product price quotes at each moment in time.

For Mexico, we use monthly prices for 271 individual products that are included in the National Consumer Price Index (NCPI). The data were collected by the *Bank of Mexico (BANXICO)* and cover the period from January 1995 to October 2006. The items included in the consumer basket are allocated among 8 groups and the entire database contains a total of 38,482 observations. Similarly to the case of Colombia, the prices published by BANXICO are expressed in index numbers.

Finally, it is important to note that it is not possible to compare the price records described for each country. This is due not only to the substantial differences that exist across the product baskets, but also to the fact that the prices of similar products across baskets are not adjusted by purchasing power parity. This does not represent a limitation in the paper since all further analysis is conducted by country and any comparisons made are done in terms of the duration of the price records and not in terms of the price levels, directly.

2.3 Specific data issues

Prior to conducting any estimation, it is important to consider a few features of micro-level pricing data, which describes the CPI price series used in this analysis. These considerations are made with the purpose of obtaining more accurate estimations of the average duration of prices.

The first relates to *temporary price discounts (sales)*, whereby a firm momentarily reduces its price only to increase it to its initial level after a short period of time. In this case, the temporarily lower price does not mean a permanent change in the regular price (Klenow and Kryvtsov, 2005). On the other hand, the same can occur with prices that are increased and shortly thereafter decreased to its initial level. However, in this case, it is intuitively difficult to relate the price change with temporary discounts. If temporary price discounts are not disregarded, then average duration of prices can be underestimated. Hence, price changes that last for a month are excluded from the analysis following the strategy utilized by Baumgartner, et al. (2004): Let the price sequence be $P_{j,t-1}$, $P_{j,t}$ and $P_{j,t+1}$, whereby $P_{j,t-1} \neq P_{j,t}$ and $P_{j,t-1} = P_{j,t+1}$, the variation of prices between periods $t-1$ and t is considered nil, that is, $\Delta P_{j,t} = 0$.

A second aspect concerning the data is that price records show seasonality, in particular those associated to products with less value added. In the time series literature, seasonal ARIMA models are typically used to decompose series into its seasonal, cyclical, tendency, and irregular components. The first component is then used to control for the seasonality effect in the time series. We do not follow this strategy, because when the statistical decomposition is used to control for seasonality effects, the periods in which the prices are maintained fixed would be distorted with the transformation of the series. Instead, in section 4, indirect controls in the form of dummy variables are used.

We should also take care of the existence of atypical data and infinitesimal price changes[5]. The atypical data are defined as data for which the price change is not too credible, such as a price variation of more than 100%. Fortunately, price changes that large are not observed in our databases. Infinitesimal price changes were considered as changes only if they showed variations greater than 0.005%, in terms of both percentage and absolute value. That is, if $|(\ln P_{j,t} - \ln P_{j,t-1}) \cdot 100| < 0.005\%$ then the change is neglected. In other words, only the percentages to a precision of three decimal points were considered in the estimations.

Finally, we use price data disaggregated only at the product level and not at the store outlet level, as is generally the case in empirical literature, given that the outlet level data are not publicly available for neither of the four countries. This could represent

[5]See Baumgartner, et al. (2004).

a clear shortcoming. Nonetheless, *product to product group* aggregation exercises done (but not presented here) suggest that, even though the magnitudes could be affected, the primary conclusions of the paper do not vary. However, our results should be interpreted as an inferior bound of the average duration, given that some price spells observed at the store outlet level could have been lost in the process of aggregation at the product level.

3 How long does the average price spell last?

We want to characterize price rigidities in the four economies being studied. A straightforward way to describe price stickiness is to compute the average duration between two price changes for a given product in a particular country[6]. Prices are considered sticky when this duration is long and flexible when duration is short. Two different approaches are used to compute the average duration of price spells, each having pros and cons. The first approach is based on survival analysis, which is also known as the duration approach. In this approach, the aggregate average duration of the price spells is estimated by directly calculating the length of the price spells observed for each of the products. The second one is the frequency approach, according to which the duration of the price spells is estimated indirectly from the probability of observing a price change at a given moment in time. Several practical advantages have been identified in the use of this last approach, including, among others, that it does not require a long time series for estimating the duration of price spells, and that it is less likely to show problems of selection bias. Its weakness, however, is that it does not allow the characterization of the full distribution of the durations (that is, the hazard function). Consequently, this approach does not make it possible to compare the results with those of the existing theoretical models. This weakness of the frequency approach, however, is considered as one of the strengths of the survival analysis approach.

As emphasized by Baudry, et al. (2004) and Aucremanne and Dhyne (2004), the average duration of prices is a crucial structural parameter in many macroeconomic models focusing on price stickiness. In fact the degree of nominal rigidity is one of the determinants of the slope of the so-called *Neo-Keynesian Phillips Curve (NKPC).*

[6] See Kovanen (2006) for a brief summary of the literature associated to this issue.

3.1 Direct estimation of the duration of price spells: Survival Analysis

This section follows closely the methodology used by Baudry, et al. (2004) and begins by providing a set of definitions and notations that will be helpful at the time of analyzing the results obtained. As mentioned in the previous section, the observations in each of the databases are comprised of price sequences $P_{j,t}$, where $j = 1, \ldots, J$ represents the individual products and $t = 1, \ldots, \tau$ denotes time. A price spell for a particular product j is defined as an episode of fixed price. The term i is an index, which identifies the episodes of fixed price for a specific product and at a particular moment in time, with $i = 1, \ldots, N_j$, and where N_j is the total number of episodes of fixed price for product j. The duration of the price spell ($T_{j,i}$) is defined as the distance in time between two price changes of the product j (with $T_{j,i} \geq 1$). Then, the i^{th} price spell can be characterized by the observed duration ($T_{j,i}$), by the price level that prevails during that price spell ($P_{j,t}$) and by the calendar time of the i^{th} price change ($t_{j,i}$).

On the other hand, we define a *price trajectory* as a succession of several episodes with fixed prices, which can be defined by the date of the first observation and the set of successive price spells. The *trajectory length* (L_j) is, therefore, the number of periods for which a product j and its price are continuously observed. The number of price records (observations) in the database is clearly the sum of the trajectory length of all products, and is denoted as $Q = \sum_{j=1}^{J} L_j$. The total number of price spells observed in the sample can be expressed as $N = \sum_{j=1}^{J} N_j$.

Since the aim of this section is to calculate an indicator of price durations from a macroeconomic point of view, the aggregation of the price spells of individual products is important. There are many alternative ways of aggregating such durations into a *macroeconomic duration* of prices. A first alternative is to calculate *the average unweighted duration of all the price spells*, which is defined as:

$$T = \sum_{j=1}^{J} \sum_{i=1}^{N_j} \frac{1}{N} T_{j,i} = \frac{Q}{N} \tag{1}$$

This first aggregate measure of the average duration assumes that all price spells are equally weighted, independently of the product and of the time when the price spell is observed. This first measure is calculated simply as the ratio between the number of observations and the total number of price spells. It is important to consider, however, that the different products within the CPI basket are likely to behave differently with respect to price rigidity. As a result, assigning equal weights to all price spells is probably not the best way to find an aggregate measure of the duration. Consequently, it seems preferable to calculate, as a second option, the duration by homogenous subgroups and then the aggregate durations, instead of estimating a general measure of the average duration. In this case, the average duration for an individual product (product j), which is obtained by averaging across the price spells of the product j, is expressed as[7]:

$$T_j = \sum_{i=1}^{N_j} \frac{1}{N_j} T_{j,i} \quad \forall j = 1, ..., J \tag{2}$$

Using equation (2), it is possible to define *the average unweighted duration of the price spells by product*:

$$T^P = \sum_{j=1}^{J} \frac{1}{J} T_j = \sum_{j=1}^{J} \frac{1}{J} \sum_{i=1}^{N_j} \frac{1}{N_j} T_{j,i} \tag{3}$$

It is important to note that this last indicator gives less weight to products that have more frequent price changes. On the contrary, the indicator of equation (1) tends to undervalue the average duration, given that in this case a greater number of price spells is observed for products with short durations.

Finally, the weights used for the calculation of the CPI (w_j) can be incorporated in this measure of the average duration of equation (3). This can be desirable since this measure applies the same weight to all product groups, which are really heterogeneous. Thus, the average duration in this third option is defined as follows:

$$T^{\omega} = \sum_{j=1}^{J} \omega_j T_j = \sum_{j=1}^{J} \sum_{i=1}^{N_j} \alpha_{j,i} T_{j,i} \tag{4}$$

with $\alpha_{j,i} = \frac{w_j}{N_j}$. Given that the primary objective of this paper is to provide approximate measures for the relevant structural macroeconomic parameters, this last indicator, which corrects the errors of the previous two measures, seems more appropriate. As it is usually the case when working with duration data, the distribution of the durations of price spells is expected to be asymmetric. More specifically, the median duration is expected to be lower than the average duration. For example, if the durations follow an

[7]Note that, in this case, similar weights are assigned to distinct price spells for a common product during the time sample.

exponential distribution homogenous across goods, as it is assumed in the Calvo (1983) model, then the median duration will be $Med(T) = -\ln(0.5)E(T) \approx 0.69E(T)$ where $E(T)$ is the expected value of the duration[8].

Table 2 presents the average durations calculated using the three indicators discussed for the four countries. Two general aspects can be emphasized from these results. First, and as expected, the average duration in each of the economies is lower if it is calculated as the average of all price spells and increases when the indicator that averages the durations by product (or individual trajectory) is used, as well as, when this indicator incorporates the CPI weights. The greatest duration is obtained using the indicator that considers the CPI weights, since such weighting gives more importance to the price spells of products that change prices less frequently. The second general aspect is related to the characteristics of the durations' distribution. As previously mentioned, an asymmetric distribution is common when one works with duration data. More specifically, the distribution tends to be skewed to the right (the median is less than the mean). This last aspect is corroborated by the data since, for each of the four countries and for all the duration measures, the mean is always greater than the median. This indicates that there is a greater concentration of observations around those products for which prices change more frequently.

At the country level, the duration calculated using the indicator that averages over all price spells ranges between a month and a half and a little over two months, with Brazil and Colombia being the countries that have the shortest and longest duration of price spells, respectively. On the other hand, when the duration is calculated by averaging the individual trajectories or products, durations increase and range between a little over a month and a half and almost three months and a half. In this case, Brazil has the shortest duration of price spells, while Chile has the longest price spells. Given these results, the first alternative indicator, referred to as the base indicator, is clearly underestimating the average duration. Finally, when the CPI weights are applied, the indicator ranges between two months and three months and a half. In this last case, Mexico and Colombia are the countries that display the shortest and longest indicators, respectively, with Mexico having the greatest flexibility in its prices and Colombia the greatest degree of rigidity. Note, once again, that this latter indicator puts in evidence the downward bias present in the previous two. Nevertheless, such bias is more evident when compared with the first indicator, that which averages over the

[8]See Baudry et al. (2004).

price spells. Hence, the analysis that follows refers only to the indicators that average by product (with and without the CPI weights).

A potential problem that arises when working with duration data is censoring. Censoring is an important phenomenon when using datasets such as the CPI, where typically the first and the last price spells of a price trajectory are censored. Aucremanne and Dhyne (2004) emphasize that censoring, which truncates some of the price spells, reduces the estimation of the average duration. Moreover, if censoring is important, eliminating the censored price spells from the sample is not a satisfactory option to solve the problem since it can generate selection bias. In general, price spells of long duration are more likely to be censored, and hence ignoring these censored spells will typically lead to the underestimation of the true average duration. The way to deal with the censoring problem involves the estimation of duration models. A simple correction for censoring described by Baudry et al. (2004) is done as follows. If T is the average duration of all the price spells, both censored and uncensored, then the estimate of the corrected average duration is $T* = T\left(\frac{N}{N^{nc}}\right)$, where N is the total number of price spells observed and N^{nc} is the total number of uncensored price spells[9].

Table 3 presents the results obtained when the correction procedure described above is applied to the estimates of the average duration for the four countries. Note that censoring does not seem to be an important phenomenon in our databases. In effect, comparing these results with those of Table 2, we observe that the average duration is underestimated by a minimum of 0.05 months (Mexico) and by a maximum of 0.15 months (Chile) when using the indicator that averages by product. In the case of the indicator that applies the CPI weights, the underestimation ranges from a minimum of 0.05 to a maximum of 0.17 months, figures corresponding to Mexico and Colombia, respectively.

To conclude this subsection, a final analysis is done of the potential heterogeneity that could exist across the different types of products within the CPI basket in terms of its average duration. Table 4 shows the average duration estimated by product groups[10] for the four countries. Results reveal that there is an important degree of heterogeneity in the duration across different product types as well across all four countries. A common fact, however, is that in all four economies, food items are the most flexible.

[9] As emphasized by Kiefer (1988), this form of correction corresponds to the maximum likelihood estimate of a constant hazard model.

[10] The product groups utilized in this analysis are those defined in the calculation of the CPI for each of the countries.

This result is very important considering the weight of food items in the CPI basket (greater than 30% in all countries[11]). An intuitive reason for the frequent price changes in the food category, as suggested by Kovanen (2006), is that in general this type of product, which are typically unprocessed goods, have value added barely exceeding their primary input costs. Consequently, firms that produce these goods do not have the capacity to absorb cost shocks. In other words, primary input costs are not diversified, and hence firms change their prices more frequently to ensure that these do not fall below their marginal costs. On the other hand, as can also be observed in the results obtained in the existing literature, there are goods that experience less frequent price changes, which could be attributed to administrative or controlled pricing, for example rental rates, the cost of transportation and communication, health and medical care fees and the cost of education[12]. Some of these products, to a greater or lesser degree and for one or another country analyzed, are found among the goods that have longer lasting price spells.

3.2 Indirect estimation of the duration of prices: Frequency Approach

As discussed in Baudry et al. (2004), Álvarez and Hernando (2004), and Aucremanne and Dhyne (2004), this approach has several strengths. First, a long span of time series is not needed in the estimation of durations if the assumptions of stationarity and homogeneity in the behavior of the price changes in the cross section dimension are valid. In other words, it is possible to estimate durations even if the sample period is very short (for instance, shorter than the average duration of a price spell). Second, this approach is likely to be more robust when specific events occur (for example, it is possible to exclude a specific month characterized by an exceptional event such as an increase in the value added tax rate). Third, this approach allows for the calculation of average durations without access to the individual records[13]. Given the limitations in the databases, this particular feature of the frequency approach is quite relevant for the present paper. Fourth, this approach does not require an explicit treatment of censuring if this is independent from the duration process, as is usually assumed in duration models. Thus, the risk of selection bias is reduced, and, moreover, the resulting

[11] See Table 1.

[12] See for example, Baumgartner, et al. (2004) and Kovanen (2006).

[13] For example, Bils and Klenow (2004) utilized data of monthly frequencies at a disaggregated sectoral level for the indirect estimation of the average duration of prices.

estimator of the average duration based on the frequency approach is consistent. On the other hand, the main disadvantage of this approach, as compared to the direct estimation of the average duration, is that it is difficult to derive the full distribution of the price duration (that is, the *hazard function*). Given this limitation, it is not possible to contrast the predictions of the theoretical models using this approach. Hence, the approach of the duration analysis will be useful when establishing the factors that determine the duration of prices.

Following Kovanen (2006), and considering that the assumptions of stationarity and homogeneity are satisfied, the *frequency of price changes* can be defined as follows: Let $I_{j,t}$ be an indicator function of a price change, defined by $I_{j,t} = 0$ if $P_{j,t} = P_{j,t-1}$ and $I_{j,t} = 1$ if $P_{j,t} \neq P_{j,t-1}$[14] for all $j = 1, \ldots, J$ and for all $t = 1, \ldots, \tau$. Thus, the average frequency of the changes in the price of product j can be defined as follows:

$$F_j = \frac{1}{\tau} \sum_{t=1}^{\tau} I_{j,t} \quad \forall j = 1, ..., J \tag{5}$$

The *measure of the duration* of the interval during which the price of product j is maintained constant, which is implicit in the frequency defined in equation (5), is calculated as:

$$T_j = -\frac{1}{\ln(1 - F_j)} \quad \forall j = 1, ..., J \tag{6}$$

where $T_j = \infty$ if $F_j = 0$ and $T_j = 0$ if $F_j = 1$. The next step in this approach, as was similarly done in the first approach, is to compute the aggregate measure of the price duration. In so doing, the following two measures are defined: the first is an unweighted average measure and the second is a measure that uses the CPI weights.

$$T = \frac{1}{J} \sum_{j=1}^{J} T_j \quad \text{and} \quad T^W = \sum_{j=1}^{J} w_j T_j \tag{7}$$

where, once more, w_j is defined as the weights used in the calculation of the CPI basket. An alternative procedure would be to first aggregate the frequency defined in equation (5) as: $F^W = \sum_{j=1}^{J} \frac{w_j}{\tau} \sum_{t=1}^{\tau} I_{j,t}$, and then calculate the implied duration specified in equation (6): $T^W = -\frac{1}{\ln(1-F^W)}$. A few comments concerning the aggregate measures of duration are necessary at this point. If the assumption of homogeneity is

[14] Note that these conditions should take into account the effect of temporary discounts, as defined in subsection 2.3.

satisfied for all store outlets and for all products, then the unweighted duration measure is a reasonable approximation of the average duration. However, if this assumption is satisfied for all store outlets but not for all products in the CPI basket, then the weighted average duration would be a more desirable indicator. Given that the databases used in this paper do not contemplate information at the outlet level it is not possible to know whether the homogeneity assumption is valid at that level. Thus, it is assumed that homogeneity is satisfied. In the previous subsection, it was found that there is no evidence in support of the assumption of homogeneity of price change behavior existing at the CPI basket product level. Hence, in this case, the weighted duration indicator (frequency) will be the most relevant indicator to use in the analysis. In spite of the evidence found, both indicators are presented to contrast the results of the previous subsection.

Estimates of the frequency of price changes and its implied durations for the four countries are presented in Tables 5 and 6. The average frequency of price changes reaches a minimum of 47% and a maximum of 66%, corresponding to Chile and Brazil, respectively. These have an implied average duration of three months and a little over a month, respectively. On the other hand, when the estimates are obtained using the CPI weights, the frequencies of price changes range from 39% in the case of Colombia to 57% in the case of Mexico. In these cases, the implied durations are three months and one month and a half, respectively. On the other hand, Figure 2 shows the behavior of the distribution of the implied duration in the frequencies of price changes. In each of the four countries this distribution shows a pronounced *left asymmetry*, as well as an important concentration of short price durations. These results are consistent with the analysis presented earlier.

The frequency approach also validates the heterogeneity existing in the duration (frequency) observed for the distinct groups of products that compose the CPI basket. Indeed, in all four countries the food sector is one of the product groups that changes prices most frequently, as opposed to other groups such as education and housing, which experience a very low frequency of price changes. In effect, the frequency of price changes for the food items is greater than 60% for each of the four countries (see Table 4), while the education and housing sectors have a frequency of price changes that do not exceed 40%.

4 State-dependent or time-dependent rules?

This section focuses on the factors that determine nominal rigidity of prices. In particular, and according to the typical distinction made in the literature with respect to how the firms set their prices, the paper seeks to find evidence supporting whether the behavior of these firms follow *time-dependent* or *state-dependent* rules.

In *time-dependent* sticky price models it is assumed that firms adjust the price of their products using a time-contingent mechanism and that the timing of such price changes are exogenously determined. In particular, a firm can either adjust prices after a fixed number of periods, as in Taylor (1999), or do so randomly, as in Calvo (1983). Both of these models feature exogenous staggering of price changes among firms and, as a result, the fraction of firms that adjust their prices is constant from one period to another. This outcome allows for an easy aggregation of the firms' price setting policies and provides a relatively simple solution of dynamic aggregate responses to monetary shocks. However, and as emphasized by Kovanen (2006), Klenow and Kryvtsov (2005) and Bils and Klenow (2004), the time-dependent sticky price models lack good microeconomic foundations.

Contrary to time-dependent models, in the *state-dependent* sticky price models it is assumed that firms endogenously choose the timing of price changes and that such changes are subject to *menu costs*. According to Dotsey et al. (1999), this implies that firms will choose to adjust their prices when specific events occur. As a result, the timing and the magnitude of the firms' price changes will depend on the state of the economy, assuming that the costs associated to price changes, or menu costs, are constant. In this context, and given the existence of an explicit cost of adjusting prices, such an adjustment would be profitable to the firms if and only if the greater price covers the cost associated to the change.

It is quite relevant to analyze the type of price-setting rule that firms implement given that the implications of state-dependent models on real output and inflation can differ dramatically from those of time-dependent models. In particular, when the state of the economy changes, due to a demand shock for example, and the firms can adjust their prices endogenously, the price level of the economy will tend to adjust more rapidly when a greater number of firms change their prices and when the adjustment is significant in magnitude. This could eliminate any effect on the real output in the short run. If the state of the economy changes particularly due to a monetary shock, in a state-dependent model the behavior of the agents could eliminate the non-neutrality of money in the short run. This does not occur in time-dependent models since the fraction of firms that change their prices is constant and the price adjustments of the economy will always be staggered[15].

A way to test the empirical validity of price-setting rules is to analyze the hazard function associated to the duration of price spells, that is, the probability that the price of a specific product changes in period t given that it has been constant up until that moment. The behavior of the hazard function differs in each of the price-setting rules and can, hence, be used to test the empirical validity of either rule. In the case of time-dependent models, the fraction of firms that change their prices in each period is constant and as a result the probability of observing a price change is also constant. State-dependent models, on the other hand, predict that the probability of observing a price change varies with the state of the economy. Additionally, in some models, this probability positively depends on the duration, that is, the longer the duration of a price spell the more likely it is to change.

The analysis in this section follows Dias et al. (2005) and applies a discrete-time parametric duration model that includes explicit controls for duration heterogeneity among different product groups and time-varying regressors. It is important to mention some explanatory points regarding the above. First, we use a discrete-time duration model because, in essence, prices change discretely. Second, we explicitly control by heterogeneity given that, as highlighted by Dias et al. (2005), if there is an important degree of duration heterogeneity in the data, as in the case of the products of the CPI basket, we could have severe distorting effects on the estimates of the aggregate hazard function[16]. Finally, we use a parametric approach with time-varying regressors to capture the effect of changes in the state of the economy on the probability that the prices change (this allows us to test whether the state-dependent rules better explain the data). In summary, we look for factors affecting the probability of observing a price change using a model of binary choice defined on the surviving population at each duration.

The parametric model considered here characterizes the hazard function for product j in period t, $h_j(t)$, as a *complementary log-log model* of the following form; see (Jenkins, 1995):

[15] See Klenow and Kryvtsov (2005) for a literature review on the differences between the implications of both sticky price models.

[16] The major implication of product heterogeneity is well known from the literature on duration models and concerns the bias of the hazard function towards negative duration dependence.

$$h_j(t) = \Pr\left[T_j = t | T_j \geq t, W_j(t)\right] = 1 - \exp\left\{-\exp\left[W_j(t)\right]\right\} \tag{8}$$

As emphasized by Kalbfleisch (2002), the specification chosen of $h_j(t)$ is the discrete-time counterpart of the continuous-time proportional hazards model. On the other hand the following linear specification is used for $W_j(t)$ in equation (8):

$$W_j(t) = \theta(T) + \alpha' Z_j + \beta' X^a_{jt} + \delta' X^-_{jt} + \gamma DT_t \tag{9}$$

where $\theta(T)$ is a duration function (T) representing the dependence of the hazard function on the duration of price spells and whose specification will be discussed later. On the other hand, Z_j is a vector of time-constant variables that are product specific. These last two controls will allow us to explicitly deal with the heterogeneity mentioned before. Similarly, X_{jt} is a vector of time-varying variables that vary by product and whose elements are incorporated in $W_j(t)$ in two different ways, X^a_{jt} is a vector containing the absolute value of the elements of X_{jt}, and X^-_{jt} is a vector containing the product of the elements of X_{jt} by a dummy variable which equals 1 if the element of X_{jt} is negative and 0 otherwise. Vector X_{jt} includes regressors that economic theory suggests may be relevant factors in explaining the probability of changes in prices. In particular, this vector includes the magnitude of the monthly inflation rate by sector (π_{jt}) and the economic growth rate (g_t) or some proxy indicator[17]. Finally, DT_t is a vector of time dummy variables, which control for seasonal and cyclical effects.

We introduce the absolute value and the negative values of X_{jt} because there are negative as well as positive values of inflation and output growth in the country samples. This situation raises the issue of distinguishing between the negative and positive effects of variables on the probability of observing a price change given that asymmetric effects are expected. The reason for this is that the costs incurred by firms when they change prices are primarily associated to the negative reaction from customers to these changes, but such a cost is not expected to be relevant when prices decrease. The fact that equation (9) includes the absolute value of X_{jt}, as well as its negative values makes it possible to perform simple tests of symmetry. In the models estimated below, the sectoral inflation rate (π_{jt}) is introduced with one lag. This is done to avoid the potential simultaneity problem since it is expected that inflation reflects changes in prices, at least at this level of disaggregation, and hence there would be a close relationship between

[17] This indicator tries to capture the demand effect on the price setting. See, for instance, Rotemberg (1982) or Ball et al. (1988) for the economic rationale in using such variables.

the dependent variable of the model (the probability of observing a price change) and sectoral inflation. Additionally, π_{jt} and g_t are defined at each point in time during the price spell and not at the end of the spell; thus the effect of these regressors can vary over time.

Finally, in the specification of $W_j(t)$ a general function $\theta(T)$ was included to capture duration dependence. As a result, for estimation purposes, a specific parametric form is required for the function. There are several parametric forms proposed in the literature of duration models to specify such a function[18]. But instead of imposing a given functional form on $\theta(T)$, we use a more flexible approach which consists of introducing an additive dummy variable for each duration in the sample. Therefore, a variable θ_T, where $T = 1, 2, \ldots, T^{max}$, is introduced, which equals 1 if the hazard function corresponds to the duration of a price spell of T months and 0 otherwise. It is worth mentioning that using this application implies the saturation of the hazard function, that is, a different parameter is considered for each duration observed in the sample. The advantage of using this flexible approach is that it makes it possible to capture the effect of variables without any additional parametric assumptions on the distribution of the individual heterogeneity.

Tables 7a to 7d illustrate the results obtained from the estimations of the parametric models for the four countries. For each of these countries, the time-varying regressors are defined as the monthly growth rates of prices at the sectoral level and the annual growth rates of some proxy measure of economic activity. Selecting such a proxy variable depended on the availability of monthly information on an aggregate activity indicator in each country. Thus, in Chile we use the monthly economic activity index (IMACEC) and in Mexico, the global economic activity index (IGAE), while in the cases of Brazil and Colombia we use the industrial production index.

A few comments are in order before going into discriminating among price-setting rules. First, heterogeneity across products is obvious and the probability of observing a price change is significantly greater in the case of food items. This is so because parameters associated to the other product groups, those that are interpreted as the difference with respect to the category eliminated (food items), are negative and statistically significant. This makes results obtained in previous sections more robust. Second, the parameter that captures the duration dependence of the hazard function is, on average,

[18]For example, the specification $\theta(T) = \log(T)$ could be used to obtain a dependence pattern similar to that of the continuous-time Weibull model or alternatively we can apply a quadratic form such as $\theta(T) = \phi_1 T + \phi_2 T^2$.

negative and statistically significant for Brazil, Chile and Mexico[19]. This provides evidence which states that the hazard functions in these countries are decreasing in spite of controlling for heterogeneity. In the case of Colombia, even though this parameter is negative it is not statistically significant and, hence, once the model controls for heterogeneity, the hazard function would not be showing, on average, a decreasing pattern. In any case, the data indicate that the hazard function never shows an increasing pattern with respect to duration. Third, and as expected, it is obvious that the seasonal effect plays an important role on the probability of observing a price change. In particular, the greater risk of a price spell terminating is observed in the months of January and December (depending on the country). Finally, the cyclical effect in all four countries seems to indicate that the probability of observing a price change has not followed a clear pattern over time. In the cases of Colombia, Chile and Mexico, results highlight that the probability of a price spell terminating is clearly smaller in all the years after 1999[20]. On the contrary, in the case of Brazil the probability of a price spell terminating is greater after 1999.

The most relevant result for this section goal is that for all countries, parameters associated to time-varying variables, sectoral inflation and economic activity growth rate, are statistically significant on an individual basis, with the exception of the negative sign of sectoral inflation and the absolute value of the economic activity growth in the case of Mexico. Nevertheless, if all parameters are considered jointly their effect on the probability of observing a price change is statistically different from zero in all four countries. In effect, the Lagrange Multiplier Test for the linear restriction $\beta = \delta = 0$ in equation (9) reaches a value greater than 300 in each of the four countries. As a result, the null hypothesis of no statistical significance is rejected. These results confirm that state-dependent rules better describe the price-setting behavior in all four countries.

Figures 3 and 4 show a simulation exercise based on the results obtained from the estimations of the models. This is basically done to have a visual idea of the effect of the time-varying regressors on the probability of observing a price change. In particular, we simulate the behavior of the hazard function in the cases of inflation or economic activity growth increasing/decreasing by two standard deviations, maintaining the other regressors constant. In general, we observe that sector inflation has an important effect on the probability of observing a price change, while the effect of economic activity growth on the probability is less important in all four countries. In both cases, the

[19] At least at the 10% significance level.

[20] All parameters are negative and statistically significant.

direction and the magnitude of the effect are different in each country.

In particular, in Brazil the effect is stronger when the inflation rate increases than when it decreases, but it maintains the same direction as the change in the inflation rate. In the case of Colombia, the effect is always positive, independently of the direction in which inflation is moving. For Chile something similar occurs as that observed in Colombia, since the effect is positive in any direction; however, when inflation is negative this positive effect is much less relevant. In Mexico, the positive effect is only observed when the inflation rate is greater than zero[21]. On the other hand, the effect of economic activity growth on the probability of observing a price change for the case of Brazil is less important than is sectoral inflation but this effect appears to be symmetric, that is, the larger the expansion of economic activity, the greater is the risk that a price spell terminates, such that when the expansion decreases so does the risk. In the cases of Colombia and Mexico the effect of this variable shows a similar pattern as that observed for Brazil, although in these two cases there is some degree of asymmetry observed towards values of lower growth. Finally, for Chile the effect of economic activity growth shows an inverse pattern (in line with the parameter signs in table 7d). That is, when economic activity growth is positive and increasing, the risk that a price spell terminates decreases.

5 Conclusions

Sticky prices are a cornerstone of Keynesian economics and a key piece for understanding modern monetary policy management around the world. In the framework of dynamic general equilibrium theory, many theoretical models of price stickiness have been developed, estimated and used for policy analysis. One overall issue has been whether price-setting behavior by less than perfect competitive firms is time-dependent or state-dependent, because the implications of monetary policy on real output and inflation depend, in a non-trivial way, on the type of rule prevailing.

Even though the theoretical development of the issue has been vast, studies that have tried to evaluate the empirical evidence of the existing theoretical models using micro-level data are scarce and are primarily focused on industrialized economies. The literature is even sparser for emerging economies. In light of the above, the objective of this paper was to contribute to the existing empirical literature by estimating the

[21]It is important to recall from previous results that when the inflation rate is negative there is no effect that is statistically significant.

frequency of price adjustment and the type of price setting rules in four representative Latin American, emerging economies: Brazil, Chile, Colombia, and Mexico.

We found that Chile and Colombia exhibit a greater degree of nominal rigidity. Prices in these countries were maintained fixed for a period of approximately 3 months, which implies that the frequency of price changes is less than 40%. On the other hand, prices change more frequently in Brazil and Mexico where the average duration in both these cases was approximately 1.5 months (the frequency in these cases exceeded 50%). Furthermore, results indicate that there is a substantial amount of heterogeneity in the duration of prices across the different product categories defined in the construction of the CPI basket in all four countries analyzed. In each case, the less-processed goods, such as food items, show more frequent price changes.

Our results show that emerging economies as the ones reported here exhibit more price flexibility than typical industrialized countries. According to Kovanen (2006), the average duration of price spells in the United States is a little over 4 months, while for European countries this duration is greater than 6 months (Italy shows even 12 months).

Finally, we also found that state-dependent price setting rules tend to better explain the data than time-dependent rules in all four countries. This contrasts with the results found for industrialized countries, where evidence is mixed. As a matter of fact, while time-dependent rules seem to explain the data in the United States, in the European countries it is state-dependent rules that dominate the price-setting behavior of firms (see for example Kovanen, 2006, Dias et al., 2005, Alvarez and Hernando, 2004, and Aucremanne and Dhyne, 2004). However, in our case the probability of a price change differs from country to country when there are changes in the state of the economy.

Using databases that are disaggregated only at the product level and not at the store outlet level (as is generally the case in empirical literature) is clearly a shortcoming of our paper. Unfortunately more disaggregated data are not available. Given that some price spells observed at the store outlet level could have been lost in the process of aggregation at the product level, our results should be interpreted as an inferior bound of the average duration. However, it is unlikely that correcting this bias would increase price spells to levels comparable to those of industrialized countries.

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Tables

Table 1: Sample Description

Country/Group	Number of Products	Number of Observations	Percentage in Database	Weight in CPI
Brazil (1999:8 - 2006:6)				
Food and Beverages	235	19,505	45.9	22.6
Communication	6	498	1.2	3.6
Education	15	1,245	2.9	4.8
Household Articles	60	4,980	11.7	5.7
Personal Expenses	43	3,569	8.4	9.3
Medical Care	40	3,320	7.8	10.7
Transportation	28	2,324	5.5	21.7
Apparel	53	4,399	10.4	5.4
Housing	32	2,656	6.3	16.2
Total	*512*	*42,496*	*100.0*	*100.0*
Colombia (1999:1 - 2006:10)				
Food	54	5,076	30.7	29.5
Culture, Entertainment and Recreation	16	1,504	9.1	3.6
Education	8	752	4.5	4.8
Other Expenses	16	1,504	9.1	7.9
Medical Care	9	846	5.1	4.0
Transportation and Communication	19	1,786	10.8	13.5
Apparel	23	2,162	13.1	7.3
Housing	31	2,914	17.6	29.4
Total	*176*	*16,544*	*100.0*	*100.0*
Chile (1998:12 - 2006:10)				
Food	162	15,390	33.6	27.2
Education and Entertainment	55	5,225	11.4	11.1
Household Articles	84	7,980	17.4	8.1
Other Expenses	8	760	1.7	3.9
Medical Care	44	4,180	9.1	9.4
Transportation	25	2,375	5.2	12.2
Apparel	75	7,125	15.6	7.9
Housing	29	2,755	6.0	20.2
Total	*482*	*45,790*	*100.0*	*100.0*
Mexico (1995:1 - 2006:10)				
Food and Beverages	116	16,472	42.8	26.3
Education and Entertainment	23	3,266	8.5	9.7
Household Articles	35	4,970	12.9	4.2
Other Services	6	852	2.2	8.0
Medical Care	29	4,118	10.7	8.5
Transportation	17	2,414	6.3	11.3
Apparel	36	5,112	13.3	6.2
Housing	9	1,278	3.3	25.8
Total	*271*	*38,482*	*100.0*	*100.0*

Table 2: Average Duration of Price Spells – Survival Analysis

Country	Number of Observations	Mean	Median	Standard Deviation
Brazil (1999:8 - 2006:6)				
All price spells	27,390	1.51	1.00	1.36
Price spells averaged by individual trajectory(*)	512	1.74	1.47	1.10
Price spells averaged by individual trajectory(*) (Weighted)	512	2.13	1.88	1.04
Colombia (1999:1 - 2006:10)				
All price spells	7,591	2.13	1.00	2.47
Price spells averaged by individual trajectory(*)	176	2.68	2.24	1.49
Price spells averaged by individual trajectory(*) (Weighted)	176	3.56	2.42	2.14
Chile (1998:12 - 2006:10)				
All price spells	21,422	2.09	1.00	2.94
Price spells averaged by individual trajectory(*)	482	3.26	2.11	3.75
Price spells averaged by individual trajectory(*) (Weighted)	482	3.42	2.12	4.09
Mexico (1995:1 - 2006:10)				
All price spells	23,747	1.60	1.00	2.09
Price spells averaged by individual trajectory(*)	271	1.86	1.63	1.32
Price spells averaged by individual trajectory(*) (Weighted)	271	2.06	1.77	1.45

(*) The average by individual trajectory for each product was done utilizing, as a weight, the inverse of number of price spells.

Table 3: Effect of the Censured Data on the Average Duration of Price Spells – Survival

Right Censored (*)	Left Censored (*)	Number of Censored Observations	Percentage with respect to the Entire Sample	Unweighted Mean (**)	Unweighted Median (**)	Unweighted Standard Deviation (**)	Weighted Mean (**)	Weighted Median (**)	Weighted Standard Deviation (**)
Brazil (1999:8 - 2006:6)									
1	0	512	1.87	1.77	1.50	1.12	2.17	1.92	1.06
0	1	512	1.87	1.77	1.50	1.12	2.17	1.92	1.06
1	1	1,022	3.73	1.81	1.53	1.14	2.21	1.95	1.08
0	0	0	0.00	1.74	1.47	1.10	2.13	1.88	1.04
Colombia (1999:1 - 2006:10)									
1	0	176	2.32	2.74	2.30	1.53	3.64	2.48	2.19
0	1	176	2.32	2.74	2.30	1.53	3.64	2.48	2.19
1	1	352	4.64	2.81	2.35	1.57	3.73	2.54	2.25
0	0	0	0.00	2.68	2.24	1.49	3.56	2.42	2.14
Chile (1998:12 - 2006:10)									
1	0	482	2.25	3.34	2.16	3.84	3.50	2.17	4.18
0	1	482	2.25	3.34	2.16	3.84	3.50	2.17	4.18
1	1	963	4.50	3.41	2.21	3.93	3.58	2.22	4.28
0	0	0	0.00	3.26	2.11	3.75	3.42	2.12	4.09
Mexico (1995:1 - 2006:10)									
1	0	271	1.14	1.88	1.65	1.34	2.08	1.79	1.47
0	1	271	1.14	1.88	1.65	1.34	2.08	1.79	1.47
1	1	542	2.28	1.91	1.66	1.35	2.11	1.81	1.49
0	0	0	0.00	1.86	1.63	1.32	2.06	1.77	1.45

(*) Takes the value of 1 if the data is censored and 0 otherwise. Double zeros imply the use of data without considering censoring.

(**) Corresponds to the estimated duration previously averaged by the individual trajectory of each product.

Table 4: Average Duration of Price Spells by Product Group – Survival Analysis

Country/Group	Unweighted			Weighted		
	Mean	**Median**	**Standard Deviation**	**Mean**	**Median**	**Standard Deviation**
Brazil (1999:8 - 2006:6)						
Food and Beverages	1.33	1.27	0.26	1.57	1.47	0.37
Communication	3.25	2.44	2.14	3.58	3.68	0.66
Education	2.95	2.53	1.28	4.17	4.50	1.32
Household Articles	1.55	1.53	0.20	1.64	1.65	0.19
Personal Expenses	2.42	1.72	2.04	2.62	2.13	1.50
Medical Care	2.41	2.13	1.01	2.35	2.25	1.05
Transportation	3.04	2.14	2.54	2.09	1.88	0.90
Apparel	1.59	1.53	0.27	1.63	1.62	0.25
Housing	1.64	1.58	0.43	1.92	2.03	0.21
Total	*1.74*	*1.47*	*1.10*	*2.13*	*1.88*	*1.04*
Colombia (1999:1 - 2006:10)						
Food	1.76	1.69	0.63	2.14	2.14	0.81
Culture, Entertainment and Recreation	2.83	2.33	1.17	2.78	2.24	1.15
Education	3.97	4.28	1.30	4.60	4.38	0.86
Other Expenses	2.23	2.25	0.60	2.19	2.42	0.45
Medical Care	2.27	2.30	0.65	1.95	2.24	0.63
Transportation and Communication	2.75	2.19	1.28	2.57	2.00	1.35
Apparel	4.70	4.38	2.03	5.12	4.84	1.76
Housing	2.69	2.19	1.30	5.55	7.08	2.24
Total	*2.68*	*2.24*	*1.49*	*3.56*	*2.42*	*2.14*
Chile (1998:12 - 2006:10)						
Food	1.65	1.43	0.71	2.01	1.48	0.97
Education and Entertainment	6.34	3.21	8.51	8.51	7.15	9.12
Household Articles	2.96	2.45	1.67	2.90	2.38	1.57
Other Expenses	4.97	4.29	3.03	3.69	2.45	2.66
Medical Care	3.07	2.25	1.80	3.84	2.74	2.37
Transportation	3.15	2.38	2.43	2.36	1.50	2.14
Apparel	4.76	4.43	3.51	4.35	1.94	3.78
Housing	3.43	3.00	2.28	2.58	2.02	1.26
Total	*3.26*	*2.11*	*3.75*	*3.42*	*2.12*	*4.09*
Mexico (1995:1 - 2006:10)						
Food and Beverages	1.48	1.48	0.37	1.71	1.65	0.49
Education and Entertainment	2.71	1.97	1.82	2.30	1.87	1.20
Household Articles	1.71	1.69	0.23	1.67	1.59	0.21
Other Services	1.73	1.60	0.29	1.55	1.51	0.10
Medical Care	1.53	1.47	0.21	1.61	1.59	0.21
Transportation	2.72	2.06	2.04	2.60	2.64	1.09
Apparel	1.79	1.75	0.24	1.81	1.79	0.21
Housing	5.07	3.26	4.57	2.53	1.79	2.64
Total	*1.86*	*1.63*	*1.32*	*2.06*	*1.77*	*1.45*

Table 5: Average Monthly Frequency of Price Changes by Product Group – Frequency Approach

Country/Group	Unweighted			Weighted		
	Mean	**Median**	**Standard Deviation**	**Mean**	**Median**	**Standard Deviation**
Brazil (1999:8 - 2006:6)						
Food and Beverages	0.77	0.78	0.13	0.67	0.68	0.15
Communication	0.38	0.41	0.17	0.28	0.26	0.06
Education	0.39	0.38	0.15	0.26	0.21	0.12
Household Articles	0.65	0.64	0.08	0.61	0.60	0.07
Personal Expenses	0.52	0.57	0.20	0.43	0.46	0.15
Medical Care	0.46	0.47	0.15	0.49	0.43	0.18
Transportation	0.44	0.46	0.19	0.51	0.52	0.13
Apparel	0.64	0.65	0.10	0.62	0.62	0.09
Housing	0.62	0.63	0.18	0.37	0.48	0.24
Total	*0.66*	*0.67*	*0.19*	*0.50*	*0.51*	*0.20*
Colombia (1999:1 - 2006:10)						
Food	0.63	0.59	0.20	0.54	0.47	0.21
Culture, Entertainment and Recreation	0.39	0.42	0.12	0.40	0.45	0.12
Education	0.28	0.23	0.10	0.23	0.23	0.06
Other Expenses	0.48	0.44	0.12	0.47	0.41	0.10
Medical Care	0.48	0.43	0.17	0.56	0.45	0.18
Transportation and Communication	0.43	0.45	0.17	0.46	0.50	0.16
Apparel	0.26	0.22	0.15	0.22	0.20	0.12
Housing	0.43	0.46	0.14	0.25	0.14	0.18
Total	*0.47*	*0.45*	*0.21*	*0.39*	*0.40*	*0.22*
Chile (1998:12 - 2006:10)						
Food	0.67	0.70	0.19	0.60	0.67	0.23
Education and Entertainment	0.28	0.30	0.16	0.19	0.13	0.14
Household Articles	0.39	0.40	0.12	0.40	0.41	0.14
Other Expenses	0.28	0.25	0.19	0.42	0.40	0.25
Medical Care	0.41	0.44	0.18	0.36	0.35	0.19
Transportation	0.46	0.42	0.24	0.60	0.66	0.26
Apparel	0.38	0.23	0.28	0.45	0.51	0.29
Housing	0.36	0.31	0.20	0.36	0.37	0.26
Total	*0.47*	*0.46*	*0.24*	*0.45*	*0.45*	*0.26*
Mexico (1995:1 - 2006:10)						
Food and Beverages	0.72	0.68	0.17	0.63	0.61	0.17
Education and Entertainment	0.47	0.51	0.18	0.50	0.54	0.16
Household Articles	0.59	0.59	0.08	0.61	0.63	0.07
Other Services	0.59	0.63	0.08	0.65	0.66	0.03
Medical Care	0.67	0.68	0.09	0.63	0.63	0.08
Transportation	0.46	0.49	0.17	0.42	0.38	0.11
Apparel	0.57	0.57	0.07	0.56	0.56	0.06
Housing	0.41	0.30	0.32	0.56	0.56	0.22
Total	*0.63*	*0.61*	*0.18*	*0.57*	*0.56*	*0.17*

Table 6: Implied Duration between two Price Changes in the Monthly Frequency Observed by Product Group – Frequency Approach

Country/Group	Unweighted			Weighted		
	Mean	**Median**	**Standard Deviation**	**Mean**	**Median**	**Standard Deviation**
Brazil (1999:8 - 2006:6)						
Food and Beverages	0.71	0.66	0.31	0.99	0.88	0.43
Communication	2.89	1.95	2.43	3.22	3.33	0.75
Education	2.53	2.07	1.42	3.90	4.25	1.48
Household Articles	0.97	0.97	0.22	1.08	1.08	0.20
Personal Expenses	1.98	1.17	2.39	2.19	1.64	1.73
Medical Care	1.91	1.58	1.11	1.83	1.77	1.13
Transportation	2.57	1.64	2.63	1.57	1.37	0.93
Apparel	1.02	0.94	0.30	1.07	1.04	0.28
Housing	1.07	1.01	0.47	1.39	1.52	0.22
Total	*1.17*	*0.90*	*1.23*	*1.62*	*1.37*	*1.15*
Colombia (1999:1 - 2006:10)						
Food	1.17	1.13	0.69	1.58	1.59	0.86
Culture, Entertainment and Recreation	2.34	1.81	1.28	2.29	1.70	1.26
Education	3.45	3.76	1.29	4.08	3.86	0.86
Other Expenses	1.69	1.73	0.64	1.66	1.88	0.49
Medical Care	1.72	1.75	0.69	1.38	1.70	0.66
Transportation and Communication	2.20	1.70	1.30	2.02	1.44	1.37
Apparel	4.40	4.08	2.29	4.84	4.59	1.98
Housing	2.18	1.64	1.38	5.11	6.56	2.31
Total	*2.17*	*1.70*	*1.62*	*3.06*	*1.94*	*2.24*
Chile (1998:12 - 2006:10)						
Food	1.06	0.83	0.78	1.47	0.91	1.07
Education and Entertainment	7.85	2.79	17.02	10.80	7.24	18.81
Household Articles	2.49	1.94	1.74	2.42	1.90	1.65
Other Expenses	4.51	3.76	3.06	3.15	1.97	2.70
Medical Care	2.57	1.76	1.89	3.42	2.28	2.55
Transportation	2.71	1.84	2.70	1.85	0.94	2.38
Apparel	4.44	3.91	3.88	3.99	1.42	4.17
Housing	3.03	2.57	2.67	2.10	1.51	1.39
Total	*3.01*	*1.61*	*6.42*	*3.26*	*1.61*	*7.25*
Mexico (1995:1 - 2006:10)						
Food and Beverages	0.86	0.89	0.43	1.11	1.07	0.54
Education and Entertainment	2.20	1.41	1.97	1.75	1.30	1.29
Household Articles	1.14	1.11	0.25	1.10	1.01	0.22
Other Services	1.15	1.02	0.30	0.96	0.92	0.10
Medical Care	0.94	0.88	0.23	1.03	1.01	0.22
Transportation	2.17	1.50	2.06	2.05	2.10	1.10
Apparel	1.22	1.18	0.25	1.24	1.23	0.22
Housing	4.84	2.80	5.09	2.03	1.23	2.92
Total	*1.29*	*1.05*	*1.44*	*1.51*	*1.20*	*1.59*

Table 7a: Brazil – Parametric Estimation of the Conditional Hazard Function

Dependent Variable: Probability of Price Change (Hazard Funtion)

Category of the Variable	Variable	Coefficient	Standard Error (*)	Probability Value
	Constant (**)	-0.735	0.137	0.073
Product Groups	Communication	-0.745	0.090	0.000
	Education	-0.739	0.059	0.000
	Household Articles	-0.209	0.021	0.000
	Personal Expenses	-0.432	0.044	0.000
	Medical Care	-0.596	0.032	0.000
	Transportation	-0.652	0.042	0.000
	Apparel	-0.221	0.021	0.000
	Housing	-0.267	0.037	0.000
Seasonal Effect	January	-0.208	0.039	0.000
	February	-0.161	0.037	0.000
	March	-0.145	0.036	0.000
	April	-0.154	0.037	0.000
	May	-0.158	0.040	0.000
	June	-0.222	0.036	0.000
	July	-0.231	0.040	0.000
	August	-0.230	0.036	0.000
	September	-0.368	0.037	0.000
	October	-0.222	0.037	0.000
	November	-0.134	0.037	0.000
Cyclical Effect	2000	0.460	0.052	0.000
	2001	0.534	0.055	0.000
	2002	0.634	0.053	0.000
	2003	0.448	0.059	0.000
	2004	0.283	0.056	0.000
	2005	0.253	0.057	0.000
	2006	0.498	0.060	0.000
State Variables	|Economic Activity Growth|	0.007	0.002	0.005
	Economic Activity Growth^{-}	0.015	0.006	0.016
	|Sectoral Inflation|	0.818	0.051	0.000
	Sectoral Inflation^{-}	0.390	0.161	0.016

(*) Standard Errors calculated using Bootstrap with 100 repetitions.

(**) Represents the average of the duration dependence ariables (defines the slope of the hazard function)

Notes:

Number of Observations	40230
Log PseudoLikelihood Value	-23401
Wald Test (42 gl)	7581
Probability LR Test Value	0.00
Reference Group	Food and Beverages
Reference Month	December
Reference Year	1999

Table 7b: Colombia – Parametric Estimation of the Conditional Hazard Function

Dependent Variable: Probability of Price Change (Hazard Funtion)

Category of the Variable	Variable	Coefficient	Standard Error (*)	Probability Value
	Constant (**)	-0.061	0.126	0.286
Product Groups	Culture, Entertainment and Recreation	-0.397	0.050	0.000
	Education	-0.742	0.067	0.000
	Other Expenses	-0.304	0.041	0.000
	Medical Care	-0.299	0.061	0.000
	Transportation and Communication	-0.426	0.042	0.000
	Apparel	-0.628	0.056	0.000
	Housing	-0.316	0.040	0.000
Seasonal Effect	January	0.207	0.050	0.000
	February	-0.186	0.064	0.004
	March	-0.172	0.052	0.001
	April	-0.241	0.055	0.000
	May	-0.461	0.061	0.000
	June	-0.370	0.061	0.000
	July	-0.385	0.057	0.000
	August	-0.340	0.053	0.000
	September	-0.494	0.052	0.000
	October	-0.422	0.056	0.000
	November	-0.403	0.056	0.000
Cyclical Effect	2000	-0.313	0.077	0.000
	2001	-0.465	0.083	0.000
	2002	-0.537	0.078	0.000
	2003	-0.607	0.077	0.000
	2004	-0.828	0.073	0.000
	2005	-0.963	0.076	0.000
	2006	-0.687	0.083	0.000
State Variables	|Economic Activity Growth|	0.008	0.004	0.038
	Economic Activity Growth$^-$	0.038	0.005	0.000
	|Sectoral Inflation|	1.568	0.104	0.000
	Sectoral Inflation$^-$	-1.162	0.318	0.000

(*) Standard Errors calculated using Bootstrap with 100 repetitions.

(**) Represents the average of the duration dependence ariables (defines the slope of the hazard function)

Notes:

Number of Observations	15420
Log PseudoLikelihood Value	-9155
Wald Test (42 gl)	4320
Probability LR Test Value	0.00
Reference Group	Food
Reference Month	December
Reference Year	1999

Table 7c: Chile – Parametric Estimation of the Conditional Hazard Function

Dependent Variable: Probability of Price Change (Hazard Funtion)

Category of the Variable	Variable	Coefficient	Standard Error (*)	Probability Value
	Constant (**)	-0.098	0.085	0.023
	Education and Entertainment	-0.833	0.032	0.000
	Household Articles	-0.573	0.019	0.000
	Other Expenses	-0.882	0.076	0.000
Product Groups	Medical Care	-0.522	0.032	0.000
	Transportation	-0.502	0.040	0.000
	Apparel	-0.562	0.037	0.000
	Housing	-0.666	0.035	0.000
	January	-0.335	0.036	0.000
	February	-0.217	0.035	0.000
	March	-0.282	0.040	0.000
	April	-0.244	0.034	0.000
	May	-0.192	0.039	0.000
Seasonal Effect	June	-0.247	0.035	0.000
	July	-0.204	0.040	0.000
	August	-0.173	0.042	0.000
	September	-0.311	0.040	0.000
	October	-0.186	0.038	0.000
	November	-0.268	0.038	0.000
	2000	-0.141	0.040	0.000
	2001	-0.306	0.043	0.000
	2002	-0.273	0.041	0.000
Cyclical Effect	2003	-0.249	0.042	0.000
	2004	-0.387	0.045	0.000
	2005	-0.316	0.039	0.000
	2006	-0.046	0.045	0.309
	|Economic Activity Growth|	-0.023	0.006	0.000
State Variables	Economic Activity Growth$^-$	0.161	0.014	0.000
	|Sectoral Inflation|	1.161	0.112	0.000
	Sectoral Inflation$^-$	0.643	0.108	0.000

(*) Standard Errors calculated using Bootstrap with 100 repetitions.

(**) Represents the average of the duration dependence ariables (defines the slope of the hazard function)

Notes:

Number of Observations		42890
Log PseudoLikelihood Value		-25862
Wald Test (42 gl)		12225
Probability LR Test Value		0.00
Reference Group	Food	
Reference Month	December	
Reference Year	1999	

Table 7d: Mexico – Parametric Estimation of the Conditional Hazard Function

Dependent Variable: Probability of Price Change (Hazard Funtion)

Category of the Variable	Variable	Coefficient	Standard Error (*)	Probability Value
	Constant (**)	-0.344	0.108	0.106
Product Groups	Education and Entertainment	-0.196	0.027	0.000
	Household Articles	-0.357	0.096	0.000
	Other Services	-0.246	0.024	0.000
	Medical Care	-0.188	0.025	0.000
	Transportation	-0.473	0.041	0.000
	Apparel	-0.394	0.032	0.000
	Housing	-0.161	0.051	0.002
Seasonal Effect	January	-0.046	0.039	0.236
	February	-0.445	0.039	0.000
	March	-0.218	0.041	0.000
	April	-0.269	0.036	0.000
	May	-0.327	0.041	0.000
	June	-0.461	0.041	0.000
	July	-0.294	0.044	0.000
	August	-0.270	0.038	0.000
	September	-0.360	0.038	0.000
	October	-0.391	0.036	0.000
	November	-0.249	0.042	0.000
Cyclical Effect	1996	0.387	0.068	0.000
	1997	0.018	0.075	0.815
	1998	0.024	0.072	0.736
	1999	-0.242	0.070	0.001
	2000	-0.591	0.077	0.000
	2001	-0.793	0.078	0.000
	2002	-0.887	0.077	0.000
	2003	-0.853	0.079	0.000
	2004	-0.870	0.078	0.000
	2005	-1.010	0.082	0.000
	2006	-0.688	0.079	0.000
State Variables	|Economic Activity Growth|	0.001	0.004	0.839
	Economic Activity Growth$^-$	-0.081	0.009	0.000
	|Sectoral Inflation|	0.594	0.036	0.000
	Sectoral Inflation$^-$	4.944	4.532	0.275

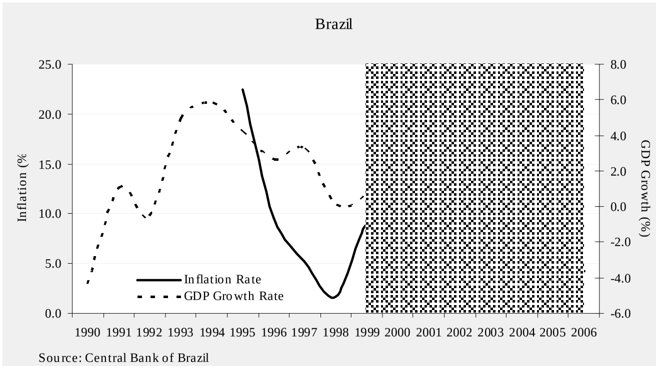
(*) Standard Errors calculated using Bootstrap with 100 repetitions.

(**) Represents the average of the duration dependence ariables (defines the slope of the hazard function)

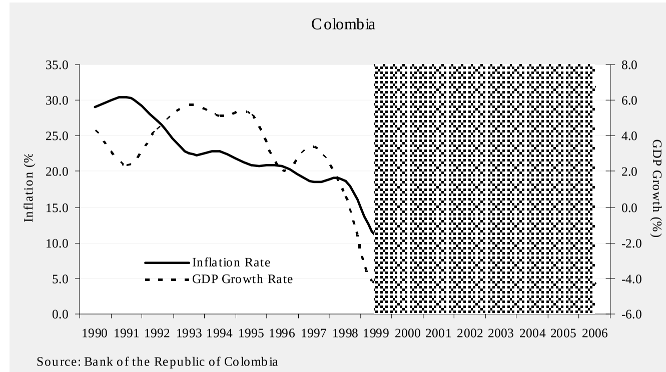
Notes:

Número de Observaciones	36385
Valor de la Pseudoverosimilitud	-18996
Wald Test (45 gl)	12872
Valor Probabilidad LR Test	0.00
Grupo de Referencia	Food and Beverages
Mes de Referencia	December
Año de Referencia	1995

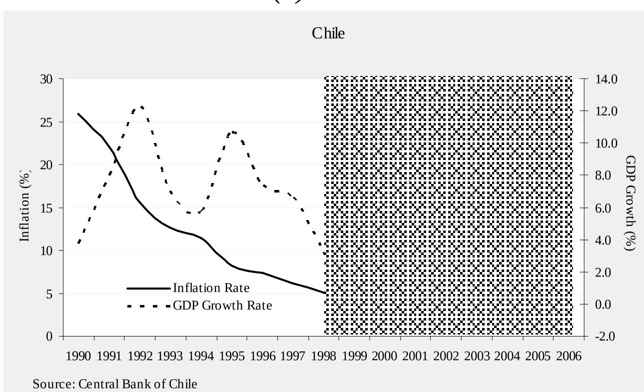
Figure 1: Inflation Rate and GDP Growth Rate for the Period 1990-2006



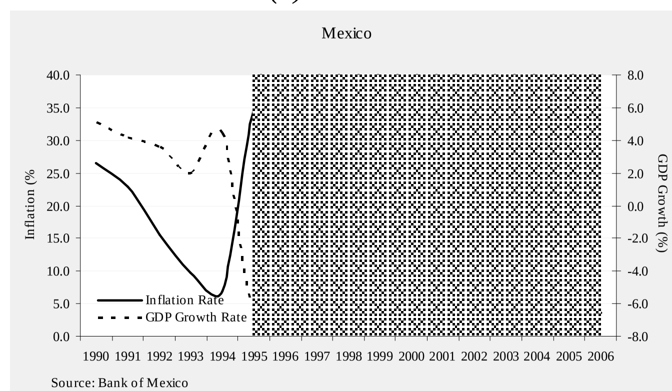
(a) Brazil



(b) Colombia

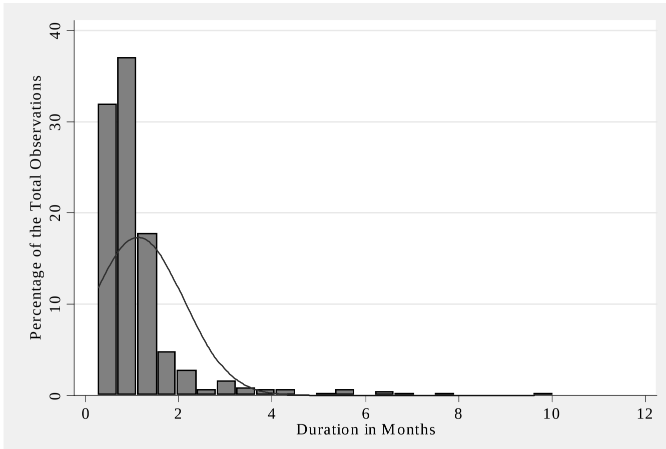


(c) Chile

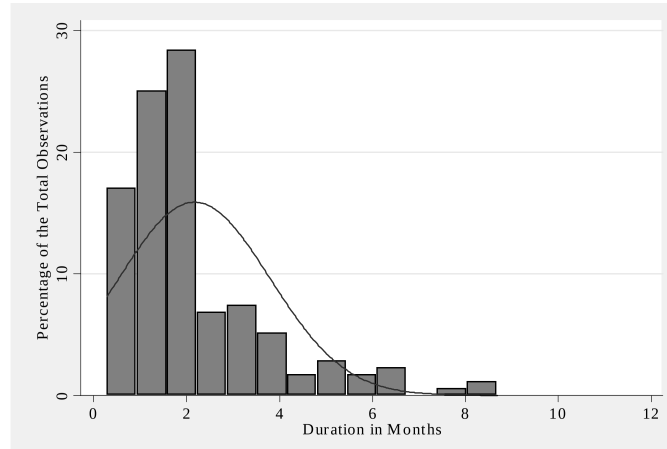


(d) Mexico

Figure 2: Implied Duration in the Frequency of Price Changes



(a) Brazil



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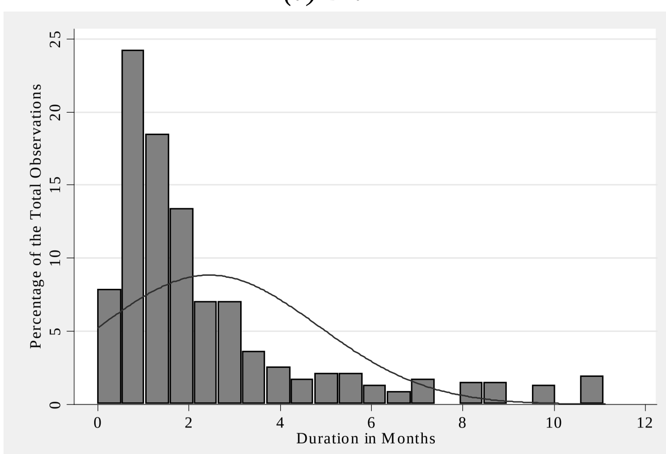

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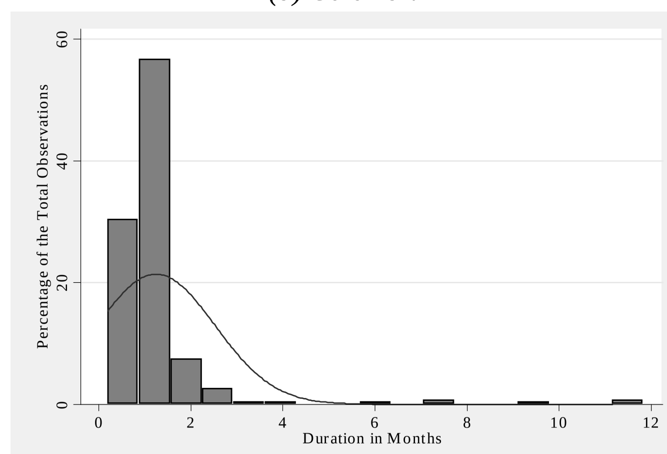
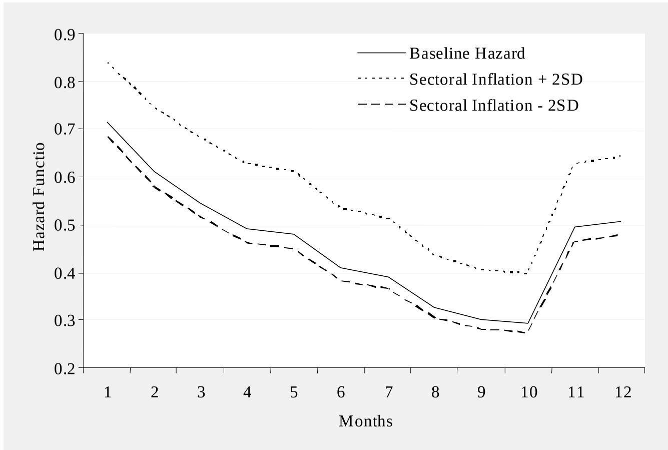
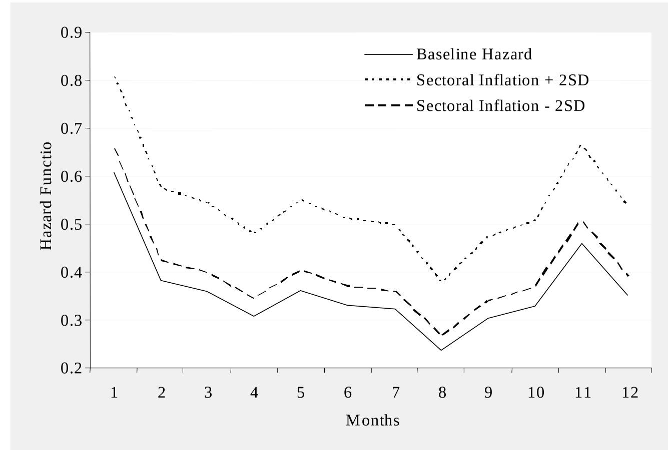


(d) Mexico

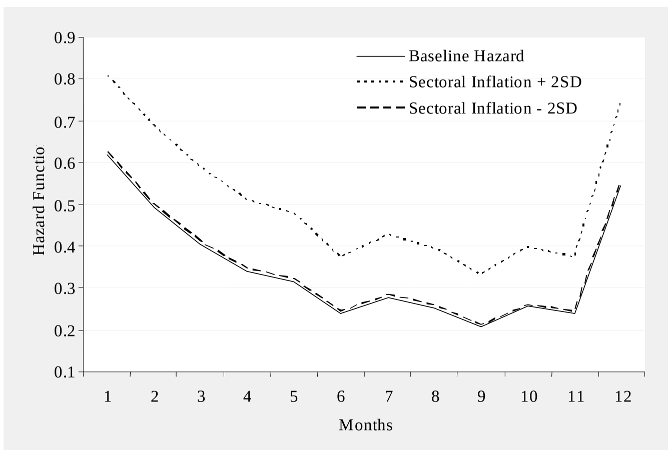
Figure 3: Effect of Sectoral Inflation on the Conditional Hazard Function



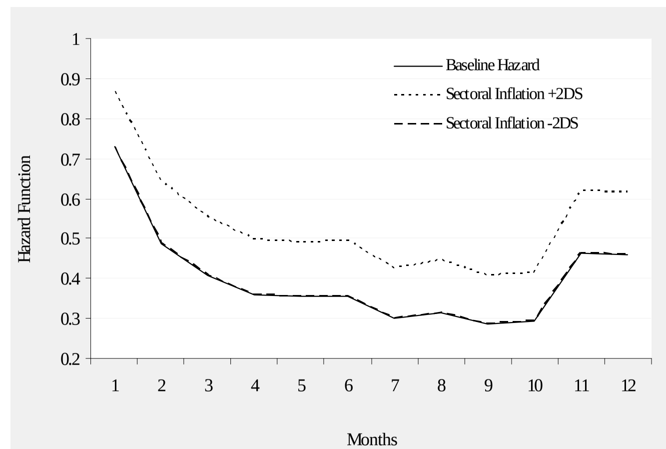
(a) Brazil



(b) Colombia

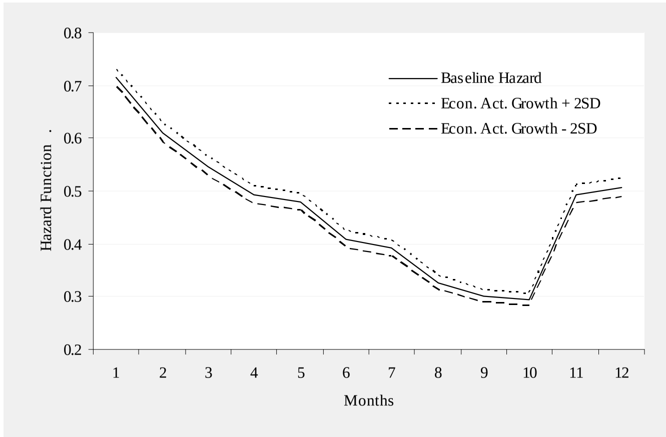


(c) Chile

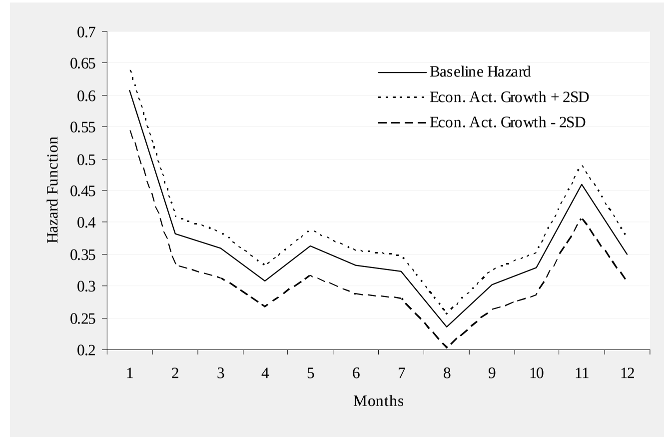


(d) Mexico

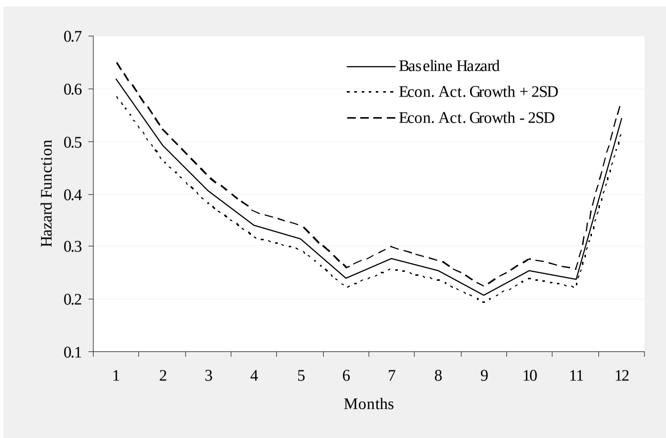
Figure 4: Effect of Economic Activity Growth on the Conditional Hazard Function



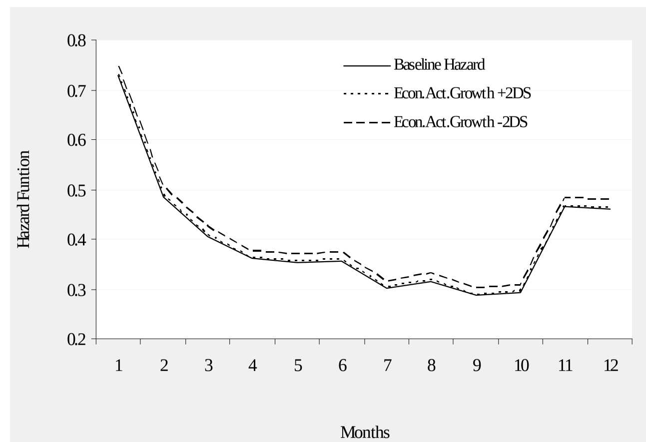
(a) Brazil



(b) Colombia



(c) Chile



(d) Mexico