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Price Setting during Low and High Inflation: Evidence from Mexico

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Price Setting during Low and High Inflation: Evidence from Mexico

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Abstract

This paper provides new insight into the relationship between inflation and consumer price setting by examining a large data set of Mexican consumer prices covering episodes of both low and high inflation, as well as the transition between the two. Overall, the economy shares several characteristics with time-dependent models when the annual inflation rate is low (below 10-15%), while displaying strong state dependence when inflation is high (above 10-15%). At low inflation levels, the aggregate frequency of price changes responds little to movements in inflation because movements in the frequency of price decreases partly offset movements in the frequency of price increases. When the annual inflation rate rises beyond 10-15 percent, however, there are no longer enough price decreases to counterbalance the rising occurrence of price increases, making the frequency of price changes more responsive to inflation. It is shown that a simple menu-cost model with idiosyncratic technology shocks predicts remarkably well the level of the average frequency and magnitude of price changes over a wide range of inflation.
JEL classification: E31, D40, C23.
Keywords: Price setting, consumer prices, frequency of price changes, time-dependent pricing, state-dependent pricing.

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1 Introduction

This paper presents new evidence on the setting of consumer prices during low and high inflation that sheds light on the empirical plausibility of competing models of price rigidities. It uses a new store-level data set containing more than six million individual price quotes that is representative of more than two-thirds of Mexican consumers' expenditures. The data starts in January 1994 and ends in December 2004. Over that 11-year period, CPI inflation rose from 6.8% in 1994 to a high of 41.8% in 1995 before falling to a low of 3.9% in 2001. Given these considerable fluctuations, this data set can potentially be used to discriminate among competing models of nominal price rigidities, as these models' predictions diverge most in the presence of large shocks.

Many macroeconomic models assume that price rigidities exist. There is, however, no consensus on how to model these rigidities. In time-dependent models, the set of firms optimizing their prices is fixed exogenously within the period.[1] In state-dependent models, on the other hand, the timing of price changes is an endogenous decision. In these models, price stickiness results from frictions like menu costs, imperfect or costly information and shifts in demand that accompany price changes.[2] Recently, several authors have argued that variants of time-dependent models can deliver empirically plausible predictions despite their simplicity.[3] Even advocates of time-dependent models would agree, however, that the performance of these models should decline as inflation becomes high or volatile. The inflation level at which time-dependent models break down remains an open question, as does the more general question of what price-setting models are empirically plausible at both low and high inflation levels.

My data set captures considerably more variation in inflation than do other studies of consumer prices with comparable product coverage.[4] As Figure 1 indicates, inflation is low and stable in the United States and Euro area relative to Mexico over the periods covered by these studies. In the case of high-inflation economies, the evidence is limited mainly to food products in Israel (Lach and Tsiddon (1992); Baharad and Eden (2004)) and Poland (Konieczny and Skrzypacz (2005)) and supermarket products in Argentina (Burstein, Eichenbaum, and Rebelo (2005)). This paper differs from these studies because my data set is representative of most goods and services in the CPI with the exception of housing rents, and I provide evidence for both high and low levels of inflation.

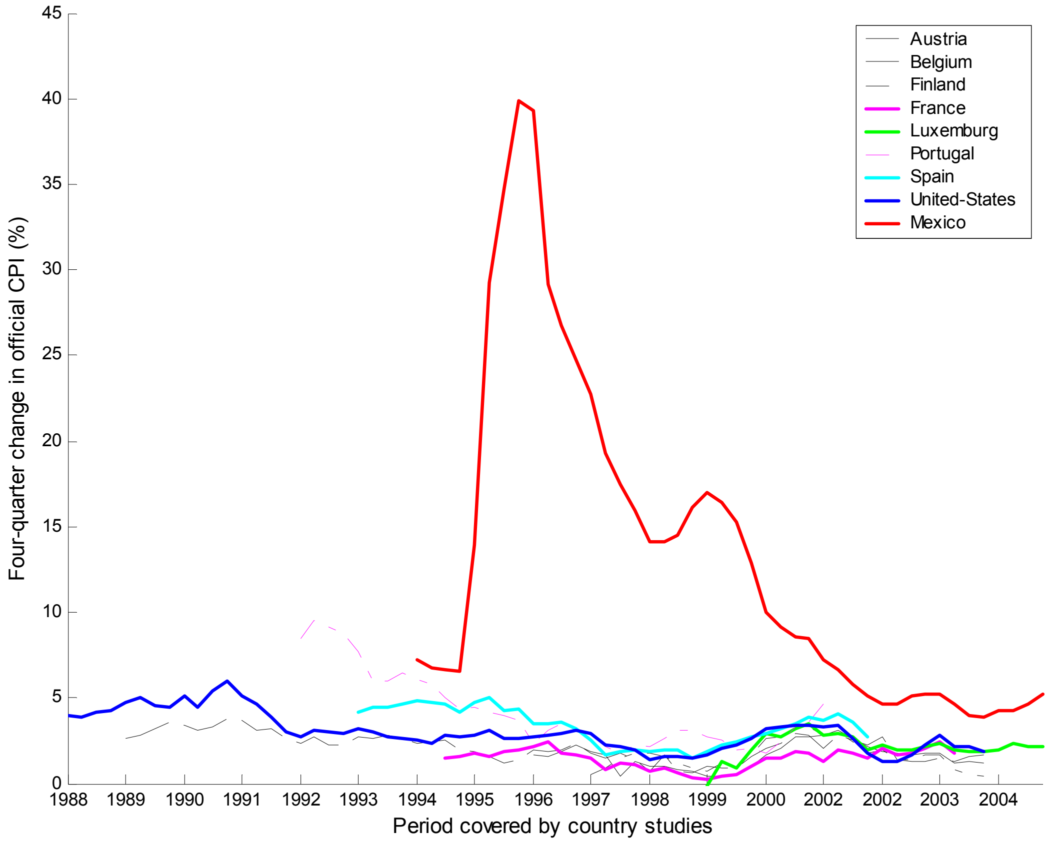
[1] Time-dependent models include Taylor's (1980) staggered pricing model, in which firms optimize every n periods, and the Calvo (1983) model, in which firms face a constant probability $1/n$ of optimizing their prices. Recent implementations of time-dependent rules can be found, for example, in Chari, Kehoe, and McGrattan (2002); Christiano, Eichenbaum, and Evans (2005); Gali and Gertler (1999); and Smets and Wouters (2004).

[2] For a modern treatment of menu-cost models, see, for example, Dotsey, King, and Wolman (1999); Danziger (1999); Golosov and Lucas (2003); Burstein (2006); and Gertler and Leahy (2006). Recent developments in models of information frictions includes Mankiw and Reis (2002); Sims (2003); and Mackowiak and Wiederholt (2004). Other state-dependent approaches include fair-pricing models (Rotemberg (2002); Rotemberg (2004)) and uncertain and sequential trading (e.g., Eden (1994); Lucas and Woodford (1993)).

[3] See Klenow and Kryvtsov (2005), Burstein (2006) and Eichenbaum and Fisher (2004).

[4] For studies on the United States, see Bils and Klenow (2004) and Klenow and Kryvtsov (2005). Dhyne et al. (2005) review the main findings for the Euro area.

Figure 1: Inflation and time coverage of U.S., Euro-area and Mexican CPI studies



I find sharp differences in the price-setting behaviors of low- and high-inflation economies: Whereas low-inflation economies exhibit several features of time-dependent pricing models, high-inflation economies show strong state dependence. More specifically, when inflation is low (below 10-15%), the frequency of price changes is only mildly correlated with inflation, especially when I restrict the sample to nonregulated goods, in which case I find no correlation. On the other hand, the average magnitude of price changes in such low-inflation environments displays a tight and linear relationship with inflation. As a result, movements in the frequency of price changes account for little of the inflation variance: at most 17% for all nonregulated products and 5% for nonregulated goods, figures that fall in line with Klenow and Kryvtsov (2005) for the United States (5%).

In contrast, when inflation is high (above 10-15%), both the frequency and average magnitude of price changes are strongly correlated with inflation. In this case, a 1-percent increase in the annual inflation rate is associated with a rise of about 0.4 percentage-point in the monthly frequency of price changes for nonregulated consumer products. Movements in the frequency of price changes therefore comprise an important component of inflation variance. This central role of the frequency of price changes in inflation dynamics is best revealed by a rise of the value added tax from 10 to 15% in April 1995: The adjustment of prices occurs almost entirely through an increased frequency of price changes — not an increased magnitude — and is completed within a month of the tax change.

Price decreases are key to the dramatically different behaviors of low- and high-inflation economies. When I decompose the frequency of price changes into the sum of the frequencies of price increases and decreases, I find that the frequency of price decreases diminishes rapidly as inflation rises from 0 to 10-15%. This decline partly offsets a simultaneous rise in the frequency of price increases, thereby dampening movements in the overall frequency of price changes. Moreover, the decline in the occurrence of price decreases relative to price increases leads to a rise in the average magnitude of price changes. This change in the composition of price changes largely explains the strong correlation between inflation and the average magnitude of price changes in my data when inflation is low. Once inflation moves beyond 10-15%, however, there are no longer enough price decreases to offset price increases, so the frequency of price changes becomes highly correlated with inflation.

The important role of price decreases for inflation dynamics in Mexico is likely to be found in the United States and euro area. At similar levels of inflation, price decreases account for 42% of price changes in Mexico, a level comparable to the euro area (42%, Dhyne et al. (2005)) and the United States (45%, Klenow and Kryvtsov (2005)). For most groups of products, however, price changes are more frequent in the United States. I conjecture that the greater number of price decreases in the United States relative to Mexico likely will have similar dampening effects on the frequency of price changes at low levels of inflation.

The above empirical findings shed light on what types of pricing models deliver realistic predictions at various levels of inflation. Overall, my results suggest that pricing models should endogenize the timing of price changes if they wish to make realistic predictions at both low and high inflation levels. Above a 10-15% inflation rate, the predictions of time-dependent models are clearly inconsistent with the strong state-dependence found in my data with respect to inflation. When inflation falls below 10-15%, the muted response of the frequency of price changes in the nonregulated good sector is more consistent, at least on the surface, with time-dependent models like Calvo's. These facts suggest that macroeconomists may need to resort to different price-setting models when focusing on either low or high inflation economies. They also present the challenge of finding a model offering empirically plausible predictions at all levels of inflation.

I calibrate a discrete-time version of the Golosov and Lucas (2003) menu-cost model. The model embeds idiosyncratic technology shocks giving rise to a distribution of both positive and negative nominal price changes. I show that the model performs remarkably well in terms of predicting the average frequency and magnitude of price changes over a wide range of inflation. In particular, the model generates a slow increase in the frequency of price changes as inflation takes off from a low level. The success of the model comes in part from the presence of offsetting movements in the frequency of price increases and decreases, and highlights the importance of idiosyncratic shocks in this class of models for delivering empirically plausible predictions.

The paper is organized as follows. In Section 2, I provide a brief overview of the Mexican macroeconomic context over the sample period. In Section 3, I describe the assemblage of my data set and discuss features of the data that are important for interpreting my results. Then, Section 4 defines the statistics computed in this paper. In section 5, I explain how the average frequency and magnitude of individual price changes differ across low- and high-inflation episodes, and I investigate the inflation pass-through resulting from an April 1995 hike in the value added tax. Section 6 offers a comparison of consumer price stickiness between the Mexican economy and that of the United States and Euro area. In Section 7, I calibrate a discrete-time version of the Golosov-Lucas model and investigate its ability to match the main empirical features of consumer price setting when subject to levels of inflation similar to the ones experienced by Mexico over my sample period. The last section provides concluding remarks.

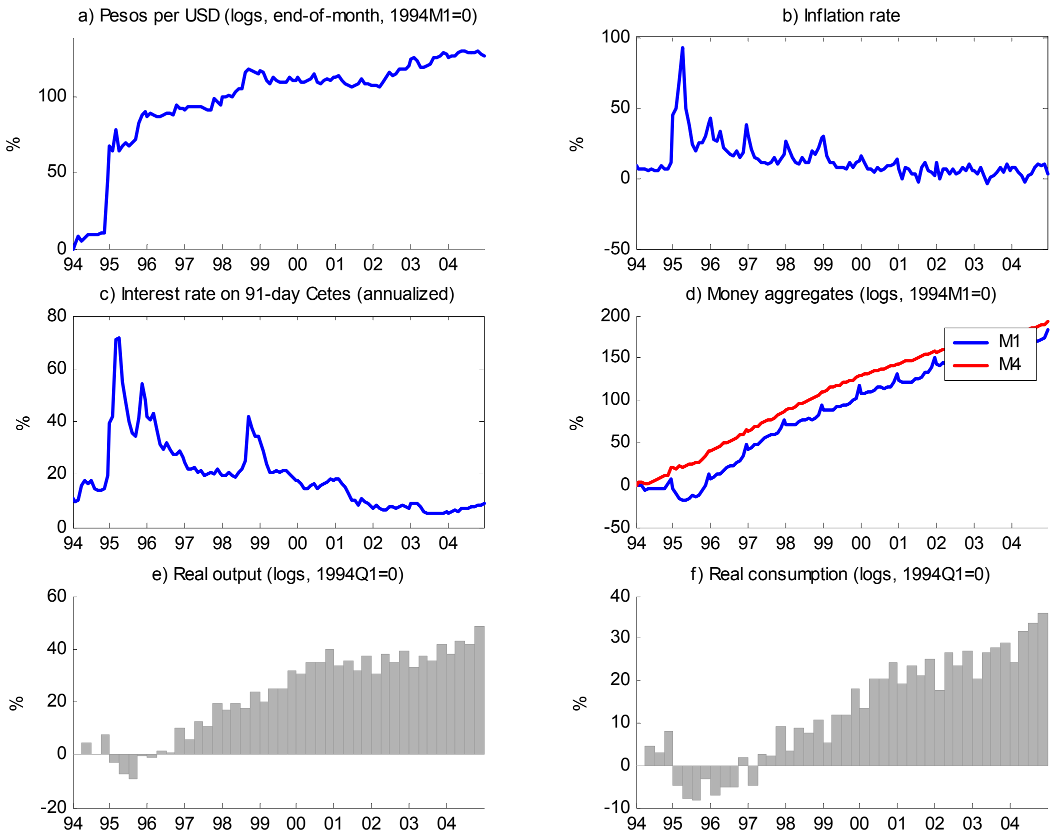
2 Macroeconomic Context

The sample period was marked by a severe economic downturn in the wake of the December 1994 peso devaluation. To most observers of the Mexican economy, however, 1994 opened rather positively.[5] Inflation had been stabilized successfully below 10 percent, a major achievement in light of the three-digit rates of the late 1980s.[6] The real interest rate also had decreased. The excess return on the three-month, dollar-denominated Tesobonos was only two percentage points above the American T-Bill. The budget deficit, seen by many as the culprit of previous economic crises, had been eliminated in 1992. Moreover, the North American Free Trade Agreement had taken effect on January 1, 1994. This treaty was part of a broad set of Mexican government initiatives to deregulate the country's economy and open it to foreign trade and capital. Foreign capital entered abundantly with a net inflow over 8% of GDP in 1993. However, growth in real GDP per capita remained modest, averaging 2.5% from 1991 to 1993. Many observers saw this situation as part of a restructuring process that soon would bring strong growth to the country.

[5] See Edwards (1997) for a review of observers' opinions in 1994.

[6] Unless otherwise indicated, all percentage figures are in logartihmic differences. The inflation rate is the annualized change in the CPI over the previous month.

Figure 2: Main macroeconomic indicators



Source: Banco de México.

The devaluation brought a radical change of mood. On December 22, 1994, the exchange rate collapsed and lost more than 40% of its value vis-à-vis the U.S. dollar in the week that followed.[7] As depicted in Figure 2, interest rates were pushed upward substantially as Banxico tightened the supply of money to prevent further erosion of the peso and a capital flight. The devaluation left a major stagflation in its wake. Inflation took off almost immediately, increasing from 6.5% in November 1994, to 44.3% in January 1995 before peaking at 92.0% in April 1995. Real output per capita contracted by 9.5% in 1995, while private consumption per capita fell by a solid 13.2%. Mexicans would have to wait until 1998 for real GDP per capita to surpass its 1994 level and until 1999 for inflation to settle below 10%.

The decline in aggregate income, coupled with a rise in fiscal evasion, brought a sharp decline in government revenues.[8] To prevent further revenue erosion, the government raised the general rate of the value added tax rate (VAT) from 10 to 15 percent on April 1, 1995. This change affected all

[7] Mexico pegged its exchange rate to the dollar in May 1992. In February 1994, the country switched to pre-announced crawling bands around the U.S. dollar.

[8] See *OECD economic surveys, 1999-2000: Mexico* for a detailed description of the taxation system.

Mexican regions, with the notable exceptions of Baja California and a corridor along the country's southern and northern borders where the rate remained at 10%.

3 Mexican Micro Data on Consumer Prices

3.1 Description of Sources

The data comprise price quotes collected by *Banco de México* (Banxico) for computing the Mexican CPI. Most price quotes correspond to narrowly defined items sold in specific outlets (e.g., corn flour, brand Maseca, bag of 1 kg, sold in outlet 1100 in Mexico City). A limited number of quotes are city-wide indexes, or the average price of a small sample of narrowly defined items belonging to the same category and outlet. Since January 1994, the official gazette of the Mexican government, the *Diario Oficial de la Federación*, has published price quotes. This publication releases each quote with a key linking the item to a specific outlet, city and good category; these keys allow me to track individual prices over time.[9] In this paper, I refer to an item's complete price history as its *price trajectory.* A price trajectory comprises one or several successive *price spells*, episodes when the price remained constant.

The data set contains 6.5 million price quotes from January 1994 to December 2004. Banxico makes individual prices available up to six months after their publication, but it does not keep a historical data set of individual prices. The data set was assembled by merging the information released in the *Diario.* The data for the months of January 1994 to February 1995 could not be extracted electronically, so they were typed from original hard paper copies of the *Diario* using double-entry keying, a process ensuring a character-wise accuracy in excess of 99.998%.[10] About 430,000 price quotes were added to the database in this way.

Precise item descriptions were published in March 1995 and August 2002. The *Diario* also includes lists of items that are periodically added, dropped or substituted from the CPI basket. Unlike additions, substitutions are not planned events. They occur when the characteristics of an item (weight, size, model, presentation, etc.) change, when an outlet stops carrying an item or, in rarer cases, when an outlet goes out of business.

The weights used in the CPI are derived from the *Survey of Households' Income and Expenditures* (ENIGH). The CPI categories are representative of all ENIGH categories accounting for at least 0.02 percent of households' expenditures. This ensures a coverage well above 95% of Mexican households' expenditures.

3.2 Sample coverage

In January 1994, the CPI contained 30,692 price quotes spread over 302 categories. By December 2004, it had expanded to more than 60,000 price quotes distributed over 315 categories. Two major revisions of the basket occurred over that period. The first occurred in March 1995, when the

[9] Items from the same outlet are attributed store keys independently to ensure confidentiality.

[10] I thank Chris Ahlin for lending me original copies of the *Diario*.

number of cities covered in the CPI grew from 35 to 46. At the same time, 29 new good categories were introduced into the basket, and 18 were abandoned. This revision had been planned long before the peso's devaluation. Secondly, in July 2002, Banxico updated the basket again to reflect the structure of Mexican households' consumption in 2000. In the process, 60 product categories merged into 27, another 36 were introduced into the basket and one was dropped. I cannot link items before and after the 2002 basket revision because of a change to the item keys.

To ensure the greatest comparability across time, I compute my core results for a sample covering January 1994 - June 2002 using the expenditure weights implemented in March 1995.[11] Unless otherwise indicated, the sample is restricted to the 266 product categories comprising nonregulated individual prices that were unaffected by the 1995 basket revision.[12] This restricted sample covers 63.4% of CPI expenditures. The largest three excluded product categories are homeowners' imputed rents, gasoline and rents, whose weight in the CPI are respectively 11.6%, 3.2% and 2.4%. This more homogenous sample contains 3.8 million price quotes from over $51,000$ price trajectories. Summary statistics of the data used in this paper are provided in Table 1.

Table 1: Summary statistics

Period	January 1994 - June 2002	July 2002 - December 2004
Price quotes		
Total	3,804,885	1,580,618
Average per month	37,303	52,687
Trajectories	51,299	99,435
Substitutions	11,291	38,981
Unweighted frequency (%)[a]		
Price changes	29.8	27.8
Price increases	20.9	16.0
Price decreases	8.9	11.7
Product categories		
Dataset	266	289
Full CPI[b]	313	315
CPI weight (%)	63.4	65.9

Notes: (a) The unweighted frequencies are computed by dividing the number of positive or negative price changes by the total number of price quotes for which a price change can be computed. (b) The total number of product categories was expanded from 302 to 313 in March 1995.

[11] These weights are derived from the 1989 ENIGH survey. They were updated using relative prices to reflect consumer expenditures in 1993.

[12] Seven product categories common to both periods were dropped from the analysis because they contained indexes rather than individual observations.

3.3 Other Aspects of the Data

I now address features of the data that are important to consider when interpreting of the results. The most significant issue is price averaging. Banxico collects prices twice monthly for all items but food; food price collection occurs four times per month.[13] The collected prices are then averaged to produce the monthly figures reported in the *Diario*. Observing the monthly average rather than the actual price of an item complicates the inference about price changes. For example, an average price of \$2 for an item is consistent with an actual price of \$2 throughout the month. It also is consistent with an actual price of \$1.50 in the first half of the month and \$2.50 in the second, or any combination of positive prices with \$2 as their average. Moreover, changes to an average price series are typically more frequent and of smaller magnitude than changes to an actual price series. For example, a price hike from \$1.50 to \$2.50 in the middle of the month results in an average price of \$2, which is \$0.50 short of the new actual price. Thus, if the actual price remains constant over the next month, another change to the average price series will be recorded.

To make my results as comparable as possible to other studies, which do not use averaged price quotes, I have constructed alternative price trajectories that filter the effect of averaging observations whenever possible. These new series correspond to the end-of-month series of actual prices, which are both consistent with the published averages and minimizes the number of price changes. In addition to being closer to the unobserved series of actual prices, the filtered series provide a lower bound on how frequently prices change. Appendix A discusses details of the filtering procedure.

Another issue in the data is that price collectors do not always directly observe prices. Indeed, sometimes an item is out of stock, out of season or, in rarer cases, the outlet is closed when the CPI agent visits. In such situations, the price from the previous period is carried forward. Although I cannot identify prices that were imputed in my sample, I do find clear indications that the number of imputations was larger at the beginning of the sample. Item substitutions represented less than 0.1% of all published price quotes in 1994, a proportion that rose to 1.2% in 2001 and 3.0% in 2004; this trend likely will create a downward bias in the estimated frequency of price changes at the beginning of the sample.[14]

Furthermore, prices are inclusive of sales as long as they are conditional on the purchase of a single item. For example, in a 3-for-2 promotion, the regular price would be reported. In such cases, the unobserved effective price is lower than the observed reported price. There is no variable in the data set signaling that an item is on sale or that a promotion is ongoing. To assess the prevalence of sales in the sample, I define sales as a price spell that lasts three months or less, begins with a price decline and is ended by a price increase of the same magnitude. When goods are weighted

[13] In the United States, the BLS collects prices monthly for food consumed at home, energy, and a few additional items with volatile prices. Other prices are collected monthly for the three largest metropolitain areas (New York, Los Angeles, and Chicago) and every other month for the remaining areas.

[14] A more systematic treatment of substitutions was implemented in 2001. Prices can now be carried forward for at most a month and a half before a substitution is sought. If the scarcity is generalized, this allowance can be extended up to three months. Systematic rotation of items was introduced in July 2002 to keep the CPI basket up to date.

by expenditure shares, sales amount to 4% of price changes over the sample period and 9% over the year prior before the 2002 basket revision. These figures are lower than the 20% reported by Klenow and Kryvtsov for the United States (cited by Bils and Klenow (2004)). This difference likely reflects a greater prevalence of sales and promotions in the United States than Mexico as well as methodological differences.[15] All the results in my paper are inclusive of unconditional sales.

In interpreting the data, one must also consider that most price quotes for the product categories of textiles, clothing, shoes and their related accessories are an average of a small sample of item prices; all items within a sample pertain to the same outlet whenever possible. Using the descriptions published in the *Diario*, I identified the exact number of items and brands within each store sample. A store sample typically contains two to four items (e.g., two cotton-based pants for men, brands Lee and Cimarron), with a mode of three for the number of both items and brands. Price changes generally are more frequent and of smaller magnitude for a sample than for its individual components, but the severity of this divergence depends on the price synchronization within the sample. For example, if an outlet runs a 30% sale on all jeans, then the average price of a sample of three pairs of jeans also decreases by 30%. I discard all store samples whenever a product category contains a large proportion of individual observations. For 34 categories encompassing all clothing and shoes categories except school uniforms, I retain only samples comprising three items and discard all other observations. I then treat those observations like other individual observations. Appendix B explores the extent of the bias this procedure introduces.

A final issue is that item substitutions often accompany changes in product characteristics, thereby raising the question of whether substitutions should be treated as price changes. The Inflation Persistence Network's approach is to assume that all substitutions not previously planned by the CPI agency involve a price change. In this paper, I instead exclude all substitutions from the computation of price changes because their treatment varies over the sample period. The main conclusions are not affected by this decision.

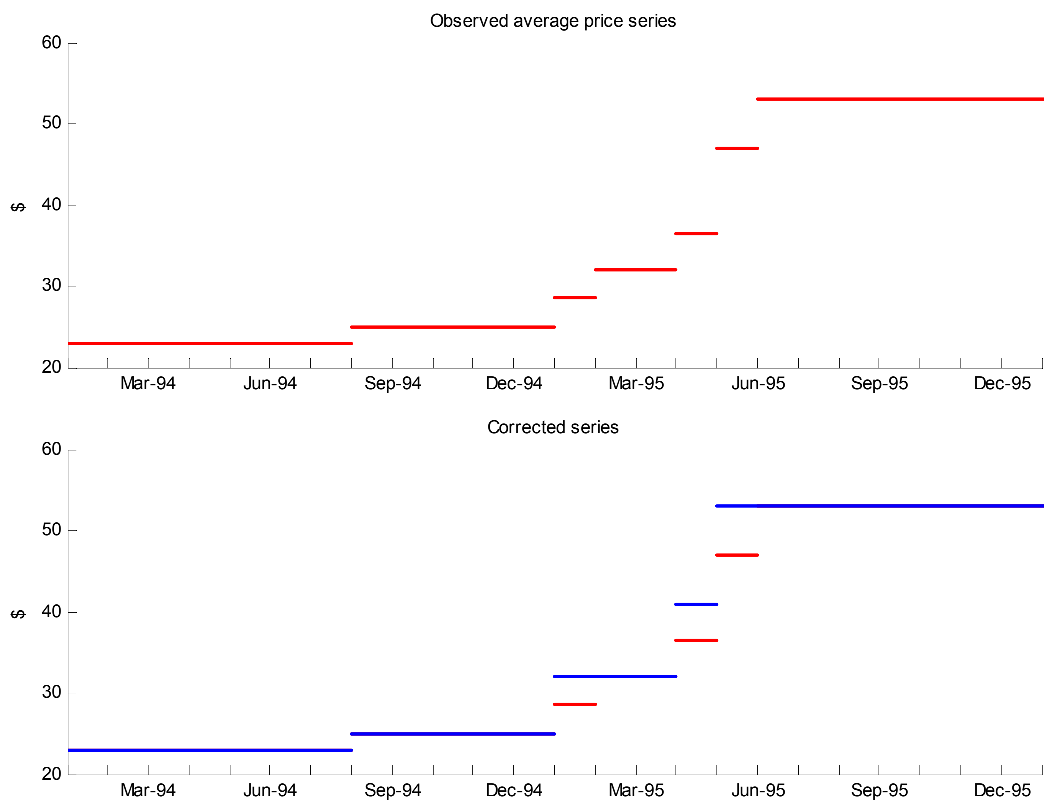
3.4 Example of Individual Price Trajectory

The next figure shows an actual price trajectory and illustrates how the effect of averaging several price observations over the month is filtered out. It displays two years of monthly average prices for a copy of the book "*The Universal History of Literature*" sold in a Mexico City outlet. This series was computed by Banxico by averaging the two prices its CPI agent collected each month. From January 1994 to December 1995, there were six changes to the series. The first happened in August 1994 when the average price increased from \$23 to \$25. Because the average price remained at \$25 in September, I conclude that the two prices collected in August also equaled \$25. The next two changes occurred in January and February 1995. The published price for January, \$28.5, is the exact average of the published prices for December and February (\$25 and \$32, respectively). This figure is consistent with the occurrence of a single change in the actual price from \$25 to \$32

[15] The BLS reports prices net of sales and promotions whenever possible. For example, a 3-for-2 promotion would result in a temporary 33% price decrease.

during the second half of January. The last three price changes occurred in May, June and July of 1995; the published price increased from \$32 to \$36.5, then to \$47 and finally to \$53. This series is consistent with a change in the actual price from \$32 to \$41 after the first price collection in May and then \$41 to \$53 after the first price collection in June. The filtered series, which contains only the last observation of each month, is displayed at the bottom of Figure 3. It contains only four price changes, and their magnitude is greater on average than those in the published average price series.

Figure 3: Illustration of a price trajectory correction



Note: The dashed line represents the actual monthly average price published in the Diario of a single copy of the book "The Universal History of Litterature" sold in a Mexico City outlet. The solid line represents the filtered point-in-time series.

4 Inflation Accounting Principles

Whenever a price is reported for two consecutive months, an indicator that a price change has occurred is created:

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

where p_{it} is the price of item i (in logs) during month t. Inflation is defined as

$$\pi_t \triangleq \sum\nolimits_{i\in\Upsilon_t} \omega_{it}\pi_{it}$$

where $\pi_{it} = p_{it} - p_{it-1}$, ω_{it} is the weight of item i, and Υ_t is the set of all items for which I_{it} is defined. For ω_{it}, I use the weight of the CPI category to which item i belongs, divided by the number of items in that category for which I can compute a price change at t. Inflation also can be expressed as

$$\pi_t \triangleq \underbrace{\left(\sum\nolimits_{i\in\Upsilon_t} \omega_{it}I_{it}\right)}_{fr_t}\underbrace{\left(\frac{\sum\nolimits_{i\in\Upsilon_t} \omega_{it}I_{it}\Delta p_{it}}{\sum\nolimits_{i\in\Upsilon_t} \omega_{it}I_{it}}\right)}_{dp_t}$$

The term fr_t, henceforth referred to as the frequency of price changes, is the total CPI weight of items whose price changes at t. The term dp_t is the average magnitude of those price changes. In the popular Calvo and Taylor models with uniform staggering of price changes, dp_t is the only possible source of variation in π_t.

It is convenient to decompose inflation further into a weighted sum of price increases and decreases:

$$\pi_t \triangleq \underbrace{\left(\sum\nolimits_{i\in\Upsilon_t} \omega_{it}I_{it}^+\right)}_{fr_t^+}\underbrace{\left(\frac{\sum\nolimits_{i\in\Upsilon_t} \omega_{it}I_{it}^+\Delta p_{it}}{\sum\nolimits_{i\in\Upsilon_t} \omega_{it}I_{it}^+}\right)}_{dp_t^+} + \underbrace{\left(\sum\nolimits_{i\in\Upsilon_t} \omega_{it}I_{it}^-\right)}_{fr_t^-}\underbrace{\left(\frac{\sum\nolimits_{i\in\Upsilon_t} \omega_{it}I_{it}^-\Delta p_{it}}{\sum\nolimits_{i\in\Upsilon_t} \omega_{it}I_{it}^-}\right)}_{dp_t^-}$$

This decomposition carries information about the relationship between the distribution of price changes and inflation. In the next section, the frequency of price increases and decreases, fr_t^+ and fr_t^-, will play a central role in the dynamics of inflation.

The statistic fr_t yields information about the economy's degree of price stickiness; all else equal, the greater fr_t is, the more flexible prices are. A closely related measure of price stickiness is the duration of price spells. Although price spells' length can be measured directly in the data, the literature generally has preferred duration measures derived from the frequency of price changes. Assuming price changes occur at a constant rate over the month, the average duration is given by $dur_t = -1/\ln(1 - fr_t)$. Aggregate measures of average or median durations are obtained by computing fr_t and dur_t at the category level and then aggregating them using the CPI product category weights.[16]

[16] The above average duration measure is biased downward because of Jensen's inequality. See Baharad and Eden (2004) and Dhyne et al. (2005) for a discussion of this bias.

5 Main Results

This section presents the main results regarding the frequency and magnitude of price changes and emphasizes their relationships to inflation. I leave aside all items whose price is regulated to focus on prices that are free to adjust. In addition, I treat separately non-regulated goods and non-regulated services as their behavior differ markedly.

5.1 Frequency

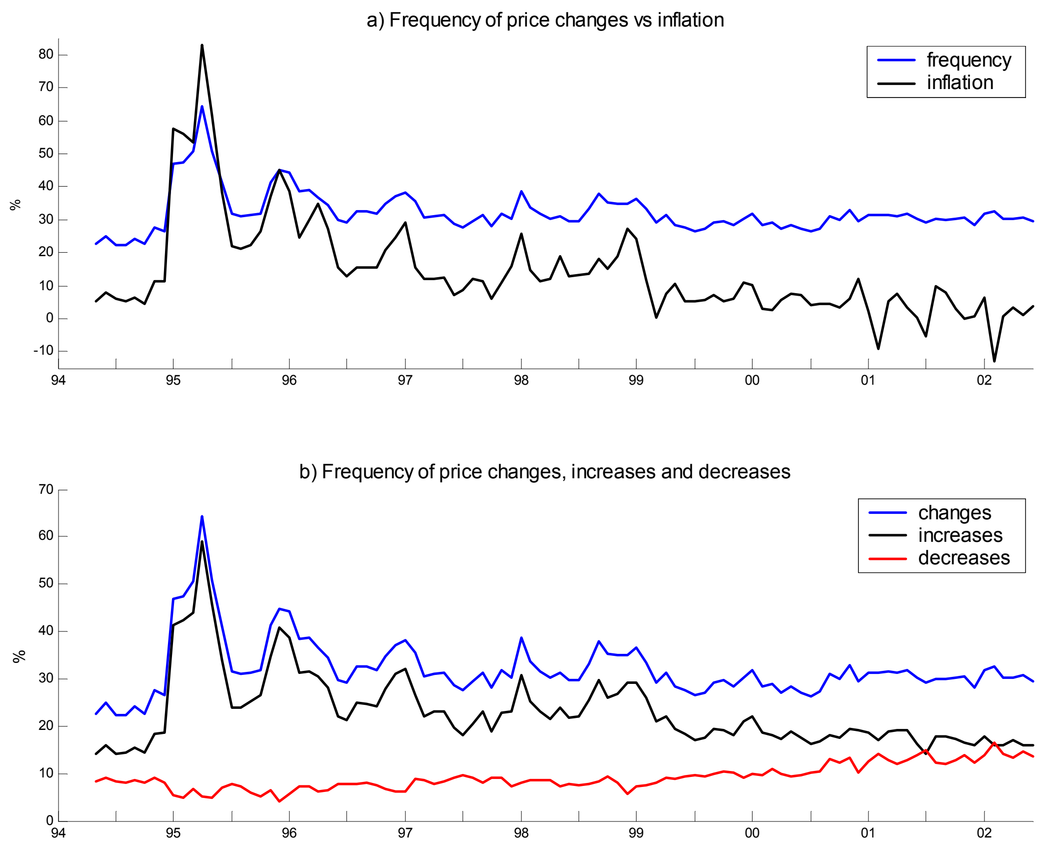
I first present the results for nonregulated goods which represents 73.1% of all expenditures in the main basket. For those items, movements in the frequency of price changes and inflation were very large over the sample period. In April 1995, the rate of inflation for nonregulated goods peaked at 82.9% (6.9% in monthly terms). This rate is much greater than the 7.2 percent average in 1994 and the 1.5 percent average in the last year of the sample. The frequency of price changes also peaked in April 1995, when the price of 64.3% of nonregulated goods, measured in CPI weight, changed over that month. This number is more than twice the average level of 24.2% in 1994 and 30.3% in the last year of the sample. In the case of services, inflation peaked at 54.3% in annual terms in April 1995 (4.5% in monthly terms).

Figure 4 presents the main time series statistics for non-regulated goods. Positive comovement between fr_t and π_t is clearly visible in the figure. The correlation coefficient between the two linearly detrended series equals 0.93 for the whole period. This correlation is largely driven by the high inflation episode, however; it falls to -0.02 if I consider only the last three years of the sample. After mid-1996, it is difficult to spot any downward trend in the frequency of price changes even though inflation trends down. The reason behind this loose relationship is apparent in the lower part of Figure 4, where I break down fr_t into fr_t^+ and fr_t^-. As inflation declined, so did the frequency of price increases. At the same time, however, price decreases became more frequent, thereby dampening movements in the frequency of price changes. A look at the correlation between fr_t^+, fr_t^- and π_t provides further evidence of this dampening effect. In the last three years of the sample, the correlation is 0.55 between fr_t^+ and π_t and -0.72 between fr_t^- and π_t. (All series are linearly detrended.) The net result is an absence of correlation between fr_t and π_t over that period.

The offsetting effect of price decreases operates mainly at low levels of inflation. Indeed, when inflation reaches above 10 to 15% in my sample, there are few price decreases left to offset movements in the frequency of price increases. At the peak of inflation, for example, only 8% of price changes were price decreases. In contrast, 45% of price changes were negative in the last year of the sample (42% if I include nonregulated services), a figure echoing those on the United States and the Euro area. This disappearance of price decreases creates the observed nonlinearity in the relationship of fr_t to π_t.

Figure 5 shows evidence of the offsetting effect from a different angle by presenting scatterplots of fr_t, fr_t^+ and fr_t^- against the inflation rate. The sample is divided into low- and high-inflation

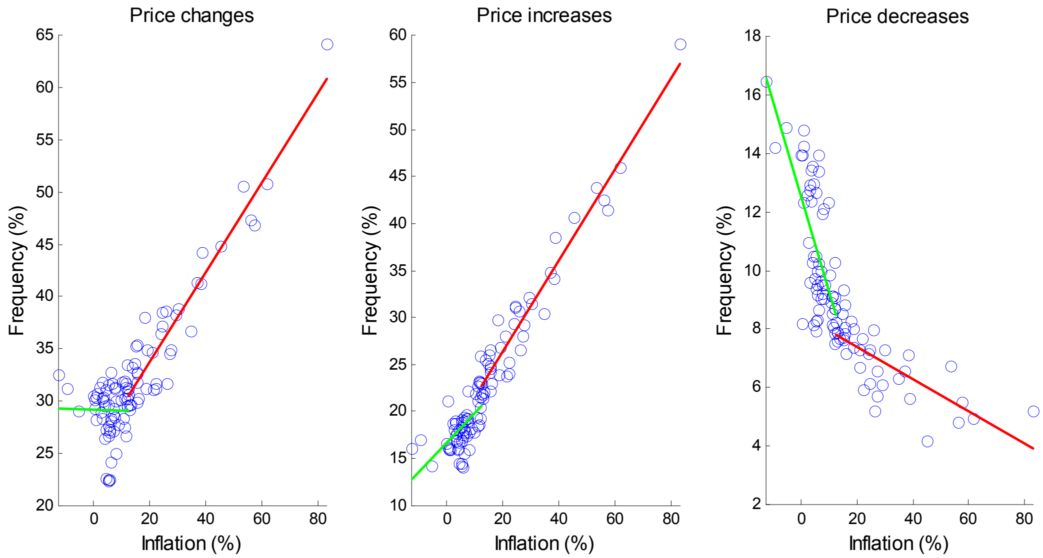
Figure 4: Frequency of price changes (nonregulated goods)



subsamples. The low-inflation subsample features a rapid fall in the frequency of price decreases as inflation takes off, thereby generating the offsetting effect. In comparison, in the high-inflation subsample, the frequency of price decreases is closer to its lower bound and responds less directly to movements in inflation. This change in behavior, seen as a "kink" in the relation, occurs for an inflation rate of $10-15\%$.[17] The plots also show the predicted values from simple linear regressions on each subsample, using 12.5% as the cutoff inflation. The regression results are presented in Table 2.

[17] A more formal way of choosing this cutoff is to regress the frequency of price decreases on inflation, allowing for a break in the relation. The hypothesis that the coefficients are equal for the two subsamples is rejected at the 1% for all points over that interval. Formal tests for choosing the break's location are sensitive to dropping all observations before April 1995.

Figure 5: Scatterplot of the frequency of price changes and inflation (nonregulated goods)



Note: Each graph displays linear regression lines using all observations below and above 12.5% annual inflation respectively. The regression statistics are presented in Table 2.

When inflation is high, there is a clear positive relation between fr_t and π_t: each percentage-point increase in the annual inflation rate is associated with a 0.37 (0.02) percentage-point increase in the frequency of price changes of nonregulated goods.[18] In stark contrast, in the low-inflation subsample, the frequency of price changes shows no statistical relation to inflation in the low inflation subsample; the best point estimate for the slope of the regression line is actually negative at -0.01 (0.07). The reason behind this very different behavior of fr_t over the low- and high-inflation subsamples can be understood by taking a second look at fr_t^+ and fr_t^-. When inflation is low, a one percentage-point change in the inflation rate has a similar effect in magnitude on fr_t^+ and fr_t^-, 0.31 (0.05) versus -0.32 (0.04), but this effect takes opposite signs. The net effect renders unresponsive fr_t to movements in inflation. As inflation moves toward high values, however, the rate at which fr_t^- falls decreases as it approaches its lower bound of 0. The frequency of price increases still has room to respond, though, resulting in the significant, positive statistical relationship that

[18]The number in parentheses is the standard error.

Table 2: Linear regression results (nonregulated goods)

Frequency of Price Changes

	fr			fr+			fr-		
Observations	Constant	π	R-square	Constant	π	R-square	Constant	π	R-square
All	26.92	0.37	0.78	15.86	0.50	0.92	11.06	-0.13	0.56
	(0.42)	(0.02)		(0.31)	(0.01)		(0.25)	(0.01)	
π<=12.5%	29.16	-0.01	0.00	16.66	0.31	0.36	12.51	-0.32	0.51
	(0.52)	(0.07)		(0.42)	(0.05)		(0.32)	(0.04)	
π>12.5%	25.14	0.43	0.90	16.66	0.49	0.94	8.47	-0.05	0.55
	(0.79)	(0.02)		(0.67)	(0.02)		(0.27)	(0.01)	

Magnitude of Price Changes

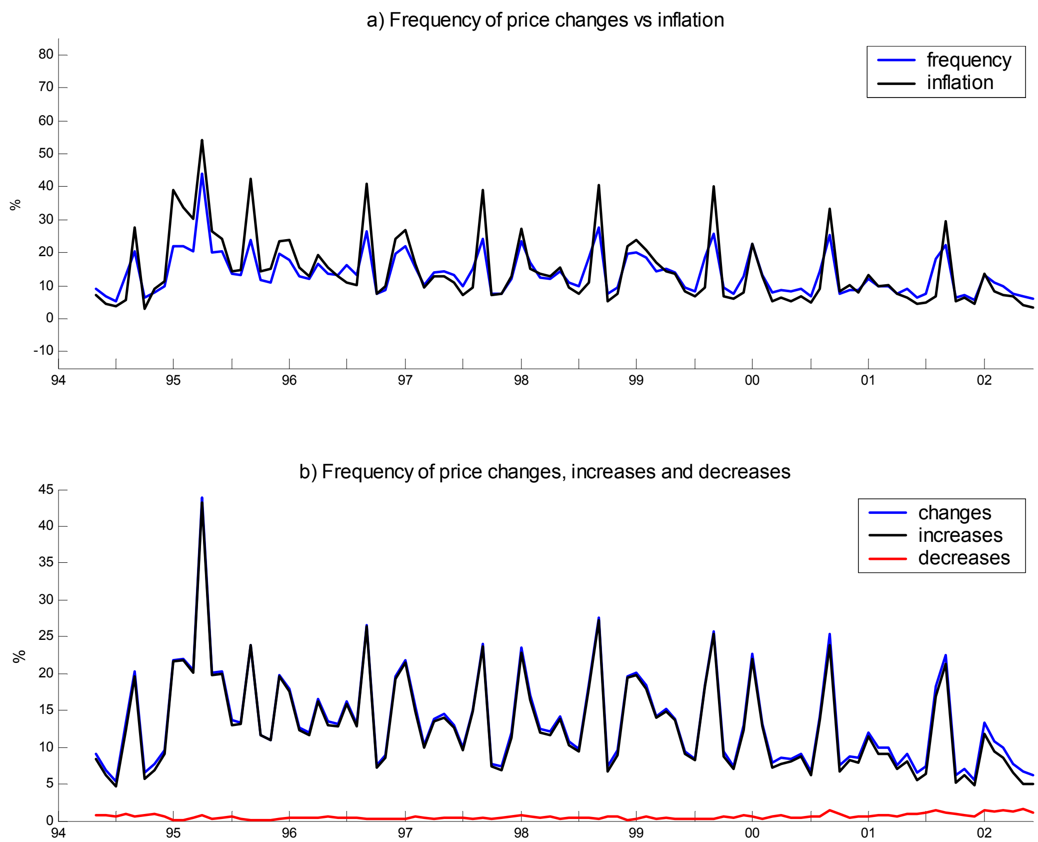
	dp			dp+			dp-		
Observations	Constant	π	R-square	Constant	π	R-square	Constant	π	R-square
All	0.91	2.02	0.92	8.58	0.54	0.34	11.06	-0.58	0.16
	(0.11)	(0.06)		(0.14)	(0.08)		(0.24)	(0.14)	
π<=12.5%	0.10	3.27	0.98	9.15	-0.42	0.03	11.99	-2.53	0.31
	(0.04)	(0.06)		(0.21)	(0.32)		(0.32)	(0.5)	
π>12.5%	2.44	1.50	0.91	7.67	0.86	0.82	10.41	-0.30	0.06
	(0.2)	(0.08)		(0.18)	(0.07)		(0.52)	(0.2)	

Note: numbers in parentheses are standard errors.

surfaces between fr_t and π_t. The offsetting effect of price decreases when inflation is low is robust to choosing any cutoff for the low- and high-inflation subsamples within the $10 - 15\%$ range. Furthermore, the results are similar if I include nonregulated services, if I drop observations before the 1995 sample revision or around the inflation peak, and if I exclude all small-store samples.

Nonregulated services represent a much smaller share of expenditures than nonregulated goods in the basket at 26.9%. The upper part of Figure 6 displays the frequency of price changes and the inflation rate of nonregulated services over the sample period. There are several notable differences in price setting behaviors with respect to nonregulated goods. First, price changes are less frequent for nonregulated services than goods, a fact noted by several author (e.g. Bils and Klenow (2004) and Dhyne et al. (2005)). Second, the frequency of price changes is a much more important margin of adjustment for services inflation than for goods. Even at low levels of aggregate inflation, I observe large increases in the price index for nonregulated services associated with important movements in fr_t. These movements have a strong seasonal component, with the large adjustments of each year occurring almost inevitably in January and September. Second, the sample peak in inflation around April 1995 is associated with a smaller rise in the frequency of price changes. The frequency averaged 10.4% in the second half of 1994 and 24.7% in the first half of 1995 compared to 24.3% and 50.2% for nonregulated goods. Finally, most nonregulated services price changes are price increases. In the last year of the sample, less than 1 out of every 8 price changes was a price decrease. The strong movements in the frequency of price changes at low levels of inflation may be associated with this relative absence of price decreases. Movements in the frequency of price decreases are negligible for the dynamics of the frequency of price changes, in sharp contrast with nonregulated goods.

Figure 6: Frequency of price changes (nonregulated services)



5.2 Magnitude of Price Changes

In the case of nonregulated goods, the average magnitude of price changes moves strongly with inflation, regardless of whether inflation is low or high. The series dp_t and π_t, displayed in Figure 7, follow similar patterns over the sample period.[19] They register sharp increases during the Tequila crisis, followed by a protracted decline and ultimately a stabilization. The correlation between the two linearly detrended series is 0.94 over the full sample period. The high inflation episode does not drive this strong correlation, as was the case with the frequency of price changes; indeed, the correlation actually *rises* to a solid 0.998 over the last three years of the sample. As the scatterplot of dp_t against π_t (Figure 8, with regression coefficients presented in Table 2) indicates, dp_t and π_t have a tight, almost linear relation when inflation is below 1% per month, or roughly 10-15 percent per year. When inflation is greater than 1% per month, the relation is still strongly positive, albeit noisier and slightly concave.

[19] The inflation series is the nonannualized monthly inflation rate to facilitate visual comparisons.

Figure 7: Average magnitude of price changes (nonregulated goods)

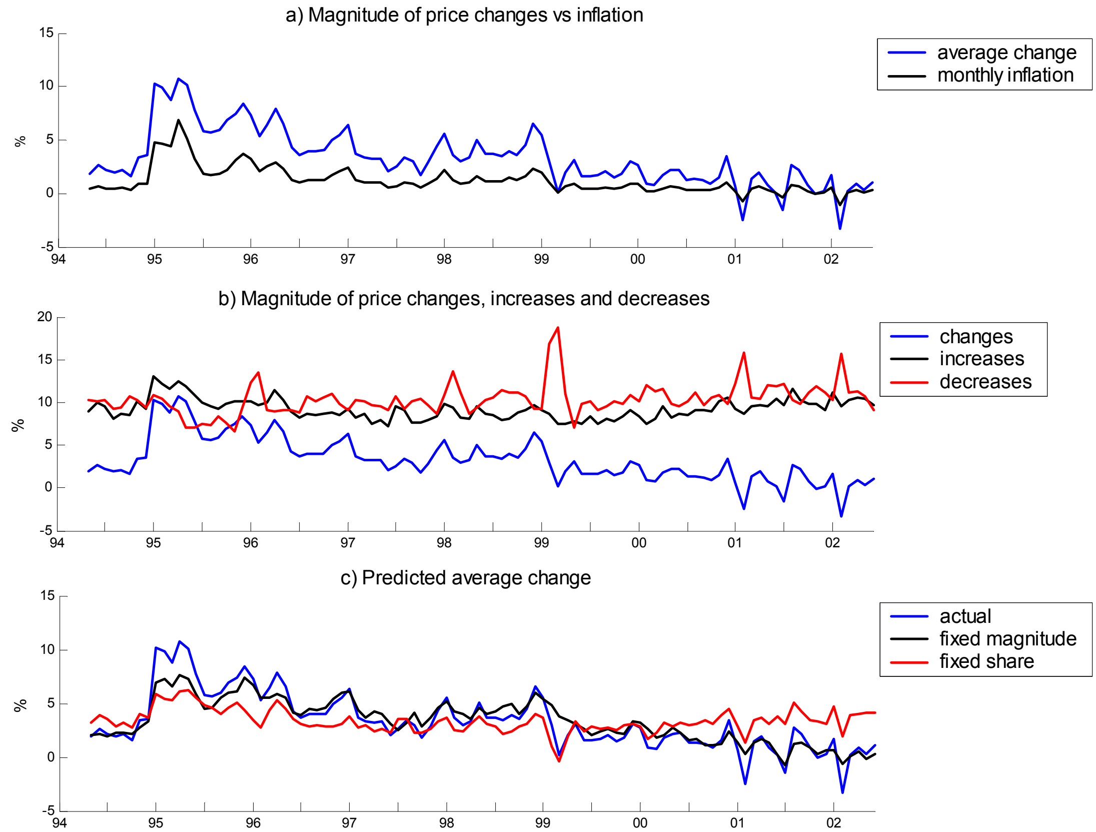
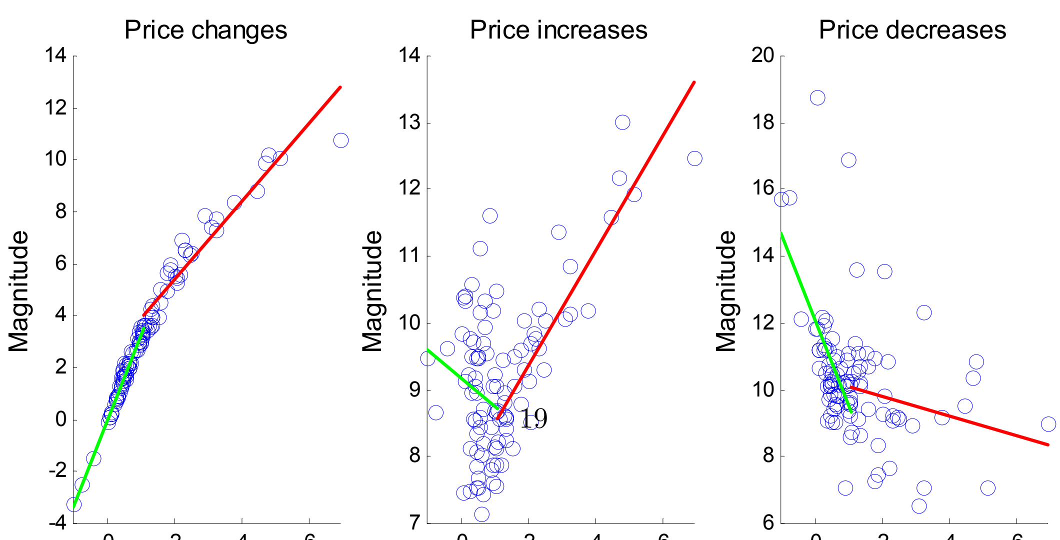


Figure 8: Scatterplot of the average magnitude of price changes and inflation (nonregulated goods)



These results should come as no surprise given the findings described earlier regarding the frequency of price changes and inflation. By definition, $\pi_t = fr_t \cdot dp_t$. When inflation is low, fr_t moves little with inflation, implying that dp_t moves strongly and almost linearly with π_t. In contrast, when inflation is greater than $10 - 15\%$ per year, fr_t moves strongly and positively with π_t. This second source of variation in π_t introduces some curvature as well as some noise in the relationship between π_t and dp_t.

To better understand what drives dp_t, it is convenient to express it as

$$dp_t = s_t \cdot \left|dp_t^+\right| - (1 - s_t) \cdot \left|dp_t^-\right|,$$

where $s_t = fr_t^+ / \left(fr_t^+ + fr_t^-\right)$ is the fraction of price increases among price changes. Thus, variations in the absolute magnitude of price increases and decreases, as well as their relative occurrence (the composition effect), affects the average magnitude of price changes. It is clear from Figure 7 that $\left|dp_t^+\right|$ and $\left|dp_t^-\right|$ are less correlated with inflation than dp_t. The point estimates for the correlation over the full sample are 0.65 and -0.23, respectively. Moreover, $\left|dp_t^+\right|$ and $\left|dp_t^-\right|$ display much less variation over the sample period than their weighted sum.[20] Except for a short period around the peak of inflation, the two series show relatively small oscillations around their sample mean: 9.2% for price increases and 10.4% for price decreases. This pattern leaves a potentially large role for movements in s_t to affect average price change. The relation between inflation and $\left|dp_t^+\right|$ or $\left|dp_t^-\right|$ also is much noisier than the relation between inflation and dp_t. The bottom of Table 2 presents results from linear regressions of the magnitude of price changes on inflation. There is no significant statistical relationship between $\left|dp_t^+\right|$ and π_t in the low-inflation sample nor between $\left|dp_t^-\right|$ and π_t in the high- inflation subsample.

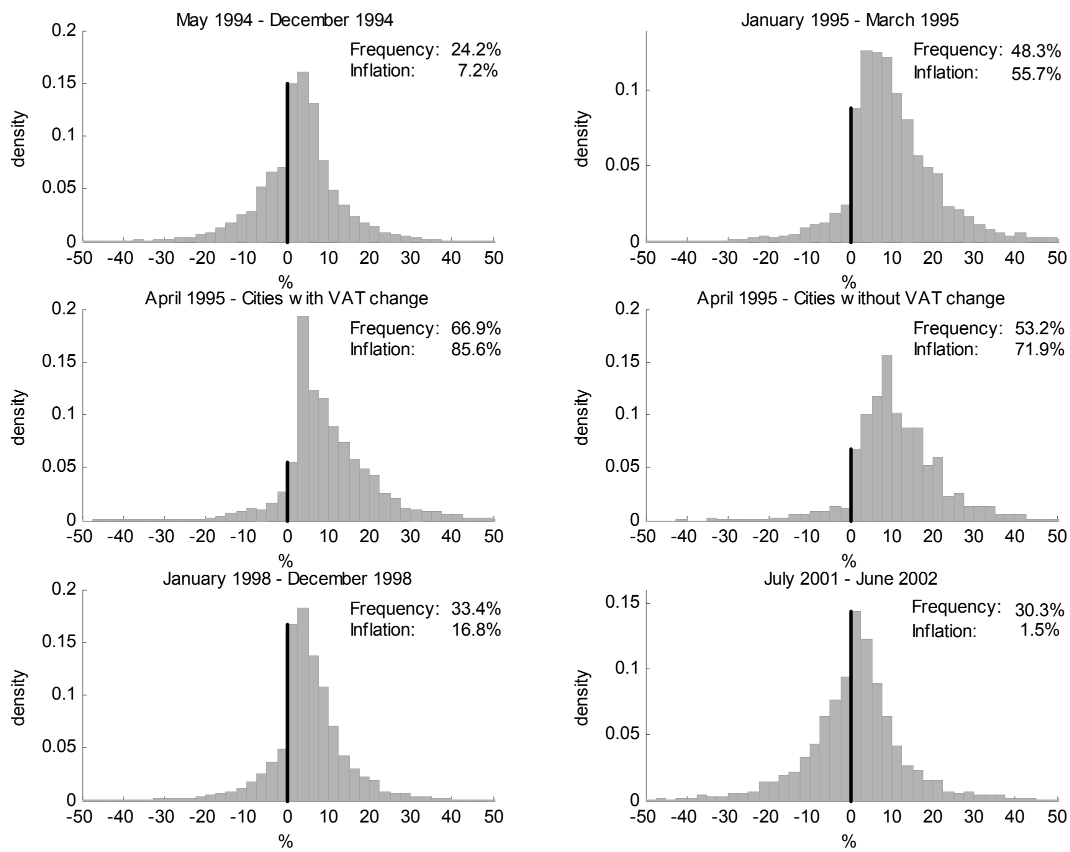
To assess the importance of this composition effect, I compute two counterfactual series in Figure 7. I obtain the first by holding s_t at its sample mean to show how movements in $\left|dp_t^+\right|$ and $\left|dp_t^-\right|$ alone affect dp_t. In the second series, $\left|dp_t^+\right|$ and $\left|dp_t^-\right|$ are held at their sample mean so the relative occurrence of price increases and decreases is the only source of variation in dp_t. The main finding indicates that the composition effect drives dp_t when inflation is below 10-15%, whereas movements in both the composition and absolute magnitude of price changes are important when inflation is high. Had s_t been constant, dp_t would have sloped up counterfactually in the last three years of the sample because of a mild upward trend in dp_t^+ after 1999. In contrast, the series allowing only for the composition effect predicts remarkably well the level of dp_t over that period. When inflation nears its peak, the composition effect alone is insufficient to match the level of dp_t, but it is a better predictor than merely allowing for changes in the absolute magnitude.

[20] The few large spikes in dp_t^-, all occuring at the beginning of the year, stem from seasonal variations in the price of a few fresh food items.

5.3 Distribution of Price Changes

There is much heterogeneity in the size of price changes at all levels of inflation. In the case of nonregulated goods, the distribution of price changes is very spread out; both small and large price changes arise (see Figure 9).[21] When inflation is low, many large and small price decreases occur. Furthermore, the entire distribution shifts to the right as inflation increases. On the other hand, price decreases, which are almost as frequent as price increases at low inflation, become less prevalent as inflation rises. This behavior leads to the weak response of the frequency and the strong response of the magnitude of price changes discussed earlier.

Figure 9: Distribution of nonzero price changes (nonregulated goods)



When inflation is high, price increases between 0 and 20% compose the bulk of price changes. The increased density of this region comes from two sources. First, prices that change often – food products in particular – see their distribution moving up. Second, several prices that would have

[21] The distribution is conditional on observing a price change such that its density integrates to one. Prices from all nonregulated product categories are used to construct the graphs.

remained fixed otherwise are updated by positive amounts. Recall that the price of 59.1% of all nonregulated items changed in April 1995 compared with only 25.6% in the last year of the sample.

The distributions are not symmetric, even when inflation is at its lowest. Indeed, small decreases are less frequent than small increases. Furthermore, price increases are more spread out than price decreases when inflation is high, but the opposite is true when inflation hovers around 1.7% in the last year of the sample. Price changes for food items primarily drive this pattern: the variance of these changes is large, and food items represent a sizable share of price changes. Other product categories have less frequent, mainly positive price adjustments. This finding support the idea that at least two product categories are required in macroeconomics models to be consistent with the empirical distribution of price changes. To produce the long tails, I need a category of items whose magnitude of price changes has a large variance. When mixed with a category displaying less variable and mainly positive changes, an asymmetry around zero could arise.

I find a clear effect of changes in the VAT on the distribution of price changes. The two middle graphs show the distribution when the 5% VAT hike occurred in April 1995. The density of the interval comprising the mode of the distribution stands out as unusually high and falls within the band corresponding to the change in the VAT. I provide a more detailed analysis of the VAT tax change in a later subsection.

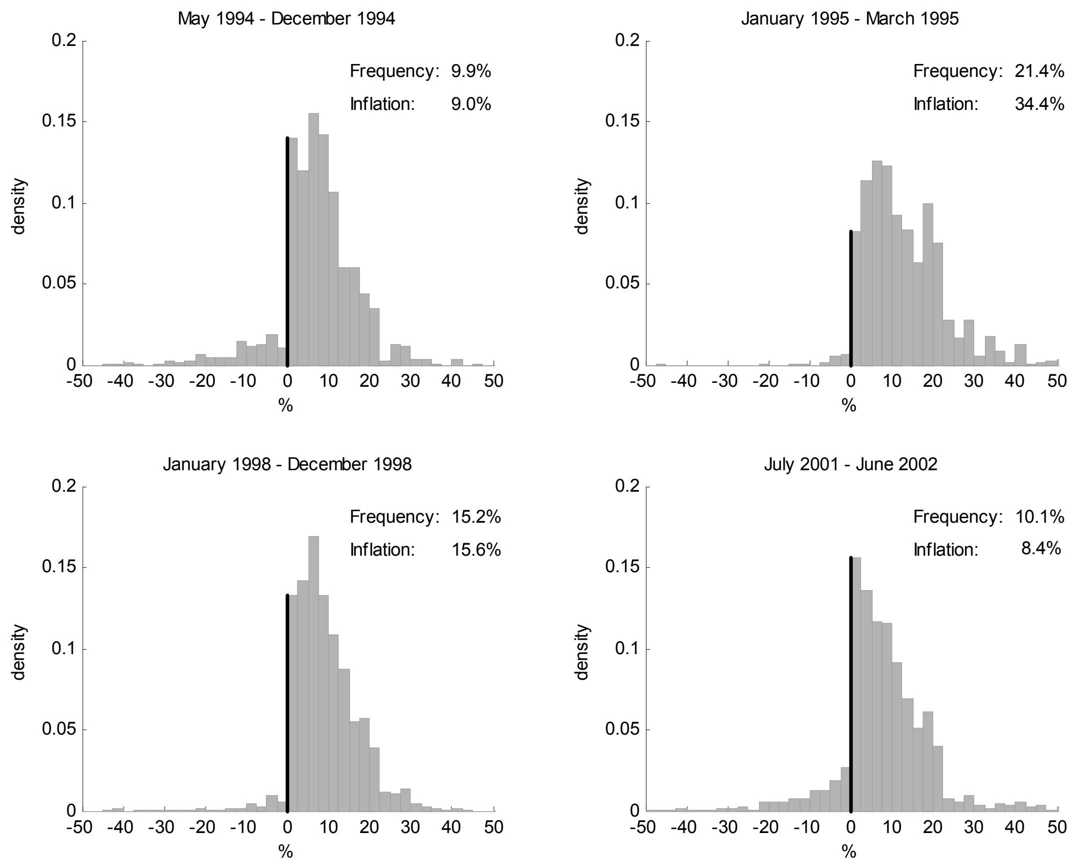
Figure 10 displays the corresponding distributions of price changes for nonregulated services. The graphs corresponding to the VAT tax change are omitted given the small number of services impacted by the change. As noted earlier, there are few price decreases for nonregulated services, even at low levels of inflation. This striking difference between the distributions of price changes for nonregulated goods versus nonregulated services offers support to the idea that an empirically successful microfounded model should embed at least two sectors. There is a slight increase in the frequency of price changes conditional on inflation toward the end of the sample period. Interestingly, the figure indicates that some of these additional price changes are price decreases.

5.4 Sector statistics

Similar to the findings for the United States and Euro area, a substantial heterogeneity in consumer price stickiness exists across major product groups in Mexico (see Figure 11).[22] In particular, *Foods and nonalcoholic beverages* stands out for its high frequency of price changes and the prevalence of price decreases. Its frequency averages 40.0% over the last three years of the sample when inflation was low, a percentage almost identical to its 40.2% average over the full sample period; in contrast, the average frequency of other groups is generally half of those numbers or less. The share of price decreases for *Food and nonalcoholic beverages* is 35.8% over the full sample and 45.3% in the last three years. Other groups experience few or no price decreases over most of the sample period. Only when inflation settled comfortably below 10% did price decreases rise mildly. Given these

[22] To facilitate comparisions, I classify each product category according to the Euro area *Classification Of Individual COnsumption by Purpose* (COICOP). I report the results for 2-digit COICOP groups using all product categories unaffected by the 1995 basket revision, regardless of whether they are regulated or not. For *Housing, water, electricity, gas and other fuels* and *Communications*, I could not compute the frequency because of a lack of data.

Figure 10: Distribution of nonzero price changes (nonregulated services)

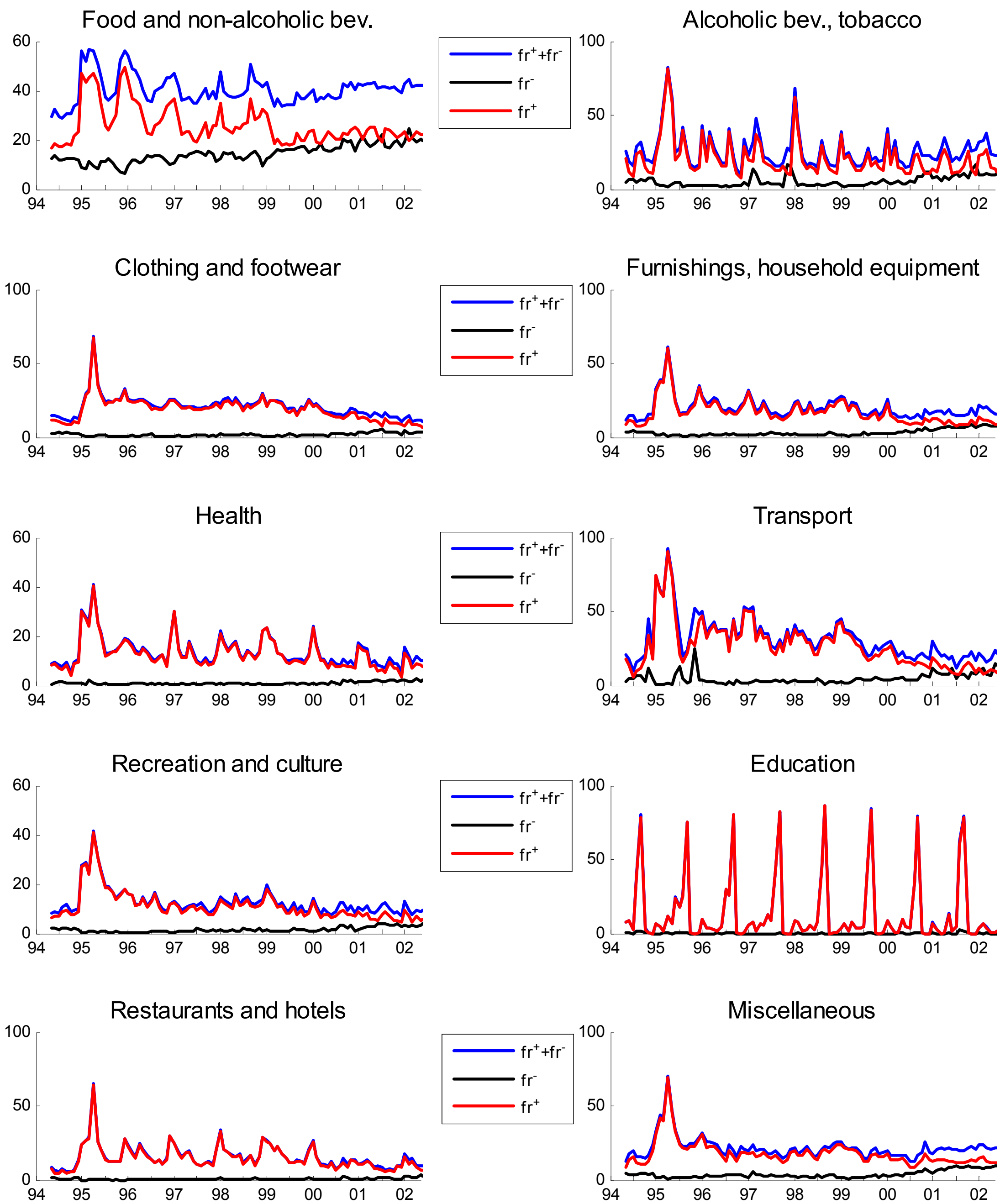


observations, food products clearly are key to the importance of price decreases at the aggregate level.

Figure 11 also shows that almost every sector rapidly felt the inflationary pressure accompanying the devaluation. In January 1995, all groups but *Education* experienced a sharp rise in the frequency of price changes. A second wave of rapid increases in the frequency of price changes also surfaced in most groups in April 1995. The clear spikes in the series relate to a change in the value added tax, which I will discuss in greater detail at the end of the section.

I also find evidence of seasonality in the timing of price changes for groups containing a large proportion of services. In particular, *Health*, *Restaurants and Hotels* as well as *Transportation* display some seasonality in January. *Education* is a striking case, with more than 90% its prices changing in either August or September and few if any prices changing at other times of the year. These seasonal patterns can be considered as a form of time dependence in which prices are adjusted at fixed time intervals. The strong seasonality particular to *Education* stems largely from the nature of the items it encompasses; tuition, registration fees and room and board in academic institutions

Figure 11: Sector frequencies of price changes



constitute the bulk of observations in that category. These items are distinctive because both the price and quantity consumed are fixed for a certain time period (say, a semester or an academic year). In that sense, they differ from the staggered pricing model where the price is fixed but the quantity can fluctuate freely.

There are less striking differences across sectors with respect to the magnitude of price changes (see Figure 12). Overall, the average magnitude of price changes is similar in magnitude across sector. The sector of *Transport* has the overall smallest price changes. The sector of *Education* also has unusually small price changes for several months of the year. Price increases are typically larger than average in September, however, when the frequency of price changes is the highest in September. Finally, I notice that the devaluation brought larger price increases mainly in the service sectors while *Food and non-alcoholic beverages* displayed little change.

Finally, I present the distributions of price changes for two-digit COICOP groups over the last two years of the sample. The purpose of this figure is to illustrate that a large amount of price change dispersion is found at lower levels of aggregations. Very small price changes are found in all COICOP group considered. A particularly large number of them is found in the *Transport* industry, which includes items such as airfares, and in *Education*, for which prices were found to be changed at regular intervals. An unusually large number of small price changes are also found in the *Clothing and footwear* sector. Recall, however, that most observations in that sector are an average the price of three similar items belonging to the same store. The large number of small price changes thus likely reflects the fact that changes to the average price are typically smaller than individual price changes themselves.

5.5 Inflation Variance Decomposition

In this section, I quantify the importance of fluctuations in the frequency and magnitude of price changes for the variance of inflation. The starting point is a first-order Taylor-series expansion of $\pi_t = fr_t dp_t$ around $\overline{fr}$ and dp_t, as implemented by Klenow and Kryvtsov (2005):

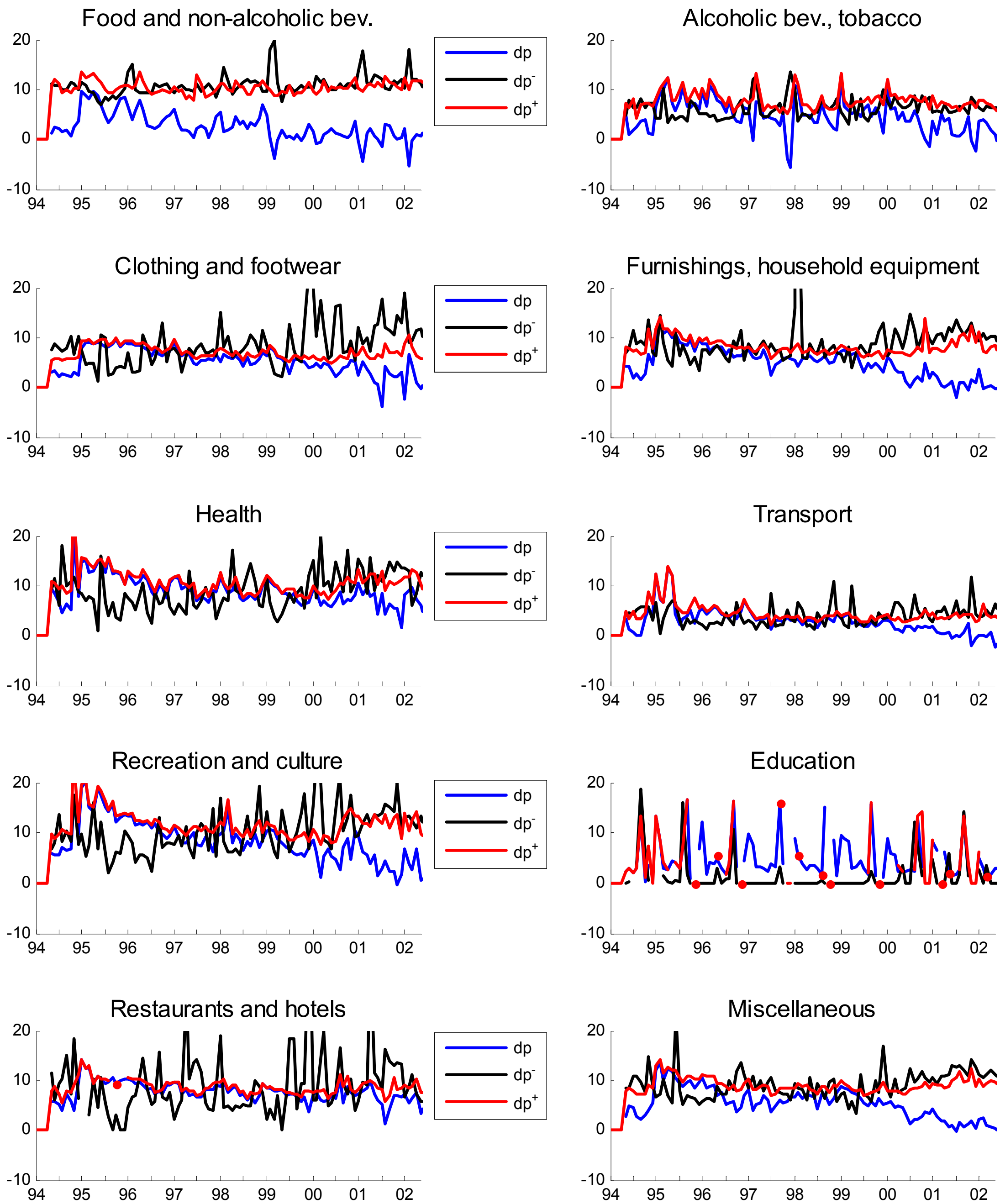
$$\pi_t = \overline{fr} \cdot \overline{dp} + \overline{fr} \cdot \left(dp_t - \overline{dp}\right) + \overline{dp}\left(fr_t - \overline{fr}\right) + \left(dp_t - \overline{dp}\right)\left(fr_t - \overline{fr}\right)$$

Taking the variance on both sides and collecting terms, one obtains

$$var\left(\pi_t\right) = \underbrace{\overline{fr}^2 \cdot var\left(dp_t\right)}_{TDP} + \underbrace{\overline{dp}^2 \cdot var\left(fr_t\right) + 2\overline{fr \cdot dp} \cdot cov\left(dp_t, fr_t\right) + O_t}_{SDP}$$

This expression provides a decomposition into a time dependent (TDP) and a state dependent (SDP) part. TDP is the only term depending solely on dp_t, whereas all terms in SDP, including the higher-order terms O_t, are functions of fr_t. In the Calvo model, as well as in the Taylor pricing model with uniform staggering, the TDP term accounts for all of the inflation variance. Finding non-zero terms in SDP therefore can serve as evidence against these time dependent models. Using U.S. CPI data for 1988-2003, Klenow and Kryvtsov find only a minor role for the terms in SDP, and

Figure 12: Sector average magnitude of price changes



around 95% of the variance in the monthly inflation series stem from fluctuations in dp_t. This aspect of the United States' recent inflation experience therefore conforms to time dependent models.

The figures for Mexico differ markedly from those for the United States. As shown in Table 3, the TDP term represents only 41.9% of the inflation variance over the full sample period, leaving a much greater role for fluctuations in fr_t. This comes as no surprise given the high correlation between fr_t and π_t over the sample period. The smaller share of variance that the TDP terms account for also appears in both the goods and services sectors. This share is particularly small for services at 14.3%, but this figure stems primarily from the strong seasonal pattern in the pricing of Education services.[23] In the case of goods, movements in fr_t also are important, with the notable exception of unprocessed food, which I will discuss shortly.

As I have shown, the high inflation episode drives the correlation between fr_t and π_t, which becomes essentially zero as inflation levels off. This elusive relationship has a direct consequence for the variance breakdown. When restricted to the low-inflation period after mid-1999, the share of inflation variance represented by the TDP climbs to 82.7%. This proportion reaches 94.9% when services are excluded, a figure comparable to Klenow and Kryvtsov's finding for the United States. In contrast, the proportion is lowest when inflation is most variable. The short subperiod before 1995 represents an intermediate case. Taken together, these findings help indicate when time-dependent models have realistic implications for the inflation variance. As Figure 8 showed, there is a tight, almost linear relation between dp_t and π_t when the latter is below $10-15\%$. This strong comovement drives the variance decomposition during the low-inflation period. Then, as inflation takes off, fr_t becomes more positively correlated with π_t and dp_t. This relationship induces a substantial role for terms involving fr_t, especially for the covariance and higher-order terms.

As noted earlier, the time-dependent part accounts for most of the variance of unprocessed food inflation, presumably because the frequency is high even when inflation is low. This finding means there is little room for the frequency to adjust when inflation takes off. I uncover support for this conjecture at the product category level: The TDP term accounts for a larger share of the variance in product categories with especially frequent price adjustments.[24]

[23] Although seasonality sometimes is interpreted as evidence of time dependency, it does not feed into the TDP term here because the benchmark assumes uniform staggering.

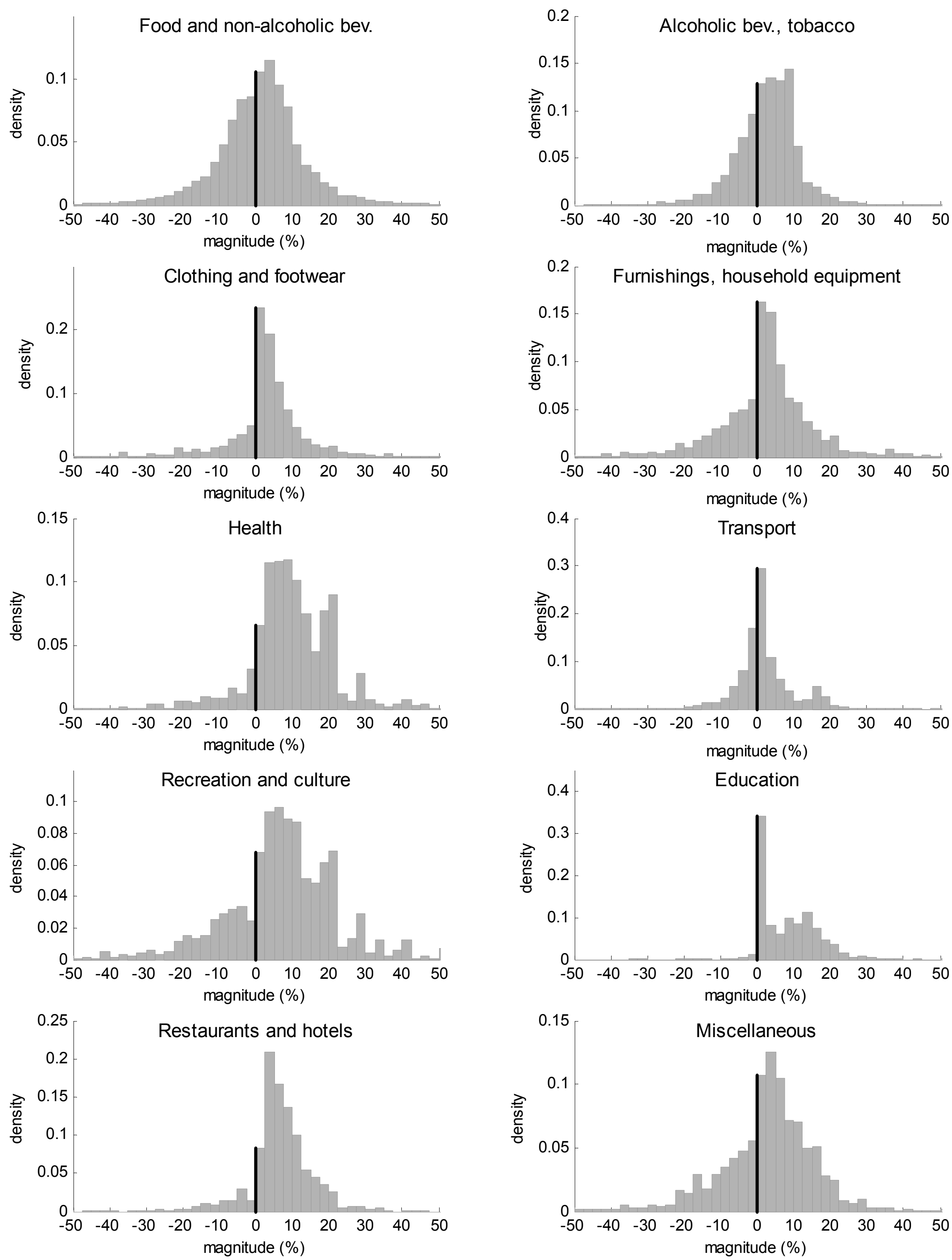
[24] A simple unweighted linear regression of the share of variance the TDP term accounts for over the average product category frequency has a slope of 0.85 for the full sample and 1.13 for the high-inflation period. Both slopes are significant at the 95% confidence level, and the respective R^2 are 0.45 and 0.78.

Table 3: Inflation variance decomposition

	Inflation		Share of Inflation Variance (%)			
	Average	Std Dev	TDP	SDP1	SDP2	Other
Full Sample Period (January 1994 - June 2002)						
Full CPI	14.4	13.2	41.9	4.6	21.6	31.9
Nonregulated goods	14.4	15.3	46.0	2.8	17.1	34.2
Unprocessed food	12.8	18.2	86.6	0.5	3.8	9.1
Processed food	15.3	18.4	32.2	4.9	18.8	44.1
Nonenergy ind. goods	14.9	15.4	27.0	8.3	24.0	40.7
Nonregulated services	14.6	10.6	14.3	35.9	26.7	23.1
Precrisis (January 1994 - December 1994)						
Full CPI	7.7	3.2	58.3	5.3	32.1	4.4
Nonregulated goods	7.2	2.8	57.2	4.6	30.5	7.7
Unprocessed food	8.7	5.2	88.9	0.6	12.3	-1.7
Processed food	6.2	3.6	61.1	6.9	32.8	-0.9
Nonenergy ind. goods	6.7	3.4	40.0	8.0	29.6	22.5
Nonregulated services	9.0	8.1	18.2	25.8	21.0	35.0
Crisis (January 1995 - June 1999)						
Full CPI	21.4	13.8	34.6	9.6	30.3	25.5
Nonregulated goods	22.5	16.1	38.8	6.7	27.4	27.1
Unprocessed food	20.1	18.3	88.0	1.2	10.3	0.5
Processed food	24.0	20.8	26.4	12.4	30.4	30.9
Nonenergy ind. goods	23.2	16.3	17.7	16.5	26.6	39.2
Nonregulated services	18.4	10.9	15.4	41.5	27.8	15.3
Postcrisis (July 1999 - June 2002)						
Full CPI	5.5	4.7	82.7	0.9	5.7	10.6
Nonregulated goods	3.9	5.0	94.9	0.2	-2.3	7.2
Unprocessed food	2.8	14.8	92.3	0.0	0.0	7.7
Processed food	4.3	4.4	92.8	1.5	2.7	3.1
Nonenergy ind. goods	4.3	3.8	86.4	1.1	10.1	2.5
Nonregulated services	10.1	8.3	11.3	32.6	17.3	38.8

Notes: The full CPI includes all nonregulated goods and services less housing rents and product categories containing an unsufficient number of individual observations.

Figure 13: Distribution of nonzero price changes (2-digit COICOP groups, July 2000 to June 2002)



5.6 Effects of the VAT Change

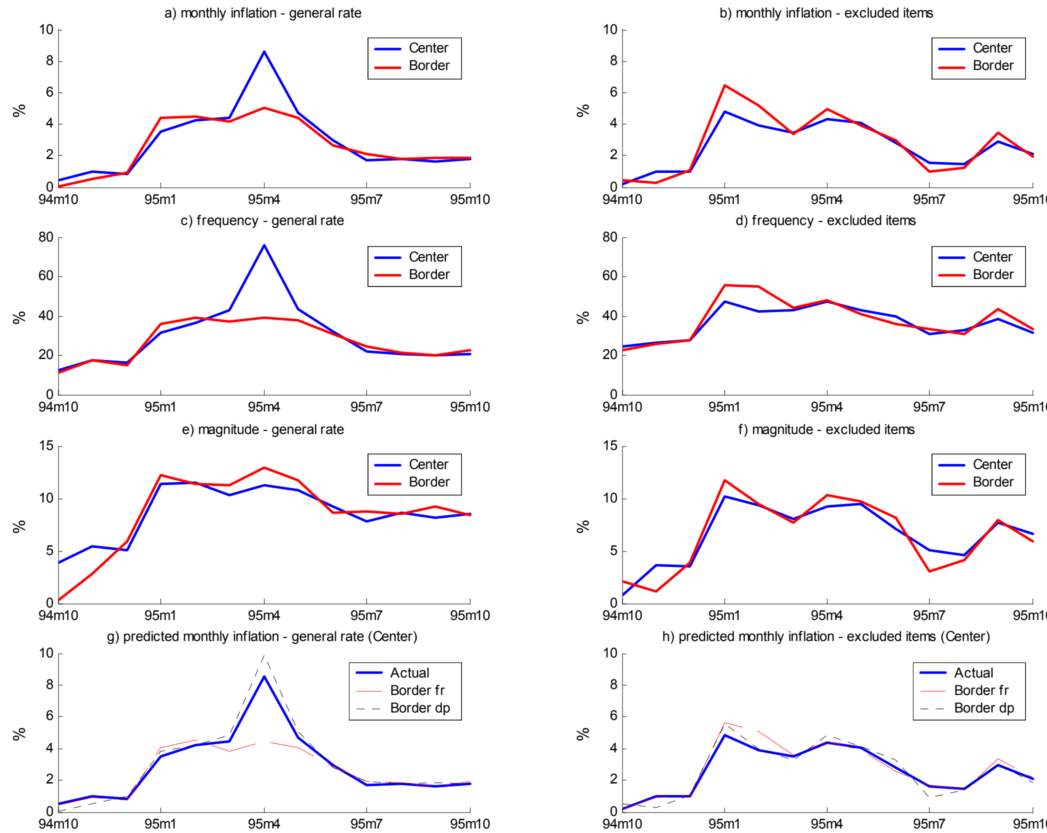
Changes to value added taxes are observable events that can reveal precious information about how an economy adjusts in response to such shocks. On April 1, 1995, the generate rate of the VAT rose from 10 to 15% everywhere in Mexico, with the exception of cities located in a corridor along the northern and southern borders, as well as the whole Baja California. Mexican retailers are required to include the VAT in their sales prices. All else equal, an increase in the VAT squeezed retailer's profit margins, thereby creating an incentive for adjusting prices upward. In TDP models, this adjustment occurs only through larger price changes. In this section, I investigate whether this prediction was actually realized.

Two features make the April 1995 VAT increase particularly interesting. First, retailers were given a very short notice of the VAT change. The decree was adopted March 18 and published in the *Diario* on March 27. A large number of price quotes for March 1995 were collected before the public learned of the change and the tax was in full force when collection started in April. Second, the change did not affect all items and cities. Prices from excluded groups of products and geographic areas can serve as controls to disentangle the effect of the VAT from other factors.

The results are presented in Figure 14. The sample was divided into four groups according to whether items are taxed rate or tax-exempt (respectively labelled "general rate" and "excluded items") and whether they are located in cities affected or unaffected by the change (labelled "Center" and "Border", respectively). Inflation rates, expressed in the graph as monthly rates, differed markedly across regions and goods in April 1995. The inflation rate of center cities exceeded the rate for border cities by 3.5 percentage points in the case of goods affected by the general rate. That same month, the difference was -0.6 percentage points for goods exempted from the VAT. These differences clearly indicate that most of the price adjustment occurred within a month. Notably, the adjustment occurred mainly through more frequent rather than larger price changes. For the items taxed under the general rate, the fraction of price changes in April is 76.2% for the cities affected by the change, and 39.2% for the cities where the rate remained at 10%. For items that are taxed-exempt, the frequency of price changes are very similar across regions where the tax rate increased (47.1%) and where it did not (47.9%). The average magnitude of price change is similar across regions, which might be surprising given that I previously noticed a spike in the price change distribution of items in cities affected by the change. The effect of the tax change on the average price increase was minute.

The sharp increase in the frequency of price changes was the main source of inflation pass-through. Direct proof of this conclusion appears at the bottom of Figure 14, where three inflation rates are reported. The first is the actual inflation rate for the cities affected by the tax; this rate is the product of the frequency and magnitude of price changes, $fr_t^{border} \cdot dp_t^{border}$. The other two series are obtained by replacing fr_t^{border} and dp_t^{border} by their respective values for cities along the borders. The three series are computed first for items under the general rate and then repeated for tax-exempt items. The predicted inflation rate is almost identical to the actual rate when I replace the magnitude of price changes. However, when I use the lower frequency of border cities, there is

Figure 14: Effect of April 1, 1995 VAT change



no increase in inflation.

Note that inflation rose more rapidly in border cities. This behavior is consistent with the greater exchange rate pass-through along the border. I found the difference in inflation to be particularly large for *Food and nonalcoholic beverages* and *Restaurants and hotels*. Although items in the latter category usually are classified as nontradables, the importance of tourism in border cities might have contributed to the greater pass-through.

Several authors have noted the effect of VAT changes on the frequency of price changes.[25] The Mexican tax change is especially interesting, however, because of its unusually large size and the regional differences in its application. The change in the frequency, over 35 percentage points, is larger than any other documented frequency change. Furthermore, because price decreases were nearly absent in April 1995, one could conjecture that their buffering effect did little to prevent the

[25]Particularly for Spain (Álvarez and Hernando (2006)), Belgium (Aucremanne and Dhyne (2004 and 2005)), France (Baudry et al. (2004)), Portugal (Dias, Dias, and Neves (2004)), Germany (Hoffmann and Kurz-Kim (2006)) and the Netherlands (Jonker et al. (2004)).

aggregate frequency from rising. However, VAT hikes do not seem to be associated with unusually large falls in fr^- in Europe.

6 International Comparisons

A priori, it is difficult to know how the findings for Mexico might generalize to other countries because there are no comparable studies with similar product and inflation coverage. In this section, I construct baskets of goods similar to the ones used for the low-inflation studies in the United States and Euro area studies. I also break down the Mexican sample into low- and high-inflation subperiods to provide more direct comparisons. In show that Mexico is an intermediate case between the United States and the Euro area in terms of price stickiness. I then compare my results with the sectorial studies done at high inflation.

6.1 Low-Inflation Studies

6.1.1 Time and Product Coverage

Three time periods of 24 months were selected. The first starts in March 1995, immediately after the CPI basket revision, and captures a period when inflation averaged nearly 30%. The second period covers the last two years of data before the second revision of the CPI basket in 2002. The third period runs from January 2003 to December 2004. The inflation rate over the last two samples is only a few percentage-points higher than the United States and Euro area studies. The third period is the most directly comparable to the U.S. and Euro-area studies in terms of methodology and product coverage.

Statistics for the frequency of price changes are computed for two different baskets. The first, the *BK basket*, has a product coverage similar to the one Bils and Klenow (2004) used for the United States. Its construction was detailed in Section 2.2.[26] This sample covers 63.4% of Mexican consumption expenditures before the 2002 revision of the CPI basket. In the third time period, I use all categories with individual observations, resulting in a CPI coverage of 65.9%. In comparison, Bils and Klenow's sample covers 68.9% of U.S. consumption expenditures. To produce comparable statistics, I classified the Mexican product categories according to the BLS classification system used from 1989 to 1997.

The second basket matches the one used by the *Inflation Persistence Network* and is consequently labeled the *IPN basket*. This smaller basket is restricted to 50 product categories to facilitate comparisons across countries. Categories are representative of 2-digit groups in the *Classification Of Individual COnsumption by Purpose* (COICOP) and of the following five main components: unprocessed food, processed food, energy, nonenergy industrial goods (NEIG) and services. Details of the basket construction are relegated to Appendix C.

[26] It excludes all product categories introduced in March 1995; their price changes are not observed until July 1995 because the first four months of all price trajectories are cut during the filtering procedure. Excluding those categories has a negligible effect on the results after July 1995.

6.1.2 Results

The results are presented in Table 4. Because they are very similar for the BK and IPN baskets, I will focus on the broad findings. The CPI inflation rate averages 27.9% in Mexico over the first time period, a rate well above the 2.3% and 1.6% averages in the U.S. and Euro-area samples, respectively. Not surprisingly, the aggregate frequency of price changes is much higher in Mexico, averaging 32.5% in the BK sample, more than twice the Euro area average, and 6 percentage points higher than the United States. The higher frequency is reflected in terms of shorter durations. The median duration in Mexico is about three months compared with 4.6 months in the United States and 10.6 months in the Euro area. I also report the average duration and the inverse of the aggregate frequency. Although both are sensitive to the underlying heterogeneity, they nevertheless confirm the previous ranking. Notably, the difference between the mean and the median declines considerably during the high-inflation period.

Table 4: Comparison of price stickiness in Mexico, the United States and the Euro area

	Mexico			United States	Euro area
Period	Mar 1995 - Feb 1997	Jul 2000 - Jun 2002	Jan 2003 - Dec 2004	Jan 1995 - Dec 1997	Jan 1996 - Dec 2000
Average inflation	27.9	4.4	3.8	2.3	1.6
Aggregate frequency					
BK sample	32.5	24.9	22.6	26.1	15.3
IPN sample	32.9	24.0	19.9	24.8	15.1
Duration					
Mean duration					
BK sample	3.1	6.6	7.0	6.7	n.a
IPN sample	3.7	6.6	7.9	n.a	13.0
Inverse of aggregate frequency					
BK sample	3.1	4.0	4.4	3.8	6.5
IPN sample	3.0	4.2	5.0	4.0	6.6
Median duration					
BK sample	3.0	5.6	5.7	4.6	n.a.
IPN sample	2.6	5.7	5.2	n.a.	10.6

Note: Figures for the United States and Euro area come from Dhyne et al (2005).

In the second and third time periods, Mexican inflation rates are much closer to their American and European counterparts than in the first time period. The frequency of price changes falls a few percentage points below that of the United States despite a slightly higher inflation rate, and it stops about five to 10 percentage points higher than that of the Euro area depending on the basket considered. Overall, the Mexican economy appears less flexible than the U.S. economy and more flexible than the Euro-area economy for comparable inflation rates.

A higher aggregate frequency does not necessarily imply increased flexibility for prices at the product-category level, however. Indeed, differences in CPI composition may also play role because of the considerable heterogeneity at the sector level documented earlier. Table 5 reports the expenditure weights for major groups of products under the BLS and COICOP classifications. The weights represent the shares of the BK and IPN baskets each special group accounts for. The most striking difference is the relatively large share of Food in the Mexican consumption basket. In contrast, both Durable goods and Services account for smaller shares in Mexico than in the United States.

Table 5: Expenditures weights of special aggregates

	Mexico		**United States**
Base year	1993	2000	1995
BK Sample			
Share of total consumption expenditures	63.4	65.9	68.9
Nondurable goods	72.4	65.1	44.1
Durable goods	11.7	11.6	14.7
Services	15.9	23.3	41.2
Food	49.4	41.2	22.6
Home furnishing	12.0	15.6	24.9
Apparel	10.7	8.6	8.5
Transportation	6.8	6.7	23.1
Medical care	4.9	6.1	7.5
Entertainment	3.8	5.1	6.2
Other	12.4	16.8	7.2
IPN Sample	**Mexico**		**Euro area**
Unprocessed food	19.2	13.5	9.3
Processed food	20.3	18.5	14.3
Energy	6.5	8.0	5.8
Nonenergy industrial goods	24.7	25.8	34.4
Services	29.2	34.2	36.2

Note: Weights with base year 1993 and 2000 were introduced by Banxico during the March 1995 and July 2002 revisions of the CPI basket.

Table 6 provides frequency statistics for the main BLS special groups, and 2-digit COICOP groups. For the high-inflation period, the frequency of price changes for the Food, Home Furnishing, Medical Care and Others categories was higher in Mexico than the United States.[27] As inflation

[27] The special group Others includes tobacco and smoking products, personal care goods and services, personal services and educational expenses.

leveled, the frequency remained higher for Food and Other in Mexico, but was comparable to the United States or lower for all other special groups. With respect to the Euro area, prices appear more flexible in Mexico for all observed inflation levels, and for all 2-digit COICOP groups except Energy. The table also indicates how differences in composition affect the aggregate frequency of price changes. Holding the frequency of special groups constant, I computed the aggregate frequency that would have resulted if Mexico had had the same category weights as the United States and Euro area. For the BK sample, using the U.S. weights for Mexico lowers its frequency from 32.5% to 31.7% for the high-inflation period and from 22.6% to 20.0% for the lowest inflation period. In the case of the IPN basket, the frequency would have dropped from 32.9 to 28.9% for the high-inflation period. In short, the relatively large share of CPI expenditures for food, particularly unprocessed food, contributes to the overall flexibility of consumer prices in Mexico.

6.2 High-Inflation Studies

The amount of empirical evidence on the setting of consumer prices during high inflation is very limited. Lach and Tsiddon (1992) consider a sample of 26 food products in Israel (mainly meat and alcohol products). For the period 1978-79, 39.5% of prices changed in their sample every month while the annual inflation rate averaged 60%. This figure is the same as the average frequency of price changes for food products in my high-inflation sample, even though the average inflation rate in Mexico (27.9%) was only half that of Israel. A related study featuring Konieczny and Skrzypacz (2005), who study the transition from a planned to a market economy in Poland. They use monthly data on 52 products, of which 37 are food products, from January 1990 to December 1996. They report a monthly frequency of price change of 59% as inflation peaked at 249% in 1990. In contrast, the frequency of price changes was 30% in 1996 when inflation averaged 19%. Interestingly, the frequency was only from 35% in 1993 although inflation was double its 1996 rate (38%). This finding supports the idea that movements in the frequency of price changes are dampened in the food sector due to the presence of price decreases. Burstein, Eichenbaum, and Rebelo (2005) conduct a weekly survey of supermarket prices for a broader basket covering 58 good categories in Argentina from March to December 2002, when the annual inflation rate averaged 33%. They find a 66.5% median frequency of price changes. This percentage is much larger than what I find for Mexico. Part of the difference is likely explained by differences in the type of outlets surveyed.[28]

7 Empirical Performance of Menu-Cost Models

In this last section, I calibrate a discrete-time version of the menu-cost model developed by Golosov and Lucas (2003). The objective is to investigate whether this state-dependent model can correctly predict the average magnitude and frequency of price changes at levels of inflation similar to the ones observed in Mexico over my sample period. This particular model was chosen because it embeds

[28] Baudry et al. (2004) report that the outlet size is positively correlated with the frequency of price changes in French CPI data.

Table 6: Comparison of the frequency of price changes between Mexico, the United States and the Euro area for some special groups

BK Sample		**Mexico**		**United States**
Period	Mar 1995 - Feb 1997	Jul 2000 - Jun 2002	Jan 2003 - Dec 2004	Jan 1995 - Dec 1997
Average inflation	27.9	4.4	3.8	2.3
Nondurable goods	35.7	29.4	28.2	29.9
Durable goods	35.8	16.9	17.8	30.3
Services	15.1	10.5	9.1	20.6
Major groups				
Food	39.5	35.2	33.8	25.3
Home furnishing	27.1	17.5	17.2	26.4
Apparel	27.0	14.4	9.1	29.2
Transportation	44.6	19.6	19.9	39.5
Medical care	17.1	10.2	11.4	9.3
Entertainment	11.1	7.3	11.8	11.3
Other	20.1	14.6	15.2	11.0
Aggregate frequency				
United States weights	31.7	20.3	20.0	26.1
Mexico weights	32.5	24.9	22.6	-
IPN Sample		**Mexico**		**Euro area**
Period	Mar 1995 - Feb 1997	Jul 2000 - Jun 2002	Jan 2003 - Dec 2004	Jan 1996 - Dec 2000
Average inflation	27.9	4.4	3.8	1.6
Unprocessed food	54.7	55.0	26.4	28.3
Processed food	34.5	20.0	12.5	13.7
Nonenergy industrial goods	55.5	39.3	18.7	9.2
Energy	28.8	16.8	54.9	78.0
Services	15.8	8.9	6.1	5.6
Aggregate frequency				
Euro area weights	28.9	19.3	26.4	15.1
Mexico weights	32.9	24.0	19.9	-

Notes: The U.S. statistics are computed using the figures in Bils and Klenow (2004) and are inclusive of sales. The figures for the Euro area are from Dhyne et al. (2005).

three desirable features. First, the presence of menu costs gives rise to infrequent, lumpy nominal price adjustments. Second, it leaves the frequency of price changes free to vary with inflation, a feature not found in most time-dependent models and in state-dependent models in which nominal prices adjust every period. Third, the model contains idiosyncratic technology shocks generating a distribution of both positive and negative price changes. The first two features means that, a priori, both the frequency and magnitude of price changes can respond to a change in inflation, while the simultaneous presence of price increases and decreases might help to generate an initially slow rise in the frequency of price changes as inflation takes off from a low level. Throughout the discussion, I focus on a stationary equilibrium with constant aggregate inflation. A discussion of the model's calibration is relegated to Appendix D.

7.1 Economic Environment

The economy consists of three types of agents. An infinitely-lived representative household supplies labor and consumes a basket of differentiated consumption goods. These goods are produced by a continuum of monopolistically competitive firms subject to idiosyncratic technology shocks, the only source of uncertainty in the economy. Finally, there is a monetary authority whose only role is to expand the money supply at a constant rate g.

7.1.1 Households

The problem of the household is to choose a sequence for consumption, $\{c_t\}$, and an hours worked, $\{n_t\}$, in order to maximize its present discounted utility,

$$\max_{\{c_t,n_t\}} \quad \sum_{t=0}^{\infty} \beta^t U\left(c_t, n_t\right),$$

subject to a budget constraint

$$P_t c_t = W_t n_t + P_t \Pi_t,$$

and a simple cash-in-advance constraint

$$P_t c_t = M_t.$$

The variable P_t is the price index at time t, W_t is the wage rate and M_t are the household's cash balances that correspond to the money stock. Real profits, Π_t, are remitted every period by intermediate firms. The budget constraint states that consumption spending equals the sum of a household's labor income and profits received from firms. Following Golosov and Lucas, I further assume that utility is separable, logarithmic in consumption and linear in labor:

$$U\left(c_t, n_t\right) = \log c_t - \psi n_t.$$

The household's problem is fully static. In the stationary equilibrium, all aggregate real quantities are constant while aggregate nominal quantities grow at the same rate as the money stock. Under the above assumptions, the intratemporal Euler equation implies that the wage rate is proportional to the stock of money.

$$\psi = \frac{W_t}{P_t c} = \frac{W_t}{M_t}.$$

Consumption is a composite of intermediate consumption goods aggregated using a Dixit-Stiglitz specification

$$c = \left(\int (c_{j,t})^{\frac{\theta-1}{\theta}} \, dj \right)^{\frac{\theta}{\theta-1}}.$$

The demand for individual consumption goods must satisfy

$$c_{j,t} = \left(\frac{p_{j,t}}{P_t} \right)^{-\theta} c$$

where the price index is given by

$$P_t = \left(\int (p_{j,t})^{1-\theta} \, dj \right)^{\frac{1}{1-\theta}}.$$

7.1.2 Intermediate Firms

There is a continuum of measure one of monopolistically competitive firms. At the beginning of the each period, firms draw idiosyncratic productivity shocks. They then decide whether to keep selling their goods at the same nominal price as in the previous period, or to incur a menu cost (expressed in units of labor), ξ, in order to optimize their price. Once prices are set for the period, firms must satisfy the demand at those prices.

The production function of the $j-th$ firm is linear in labor

$$y_{j,t} = c_{j,t} = \phi_{j,t} n_{j,t}.$$

I assume that labor productivity, $\phi_{j,t}$, evolves according to

$$\log \phi_{j,t} = (1-\rho) \log \bar{\phi} + \rho \log \phi_{j,t} + \varepsilon_{j,t},$$

where technological innovations, $\varepsilon_{j,t}$, are drawn from a normal distribution $N\left(0, \sigma_\varepsilon^2\right)$.

Firms maximize the present discounted value of their profits. It is convenient to express their problem recursively in order to solve it using dynamic programming techniques. Let $V(\phi; p)$ be the Bellman equation of an optimally behaving firm just before it decides whether to change its nominal price or not. The state of the firm comprises its nominal price relative to the price index, p, and its technological level, ϕ. The value function is given by

$$V(\phi; p) = \max_{\{\text{no price change, price change}\}} \{V_{nc}(\phi; p), V_c(\phi)\},$$

where $V_{nc}(\phi; p)$ is the value function associated with the firm's decision to keep its nominal price constant in the current period and behave optimally thereafter, and $V_c(\phi)$ is the corresponding value function of a firm choosing to optimize its nominal price in the current period. These functions are expressed as

$$V_{nc}(\phi; p) = \pi(\phi; p) + \beta \int V\left(\phi'; \frac{p}{1+g}\right) d\mu(\phi'|\phi).$$

and

$$V_c(\phi) = \max_{\tilde{p}} \quad \pi(\phi; \tilde{p}) + \beta \int V\left(\phi'; \frac{\tilde{p}}{1+g}\right) d\mu(\phi'|\phi) - \xi \frac{W}{P},$$

respectively. The first right hand-side term, $\pi(\phi; p)$, is the period gross profit function. Taking into account the production function and the demand curve, it is expressed as $\pi(\phi; p) = \left(p - \frac{1}{\phi}\frac{W}{P}\right) p^{-\theta} c$. The integral gives the expected value function in the next period, taking into account price erosion due to inflation and the distribution of technology shocks.

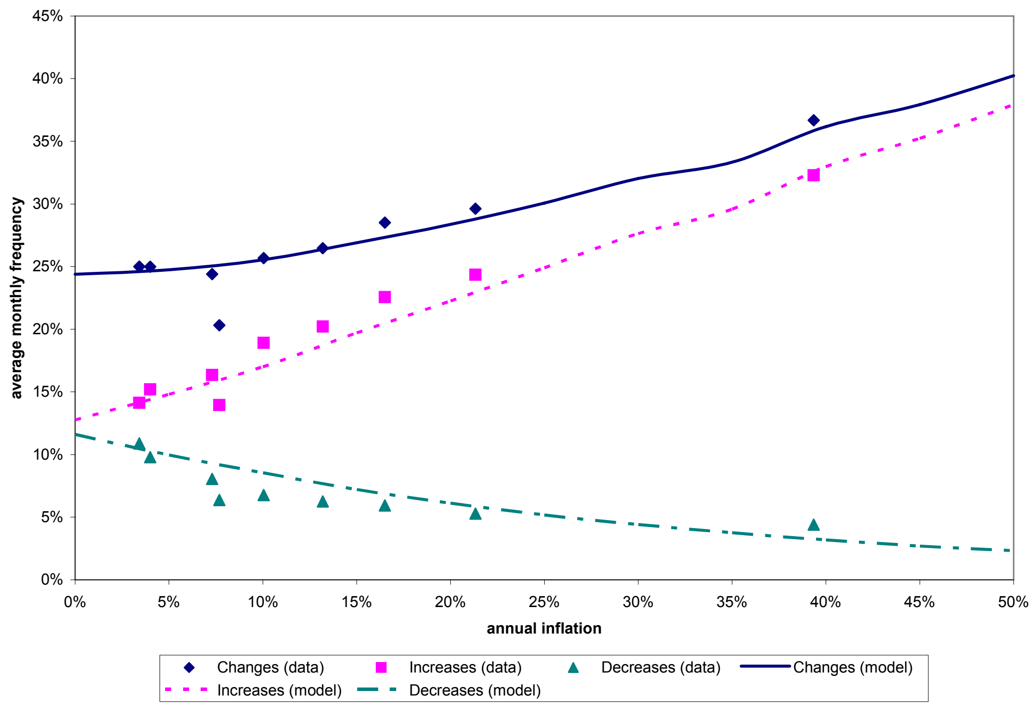
7.2 Main Results

As described in Appendix D, the model is calibrated to match the average frequency and magnitude of price changes over the last two years of the sample, a period when annual inflation averaged 4.5 percent. The model's predictions are then recorded for steady state inflation rates ranging from 0 to 50 percent. Overall, the model matches remarkably well the behavior of the average frequency and magnitude of price changes. The fit of the frequency of price changes is reported in Figure 15. The diamonds, squares and triangles represent the average monthly frequency of price changes, increases and decreases, respectively, for each calendar year in the sample. The lines indicate the corresponding predictions of the model. As inflation is increased from a low to a high level, the model produces a slow rise in the average monthly frequency of price changes similar to the one observed in the data. The main outlier is the year 1994 for which the model predicts a frequency of price changes around 26% compared to 21.2% in the data. This poor fit may be related to data collection and sample composition issues (see Section 3 for a discussion). The model fares rather well at reproducing the underlying opposite movements in the average frequency of price increases and decreases. The model's simple calibration slightly underpredicts the size of the initial fall in the frequency of price changes and simultaneous rise in the occurrence of price increases, although any strong judgement on this aspect is also potentially subject to data issues.

As shown in Figure 16, the model fits equally well the average magnitude of price changes. When inflation is low, the average magnitude of price changes responds almost linearly to a change in steady state inflation, a counterpart to the weak response of the frequency of price changes. Interestingly, the goodness of fit arises despite much poorer fits of the average magnitudes of price increases and decreases. Figure 16 thus hints that in the model, as it is the case in the data, movements in the average magnitude of price changes are driven mainly by changes to the relative occurrence of price increases and decreases, not by movements in the average absolute magnitude.

It has been argued by Rotemberg (2004) that menu-cost models often imply movements in the

Figure 15: Average frequency of price changes predicted by the model compared to the sample annual averages

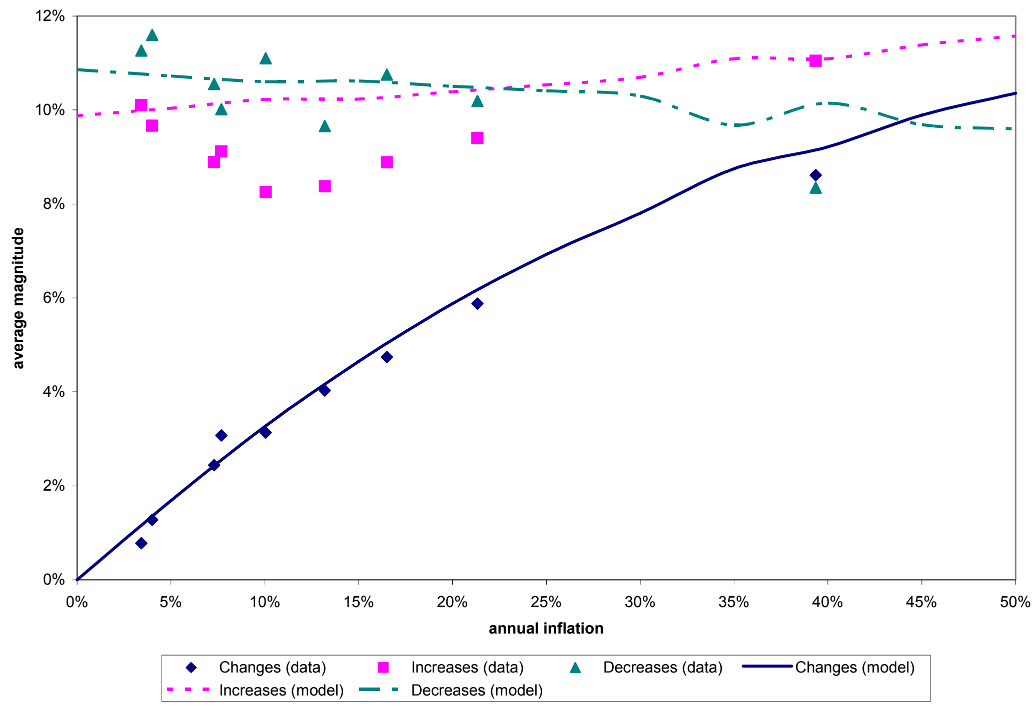


size of price changes that are *too large* compared to the data. Rotemberg illustrates this point using a version of the Sheshinski and Weiss (1977) menu-cost model in which idiosyncratic shocks are absent. Under a wide range of parameter values, he finds that this model overpredicts movements in the size of price changes as average inflation varies. This conclusion clearly does not apply to the menu-cost model considered above: The average absolute magnitude of price changes moves little with inflation. This is despite a clear prediction of menu-cost models that the width of the Ss band widens when steady state inflation increases[29]. In the steady state of the Sheshinski and Weiss model, the average and absolute magnitude of price changes are identical because all price changes are positive whenever inflation is positive and predictable. In the Golosov-Lucas model, the two statistics are disconnected due to the presence of price decreases.

As I have shown, the Golosov-Lucas model is consistent with key features of individual consumer price setting at both relatively low and high levels of inflation. Despite this success, the model suffers from several known inconsistencies with the data. As discussed by Golosov and Lucas (2003) and Midrigan (2006), the model generates too few small price changes and has an implausibly small

[29] The gentle fall in the average magnitude of price decreases in Figure 16 seems inconsistent with this prediction. It occurs in the model because the proportion of very large price decreases falls with inflation. As inflation takes off, technology shocks must be increasingly large to generate price decreases of a given magnitude due to greater relative price erosion. Depending on the idiosyncratic shock distributional assumptions, the average magnitude of price decreases might therefore fall over some inflation range, despite a rise the threshold.

Figure 16: Average magnitude of price changes, increases and decreases predicted by the model compared to the sample's annual averages



amount of intrinsic persistence. Nevertheless, my findings offer hope that a state-dependent model addressing these short-comings, such as a model in which the hypotheses of constant and time-invariant menu costs are relaxed, might provide a good fit the average magnitude and frequency of price changes if it embeds a distribution of positive and negative price changes.

8 Conclusion

This paper provides new evidence about the relationship between inflation and the adjustment of individual consumer prices. It uses a large dataset of Mexican consumer prices covering episodes of both low and high inflation, as well as the transition between the two. The overall portrait is of an economy sharing several characteristics of time dependent models when inflation is low (below 10-15%), while displaying strong state dependence when inflation is high (above 10-15%).

At low inflation levels, the frequency of price changes varies little and its relationship to inflation is elusive. In contrast, the average magnitude of price change covaries strongly with inflation. As a result, movements in the frequency account for little of the inflation variance of inflation. Thus, at low inflation levels, the economy resembles time-dependent models with a constant frequency of price changes. When annual inflation runs above 10-15%, however, inflation becomes positively correlated with the frequency of price changes: A one percentage-point increase in the annual inflation rate is associated with a roughly 0.4-percentage-point increase in the frequency of price changes of nonregulated goods. Variations in both the frequency and magnitude of price changes are key in determining the variance of inflation. In this sense, my analysis provides a natural distinction between low- and high-inflation environments: In a low-inflation environment, price decreases matter.

Behind the radically different behaviors of the low- and high-inflation economies lies the central role of price decreases. As inflation varies, opposite movements in the frequency of price decreases offset movements in the frequency of price increases. When inflation is low, this mechanism is strong enough to render the frequency of price changes of nonregulated goods unresponsive to movements in inflation. When inflation is high, however, too few price decreases are left to counterbalance movements in the frequency of price increases. In this situation, the economy displays strong state dependence with respect to inflation.

Several authors (e.g., Dhyne et al. (2005)) have argued that macroeconomics models should incorporate at least two sectors. The first sector, which corresponds to food products in Mexico, features very flexible prices that respond to frequent idiosyncratic shocks. The other sectors encompass a greater degree of price stickiness to capture items with infrequent and lumpy price adjustments. My analysis reinforces this view by showing the central role of price decreases in the dynamic of inflation in the sectors displaying the largest price flexibility.

One important challenge is to find a price-setting model offering empirically plausible predictions at both low and high levels of inflation. I have shown that the Golosov-Lucas menu-cost model offers some important success. The key to the model's good fit of the average frequency and magnitude of price changes is the joint presence of nominal rigidities and idiosyncratic shocks generating a distribution of both negative and positive nonzero price changes that is free to move with the level of inflation. Note that time-dependent models such as Calvo are not inconsistent with the presence of a distribution of both positive and negative price changes, however. In fact, it is possible to augment the baseline Calvo model with idiosyncratic technology shocks and obtain, after linearization, the same reduced-form equation for inflation. While this alternative model generates movements in the relative share of price decreases and increases, it fails to produce a rise in the frequency of price changes as inflation takes off.

Finally, my analysis suggests the "right" price-setting model might depend importantly on the characteristics of the shock at hand. I documented that a hike in the value added tax led to an almost complete pass-through after one month, most of which occurred through a high frequency of price changes. The speed of transmission was much higher than the speed commonly assumed for monetary and technology shocks. Price-setting models generating highly persistent responses to all types of shocks would mispredict the price adjustment entirely.

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A Price Averaging

In Mexico, price collectors visit outlets four times every month to collect prices of food items, and they visit twice per month to collect prices for all other items. The prices published in the *Diario* are an average of the prices collected over the month. In this appendix, I first discuss how observing a price's average rather than its actual value complicates inferences about the timing and magnitude of price changes. I then describe how I filtered the data to make the results in this paper more directly comparable to results from studies using prices collected once per month.

A.1 Effects of Averaging on Frequency and Magnitude

Suppose a price collector observes the price of an item twice every month and then computes two time series. The first is a simple average of the prices collected over the month (the average-price series). The other contains the second price collected each month (the point-in-time series). The average-price series corresponds Banxico's current method, whereas point-in-time series are used in the United States and Euro area.

Changes to the average-price series typically are more frequent and of a smaller magnitude than changes to the point-in-time series. To illustrate this point, consider a price that is constant over the months $t-1$, t and $t+1$, with the exception of a single adjustment at month t. If the price changes before the first price is collected at t, then both prices collected over that month equal the new price. Thus, the average- and point-in-time series are identical and correctly reflect the timing and magnitude of the actual price change. If the price change occurs between the two price collections, the point-in-time series still accurately represents the actual price. The average-price series, on the other hand, now displays *two* price changes: one at month t and one at $t+1$. The average-price series records a second price change because the average price at t has increased by only half of the change in the actual price. Finally, if the price adjustment occurs after the second collection, both the average price and point-in-time series display a change of the correct magnitude but with a one-month lag.[30]

A.2 Filtration of Average Price Trajectories

In the above example, a price change detected at the second price collection created two consecutive price changes of equal magnitude in the average-price series. My strategy entails finding such patterns and constructing a trajectory for the last price collected over the month that matches the average price and minimizes the number of price changes.

A.2.1 Two consecutive price changes

Let p_t^i be the unobserved $i-th$ price of an item for which collection happens twice a month, and let $\bar{p}_t = \left(p_t^1 + p_t^2\right)/2$ be its observed monthly average. Consider the case of two consecutive price changes starting at month t. (Additional price changes might precede or follow them.) If

$$\bar{p}_t = \frac{\bar{p}_{t+1-}\bar{p}_{t-1}}{2}$$

then I can construct a bimonthly sequence $\left\{\left(p_\tau^1, p_\tau^2\right)\right\}_{\tau=t-1}^{t+1}$ consistent with the observed average price sequence $\{\bar{p}_\tau\}_{\tau=t-1}^{t+1}$ that features no price change at $t+1$. I simply set $p_{t-1}^i = \bar{p}_{t-1}$ and $p_{t+1}^i = \bar{p}_{t+1}$, and assume the price change occurred between the two price collections at t so that $p_t^1 = \bar{p}_{t-1}$ and $p_t^2 = \bar{p}_{t+1}$. The point-in-time sequence using the last price collected each month, $\left\{p_{t-1}^2, p_t^2, p_{t+1}^2\right\}$, features no price changes at $t+1$.

Similarly, consider an item whose price is collected four times per month. If

$$\bar{p}_t = \frac{(5-d_t)\,\bar{p}_{t-1} + (d_t-1)\,\bar{p}_{t+1}}{4}$$

for some $d_t \in \{2,3,4\}$, I can construct a sequence $\left\{\left(p_\tau^1, p_\tau^2, p_\tau^3, p_\tau^4\right)\right\}_{\tau=t-1}^{t+1}$ consistent with the observed average price sequence that contains no price change at $t+1$. As before, I set $p_{t-1}^i = \bar{p}_{t-1}$ and $p_{t+1}^i = \bar{p}_{t+1}$. I then assume a unique price change was detected at the d_t-th visit of the price collector at t so that $p_t^{i<d_t} = \bar{p}_{t-1}$ and $p_t^{i\geq d_t} = \bar{p}_{t+1}$. The point-in-time sequence $\left\{p_\tau^4\right\}_{\tau=t-1}^{t+1}$ contains no change at $t+1$, and all its elements are strictly positive. Moreover, aside from possible rounding issues, there is at most one sequence $\left\{\left(p_\tau^1, p_\tau^2, p_\tau^3, p_\tau^4\right)\right\}_{\tau=t-1}^{t+1}$ consistent with $\{\bar{p}_\tau\}_{\tau=t-1}^{t+1}$ that features no price change within periods $t-1$ and $t+1$ and contains a single change at t.[31]

[30] If several price changes occur within a month, then the magnitude of price changes can be either under- or overestimated.

[31] Rounding occurs because the price of items sold for a specific volume or weight generally are converted into a standard unit before appearing in the *Diario*. For example, the price of a 300 ml bottle of juice would be multiplied by 10/3 to be expressed in pesos per liter.

A.2.2 Multiple price changes

Suppose now there are $N > 2$ consecutive changes to the average-price series starting at t. If the price of the item is collected twice per month and the following condition holds

$$\sum_{n=0}^{N-2} (-1)^n \bar{p}_{t+n} = \left(\bar{p}_{t-1} + (-1)^N \bar{p}_{t+N-1}\right)/2, \tag{1}$$

then I can construct a unique bimonthly series $\left\{\left(p_\tau^1, p_\tau^2\right)\right\}_{\tau=t-1}^{t+N}$ that is (a) consistent with the observed monthly averages $\{\bar{p}_\tau\}_{\tau=t-1}^{N-1}$, (b) features no price change within periods $t-1$ and $t+N-1$, (c) has at most one price change per period detected at price collector's second visit and such that (d) the point-in-time sequence $\left\{p_\tau^2\right\}_{\tau=t-1}^{t+N-1}$ features no price change at $t+N-1$. This series is constructed by setting $p_{t-1}^i = \bar{p}_{t-1}$, $p_{N-1}^i = \bar{p}_{N-1}$, and then constructing recursively

$$\begin{aligned} p_{t+n}^1 &= p_{t+n-1}^2 \\ p_{t+n}^2 &= 2\bar{p}_{t+n} - p_{t+n-1}^2 \end{aligned}$$

for $n = 0, ..., N-2$.

Similarly, consider the case of an item whose price is collected four times per month. If there exists $(d_t, ..., d_{t+n}, ...d_{t+N-2})$, with $d_n \in \{2, 3, 4\}$, such that the following relation holds:

$$\begin{aligned} &\sum_{n=1}^{N-1} (-1)^{n+1} \left(\prod_{j=1}^{n-1} (5 - d_{t+j})\right) \left(\prod_{j=n+1}^{N-1} (d_{t+j} - 1)\right) \bar{p}_{t+n-1} \\ = &\left(\prod_{n=1}^{N-1} (d_{t+n} - 1)\right) \frac{\bar{p}_{t-1}}{4} + (-1)^N \left(\prod_{n=1}^{N-1} (5 - d_{t+n})\right) \frac{\bar{p}_{t+N-1}}{4} \end{aligned} \tag{2}$$

then I can construct a sequence of prices collected $\left\{\left(p_\tau^1, p_\tau^2, p_\tau^3, p_\tau^4\right)\right\}_{\tau=t-1}^{t+N-1}$ that is (a) consistent with the observed monthly averages $\{\bar{p}_\tau\}_{\tau=t-1}^{N}$, (b) features no price change within periods $t-1$ and $t+N-1$, (c) contains a unique price change detected at $(d_t, ..., d_n, ...d_{t+N-2})$ and such that (d) there is no change at $t+N-2$ in the monthly point-in-time series $\left\{p_\tau^4\right\}_{\tau=t-1}^{t+N-1}$. I proceed by setting $p_{t-1}^i = \bar{p}_{t-1}$, $p_{t+N-1}^i = \bar{p}_{t+N-1}$ and then recursively computing

$$p_{t+n}^i = \begin{cases} p_{t+n-1}^4 & \text{if } i < d_{t+n} \\ \left(4\bar{p}_{t+n} - (d_{t+n} - 1)\, p_{t+n-1}^4\right)/(5 - d_{t+n}) & \text{otherwise} \end{cases}.$$

Notice that if (1) or (2) is satisfied for some $d_{t+n} = 1$, there is no need to adjust the average price at $t+n$. Unlike the case of two consecutive price changes, there is no guarantee that $\left\{\left(p_\tau^1, p_\tau^2\right)\right\}_{\tau=t-1}^{t+N}$ and $\left\{\left(p_\tau^1, p_\tau^2, p_\tau^3, p_\tau^4\right)\right\}_{\tau=t-1}^{t+N-1}$ have strictly positive entries. In the case of food items, there also might be more than one sequence of detection times $(d_t, ..., d_{t+n}, ...d_{t+N-2})$ such that condition (2) is satisfied. Thus, in the implementation of the filter, one should make a correction only if it is plausible.

A.2.3 Implementation of the filter

The filter is applied on an average-price series to extract a point-in-time series of the last price collected over the month. The identifying assumptions are stringent enough to recover the full set of prices collected, $\{p_t^i\}$. Those assumptions are:

a) The actual price changes at most once per month;

b) If $\bar{p}_t = \bar{p}_{t-1}$, then $p_t^i = p_{t-1}^i = \bar{p}_t$;

c) For the first month t_0 of a price trajectory, $p_{t_0}^i = \bar{p}_{t_0}$;

d) Starting with $N = 2$, I identify all sequences of N consecutive changes to the average-price series. Starting with the oldest sequence of such consecutive price changes,

   Bimonthly observations
   if (1) holds and no elements in $\{p_{t+n}^i\}_{n=-1}^{N-1}$ previously have been set to a particular value, then I construct a candidate sequence of collected prices $\{\tilde{p}_{t+n}^i\}_{n=-1}^{N-1}$ as described above. If all elements of $\{\tilde{p}_{t+n}^i\}_{n=-1}^{N-1}$ are strictly positive, and the absolute price changes are smaller than $\ln(5)$, I set $\{p_{t+n}^i\}_{n=-1}^{N-1} = \{\tilde{p}_{t+n}^i\}_{n=-1}^{N-1}$. I then repeat the procedure with the next sequence of N consecutive price changes.

   Food items
   for all possible detection times $(d_t, ..., d_n, ...d_{N-2})$, $i_n \in \{2, 3, 4\}$ such that (2) holds, I construct a candidate sequence of collected prices $\{p_{t+n}^i\}_{n=-1}^{N-1}$ as described above. I discard all sequences containing negative prices or price changes greater than $\ln(5)$. If some candidate corrections remain, I randomly select one of them and use it to set $\{p_{t+n}^i\}_{n=-1}^{N-1}$. I repeat the procedure with the next sequence of N consecutive price changes.

   Once all cases with $N = 2$ have been considered, I repeat the entire procedure again with $N = 3, 4, ..., \bar{N}$.

e) For all other cases, I set $p_t^i = \bar{p}_t$.

Once I have identified $\{p_t^i\}$, I easily can recover the price trajectories for the last price of the month, $\{p_t^2\}$ or $\{p_t^4\}$.

A.3 Discussion of the Filter

In practice, I allow the left- and right-hand sides of (1) and (2) to differ by up to 0.005 to account for the rounding of prices. In the case of food items, I find a multiplicity of candidate solutions in

Table 7: Performance of the filter

N	Cases	Exact	Mixed	Spurious
2	$142,730$	94.5%	1.0%	4.5%
3	$7,138$	75.8%	2.1%	22.1%
4	$1,415$	32.9%	2.9%	64.2%
5	596	12.2%	4.0%	83.7%

3% of the cases for which (2) is satisfied when $N = 3$. This proportion grows to 10% when $N = 5$. As a robustness check, I apply the filter for food items on the price trajectories of bimonthly items. Any correction made with $i_{t+n} = 2$ or $i_{t+n} = 4$ for some n indicates the filter spuriously eliminates a price change not induced by averaging. The filter's performance for various N is presented in Table 7.

In the case of two consecutive price changes, the filter corrects $142,730$ sequences. Of those sequences, 94.5% have a corresponding unique solution with $i_t = 3$. For an additional 1.0% of cases, a solution with $i_t = 3$ is mixed with a spurious solution. In less than one sequence out of twenty, the criterion is satisfied but all candidate solutions have either $i_{t+n} = 2$ or $i_{t+n} = 4$. As N increases, the proportion of spurious corrections grows quickly. The number of cases detected falls even more rapidly, however, which suggests that leaving long sequences of price changes uncorrected should not effect the overall results. For those reasons, I set $\bar{N} = 3$ for food items and $\bar{N} = 4$ for bimonthly observations, which are not subject to multiplicity issues. Before computing the statistics in this paper, I drop the first four observations of each price trajectory because they cannot be filtered for all values of N considered.

Finally, all the results in this paper regarding the relationship between inflation and price setting stand if I use the published averaged data directly. The main effect of filtering is to reduce the occurrence of price changes, lowering fr, fr^+, and fr^- while increasing the average absolute magnitude of price changes dp, dp^+ and dp^-.

B Store Samples

Store samples are used to deal with the high turnover rate of individual items in the clothing categories. When the price of one item in the sample is no longer available, it is substituted by a similar item whose price has been tracked simultaneously. The average price of the sample is then rescaled to avoid creating a price change. The Diario does not report such substitutions. If no substitute is available in the store, the CPI agent might use the price of an item with similar characteristics from a different outlet. For 34 product categories, Banxico mainly reports prices pertaining to store samples rather than to individual items. Using the descriptions published in the *Diario*, I counted the number of items in each sample and discarded those that did not comprise exactly three elements, the most common sample size.

In this paper, I treat those observations are treated like individual items, which might create an upward bias in the frequency of price changes: Only one item price needs to change to induce a change in the average price in the sample. Moreover, the absolute magnitude of changes typically will be smaller than the underlying changes to individual prices. A lower bound on the aggregate frequency of price changes in the CPI was derived by assuming independent price changes within store samples.[32] Under this assumption, the average biases are 1.3 percentage points for nonregulated products and 1.7 percentage points for nonregulated goods in the sample. All the main patterns found in the data are preserved.

C IPN Basket

This appendix details the construction of products baskets similar to that of the Inflation Persistence Network. The original product categories in the IPN basket are listed in Tables 8 and 9 along with corresponding matches for Mexico. I use the same method as the IPN to construct product category weights. I first assign a 2-digit COICOP group and one of the five main components (unprocessed food, processed food, nonenergy industrial goods, energy and services) to each product category in the Mexican CPI, and exclude product categories under *Health Care*, *Education*, *Cars* and *Electricity*. I then compute the total weight of each stratum — a combination of a COICOP group and main component — for the remaining categories. Finally, the item weights in each stratum are set such that relative weights are the same as in the CPI and add up to the stratum share of all consumer expenses considered.[33] The flip side of this procedure is that some product categories are attributed a disproportionate share of the basket weight because other categories selected within their stratum have relatively small expenditure shares. Milk is the clearest example, receiving more than 13% of the IPN basket weight while accounting for less than 2% of total CPI expenditures.

There are a few product categories in the IPN basket that lack direct matches in the Mexican CPI. Following the IPN procedure, substitutes are randomly chosen within the same stratum. Substitutes are sought before the 2002 basket revision for *Mineral water*, *Dog Food*, *Fax Machine*, *Hotel Room* and *Videotape Hiring* because no category with individual observations was available at this time[34]. Furthermore, *Gasoline*, *Car Maintenance* and *Household Maintenance* in the Mexican CPI are matched with several products in the IPN basket when no finer breakdown is available. In the case of *Gasoline*, I use city indexes because there is no alternative category with individual prices in the same stratum. Gas stations are required to post prices set by the Mexican government, and changes follow pre-established rules that are updated periodically. The *Household Maintenance*

[32] If the frequency of price change is fr_3 for a sample of three items, and individual price changes are independent within the sample, then the frequency of price changes of an individual item is $fr_1 = 1 - (1 - fr_3)^{1/3}$.

[33] The IPN classifies *Frozen spinash* under process food even though it is part of unprocessed food according to the COICOP classification. To ensure the greatest comparability between our baskets, I exceptionally treat the corresponding Mexican product category as processed food in the derivation of the statistics related to the IPN basket.

[34] A *Fax Machine* is categorized as a communication service under the COICOP, even though it refers to the price of acquiring the good, if no break down between telephone and telefax equipment and services is available. A substitution was sought in the Mexican sample because fax machines fall into a product category associated with a different stratum.

and *Photographic items* product categories from the Mexican CPI mixes both goods and services before 2002 and for the entire time period, respectively. Separate indexes for goods and services are computed by classifying each items within those product categories accordingly. The weights in the IPN sample are then set proportionally to each stratum's share of observations in the product category.

Finally, four product categories in the Mexican basket, *Household Maintenance*, *Other electric devices*, *Other entertainment* and *Phone Line*, were introduced in March 1995. The frequency statistics for March to June 1995 must be imputed for those categories because the filter eliminates the first few observations of every trajectory. In the case of *Household Maintenance* and *Other electric devices*, the frequency of price changes for March to June 1995 is imputed using a linear projection on the frequency of price changes of nonregulated goods subject to the value added tax and a linear trend. For *Phone Line* and *Other entertainment*, the procedure is repeated using nonregulated services subject to the value added tax and a linear trend.

D Calibration of the Golosov-Lucas Model

Some parameters of the model are taken directly from the literature while others are chosen to match particular moments of the distribution of price changes. For the elasticity of substitution across items, I pick a value of 7, the same number as Golosov and Lucas. The discount factor is set to $(1.05)^{-1/12}$, while the log of inflation is calibrated to 0.045/12, its sample average over the July 2000 to June 2002 period. The persistence of technology shocks is set to 0.75, a value similar to that implied by Golosov and Lucas' quarterly calibration ($.55^{1/3} \approx 0.82$ per month) but higher than Midrigan's (0.5 per month). The remaining free parameters are the marginal disutility of labor, ψ, the variance of technological innovations, σ_ε^2, and the size of menu costs, $\bar{\xi}$. The parameter ψ is chosen so that households would work exactly 25% of their time if menu costs were zero. The other two parameters are calibrated so that the model matches exactly the average frequency of price changes and the average absolute magnitude of nonzero price changes in the data. The calibrated values are 0.0029 and 0.00511 for σ_ε^2 and $\bar{\xi}$, respectively.

The model is solved using dynamic programming techniques. As a first step, I guess a value for the price index from which I derive aggregate consumption and the real wage. The value functions are then approximated using Chebyshev polynomials. Conditional on the aggregate variables, a fixed point is found by value function iteration and the policy functions are recovered. A long Markov chain is then generated by sampling from the distribution of shocks and assuming that firms behave according to the policy functions. A price index is computed from the Markov chain and the associated aggregate quantities are derived. Finally, the initial guess for the price index is updated. The procedure is repeated until convergence.

Table 8: Correspondence table with IPN sample (March 1995 - June 2002)

2-digit COICOP	Main component	IPN description	Mexican description	Key	Weight	Frequency Mar 1995 - Feb 1997	Frequency Jul 2000 - Jun 2002
1	UF	Steak	Special beef cuts	21	7.50	38.7	23.8
1	UF	Fresh fish	Mojarra fish	42	3.44	66.2	57.7
1	UF	Lettuce	Lettuce	99	1.89	76.3	87.2
1	UF	Banana	Banana (tabasco)	71	6.41	65.8	83.6
1	PF	Milk	Pasteurized milk	49	11.66	62.9	14.3
1	PF	Sugar	Sugar	109	3.79	46.4	13.2
1	PF	Frozen spinach	Canned vegetables	107	0.41	55.3	27.9
1	PF	Mineral water	Bottled juices and nectars	133	0.54	56.6	23.8
1	PF	Coffee	Instant coffee	113	1.08	76.3	28.5
2	PF	Whisky	Rum	135	0.62	50.4	29.9
2	PF	Beer in a shop	Beer	134	2.22	63.0	9.3
3	NEIG	Socks	Socks	216	0.67	45.3	18.9
3	NEIG	Jeans	Cotton-based pants (men)	210	1.73	37.0	22.5
3	NEIG	Sport (shoes)	Tennis shoes	248	3.15	32.7	21.0
3	NEIG	Shirt (men)	Shirts (men)	213	2.68	38.7	25.8
3	S	Dry (cleaning)	Laundry and dry cleaning	182	0.77	20.7	8.6
4	NEIG	Acrylic (painting)	Housing maintenance (goods)	364	1.85	47.5	15.2
4	NEIG	Cement	Housing maintenance (goods)	364	-	-	-
4	S	Hourly rate of an electrician	Housing maintenance (services)	364	0.40	28.1	10.5
4	S	Hourly rate of a plumber	Housing maintenance (services)	364	-	-	-
4	E	Heating oil	Heating oil	367	1.77	59.6	7.7
5	NEIG	Toaster	Other electric devices	336	0.32	28.8	13.4
5	NEIG	Electric bulb	Electric bulbs	180	0.63	48.6	15.5
5	NEIG	1 type of furniture	Bedroom sets	270	4.46	26.2	14.8
5	NEIG	Towel	Towels	279	1.00	28.3	11.2
5	S	Domestic services	Domestic services	181	1.68	20.7	2.2
7	E	Fuel type 1	Gasoline	351	4.70	100.0	35.4
7	E	Fuel type 2	Gasoline	351	-	-	-
7	NEIG	Car tyre	Car tire	356	0.57	49.6	15.4
7	S	Hourly rate in a garage	Car maintenance	354	5.74	29.4	9.9
7	S	Car wash	Car maintenance	354	-	-	-
7	S	Balancing of wheels	Car maintenance	354	-	-	-
7	S	Taxi	Taxi	342	6.10	32.1	1.0
8	S	Fax machine	Phone line	381	2.62	8.6	0.0
9	NEIG	Television set	Televisions and VCRs	319	2.25	39.2	11.5
9	NEIG	Dog food	Magazines	334	1.04	19.3	0.0
9	NEIG	Tennis ball	Sport equipment	325	0.25	29.6	10.6
9	NEIG	Construction game (Lego)	Toys	324	0.23	21.7	5.9
9	S	Movie	Movie	327	1.62	16.4	14.1
9	S	Videotape hiring	Other entertainment	371	0.39	15.8	0.7
9	S	Photo development	Photographic items (services)	323	0.18	41.5	11.3
11	S	Hotel room	Night club	328	0.38	33.6	5.0
11	S	Glass of beer in a café	Bars	160	2.04	35.5	4.2
11	S	1 meal in a restaurant	Restaurants, pubs and similar	163	3.80	25.4	9.7
11	S	Hot-dog	Snackbars	161	1.58	23.3	7.9
11	S	Cola based lemonade in a café	Coffeeshops	162	0.42	38.1	6.8
12	NEIG	Toothpaste	Toothpaste	193	3.23	70.1	15.9
12	NEIG	Suitcase	Purses, suitcases and belts	250	0.67	33.3	8.0
12	S	Haircut (men)	Haircut	200	1.10	8.9	1.8
12	S	Hairdressing (ladies)	Beauty salon	201	0.41	11.9	9.6

Notes:

2-digit COICOP: (1) Food and non-alcoholic beverages, (2) Alcoholic beverages, tobacco and narcotics, (3) Clothing and footwear, (4) Housing, water, electricity and other fuels, (5) Furnishing, household equipment and routine, (7) Transport, (8) Communication, (9) Recreation and culture, (11) Restaurants and hotels, (12) Miscellanous goods and services.

Main component: (UF) Unprocessed food, (PF) Processed food, (NEIG) Nonenergy industrial goods, (E) Energy, (S) Services.

Table 9: Correspondence table with IPN sample (January 2003 - December 2004)

2-digit COICOP	Main component	IPN description	Mexican description	Key	Weight	Frequency Jan 2003 - Dec 2004
1	UF	Steak	Special beef cuts	25	2.33	28.2
1	UF	Fresh fish	Mojarra fish	37	3.06	56.4
1	UF	Lettuce	Lettuce	83	1.87	86.1
1	UF	Banana	Banana	58	6.26	73.5
1	PF	Milk	Pasteurized milk	43	10.43	18.0
1	PF	Sugar	Sugar	98	1.16	26.1
1	PF	Frozen spinach	Canned vegetables	94	0.25	24.8
1	PF	Mineral water	Bottled water	102	1.98	23.3
1	PF	Coffee	Instant coffee	99	0.66	34.8
2	PF	Whisky	Rum	119	0.31	37.9
2	PF	Beer in a shop	Beer	116	3.65	21.3
3	NEIG	Socks	Socks	136	0.25	17.6
3	NEIG	Jeans	Cotton-based pants (men)	137	1.79	12.5
3	NEIG	Sport (shoes)	Tennis shoes	163	2.94	13.0
3	NEIG	Shirt (men)	Shirts (men)	134	2.09	14.9
3	S	Dry (cleaning)	Laundry and dry cleaning	169	0.65	14.2
4	NEIG	Acrylic (painting)	Housing maintenance (goods)	184	1.20	13.5
4	NEIG	Cement	Housing maintenance (goods)	184	-	-
4	S	Hourly rate of an electrician	Housing maintenance (services)	186	2.76	10.2
4	S	Hourly rate of a plumber	Housing maintenance (services)	186	-	-
4	E	Heating oil	Domestic gas	189	2.61	88.5
5	NEIG	Toaster	Other electric devices	216	2.48	17.6
5	NEIG	Electric bulb	Electric bulbs	226	0.79	8.1
5	NEIG	1 type of furniture	Bedroom sets	213	1.87	10.5
5	NEIG	Towel	Towels	239	0.56	11.6
5	S	Domestic services	Domestic services	194	2.11	10.0
7	E	Fuel type 1	Gasoline	313	5.37	14.0
7	E	Fuel type 2	Gasoline	314	-	-
7	NEIG	Car tyre	Car tire	316	0.34	27.9
7	S	Hourly rate in a garage	Car maintenance	321	1.86	10.0
7	S	Car wash	Car maintenance	322	-	-
7	S	Balancing of wheels	Car maintenance	323	-	-
7	S	Taxi	Taxi	307	6.18	5.4
8	S	Fax machine	Phone line	193	5.11	3.4
9	NEIG	Television set	Televisions and VCRs	221	2.11	12.0
9	NEIG	Dog food	Pet food	360	0.79	20.8
9	NEIG	Tennis ball	Sport equipment	364	0.17	9.5
9	NEIG	Construction game (Lego)	Toys	358	2.57	18.1
9	S	Movie	Movie	349	2.81	47.7
9	S	Videotape hiring	Videotape hiring	362	0.43	8.2
9	S	Photo development	Photographic items (services)	361	0.28	17.3
11	S	Hotel room	Hotel room	348	0.15	38.4
11	S	Glass of beer in a café	Bars	380	0.65	10.7
11	S	1 meal in a restaurant	Restaurants, pubs and similar	379	3.60	11.2
11	S	Hot-dog	Snackbars	378	5.52	12.4
11	S	Cola based lemonade in a café	Coffeeshops	381	0.27	13.2
12	NEIG	Toothpaste	Toothpaste	284	4.71	33.7
12	NEIG	Suitcase	Purses, suitcases and belts	171	1.16	6.1
12	S	Haircut (men)	Haircut	279	1.43	11.5
12	S	Hairdressing (ladies)	Beauty salon	280	0.41	5.8

Notes:
2-digit COICOP: (1) Food and non-alcoholic beverages, (2) Alcoholic beverages, tobacco and narcotics, (3) Clothing and footwear, (4) Housing, water, electricity and other fuels, (5) Furnishing, household equipment and routine, (7) Transport, (8) Communication, (9) Recreation and culture, (11) Restaurants and hotels, (12) Miscellanous goods and services.
Main component: (UF) Unprocessed food, (PF) Processed food, (NEIG) Nonenergy industrial goods, (E) Energy, (S) Services.