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Author
Elberg, Andres

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Three Essays on Retail Price Dynamics

by

Andrés Eduardo Elberg

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Committee in charge:
Professor Maurice Obstfeld, Chair
Professor Yuriy Gorodnichenko
Professor Pierre-Olivier Gourinchas
Professor Andrew K. Rose

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Abstract

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Andrés Eduardo Elberg
Doctor of Philosophy in Economics

University of California, Berkeley

Professor Maurice Obstfeld, Chair

This dissertation consists of three essays on the dynamics of retail prices.

The first chapter uses a novel data set of weekly-sampled store-level retail prices for narrowly defined goods observed across 12 cities in Mexico to study the relative magnitude of aggregation biases in estimates of convergence to the Law of One Price (LOP). I find that temporal aggregation can severely bias estimates of persistence in relative prices. Both panel estimations of higher-order autoregressive processes and Monte Carlo experiments suggest that using quarterly aggregated data (from weekly-sampled data) can overestimate the half-life of deviations from the Law of One Price (LOP) by a factor of 4. I do not find evidence that pooling across goods with heterogeneous dynamics biases persistence estimates. The analysis also suggests that intercity prices converge rapidly to the LOP in an absolute sense (the median half-life is estimated at 3 weeks) and the existence of only a weak association between price gaps across cities and physical distance.

The second chapter studies patterns of retail price adjustment at the store level using a unique scanner data set of weekly retail prices, quantities sold and wholesale costs for a cross-section of retailers in Chile. In line with evidence reported for the U.S. (Eichenbaum, Jaimovich and Rebelo, 2010; Klenow and Malin, 2010), posted prices tend to revolve around more persistent reference prices. The implied duration of reference prices is estimated at 2-3 quarters versus 3-4 weeks in the case of posted prices. I find strong evidence that reference prices respond to retailer-level shocks. Comovement in the reference price of a given barcode across retailers is found to be significantly larger for stores belonging to the same retail chain than for stores that belong to different retail chains. Furthermore, most of the variation in the frequency of reference price adjustment is explained by "chain effects". Evidence on the synchronization of price changes suggests that price changes tend to be staggered across stores belonging to different retail chains but synchronized within chains.

The third chapter uses a scanner dataset including weekly prices and costs from a large retailer in Chile to study the relationship between price rigidities and intra-national deviations from the law of one price (LOP). I find that, controlling for transportation costs (proxied by distance), more flexible prices are associated with a larger volatility of deviations from the LOP. The effect is econominally non-negligible and holds for both retail- and wholesale-level prices. The distance equivalent of a 0.01 change in the frequency of retail (wholesale) price change is estimated at 370 (294) kilometers.

To Sebastián

Contents

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Chapter 1

Revisiting the Law of One Price: Evidence from Weekly Store-Level Data

1.1 Introduction

The proposition that, absent trade barriers, a commodity should sell for an identical price in different locations (i.e. the law of one price) is a central concept in international economics. Several models in international finance, for instance, rely on the law of one price (LOP) as a key building block. In spite of its centrality to the field, the LOP has systematically been rejected by the data. Most of the extensive body of empirical work on the topic has reported large deviations from the LOP which (at best) take long periods of time to be eliminated.

The evidence, however, must be weighed carefully. One problem shared by most, if not all, studies on the topic has to do with data limitations. Prices are usually not available at the level of narrowly defined goods but instead correspond to prices for broadly defined product groups (see Broda and Weinstein, 2007 for a discussion). This makes testing for the LOP difficult for two reasons. First, the LOP requires, by assumption, that the commodities being compared vary only on the location where they are sold. This problem would not be as serious if prices within categories displayed a high degree of comovement. Recent research by Broda and Weinstein (2007), using a large dataset of barcode data for several cities in the U.S. and Canada, show that this is not the case. There is wide variation in the behavior of prices even within relatively narrow product groups. A related problem, that may arise in the study of relative price dynamics, is that pooling across several individual goods that exhibit heterogeneous dynamics might introduce a bias in the estimates of persistence in relative prices (Imbs et al., 2005). Imbs et al. (2005) show that for plausible parameter values, estimating convergence in relative prices using price indices that aggregate across several sectors is likely to cause estimates of persistence to be upwardly biased.

There is a second dimension on which data limitations affect the inferences made on the speed with which relative prices converge to the LOP: Prices are usually observed at lower frequencies than the frequency at which they are (pressumably) generated. Recent evidence from the empirical macroeconomics literature (e.g. Midrigan, 2006; Nakamura and Steinsson, 2008) shows that retail prices tend to be set weekly. The data analyzed by studies on spatial relative prices, however, correspond to prices observed at lower frequencies –mostly quarterly and annually. As argued by Taylor (2001), using temporally aggregated prices to estimate convergence to parity can lead to an overestimation of the persistence observed in relative prices. This is a particularly important problem in the case of studies that analyze broad price indices (Taylor, 2001, points out that statistical agencies tend to report temporally averaged prices) but is also present in studies that focus on prices for narrowly defined goods (e.g. Broda and Weinstein, 2007).

This paper has two related goals. First, it aims at assessing the magnitude and determinants of deviations from the LOP in the short-run, and the speed of convergence in spatialrelative prices in the long-run using a novel dataset which is less likely to be affected by the aggregation issues afflicting previous studies in the area. The dataset consists of a panel of prices for 83 narrowly defined branded goods sampled at the weekly frequency from stores located across 12 cities in Mexico. Examples of a good in the sample include "350 ml. can of Coca-Cola" and "170 grs. box of Kellogg's Cornflakes".

A second major goal of the paper is to assess the relative importance of the different aggregation biases that affect estimates of persistence in relative prices. The fact that the data is highly disaggregated on a cross-sectional and temporal dimensions allows me to evaluate the magnitude of the biases directly by aggregating the observed price series. I then examine the robustness of the results using Monte Carlo experiments. The analysis of price deviations across cities suggests that the market presents a relatively high degree of integration. Short-run deviations from the LOP across average city prices are small relative to those reported in the literature. The price gaps betwen cities appear to be only weakly associated to the distance separating two cities. The estimated effect of distance on price differentials is almost identical to the one found by Broda and Weinstein (2007) for U.S. cities using price data at a similar level of disaggregation.

I find strong evidence of convergence towards the LOP. Unit root tests -performed both on panels for each good and on individual good/city-pair series–overwhelmingly reject non-stationarity in relative price series. Furthermore, I find evidence consistent with convergence taking place in an absolute sense. In most cases, intercity price differentials converge to a constant which is insignificantly different from zero (both on a statistical and an economic sense). Interestingly, deviations from the LOP appear to converge at a remarkably rapid rate. Using recursive mean adjustment to control for small sample bias –which most likely tends to attenuate persistence estimates–I find a half-life of deviations from the LOP on the order of 3.4 weeks. By comparison, Parsley and Wei (1996) find a half-life of deviations from LOP between U.S. cities ranging between 4 and 5 quarters while Broda and Weinstein (2007) report a half-life of 2.9 quarters between Canadian cities. The estimates of Fan and Wei (2006) for the half-life of LOP deviations between Chinese cities (2.4 months) using monthly data is closer to the estimated persistence found in this paper.

I then turn to studying the consequences of estimating persistence using aggregated data. The results show that temporally aggregating the data can cause a severe bias in the estimates of persistence in relative prices. Estimating the rate of convergence to the LOP using monthly and quarterly aggregated data causes one to overestimate the half-life of a deviation from the LOP by a factor of 2 and 4, respectively. These findings are confirmed by the results of Monte Carlo experiments. In contrast, I find no evidence that pooling across individual goods featuring heterogeneous dynamics causes an overestimation of persistence. In order to avoid confounding the effect of heterogeneous dynamics across goods with the effect of heterogeneous dynamics across locations I estimate panels at the city-pair level. The estimations for each city-pair (using Mexico City as a reference city) show that the average half-life across goods is not systematically different from the half-life estimated from pooling across goods.

The remainder of the paper is organized as follows. The next section reviews the literature on price differences across locations. Section 3 describes the data used in the analysis. Section 4 is devoted to the analysis of short-run deviations from LOP. Here I describe the distribution of price deviations across cities and examine the relation between price gaps and distance. Section 5 turns to studying whether the LOP holds as a long-run phenomenon. It presents the results of unit root tests and estimates of half-lives of deviations from the LOP. The following two sections of the paper turn to studying the consequences of aggregation. Section 6 studies the effects of estimating convergence using low-frequency data. Section 7 examines the effects of cross-sectional aggregation for the estimates of speed of convergence. The last section presents some concluding remarks.

1.2 Literature Review

There is an extensive literature studying deviations from the LOP. With the exception of a few papers that focus on specific goods (e.g. Cumby (1996), Ghosh and Wolf (1994), Goldberg and Verboven (2005)), most studies have relied on prices for broad good categories or on prices collected through surveys in which goods are not necessarily identical across locations (see Broda and Weinstein, 2007). Because of this feature of the data, these papers have focused on the examination of a weaker version of the LOP, the relative LOP, which states that changes, instead of levels, in (logged) common currency prices should be equalized across locations.

Early tests of the relative LOP in an international context include Isard (1977) and Richardson (1978). Isard (1977) examines the co-movement of exchange rates and common-currency relative price indexes for 4- and 5- digit SITC industries in the U.S., Germany and Japan, and finds strong evidence against the relative version of the LOP. Richardson's (1978) analysis of commodity groups in the U.S. and Canada also reveals flagrant violations to the LOP.

Engel and Rogers (1996) study relative price volatility[1] across 14 U.S. cities and 9 cities in Canada. They report a positive effect of distance on relative price dispersion and, interestingly, find a significant "border" effect: Price dispersion between cities located in different countries is substantially higher than price dispersion between equally distant cities located within a country (their estimate of the distance equivalent of the border is 75,000 miles). Recent research by Gorodnichenko and Tesar (2007) and Broda and Weinstein (2007), however, cast doubt on the magnitude of the border effect reported by Engel and Rogers (1996).

[1]Engel and Rogers (1996) focus on the standard deviation of differenced logged price gaps between cities.

Recent work on relative price deviations across countries include Crucini, Telmer and Zachariadis (2005) and Broda and Weinstein (2007). Crucini, Telmer and Zachariadis (2005) study intra-European prices using a panel of 1,800 retail prices in all European Union countries over five-year intervals between 1975 and 1990. They report smaller departures from the LOP than found by previous studies: Most price deviations for higher income countries lie within the interval +/- 10 percent. Broda and Weinstein (2007) use quarterly barcode data on prices and quantities sold for a large number of UPCs (Universal Product Code) across 10 cities in the U.S. and 6 regions in Canada[2]. They find the typical standard deviation of log price differences between cities to be 22.3 percent in the U.S., 18.7 percent in Canada, and 26.7 percent for cities located across the border. Broda andWeinstein (2007) also report a relatively small effect of distance on price deviations.

Some research has studied whether the LOP holds as a long-run phenomenon. Here the standard practice has involved testing for the presence of a unit root in the process of inter-location relative prices. Crucini and Shintani (2008) use a micro-panel of retail prices collected by the Economist Intelligence Unit's Worldwide Cost of Living Survey. The panel consists of prices for about 300 goods and services across 79 countries and 13 major US cities observed annualy over the period 1990-2005. They find strong support for convergence to conditional LOP (they are able to reject the unit root hypothesis for all the goods in their sample) but only limited support for convergence to absolute LOP –they reject absolute convergence for 75 percent of the goods (at the one percent significance level). In terms of speed of convergence, they find a median half-life of 18 months when pooling all international locations. Persistence in relative prices is found to be similar across OECD countries as within the U.S. (half-lives of 19 and 18 months, respectively) and smaller across less-developed-countries (half-life of 12 months).

Broda and Weinstein (2007) reject the unit root hypothesis at the one percent level both within countries and for cities located across the U.S.-Canada border. Furthermore, they find that relative prices converge to a long-run level that, although significantly different from zero in a statistical sense, it is small in magnitude–the absolute deviation lies between 0.9 and 1.5 percent for Canadian provinces and between 0.6 percent and 3.3 percent for cross-border location pairs. They estimate a half-life of shocks to relative prices of 2.9 quarters for intranational locations and of 4.1 quarters for cities/provinces located across the border.

The flagrant failure of the LOP in an international context led some researchers to shift their focus to the study of price deviations within countries. As arbitrage within a country is, in principle, unhindered by policy-imposed trade barriers or exchange rate fluctuations, price deviations for identical goods across locations –unaccounted for by transportation costs, nominal rigidities or other distribution services–can be fully attributed to unexploited arbitrage opportunities. Parsley and Wei (1996) study a panel of 51 consumer goods in 48 U.S. cities and estimate an average half-life of deviations from the LOP ranging between 4 and 5 quarters. They also find that convergence occurs at a lower speed for more distant cities and that persistence is higher for smaller price deviations. Engel and Rogers

[2] Broda and Weinstein's (2007) data for Canada include average prices and quantities for 490,000 UPCs over the period 2001-2004, while their U.S. data include prices and quantities for 700,000 UPCs at the national level for the period 2001-2003 as well as price and quantity data on every purchase made by 3,000 households across U.S. cities in the third quarter of 2003.

(2001) study 43 broad good categories across 29 U.S. cities and find deviations from the (proportional) LOP to be less pronounced in the U.S. than in the international data. They find that while distance accounts for a significant amount of variation in prices between city pairs, most of this variation is explained by nominal price stickiness. Cechetti, Mark and Sonora (2002) study conditional convergence to the LOP using a panel of annual price indices for 19 U.S. cities over the period 1918-1995. They find relative price levels to be highly persistent –the half-life of deviations from LOP is estimated at 9 years. Ceglowski (2003) studies relative prices for 45 consumer goods across 25 cities in Canada and estimates a median half-life of deviations from LOP of 0.55 years. Fan and Wei (2006) examine the extent of price deviations across cities within mainland China and find average half-lives of 1.4 months, 2.4 months and 2.3 months for perishable consumer goods, non-perishable consumer goods and services, respectively. To the best of my knowledge, the only study examining price convergence within a Latin American country is Sonora (2005), who examines CPI convergence among 34 cities in Mexico over the period 1982-2000. He finds evidence of stationarity in aggregate relative prices and estimates a half-life of deviations from parity ranging between one and two years –a substantialy faster speed of convergence than the one found by Cecchetti, Mark and Sonora (2002) for the U.S. using similar data. Recent research on inter-location relative prices has also contributed to shed light on the relationship between persistence at the micro and aggregate levels. In an influential paper, Imbs, Mumtaz, Ravn and Rey (2005) claim that, under cetain conditions, aggregation across sectors with heterogeneous dynamics overstates the average persistence exhibited by the sectoral data. Crucini and Shintani (2008) compare the median persistence found from their micro data with persistence estimates using offi cial CPI data and only find evidence of aggregation bias across U.S. cities; no presence of aggregation bias is found in their international sample. Broda and Weinstein (2007) use quantity data to construct product-group price indexes and find a substantial aggregation bias. Aggregating the data using only common goods across locations rises the half-life of a shock to relative prices from 4 to 13 quarters within Canada and from 9 to 13 for cross-border locations. However, they find no evidence of the type of aggregation bias suggested by Imbs et al. (2005). They claim that the difference in persistence found using aggregate and disaggregate data can be explained by strong non-linearities present in their data –larger price deviations tend to be eliminated at a faster rate than smaller ones. According to Broda and Weinstein (2007), as aggregation across goods reduces nonlinearities by cancelling out large price deviations, it induces a higher degree of persistence in relative prices.

The literature has paid less attention to another type of aggregation bias, temporal aggregation, and more generally to the consequences of using low frequency data for studying inter-location price differentials. In Section seven, I turn to quantifying the size of the temporal aggregation bias in my data.

1.3 Data

The data consist of a panel of store-level prices for 83 consumer products observed across 12 cities in Mexico[3]. Items are highly narrowly defined branded products8 such as "350 grs. box of Kellogg's Cornflakes", and "150 ml. can of Coca-Cola."[4] The products are mostly low ticket items[5] that can be categorized as foodstuffs accounting for about 12 percent of Mexico's CPI. Information is available identifying the stores where prices are observed as well as (when appropriate) the retail chain to which the store belongs, and the city where the store is located. Stores include supermarkets, convenience stores, drugstores, "mom & pop" stores, and open-air markets. They include both domestic retailers (e.g. Comercial Mexicana, Gigante, and Soriana) and foreign multinational retailers (e.g. Auchan, Carrefour, 7-Eleven, and Wal-Mart). Importantly, prices are available at the weekly frequency for the period spanned between the first week of 2001 and the last week of 2007. To my knowledge, this is the first study in using weekly sampled data to analyze deviations from the LOP in retail markets. This is significant, as recent evidence of price-setting behavior at the retail level suggests that retailers change their prices on a weekly basis.

Data were collected by Mexico's Office of the Federal Attorney for Consumer Protection (Profeco, for Procuraduría Federal del Consumidor). Profeco regularly surveys prices for about 2,000 goods in 1,200 stores across 26 cities in Mexico. The data are then processed and used to provide consumers with comparative information on the stores charging maximum and minimum prices for a product in a given city[6]. The data collection process is performed by Profeco's own personnel who visit stores on a daily basis, each store being surveyed at least once a week. Price collectors enter list prices in portable PC's which instantly transmit the information to Profeco's headquarters where they are checked for consistency. The accuracy of the data is further checked by supervisors who visit some of the stores to ensure there are no errors in the prices reported by price collectors.

The original dataset includes a total of 8.5 million price quotes collected from 1,129 retail stores in 12 cities in Mexico. The maximum length of a price series in a given city is 364 weeks (spanning the period between the first week of 2001 and the last week of 2007). I cleaned the data as follows. First, I required data on a good to be available in a given city at least for the period spanning between mid 2001 and mid 2007. This reduced the sample to 79 goods available in 11 cities[7]. Second, I removed those observations lying outside a +/- 3 standard deviations band about their mean –both on a time-series and cross-sectional dimensions–so as to purge the data from outliers. The final dataset contains 5.9 million price quotes collected from 982 stores in 11 cities. Table I.1 presents statistics summarizing

[3]Cities included in the sample are: Guadalajara, Mérida, Mexico City, Monterrey, Morelia, Oaxcaca, Puebla, Querétaro, Tijuana, Toluca, Veracruz and Villahermosa.

[4]A full description of the products included in the dataset is provided in Table AI.1 in the Appendix.

[5]Average prices for goods in the sample fluctuate between roughly one quarter of a U.S. dollar ("Pasta for Soup") and 10 U.S. dollars ("Dry Milk"). See Table 1.

[6]Profeco published the information on stores charging maximum and minimum prices in the following website: http://www.profeco.gob.mx/precios/quienesquien.asp

[7]The goods excluded from the sample are: "Kraft mayonnaise, 195 grs. jar", "Tang instant juice, 30 grs. sachet", "Dos Equis beer, six-pack of 340 ml.", and "Pond's solid cream, 300 grs. jar". The city of Tijuana was excluded from the sample as price collection was discontinued in early 2007.

the dataset.

Correction for "Sales". A potentially important issue in the analysis of retail price data is the way "sales" or temporary price cuts should be treated. Some authors argue that retail prices should be purged from sales as this type of price adjustment, the argument goes, is not driven by economic fundamentals (e.g. Nakamura and Steinsson (2008)). The question of whether sales should be removed from the data should not, however, be a major issue in the case of the particular dataset used in this paper as Profeco aims at collecting only regular prices. In order to make sure that no sales remained in the dataset which could distort the results, I implemented a sales filter that identified a sale as a drop in the price of a good lasting for at most three weeks that is subsequently reversed towards the previous regular price or to a new regular price (similar sale filters are implemented by Midrigan (2006) and Nakamura and Steinsson (2008)). I also corrected for price increases ("reverse sales") lasting less than four weeks. As expected, sales appear to be considerably less pervasive in my data than in previous studies focusing on data for the U.S. Only three and two percent of price quotes correspond to sales and "reverse sales", respectively. I replicated the most important results found in this paper using the data purged from sales and reverse sales and the results were basically unaffected by the correction.

1.4 Short-Run Deviations from the Law of One Price

This section examines how the price of identical goods varies across locations. A good is defined by its product category (e.g. soft drink), brand, type of packaging, and size. In particular, the definition of a good does not include the type of outlet where the item is sold (e.g. hypermarket vs. "mom and pop" store). Letting p_{ist}^k denote the natural logarithm of the price of good k, sold by store s; in city i; in week t, the price deviation from its cross-sectional geometric average (in logs) is

$$p_{ist}^k - \left(\frac{1}{NS}\right)\sum_s \sum_i p_{ist}^k \tag{1.1}$$

where S is the total number of stores in each city, N is the total number of cities and the formula assumes, for simplicity, an equal number of stores per city. Figure I.1 presents the kernel density of (log) price deviations pooling across cities, stores, goods and time periods. Since average prices have been subtracted from each price, the variation captured in Figure I.1 is purely cross-sectional. The distribution of price deviations is centered at zero and has a standard deviation of 0.085. Excluding the top and bottom 1 percent of the observations, demeaned log prices range between -20.2 percent and 23.6 percent. The distribution of price deviations appears to have remained roughly unchanged over the period under study. Figure I.2 shows the evolution of selected sample moments (the 5th, 25th, 50th, 75th and 95th percentiles) of the distribution of price deviations over the period 2001-2007. There is a slight "tightening" in the distribution at around mid-2002 when the band containing all observations between the 5th and 95th percentile contracts to +/- 15 percent from +/- 20 percent.

The distribution of price deviations is similar across cities (see Figure I.3). The dispersion in logged price deviations, measured by the standard deviation, ranges between

7.8 percent (Mexico City) and 10.5 percent (Veracruz). Price deviations present a larger variation across goods. The standard deviation of logged price deviations fluctuates between 2.8 percent (pasteurized milk, Alpura) and 12.8 percent (paper napkins, LyS).

I now turn to examining deviations in city-level prices. I define the (log) price differential between city i and a benchmark city j for good k, in week t as

$$q_{ik,t} = \ln\left[\frac{1}{S_i}\sum_{s=1}^{S_i} P_{ist}^k\right] - \ln\left[\frac{1}{S_j}\sum_{s=1}^{S_j} P_{jst}^k\right] \tag{1.2}$$

where P_{ist}^k is the price of good k, sold in store s, in city i, in week t and S_i is the total number of stores in city i[8]. In what follows I use Mexico City as the benchmark city. The results are essentially unchanged if, instead, I use Guadalajara or Monterrey as benchmark cities[9]. I also checked the robustness of using the simple within-city average as a measure of city prices by using, instead, other two measures of city prices: (i) the median price; and (ii) the average price from the four retail chains with the largest market shares. No important differences where found when using those alternative measures.

Table I.2 presents summary statistics on the magnitude and dispersion of price gaps across cities. Column 1 in Table I.2 shows summary statistics for the median price gap, where the median is calculated across city-pairs for each good and week. The median price gap between cities for the average good/week is zero with a standard deviation of 3 percent. The mean absolute deviation for the average good/week equals 3.9 percent and has a standard deviation (across goods and weeks) of 2.3 percent (see Column 2 in Table I.2). Finally, the average (across goods and weeks) standard deviation of intercity price differentials (across city-pairs) is equal to 4.3 percent and its standard deviation across goods and weeks equals 2.1 percent.

The evidence presented in Table I.2 is consistent with the presence of only modest deviations from the LOP. The mean gap in the price of an identical good between cities is about 4 percent. By comparison, Broda and Weinstein (2007) report an average median absolute deviation of 11.3 percent across U.S. cities and 8.3 percent across Canadian cities – that is, more than twice the mean absolute deviation found in the Mexican data[10]. Similarly, Parsley and Wei (1996) report a mean absolute deviation of price gaps between U.S. cities of 12.5 percent. The finding of relatively small price gaps between cities is consistent with a low degree of segmentation in the markets for the goods included in the sample.

1.4.1 The Role of Geography

This subsection turns to investigating the impact of distance on deviations from the LOP. Economic theory suggests that violations to the LOP should be more prevalent between cities located farther apart, as greater transportation costs create a band within

[8]This notation assumes that the number of stores per city is constant over time. This is only a simplification. In the data, there is variation in the number of stores surveyed in a city over time.

[9]The results are also robust to using all $N(N-1)/2$ city-pairs instead of defining a benchmark city.

[10]Broda and Weinstein (2007) compute the median absolute deviation for a single time period (the fourth quarter of 2003) and across city-pairs (instead of goods, as I report in Table 2). When I performed the calculations across city-pairs and time periods the average mean absolute deviation is unchanged.

which relative prices can fluctuate without inducing arbitragers to exploit the observed price gap. Most previous literature has found supportive evidence to this notion both across countries (e.g. Engel and Rogers (1996)) and intra-nationally (e.g. Parsley and Wei (1996)). In order to assess the role of distance in explaining price gaps I estimate the following regression equation by OLS :

$$|q_{ik,t}| = \alpha_k + \delta_i + \beta \ln Dist_i + \varepsilon_{ik,t}$$

where $|q_{ik,t}|$ is the absolute price deviation for good k between city i and Mexico City observed in week t, α_k are good fixed-effects, δ_i are city fixed-effects, and $\ln Dist_i$ is the natural log of distance between city i and Mexico City, calculated using the "greater circle" method[11]. The results of the estimation are presented in Table I.3. Although the distance variable is highly significant in a statistical sense, the magnitude of its effect on the price gap is small. The point estimate is 0.0060 when only city fixed effects are included in the regression and 0.0066 when both good and city fixed effects are included. Loosely speaking, this implies that the price gap between Veracruz (one of the cities bracketing the city located at the median distance from Mexico City) and Mexico City for a given good is 1.5 percentage points lower than the price gap between Mexico City and Merida, a city located more than three times farther away from the capital than Veracruz. The estimated effect of distance on price deviations is substantially smaller than the one found by Parsley and Wei (1996) for the U.S. (point estimate of 0.02) and closer to the findings of Broda and Weinstein (2007). These authors report point estimates of 0.0068 and 0.0213 for the U.S. and Canada, respectively. In order to facilitate comparison with previous work I also performed the estimations on the effects of distance using another measure of price dispersion: The standard deviation of price differentials across time. Engel and Rogers (1996) examine the effects of distance (and the presence of an international border) on this measure of inter-city price dispersion. The results, presented in Table I.4, are similar to the ones obtained for the absolute price gap. The estimated coefficient for distance is highly statistically significant but small in an economic sense (the point estimates range between 0.007 and 0.009).

As pointed out above, Broda and Weinstein (2007) find a similar estimate for the effect of distance on price deviations across cities as the one reported here. They show that the impact of distance on price deviations rises substantially (between 5 and 10 times) when they measure price gaps using indexes that aggregate prices for individual UPCs and attribute this finding to compositional effects –the fact that the set of common goods in the price indexes of two cities falls systematically with distance. Gourinchas et al. (2010), on the other hand, fail to find a positive effect of aggregation on LOP deviations.

1.5 The Law of One Price in the Long-Run

In this section I turn to studying convergence of inter-city prices in the long-run. I assume that the relative city price between a city i and the benchmark city (i.e. Mexico

[11]The results were unaffected when using other distance measures such as the official distance between cities published by the Mexican government and the travel time between two cities.

City) for a given good k follows an autoregressive process of order p, which can be written in its augmented Dickey-Fuller (ADF) form as

$$\Delta q_{ik,t} = \alpha_{ik} + \beta_{ik} q_{ik,t-1} + \sum_{j=1}^{p-1} \gamma_{ikj} \Delta q_{ik,t-j} + \varepsilon_{ik,t} \quad , \quad t = 1, ..., T \tag{1.3}$$

where $\varepsilon_{ik,t} \sim iid(0, \sigma_\varepsilon^2)$.It must be noticed that the choice of a benchmark city against which to measure price differentials might affect the estimation of convergence towards the LOP. In order to ensure the results presented below are robust to the selection of the benchmark city I replicated the analysis using all possible city-pairs and found that the main results remained essentially unchanged.

1.5.1 Unit Root Tests

I start by testing for the presence of a unit root in the process of inter-city prices. It is well known that univariate unit root tests suffer from lack of power when autoregressive roots are in the proximity of unity. In order to avoid this problem, and following much of the literature, I test for a unit root using a more powerful panel unit root test. Since each panel is large in the T dimension (360 weeks) but small in the N dimension (there are only 10 bilateral city prices per good), it is inappropriate to assume independence across cross-sectional units (i.e. cities). I accordingly use the multivariate augmented Dickey Fuller (MADF) test developed by Sarno and Taylor (1998) which accounts for the contemporaneous cross-sectional correlation across panel units. The MADF test is based on a seemingly unrelated regression estimation of the system:

$$q_{ik,t} = \alpha_{ik} + \beta_{ik} q_{ik,t-1} + \sum_{j=1}^{p_k} \rho_{ikj} q_{ik,t-j} + \varepsilon_{ik,t} \quad , \quad t = 1, ..., T; i = 1, .., N \tag{1.4}$$

where $\rho_{ik} = 1 + \beta_{ik}$. The unit root testing problem is: $H_0 : \sum_{j=1}^{p} \rho_{ikj} - 1 = 0 \ \forall \ i = 1, ...N.$. That is, the null hypothesis states that all N series contain a unit root. A potentially important issue in unit root testing has to do with the choice of the truncation lag, p. It is well known that both size and power of the tests depend on the number of lagged first differences included in the estimation[12]. The inclusion of too few lags improves power at the expense of introducing greater size distortions. I chose the truncation lag using the Akaike information criterion setting the maximum lag at 26. As noted below, the results of the panel unit root tests are robust to the selection of any truncation lag between zero and 26. The data overwhelmingly rejects the unit root hypothesis. Nonstationarity is rejected for all 79 goods at the 5 percent level of significance. It must be noted that in the totality of the goods the unit root hypothesis was rejected for any number of lags ranging between zero and 26.

One potential problem with the MADF test is that it rejects the null hypothesis

[12] See, for example, Schwert (1989), Agiakloglou and Newbold (1991), Harris (1992), and Ng and Perron (1995, 2001).

even when a single series within the panel is stationary. In order to explore whether the rejection of nonstationarity is driven by a few stationary relative city prices within each panel, I tested for the presence of a unit root in each series separately using a univariate ADF test. I find that the average fraction of total series for which the test rejects a unit root at 5 percent significance level is 62 percent. This is a high rejection rate compared to the results reported by other intra-national studies of the LOP. Fan and Wei (2006), studying inter-city price differentials in China, reject the unit root hypothesis in 40 percent of the cases for the average good, while Ceglowski (2003) reports an average rejection rate of 45 percent of the inter-city prices in Canada. Thus, the results of the univariate unit root tests tend to confirm the conclusion derived from the panel unit root test. There is substantial evidence favoring the hypothesis of convergence towards the law of one price.

1.5.2 Absolute versus Conditional LOP

Having found supportive evidence for convergence to the LOP, I turn now to examining the issue of whether inter-city prices converge in an absolute or relative sense. Under the absolute version of the LOP, prices in different locations tend to equality in the long-run. More formally,

Definition 1 *(Absolute LOP). Relative prices converge to the absolute LOP iff*

$$\lim_{t \to \infty} P\left(|q_{ik,t}| > \varepsilon\right) = 0, \quad \varepsilon > 0 \tag{1.5}$$

According to the weaker conditional version of the LOP, spatial relative prices converge to a non-zero constant,

Definition 2 *(Conditional LOP). Relative prices converge to the conditional LOP iff*

$$\lim_{t \to \infty} P\left(|q_{ik,t} - \alpha_{ik}| > \varepsilon\right) = 0, \quad \varepsilon > 0, \ \alpha_{ik} \neq 0 \tag{1.6}$$

Most previous work has focused on testing for the conditional version of the LOP[13]. This essentially responds to the constraints imposed by data limitations. As pointed out above, a large fraction of studies on the LOP have relied on price indices which, by construction, do not provide information on absolute price levels. An advantage of the price data used in this paper is that absolute prices can be meaningfully compared across locations, which allows me to test for the absolute LOP.

The evidence lends strong support to the hypothesis that relative prices converge towards the absolute LOP. Only in 43.5 percent of the cases is the constant term significant at the 5 percent level, and in only 7.3 percent of the cases the constant term is significant at the 1 percent level. Estimates of long-run average deviations from LOP, $\mu_{ik} = \alpha_{ik} / \left(1 - \sum_{j=1}^{p_k} \rho_{ikj}\right)$, are also small in magnitude. Column 3 in Table I.5 presents

[13] Broda and Weinstein (2007), who analyze a panel of highly disaggregated data, are among the few studies that examine convergence to the absolute LOP.

the estimated long-run deviations from the LOP (in absolute value) for each good in the sample[14]. They fluctuate between 0.1 percent and 1.4 percent with an average of 0.5 percent. By comparison, Broda and Weinstein (2007) who analyze prices of exactly identical goods across U.S. and Canadian cities, report long-run average deviations from LOP at the city level, ranging between 0.9 percent and 1.5 percent for Canadian cities[15]. They interpret the evidence as providing strong support in favor of the absolute LOP.

1.5.3 Estimates of Speed of Adjustment towards LOP

This subsection examines the rate at which prices are estimated to converge towards the LOP. Studies on the LOP and PPP have typically relied on the half-life of a deviation from parity as a measure of speed of convergence. This is defined as the time it takes for half the effect of a shock to dissipate. In autoregressive models of order one, AR(1), the half-life is given by $h = \ln(0.5)/\ln(\widehat{\rho})$ where $\widehat{\rho}$ is an estimate of the (first-order) autoregressive coefficient. In more general models, as the one estimated here, the previous expression serves only as an approximation to the true half-life as in this case convergence does not necessarily occur at a constant rate. In those cases, the half-life can be estimated as the largest k such that $\widehat{IRF}(k-1) > 0.5$ and $\widehat{IRF}(k) \leq 0.5$ where $\widehat{IRF}(k)$ is the estimated impulse- response function in period k. In what follows, I report the half-lives using the estimated impulse-response functions. The estimates presented in Column 1 of Table I.5 point to a considerably faster speed of convergence to LOP than found by previous studies. Estimated half-lives vary between 2.1 weeks (McCormick mustard, 430 grs. jar) and 11.5 weeks (Royal baking powder, 220 grs. can) with the median and average goods exhibiting a half-life of 3.1 weeks and 3.4 weeks, respectively. By way of comparison, Parsley and Wei (1996) in their study of inter-city price differentials in the U.S. find a half-life of deviations from the LOP ranging between 4 and 5 quarters, while Broda and Weinstein (2007) estimate a half-life of LOP deviations between Canadian cities of 2.9 quarters. The results reported above are closer to the findings by Fan and Wei (2006), who report a median half-life of 2.4 months for intra-national deviations from the LOP in China.

Small Sample Bias. One potential problem with calculating half-lives using the estimates from equation 1.4 directly is that OLS estimates are likely to be biased in small samples. The literature on LOP and PPP has usually assumed that small sample bias induces an underestimation of the true persistence in the autoregressive process. This, however, is only true in the case of autoregressive processes of order one, AR(1) (Marriott and Pope, 1954; Kendall, 1954). In higher order processes, the bias induced by OLS can go in either direction (Stine and Shaman, 1988, 1989).

In order to correct the estimates for small sample bias, I relied on the method of recursive mean adjustment (Shin and So, 2001; Shin, Kang and Oh, 2004)[16]. The results corrected for small sample bias suggest that the effects of small sample bias in the estimates

[14]Long-run deviations from the LOP presented in Table 3 correpond to averages for each good across city-pairs.

[15]In the case of Mexico, I find that average long-run deviations from LOP at the city level fluctuate between 0.33 percent (Merida) and 0.87 percent (Morelia).

[16]Chen and Engel (2005), among others, use recursive mean adjustment to correct for small sample bias in estimates of relative price convergence.

presented above is negligible. The average half-life of deviations from the LOP is estimated at 3 weeks using recursive mean adjustment.

Measurement Error. Another source of attenuation bias that might be affecting the results is measurement error due, for example, to mistakes made in the price collection process. Suppose that instead of observing the true relative price q_{it} one observes the variable

$$q_{it}^{*} = q_{it} + v_{it} \tag{1.7}$$

where v_{it} is distributed i.i.d. with mean zero and variance σ_v^2. In this case, OLS estimation of equation

$$q_{i,t}^{*} = \alpha_i + \sum_{j=1}^{p} \rho_{ij} q_{i,t-j}^{*} + e_{i,t} \tag{1.8}$$

where product indexes have been suppressed for simplicity and $e_{i,t} = -v_{it} + \sum_{j=1}^{p} \rho_{ij} v_{i,t-j} + \varepsilon_{it}$ leads to inconsistently estimated coefficients as the error term is correlated with the explanatory variables. In order to assess this possibility I performed a Hausman test for endogeneity using as instrumental variables the lags $\{q_{it-p-1}, ..., q_{it-2p}\}$[17]. The results of the Hausman test do not indicate the presence of classical measurement error in the data.

1.6 Estimates of Speed of Convergence to LOP using Lower-Frequency Data

This section turns to studying the consequences of estimating convergence in relative prices using aggregated data. The present section focuses on the effects of temporal aggregation while the next one examines the problems associated to cross-sectional aggregation. Studies of relative price dynamics have typically relied on price data observed at low frequencies. While most studies analyze relative prices observed quarterly or annually, evidence reported by studies of price-setting behavior (e.g. Midrigan, 2006; Nakamura and Steinsson, 2008) suggests that retail prices are set at a weekly frequency. In this section, I exploit the that my data is available at a weekly frequency to study the consequences of estimating convergence to the LOP using lower frequency data.

The time-series literature recognizes two schemes under which low frequency series can be generated from the original high-frequency ones: Systematic sampling and temporal aggregation. Systematic sampling occurs when observations of a time series are sampled at regular intervals, as when end-of-period prices are observed. Studies of the LOP using systematically sampled data include, among others, Parsley and Wei (1996), Ceglowski (2003) and those analyzing data from the Economist Intelligence Unit's Worldwide Cost of Living Survey such as Rogers (2007) and Crucini and Shintani (2008). Temporal aggregation occurs when the time series available to the researcher are either sums or averages of the original series over a given time interval, as when quarterly or yearly averages are observed.

[17] Imbs et al. (2005), among others, use this test to assess the presence of measurement error in their data.

Broda and Weinstein (2007), for example, study convergence to the LOP using quarterly averaged data. Studies analyzing price indices may also be implicitly using temporally aggregated data as some statistical agencies collect prices at a higher frequency than the one at which the price indexes are constructed and reported (see Taylor, 2001, for further details). In Mexico, for example, the CPI is constructed and reported on a monthly basis but prices are sampled twice a month with food items being sampled as frequently as four times a month (Gagnon 2007). There is an extensive literature studying the consequences of systematic sampling and temporal aggregation in the estimation of time series models. Especially relevant for testing of the LOP are studies examining the consequences of systematic sampling and temporal aggregation on unit root tests. Teles, Wei and Hodgess (2008) find that both the empirical significance and power of Dickey-Fuller tests are affected by temporal aggregation and that these effects are stronger the greater the order of aggregation.

Taylor (2001) examines the consequences of using low-frequency data in the study of convergence to LOP and PPP when the assumed data generating process is an autoregression of order one, AR(1). He shows that while systematic sampling negatively affects estimates of persistence, temporal aggregation leads to an upward bias in persistence estimates which is increasing in the degree of temporal aggregation. The intuition for the inconsistency in the estimates of persistence under temporal aggregation can be seen as follows. Suppose that the original data generating process for the price gap, qt, is an AR(1):

$$q_t = \rho q_{t-1} + \varepsilon_t, \quad t = 1, ..., T$$

where $\{\varepsilon_t\}$ is an $i.i.d.$ sequence with variance σ_ε^2. The observed price data are non-overlapping K-period averages of the original data. The observed, temporally-aggregated, variable is thus given by

$$Q_s = (1/K) \sum_{j=1}^{K} q_{K(s-1)+j}$$

where $s = 1, ..., T/K$ indexes time units at which prices are actually observed. The temporally aggregated model is an ARMA(1,1):

$$Q_s = \phi Q_{s-1} + u_s$$

where $u_s = (1/K) \sum_{j=1}^{K} \sum_{l=1}^{K} \rho^{l-1} \varepsilon_{K(s-1)+j-k}$.Thus, as Q_s and u_s are correlated, the OLS estimator of ϕ is inconsistent[18]. Consistent estimates of persistence can be obtained in the presence of temporal aggregation using alternative estimators (e.g. instrumental variables, GMM). Chambers (2005), for example, proposes a maximum likelihood estimator to find consistent estimates of half-lives. The literature on PPP and the LOP, however, has

[18] Chambers (2005) shows that

$$p \lim \widehat{\phi} = \phi + \frac{\rho\left(1-\rho^{2K}\right) - K\rho^K\left(1-\rho^2\right)}{K\left(1-\rho^2\right) - 2\rho\left(1-\rho^K\right)}$$

for the most part ignored the problem. The following subsection quantifies the magnitude of the bias introduced by the use of temporally aggregated prices.

1.6.1 Effects of Temporal Aggregation

Since the data is available at the weekly frequency, I can directly assess the magnitude of the temporal aggregation bias by replicating the estimations conducted in Section 5 using temporally aggregated series. Specifically, I estimated the system

$$Q_{ik,s} = \alpha_{ik} + \sum_{j=1}^{p_k} \rho_{ikj} Q_{ik,s-j} + u_{ik,s}, \quad s = 1, ..., T/K;\ i = 1, ..., N \tag{1.9}$$

for each good k using non-overlapping averages of relative prices at the (approximately) monthly and quarterly frequencies (i.e. $K = 4$ and $K = 13$), $Q_{ik,s} = \ln\left[(1/K)\sum_{j=1}^{K} P_{ik,K(s-1)+j}\right] - \ln\left[(1/K)\sum_{j=1}^{K} P_{MCk,K(s-1)+j}\right]$, where $P_{ik,s}$ and $P_{MCk,s}$ are the prices of good k in city i and Mexico City in period s, respectively. Estimations using temporally aggregated data reveal the presence of an important upward bias in the estimated half-lives of deviations from LOP. Figure I.4 compares the distribution of half-lives (expressed in weeks) obtained using temporally disaggregated (weekly) data with those obtained from monthly and quarterly averaged prices. There is a clear shift to the right in the estimated distributions of half-lives obtained from aggregate data relative to that obtained from weekly data and this shift is more pronounced the higher is the order of aggregation. The median half-life rises from 2.8 weeks, when estimated using weekly-sampled data, to 6.4 weeks and 12 weeks when estimated using monthly and quarterly aggregated data, respectively.

Figure I.5 compares the estimated half-lives using temporally disaggregated data with estimates using monthly and quarterly averaged prices at the good level. In all cases the median half-life is increasing in the order of aggregation.

1.6.2 Monte Carlo Experiments

In this subsection I explore the robustness of the findings on the effects of temporal aggregation by performing Monte Carlo experiments. I generate series with sample size T using as the data-generating process the AR(p) model:

$$q_t = \alpha + \sum_{j=1}^{p} \rho_j q_{t-j} + \varepsilon_t \tag{1.10}$$

where $\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right)$ .I calibrate the lag structure and parameters to match those estimated for the median good. The set of parameter values used in the simulations is:

$$(p, \rho_1, \rho_2, \alpha, \sigma_\varepsilon) = (2, 0.717, 0.101, -0.001, 0.022)$$

I then obtain temporally aggregated series by calculating non-overlapping averages

$Q_s = (1/K) \sum_{j=1}^{K} q_{K(s-1)+j}$, $s = 1, ..., T/K$, for $K = 4$ and $K = 13$. I compute half-lives for both disaggregated and aggregated series using the estimated impulse response functions. Each experiment was conducted with 2,500 draws.

Table I.6 presents the results of the simulations for different sample sizes. The median half-life using monthly aggregated data (K = 4) is estimated at 2.5 months, regardless of the length of the sample. This is about 2.4 times the half-life obtained from weekly sampled data, which is very close to the bias factor found in the previous subsection. When quarterly aggregated data is used in the estimations, the median half-life ranges between 1.3 quarters and 1.7 quarters. Using a long series of 300 quarters (so that small sample bias is unlikely to affect the results), the bias factor introduced by temporal aggregation approaches 4.7.

1.7 Cross-Sectional Aggregation

Studies of relative price dynamics have typically relied on data consisting of prices for broadly defined goods or sectors (see Broda and Weinstein, 2007). Using price measures that aggregate across several individual goods might pose problems for the estimation of the speed at which prices converge to parity. Imbs et al. (2005) show that when individual sectors exhibit heterogeneous dynamics, estimates of relative price convergence that assume a common set of persistence parameters are likely to be biased upwards. As an illustration, assume that relative prices for a given city-pair follows a first-order autoregressive process,

$$q_{k,t} = \alpha_k + \rho_k q_{k,t-1} + \varepsilon_{k,t} \tag{1.11}$$

where both intercepts and slopes vary across goods. Assume that $\alpha_k = \alpha + \eta_k^\alpha$ and $\rho_k = \rho + \eta_k^\rho$.Suppose one estimates the degree of persistence in the process of $q_{k,t}$ assuming no heterogeneity in persistence across goods, that is, using the specification

$$q_{k,t} = \alpha + \rho q_{k,t-1} + v_{k,t} \tag{1.12}$$

where $v_{k,t} = \eta_k^\alpha + \eta_k^\rho q_{k,t-1} + \varepsilon_{k,t}$. Since the lagged dependent variable appears in the error term, estimates of persistence will be inconsistent if the estimation procedure does not allow for heterogeneous dynamics across goods. The sign of this bias is in general ambiguous. However, Imbs et al. (2005) show that under plausible conditions it is positive and larger the greater the heterogeneity in the dynamics of individual series. They confirm that the bias is positive in the dataset they analyze.

Broda and Weinstein (2007), on the other hand, find no evidence of the type of bias stressed by Imbs et al. They find a similar estimate of the half-life of deviations from LOP whether or not they allow for heterogeneous dynamics across individual goods. Crucini and Shintani (2008)'s findings point in the same direction. In this section, I assess the relevance of this type of bias in the data. It is important to distinguish between a cross-sectional aggregation bias due to heterogeneity in persistence across individual goods and a cross-sectional aggregation bias due to pooling across locations (Choi, Mark and Sul, 2006). Choi et al. (2006) argue that if observations are drawn from a mixed panel in which the relative prices for a fraction of location-pairs are nonstationary, pooling across locations can give rise to an important aggregation bias. In order to isolate the effect of heterogeneous dynamics across goods from the effect of heterogeneous dynamics across cities, I compare the estimates obtained when allowing for heterogeneous autoregressive coefficients with those obtained when pooling across goods for a given city. The estimated model for each city $i = 1, ...N$ is

$$q_{kt} = \alpha_k + \sum_{j=1}^{p} \rho_{kj} q_{kt-j} + \varepsilon_{k,t}, \quad t = 1, ..., T; \; k = 1, ..., K \tag{1.13}$$

where the index for cities has been suppressed for simplicity. Table I.7 compares the averagehalf-lives obtained by letting ρ_{kj} vary across goods, $k = 1, ..., K$, with the half-life obtained by imposing a single set of persistence parameters $(\rho_1, ..., \rho_K)$ for each city. I estimated the half-life pooling across goods using a fixed-effects estimator and chose the truncation lag p using a general to specific technique in which I set the maximum number of lags at 26. The half-lives, computed from the estimated impulse-response function, were robust to estimation using the seemingly unrelated regression estimator (SURE). The persistence coeffi cients for the individual good processes were estimated using SURE and the same number of lags used in the case of pooling.

The results reported in Table I.7 suggest that heterogeneity in persistence across goods is not an important source of bias in the data. The half-life of a LOP deviation is larger when pooling across goods only in 3 out of 10 cities, and in those cases the overestimation of the half-life is negligible. The half-life of the median city estimated when pooling across goods is almost the same as (actually slightly lower than) the half-life of the median city obtained from the disaggregated data (2.8 weeks vs. 3 weeks). One possible explanation to the finding of no heterogeneity bias is that persistence does not actually exhibit much variation across goods in the sample. The fact that all products in the sample belong to the food and health care sectors makes this specially plausible. However, as Table I.8 shows, variation in persistence across goods is substantial. For each of the 10 cities in the sample, persistence –measured by the sum of the estimated autoregressive coefficients–exhibits a high degree of dispersion across goods –the standard deviation of the persistence measure in a given city is about 0.13. This large variation in persistence across goods is consistent with the finding of Broda and Weinstein (2007) of a substantial heterogeneity in price behavior within narrow product groups.

1.8 Concluding Remarks

This paper has studied price differences across cities in Mexico using highly disaggregated price data. Three major results emerge from the analysis. First, using low frequency data for studying relative price dynamics can lead to a large upward bias in the estimates of persistence. Half-lives of deviations from the LOP derived from monthly and quarterly aggregated data is found to be 2 and 4 times (respectively) as large as the half-life of a shock to LOP estimated from weekly data. The results using actual price data and allowing for higher-order processes for relative prices point in the same direction as those reported by Taylor (2001) for the case of price gaps following an AR(1). As pointed out in

Section 1, this problem a- icts both studies that analyze price indexes (as statistical agencies tend to report average prices) as well as studies focusing on narrowly defined goods (e.g. Broda and Weinstein, 2007). The message for future work on relative price dynamics should be clear. Using temporally disaggregated data can be critical for obtaining reliable estimates of half-lives as the bias introduced by aggregation can be large. In particular, temporal aggregation appears to be a more pernicious source of bias than aggregation across individual goods that exhibit heterogeneous dynamics. In contrast to the findings of Imbs et al. (2005), the results showed that pooling across goods with varying convergence rates does not affect estimates of persistence in any systematic way. The results, in this respect, are consistent with those reported by Broda andWeinstein (2007) and Crucini and Shintani (2008). Second, the evidence points to a remarkably fast convergence rate towards the LOP.

The estimated half-life of 3 weeks implies a substantially lower persistence in the process of relative prices than previously reported in the literature. Furthermore, the evidence suggests that average prices across cities tend to be equalized in the "long-run". An important question left for future research is the mechanism that can account for this fast rate of convergence in intercity prices.

A third finding of this paper is the absence of an economically significant relation beween price gaps and physical distance. While this does not necessarily imply that trade barriers between cities (e.g. transportation costs, etc.) are low, it is interesting to note the difference between this estimate and those obtained using more aggregated data. As pointed out above, Broda and Weinstein (2007) show that one possible explanation to this discrepancy is the fact that the set of non-overlapping goods included in price indexes is larger for cities located farther apart.

Chapter 2

Reference Prices and Costs in the Cross-Section: Evidence for Chile

2.1 Introduction

Recent research on the patterns of price adjustment at the micro level has uncovered a tendency for retail prices to display sales-like behavior. Retail prices are characterized by large and frequent temporary departures (typically falls) from more persistent underlying prices (Eichenbaum, Jaimovich and Rebelo, 2010; Kehoe and Midrigan, 2007; Klenow and Malin, 2010; Nakamura and Steinsson, 2008). Research by Nakamura and Steinsson (2008) has found that price adjustments of a more transitory nature provide an important contribution to overall price flexibility. Studying a panel of consumer prices underlying the U.S. CPI, they find that removing temporary markdowns or "sales" from the original price series increases the duration of prices from about 4 months to 7-10 months[1]. The increased price flexibility derived from the use of "sales" on the part of retailers has potentially important consequences for monetary economics. If "sales" are nonorthogonal to a monetary policy shock, then sticky price models should account for the changes in price flexibility induced by sales activity in the face of a monetary policy shock.

This paper studies patterns of price adjustment using a unique scanner data set of weekly prices, costs and quantities sold from a cross-section of Chilean retailers. The primary dataset includes retail prices and quantities sold for some 60,000 barcodes sold in 180 stores belonging to 13 supermarket and drugstore chains over the period 2005-2008. A secondary data set includes wholesale costs for the largest two retail chains over the same period for a subset of the barcodes included in the primary data set. Two important features of the data are the availability of a high quality measure of costs (replacement costs) for one of the retailers and the fact that price and quantity data are available for a cross-section of retailers. Typically, previous studies using scanner data have focused on a single retail chain[2] (e.g. Eichenbaum et al. 2010, Kehoe and Midrigan 2007, Midrigan 2009, and several

[1] The magnitude of temporary price adjustments is also about twice as large as the size of –more persistent– regular price changes, which also contributes to a greater degree of price flexibility (Nakamura and Steinsson, 2008).

[2] An exception is Nakamura (2008) who analyzes a cross-section of retailers in the U.S. Her panel is,

other papers that use *Dominick's* data set) and/or have relied on a lower quality measure of costs –average costs of items in inventory[3] (e.g. Burstein and Hellwig 2007, Midrigan 2009 and other papers that use *Dominick's* data set).

In line with evidence reported for the U.S. (Eichenbaum et al. 2010, Klenow and Malin 2010), retail prices in the Chilean data tend to revolve about more persistent reference prices[4]. Posted prices are equal to reference prices about 62 percent of the time[5] and have a weighted average frequency of price change of 0.29 per week (an implied duration of 3.4 weeks). In contrast, the typical reference price is adjusted every 2-3 quarters.

Exploiting the cross-sectional dimension of the data I examine how reference prices for a given product covary across retail chains. If reference prices capture primarily shocks which are common across retailers –as is the case with shocks originating at a previous stage of the production chain– we would expect covariation across stores within chains to be similar to covariation across all stores. The data, however, strongly rejects the hypothesis that "chain effects" are unimportant in explaining price comovement. Controlling for product and category effects, the correlation coefficient between the prices of a given barcode across stores is about 0.3 larger when the stores belong to the same retail chain. Evidence on the variance decomposition of the frequency of reference price adjustment points in the same direction. About 60 percent of the variation in the frequency of reference price changes is explained by variation across retail chains. The evidence is consistent with Nakamura (2008) who finds that most of the variation in U.S. retail prices is explained by variation across stores within chains but not across chains. The present paper shows that retailer-specific effects matter even in the case of reference price movements.

Prices are found to be substantially less volatile than in the U.S. This is in part due to the fact that temporary price changes are smaller in magnitude than permanent price changes (i.e. changes in reference prices). The size of price changes is on average small, in comparison to the magnitude of price changes previously reported in the literature. I also find evidence that retail chains tend to set prices at two levels: At the chain level and the store level. Chain level prices, proxied by the modal price across stores within a chain, do not correspond to reference prices and are significantly less persistent than them (they are changed every 5 weeks, on average).

Evidence on the behavior of markups reveals that pass-through of changes in wholesale costs is relatively rapid. Markups exhibit a remarkably small volatility. As in Eichenbaum et al. (2010) the retailer appears to choose the duration of reference prices in order to keep the markups within narrow bounds. There is evidence that the probability of repricing is increasing in the gap between the current and average markup.

Finally, I examine the degree of synchronization in the timing of posted and reference price changes. In line with evidence reported for the U.S. (see Klenow and Malin, 2010) I find evidence that both reference and posted price changes tend to be staggered

however, more limited over the temporal dimension (only one year of price data is available).

[3] An exception is Eichenbaum et al. (2010) who use a measure of replacement costs.

[4] Eichenbaum et al. (2010) define reference prices as the most quoted price in a given quarter. In this paper I use an alternative (but similar) definition proposed by Chahrour (2009), who defines a reference price as the most quoted price within a 13 week rolling window centered in the current week.

[5] The reference price phenomenon does not apply to all retailers, however. In one of the largest supermarket chains, prices do not appear to revolve around an attractor price.

across retailers. Price adjustment within stores, on the other hand, tend to be synchronized. Lach and Tsiddon (1996) present similar evidence for retailers in Israel.

The paper is organized as follows. The next section presents a review of the related literature. Section 3 describes the data sets I use in the analysis. Section 4 characterizes the behavior of reference prices in the data. Section 5 examines the behavior of wholesale costs and markups. Section 6 studies price synchronization within and across stores. Section 7 presents a quantitative model which is able of capturing salient features of the data, in particular, the greater persistence exhibited by reference prices. Finally, Section 7 concludes.

2.2 Related Literature

This paper is primarily related to the growing literature that studies patterns of price adjustment at the micro level[6]. The seminal paper in this literature is Bils and Klenow (2004), who study the timing of price adjustment underlying the U.S. CPI. Bils and Klenow's major finding is that prices tend to be adjusted much more frequently than previously thought on the basis of studies focusing on narrower sets of goods. While the conventional wisdom by the late 1990s held that prices were changed about once a year (e.g. Taylor 1999), Bils and Klenow (2004) found a median duration of a price change of 4.3 months. This result had important implications for the business cycles literature, as it made price stickiness a less plausible explanation for the observed effects of monetary shocks on economic activity. In particular, the high frequency of price adjustment would require a larger "contract multiplier" in order to be consistent with the available empirical evidence on the real effects of changes in the stock of money[7].

Subsequent research by Nakamura and Steinsson (2007) led to an important qualification to Bils and Klenow's (2004) results. Using the BLS research database, which includes the actual prices underlying the U.S. CPI, they found that temporary price cuts or "sales" were prevalent in the data and that filtering out short-lived prices led to a substantial increase in price durations. They estimated an implied duration of regular prices (i.e. sales-removed prices) ranging between 7 months and 10 months. This finding by Nakamura and Steinsson opened up a debate about the appropriateness of removing temporary prices from the data when calibrating quantitative macro models featuring sticky prices. Purging the price data from short-lived prices would only be appropriate if "sales" are orthogonal to monetary policy shocks. If, instead, "sales" respond to unexpected changes in the stock of money, then quantitative macro models should incorporate a motive for firms to choose both regular and temporary prices. Kehoe and Midrigan (2007) study an extended menu cost economy in which price-setters face a fixed cost to adjusting prices for an indefinite period of time and, in addition, have the option of paying another (smaller) menu cost for adjusting prices for a single period. The model yields price dynamics that are able to mimic some salient features of the retail price data[8]. Kehoe and Midrigan (2007) then examine the implications of calibrating standard sticky price models (both menu cost and Calvo

[6] Klenow and Malin (2010) provide a survey of the literature.

[7] On the empirical evidence on the effects of monetary policy on prices and output see, for example, Christiano, Eichenbaum and Evans (1999).

[8] Kehoe and Midrigan (2007) calibrate their model to match 13 stylized facts from *Dominick's* data set including the frequency of price changes, size of price changes and price dispersion including and excluding

models) to the frequency of price changes both including and excluding sales. They find that models that match the data including (excluding) sales tend to understate (overstate) the real effects of monetary policy. They further show that standard menu cost models calibrated to match the fraction of prices at the annual mode –instead of the frequency of price changes– are able to better approximate the effects of a monetary shock derived from their extended menu cost model.

Guimaraes and Sheedy (2010) study an economy in which sales arise endogenously as a result of price-setters engaging in intertemporal price discrimination in an environment characterized by the presence of two types of consumers: low-price sensitive "loyal" customers and high-price sensitive "bargain hunters". They find that sales do not contribute to greater price flexibility in response to monetary policy shocks. The reason is strategic substitutability in sales. The incentives for a firm to increase sales are greater the more other firms choose not to use sales. In the face of an aggregate shock, such as a monetary policy shock, firms find it optimal not to vary sales and therefore price responses to the monetary shock are unrelated to changes in sales activity.

Even if consensus is reached on the convenience of purging the data from temporary prices, it remains to be decided how "sales" should be defined. An alternative approach that dispenses with the need of adopting a definition of "sales" was proposed by Eichenbaum, Jaimovich and Rebelo (2010). Analyzing a scanner data set from a large U.S. retailer, they observed that posted prices had a tendency to revolve around reference prices, defined as the most quoted price in a given quarter. They established that reference prices are important according to several different metrics (such as the fraction of the time at which posted prices are equal to reference prices and the fraction of revenues made at reference prices) and that they are substantially more persistent than posted prices. While weekly posted prices are changed every 2-3 weeks, the average implied duration of a reference price is about 1 year. Calibrating a partial equilibrium model to match some of the moments of the price data, Eichenbaum et al. find that even in the presence of highly flexible posted prices, monetary shocks can have persistent effects on economic activity provided that reference prices are adjusted less frequently.

While Eichenbaum et al. (2010) focus primarily on the time-series dimension of retail prices and costs, Eden and Jaremski (2009) analyze the cross-sectional distribution of prices using Dominick's data set. Specifically, they focus on the chain dimension of the data. Based on empirical evidence suggesting that retail chains tend to set prices both at a chain and a store level, they analyze the behavior of modal prices across stores within a chain. They show that about 75 percent of the prices each week are equal to the modal price across stores and that modal prices are quite flexible –they have a frequency of price change of 0.35 per week. They interpret this latter fact as an indication that the distribution of prices tends to respond rapidly to aggregate shocks.

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sales.

2.3 Data

The primary data set corresponds to weekly scanner data from the largest supermarket[9] chains operating in the Santiago de Chile metropolitan area over the period 2005-2008 (156 weeks). The data were provided by a market research firm and consist of weekly revenue and quantities sold for about 60,000 European Article Numbers (EANs)[10]. The data include 181 stores belonging to 12 supermarket chains[11] and one chain of convenience stores, which comprise nearly the totality of stores of this type operating in the Santiago metropolitan area.

It is important to note that the degree of supermarket penetration in Chile is high relative to other countries in Latin America. About 80 percent of foodstuffs sales is accounted for by supermarkets, hypermarkets and convenience stores, the remainder 20 percent being accounted for by the so-called "traditional sector" which includes small independent grocery stores (USDA 2009). The data set also includes information on the location of each store, providing the street and commune[12] where a store is located. I use the same product categorization used by the market research firm which provided the data. The products in the sample belong to 190 categories comprising mainly foodstuffs, drugstore and healthcare product (examples of categories include "Breakfast Cereal", "Pasta", "Beer"; see Table II.1 for a full description of the categories included in the sample). I made several adjustments to the original data set. First, I corrected for outliers by treating prices which lie outside a +/- 3 standard deviations from the series mean as missing observation, where each series corresponds to a store and barcode. Second, I required that each price series had at least one unbroken spell of 13 weeks. Finally, I eliminated all those series with less than 30 observations in the whole sampling period. The imposition of these criteria reduced the total number of observations to slightly more than 60 million data points. Table II.2 presents descriptive statistics on the main dataset used in the analysis. Note that the number of observations in the last year of the sample period is substantially smaller than in the earlier period. This is primarily due to a fall in the number of barcodes available from about 20,000 to close to 6,000. Also, data on quantities of goods sold in the later period is only available for the largest two retail chains (Jumbo and Lider). This imposed a trade-off between the use of longer series and the use of a richer cross-section of prices which in addition included data on expenditure weights at the store/barcode level. I chose to carry out the analysis using the shorter period spanned between week 40 of 2005 and week 32 of 2007. The main conclusions of the analysis are essentially unchanged when I use

[9]By supermarket I mean any self-service store with at least three cash registers (this is the definition used by the Statistical National Agency, INE, in Chile). Thus, both traditional supermarkets and hypermarkets are included in this definition.

[10]EAN-13 is a barcode symbology prevalent in Europe and Latin America which is similar to the Universal Product Code (UPC) symbology commonly used in the U.S.

[11]By "chain" of supermarkets I mean a group of two of more stores that share a given format (e.g. hypermarket, traditional supermarket, discout store) and brand (e.g. Jumbo, Lider). As is discussed in the Appendix, the largest Chilean retailers typically operate several brands. I have chosen to consider each brand/format as a separate chain because the data suggest that there is important variation in price setting policies across brand/formats within chains.

[12]A "commune" is the smallest adiministrative unit in Chile. The Metropolitan Region is divided into 52 communes.

data for the full sampling period.

The measure of retail prices for a given product/store used in the paper is simply obtained by dividing weekly revenue by the quantity sold in that particular product/store. There is strong international evidence that retail chains revise their prices weekly (e.g. Eichenbaum et al. 2010). Informal conversations between the author and executives from the Chilean supermarket industry who participated in the price setting process on a regular basis confirmed that this also applies in the Chilean case. Thus, it is unlikely that observing prices weekly –instead of, say, daily– might lead to an underestimation of the frequency of price adjustment. Other sources of measurement error can, however, potentially affect the results in the paper. These are mainly associated to the use of discounts which are not reflected in the available price measure. Examples include the use of frequent buyer cards, promotions of the type "buy two and pay one", and the use of discount coupons. To the extent that retailers make extensive use of these types of discounts, true prices faced by consumers will tend to differ from the measured prices and hence the estimated price flexibility will tend to understate the true degree of price flexibility. Furthermore, if different retail chains rely on these discount mechanisms to a different extent, measured differences in the frequency of price adjustment can be erroneously attibuted to actual differences in price setting behavior.

A second data set includes total costs and quantities sold for two large retail chains. These data were provided directly by the retailers to the author. Data are available weekly, for the same 2005-2008 period and for a subset of the products in the primary data set. Table II.3 presents summary statistics on this secondary data set. The measures of cost available from the two retailers differ in their quality. In one case, costs correspond to the average cost of products in inventory. Hence, it is not a measure of current prices at the wholesale level but it averages the historical costs at which items in inventory were acquired. The measure of cost included in the popular *Dominick's* data set used by several papers on price adjustment (Midrigan 2009, Kehoe and Midrigan 2007, among others) corresponds to the average costs of items in inventory.

The measure of costs provided by the second retailer is of a higher quality. This measure corresponds to current prices charged by sellers at the wholesale level and are treated by the retailer as a measure of replacement cost. These costs are inclusive of shipping and handling costs. It should be pointed out that the Chilean distribution chain has evolved over the years to a structure in which intermediaries between manufacturers and retailers have tended to disappear. Thus, the measure of wholesale cost available corresponds in most cases to the price charged directly to the retailer by the manufacturer. One potential source of measurement error in the measure of wholesale costs has to do with the payment of allowances by wholesalers. It is a common practice in the supermarket/hypermarket industry that wholesalers pay the retailer a lump sum amount in exchange for displaying their products in certain areas within the store or for introducing a new product.

2.4 Characterization of Reference Prices

This section describes the behavior of reference prices as compared to the behavior of posted prices in the Chilean data and provides greater details on the nature of reference prices. In particular, it examines whether reference prices capture movements in underlying fundamentals of a given product (such as productivity shocks) or whether, instead, they possess a retailer specific component.

The reasons for focusing on reference prices as opposed to regular prices (i.e. posted prices which exclude "sales" or temporary price markdowns) are basically two. First, identifying sales prices involves adopting a mostly arbitrary definition of a sale. Second, and more importantly, "sales" prices in the data do not appear to be as prevalent as has been reported for the U.S. and European retailers. Using a standard sales filter which identifies a sale as any price decrease which is fully reversed over a four week period, I find that less than five percent of prices in the data correspond to "sales"[13]. In contrast, Kehoe and Midrigan (2007) report that 83 percent of price changes in the *Dominick's* data set occur during a "sales" period.

2.4.1 Reference Prices Defined

Eichenbaum et al. (2010) define reference prices (costs) as the most quoted price (cost) in a given calendar quarter. A problem with this approach is that it may give rise to spurious reference price changes or to fail to identify a reference price change. If the price setter does not make adjustment decisions on reference prices on a quarterly basis then the researcher might wrongly identify departures from reference prices what are actually changes in the underlying reference price series (Chahrour 2009). Chahrour (2009) corrects for this limitation in Eichenbaum et al.'s definition by proposing an algorithm that identifies reference prices using a rolling window of 13 weeks centered in the current week. As in Eichenbaum et al. a reference price (cost) is the most commonly quoted price (cost) within a given window[14]. In what follows I use Chahrour's (2009) definition of reference (or attractor) prices but I also present results based on Eichenbaum et al.'s definition in order to facilitate comparison with their work.

Panels a) to d) in Figure II.1 display the behavior of posted and reference prices using Chahrour's definition for a number of selected products in a given store: Kellogg's Cornflakes, 500 grams box, Budweiser Beer, 1 liter; Nescafe Instant Coffee, 170 grams, decaf; and Coca-Cola, 350 c.c. The charts suggest that prices tend to spend a large fraction of the time at their reference values. As in Eichenbaum et al. (2010) reference prices are important according to several metrics. The next subsection describes the evidence on the importance of reference prices in the data.

2.4.2 Importance of Reference Prices

Once at their reference levels, posted prices have a tendency to remain at their reference values and to come back to them when they depart from reference levels. The following matrix presents the estimated transitional probabilities between the states the two states: reference (=1) and nonreference (=0). The first row presents the probabilities that the posted price next period will be at its reference value (column 1) and nonreference

[13]Only 4.6 percent of all prices in the data are "sales" prices.

[14]See the Appendix to Chahrour (2009) for a description of the algorithm used in defining reference or attractor prices.

value (column 2) given that this period it was at its reference level. The second row presents the same information conditional on a posted price different from the reference price this period.

$$\begin{array}{c} 1 \\ 0 \end{array} \begin{bmatrix} 0.727 & 0.273 \\ 0.522 & 0.478 \end{bmatrix}$$

The evidence thus suggests that reference prices act as attractors for posted prices. The probability of a price remaining at a reference value is about 0.73. A nonreference price has a 0.48 probability of moving to a reference price next period. Posted prices spend a large fraction of the time at their reference levels. According to Table II.4 posted prices are equal to reference prices about 62 percent of the time.

These results do not hold, however, across all retail chains. As can be seen from Table II.4, posted prices are equal to reference prices only 28 percent of the time in the case of one of the retail chains.Thus the reference price concept, while useful in describing price dynamics for most retailers in the sample it does not appear as a necessary trait of retail pricing. It should be pointed out that the retailer for which reference prices do not appear to act as attractors for posted prices is one of the important players in the Chilean supermarket industry.

Other metrics for judging the importance of reference prices include the percentage of total revenue that are made at reference prices. Table II.5 presents the share of total revenues that are made at reference prices. Most retailers obtain more than 60 percent of their revenue from sales made at reference prices.

2.4.3 Persistence of Reference Prices

Reference prices are substantially more rigid than posted prices. Column 3 in Table II.6 presents summary statistics on the frequency of reference price adjustment taken across categories. The median frequency of reference price adjustment across categories equals 0.029, which implies a duration of 40 weeks. Using revenue shares as weights, the weighted average median frequency of price adjustment is 0.04 –an implied duration of 25 weeks. That is, the typical reference price remains unchanged for about 2 to 3 quarters. The results using Eichenbaum et al.'s definition of reference price are similar (see Columns 5 and 6 in Table II.6). By way of comparison, Eichenbaum et al. (2010) find that reference prices in their data have an average duration of 3.7 quarters.

Column 1 of Table II.6 presents summary statistics on the frequency of price adjustment for posted prices. The statistics presented in Table II.6 are computed across categories for the median product/store within each category. The median frequency of a price change equals 0.28. Column 2 of Table II.6 shows the implied duration of a posted price, computed as the reciprocal of the frequency of price adjustment. The implied duration of the median posted price is equal to 3.6 weeks.

Frequencies of posted price adjustment are similar to the one reported by studies that analyze U.S. scanner data. EJR find that posted prices change, on average, about every 2.4 weeks in the case of the large retailer they study. Kehoe and Midrigan (2008), using *Dominick's* dataset, report an average frequency of price change of 0.33 –an implied duration of 3 weeks. The implied duration of a price change found in the data is also close to previous estimates made using consumer price data for Chile. Medina, Rappoport and Soto (2007) analyzing a micro dataset of prices underlying the Chilean CPI find an average duration prices in the food sector of about one month.

In line with results reported for the U.S. and Europe, there is large heterogeneity in the frequencies of price adjustment –both on posted and reference prices– across categories (see Figures 3 and 4). Table II.7 shows that there is also a large variation on both the frequency of reference and posted prices across retail chains. The median reference price does not change at all in two of the retail chains, while it changes every 13 weeks in the highest reference price adjuster. Variation in the frequency of price adjustment across retailers is smaller for reference prices than for posted prices, as we would expect if reference prices capture more permanent, common shocks across retailers. The coefficient of variation of the frequency of reference and posted prices across retailers equals 0.8 and 0.95, respectively.

While frequencies of posted and reference price changes are similar to the figures reported by previous work, the relatively small size of price changes observed in the data suggests that prices are not as flexible as the evidence on frequencies of price adjustment might suggest. The weighted median price change in posted prices equals 2.7 percent (see Column 1 in Table II.8). By way of comparison, Kehoe and Midrigan (2007) and Eichenbaum et al. (2010) report an average size of a price change of about 16-17 percent (the median size of a price change in EJR's data is 12 percent). Kehoe and Midrigan (2007) find that only 25 percent of price changes are smaller than 4 percent. Burstein and Hellwig (2007), also using *Dominick's* data, find an average size of non-zero price changes of 10 percent when excluding temporary markdowns and 13 percent otherwise.

There is little dispersion in the magnitude of posted price changes across retail chains (see Column 1 of Table II.9). Median absolute logged price changes vary between 1 percent and 4.6 percent. The size of price changes exhibits little variation also across categories –the standard deviation across categories equals 1.1 percent (Column 1 of Table II.8).

In contrast to what has been observed in U.S. data, changes in prices of a more permanent nature are larger in magnitude than more transient price changes. Column 2 of Table II.8 shows that the weighted median absolute logged price change across categories equals 4.7 percent (5.7 percent using Eichenbaym et al.'s definition of a reference price). Studies that examine U.S. data document that temporary price changes tend to be substantially larger in size than more permanent price changes. Nakamura and Steinsson (2008), for instance, report that price adjustments associated to sales are about twice as large as regular price changes. Klenow and Kryvtsov (2008) find an average absolute price change of 14 percent in posted prices and 11 percent in regular prices.

2.4.4 Hazard Functions

This subsection turns to examining the behavior of frequencies of price adjustment conditional on the age of a price (i.e. the hazard function). The hazard rate measures the rate at which prices change at time t given that they have remained unchanged until t. Letting T denote a random variable measuring the time since the last price change and t a realization of T, the hazard function, $\lambda(t)$, is defined (in continuous time) as

$$\lambda(t) \equiv \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t | T \geq t)}{\Delta t}$$

Following Klenow and Kryvtsov (2008), I estimate hazard rates as a weighted average of repricing indicators conditional on the price age τ,

$$\lambda_\tau \equiv \frac{\sum_k \sum_s \sum_t \widetilde{\omega}_{ks,t} I\left\{p_{ks,t}^{ref} \neq p_{ks,t-1}^{ref}\right\} I\left\{\tau_{ks,t} = \tau\right\}}{\sum_k \sum_s \sum_t \widetilde{\omega}_{ks,t} I\left\{\tau_{ks,t} = \tau\right\}}$$

where $p_{ks,t}^{ref}$ denotes the reference price of product k in store s at time t and $\widetilde{\omega}_{ks,t}$ correspond to standard expenditure weights (which add up to one across prices in a given week) divided by the number of weeks for which there are prices with determinate ages. In order to control for potential bias arising from censored spells I exclude from the analysis those spells that are either left- of right-censored. Figure II.5a depicts the estimated hazard function for reference prices pooling across all products and stores. The estimated hazard function is roughly decreasing for price ages ranging between 1 and 52 weeks (the range within which most price durations lie) and exhibits a spike at about 26 weeks.

Decreasing hazard rates estimated by pooling across stores and products might be a reflection of heterogeneous unconditional hazards in the sample (see for example Kiefer 1988). In order to account for this possibility, I follow Klenow and Kryvtsov (2008) in adjusting repricing indicators by a fixed effect for each decile of the distribution of unconditional hazards. I first compute unconditional hazards for each product/store, I then assign each series to one decile and finally compute the unconditional hazard for each decile. Letting these fixed effects be denoted by $\gamma_{d(u,s)}$, the adjusted hazards rates are computed as

$$\widehat{\lambda}_\tau \equiv \frac{\sum_k \sum_s \sum_t \widetilde{\omega}_{ks,t} \left[I\left\{p_{ks,t}^{ref} \neq p_{ks,t-1}^{ref}\right\} / \gamma_{d(k,s)}\right] I\left\{\tau_{ks,t} = \tau\right\}}{\sum_k \sum_s \sum_t \widetilde{\omega}_{ks,t} I\left\{\tau_{ks,t} = \tau\right\}}$$

The chart describing the relation between these adjusted hazards rates and the age of the price is presented in Figure II.5b. As expected, the negative slope exhibited by the non-adjusted hazard function is less pronounced once one adjusts for heterogeneity. The adjusted hazard function appears to be essentially flat with a spike about 26 weeks. The estimates hazard functions for posted prices instead of reference prices are qualitatively similar. Unadjusted hazard functions appear to be decreasing, especially for low-duration prices, while adjusted hazards appear to be roughly flat. This pattern of conditional hazards is consistent with evidence reported for the U.S. and Europe (Klenow and Malin, 2010).

2.4.5 Reference Prices and Chain-Level Prices

There is substantial evidence that retail prices tend to be set in two stages: At the chain level and at the store level (Levy, Dutta, Bergen and Venable 1998; Eden and

Jaremski 2009)[15]. As pointed out by Eden and Jaremski (2009), this two-level decision marking process is consistent with the exploitation of economies of scale in information processing and decision making on the part of retail chains.

In this subsection I examine the extent to which reference prices correspond –in the context of multiproduct stores– to those prices set in a centralized fashion with nonreference prices representing departures from chain-level prices by individual stores in response to store-level shocks. A close correspondence between chain-level prices and reference prices would provide additional clues on the determinants of reference price movements. I start by examining the evidence on two-stage price setting.

The median supermarket chain keeps posted prices equal to modal prices 87 percent of the time (see Table II.10). Only in the case of one retail chain, modal prices appear not to be important (posted prices are equal to modal prices only 36 percent of the time); this supermarket chain coincides with the one for which reference prices appear to be unimportant. Thus, evidence is supportive of multi-level pricing decision making in which most price changes are decided at the chain level. The following transition matrix summarizes movements of posted prices to and from modal prices.

$$\begin{array}{c} 1 \\ 0 \end{array} \begin{bmatrix} 0.712 & 0.288 \\ 0.517 & 0.483 \end{bmatrix}$$

Modal prices are significantly less persistent than reference prices. While the typical reference price is changed every 2-3 quarters, the median modal price is changed every 5 weeks or 0.38 quarters (see Table II.11). Thus, the evidence suggests that retail chains not only decide on changes in reference prices at a centralized level but also decide changes in posted prices to and from nonreference prices. It is not the case that nonreference prices correspond to departures from modal prices at a given store. The following conditional probabilities estimated from the data provide more direct evidence on the relation between modal and reference prices:

$$\begin{aligned} prob(p = p^{ref} | p = p^{\text{mod}}) &= 0.782 \\ prob(p = p^{\text{mod}} | p = p^{ref}) &= 0.899 \\ prob(p = p^{ref} | p \neq p^{\text{mod}}) &= 0.219 \\ prob(p = p^{\text{mod}} | p \neq p^{ref}) & \quad 0.409 \end{aligned}$$

Hence, there is roughly a 0.22 probability that conditional on a price being set at a centralized level (i.e. it is a modal price) it corresponds to a nonreference price. Note,

[15]Informal conversations between the author and executives from the Chilean supermarket industry who participated in the price setting process on a regular basis suggest that this practice is also common among Chilean retailers.

however, that knowledge of a price being at the mode makes more likely that a price is a reference price as the unconditional probability of a price being at its reference value is only equal to 0.62 (versus a 0.78 conditional probability).

I examine the extent to which modal prices capture common shocks across retailers estimating a variance components model. I use the following specification

$$Y_{ik} = \mu + \alpha_k + \beta_i + \varepsilon_{ik} \tag{2.1}$$

where Y_{ik} is the frequency of modal price adjustment of good k in chain i, α_k are product-level effects, β_i are chain-effects and ε_{ik} is a disturbance term. I assume that product effects, chain effects and idiosyncratic effects are distributed normal with zero mean and constant variance and estimate the model by maximum likelihood. If modal prices respond primarily to aggregate shocks, originating at the good level, then we would expect the chain effect not to explain a large fraction of the variation in the frequency of modal price changes. The evidence suggest, instead, that the frequency of modal price change has a substantial chain component. The results of the variance decomposition, presented in Table II.12, imply that only 1.5 percent of the variation in the frequencies of modal prices is explained by variation across products, 71 percent of the variation is explained by variation across chains and the remaining 28 percent of the variation in the frequency of modal prices is completely idiosyncratic to a particular product and chain.

2.4.6 Do Reference Prices Respond only to Manufacturer Level Shocks?

This subsection examines the extent to which changes in reference prices capture common shocks across retailers. Nakamura (2008) studies this question for posted prices using a rich cross-section of U.S. retailers. She finds that most of the variation in sales-inclusive prices for a given barcode or Universal Product Code (UPC) can be explained by variation common to stores within chains (but not across chains), suggesting that retailers pricing policies (i.e. intertemporal discrimination) drive most of the variation in retail prices. The question is important from a modeling point of view. Models in macroeconomics, international economics and industrial organization typically assume that price-setters face productivity shocks and preference shocks originating at the manufacturing level (i.e. abstracting from a possible role played by retailers). If retailers pricing policies are important in driving retail prices though, then explaining the movements of retail prices would require introducing a motive for intertemporal price discrimination explicitly (see Guimaraes and Sheedy, 2010, for an example applied to macroeconomics).

I measure the comovement in reference prices across stores using Pearson's correlation coefficient between the reference prices of a given product in any two stores. I estimate correlations using monthly averaged prices and, for computational purposes, I restrict the analysis to the 33 product categories which represent 75 percent of total revenues in the sample[16]. I study this question using the following specification:

$$Corr_{kcl} = \beta_0 + \beta_1 INTRA_l + \sum_{k=1}^{K} \delta_k D_k + \sum_{c=1}^{C} \gamma_c F_c + \varepsilon_{kcl} \tag{2.2}$$

where the dependent variable is Pearson's correlation coefficient between the price of product k in category c between two stores indexed by l. The explanatory variable of interest, $INTRA_l$, is a dummy variable which takes on the value one if the two stores in store-pair l belong to the same retail chain and zero otherwise. The variables D_k and F_c represent product and category dummy variables, respectively. Table II.13 presents the results of estimating the above specification by OLS both using reference prices (Panel A) and posted prices (Panel B). Panel A in Table II.13 shows that comovement between the reference prices of a given product is significantly different when the stores belong to a given retail chain. The correlation coefficient for stores within a chain is about 0.3 higher than for stores that belong to different chains. It increases from about 0.5 in the case of stores belonging to different chains to about 0.8 for stores belonging to the same chain.

Further evidence on the role played by retail chains in the dynamics of reference prices comes from decomposing the variation in the frequency of reference price adjustment. I decompose the variation in the frequency of reference price adjustment using the following specification:

$$Y_{ijk} = \mu + \alpha_k + \beta_i + \gamma_j + \varepsilon_{ijk} \tag{2.3}$$

where Y_{ijk} denotes the frequency of reference price change for product k sold in store j which belongs to retail chain i, μ is a constant term, and α_k, β_i and γ_j represent product, chain and store random effects, respectively, while ε_{ijk} is a disturbance term associated to a particular product, store and chain. As in the previous subsection, I assume that the random coefficients are distributed normal with zero mean and constant variance. The estimation considers only products sold in at least six different retail chains.

The results of estimation of equation 2.3 are presented in Table II.14. Variation across products, while controlling for store and chain effects, is relatively limited. In contrast, 63 percent of the variation in the frequency of reference price changes is driven by chain effects. The fraction of total variation explained by variation across stores within chains is relatively small, which provides further evidence that reference prices tend to be set at the chain level and, more importantly, that reference prices have an important chain-specific component. If reference prices were mainly driven by shocks originating at a previous stage of the distribution chain, then we would expect chain effects to be smaller as frequencies of reference price adjustment would be primarily explained by common shocks across chains. The evidence is, thus, consistent with Nakamura's (2008) findings.

Figure II.6 displays the relation between the frequencies of posted and reference price adjustment at the chain level. Chains that adjust posted prices relatively more frequently also tend to adjust reference prices more frequently. This provides further evidence that the dynamics of reference prices are driven to an important extent by retailer-level effects.

[16] In addition, I use only prices which are available for at least 6 retail chains and for at least 22 months.

2.5 Reference Prices and Reference Costs

The relation between reference prices and reference costs offers further evidence into the nature of the former. As noted in Section 3, cost data are available for two of the retail chains in the primary data set. In one of these cases, the cost data correspond to a measure of replacement costs, and hence reference costs can be meaningfully extracted from the observed cost series. I thus, focus on the data for this particular retailer to examine the behavior of reference costs.

Reference costs share several of the features observed in reference prices. First, posted costs spend most of the time at their reference values. Weekly costs are equal to reference costs in almost 80 percent of the weeks. The typical nonreference cost is lower than the reference value, only about 14 percent of non-reference costs correspond to posted costs that exceed reference costs. The importance of reference costs is similar across categories. The percentage of weekly costs that correspond to reference costs fluctuates between 62 percent ("Whisky") and 88 percent ("Men Fragances").

Second, reference costs are more persistent than posted costs. The implied duration of the median frequency of posted cost changes across categories is about 10 weeks. This is about twice the implied duration of retail prices within the comparable subset of categories (see Columns 1 and 2 in Table II.15). Reference costs, on the other hand, change about every 20 weeks while comparable reference prices change every 30 weeks (see Columns 3 and 4 in Table II.15). Reference prices and costs appear to be as sticky when computed using Eichenbaum et al.'s definition. The frequency of reference prices and costs is about 0.03 under their definition. Third, the frequency of posted and reference cost changes is highly heterogeneous across categories (see Figures 7a and 7b). Fourth, cost changes are small in magnitude. The average change in posted costs equals 1.5 percent, and the average reference cost change equals 2.4 percent. Thus, as in the case of retail prices, changes in reference costs tend to be larger than changes in posted costs (see Table II.16).

Eichenbaum et al. (2010) observe that prices in their data set tend not to change unless costs also change contemporaneously. In contrast, I find that conditional on a posted (reference) cost change, posted (reference) prices change only 33 (6) percent of the time. This might suggest that the retailer tends to delay cost pass-through to retail prices. Consistent with this view, the average markup conditional on a cost change is statistically significantly smaller than the average markup conditional on costs remaining unchanged. The magnitude of the markup differential is however small (on the order of two percentage points), which suggests that prices do respond to an important extent to cost changes (see Table II.17).

Markups appear to be remarkably stable over time. Table II.18 presents the median time-series standard deviation of markups[17] at the category level. The median standard deviation of markups across categories equals 0.047. By way of comparison, Eichenbaum et al. (2010) find a substantially higher markup volatility in the case of the large US retailer they study. They report a time-series standard deviation of markups of 0.11. As can be seen from Table II.18 there is little variation in the markup volatility across categories. The cross-sectional standard deviation of markup volatility equals 0.01. Thus the retailer keeps

[17] The markup of product k in week t is defined as $\mu_{kt} \equiv \ln(P_{kt}/C_{kt})$.

the markups fairly stable over time across different product categories.

The cross-sectional dispersion of markups is similarly modest in magnitude. Due to confidentiality reasons, I am unable to present statistics on the actual level of markups. Evidence on the deviation of the median markup within a category form the average markup across categories is presented in Figure II.8. All markup deviations lie within a +/- 10 percentage points band about the average markup. The standard deviation of markups across categories equals 0.041.

There is evidence that the retailer chooses price duration so as to keep markups within narrow ranges. Eichenbaum et al. (2010) find evidence of this same type of state-dependence in their data. Figure II.9 depicts the relation between the probability of price change and the gap between the current markup and the average reference markup[18]. The figure suggests that the retailer adjusts its price so as to keep the markup close to its average reference level. The probability of a price change conditional on the markup being more than five percentage points apart from the reference markup is about 0.4. When the markup is at the reference level, on the other hand, the probability of the retailer adjusting its price drops to about half that figure (i.e. about 0.2).

2.6 Synchronization of Price Changes

In this section, I turn to examining the degree of synchronization versus staggering in the timing of price changes both across and within stores. Staggering in price adjustment across price-setters has important implications for the effects of aggregate shocks on real variables. Some degree of staggering in price setting decisions is a necessary, though not a sufficient (see Caplin and Spulber, 1987 for an example), condition for a monetary shock to have persistent effects on output. In the case of multiproduct price-setters it is of interest to understand the extent to which staggering occurs across stores versus across products (within stores). As pointed out by Lach and Tsiddon (1996), the two types of staggering have different implications for price dynamics. In addition, evidence on the degree of within store synchronization in price changes can help us discriminate between competing hypothesis about the technology of price adjustments (Sheshinski and Weiss, 1992).

2.6.1 Synchronization within Stores

I start by examining the degree of synchronization of price changes within stores. Prices tend to be synchronized within stores when the technology of price adjustment is characterized by increasing returns as well as when prices have positive interactions in the profit function (Sheshinski and Weiss, 1992). Sheshinki and Weiss (1992) distinguish between "menu costs" and "decision costs" of price changes. While "menu costs" do not change with the number of prices changed, "decision costs" are increasing in the number of adjusted prices. Thus, when the cost of price change take the form of "menu costs" intra-store price adjustments tend to be bunched together. Midrigan (2009) offers a model

[18] Reference markup is defined as $\mu_t^{ref} \equiv \ln(P_t^{ref}/C_t^{ref})$, where P_t^{ref} is the reference price in week t and C_t^{ref} is the reference cost in week t.

of a multiproduct price-setter which exploits this idea to account for the presence of small price changes observed in U.S. data.

Figure II.10 presents the distribution of f_{st}, the fraction of price changes within store s at time t,

$$f_{st} = \frac{\sum_k I\left\{p_{ks,t} \neq p_{ks,t-1}\right\}}{N_{st}}$$

where N_{st} is the number of products sold in store s at time t.There is a large dispersion in the fraction of within store price changes and most of the probability mass is concentrated in values in between zero and one, suggesting that perfect synchronization of price changes within stores is not a feature of the data generating process. One way of assessing the extent of staggering in the data, suggested by Fisher and Konieczny (2000), is to compare the standard deviation of the fraction of price changes to the hypothetical standard deviations that would be observed in the cases of perfect synchronization –in which the price-setter either changes all or none of the prices in a given time period– and uniform staggering –in which the price-setter changes a constant fraction of all prices in every period. In the case of perfect synchronization, the fraction of price changes takes only the values zero or one, and hence its variance is equal to $\overline{f}_s(1-\overline{f}_s)$, where $\overline{f}_s$ is the average proportion of price changes within store s. With uniform staggering, on the other hand, the fraction of price changes takes the same value every period and, hence, its standard deviation is equal to zero. The Fisher-Konieczny index (FK) can be defined as (Dias et al., 2005)

$$FK_s = \sqrt{\frac{1}{T}\frac{\sum_{t=1}^{T}\left(f_{st}-\overline{f}_s\right)^2}{\overline{f}_s\left(1-\overline{f}_s\right)}} = \frac{S_f}{\sqrt{\overline{f}_s\left(1-\overline{f}_s\right)}}$$

where $S_f = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(f_t-\overline{f}_s\right)^2}$is the sample standard deviation of f_{st}. It takes the value of one in the case of perfect synchronization and zero in the case of uniform staggering. Figure II.11 shows the distribution of the FK index for within-store synchronization in posted prices. The results suggest that posted price adjustments are neither perfectly synchronized not are they uniformly staggered within stores. On average, the variance of the within-store fraction of price changes is about 21 percent of the hypothetical variance under perfect synchronization. While there is some dispersion in the FK index across retail chains (see Table II.19), the value of the index is still smaller than 0.22 in the larger retailers (representing above 60 percent of market sales). The degree of staggering in within-store reference price changes is similar to the one observed in posted prices (the average FK index for reference prices equals 0.22).

One interpretation of the lack of evidence supporting within-store price synchronization is that synchronization of price changes occurs at a finer product category level. It might be reasonable to assume that stores are more likely to exploit economies of scope in price setting at the category level than between products belonging to different categories, as products in the same category are usually located in the same aisles within the stores which would presumably reduce the marginal cost of changing a second price within a category (Midrigan, 2009). In addition, it is more likely that products within a category are hit by symmetric shocks.

Figure II.12 presents the distribution of the FK index for within product category price changes. The fraction of price changes f_{cst} that enters the calculation of the index in this case is given by

$$f_{cst} = \frac{\sum_k I\left\{p_{kcs,t} \neq p_{kcs,t-1}\right\}}{N_{cst}}$$

where N_{cst} is the number of products sold within category c in store s at time t. The distribution of the FK index is shifted to the right relative to the distribution of the index for within-store price changes. The average FK index is twice as large as when calculated at the level of the whole store. This suggests that stores tend to synchronize price changes within product categories and is consistent with the view that stores face fixed costs of price adjustment (i.e. "menu costs" as opposed to "decision costs") at the product category level.

Variation in the FK index is essentially explained by both variation across retail chains and product categories. Table II.20a presents the results of estimating the following variance components model by restricted maximum likelihood:

$$FK_{crs} = \mu + \alpha_c + \beta_r + \gamma_s + \epsilon_{crs}$$

where α_c denotes category effects, β_r denotes retail chain effects, γ_s denotes store effects and ϵ_{krs} is a random disturbance term. All variance componentes are assumed to be normally distributed with mean zero and constant variance: $\alpha_c \sim N(0, \sigma_\alpha^2)$, $\beta_r \sim N(0, \sigma_\beta^2)$, $\gamma_s \sim N(0, \sigma_\gamma^2)$ and $\epsilon_{crs} \sim N(0, \sigma_\epsilon^2)$. About three quarters of the total variation in FK is explained by category (42 percent) and retail chain (35 percent) effects. The results suggest that both heterogeneity in idiosyncratic shocks at the category level and heterogeneity in the pricing policies of retail firms influence the degree of synchronization of price changes within categories. The fact that store effects explain about 1 percent of total variance in FK suggests that retail chains make pricing decisions at a centralized level.

There is a higher degree of synchronization of price changes within categories for reference prices. The average FK index in this case is 0.5. This is not surprising, as movements in reference prices are likely to capture common shocks across products and retailers. Interestingly, the importance of retail chain effects in explaining the variation in the synchronization of reference prices within product categories is substantially smaller than in the case of posted prices (see Table II.20b). The fact that most of the variation in the synchronization index for reference price changes is due to "product category effects" suggests that idiosyncratic retailer pricing policies play a weaker role in determining the behavior of reference prices.

2.6.2 Synchronization Across Stores

Figure II.13 presents the empirical distribution of f_{kt}, the fraction of stores changing the price of product k at time t, given by

$$f_{kt} = \frac{\sum_s I\left\{p_{ks,t} \neq p_{ks,t-1}\right\}}{N_{kt}}$$

where N_{ut} is the number of stores selling product u at time t. About a third of stores changes the price of a given product in a given week. The empirical distribution of f_{ut} is centered at 0.31 and exhibits a large dispersion (the standard deviation is equal to 0.19).The distribution of the FK index for across-stores synchronization is displayed in Figure II.14. As in the case of within-store price changes, the evidence does not favor perfect synchronization nor uniform staggering. Percentiles 1 and 99 of the distribution of the FK index are 0.05 and 0.82, respectively. The distribution is centered at 0.31, which suggests that while weekly price changes across stores are more synchronized than within stores, the pattern of price changes across stores appears to adjust more closely to a situation of perfect staggering.

While the FK index is helpful in assessing whether price changes across stores are characterized by perfect synchronization or uniform staggering, it is difficult to interpret when it takes intermediate values between 0 and 1. An alternative approach to assessing the extent to which the price adjustment decisions of different price setters are interdependent involves estimating a discrete choice model (Fisher and Konieczny, 2000; Midrigan, 2009). Letting Y_{ijt} denote a dichotomous variable which takes the value 1 if the price of a given product (the product subindex is omitted for notational convenience) is changed at time t by store j belonging to chain i, the reduced form specification is given by

$$Y_{ijt} = \beta_0 + \beta_1 FRACOWN_{ijt} + \beta_2 FRACOTHER_{ijt} + \zeta_t + \epsilon_{ijt}$$

where $FRACOWN_{ijt}$ is the fraction of other stores within the same chain changing the price of the product at time t; $FRACOTHER_{ijt}$ is the fraction of stores belonging to other chains changing the price of the product in period t, ζ_t denote time effects and ϵ_{srt} is a disturbance term. The results of the probit estimation are presented in Table II.21. The estimation is carried out for monthly aggregated data on reference price changes. The results are consistent with strong synchronization of within-chain synchronization but do not favor across chain synchronization. An increase in the fraction of other stores within the same chain from 0 to 1 is roughly associated to an increase of 0.68 in the probability of a reference price change. The probability of a reference price change actually decreases when the fraction of stores in other chains increases. An increase in the fraction of stores in other chains from 0 to 1 is associated to a fall in the probability of reference price changes of about 0.01. Thus, the evidence is consistent with synchronization in price changes of a given good within price-setters and staggering of price adjustments across price-setters.

2.7 A Model

This section presents a partial equilibrium model in the spirit of Eichenbaum et al. (2010) which is capable of capturing several salient features of the data reported above. As in Eichenbaum et al., it features a monopolistic firm which chooses price plans, consisting of a set of prices. The firm can costlessly change prices within a price plan but must pay a fixed cost in order to choose a new price plan. This specification of the technology of price adjustment can at the same time account for the fact that reference prices act as attractors for the price process and for the fact that nonreference price changes are smaller in magnitude than reference price changes.

Consider a monopolistic firm which produces and sells a single product and faces a demand function

$$q_t = Y p_t^{-\theta}$$

where q_t is the quantity demanded of the good, p_t is the firm's price, Y is a scale parameter, and θ is the price-elasticity of demand. The firm's unit costs c_t are assumed to follow the AR(1) process:

$$\log(c_t) = \rho \log(c_{t-1}) + \epsilon_t$$

where ϵ_t is a disturbance term which is normally distributed with mean zero and variance σ_ϵ^2. Firm's profits are thus given by

$$\pi_t = Y p_t^{-\theta} \left(p_t - c_t\right)$$

As in EJR, the firm chooses a price plan Ω, which is defined as a set of prices p_t. The firm can costlessly change prices within a plan but must incurr a fixed cost ϕ in order to change the plan.

Let s denote the state and $F\left(s'|s\right)$ denote the conditional density of s' given s. Denote by $V\left(\Omega, s\right)$ the value of the firm when there is no change in its price plan, Ω, and the state is s. Let $W(s)$ be the value of the firm when it changes its plan. These two value functions are given by:

$$V\left(\Omega, s\right) = \max_{p\in\Omega}\left[\pi_t\right] + \beta \int \left\{\max\left[V\left(\Omega, s'\right), W(s')\right]\right\} dF\left(s'|s\right)$$

and

$$W(s) = \max_{p\in\Omega',\Omega'} \left\{\pi_t - \phi + \beta \int \left\{\max\left[V\left(\Omega', s'\right), W(s')\right]\right\} dF\left(s'|s\right)\right\}$$

where β is a discount factor.

Calibration and Solution. I simplify the problem by considering only price plans with cardinality two. I solve the model using value function iteration on a grid. Tauchen's (1986) method is used to approximate the process followed by unit costs using a Markov chain. There are six free parameters in the model: $\beta, Y, \theta, \rho, \sigma_\epsilon^2$ and ϕ. I calibrate the model so that a period corresponds to one week. I accordingly set the discount factor

β equal to 0.999. The demand elasticity θ is set at 4 so as to match the average markup assuming that all retailers face the same replacement costs. The values of parameters ρ and σ_ϵ^2 governing the dynamics of unit costs and the cost of price plans adjustment ϕ are chosen so as to match the following moments: The frequency of reference price adjustment; the size of reference price changes; and the standard deviation of weekly markups.

The model is able to capture the coexistence of sticky reference prices and more flexible posted prices. Setting the menu costs, ϕ, at 0.03 the model yields an implied duration of posted and reference prices of 3.5 and 25 weeks, respectively, which matches the durations implied by the data.

2.8 Concluding Remarks

This paper examined evidence on retail price adjustment from a cross-section of Chilean retailers. Patterns of price adjustment are found to be similar to the ones reported for the U.S. in that posted prices revolve about more persistent attractor prices.Posted prices spend most of the time at their reference values and tend to return to their reference values soon after having departed from them. In contrast to retail price behavior observed in the U.S., however, temporary price changes in the data are of a smaller magnitude and they tend not to return to the previous price. One of the paper's main findings is the fact that reference price changes have a significant retailer-specific component. Comovement in the price of a given product across stores is significantly more pronounced when two stores belong to the same retail chain than otherwise. Furthermore, most of the variation in the frequency of reference price changes is explained by variation across chains. This implies that reference price movements are not only explained by productivity and preference shocks originating at the manufacturer level but are also driven by retailers' pricing policies. This is somewhat surprising as one would expect more permanent reference prices to primarily reflect common shocks across retailers. There is also evidence that retail chains tend to set most of their prices in a centralized fashion. These chain-level prices are, however, adjusted significantly more frequently than reference prices.

Evidence of synchronization of reference price adjustment suggests that neither perfect price synchronization (in which either all the stores change the price of a given product in a given period or none of them do) nor uniform staggering (in which a constant fraction of all stores changes prices each period) is supported by the data. There is evidence of within product category synchronization in the timing of price changes which suggests that the technology of price adjustment might be characterized by a fixed cost of changing a given price plus a small marginal cost of changing an additional price within the same product category. Evidence on across-stores price synchronization suggests that prices for a given product tend to be synchronized across stores within chains but not across stores from different chains. The evidence is thus consistent with within price-setter synchronization but staggering across price-setters. Lach and Tsiddon (1996) report a similar finding for Israeli grocery stores.

Chapter 3

Sticky Prices and Intra-National Deviations from the Law of One Price

3.1 Introduction

A long standing question in international finance has to do with the magnitude and determinants of cross-border price differentials. The literature has tipically found that cross-border price differentials are large and larger than price gaps for cities located within national borders (e.g. Engel and Rogers, 1996; Gourinchas, Gopinath, Hsieh and Li, 2010). As pointed out by Parsley and Wei (1996) and Crucini, Shintani and Tsuruga (2010), studying intra-national deviations from the law of one price (LOP) can be helpful in understanding the determinants of cross-border price differentials as the former are not affected by factors associated to crossing an international border such as exchange rate fluctuations and trade policy.

In this paper, I investigate the relation between price stickiness and deviations from the LOP within national borders. I study this question empirically using scanner data from a large supermarket chain in Chile which includes retail prices, wholesale costs and quantities sold for about 10,000 barcodes sold across eight Chilean cities over the period 2002-2006. Crucini et al. (2010) examine the question of how price rigidities are related to deviations from the LOP within borders both theoretically and empirically. They present a stochastic general equilibrium model featuring Calvo pricing and show that a lower degree of price rigidities is associated to larger deviations from the LOP (measured as the volatility of price differentials for a given good). Their empirical analysis which uses data for a number of cities in Japan lends support to the main implications of their model: Variations in LOP deviations are positively related to transportation costs (proxied by geographical distance) and negatively related to the extent of price rigidities.

One advantage of the data analyzed in this paper over the dataset used by Crucini et al. is that prices correspond to a measure of transaction prices. Aside from possible measurement errors, observing changes in posted prices over time allows me to precisely estimate frequencies of price adjustment. In contrast, Crucini et al. use an average price across stores within a given city. One problem with inferring frequencies of price adjustment from average prices is that one might underestimate the frequency of price change if price adjustments implemented in the same period by different stores cancel each other out. More importantly, as Crucini et al. point out, frequencies of price adjustment computed from average city prices are likely to be upwardly biased as larger cities for which a larger number of stores are surveyed are more likely to report a price change in a given month. The authors attempt to correct for this bias by assuming that price-setting decisions are independent across stores, an assumption which might not be borne out in the data. Perhaps the main advantage of Crucini et al.'s dataset over the one I use in this paper is coverage. While Crucini et al.'s dataset includes more than 70 cities in Japan, my data covers only 8 cities in Chile. In addition, my analysis focuses on a single retail chain, which might be unrepresentative of the pricing behavior of retailers as a whole. In Elberg (2010), however, I find evidence that price setting patterns for this retailer are similar to those observed for the typical retailer in the Santiago metropolitan area over the period 2005-2008.

The main result in this paper is supportive of Crucini et al.'s analysis. Results from my baseline specification show that, controlling the distance, the effect of price flexibility (proxied by the frequency of price adjustment) on the variability of relative prices is positive, statistically significant, and economically important. The distance-equivalent of a 0.01 change in the frequency of price change is estimated at 370 kilometers (about 15 times the distance-equivalent estimate found by Crucini et al.).

The rest of the paper is organized as follows. Section 2 provides a a brief literature review. Section 3 describes the data. Section 4 reports evidence on retail and wholesale prices gaps across cities. Section 5 presents evidence on the extent of price stickiness at the retail and wholesale levels. Section 6 presents the main result of the paper. Section 7 concludes.

3.2 Literature Review

There is a vast literature studying the magnitude and determinants of price deviations between geographically distant locations. The typical finding in the literature are large and persistent deviations from the LOP, regardless of whether prices are observed in cities located within or across borders.

Cross-border LOP deviations are, however, found to be more pronounced than within country LOP deviations. The seminal article highlighting the importance of the "border effect" is Engel and Rogers (1996). Studying sectoral price indexes for 14 U.S. cities and 9 cities in Canada they find that price dispersion between cities located in different countries is substantially higher than price dispersion between equally distant cities located within a country. They estimate the distance equivalent of the border at 75,000 miles. Gourinchas, Gopinath, Hsieh and Li (2010) find a significant boder effect using barcode data from a large North American retailer. Engel and Rogers (1996) attribute part of the explanation of the border effect to nominal price stickiness. If prices do not move as rapidly as exchange rates, then relative cross-border prices will tend to exhibit a greater volatility.

The relation between price stickiness and persistence and volatility of cross-border sectoral real exchange rates is formally studied in Kehoe and Midrigan (2007). They show that in an economy featuring Calvo pricing, greater price stickiness is associated to greater conditional volatility and persistence in sectoral real exchange rates. The main quantitative predictions of the model are, however, not borne out in the data. Crucini, Shintani and Tsuruga (2010) is, to my knowledge, the first attempt at examining the relation between sticky prices and intra-national deviations from the LOP. The authors present a general equilibium model in the spirit of Kehoe and Midrigan (2007). The model implies that a higher degree of price flexibility is associated with greater variability in deviations from the LOP across cities. The intuition for this result is straightforward. The higher is the measure of firms changing prices in a given city, the greater is the passthrough from changes in marginal costs to retail prices. With segmented markets, passthrough in other cities will not be as large and, hence, relative prices across cities will tend to be more volatile. Crucini et al (2010) then adapt Engel and Rogers (1996) regression framework to the estimation of the effect of price stickiness on the variability of price differentials across cities. The empirical analysis relies on a micro dataset of prices across cities in Japan. They find strong support for the relation between price stickiness and deviations from the LOP implied by their theoretical model. Goods exhibiting a greater degree of price stickiness tend to present more variation in their relative prices across cities. They estimate the distance equivalent of an fall of 0.01 in the frequency of price change at 24-27 kms.

3.3 Data

The data were provided by a large supermarket chain based in Chile with operations in several countries in South America (Argentina, Chile, Ecuador and Paraguay). The dataset includes weekly retail prices, wholesale costs, and quantities purchased for about 10,000 barcodes sold in eight stores located across eight different cities in Chile over the period 2002-2006[1]. Figure AIII.1 in the Appendix presents a map identifying the geographical location of each city. The maximum distance between two cities in the sample is 2,814 kilometers (Iquique-Puerto Montt) and on average cities are located 986 kilometers apart.

The retailer reports total revenue and number of units sold weekly at the product and store level. Weekly posted prices for a given store and product are then inferred from the relation

$$\text{Total Revenue} = \text{Price} \times \text{Quantity}$$

Posted prices are inclusive of sales (i.e. temporary markdowns) and have not been adjusted for promotions (e.g. "buy two units of an item and pay one"). The retailer does not identify products which are subject to a promotion in a given week and hence, my results on the frequency of price adjustment might overestimate the degree of price rigidities actually present in the data. In many cases, there were missing prices due to stockouts or zero demand for the item in a given week. In those cases, I replaced the price with the first price available for the item at the same store in a later week. I followed the same procedure to deal with missing observations for wholesale costs.

The retailer reports two measure of costs. One is a measure of the weighted average

[1]The cities included in the sample are: Iquique, Coquimbo, Viña del Mar, Santiago, Rancagua, Concepción, Temuco and Puerto Montt.

costs of goods in inventory. The second one, a higher quality measure of costs, corresponds to the current wholesale cost and is treated by the retailer as a measure of replacement costs. This second measure is only available for the period 2002-2003. Beginning in 2004, the retailer changed its cost accounting procedures after being acquired by another retail chain. The results on the frequency of cost adjustments were obtained using exclusively the data on the replacement costs for the period 2002-2003.

Table III.1 presents summary statistics on the main dataset.

3.4 Evidence on Price and Cost Dispersion Across Cities

Let $q_{ki,t}$ denote the price of good k in city i relative to the price of the same good in a benchmark city (Santiago) in week t (in logs),

$$q_{ki,t} = \ln P_{ki,t} - \ln P_{kSantiago,t}$$

Panel A of Table III.2 presents summary statistics on the price deviations of a given product between two cities. The statistics presented in Table III.2 correspond to the median absolute deviation, the mean absolute deviation and the maximum absolute deviation of $q_{ki,t}$ in a given week (week 10 of 2003) computed across products for a given city-pair. The mean absolute deviation of $q_{ki,t}$ is about 0.04. Absolute deviations between cities are similar in magnitude to the ones reported for Canadian cities by Gourinchas et al. (2010), who also study inter-city price deviations using price data from a large supermarket chain. While price gaps between cities provide a measure of transaction costs in integrated markets, they provide only a lower bound for trade costs when cities are segmented (Gourinchas et al., 2010).

In line with what we would expect based on an arbitrage argument, price deviations across cities are found to be smaller at the wholesale level (see Panel B of Table III.2). This is not surprising as goods at the wholesale level are presumably more tradable than those at the retail level. Retail prices include some extra nontradable components such as rents and labor costs. In addition, the volumes involved in wholesale transactions are larger than in the case of retail transactions and hence it is more likely that a given price gap gets arbitraged away.

Further evidence on the role of wholesale costs in driving deviations from the LOP at the retail level comes from decomposing the variation in retail price gaps into variation in cost and markup deviations. We can decompose the change in relative prices into a change in relative cost and relative markups as follows

$$\Delta q_{ki,t} = \Delta \ln \left(\frac{\mu_{ki,t}}{\mu_{kSantiago,t}} \right) + \Delta \ln \left(\frac{C_{ki,t}}{C_{kSantiago,t}} \right) \tag{3.1}$$

The results of a variance decomposition of $\Delta q_{ki,t}$ into its two components[2] reveals that most of the variation (about 60 percent) in relative prices is accounted for by variation in relative markups. This is consistent with the finding that the LOP holds better in the

[2] As in Gourinchas et al. (2010) I attribute half of the covariance between costs and markups to each component.

case of prices at the wholesale level and suggests that the retailer's pricing policies play a relatively important role in explaining price deviations across cities.

3.5 Evidence on Price Rigidities

This section documents the evidence on the rigidity of retail prices and wholesale costs. It is well known that using duration of price spells as measures of price rigidity is problematic due to the presence of censored spells. Thus, following most of the recent literature, I measure price rigidities using the "frequency approach". The frequency of a price change is given by

$$fr_{ki} = \frac{\sum_{t=1}^{T} I\left\{P_{ki,t} \neq P_{ki,t-1}\right\}}{\sum_{t=1}^{T} I\left\{P_{ki,t} \in \Omega_{ki}\right\}}$$

where $I\{\cdot\}$ is an indicator function that takes on the value 1 if its argument is true and zero otherwise and Ω_{ki} is the set of all non-missing prices for good k in city i.

Table III.3 presents summary statistics on the frequency of posted price changes. The median frequency of (retail) price changes equals 0.076 per week, an implied duration of about 13 weeks. The distribution of frequencies of price adjustment across products and stores exhibits a long right tail. The average frequency of price changes is equal to 0.13 per week, which implies a price duration of 7.7 weeks. Posted retail prices appear to be more rigid than reported by previous studies of retail price setting focusing on North American retailers. Eichenbaum, Jaimovich and Rebelo (2010), for instance, report an implied duration of 2-3 weeks for the median retail price. In line with results previously reported in the literature, price rigidity in retail prices is highly heterogeneous across categories. Figure III.1a shows the average frequency of price changes by category. The standard deviation of the frequency of price changes across categories is 0.06.

Wholesale costs are slightly more rigid than retail prices. The median (mean) frequency of price adjustment at the wholesale level equals 0.06 (0.1) which implies a duration of about 17 (10) weeks for the median (mean) cost. As in the case of retail prices, there is a large heterogeneity in the frequency of cost changes across categories (see Figure III.1b).

3.6 Price Rigidities and LOP Deviations

This section turns to examining the relation between volatility in relative prices across cities and price rigidities. The baseline specification is similar to the one estimated by Crucini et al. (2010)

$$V\left(q_{ik,t}\right) = \alpha + \beta \ln Dist_i + \gamma fr_k + \sum_{i=1}^{N} \delta_i D_i + \epsilon_{ik} \tag{3.2}$$

where $V\left(q_{ik,t}\right)$ is the time variation in the relative price of good k between city i and the benchmark city (Santiago), $\ln Dist_i$ is the natural logarithm of distance (in kilometers) between city i and the benchmark city, fr_k is the frequency of price change per week, D_j are city dummies, and ϵ_{ik} is a disturbance term.

Table III.4 presents the results of the OLS estimation of Equation 3.2. The results are supportive of the hypothesis that price rigidities are important in explaining the variation in deviations from the LOP at the retail level (see Panel A in Table III.4). The coefficient on the frequency of price change is both highly statistically significant and has the expected sign. Less rigid prices are associated to larger variations in relative prices across cities. Furthermore, the estimated coefficient on the frequency of price change variable is important economically. A measure of the importance of this variable is the "distance equivalent" of a given change in the frequency of price adjustment. An estimate of the distance equivalent of a reduction of 0.01 in the frequency of price adjustment, $\widehat{\Delta}$, can be obtained as the solution to

$$\widehat{\beta}\ln\left(\overline{Dist}\right)+\widehat{\gamma}\overline{fr}=\widehat{\beta}\ln\left(\overline{Dist}+\widehat{\Delta}\right)+\widehat{\gamma}\left(\overline{fr}-0.01\right)$$

or

$$\widehat{\Delta}=\overline{Dist}\left[\exp\left(0.01\widehat{\gamma}/\widehat{\beta}\right)-1\right] \tag{3.3}$$

where $\overline{Dist}$ and $\overline{fr}$ are the average distance and frequency of price change, respectively. The estimated distance equivalent of a 0.01 reduction in the frequency of adjustment of retail prices is equal to 370 kilometers. This is substantially larger than the implied distance equivalent found by Crucini et al. (2010) for price stickiness across Japanese cities –between 24 and 27 kilometers.

Results for prices at the wholesale level are qualitatively similar to the ones reported for retail prices (see Panel B in Table III.4). Both distance and frequency of price changes are statistically significant and have the expected sign a priori. While smaller, the magnitude of the effect of price rigidities on LOP deviations is still large. The distance equivalent of a 0.01 reduction in the frequency of price change is equal to 196 kms.

3.6.1 Estimations by Category

Table III.5 presents the results of estimating the baseline specification at the category level. The results confirm that goods exhibiting a greater degree of price rigidity tend to present smaller deviations from the LOP. In 33 out of 48 categories the coefficient associated to the frequency of price adjustment is positive and significant at the 5 percent level. More importantly, the magnitude of the effect of price stickiness is economically non-negligible. The median and average distance-equivalent of a 0.01 reduction in the frequency of price change, $\widehat{\Delta}$, equal 105 kms. and 294 kms, respectively. The dispersion in the distance equivalent of a change in price rigidity is, however, large. The 5th and 95th percentiles of $\widehat{\Delta}$ equal 26 kms. and 447 kms., respectively.

3.7 Conclusions

This paper has examined the relationship between price rigidities and LOP deviations in the intra-national context using highly disaggregated barcode data. The results show that, controlling for transportation costs (proxied by geographical distance), more rigid prices are associated to lower deviations from the LOP both at the retail and wholesale level. The effect of price rigidities on relative price variability is found to be large. The effect of a 0.01 increase in the average frequency of price adjustment on the variability of LOP deviations is equivalent to an increase of 370 kms. in the average distance between cities. The results are qualitatively similar to those found by Crucini et al. (2010) in their analysis of intra-national price deviations in Japan.

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Table I.1. Descriptive Statistics

No. of Observations	5,902,178
No. of Cities	11
No. of Stores	982
No. of Products	79
Summary Statistics for Prices (in levels)	
Mean	15.4
Median	12.5
St. Dev.	15.0
Minimum	2.9
Maximum	107.2

Notes: Cities in the sample include Guadalajara, Merida, Mexico City, Monterrey, Morelia, Oaxaca, Puebla, Queretaro, Toluca, Veracruz and Villahermosa (Figure I.A1 presents a map showing their location within Mexico). Prices expressed in current Mexican pesos. The average exchange rate for the period 2001-2007 is 10.54 MXN/US$. Table AI.1 provides a description of the goods in the sample.

Table I.2. Deviations from the Law of One Price

	Median (1)	MAD (2)	Standard Deviation (3)
Mean	-0.0003	0.0392	0.0428
Median	0.0006	0.0347	0.0389
Standard Deviation	0.0329	0.0227	0.0214

Notes: Statistics in columns (1)-(3) are calculated for a given good and week across city-pairs. Statistics across rows are capture variation across goods and weeks. MAD (Column 2) refers to the mean absolute deviation.

Table I.3. Distance and Price Gaps between Cities

	$\lvert q_{ik,t} \rvert = \alpha_k + \delta_i + \beta \log Dist_i + \varepsilon_{ik,t}$	
	(1)	(2)
$\log Dist_i$	0.0061	0.0035
	(0.0004)***	(0.0001)***
City fixed effects	Yes	Yes
Good fixed effects	No	Yes
R-sq	0.52	0.57
No. of Observations	265,963	265,963

Notes: Distance calculated using the greater circle method. Robust standard errors in parenthesis.
*** significant at 1% level.

Table I.4. Distance and Price Dispersion

	$\sigma_{ik} = \alpha_k + \delta_i + \beta \log Dist_i + \varepsilon_{ik}$	
	(1)	(2)
$\log Dist_i$	0.0068	0.0085
	(0.0003)***	(0.0005)***
City fixed effects	Yes	Yes
Good fixed effects	No	Yes
R-sq	0.89	0.97
No. of Observations	790	790

Notes: Distance calculated using the greater circle method. Robust standard errors in parenthesis.
*** significant at 1% level.

Table I.5. Convergence to the Law of One Price

$$q_{ik,t} = \alpha_{ik} + \sum_{j=1}^{p_k} \rho_{ikj} q_{ik,t-j} + \varepsilon_{ik,t}$$

Good	Half-life (1)	$\sum_{j=1}^{p_k} \rho_{ikj}$ (2)	$\left\| \alpha_{ik} / \left(1 - \sum_{j=1}^{p_k} \rho_{ikj} \right) \right\|$ (3)	p_k (4)
1	4.34	0.84	0.01	2
2	3.86	0.81	0.00	1
3	4.83	0.81	0.00	2
4	3.51	0.80	0.00	2
5	3.37	0.80	0.01	2
6	2.91	0.77	0.00	1
7	2.30	0.78	0.01	3
8	2.38	0.71	0.01	1
9	2.98	0.77	0.01	1
10	4.20	0.79	0.00	1
11	3.08	0.78	0.00	2
12	2.77	0.80	0.00	3
13	2.35	0.72	0.00	1
14	3.42	0.80	0.00	1
15	5.92	0.85	0.00	1
16	2.88	0.78	0.01	2
17	3.13	0.76	0.01	1
18	3.14	0.80	0.00	2
19	3.66	0.81	0.00	2
20	3.06	0.74	0.00	1
21	3.21	0.80	0.00	2
22	4.07	0.79	0.01	1
23	3.30	0.82	0.00	3
24	2.49	0.74	0.01	1
25	3.58	0.83	0.00	2
26	4.13	0.86	0.00	3
27	2.62	0.76	0.00	2
28	2.89	0.77	0.01	1
29	2.81	0.80	0.00	2
30	3.02	0.79	0.01	1

Table I.5 (cont.) Convergence to the Law of One Price

Good	Half-life	$\sum_{j=1}^{p_k} \rho_{ikj}$	$\left\lvert \alpha_{ik} / \left(1 - \sum_{j=1}^{p_k} \rho_{ikj}\right) \right\rvert$	p_k
	(1)	(2)	(3)	(4)
31	3.29	0.79	0.00	1
32	2.96	0.77	0.00	1
33	3.10	0.77	0.01	1
34	3.03	0.78	0.00	1
35	3.15	0.80	0.00	2
36	3.41	0.75	0.01	1
37	11.48	0.93	0.00	2
38	9.77	0.93	0.00	2
40	3.17	0.78	0.01	2
41	2.54	0.77	0.01	2
42	3.09	0.78	0.01	1
43	3.93	0.82	0.01	1
44	3.39	0.82	0.00	2
45	3.10	0.77	0.00	1
46	2.97	0.79	0.01	2
47	3.80	0.80	0.01	1
48	3.51	0.80	0.00	2
49	2.92	0.79	0.00	2
50	3.59	0.82	0.00	2
51	5.79	0.87	0.00	2
52	2.91	0.79	0.01	2
53	3.03	0.77	0.01	1
54	2.68	0.75	0.01	1
56	3.08	0.74	0.01	1
58	2.88	0.79	0.01	2
59	2.95	0.83	0.00	3
60	3.12	0.79	0.00	2
61	2.12	0.70	0.01	1
62	3.17	0.81	0.00	2

Table I.5 (cont.) Convergence to the Law of One Price

Good	Half-life	$\sum_{j=1}^{p_k} \rho_{ikj}$	$\left\| \alpha_{ik} / \left(1 - \sum_{j=1}^{p_k} \rho_{ikj}\right) \right\|$	p_k
	(1)	(2)	(3)	(4)
63	2.55	0.73	0.01	1
64	3.50	0.80	0.00	1
65	2.82	0.73	0.01	1
66	2.77	0.77	0.01	1
67	3.66	0.80	0.01	2
68	3.19	0.81	0.01	2
69	3.62	0.83	0.00	2
70	2.70	0.78	0.00	2
71	3.38	0.77	0.01	1
72	3.88	0.84	0.00	2
73	2.66	0.77	0.01	2
75	2.88	0.79	0.01	2
76	3.15	0.83	0.00	3
77	2.64	0.79	0.00	3
78	3.47	0.77	0.00	1
79	3.48	0.83	0.00	2
80	3.54	0.79	0.00	1
81	3.20	0.78	0.01	1
82	3.71	0.79	0.01	1
83	2.77	0.77	0.01	2
Mean	3.44	0.79	0.01	1.63
Median	3.14	0.79	0.00	2.00
St. Dev.	1.34	0.04	0.00	0.64

Notes: Estimates of persistence were obtained using a SURE model. The half-life of a shock to the Law of One Price is computed using the estimated impulse response function. The optimal number of lags was obtained using the Akaike criterion. All figures correspond to averages across city-pairs. Table A1 lists all the goods in the sample.

Table I.6. Monte Carlo Experiments on Temporal Aggregation

Data generating process:

T/K	Half-lives K=4	Half-lives K=13	Bias Factor K=4	Bias Factor K=13
50	2.50	1.72	2.48	5.46
100	2.48	1.44	2.43	4.54
150	2.48	1.34	2.42	4.22
300	2.50	1.28	2.42	4.02

Notes: Results based on 2500 draws from an AR(p) process calibrated to match estimated coefficients for the median good: $(p, \rho_1, \rho_2, \alpha, \sigma_\varepsilon) = (2, 0.717, -0.001, 0.022)$. Bias factor calculated as the ratio between the median half-life estimated using aggregated data and the median half-life using disaggregated data.

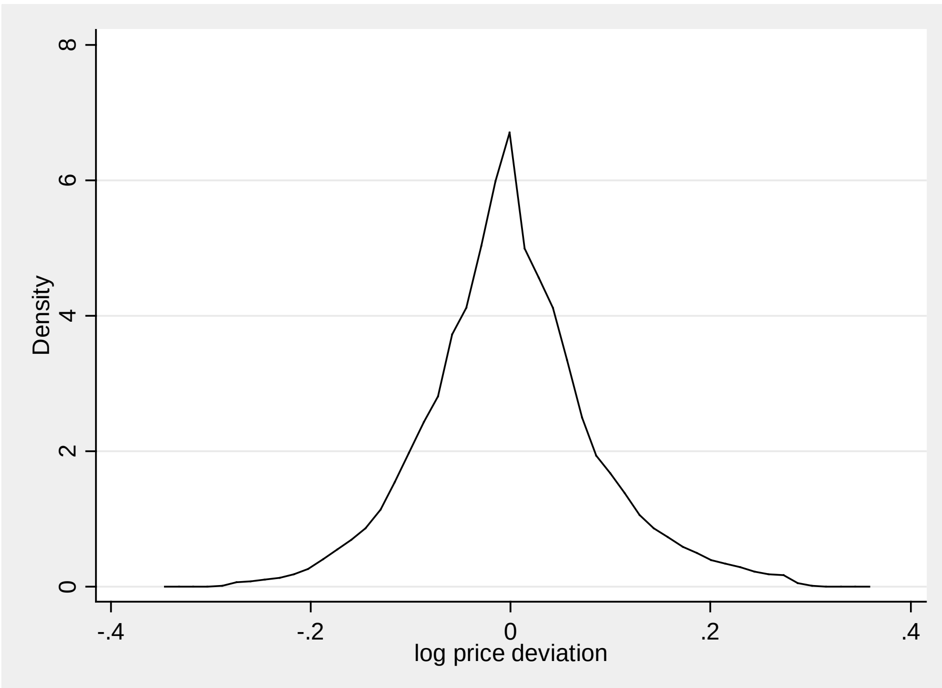
Table I.7. Heterogeneity Bias

$$q_{kt} = \alpha_k + \sum_{j=1}^{p} \rho_{kj} q_{kt-j} + \varepsilon_{kt}, \ k = 1,\ldots,K; t = 1,\ldots,T$$

City	p (1)	Disaggregated Estimation: Half-life (average) (2)	Aggregate Estimation: Half-life (3)	Bias Factor (4)
Guadalajara	13	3.58	4.01	1.12
Merida	25	5.56	3.91	0.70
Monterrey	21	4.30	3.58	0.83
Morelia	25	2.91	1.89	0.65
Oaxaca	24	3.01	2.86	0.95
Puebla	22	2.99	3.37	1.13
Queretaro	19	2.69	2.73	1.02
Toluca	9	2.88	2.52	0.87
Veracruz	26	3.49	2.71	0.78
Villahermosa	25	2.08	1.45	0.70

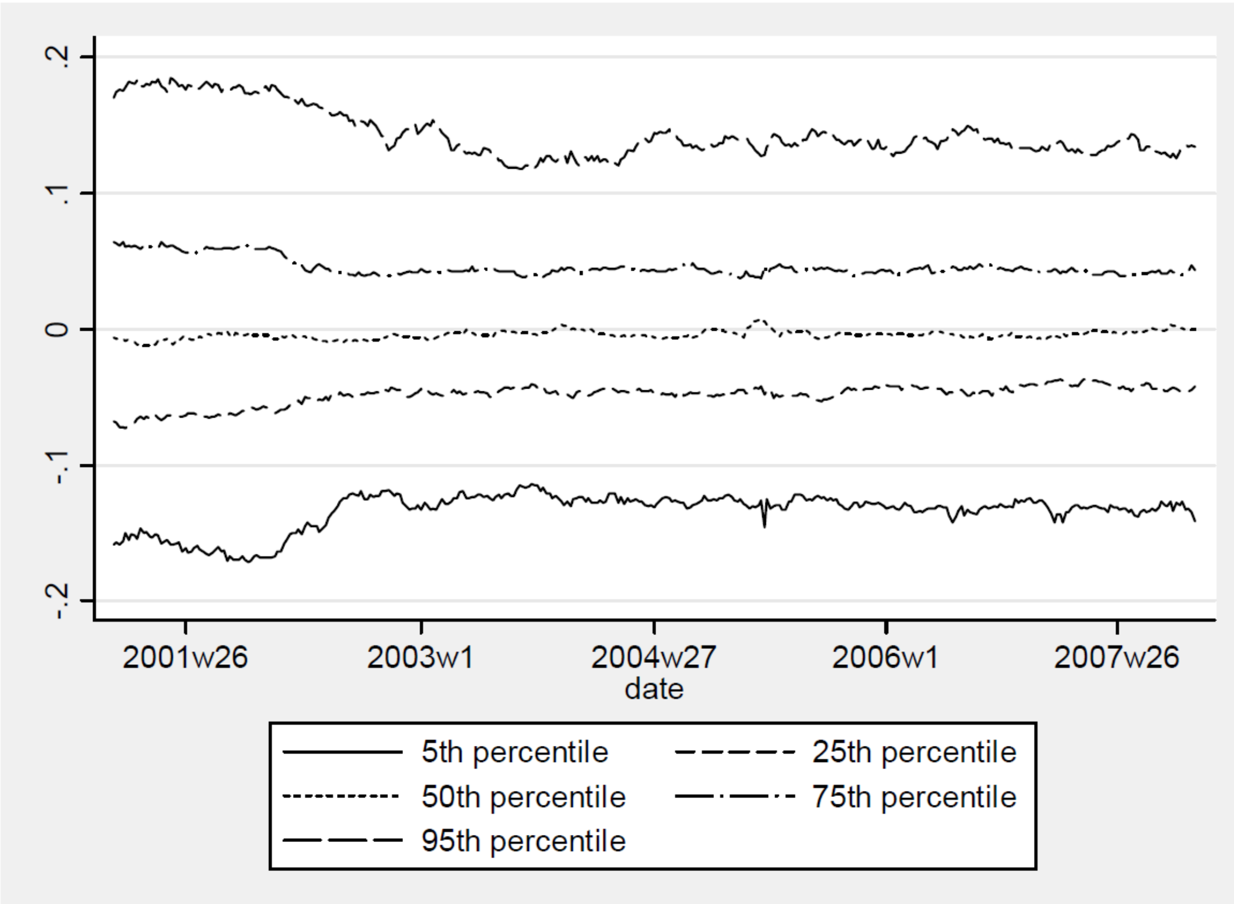
Notes: Truncation lags (p) were obtained from a general-to-specific method with a maximum of 26 lags. Average half-lives from heterogeneous persistence coefficients correspond to the average half-life across goods for a given city. Estimations were performed using the SURE estimator. Estimation of persistence pooling across goods were performed using a fixed effects estimator. The bias factor corresponds to the quotient between the half-life obtained from pooling across goods and the average half-life obtained when allowing for persistence to vary across goods.

Figure I.1. Distribution of (log) Price Deviations



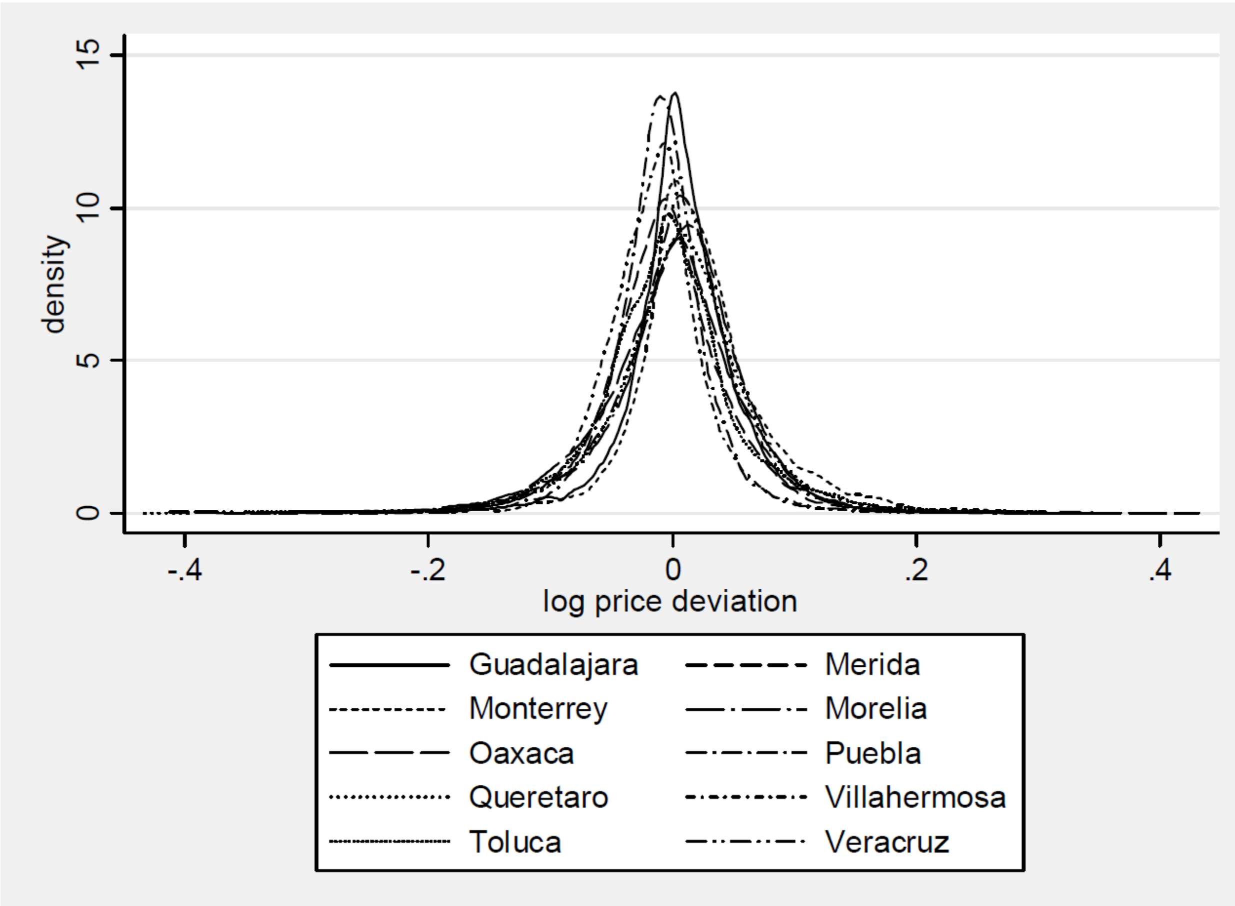
Notes: Price deviations calculated as the difference in the log price of good k in week t (collected at a given store) and the average price of good k in week t across all stores in the sample. The distribution pools all price differentials across goods, stores and weeks.

Figure I.2. Distribution of (log) Price Deviations Over Time



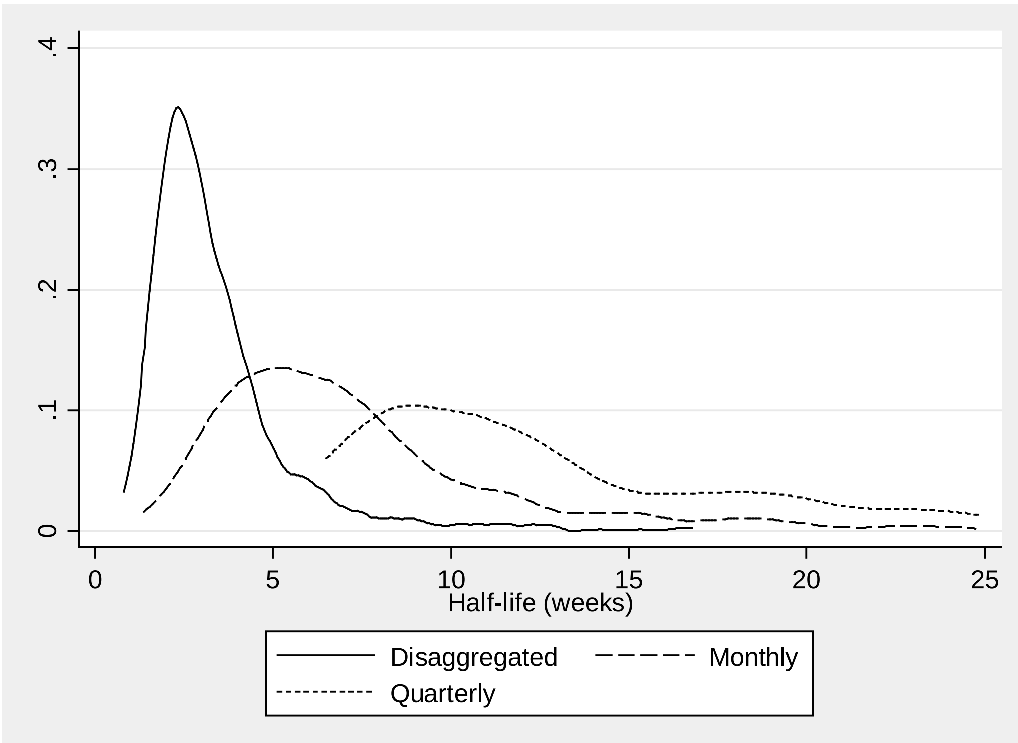
Notes: Price deviations calculated as the difference in the log price of good k in week t (collected at a given store) and the average price of good k in week t across all stores in the sample.

Figure I.3. Distribution of (log) Price Deviations by City



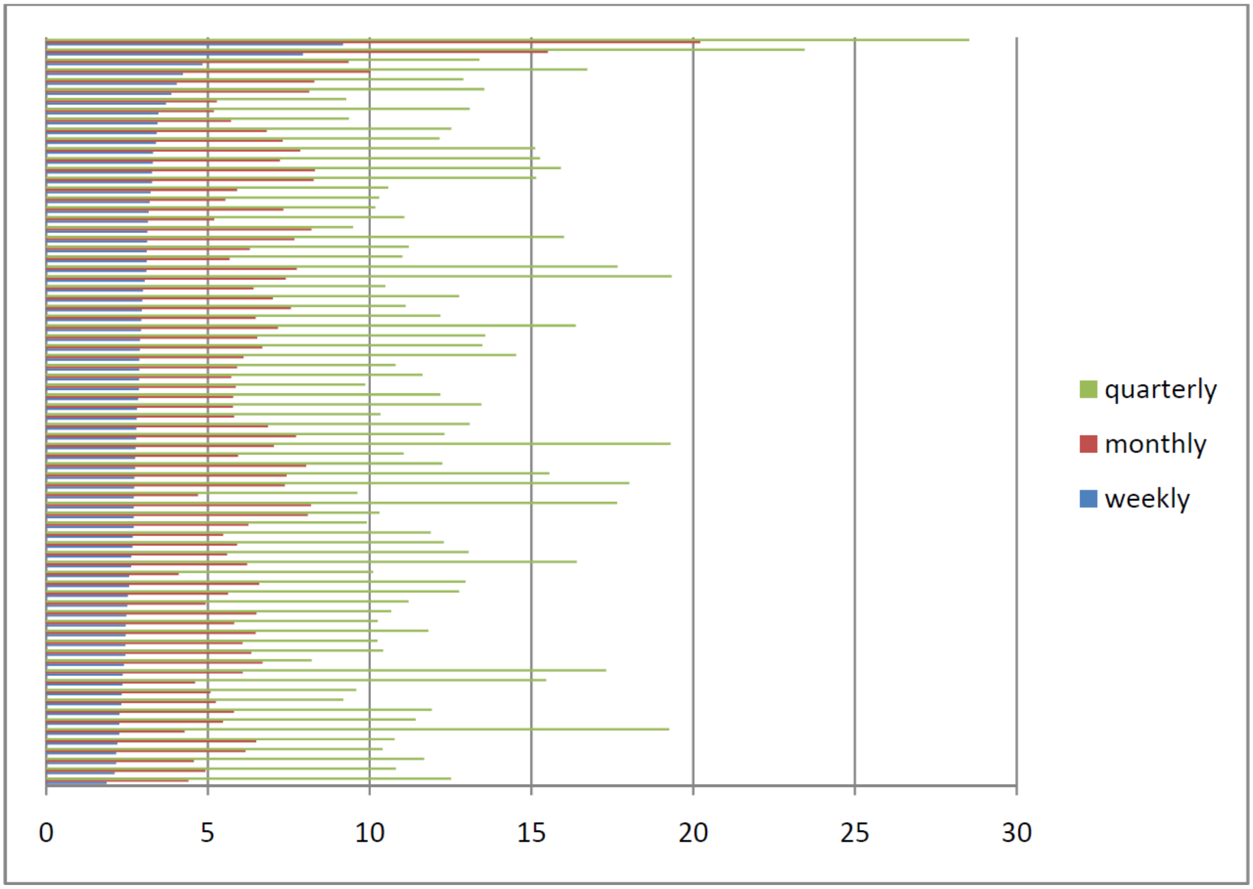
Notes: Price deviations calculated as the difference in the log price of good k in week t (collected at a given store) and the average price of good k in week t across all stores in the sample. The distribution pools all price differentials across goods, stores and weeks in each city.

Figure I.4. Effects of Temporal Aggregation on Estimated Half-lives



Notes: Half-lives calculated from the estimated impulse response function. Half-lives with temporally disaggregated data correspond to estimates of half-lives using weekly sampled prices. Half-lives for monthly and quarterly aggregated data obtained using 4- and 13- period nonoverlapping price averages.

Figure I.5. Effects of Temporal Aggregation on Estimated Half-Lives by Good



Notes: Half-life for each good computed as the median across city pairs.

Table II.1 Product Categories included in the Sample

1	CLOTH STAIN REMOVER	36	CHAMPAGNE	71	SUN FILTERS
2	BABY ACCESSORIES	37	CHANCHACAS	72	BABY FORMULAS
3	CAT AND DOG ACCESSORIES	38	CIGARETTES	73	MATCHES
4	VEGETABLE OIL	39	KITCHENETTES	74	WOMEN FRAGRANCES
5	AGENDAS	40	COCKTAIL	75	MEN FRAGANCES
6	WATER	41	DOG AND CAT FOOD	76	BABY FRAGANCES
7	CHILLI SAUCE	42	FOOD CANS	77	FROZEN FOOD
8	SWEET BISCUITS	43	CONVENIENCE FOOD	78	CANNED FRUITS
9	LIGHTBULBS	44	FOOD PRESERVATIVES	79	COOKIES AND CHOCOLATES
10	CLOTH STIFFENER	45	LIQUID PAPER	80	CLOTH HANGERS
11	RICE	46	COSMETICS	81	GUM
12	PERSONAL CARE	47	COTTON SWABS	82	SYNTHETIC GLOVES
13	VACUUM CLEANER	48	COFFEE CREAM	83	FROZEN HAMBURGERS
14	PORTABLE AUDIO	49	MILKCREAM	84	FLOUR
15	SUGAR	50	FACIAL CREAM	85	ICECREAM
16	HAIR CONDITIONER	51	SHAVING CREAM	86	ELECTRIC WATER BOILER
17	SODA	52	BABY RASH CREAM	87	HERBS AND SPICES
18	SHOE POLISHER	53	HAND AND BODY CREAM	88	CHLORINE (BLEACH)
19	CAKES	54	NOTEBOOKS	89	RAZOR BLADES
20	SKETCH NOTEBOOKS	55	FOOTCARE	90	MICROWAVES
21	BALL PEN	56	DEPILATORY ITEMS	92	PRINTERS
22	KITCHEN PANS	57	HOME SPRAY	93	INSECTICIDE
23	TRASH BAGS	58	DEODORANTS	94	CLOTH WASHING SOAP
24	COFFEE	59	CLOTHES DETERGENT	95	TOILET SOAP
25	COLOR PENCILS	60	FRUIT CANDIES	96	FLAVORED JUICE POWDER
26	BROTH	61	LIGHTERS	97	TOYS
27	AUDIO CAR	62	SWEETENER	98	KETCHUP
28	SWEETS	63	ENERGY DRINKS/ NECTARS	99	WASHING MACHINES
29	SAUSAGES	64	MOUTH WASH ITEMS	100	DISH WASHER
30	TOOTHBRUSH	65	FOOD PLASTIC CONTAINERS	101	CONDENSED MILK
31	WAX	66	STEREOS	102	POWDER MILK
32	CEREAL BAR	67	SPECIFIC MEDICINES	103	MILK CREAM
33	BREAKFAST CEREAL	68	SHOE SPONGES	104	PULSES
34	PROCESSED CEREAL	69	EXTRACTS AND ESSENCES	105	BAKERS YEAST
35	BEER	70	PASTA	106	OFFICE SUPPLIES

Table II.1 Product Categories included in the Sample (cont.)

107 COGNAC	142 PREMIUM FISH	177 FEMENINE PADS
108 GIN LIQUOR	143 BATTERIES	178 BABY WIPES
109 RON LIQUOR	144 PISCOS	179 KITCHEN UTENSILS
110 VERMOUTH LIQUOR	145 ELECTRIC IRON	180 CANNED VEGETABLES
111 VODKA	146 CHICKEN	181 CANDLES
112 HOME CLEANING ITEMS	147 BAKING POWDER	182 FROZEN VEGETABLES
113 FLOOR CLEANING ITEMS	148 POWDER DESSERTS	183 BULK FROZEN VEGETABLES
114 TOILET CLEANING ITEMS	149 FIRST AID ITEMS	184 BULK VEGETABLES AND FRUITS
115 FURNITURE POLISHER	150 CAR CARE ITEMS	185 VINEGAR AND LEMON
116 BUTTERSCOTCH	151 FEMENINE CARE ITEMS	186 WINES
117 BUTTER	152 MASHED POTATO	187 STEEL DISH CLEANER
118 LOWFAT BUTTER	153 CHEESE	188 STEEL FLOOR CLEANER
119 MARGARINE	154 REFRIGERATOR	189 WHISKY
120 FROZEN SEAFOOD	155 DVD PLAYER	190 YOGHURT
121 CANNED SEAFOOD	156 MILK FLAVORING	
122 FROZEN PASTA AND DOUGH	157 JUICE MAKER	
123 MAYONNAISE	158 SALT	
124 MARMALADE	159 TOMATO SAUCE	
125 MIX FOR CAKES	160 SWEET SAUCE	
126 MONITORS	161 SAUCE AND DRESSING	
127 MUSTARD	162 DENTAL THREAD	
128 FRUIT JUICES	163 NAPKINS	
129 POTS AND PANS	164 SHAMPOO HAIRCARE	
130 BREAD	165 SNACKS	
131 DIAPERS	166 SOUPS AND CREAMS	
132 DISHCLOTH AND SYNTHETIC FABRICS	167 STYLING AND FIXERS	
133 DISPOSABLE HANDKERCHIEF	168 CLOTH SOFTENER	
134 TOILETTE PAPER	169 NUTRITIONAL SUMPLEMENTS	
135 BABYFOOD	170 BABYPOWDER	
136 TOOTHPASTE	171 PREPAID PHONE CARDS	
137 TURKEY	172 TEA	
138 ADHESIVES	173 ICED TEA	
139 NEWSPAPERS	174 TV	
140 FROZEN FISH	175 WATERCOLORS	
141 GENERIC FISH	176 HAIR DYE	

Table II.2 Primary Sample: Descriptive Statistics

	2005	2006	2007	2008
No. of obs.	7,115,400	24,564,368	19,750,927	5,797,261
No. of stores	89	107	158	157
No. of chains	10	10	11	11
No. of barcodes	18,242	23,348	21,114	6,236
	Price Statistics			
Average	965.0	974.2	1,022.9	1,056.6
Median	659.0	685	724.5	773.3
Standard dev.	1,060.4	1056.0	1,066.8	1,045.1
	Quantity Statistics			
Average	46.7	43.2	42.7	47.0
Median	15.0	15.0	15.0	17.0
Standard dev.	135.3	123.4	118.0	125.7

Notes. The sampling period spans weeks 34 of 2005 to week 24 of 2008. Retail chains included in the sample are: Bandera Azul, Ekono, Jumbo, Las Brisas, Lider, Maicao, Montecarlo, Montserrat, OK Market, Puerto Cristo, Ribeiro, Santa Isabel and Unimarc. Price statistics are expressed in nominal Chilean pesos.

Table II.3 Secondary Sample: Descriptive Statistics

No. of obs.	5,802,369
No. of barcodes	3,063
No. of categories	34
	Cost Statistics
Average	753.5
Median	567.0
Standard dev.	711.6

Notes. Cost data come from a single retail chain. The data covers the period spanned between weeks 30 of 2005 and week 24 of 2008. Cost statistics are expressed in nominal Chilean pesos.

Table II.4 Importance of Reference Prices

Fraction of Posted Prices At, Below and Above Reference Prices

	Chahrour's Definition			EJR's Definition		
Chain	At Reference (%)	Below Reference (%)	Above Reference (%)	At Reference (%)	Below Reference (%)	Above Reference (%)
B. Azul	76.1	20.8	3.1	77.6	16.3	6.1
Economax	82.1	16.3	1.6	83.3	12.8	3.9
Ekono	80.3	17.4	2.4	79.1	10.9	10.0
Jumbo	27.9	58.9	13.2	28.9	54.9	16.1
Lider	72.0	24.4	3.6	75.2	13.8	10.9
Maicao	86.9	10.9	2.2	87.7	7.2	5.1
Montserrat	76.6	20.7	2.7	77.4	15.5	7.0
Pto. Cristo	79.1	18.8	2.2	79.9	12.4	7.7
Ribeiro	72.4	23.8	3.8	73.2	19.0	7.8
Santa Isabel	66.4	28.6	5.0	67.3	22.2	10.5
Unimarc	61.1	32.8	6.1	61.4	29.4	9.2
Pool	62.0	32.1	5.9	63.5	25.7	10.8

Notes. Chahrour's definition of reference prices is based on an algorithm that identifies a reference price as the most quoted price in a rolling window of 13 weeks centered in the current week. See the Appendix to Chahrour (2009) for a full description of the algorithm. EJR stands for Eichenbaum, Jaimovich and Rebelo (2010) who define a reference price as the most quoted price in a given calendar quarter.

Table II.5 Importance of Reference Prices

Fraction of Total Revenue Made at Reference Prices, by Chain

	Chahrour's Definition			EJR's Definition		
Chain	At Reference (%)	Below Reference (%)	Above Reference (%)	At Reference (%)	Below Reference (%)	Above Reference (%)
B. Azul	64.6	30.4	5.0	64.4	9.1	26.5
Economax	65.1	31.3	3.6	66.7	7.4	25.8
Jumbo	19.4	65.9	14.7	20.4	19.1	60.6
Lider	61.4	33.0	5.6	66.3	14.6	19.1
Maicao	83.4	14.2	2.4	83.1	6.2	10.7
Montserrat	60.9	34.8	4.3	63.1	10.6	26.3
Pto. Cristo	64.9	30.9	4.2	67.0	11.8	21.2
Ribeiro	58.5	36.2	5.3	59.8	10.3	29.8
Santa Isabel	47.5	44.9	7.6	49.7	15.1	35.2
Unimarc	44.4	47.3	8.2	45.1	12.0	42.9
Pool	41.9	48.7	9.4	44.2	40.2	15.6

Note: Computations are made for the shorter period mid 2005- mid 2007 for which quantity data is available for all the stores. Chahrour's definition of reference prices is based on an algorithm that identifies a reference price as the most quoted price in a rolling window of 13 weeks centered in the current week. See the Appendix to Chahrour (2009) for a full description of the algorithm. EJR stands for Eichenbaum, Jaimovich and Rebelo (2010) who define a reference price as the most quoted price in a given calendar quarter.

Table II.6 Frequency of Price Change

Summary Statistics Across Product Categories

	Posted		Reference (Chahrour)		Reference (EJR)	
	(1) Frequency	(2) Duration	(3) Frequency	(4) Duration	(5) Frequency	(6) Duration
Median	0.279	3.583	0.029	40.000	0.026	38.987
Mean	0.357	2.802	0.030	33.526	0.024	41.568
Weighted mean	0.294	3.402	0.040	25.000	0.032	31.183
Standard dev.	0.233	--	0.020	--	0.014	--

Note. The weighted median is obtained using the weights corresponding to the period mid 2005-mid 2007, for which quantity data is available for all stores. Statistics are computed for the median frequency across categories. Duration corresponds to "implied duration" computed as the reciprocal of the frequency of price change. Chahrour's definition of reference prices is based on an algorithm that identifies a reference price as the most quoted price in a rolling window of 13 weeks centered in the current week. See the Appendix to Chahrour (2009) for a full description of the algorithm. EJR stands for Eichenbaum, Jaimovich and Rebelo (2010) who define a reference price as the most quoted price in a given calendar quarter.

Table II.7 Frequency of Price Changes by Chain

Chain	Posted Prices		Reference Prices (Chahrour)		Reference Prices (EJR)	
	(1) Frequency	(2) Implied Duration	(3) Frequency	(4) Implied Duration	(5) Frequency	(6) Implied Duration
Bandera Azul	0.200	5.000	0.016	62.000	0.000	--
Economax	0.074	13.500	0.000	--	0.000	--
Ekono	0.161	6.200	0.032	31.000	0.032	31.000
Jumbo	0.843	1.186	0.077	13.000	0.053	19.000
Lider	0.165	6.057	0.037	26.800	0.030	33.000
Maicao	0.080	12.550	0.000	--	0.000	--
Montserrat	0.100	10.000	0.021	48.000	0.016	64.000
Puerto Cristo	0.098	10.250	0.027	37.000	0.020	50.000
Ribeiro	0.212	4.714	0.023	43.000	0.016	63.000
Santa Isabel	0.250	4.000	0.036	28.000	0.029	34.000
Unimarc	0.375	2.667	0.033	30.500	0.024	42.000
Median	0.165	6.057	0.027	37.000	0.020	50.000
Mean	0.233	4.300	0.027	36.395	0.020	50.020
St. Dev.	0.221	--	0.021	--	0.016	--

Notes. Frequency corresponds to the median frequency across chains of the frequency calculated at the barcode/store level. Implied duration computed as the reciprocal of frequency and expressed in weeks. Chahrour's definition of reference prices is based on an algorithm that identifies a reference price as the most quoted price in a rolling window of 13 weeks centered in the current week. See the Appendix to Chahrour (2009) for a full description of the algorithm. EJR stands for Eichenbaum, Jaimovich and Rebelo (2010) who define a reference price as the most quoted price in a given calendar quarter.

Table II.8 Size of Price Changes

Summary Statistics Across Product Categories

	Posted Prices	Reference Prices (Chahrour)	Reference Prices (EJR)
	(1)	(2)	(3)
Median	0.025	0.043	0.049
Mean	0.024	0.044	0.048
Weighted median	0.027	0.047	0.057
Standard dev.	0.011	0.019	0.026

Notes. Weighted median calculated using revenue shares for the period mid 2005-mid 2007. Chahrour's definition of reference prices is based on an algorithm that identifies a reference price as the most quoted price in a rolling window of 13 weeks centered in the current week. See the Appendix to Chahrour (2009) for a full description of the algorithm. EJR stands for Eichenbaum, Jaimovich and Rebelo (2010) who define a reference price as the most quoted price in a given calendar quarter.

Table II.9 Size of Price Changes by Chain

	Posted Prices	Reference Prices (Chahrour)	Reference Prices (EJR)
	(1)	(2)	(3)
Bandera Azul	0.031	0.046	0.052
Economax	0.033	0.062	0.075
Ekono	0.022	0.061	0.068
Jumbo	0.010	0.012	0.016
Lider	0.032	0.055	0.069
Maicao	0.027	0.053	0.059
Montserrat	0.046	0.059	0.070
Puerto Cristo	0.026	0.049	0.058
Ribeiro	0.022	0.051	0.058
Santa Isabel	0.029	0.052	0.062
Unimarc	0.037	0.046	0.053
Median	0.029	0.052	0.059
Mean	0.028	0.050	0.058
St. Dev.	0.009	0.014	0.016

Notes. Chahrour's definition of reference prices is based on an algorithm that identifies a reference price as the most quoted price in a rolling window of 13 weeks centered in the current week. See the Appendix to Chahrour (2009) for a full description of the algorithm. EJR stands for Eichenbaum, Jaimovich and Rebelo (2010) who define a reference price as the most quoted price in a given calendar quarter.

Table II.10 Importance of Chain-Level Modal Prices

Fraction of Posted Prices at the Mode

Bandera Azul	0.935
Economax	0.909
Jumbo	0.396
Lider	0.813
Maicao	0.932
Montserrat	0.912
Puerto Cristo	0.876
Ribeiro	0.868
Santa Isabel	0.788
Unimarc	0.710
Median	0.872
Mean	0.814
St. Dev.	0.163

Notes. Modal prices are computed as the mode of prices for a given product across stores within a chain.

Table II.11 Frequency of Modal Price Change

	Frequency	Duration
Bandera Azul	0.281	3.565
Economax	0.134	7.490
Jumbo	0.781	1.280
Lider	0.138	7.228
Maicao	0.127	7.869
Montserrat	0.181	5.523
Puerto Cristo	0.143	6.997
Ribeiro	0.244	4.094
Santa Isabel	0.237	4.221
Unimarc	0.242	4.139
Median	0.209	4.872
Mean	0.251	5.241
St. Dev.	0.195	2.138

Notes. Modal prices are computed as the mode of prices for a given product across stores within a chain.

Table II.12 Variance Decomposition of the Frequency of Modal Price Change

$$Y_{ik} = \mu + \alpha_k + \beta_i + \varepsilon_{ik}$$

Component	Estimate	Explained variance (%)
product	0.0015 (0.0003)	1.5
Chain	0.0716 (0.0254)	70.5
Residual	0.0285 (0.0254)	28.0

Note. Standard error in parenthesis. Model estimated by Maximum Likelihood.

Table II.13 Price Comovement Across and Within Retail Chains

$$Corr_{kcl} = \beta_0 + \beta_1 INTRA_l + \sum_{k=1}^{K} \delta_k D_k + \sum_{c=1}^{C} \gamma_c F_c + \varepsilon_{kcl}$$

Panel A. Reference Prices	
$INTRA_l$	0.2943
	(0.0008)
Adj. R2	0.3067
N	598,826
Panel B. Posted Prices	
$INTRA_l$	0.3009
	(0.0007)
Adj. R2	0.3565
N	598,826

Notes. The dependent variable is the correlation coefficient between the monthly averaged prices (in levels) of product *k* in category *c* in a pair of stores indexed by *l*. The model is estimated by OLS. Standard errors in parenthesis.

Table II.14 Variance Decomposition of the Frequency of Reference Price Change

$$Y_{ijk} = \mu + \alpha_k + \beta_i + \gamma_j + \varepsilon_{ijk}$$

Component	Estimate	Explained variance (%)
product	4.53E-11 (2.07E-08)	1.79E-06
Chain	0.0016 (0.0003)	63.8
Store	0.0007 (0.0007)	27.5
Residual	0.0002 (0.0070)	8.7

Note. Standard error in parenthesis. Model estimated by Maximum Likelihood.

Table II.15 Frequency of Cost Change

Summary Statistics Across Product Categories

	Posted		Reference (Chahrour)		Reference (EJR)	
	(1) Cost	(2) Price	(3) Cost	(4) Price	(5) Cost	(6) Price
Median	0.104	0.200	0.049	0.033	0.032	0.029
Mean	0.117	0.205	0.046	0.032	0.030	0.027
Standard dev.	0.068	0.059	0.020	0.010	0.012	0.007

Notes. Even numbered columns present price frequencies computed across the same categories for which cost frequencies were calculated for comparison purposes. Chahrour's definition of reference prices is based on an algorithm that identifies a reference price as the most quoted price in a rolling window of 13 weeks centered in the current week. See the Appendix to Chahrour (2009) for a full description of the algorithm. EJR stands for Eichenbaum, Jaimovich and Rebelo (2010) who define a reference price as the most quoted price in a given calendar quarter.

Table II.16 Size of Cost Changes

Summary Statistics Across Product Categories

	Weekly Costs	Reference Costs (Chahrour)
	(1)	(2)
Median	0.012	0.023
Mean	0.015	0.024
Standard dev.	0.012	0.012

Table II.17 Markups and Cost Adjustments

A. Posted Markups	
$E[\mu \mid \Delta C > 0] - E[\mu \mid \Delta C = 0]$	-0.0209***
	(0.0002)
$E[\mu \mid \Delta C < 0] - E[\mu \mid \Delta C = 0]$	-0.0173***
	(0.0002)
B. Reference Markups	
$E[\mu^{ref} \mid \Delta C^{ref} > 0] - E[\mu^{ref} \mid \Delta C^{ref} = 0]$	-0.0268***
	(0.0008)
$E[\mu^{ref} \mid \Delta C^{ref} < 0] - E[\mu^{ref} \mid \Delta C^{ref} = 0]$	0.2924***
	(0.0012)

Note: (***) denotes significance at 1 percent level.

Table II.18 Markup Volatility by Product Category

Category	Volatility
CLOTHES STAIN REMOVER	0.053
VEGETABLE OIL	0.047
WATER	0.052
HAIR CONDITIONER	0.043
SODA	0.040
COFFEE	0.054
TOOTHBRUSH	0.039
CEREAL BAR	0.065
BREAKFAST CEREAL	0.052
BEER	0.033
COCKTAIL	0.058
HOME SPRAY	0.029
DEODORANTS	0.033
CLOTHES DETERGENT	0.034
PASTA	0.048
WOMEN FRAGRANCES	0.042
MEN FRAGANCES	0.043
FROZEN FOOD	0.049
CANNED FRUITS	0.057
COOKIES AND CHOCOLATES	0.062
CHLORINE (BLEACH)	0.035
RAZOR BLADES	0.040
INSECTICIDE	0.044
TOILET SOAP	0.049
DISH WASHER	0.039
RON LIQUOR	0.055
FRUIT JUICES	0.050
BABYFOOD	0.042
TOOTHPASTE	0.029
SHAMPOO HAIRCARE	0.047
CLOTH SOFTENER	0.072
TEA	0.062
WHISKY	0.043
Median	0.047
Mean	0.047
Standard dev.	0.010

Table II.19 Within-Store Synchronization of Price Changes by Chain

Fisher-Konieczny Index

Chain	Average	St. Dev.
Bandera Azul	0.409	0.006
Economax	0.249	0.055
Ekono	0.360	0.092
Jumbo	0.079	0.018
Lider	0.235	0.031
Maicao	0.320	0.059
Montserrat	0.207	0.041
Puerto Cristo	0.199	0.135
Ribeiro	0.335	0.046
Santa Isabel	0.167	0.036
Unimarc	0.184	0.020
Median	0.250	0.041
Mean	0.235	0.049
St. dev.	0.098	0.037

Table II.20a Variance Decomposition of Within-Category Fisher-Konieczny Index (Posted Prices)

$$FK_{krs} = \mu + \alpha_k + \beta_r + \gamma_s + \varepsilon_{krs}$$

Component	Estimate	Explained variance (%)
Category	0.0324 (0.0036)	42.1
Chain	0.0266 (0.0120)	34.6
Store	0.0011 (0.0001)	1.4
Residual	0.0169 (0.0002)	22.0

Note. Standard error in parenthesis. Model estimated by Restricted Maximum Likelihood.

Table II.20b Variance Decomposition of Within-Category Fisher-Konieczny Index (Reference Prices)

$$FK_{krs} = \mu + \alpha_k + \beta_r + \gamma_s + \varepsilon_{krs}$$

Component	Estimate	Explained variance (%)
Category	0.0420 (0.0047)	54.0
Chain	0.0118 (0.0054)	15.2
Store	0.0015 (0.0002)	1.9
Residual	0.0224 (0.0002)	28.8

Note. Standard error in parenthesis. Model estimated by Restricted Maximum Likelihood.

Table II.21 Synchronization of Across-Stores Reference Price Ajustment

Probit Estimation

$$Y_{srt} = \beta_0 + \beta_1 FRACOWN_{srt} + \beta_2 FRACOTHER_{srt} + \zeta_t + \varepsilon_{srt}$$

Variable	Coefficient	Marginal Effect
$FRACOWN_{srt}$	3.923***	0.675***
	(0.002)	(0.001)
$FRACOTHER_{srt}$	-0.081***	-0.013***
	(0.003)	(0.001)

Note. Standard error in parenthesis. (***) denotes significance at 1 percent level.

Figure II.1 Posted and Reference Prices for Selected Products

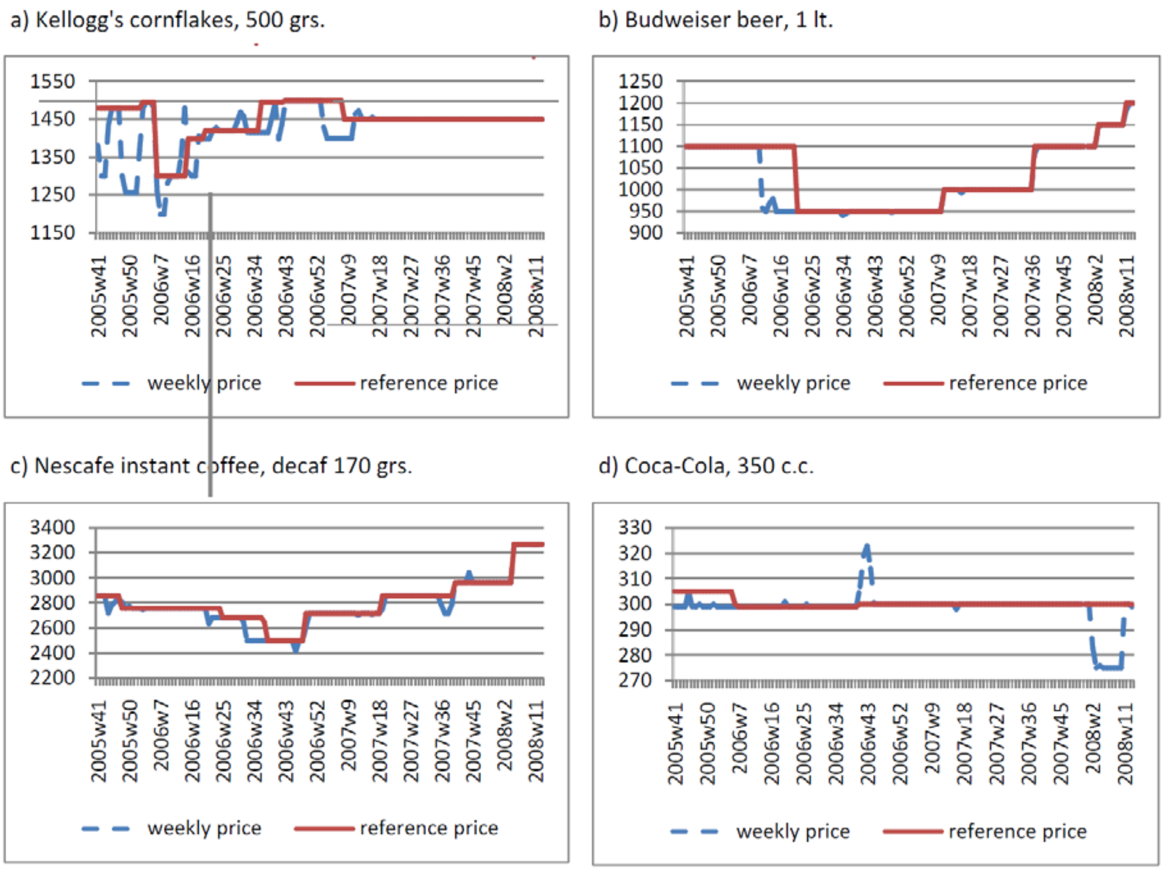


Figure II.2 Importance of Reference Prices

Fraction of the Time Spent by Posted Prices at Reference Prices by Category

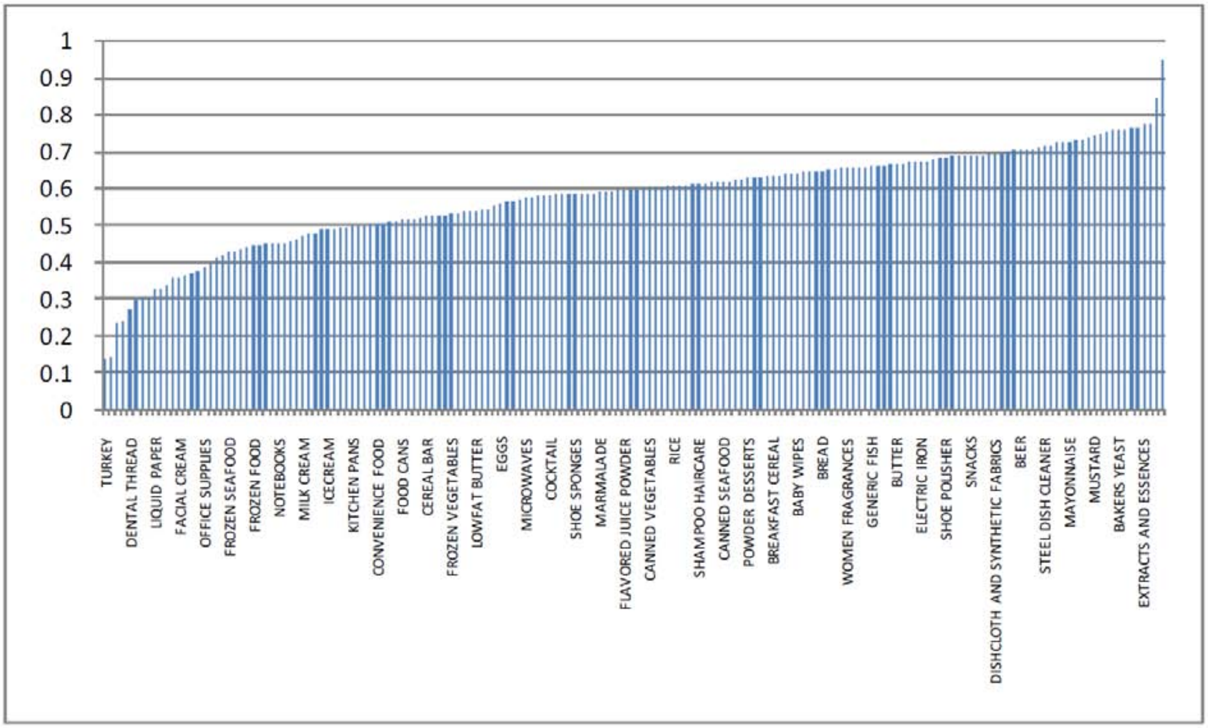


Figure II.3 Frequency of Posted Price Change by Category

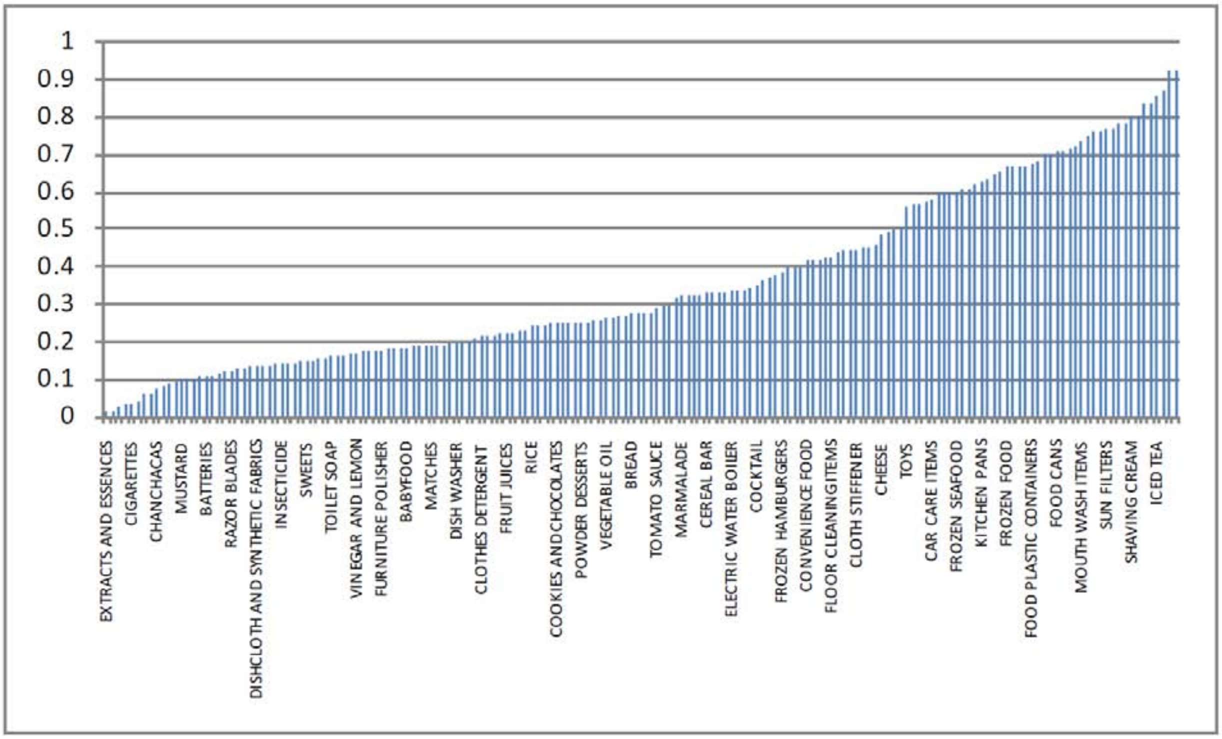


Figure II.4 Frequency of Reference Prices by Category

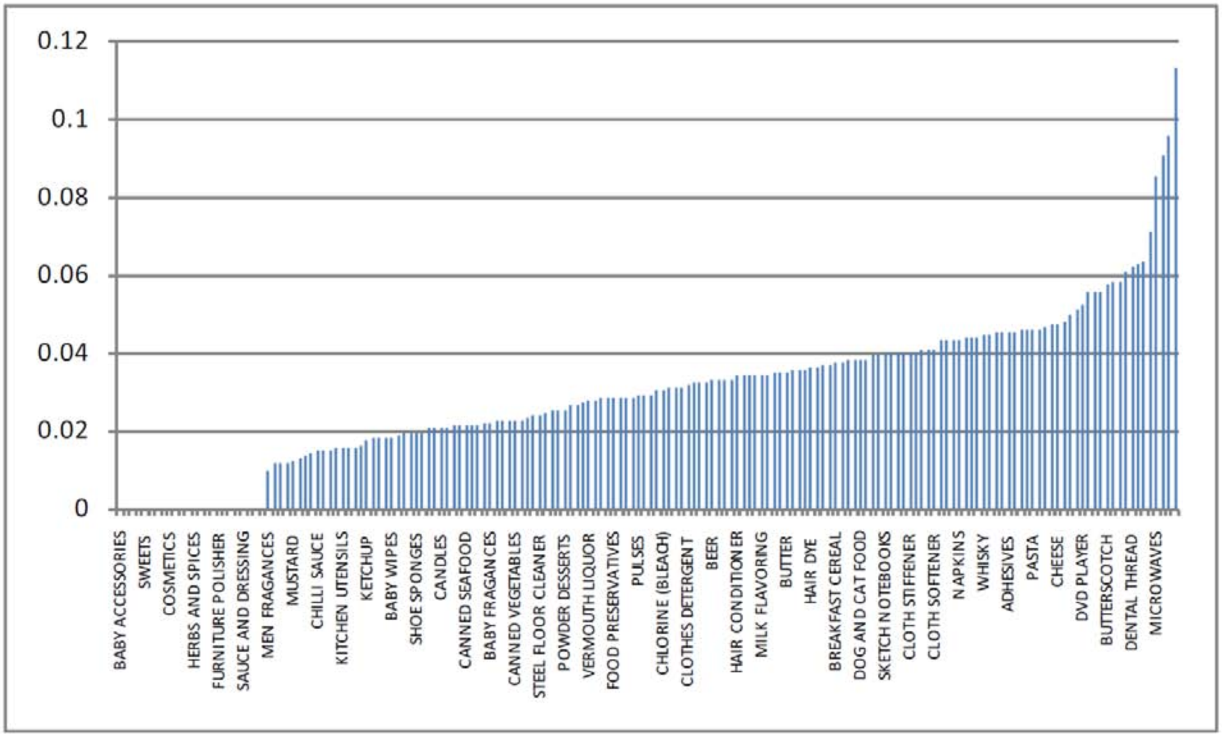


Figure II.5a Estimated Hazard Function for Posted Prices

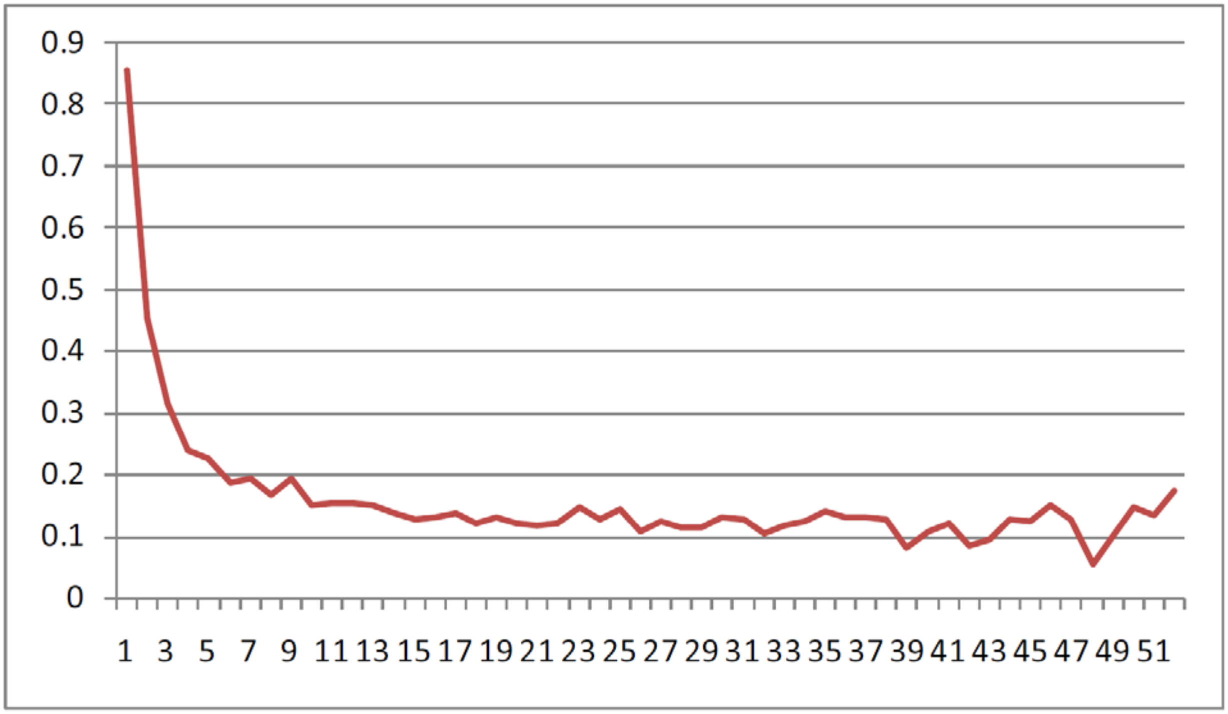


Figure II.5b Adjusted Hazard Function for Posted Prices

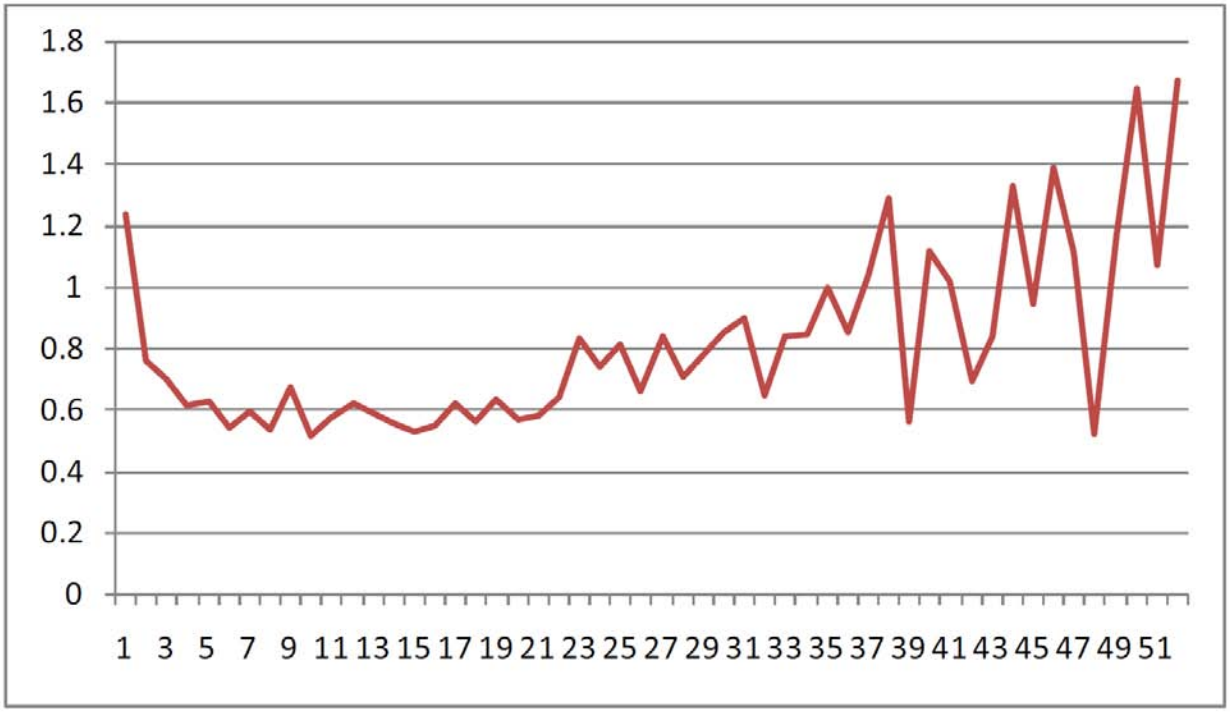
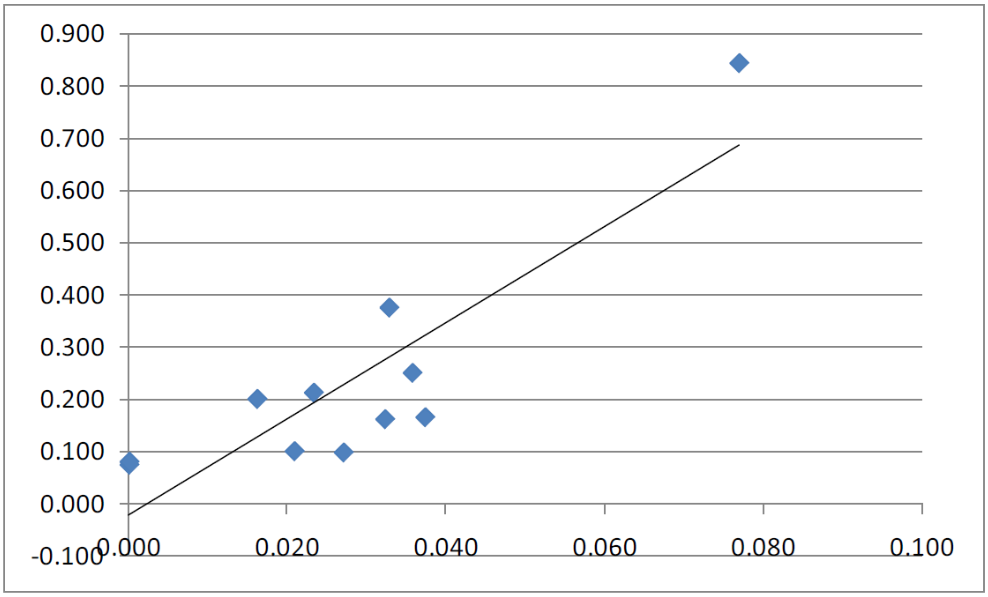


Figure II.6 Posted Price vs Reference Price Frequencies by Chain



Notes. Chain level frequencies are computed as the average frequency of price adjustment within chains.

Figure II.7a Frequency of Posted Cost Changes

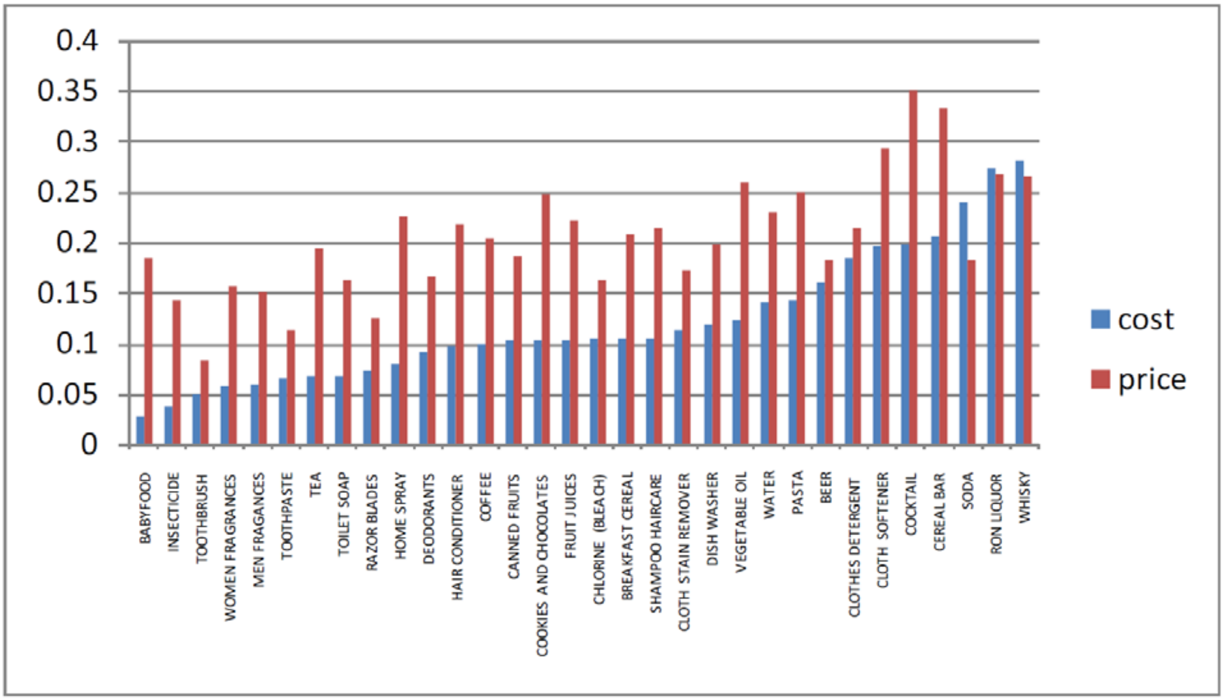


Figure II.7b Frequency of Reference Cost Changes

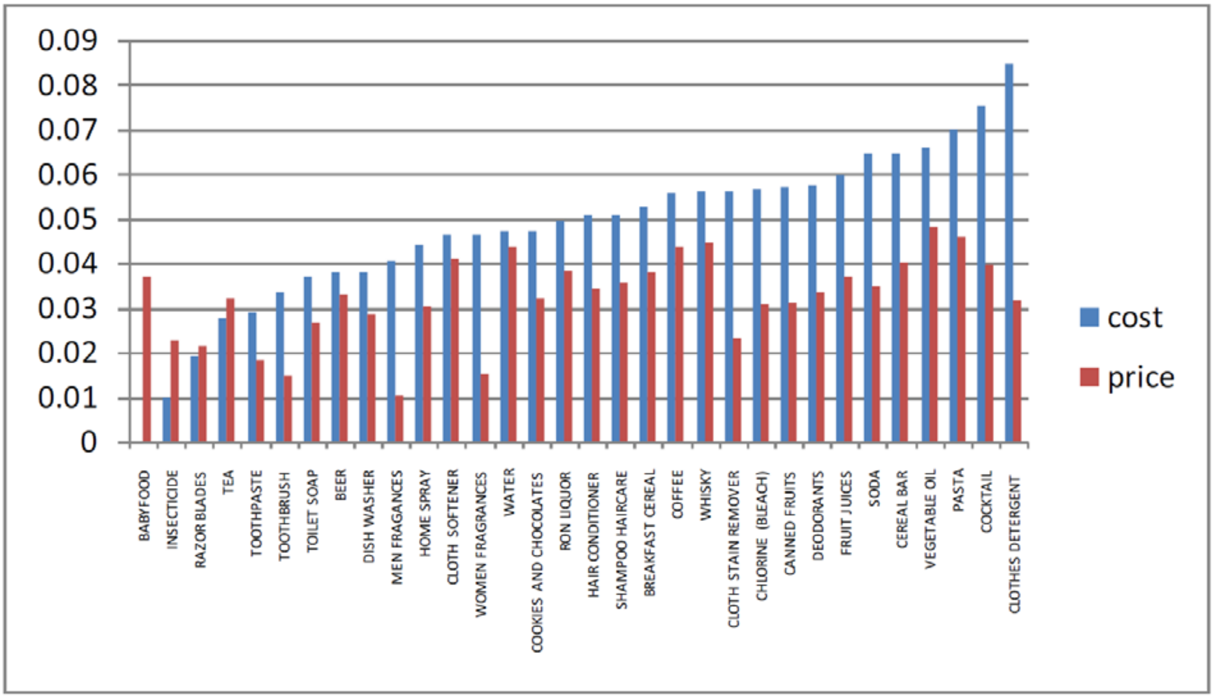


Figure II.8. Cross-Sectional Markup Deviations

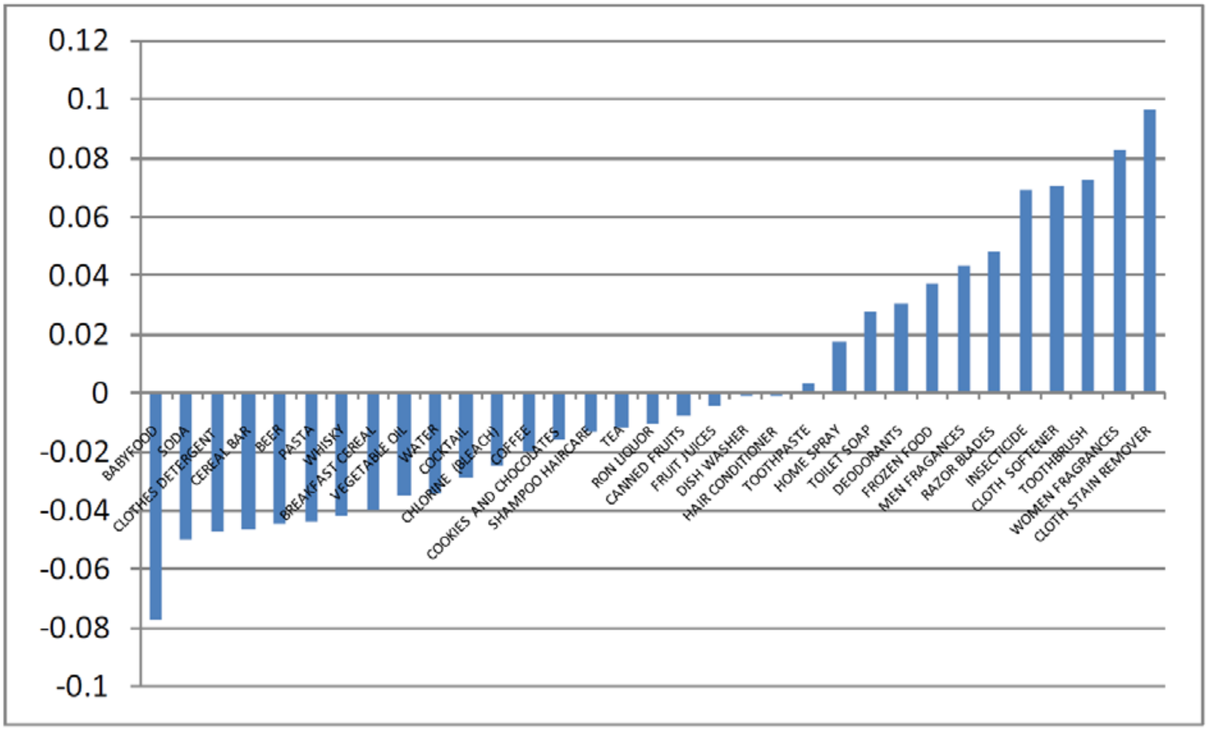


Figure II.9 Deviation from Reference Markup and Probability of Repricing

Figure II.10 Distribution of the Fraction of Price Changes Within a Store

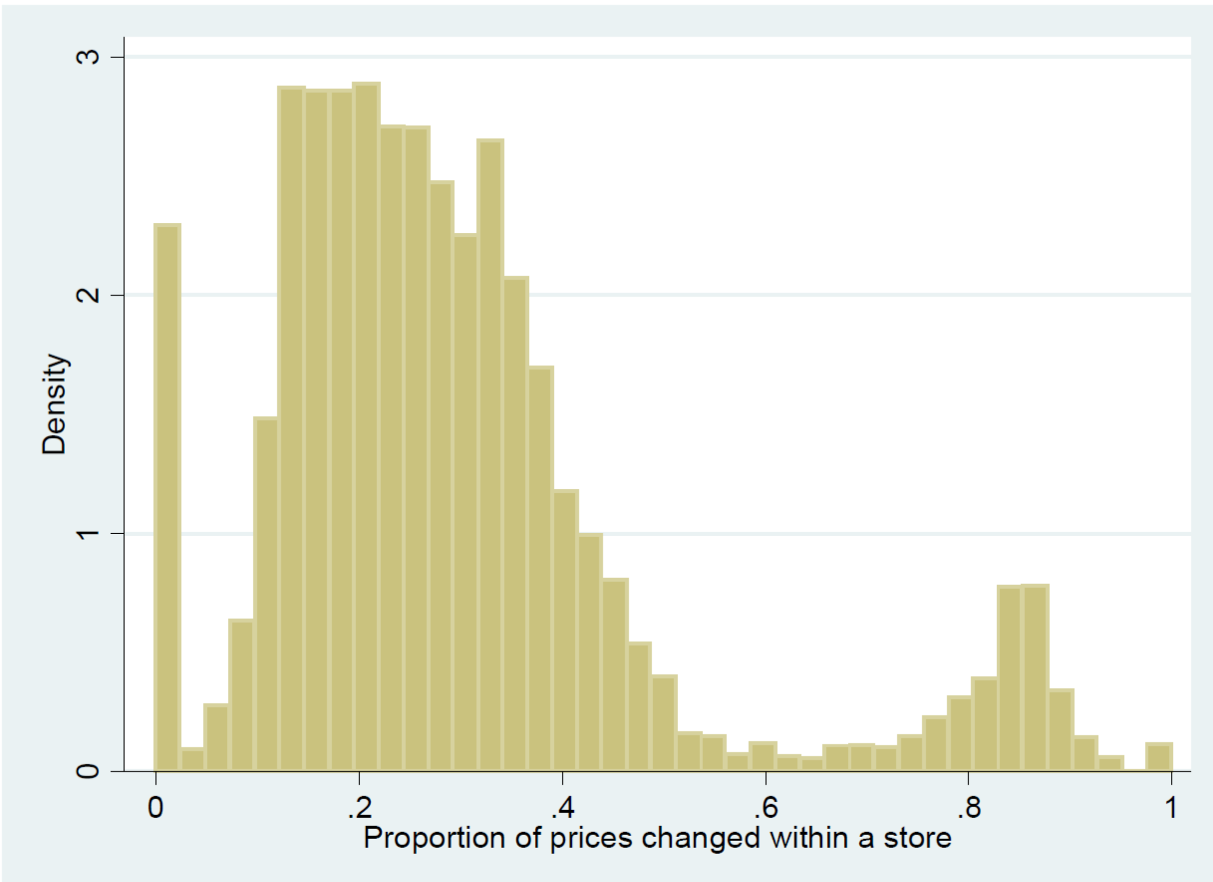


Figure II.11 Within-Store Price Synchronization

Distribution of Fisher-Konieczny Index (Posted Prices)

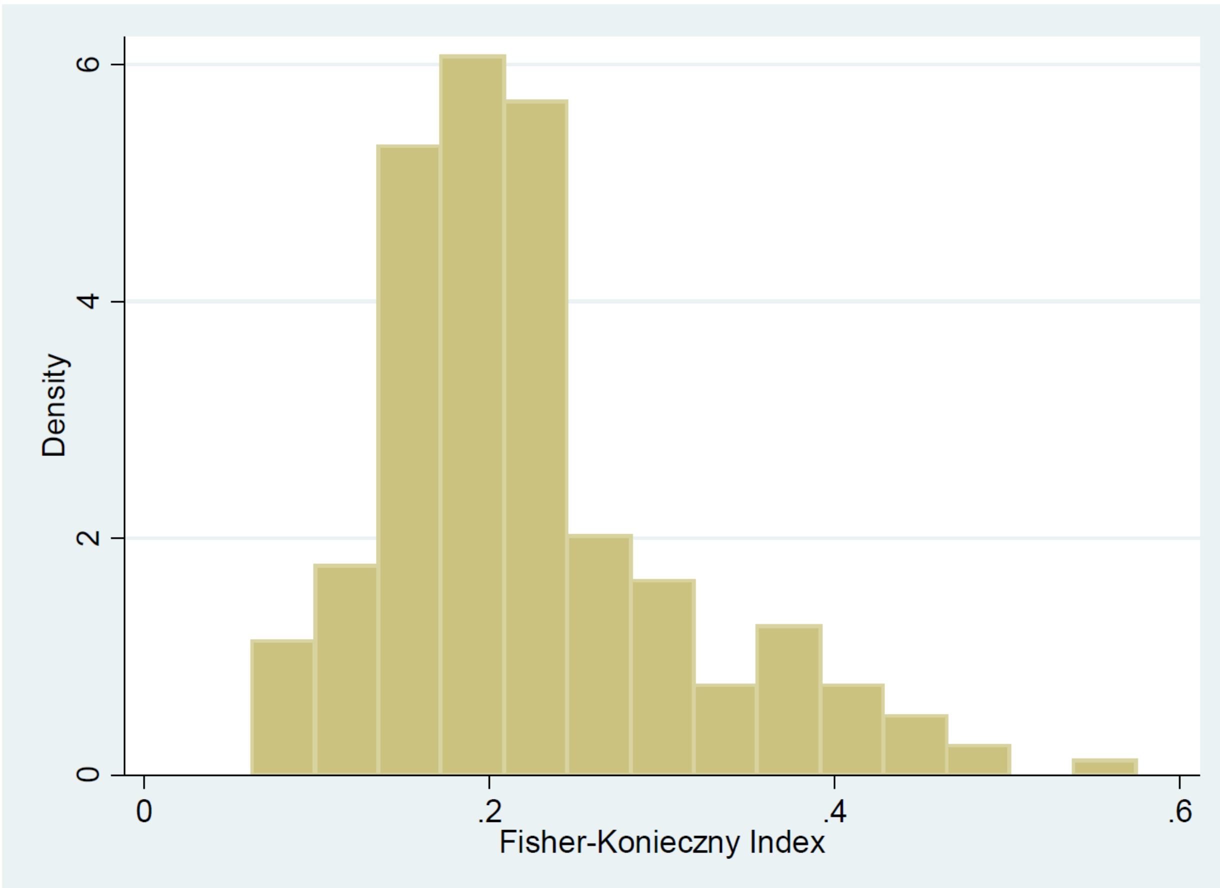


Figure II.12 Synchronization of Price Changes Within Product Categories

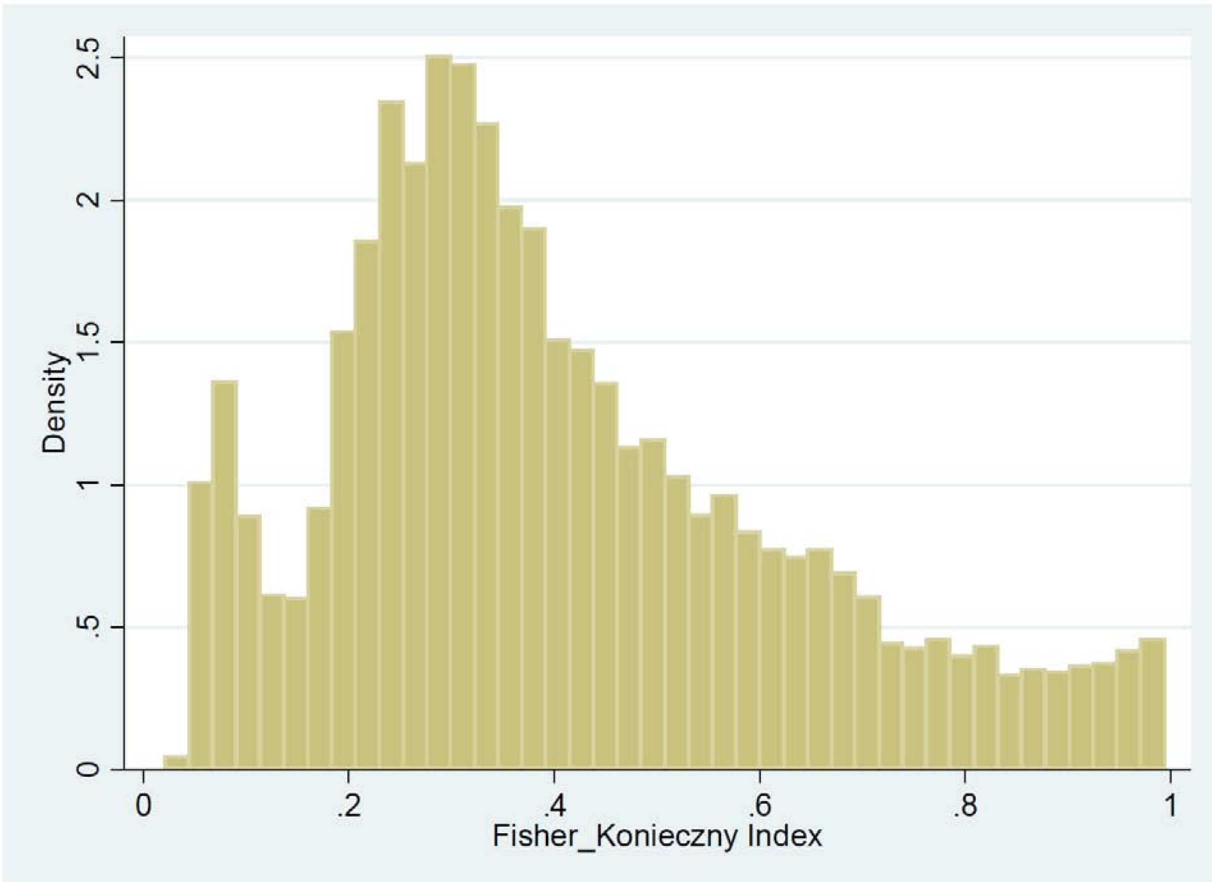


Figure II.13 Across-Stores Synchronization of Price Adjustment

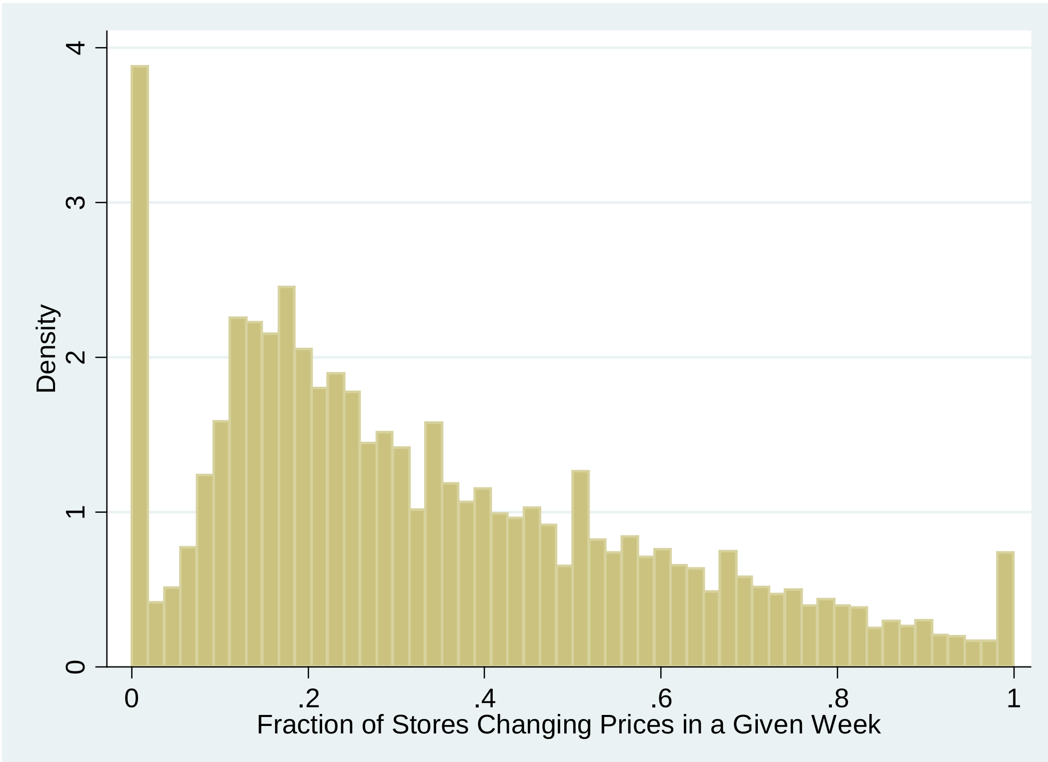


Figure II.14 Distribution of Price Changes Across Stores

Fisher-Konieczny index

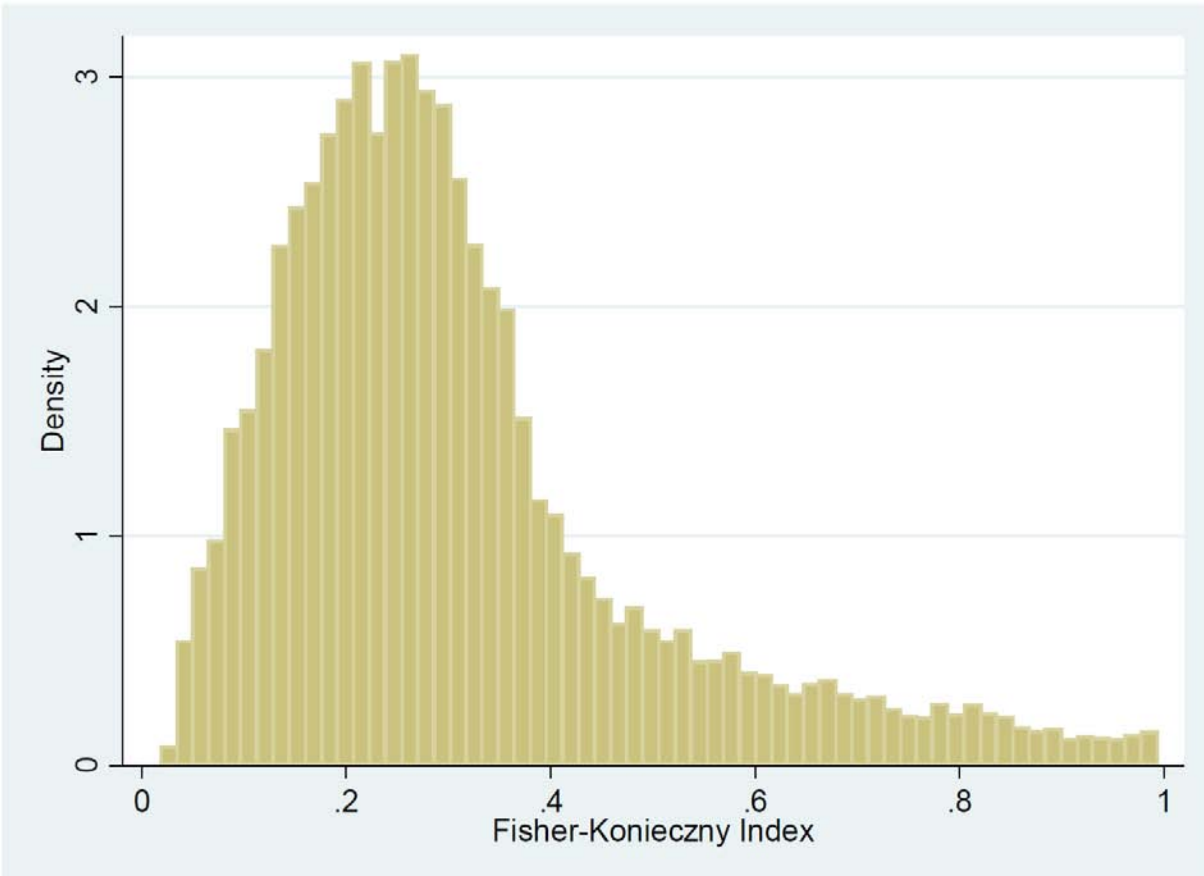


Table III.1 Descriptive Statistics

No. of obs.	4,294,298
No. of stores	8
No. of cities	8
No. of barcodes	13,756
Price Statistics	
Average	1,368
Median	929
Standard dev.	1,567
Cost Statistics[1]	
Average	1,239
Median	836
Standard dev.	1,463

Notes: Price and cost statistics expressed in Chilean pesos. (1) Cost statistics are computed for the period 2002-2003 for which replacement cost data are available.

Table 2. Deviations from the Law of One Price

A. Retail Prices	Mean Absolute Dev. (1)	Median Absolute Dev. (2)	Maximum Absolute Dev. (3)
Average	0.036	0.000	0.272
Median	0.036	0.000	0.260
Standard dev.	0.006	0.000	0.032
B. Wholesale Costs			
Average	0.010	0.000	0.273
Median	0.010	0.000	0.260
Standard dev.	0.001	0.000	0.022

Notes. Statistics on absolute deviations presented in columns (1)-(3) are computed across goods at a given week (week 10 of 2003). Statistics across rows are computed across city-pairs.

Table III.3 Frequency of Price Adjustment

	Retail Prices (1)	Wholesale Costs (2)
Median	0.076	0.058
Average	0.130	0.098
Standard dev.	0.148	0.113
5th percentile	0.000	0.000
95 percentile	0.462	0.327

Note: Statistics on wholesale costs are computed over the period 2002-2003 for which data on replacement costs are available.

Table III.4 LOP Deviations and Price Stickiness

$$Var\left(q_{it}^{k}\right) = \alpha + \beta \ln(Distance_i) + \gamma Freq_k + \sum_{j=1}^{J} \delta_j D_j + \varepsilon_{it}^{k}$$

Panel A: Retail Prices	
$\ln(Distance_i)$	0.0041
	(0.0003)
$Freq_k$	0.2273
	(0.0062)
N	14922
Adjusted R2	0.262
Panel B: Wholesale Costs	
$\ln(Distance_i)$	0.0028
	(0.0001)
$Freq_k$	0.0181
	(0.0043)
N	8793
Adjusted R2	0.135

Table III.5 Effects of Price Rigidities on the Volatility of LOP Deviations

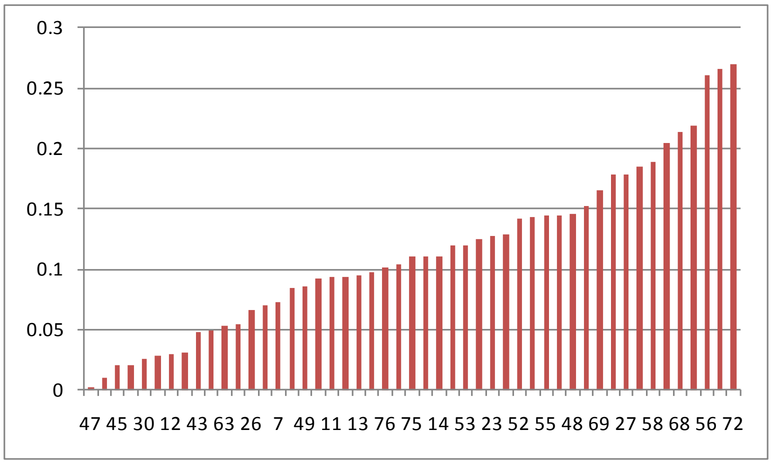
Distance-Equivalent of an Increase in Price Rigidities

	Distance Equivalent (kms.)
Median	105.0
Average	294.5
Standard dev.	721.0
5th percentile	26.1
95 percentile	464.6

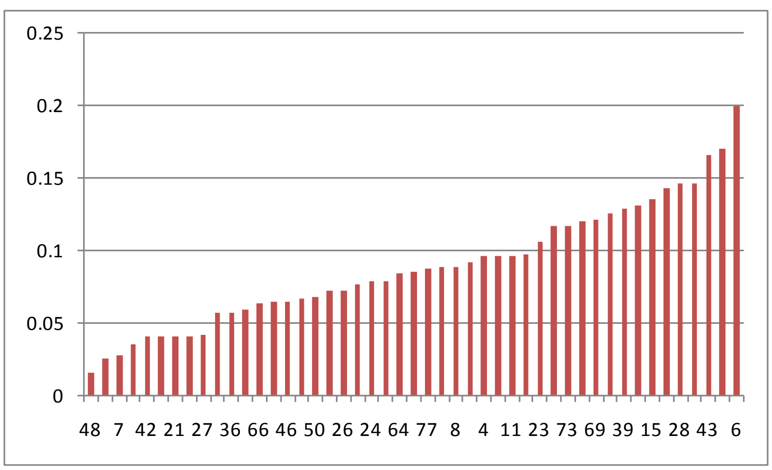
Notes: Statistics computed across categories. Distance equivalent computed for a decrease of 0.01 in the frequency of price adjustment

Figure III.1 Frequency of Price Adjustment by Category

a. Retail Prices



b. Wholesale Costs



Appendix

The Supermarket Industry in Chile: Structure and Major Actors

This appendix presents a brief overview of the Chilean supermarket industry.

The supermarket industry in Chile represents about 26 percent of total sales in the retail sector and about 80 percent of the sales of groceries (USDA, 2009), the remaining 20 percent being represented by independent stores (e.g. Mom and pop stores). The Chilean supermarket industry has undergone substantial structural change over the last 15 years (Díaz, Galetovic and Sanhueza 2008, Galetovic and Sanhueza 2006, Lira 2005). One mayor effect of this restructuring process has been the industry's evolution towards greater concentration . In 1997, the combined market share of the largest two retailers, D&S --controlled since January 2009 by the U.S.-based retailer Wal-Mart-- and Santa Isabel, amounted to 33.2 percent (Díaz, Galetovic and Sanhueza 2008). Following several waves of mergers and acquisitions[1], by 2006 the largest two firms, by then D&S and Cencosud, accounted for more than 60 percent of the market, which totalled sales for $9.6 billion in 2008. Further restructuring occurred over the period 2007-2008 led to the emergence of two new players, SMU and Supermercados del Sur. By the end of 2009, five mayor players could be identified in the industry : D&S, with 34 percent of the market; Cencosud, with 29.3 percent; SMU, with about 16 percent; Supermercados del Sur with 8 percent; and Falabella-Tottus with 6 percent of the market (Estrategia newspaper, December 22, 2009).

Major Chilean retailers have typically followed multi-format strategies. Formats include basically hypermarkets, traditional supermarkets, discount stores and convenience stores. D&S operates three different formats under three different brands: Hypermarkets, under the brand Hiper Lider; traditional supermarkets, under the brand Express de Lider; and discount stores under the brands Ekono (re)introduced in January, 2007, and SuperBodega Acuenta. Cencosud, operates hypermarkets under the brand Jumbo and supermarkets under the brand Santa Isabel.

[1] Cencosud acquired Santa Isabel in 2003, Montecarlo and Las Brisas in 2004, and Economax and Infante in 2006; D&S acquired Carrefour in 2004.

Table AI.1. Products included in the Dataset for Mexico

Code	Product	Brand	Presentation	Quantity
01	Wheat flour	Maseca	Package	1 kg.
02	Wheat tortilla	Milpa Real	Bag	500 grs.
03	Sliced bread	Bimbo	Package	680 grs.
04	Sliced bread	Wonder	Package	680 grs.
05	Pasta for soup	Moderna	Package	200 grs.
06	Cookies	Gamesa	Box	1 kg.
07	Breakfast cereal	Kellogg's	Box	500 grs.
08	Breakfast cereal	Nestle	Box	500 grs.
09	Breakfast cereal	Kellogg's	Box	510 grs.
10	Tuna in oil	Dolores	Can	174 grs.
11	Dry milk	Nido	Can	1.8 kg.
12	Dry milk	Nido	Can	900 grs.
13	Evaporated milk	Carnation	Can	410 grs.
14	Condensed milk	Nestle	Can	397 grs.
15	Condensed milk	Nestle	Can	100 grs.
16	Yoghurt	Yoplait	Cup	150 grs.
17	Pasteurized milk	Alpura	Box	1 lt.
18	Cooking oil	La Gloria	Bottle	1 lt.
19	Cooking oil	Mazola	Bottle	1 lt.
20	Cooking oil	1-2-3	Bottle	1 lt.
21	Cooking oil	Capullo	Bottle	1 lt.
22	Veg. shortening	Inca	Package	1 lt.
23	Elote	Del Monte	Can	225 grs.
24	Chile peppers	La Costena	Can	220 grs.
25	Tomato puree	Del Fuerte	Box	1 kg.
26	Green peas	Del Fuerte	Can	225 grs.
27	Baby food	Gerber	Jar	113 grs.
28	Jam	McCormick	Jar	270 grs.
29	Peaches in syrup	La Costena	Can	820 grs.
30	Brown sugar	Unbranded	Bag	2 kg.

Table AI.1 (cont.). Products included in the Dataset for Mexico

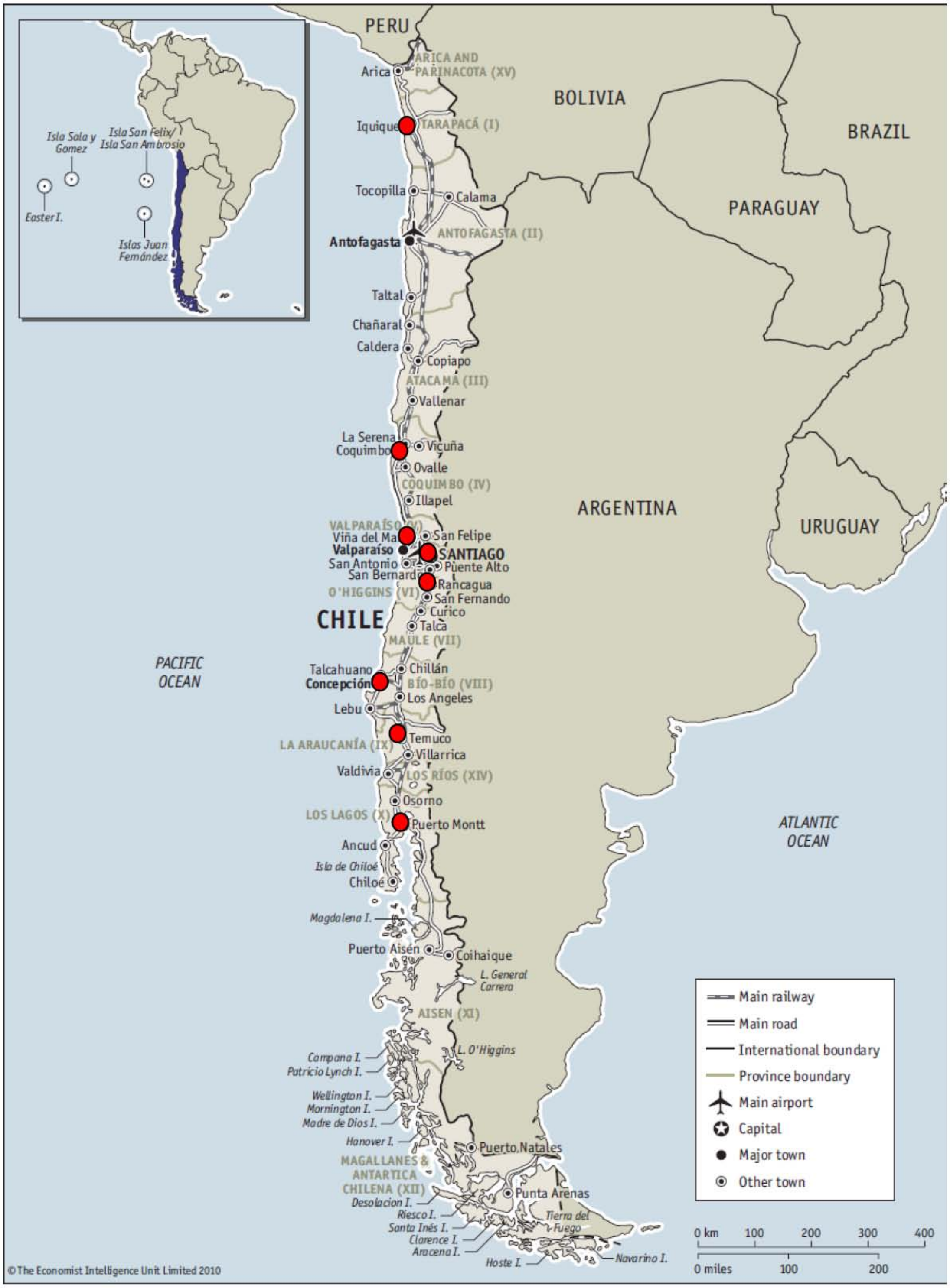
Code	Product	Brand	Presentation	Quantity
31	Instant coffee	Nescafe	Jar	100 grs.
32	Instant coffee	Nescafe	Jar	200 grs.
33	Instant coffee (dec.)	Nescafe	Jar	200 grs.
34	Instant coffee	Dolca	Jar	100 grs.
35	Instant coffee	Dolca	Jar	200 grs.
36	Mineral water	Bonafont	Bottle	1.5 lts.
37	Soft drink	Coca-Cola	Can	355 ml.
38	Soft drink	Pepsi	Can	355 ml.
39	Mayonnaise	Kraft	Jar	195 grs.
40	Mayonnaise	Kraft	Jar	350 grs.
41	Mayonnaise	McCormick	Jar	190 grs.
42	Mayonnaise	McCormick	Jar	390 grs.
43	Mustard	Kraft	Jar	395 grs.
44	Mustard	McCormick	Jar	430 grs.
45	Mustard	McCormick	Jar	210 grs.
46	Table salt	La Fina	Bag	1 kg.
47	Table salt	La Fina	Can	1 kg.
48	English sauce	WC & B	Bottle	145 ml.
49	Spicy sauce	Bufalo	Bottle	150 grs.
50	Vinegar	Clem. J.	Bottle	1 kg.
51	Baking powder	Royal	Can	220 grs.
52	Drink mix	Choco milk	Bag	400 grs.
53	Drink mix	Choco milk	Can	400 grs.
54	Chocolate	Abuelita	6 bars	90 grs.
55	Instant juice	Tang	Sachet	30 grs.
56	Instant gelatin	D' Gari	Bag	170 grs.
57	Beer	Dos Equis	Six-pack	340 ml.
58	Bleach	Cloralex	Bottle	950 ml.
59	Bleach	Clorox	Bottle	930 ml.
60	Detergent	Foca	Bag	1 kg.

Table A1 (cont.). Products included in the Dataset

Code	Product	Brand	Presentation	Quantity
61	Detergent	Ace	Bag	001 kg.
62	Dishwasher powder	Axion	Bag	001 kg.
63	Washing soap	Zote	Bar	400 grs.
64	Floor cleaner	Ajax	Bottle	001 lt.
65	Floor cleaner	Fabuloso	Bottle	001 lt.
66	Floor cleaner	Maes. lim.	Bottle	001 lt.
67	Floor cleaner	Pinol	Bottle	001 lt.
68	Laundry softener	Suavitel	Bottle	001 lt.
69	Laundry softener	Vel Rosita	Bottle	001 lt.
70	Toothpaste	Colgate	Tube	125 ml.
71	Toothpaste	Colgate	Tube	100 ml.
72	Liquid cream	Hinds	Bottle	420 ml.
73	Liquid cream	Lubriderm	Bottle	480 ml.
74	Solid cream	Pond's	Jar	300 grs.
75	Deodorant	Speed St.	Bar	045 grs.
76	Deodorant	Mum	Roll-on	065 ml.
77	Toilet soap	Camay	Bar	150 grs.
78	Toilet soap	Palmolive	Bar	150 grs.
79	Toilet soap	Zest	Bar	150 grs.
80	Shampoo	Caprice	Bottle	900 ml.
81	Paper napkins	LyS	Packet	250 u.
82	Paper napkins	Petalo	Packet	250 u.
83	Paper napkins	Regio	Packet	250 u.

Figure AI.1. Geographical Location of Cities in the Sample

Figure AIII.1 Geographical Location of Stores from Chilean Retailer



Note. Cities included in the sample are identified with the symbol ●