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A REASSESSMENT OF FLEXIBLE PRICE EVIDENCE USING SCANNER DATA: EVIDENCE FROM AN EMERGING ECONOMY

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Abstract

In this paper we use a new database of scanner-level prices for the Chilean economy to characterize the microeconomic behavior of prices during a period of high inflation. We are able to characterize the price-setting behavior by supermarket chain. The evidence indicates that there is significant heterogeneity in the pricing behavior of individual retailers. Analyzing the source of shocks, results show that even though chain-specific shocks account for a sizable fraction of the observed variation, common (i.e. countrywide) shocks to individual goods and product categories are the most important factors to explain the behavior of prices. In other words, the pricing strategy of retailers seems less important in developing countries to explain microeconomic price dynamics.

Resumen

En este trabajo se utiliza una nueva base de precios de supermercados en Chile para caracterizar su comportamiento micro durante un período de alta inflación. Los datos son tomados a través de lectores de códigos de barras en distintos supermercados y permiten identificar características particulares del comportamiento de cada cadena. La evidencia sugiere que hay un elevado grado de heterogeneidad en la forma en la que cada cadena pone los precios de sus productos. Además, analizando el origen de los shocks, se encuentra que, a pesar de que los shocks a nivel de cadena representan una fracción importante de las variaciones de precios, son los shocks agregados los factores que mejor explican el comportamiento de los precios en Chile. En otras palabras, las estrategias de fijación de precios parecen ser menos relevantes para explicar la dinámica micro de los precios en economías emergentes.

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1 Introduction

Real effects of monetary policy depend critically on price-setters' behavior. Consequently, an increasing number of studies have used micro price data to identify how a "typical" pricing strategy looks like. This research agenda has uncovered a number of facts critical to understand the mechanisms by which monetary shocks are transmitted to the economy [1]. The first papers in this literature analyze good-level data that statistical agencies survey to construct CPI. Even though these earlier work unveiled important facts, CPI data contains only few products per seller which precludes the identification of retail specific behavior. Only recently some studies have analyzed scanner data that include a large number of well identified articles per seller. However, most of them have data for only one retail chain, and so it is not possible to make comparisons across sellers, an aspect of the data that recent works have shown to be relevant (see for example, Nakamura (2008) and Eichenbaum, Jaimovich, and Rebelo (2008)). Along with this, most of the papers use data from advanced economies in environments of low inflation.

In this paper we contribute to fill some of the gaps in the literature by analyzing a large database that contains price information for a large number of products sold in each store of the majority of Chilean supermarket chains during a period of significant swings in the aggregate rate of inflation. With this data we can identify differences in price setting behavior across firms for a very well defined set of products.

We start by characterizing supermarket pricing strategies and comparing them across chains. Since describing pricing strategies can be a very cumbersome process, we summarize chains' pricing behavior using standard statistics used in macro monetary models to describe price dynamics. In particular, we assume that price strategies are a combination of frequency

[1] Starting with seminal contributions of Bils and Klenow (2004) and Nakamura (2008). There have been a plethora of micro pricing studies. See Klenow and Malin (2010) for a complete overview of this topic.

of price changes, size of price changes and synchronization of price changes across stores in a given chain.

When we compare chain pricing behavior significant and systematic differences across chains emerge clearly from the data. In particular, we find that chains choose very different combinations of frequency and size of price changes. In fact, there are chains that on average change 80% of its prices every week by an average amount of 2%, while others change less than a third of its prices every week, but by more than 4.5% on average. Chains also differ in the degree of synchronization across their own stores, with some chain changing prices of the same products in many stores at the same time and other doing the opposite.

In spite of these differences, chains' pricing strategies share one important characteristic: their behavior seems to be time dependent. Several features of the pricing behavior of firms suggest indeed that the supermarket chains in Chile tend to wait a predetermined (exogenous) amount of time to change their prices. The features suggestive of time dependency are the presence of a considerable amount of small price changes, a negative relation between the (absolute) size of price changes and the frequency of price changes, and nearly flat hazard rate functions for price changes are indicative of the presence of time dependent strategies.

We then analyze the importance of chain behavior for the overall volatility of prices by decomposing the variance of price changes for each good in a particular store in aggregate and idiosyncratic components. Our findings indicate that around 35% of the variance in price changes is related with product/chain shocks. This is a smaller number than what has been found for the U.S. where chain/product shocks explain more than 60% of price variation. The other 65% of price variation in Chile is mostly explained by shocks that affect all products in a category and all stores in the country at the same time. That implies that there are two main forces driving prices in Chilean supermarkets: aggregate shocks that affect almost all products in a category and almost everywhere, and the particular behavior of chains with respect to individual goods within an already narrowly defined category.

Finding that economy-wide shocks explain the majority of price movements in Chile is not surprising since inflation was more than 7% on average during the period covered in our study. On the other hand, the non-negligible 35% of price volatility that we attribute to product-store shocks is related to chain level pricing strategies. In particular our results suggest that the observed variation in the price of a good X in a given store seems to be driven by decisions taken at each store for the price of X and not necessarily for the other goods in the same category of X. This can be rationalized as part of a strategy where chains try to alter relative prices of goods within each category as a strategy for attracting clients, but not as a response to aggregate shocks.

To further investigate the relative importance of chain level shocks, we follow recent contributions made in Eichenbaum, Jaimovich, and Rebelo (2008) and construct the so called reference price: "the most quoted price in a reference period". The reference price is calculated for each good at each store and serves then as a filter for short term fluctuations in prices. This filter is useful for our purpose since, as stated by Klenow and Malin (2010), by dropping a considerable amount of short lived prices, reference price changes should be responding mainly to aggregate shocks rather than to idiosyncratic store or chain shocks. Our analysis of reference prices indicate clearly that they behave very differently than the unfiltered data: reference prices look stickier with changes that are larger and less synchronized than raw price changes. More over, hazard rates are clearly upward sloping, suggesting that reference price strategies are state dependent. Considering all these pieces of evidence together one can conclude that, hidden in very flexible and time dependent raw prices, there lies a stickier state dependent reference price strategy.

With respect to chain heterogeneity, we find that there are still small differences in the frequency of reference price changes, but larger differences in the size of changes. In fact, when we decompose the variance of changes in reference prices we still find that around 25% of the variance is related with product/chain shocks.

The paper is related to a large literature that has tried to understand price dynamics. The list of important papers is large and we do not pretend to review it here (see Klenow and Malin (2010) and papers cited in footnote 1). We only mentioned some works we think are more related to our study.

First, Ellis (2009) examines how prices behave for around 280 products in 240 different supermarkets across Great Britain. He finds that prices change quite frequently, there are many small price changes, and there is no clear link between how much a price changes by and how long it has been since the last time it changed. Our paper complement his study in at least two respects. First, we analyze scanner data from a developing country where inflation was on average 7% through out the sample. Second, we report statistics by chain uncovering considerable differences across them.

Nakamura (2008) analyzes a large cross-sectional price database from AC Nielsen with more than 7000 grocery stores across the U.S. She performs an analysis similar to ours and finds that her results "suggest that most of the observed price variation arises from retail-level rather than manufacturer-level demand and supply shocks". Our paper differs from hers in two respects. First, we document actual differences in pricing strategies across retail chains. Second, we analyze the importance of chain behavior in both raw prices and reference prices, discovering that chain level shocks are important for the dynamic of both types of prices. However, in our sample chain effect seems to be less important than in her sample. We attribute this to the fact that in Chile inflation was higher.

Eichenbaum, Jaimovich, and Rebelo (2008) use scanner data from a large U.S. food and drug retailer and find that, at the retailer level, prices are quite flexible. However, they claim that this large degree of flexibility is not relevant for monetary police, since what really matters is the behavior of reference prices, which are much more sticky. As in their paper, we find that reference prices are relevant for explaining retail pricing behavior (but with different intensity across chains). In addition, we find that these prices have a considerably larger duration than raw prices and that they seem to be state dependent. We contribute to this literature by showing that reference price behavior could differ across chains in frequency and size of price changes. In fact, we find that for some chains reference prices are equal to actual prices for more than 60% of the time, while for others this is the case for less than 30% of the time. Our work also differs from Eichenbaum, Jaimovich, and Rebelo (2008) in that we study the type of shocks that underlie reference price change variability.

As we mentioned above, most of the evidence about price dynamics analyzed in the literature is for developed countries. Of course, data availability implies that this gap between the number of studies considering developed and developing countries is even larger if one focused on scanner price data. One exception is a recent paper by Cavallo (2010). The author together with Roberto Rigobon from MIT started in 2007 The Billion Prices Project: an academic initiative that uses the internet to collect daily price data from hundreds of retailers around the world.[2] Cavallo (2010) used this data to perform a detailed analysis of price dynamics in four Latin American countries including Argentina, Brazil, Chile and Colombia. Our work differs from his in several respects. First, we use actual store data instead of internet collected one; second our sample includes almost all important retail chains in Chile and so we are able to identify the behavior of different chains. Finally, we use our data to perform variance decomposition analysis to investigate the source of price variation. Somewhat surprisingly since his data as ours came from Chilean supermarkets,

[2] Information about this project could be find at http://www.billionpricesproject.org/.

our findings are in sharp contradiction with his. In fact, Cavallo (2010) reports that prices in Chile are sticky and follow state dependent paths.

Apart from the paper by Cavallo (2010), the only other paper that uses Stock Keeping Unit (SKU) level data for a developing economy is the work by Borraz and Zipitría (2010) that studies the case of Uruguay. In comparison to our paper, Borraz and Zipitría (2010) for daily data but for a much smaller number of goods (149 vis a vis the 22,000 in our paper). Their results are similar to ones we report below in terms of the degree of price flexibility although they do not explore the differences in the pricing strategies across different supermarket chains.

The rest of the paper is organized as follows. The next Section describes the data used in the paper. In Section 3 we characterize the pricing strategies of the retail chains using traditional statistics used in the macroeconomic literature. A variance decomposition analysis is developed in Section 4 and Section 5 examines the evidence for the reference prices. Section 6 concludes.

2 Data

We use a data set on prices collected by AC Nielsen, a marketing research firm. The data consists of weekly prices of goods sold in 288 stores in Chile during 104 weeks. In other words each unit of observation in our database is uniquely identified by a date, product code and store. Taken as a whole, store and product set up the cross-sectional dimension of the data.

Regarding the data's store dimension, we have observations for 288 stores across Chile. These stores belong to 16 supermarket chains, which in total account for at least 75% of the market share according to the ASACH (Asociación Gremial de Supermercados de Chile).[3] Of the 16 chains in our data set, we only consider the biggest five chains for our analysis. Overall, these chains own 249 supermarket stores of 288 supermarkets available in the data set and account for about 68% of the market share according to ASACH. We use only these five chains because the other chains are mainly either local chains with few stores or chains that have been merged or acquired (and have also changed their name) during the sample period. In addition, according to Lira, Ugarte, and Vergara. (2008) the Chilean supermarket industry is concentrated around major chains which have expanded throughout Chile exploiting economies of scale related to the latest world technological advances. Due to property rights restrictions we will name Chains using numbers from 1 to 5.

In turn, the product dimension consists of around 22,000 different goods identified by a unique (SKU). These SKUs are divided in 30 categories of products, which in total account for the 7.23% of Chilean CPI. Table 1 shows all the product categories in our data base and their respective weights in the Chilean CPI.

Obviously, neither all these products are sold by all of the stores nor all the products are sold every week. Therefore, some of the price series could have a large amount of missing values. In fact, a great proportion of the series at the price-store level have a lot of missing values. To cope with this problem and to have a relatively manageable data set, we use a small proportion of all the available SKUs.[4] Firstly, we decided to filter the data choosing the top 10 SKUs with more observations in each of the 30 categories of products. By reducing the sample of products to 300 we get a more manageable data base. Secondly, we dropped all SKU-store series that have more than three consecutive missing values after the first week this product was sold in this store. Table 2 shows the number of stores, product per store and total observations in each chain after applying all these filters. Then, we work with

[3] ASACH is an industry association that groups almost all supermarkets in Chile.
[4] The total number of observations in the data set is close to 400 million.

approximately 4.7 million observations.

Finally, the sample starts from the third week of July 2007 and ends the second week of July 2009 (104 weeks). During this period, as other economies did, Chilean 12-month headline inflation experienced a boom/bust episode without precedent since the implementation of the inflation targeting framework. Inflation began picking up at 3.8%, reaching a peak of 9.9% in November 2008, and ending up at 0.3% towards early July 2009. Figure 1 shows inflation dynamics during the sample period.

At this point, it is worth discussing three important issues. First, it is important to mention that AC Nielsen collects prices on Sunday. This could be an important characteristic of the data since most of sales take place between Monday and Friday. Maybe as a consequence of this phenomenon, and as we will discuss in more detail later, it seems that Chilean supermarket prices are not severely affected by temporary sales. Second, as we only chose the products with more observations in each category, we are discarding sales that involve bundling two or more products together. These kinds of combined products are assigned an SKU that is different from each of its individual products. Additionally, these kinds of sales are available for short time periods and in few stores. Therefore, their associated SKUs will not have enough observations to be considered according to our selection criterion. Finally, we did not replace missing values. Therefore, most of the results presented in this paper are obtained using original price series (or raw prices) and including missing values.

Throughout this paper, our measure of price will be:

$$p_{ijt} = \ln\left(P_{ijt}/\overline{P}_{ij}\right) \tag{1}$$

Where P_{ijt} it is the price of the product i, sold at the store j during the week t, and $\overline{P}_{ij}$ is the average price of the product i sold at the store j across the whole sample. This price change measure has the advantages that it deals with the problem of having different measurement units for different products and that it is expressed in percentage points. Generally, when we talk about price changes we will be making reference to weekly price changes except if we mention another measure explicitly. In what follows we will refer to (1) as the raw price and this measure will be used in all the calculations that follow.

3 Chain pricing behavior

As was mentioned above, one contribution of our analysis is to highlight differences in chain's pricing behavior. An obvious problem is that describing pricing strategies can be a very cumbersome process since those strategies can differ in many dimensions. In order to simplify the analysis we decide to summarize chain's pricing behavior using standard statistics used in macro monetary models to describe price dynamics. [5]

We focus on three dimensions then on the following three dimensions to describe pricing strategies: (i) frequency of price change, (ii) size of price change and (iii) the synchronization of price changes across stores in a given chain.[6] Even using this very simple way to describe chain strategies we were able to uncover significant differences across main Chilean supermarket chains as we detail now.

We start exploring how frequently stores change prices. To do this, we compute weekly and monthly frequency of price changes at the SKU/store level (i.e. how often the price of a 2-liter bottle of coke changes in a given store). Frequency is computed in the standard way

[5] See Klenow and Malin (2010)for a complete review of studies of price dynamics with focus in macro models.

[6] We also consider the use of sales as part of chain's strategies by considering the behavior of regular prices (i.e. the price when the good is not on sale) computed using the filter proposed by Nakamura and Steinsson (2008). However, after applying the filter we found out that the distribution of price changes was very similar to the non filtered data. This suggests that the sales identified by the filter were not real sales. Statistics for regular prices are available upon request.

by averaging an indicator variable that takes the value of one when the price of a particular good in a given store changes relative to its value one or four weeks ago for weekly and monthly frequency respectively. Then we compute the mean and several percentiles across all goods sold by a given store in our sample. Finally, we calculate the chain frequency of price changes by taking the average across all stores that belong to the same chain (see appendix A for details about the calculations). Results of these calculations are presented in Table 3 for both weekly (Panel A) and monthly (Panel B) frequencies. The salient fact is that prices appear to be quite flexible in Chilean supermarkets. On average, chains change 54% of prices every week. That means an average duration of only 1.3 weeks. This represents a high frequency of price changes in comparison to other studies that have use scanner data. For instance, Ellis (2009) reports that English supermarket change around 40% of prices every week (including fresh food, a category that is not present in our sample). In the case of the U.S., Eichenbaum, Jaimovich, and Rebelo (2008) report a weekly change of 43% while Campbell and Eden (2005) compute a frequency of price change of 23%. Additionally, if we consider the frequency of monthly price changes results are similar. In our sample the average frequency across chains is 67%, much larger than the ones reported for the U.S. by Nakamura (2008) (43%), Midrigan (2005) 45% and Burstein and Hellwig (2007) 41%, all of them for the United States.[7] However, the only study for Chilean prices (Medina, Rappoport, y Soto (2007)) shows that prices are very flexible in Chile, in fact, using CPI data they compute an average monthly frequency of price change of 46% for all CPI items and 100% for food related products. Finally, Cavallo (2010) is in complete contradiction with our data. This work is the only other study that also uses data from Chilean supermarkets to study pricing dynamics. He uses "scrapped" data, which is data collected from supermarket's website. He finds that Chilean prices are extremely sticky. In particular, using daily prices he found that

[7]Results are more striking if these results are compared to CPI price data that usually shows prices that are stickier than scanner data.

only 0.6% of prices change on an average day which implies that prices change on average every 166 days. Discrepancies with our results could be explained, in part, by differences in the goods included in his sample. However, it casts some doubts on the representativeness of Internet data. We will discuss this point again in more detail below.

A second point that emerges from Table 3 is that behind the high average frequency of price changes there is a significant amount of heterogeneity across supermarket chains. In fact, weekly frequencies range from more than 86% in Chain 1 to little more than 30% in Chain 2. In fact, 3 of the 5 chains exhibit frequency levels similar to those reported for developed countries. Differences in how often chains change prices are even more striking when one consider the distribution of frequency of price changes. As explained earlier, statistics in Table 3 were calculated at store level and then averaged across all stores in a chain, so the x% percentile indicates the (average) frequency of price change of the x% of goods that change price less often. From this perspective, a striking feature of Chilean supermarkets is that the 1% of goods with lower frequency of price change in Chain 1 change prices more often than the 10% of goods with higher frequency of price change in Chain 2. This reveals a significant degree of heterogeneity in the pricing behavior of supermarket chains. When monthly changes are considered, results are basically unchanged and again it is possible to identify notorious differences across chains.

The second element in our description of chain pricing strategies is the size of price changes. Those statistics are presented by chain in Table 4. In panels A to D we present statistics for both strictly positive and strictly negative price changes at both weekly and monthly frequencies. Again data has been constructed at store level (all goods sold in a particular store) and then averaged across all stores in a chain.

There are several aspects of the data which are relevant for our analysis. We highlight features of weekly changes, but it should be noted that monthly changes behave in a very similar manner. First, both positive and negative average price changes (panels A and B) range from 3 to 5% depending on the chain. Along with this, the size of price changes appears to be negatively correlated with the frequency with which those changes occur: chains that change prices less often are also chains that change prices by a smaller amount. A second notable feature of the data, is that there are an important number of very small price changes in both: the upward and the downward direction. For example, the (average) size of the 10% percentile of price increases in chain 1 is less or equal than 1%. In other words, in an average store of Chain 1 the smallest 10% of prices increases is less than 1%. [8] The existence of an important amount of small price changes is common to all chains in our sample, regardless how often they change prices.

To see this more clearly, Figure 2 plots the average frequency of price changes against the size of price changes in every store for the five chains in our sample. Panel (a) presents weekly strictly positive price changes and frequencies while Panel (b) does the same for weekly strictly negative changes. It is evident that there are notorious differences across chains. While stores in Chain 1 change prices very frequently and in a small amounts, stores of Chain 2 do the opposite. Interestingly, there is a clear negative relation between the (absolute) size of price changes and the frequency of price changes for both positive and negative changes among stores that belong to the same chain. This negative relation plus the existence of a considerable amount of small price changes (that are not optimal in a menu cost model) are suggestive of a time dependent price strategy. Obviously, it is only suggestive since menu cost models could also generate behavior like these ones. Looking at the behavior of stores within each particular chain, Figure 2 suggests that pricing strategies of stores are mainly determined by the chain to which they belong. The only exception

[8] If the prices we study data were extracted from weekly (or monthly) sales and volume data, this high frequency of small price changes could be the results of intra-week sales. As described earlier our data is collected on Sundays so we can discard the previous hypothesis as the source of these very frequent changes.

to this pattern is Chain 4 whose stores vary significantly in the dimensions analyzed here. Finally, Table 4 shows that price changes are symmetrically divided between increases and decreases. This is worth highlighting, since the period under study is one with relative high inflation in the country and particularly in the goods we are studying.

In addition, to help further elucidate if chains follow a time-dependent or a state-dependent pricing strategy we also compute hazard functions. This technique is useful because when estimating price duration using the frequency approach, one assumes implicitly that the probability of a price change is independent of the time elapsed since the last price change. In other words, it assumes a constant hazard rate. Hence, exploring the possibility of a non constant hazard rate adds relevant information to study the degree of price stickiness in the economy. On the other hand, since state dependent and time dependent models have different predictions for the shape of the hazard rates, the analysis of hazard functions can allow us to gauge which of these price strategies is a more accurate description of Chilean supermarkets. In general, while time dependent models predict constant hazard rates, state dependent models predict upward sloping ones. Since pooling observations from all chains together could lead to problems such as the survival bias that arises in the context of heterogeneity in the frequency of price change turning hazard rates flatter, we compute hazard functions by chain. Figure 3 shows the hazard rates computed for each chain in our sample. As it can be seen, with the exception of Chain 5, hazard rates are very flat, somewhat not rejecting the idea that firms follow a time dependent strategy.

Finally we look how synchronized are price changes within a chain. For doing this we measure synchronization using the Fisher and Konieczny (2000) indicator, which takes a value of 1 if synchronization is perfect and a value of 0 when price changes are uniformly staggered (see appendix A for the computational details of this indicator). The synchronization indicator is computed for the same SKU in all stores that belong to the same chain, so it captures how synchronized are price changes of the same product within all establishments of the same chain. Given this, a value of synchronization indicator close to one in a given chain is evidence that when the price of a particular good change it does in most of the stores of that chain. In Table 5 we present the average of this indicator across all products sold by a chain. As can be seen there are considerable differences in synchronization across chains: some of them appear to change prices in almost all their stores at the same time (Chain 3) while others show little synchronization like Chain 1. In general, we see that chains that change prices more frequently are also those chains that are less synchronized.

Overall, the evidence presented thus far points toward significant and systematic differences in pricing behavior across chains. On the one hand there are chains that change prices very frequently, in a small amount and with almost no synchronization across stores. On the other hand, there are chains that change prices less often, in larger amounts and at the same time in most of the stores. With the exception of Chain 4, all stores in a chain behave very similarly, which is consistent with pricing strategies designed at the chain level (as opposed to store-specific strategies). Surely, there are different ways of interpreting these results. We think it reflects different ways of facing competition and it represents changes in relative price between stores. We explore this point in the next section. However, it could also be the case that different practices reflects different bargaining powers with providers. We think this is not the case since Chilean supermarket industry is highly competitive and dominated by large economic groups that most probably has the chance to close very similar deals with their providers.[9]

Finally, in spite of the significant heterogeneity across chains there are some common facts that are important to mention. First, prices are very flexible in the sense that average duration is very small. Second, there are a lot of small price changes. Third, hazard rates

[9]For a complete description of the degree of competition of Chile's supermarket industry see Díaz, Galetovic, and Sanhueza (2009).

looks flat. Altogether, this evidence suggest that Chilean supermarket chains follow a time dependent strategy, but with different frequencies of price changes. These results are in sharp contradiction with findings in Cavallo (2010), who finds that prices in Chile are very sticky, price changes are large and price strategies seem to be state dependent. We think that differences between his and our work are partially explained by differences in the set of goods considered. However, the differences between both results are so large that we think internet prices behave different from store prices. At the end of the paper we will go back to this issue and show that the behavior of reference prices matches better the evidence presented by Cavallo (2010).

4 Decomposing Price Variability

The analysis in the preceding sections has established that the behavior of retail prices in Chile exhibits a significant degree of heterogeneity across chains. In this section we try to disentangle the different sources of that heterogeneity using the method proposed by Nakamura (2008). This method is a mixed model or two-way error component model as described in Baltagi (2008). Intuitively, this method identifies six possible sources to explain why the price of good i sold in store j increases in week t :

- The entire category of goods to which i belongs increases its price in week t either in:
  - All the stores in the country.
  - All the stores which as j belong to a particular retail chain.
  - Only in store j
- Only the individual good i shows an increase of its price either in:
  - All the stores in the country

- All the stores which as j belong to a particular retail chain.
- Only in store j

The model is estimated by maximum likelihood and it is computationally intensive. Taking this into account we implemented some modifications to the approach followed by Nakamura (2008). First, we work with first differences of the raw prices. The main reason for doing this is that inflation in Chile during the period we analyze was markedly higher than in Nakamura (2008)'s sample. Given this it is very likely that prices in levels exhibit serial correlation in Chile. Unfortunately, estimating the model allowing for correlation among the shocks over time requires significant computing resources so we opt to take the first difference of our data at the store level.

Another consideration is that the geographical distribution of retail chains is not homogeneous across the different regions (i.e. states) of Chile. In particular, there are some regions where there are very few chains. Along with this, in many cities of the country there is only one store of some chains which makes very difficult the identification of shocks among stores and chains. This is an important consideration because the model needs to be estimated separately for each category-city combination due to computer processing restrictions. After taking into account all these facts we decided to restrict our attention to the Region Metropolitana where the capital is located. This region concentrates around 40% of the country's population.

The results of the variance decomposition exercise are presented in Table 10. Results show that shocks that affect simultaneously goods in the whole region that are tied to either the specific good or the whole category explain on average almost 62% of the variance of the change of prices.[10] At the same time, shocks associated with retail chains constitute

[10]This is the result of adding the averages of columns (3) and (6).

around 35% of the observed variance of prices indicating that store specific shocks are the least important factor.[11] Our results contrasts to those reported by Nakamura (2008) who reports a much more important role for store-specific factors. One possible explanation for this discrepancy is that we analyze a period of higher aggregate inflation. Moreover, one of the leading elements to explain the increase of inflation was the steep increase in the price of oil which affects production cost of several products through energy prices. The degree of variation attributed to chain shocks is by no means trivial and it is consistent with the noticeable degree of heterogeneity on pricing strategy across super market chains that we documented before.

5 Further Evidence: Analysis of Reference Prices

So far, we showed that supermarket chains change prices very often, but the way they do it differs considerably across chains. Even more, we presented evidence that this heterogeneity explains a relevant part of the variance of price changes in our sample. In particular, the evidence suggested that an important part of variability of prices are related to chain/product shocks, what implies that there is a lot of variability in relative prices for a given product across chains.

Given the large degree of flexibility and the importance of chain idiosyncratic shocks, a natural question that follows is how can these prices account for real effects of monetary policy? In a recent paper, Eichenbaum, Jaimovich, and Rebelo (2008) propose a way of measuring sticky "reference" prices amidst shorter-lived new prices. They define the reference price for each SKU as the modal price in each quarter. Then, using a simple model, they use such reference prices to point out that their frequency of changes is the key to monetary

[11]The contribution of the retail chain shocks is obtained adding the averages of columns (2) and (4).

non-neutrality. Therefore, they suggest that from a macroeconomic point of view little and frequent price changes are not very important and that what matters is the behavior of reference prices.

In this section we calculate the "reference" price series for each SKU-store price series. However, we calculate them in the same fashion as Klenow and Malin (2010) taking the modal price in a moving window. Klenow and Malin (2010) consider a 13-month window centered on the current month. Since inflation was high in Chile during this period, we consider a much shorter window of 13 weeks centered in the current week. As Klenow and Malin (2010), we broke ties in favor of the highest price.

Our results support the view proposed by Eichenbaum, Jaimovich, and Rebelo (2008) for the U.S.: reference prices seem to be important in Chilean supermarkets. Using a 13 weeks size window we find that the posted price equals the reference price 56% of the time and that reference price appears in the window 51% of the time on average. However, the importance of reference prices results varies across chains. In fact, as it is shown in Table 6 the average proportion of time that posted price equals the reference range from 26 in Chain 1 to 65% in Chain 2. In the same vein, the proportion of times that the reference price appears in the window range from 27 in Chain 1 to 71% in Chain 2.

5.1 Reference price strategies

We describe reference price in the same way we described raw prices in Section 3: first we analyze the frequency of price changes, then the average size of price changes, and finally we document the degree of synchronization across stores that belong to the same chain.

Starting with the frequency of price changes, Table 7 shows that as expected, reference prices change less often than raw prices. In particular, panel A of Table 7 shows that the average weekly frequency of reference price changes is only 9%, which implies an average duration of more than ten weeks. That is, reference prices have a duration that is almost 8 times the duration of raw prices. In all chains except in Chain 1 there are a bunch of goods with unconditional reference price duration of more than a year (or a frequency close to 2%) and the top 1% of more flexible prices have an average duration within 4 and 6 weeks. So even though raw prices look very flexible, this is not the case for reference prices.

With respect to the size of price changes Table 8 shows that, on average, weekly positive price changes are between 60 and 100% larger than average price changes of raw prices, and that in almost all chains there are few small price changes. With respect to price decreases results are similar. Interestingly and in contrast with raw price behaviors, the distribution of price increases and decreases is not symmetric. In fact, the chance of seeing larger positive changes is higher than the chance of seeing large negative changes. This is consistent with a country where national inflation was around 7% during this period and almost 10% on average for goods included in our sample. The fact that raw price changes are symmetric and references price are not in a context of inflation reinforces our suspicion that much of the raw price changes are related to chain strategies to compete for clients, rather than with changes in the underlaying state of the economy. We will go back to this issue below when we will decompose reference price variance.

Putting together the reduction in frequency and the increased of average price changes, one could suspect that reference price strategy could be different from raw price strategy regarding their degree of time or state dependency. We corroborate this intuition by computing hazard rates for reference prices. As shown in Figure 4, in accordance with a common implication of some state dependent models the hazard rate of all chains are upward sloping.

Finally, Table 9 shows the degree of coordination in reference price changes across stores that belong to the same chain. It confirms that the degree of synchronization of reference prices is smaller than for raw prices suggesting that deviations from reference prices are more coordinated across stores in a given chain than changes in the reference price itself.

As a robustness check of our results we also performed a variance decomposition analysis as the one described in Section 4 for the reference prices. Results of the variance decomposition of the first difference of the (log) reference prices appear in Table 11. As it can be inferred, the importance of aggregate shocks increases in comparison with raw price results: both of them account now for over 70% of the variance. Also as expected, the importance of the chain level shocks is also lower in the case of reference prices.

Altogether, the evidence for reference prices suggests first that this measure of price is important since a large fraction of actual prices are equal to reference prices. Second, reference prices behave differently from raw prices. In particular, they are much stickier, they change by larger amounts and their changes are less coordinated across stores given a particular chain. Third, and in contrast to raw prices, evidence suggests that reference price dynamics are state dependent. Finally, even though references prices are less sticky than internet prices analyzed by Cavallo (2010), their behavior is much more similar. This posits that many of the small and very frequent price changes that we found in the raw data are not present in the internet data.

6 Conclusion

The analysis of scanner level data has been a very active field of research in recent years. Up to our knowledge, most of the evidence available today is for industrialized countries and reports a relatively high degree of price flexibility. In this paper we have examined for the first time evidence for an emerging economy which also experienced a bout of higher than average inflation during the period under study. The evidence presented in this paper suggests two salient features of prices in this economy: there is a high degree of flexibility and significant heterogeneity of the pricing strategy across chains. Nevertheless the analysis also suggests a measure of prices more relevant for the design of monetary policy (reference prices) which exhibits more rigidity than what the raw data suggests. Two intertwined conclusions emerge from this analysis. First, a significant fraction of the reported flexibility of the scanner-level prices appears to be related to the sales strategies of particular retailers. And secondly, the reference prices still appear to be driven mostly by economy-wide shocks.

Along with these findings, our paper suggests also several avenues for future research. Most of these are related to the significant degree of heterogeneity in pricing strategy across retail chains. First, understanding the economic factors that underlie the choice of pricing strategy by each chain is an important issue. This could be tackled exploiting the variation in stores concentration across the different cities in our sample. With this one could gauge whether more intense competition within chains and stores leads to higher short term flexibility of prices. Potentially these issues have important implications to anticipate what could happen to the short term volatility of inflation if new mergers and acquisitions are observed in Chile's supermarket industry.

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Table 1: Product Categories

Category	Weight	Category	Weight
Cooking Oil	0.28	Powder juices	0.11
Rice	0.19	Powder milk	0.26
Soft Drinks	1.5	Milk	0.56
Coffee	0.13	House cleaners	0.35
Toothbrushes	0.08	Mayonnaise	0.13
Cereals	0.17	Disposable diapers	0.29
Face Creams	0.12	Toothpaste	0.08
Hand and Body Creams	0.12	Batteries	0.06
Air Fresheners	0.08	Sanitary napkins	0.09
Deodorant	0.15	Cheese	0.61
Laundry detergent	0.48	Hair shampoo	0.25
Dry pasta	0.27	Snacks	0.16
Sunscreens	0.07	Hair dyes	0.1
Shaving razors and blades	0.05	Yoghurt	0.34
Bath Soaps	0.08	Frozen desserts	0.07

Table shows all the product categories in our data base and their respective weights in the Chilean CPI.

Table 2: Basic Data of Chains in the Sample

	Number of Stores	Avg. UPC per Store	Number of Obs.
Chain 1	20	240.3	492,938
Chain 2	80	231.8	1,883,594
Chain 3	19	143.2	274,790
Chain 4	105	173.9	1,845,509
Chain 5	24	77.8	183,367

Table shows basic statistic by chain after keeping data from the top 5 supermarket chains, the top 10 SKUs with more observations and after dropping the SKU-store series that have more than three consecutive missing values after the first week this product was sold in this store.

Table 3: Frequency of price changes

	Mean	Std. Dev.	Percentile						
			1%	10%	25%	50%	75%	90%	99%
	Panel A: Weekly Changes								
Chain 1	0.865	0.100	0.537	0.660	0.821	0.891	0.937	0.963	0.991
Chain 2	0.308	0.134	0.076	0.118	0.205	0.293	0.395	0.494	0.653
Chain 3	0.353	0.187	0.048	0.087	0.189	0.348	0.481	0.624	0.766
Chain 4	0.677	0.171	0.208	0.353	0.569	0.708	0.808	0.872	0.940
Chain 5	0.501	0.175	0.114	0.234	0.375	0.481	0.632	0.758	0.846
Average	0.541	0.154	0.197	0.290	0.432	0.544	0.651	0.742	0.839
	Panel B: Monthly Changes								
Chain 1	0.897	0.092	0.573	0.712	0.860	0.923	0.961	0.982	0.998
Chain 2	0.514	0.194	0.142	0.213	0.360	0.503	0.663	0.789	0.901
Chain 3	0.533	0.215	0.102	0.180	0.343	0.554	0.719	0.798	0.918
Chain 4	0.765	0.166	0.266	0.438	0.674	0.803	0.893	0.944	0.982
Chain 5	0.664	0.181	0.194	0.339	0.552	0.657	0.813	0.900	0.970
Average	0.674	0.170	0.256	0.377	0.558	0.688	0.810	0.883	0.954

Table shows statistics of frequency of price changes by chain. Statistics were calculated at store level and then averaged across all stores in a chain, so the x% percentile indicates the (average) frequency of price change of the x% of goods.

Table 4: Size of price changes

	Mean	Percentile						
		1%	10%	25%	50%	75%	90%	99%
	Panel A: Weekly Positive Changes							
Chain 1	0.029	0.008	0.010	0.017	0.027	0.039	0.049	0.073
Chain 2	0.045	0.015	0.019	0.030	0.040	0.056	0.073	0.121
Chain 3	0.047	0.012	0.021	0.031	0.041	0.058	0.081	0.121
Chain 4	0.040	0.008	0.013	0.023	0.034	0.050	0.071	0.116
Chain 5	0.049	0.017	0.023	0.034	0.045	0.060	0.076	0.140
	Panel B: Weekly Negative Changes							
Chain 1	-0.025	-0.070	-0.052	-0.034	-0.023	-0.014	-0.009	-0.005
Chain 2	-0.034	-0.103	-0.068	-0.043	-0.031	-0.021	-0.014	-0.007
Chain 3	-0.047	-0.136	-0.108	-0.059	-0.040	-0.026	-0.019	-0.008
Chain 4	-0.036	-0.111	-0.083	-0.046	-0.031	-0.020	-0.012	-0.006
Chain 5	-0.047	-0.161	-0.088	-0.059	-0.043	-0.030	-0.023	-0.013
	Panel C: Monthly Positive Changes							
Chain 1	0.050	0.012	0.018	0.033	0.046	0.063	0.083	0.122
Chain 2	0.068	0.022	0.030	0.047	0.062	0.083	0.106	0.165
Chain 3	0.067	0.016	0.031	0.048	0.059	0.076	0.111	0.174
Chain 4	0.062	0.013	0.023	0.042	0.056	0.077	0.102	0.169
Chain 5	0.067	0.028	0.035	0.050	0.062	0.079	0.101	0.182
	Panel D: Monthly Negative Changes							
Chain 1	-0.041	-0.120	-0.088	-0.054	-0.038	-0.022	-0.012	-0.006
Chain 2	-0.051	-0.144	-0.102	-0.066	-0.047	-0.031	-0.019	-0.007
Chain 3	-0.065	-0.171	-0.145	-0.082	-0.057	-0.039	-0.025	-0.007
Chain 4	-0.054	-0.155	-0.114	-0.069	-0.048	-0.032	-0.017	-0.007
Chain 5	-0.062	-0.187	-0.117	-0.079	-0.057	-0.040	-0.029	-0.019

Table shows percentiles distribution of positive and negative reference price changes for weekly and monthly price changes frequencies. Data has been constructed at store level (all goods sold in a particular store) and then averaged across all stores in a chain.

Table 5: Synchronization across stores that belong to the same chain

	Number of Stores	Synchronization Indicator
Chain 1	20	0.363
Chain 2	80	0.709
Chain 3	19	0.961
Chain 4	105	0.456
Chain 5	24	0.777

Table shows the degree of coordination in price changes across stores that belong to the same chain. The synchronization indicator is computed for the same SKU in all stores that belong to the same chain (see appendix A for the computational details of this indicator).

Table 6: Reference prices

	% Posted = Reference	% Reference in Window
CHAIN 1	26	27
CHAIN 2	65	71
CHAIN 3	62	67
CHAIN 4	41	44
CHAIN 5	53	57

Table shows the average proportion of time that posted price equals the reference price, and the proportion of times that the reference price appears in the window, conditioning by chain. Reference price calculations have been carried out by using a 13 weeks size window.

Table 7: Frequency of price changes, Reference prices

	Mean	Percentile						
		1%	10%	25%	50%	75%	90%	99%
Panel A: Weekly Changes								
Chain 1	0.159	0.025	0.060	0.120	0.158	0.199	0.236	0.293
Chain 2	0.063	0.005	0.019	0.044	0.058	0.079	0.103	0.146
Chain 3	0.069	0.014	0.022	0.045	0.067	0.093	0.113	0.149
Chain 4	0.100	0.007	0.024	0.058	0.096	0.137	0.174	0.236
Chain 5	0.074	0.006	0.019	0.044	0.066	0.094	0.132	0.225
Average	0.093	0.011	0.029	0.062	0.089	0.121	0.152	0.210
Panel B: Monthly Changes								
Chain 1	0.427	0.086	0.184	0.348	0.440	0.521	0.584	0.679
Chain 2	0.226	0.016	0.074	0.164	0.224	0.286	0.350	0.463
Chain 3	0.242	0.053	0.091	0.161	0.244	0.316	0.366	0.445
Chain 4	0.302	0.021	0.092	0.206	0.305	0.399	0.474	0.582
Chain 5	0.243	0.027	0.077	0.161	0.230	0.311	0.404	0.537
Average	0.288	0.041	0.104	0.208	0.289	0.367	0.435	0.541

Table shows the frequency of price changes for reference prices. We compute weekly and monthly frequency of price changes at SKU/store level. Frequency is computed in the standard way by averaging an indicator variable that takes value of one when the price of a particular good in a given store change relative to its value one or four weeks ago for weekly and monthly frequency respectively. Then several percentiles across all goods sold by a given store in our sample.

Table 8: Positive and Negative Reference Price Changes

	Mean	Percentile						
		1%	10%	25%	50%	75%	90%	99%
Panel A: Weekly Positive Changes								
Chain 1	0.047	0.005	0.013	0.026	0.039	0.058	0.085	0.167
Chain 2	0.092	0.025	0.038	0.062	0.083	0.112	0.149	0.248
Chain 3	0.085	0.015	0.033	0.057	0.077	0.103	0.141	0.238
Chain 4	0.071	0.014	0.023	0.041	0.061	0.087	0.122	0.263
Chain 5	0.087	0.010	0.029	0.054	0.079	0.112	0.146	0.231
Panel B: Weekly Negative Changes								
Chain 1	-0.030	-0.145	-0.084	-0.039	-0.022	-0.010	-0.004	-0.002
Chain 2	-0.065	-0.196	-0.139	-0.083	-0.058	-0.038	-0.020	-0.003
Chain 3	-0.084	-0.250	-0.199	-0.109	-0.070	-0.051	-0.026	-0.008
Chain 4	-0.048	-0.205	-0.131	-0.063	-0.037	-0.020	-0.007	-0.001
Chain 5	-0.067	-0.265	-0.166	-0.085	-0.055	-0.037	-0.019	-0.004
Panel C: Monthly Positive Changes								
Chain 1	0.057	0.005	0.018	0.035	0.049	0.069	0.100	0.187
Chain 2	0.094	0.025	0.038	0.063	0.085	0.114	0.151	0.256
Chain 3	0.087	0.015	0.032	0.059	0.078	0.107	0.146	0.261
Chain 4	0.077	0.016	0.028	0.047	0.067	0.094	0.128	0.277
Chain 5	0.091	0.011	0.031	0.058	0.081	0.118	0.153	0.245
Panel D: Monthly Negative Changes								
Chain 1	-0.034	-0.160	-0.092	-0.045	-0.026	-0.011	-0.004	-0.002
Chain 2	-0.064	-0.192	-0.136	-0.083	-0.057	-0.037	-0.020	-0.003
Chain 3	-0.082	-0.252	-0.198	-0.104	-0.069	-0.049	-0.025	-0.007
Chain 4	-0.050	-0.205	-0.134	-0.066	-0.040	-0.021	-0.008	-0.001
Chain 5	-0.069	-0.274	-0.164	-0.087	-0.057	-0.039	-0.021	-0.004

Table shows percentiles distribution of positive and negative reference price changes for weekly and monthly price changes frequencies. Data has been constructed at store level (all goods sold in a particular store) and then averaged across all stores in a chain.

Table 9: Synchronization of Reference Price Changes

	Mean	Percentile					Number
		1%	25%	50%	75%	90%	of Stores
Chain 1	0.256	0.228	0.271	0.299	0.331	0.378	20
Chain 2	0.544	0.271	0.433	0.504	0.582	0.643	80
Chain 3	0.669	0.558	0.728	0.792	0.853	0.913	19
Chain 4	0.357	0.159	0.266	0.309	0.349	0.410	105
Chain 5	0.795	0.347	0.472	0.534	0.595	0.649	24

Table shows the degree of coordination in reference price changes across stores that belong to the same chain. The synchronization indicator is computed for the same SKU in all stores that belong to the same chain (see appendix A for the computational details of this indicator).

Table 10: Variance Decomposition

	UPC			Category		
	(1) Store	(2) Chain	(3) All	(4) Store	(5) Chain	(6) All
Cooking Oil	41.4	6.2	0.0	0.0	0.0	64.5
Rice	22.6	18.4	6.6	0.0	0.0	53.3
Soft Drinks	14.9	11.8	0.0	0.0	0.9	71.7
Coffee	17.4	10.9	0.9	0.0	1.4	62.2
Toothbrushes	7.2	45.3	9.2	1.7	0.2	37.3
Cereals	0.1	25.9	9.6	0.0	3.2	68.5
Skin cream	0.0	46.4	21.6	1.9	10.3	11.5
Body cream	0.0	17.4	7.0	0.0	0.8	64.3
Air freshener	3.2	64.8	16.4	3.1	0.0	12.9
Deodorant	0.0	45.7	21.5	0.0	0.0	39.0
Laundry Detergent	18.0	11.7	2.4	0.0	5.5	72.7
Pasta	51.3	14.9	0.3	3.1	11.3	17.9
Sunblock	6.9	34.7	11.6	0.0	4.8	41.6
Shavers	0.0	29.7	13.3	0.0	0.0	43.4
Powder Milk	10.4	16.6	0.0	0.0	2.8	70.5
Milk	1.7	38.2	5.6	0.1	4.9	37.0
Mayonaise	29.2	17.1	0.0	4.0	2.3	42.7
Diapers	3.1	34.2	9.9	0.0	7.5	45.6
Toothpaste	2.5	25.4	4.7	3.9	18.8	58.3
Batteries	3.8	23.4	7.3	0.0	0.5	69.1
Sanitary Napkins	3.7	8.5	0.7	0.0	0.2	86.1
Cheese	3.8	25.0	20.5	4.8	1.5	43.9
Shampoo	0.9	30.5	12.3	0.0	0.8	58.6
Yoghurt	2.7	68.3	17.0	0.0	1.9	42.5
Yoghurt 2	13.4	28.6	4.9	0.0	22.2	58.5
Average	10.3	28.0	8.1	0.9	4.1	50.9

The model is estimated only for the Region Metropolitana. Some categories in the sample are not reported because the solution obtained with the software was not economically meaningful. The rows don't add exactly to 100% because of approximation errors of the maximum likelihood algorithm.

Table 11: Variance Decomposition Reference Prices

	UPC			Category		
	(1)	(2)	(3)	(4)	(5)	(6)
	Store	Chain	All	Store	Chain	All
Cooking Oil	35.8	11.9	6.4	0.0	2.9	54.8
Rice	14.8	8.6	12.9	0.0	10.4	57.1
Soft Drinks	12.1	8.7	0.6	0.0	2.2	78.8
Coffee	17.6	9.5	0.2	0.0	1.8	66.0
Toothbrushes	4.8	18.9	12.1	2.1	2.5	47.2
Cereals	2.0	11.8	10.5	0.0	0.0	75.7
Skin cream	0.0	23.1	9.2	4.2	8.5	45.6
Body cream	0.0	7.6	10.8	0.0	1.6	61.6
Air freshener	3.5	54.0	6.2	5.8	1.7	41.2
Deodorant	0.1	28.7	16.4	0.4	0.0	56.5
Pasta	45.0	19.3	0.6	3.9	17.1	24.5
Sunblock	11.9	16.3	10.6	0.0	4.0	51.6
Shavers	3.5	16.2	11.4	0.0	0.0	63.4
Soap	20.6	16.0	0.0	2.8	0.0	59.4
Powder Milk	9.7	10.4	0.6	0.0	0.1	78.5
Milk	1.0	17.1	12.6	1.4	0.2	53.1
House Cleaners	4.7	28.4	37.1	0.0	0.0	52.3
Mayonaise	24.0	25.1	0.5	3.8	0.5	47.4
Diapers	0.9	22.1	4.6	0.0	1.6	58.4
Toothpaste	9.6	24.6	2.7	7.4	4.3	67.5
Batteries	6.1	13.0	9.9	0.0	4.9	67.1
Sanitary Napkins	6.5	6.9	1.0	0.0	0.6	83.2
Cheese	3.0	35.2	13.5	0.3	2.8	52.8
Shampoo	0.0	18.6	12.1	0.0	0.0	70.8
Yoghurt	5.1	26.1	0.0	0.9	0.0	70.7
Yoghurt 2	2.3	10.3	3.6	1.4	2.3	78.8
Average	9.4	18.3	6.7	1.3	2.7	61.0

The model is estimated only for the Region Metropolitana. Some categories in the sample are not reported because the solution obtained with the software was not economically meaningful. The rows don't add exactly to 100% because of approximation errors of the maximum likelihood algorithm.

Figure 1: Inflation

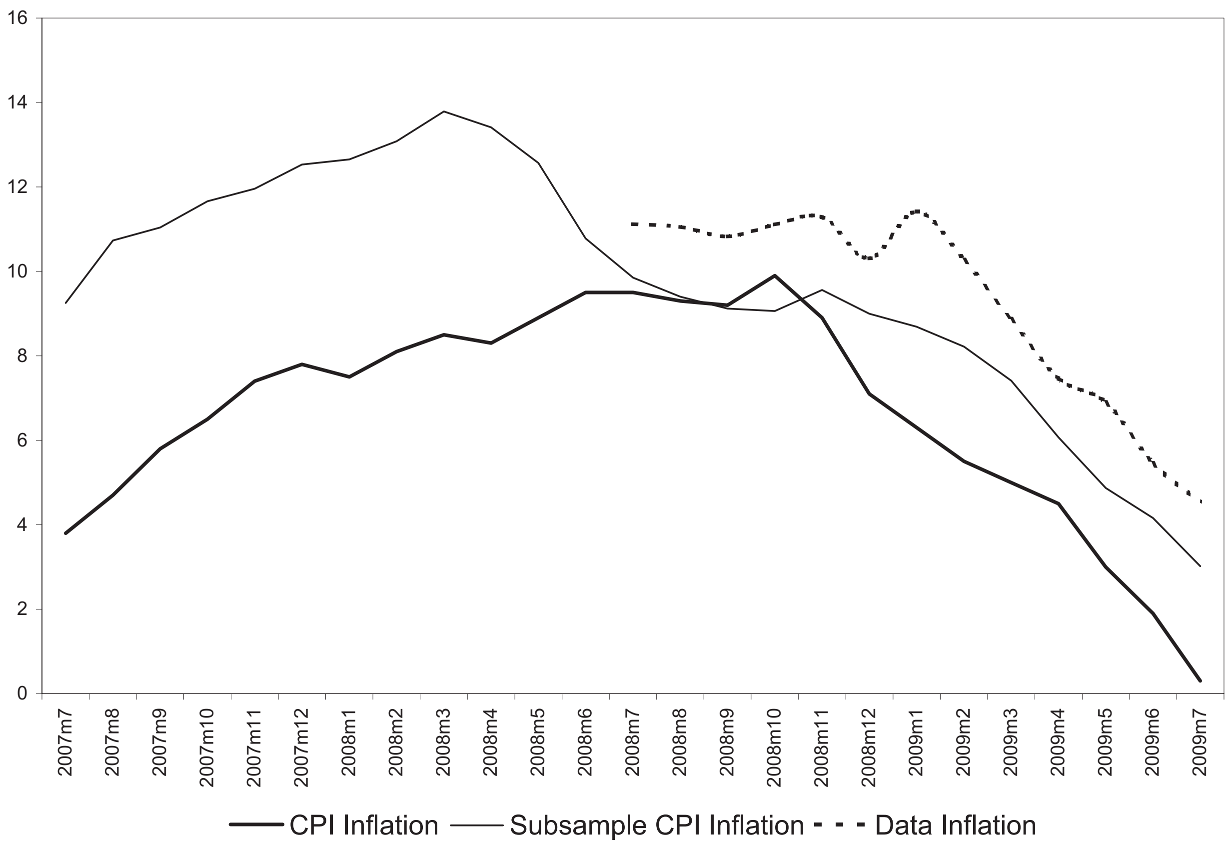


Figure 2: Size and Frequency of Price Changes

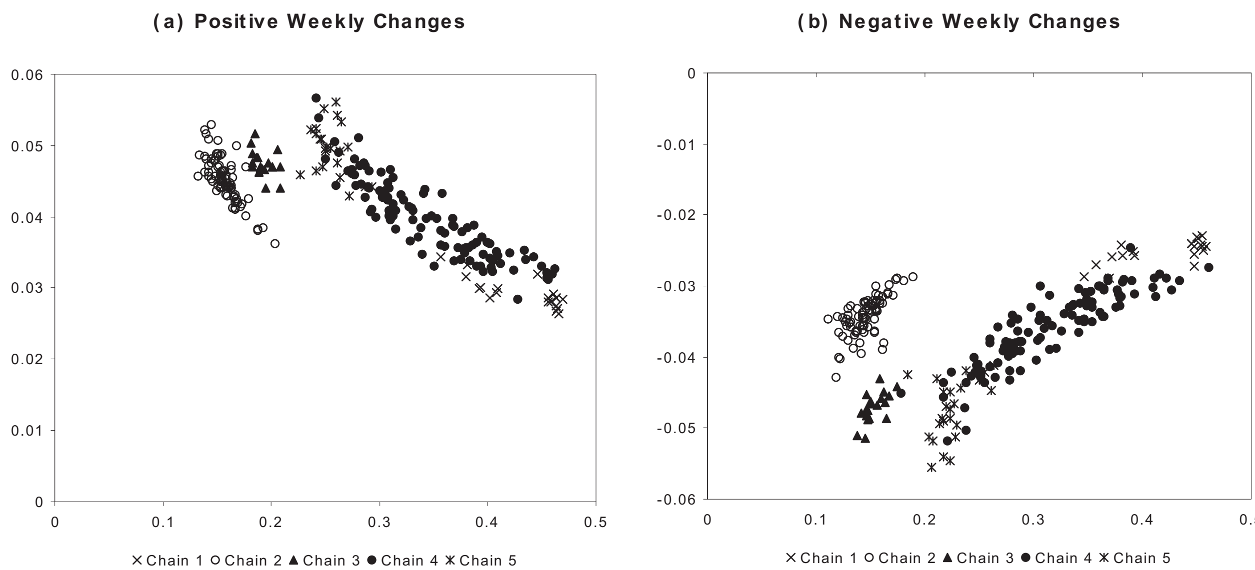


Figure 3: Hazard Function by Chain

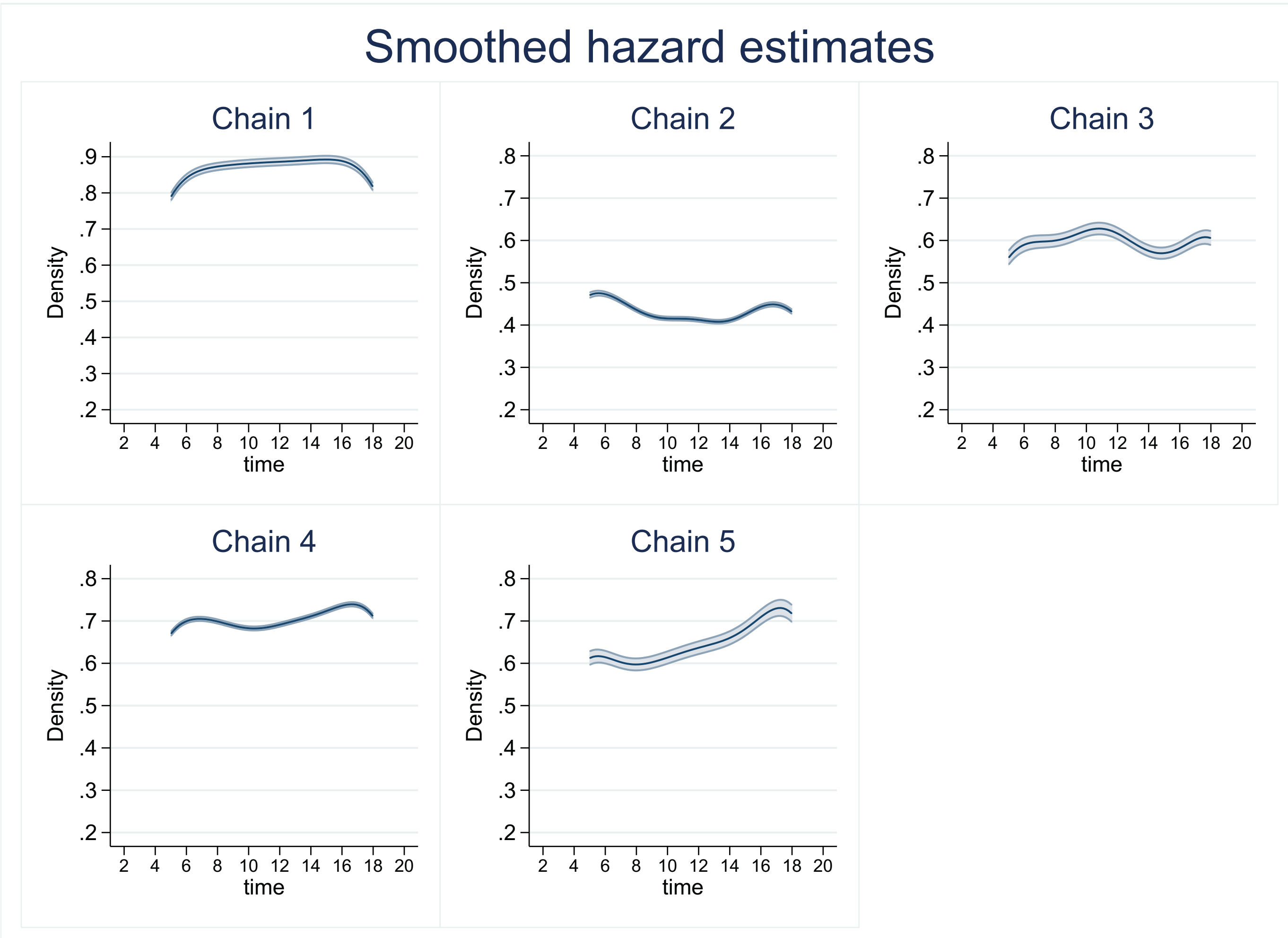
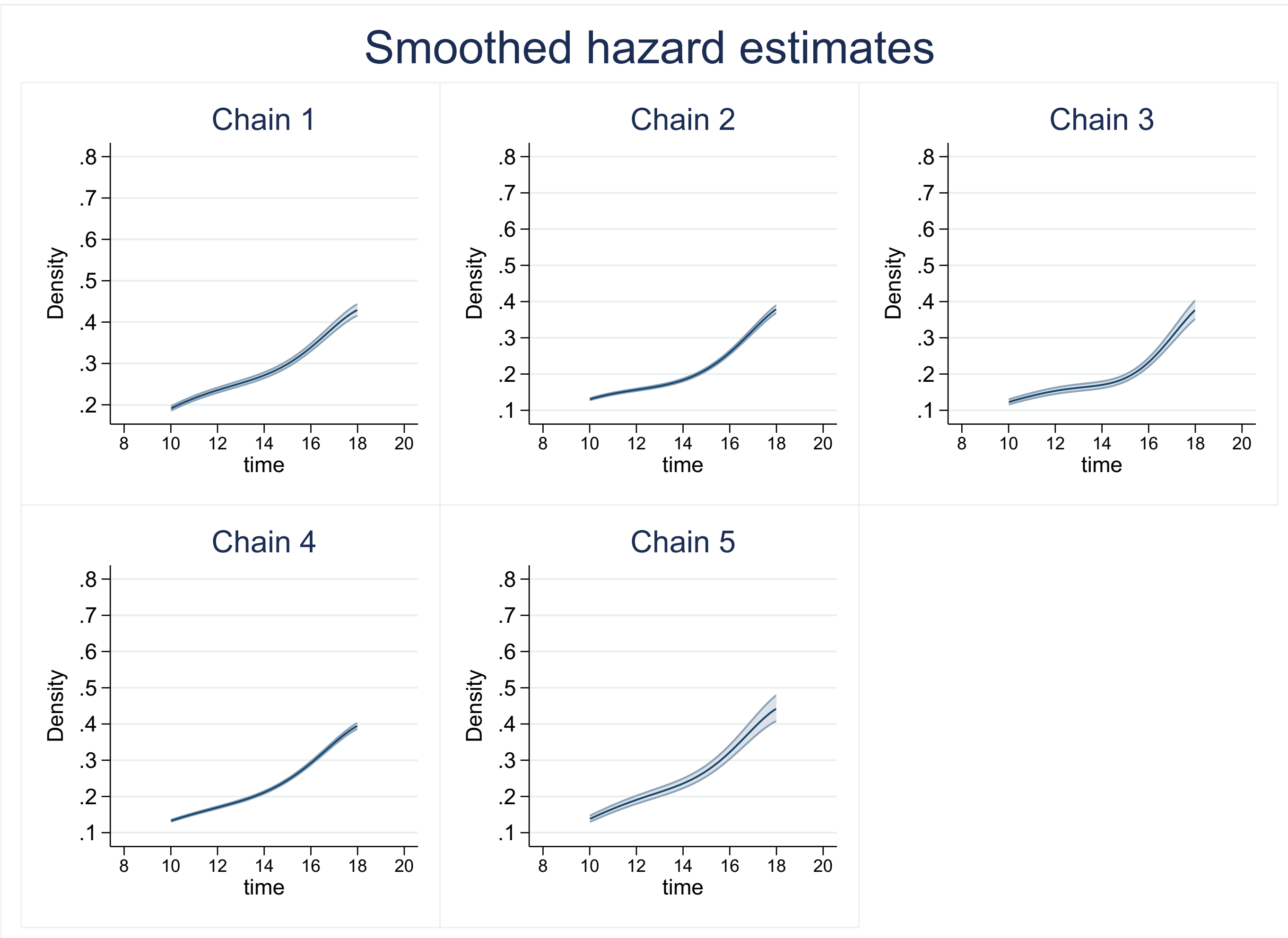


Figure 4: Hazard Function by Chains - Reference Prices



A Details of Calculations

A.1 Frequency of Price Changes

Weekly frequency of price changes: We first compute the indicator variable,IW_{ijt}, where:

$$IW_{ijt} = \begin{cases} 1\ if\ p_{ijt} - p_{ijt-1} \neq 0 \\ 0\ if\ p_{ijt} - p_{ijt-1} = 0 \end{cases} \tag{2}$$

Then, the weekly frequency of price chage for supermarket chain "A", WFr_A, is calculated as:

$$WFr_A = \frac{1}{N_{jA}} \sum_{j \in A} \left(\frac{1}{N_{Ij}} \sum_{i \in I_j} \left(\frac{1}{T_{ij} - 1} \sum_{t \in T_{ij}} IW_{ijt} \right) \right) \tag{3}$$

Where N_{jA} is the total number of stores in chain A, N_{Ij} is the total number of products sold in store j, I_j is the set of all products sold in store j, and T_{ij} is the total number of weeks that product i was sold in store j.

Monthly frequency of price changes: Again, we first compute the indicator variable,IM_{ijt}, where:

$$IM_{ijt} = \begin{cases} 1\ if\ p_{ijt} - p_{ijt-4} \neq 0 \\ 0\ if\ p_{ijt} - p_{ijt-4} = 0 \end{cases} \tag{4}$$

Then, the weekly frequency of price chage for supermarket chain "A", MFr_A, is calculated as:

$$MFr_A = \frac{1}{N_{jA}} \sum_{j \in A} \left(\frac{1}{N_{Ij}} \sum_{i \in I_j} \left(\frac{1}{T_{ij} - 4} \sum_{t \in T_{ij}} IW_{ijt} \right) \right) \tag{5}$$

A.2 Size of Price Changes

Weekly average size of price changes in chain A is calculated as follows:

$$W\Delta p_A = \frac{1}{N_{jA}} \sum_{j \in A} \left(\frac{1}{N_{Ij}} \sum_{i \in I_j} \left(\frac{\sum_{t \in T_{ij}} IW_{ijt} \times \Delta_{-1} p_{ijt}}{\sum_{t \in T_{ij}} IW_{ijt}} \right) \right) \tag{6}$$

And, monthly average size of price changes in chain A is calculated as

$$M\Delta p_A = \frac{1}{N_{jA}} \sum_{j \in A} \left(\frac{1}{N_{Ij}} \sum_{i \in I_j} \left(\frac{\sum_{t \in T_{ij}} IM_{ijt} \times \Delta_{-4} p_{ijt}}{\sum_{t \in T_{ij}} IM_{ijt}} \right) \right) \tag{7}$$

Where $\Delta_{-1} p_{ijt}$ is the difference between one price and the same price one week before and $\Delta_{-4} p_{ijt}$ is the difference between one price and the same price four weeks before. Since we have defined prices $p_{ijt} = \ln\left(P_{ijt}/\overline{P}_{ij}\right)$, these differences are meassured in percentage terms.

A.3 Hazard Functions

To calculate hazard functions we use the Nelson-Aalen non-parametric estimator. In particular, we use a gaussian kernel and a two weeks bandwidth. We also compute hazard functions we the epanechnikov kernel and different bandwidths and results do not vary significantly.

A.4 Synchronization

To meassure the degree of synchorization beetween a set of prices we use the FK indicator due to Fisher and Konieczny (2000). The FK indicator can be computed as follows:

$$FK = \sqrt{\frac{1}{T}\frac{\sum_{t=1}^{T}(p_t - \bar{p})^2}{\bar{p}(1-\bar{p})}} = \frac{\sqrt{s_p^2}}{\sqrt{\bar{p}(1-\bar{p})}} \tag{8}$$

where p_t denote the proportion of price changes into a set of all posible price changes between period t and period $t-1$, and $\bar{p} = \sum_{t=1}^{T} \frac{p_t}{T}$ and $S_{p_t}^2$ are the sample mean and variance (across time) of p_t, respectively.

Our meassure of price change synchronization consists on synchronization of one particular product across all stores from a particular chain. Therefore, to obtain a measure of the level of synchronization across chains' store, we calculate the FK indicator for each SKU and then we average across SKU. Where each FK indicator is obtained considering each chain separately.

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