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Heterogeneous price dynamics, synchronization, and retail chains: evidence from scanner data

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Heterogeneous Price Dynamics, Synchronization, and Retail Chains: Evidence from Scanner Data

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Abstract

This paper uses a novel scanner data set to study price setting decisions of major retailers in an emerging market economy. I find evidence of heterogeneous pricing dynamics across retail chains. Heterogeneity is especially pronounced in the case of posted (as opposed to reference) prices. Furthermore, retail chains appear to set prices in a centralized fashion: most barcode-store level prices coincide with the intrachain modal price. The relationship between reference and chain-wide prices reveals that deviations from reference prices cannot be solely attributed to shocks to local market conditions. In line with results on retail chain pricing, I find strong evidence of synchronization of price changes across stores within chains but weaker evidence of synchronization across retail chains. The evidence is also consistent with synchronization of price changes within retail stores.

Keywords: Pricing setting, retail, emerging economy, scanner data

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1 Introduction

Recent years have witnessed renewed interest in the empirical study of firms' price-setting behavior.[1] Interest in this area has been spurred both by the crucial role played by price stickiness in New Keynesian macroeconomics and by the increasing availability of rich micro data sets (Klenow and Malin, 2011). The body of evidence accumulated over the past decade has allowed researchers to better inform theoretical pricing models and to assess the role of price stickiness in generating persistent responses of output to monetary shocks.

While much has been learned about price-setting behavior at the product level –and the way price-setting rules vary across products and sectors (e.g., Bils and Klenow, 2004; Dhyne et al., 2006)– little is known about the way pricing behavior varies across individual retail stores. In particular, little evidence has been produced on the way price-setting rules for a given product vary within and across multistore retailers.[2,3]

Understanding how price-setting behavior varies across retail chains is important for a number of reasons. First, multistore retailers account for a large fraction of retail activity in developed and emerging economies.[4] Second, understanding the way price-setting rules vary across retailers can shed light on the factors influencing price dynamics. Third, retailer pricing policies have implications for the extent to which price changes are synchronized across stores.[5]

In this study, I use a novel scanner data set from an emerging economy to shed light on the importance of retail chains in driving price dynamics. The data set is especially well

[1] The seminal work in the literature is Bils and Klenow (2004). Klenow and Malin (2011) and Nakamura and Steinsson (2013) survey the literature.

[2] Evidence suggesting the importance of retail chains in driving price dynamics is provided by Nakamura (2008) and Nakamura et al. (2011). Nakamura et al. (2011) study retail price-setting on three product categories in the US and find that frequencies of price adjustment vary systematically across chains.

[3] In what follows, I refer to "retailers" and "retail chains" indistinctively.

[4] For example, multi-store retailers account for 60 percent of sales in US retail (Aguirregabiria and Vicentini 2012). For evidence on the importance of retail chains in emerging economies, see Reardon et al. (2005).

[5] In addition, Nakamura et al. (2011) highlight the fact that understanding how price dynamics vary within and across retail chains has implications for inflation measurement.

suited for this purpose. It contains weekly barcode-store level prices and quantities sold for approximately 60,000 barcodes and 281 stores belonging to 14 retail chains operating in Chile over a two-year period.

A noteworthy feature of the data is their inclusion of price and quantity information for several retail chains. Typically, scanner data sets are available for a single retailer (Nakamura and Steinsson, 2013). If heterogeneity in price-setting behavior across retailers is important, then inferences made from the behavior of a single retail chain can be misleading. In addition, the vast majority of papers studying price-setting in emerging economies use price data underlying the construction of the CPI.[6,7] While comprehensive in scope, CPI data are usually available at lower frequencies and provide no information on actual quantities sold.

Consistent with the view that retail chains are important in explaining heterogeneous price dynamics, I find that most of the variation in the frequencies of price change is common across stores belonging to a given retail chain. Variation that is common across all stores that are part of a particular retail chain account for 56 percent of the intra-category variation in the frequencies of posted price adjustment. Retail chains are also found to play a significant role in driving *reference* price dynamics. Approximately 52 percent of the variation in the frequencies of reference price adjustment within a category is common to all stores within a particular retail chain (and not to stores across retail chains). Heterogeneity in frequencies of price adjustment is found to be more pronounced for posted than for reference prices. The weighted median frequency of posted price change varies by as much as a factor of about 3 (vs. 1.2 in the case of reference prices) between retailers. This is consistent with the view that movements in reference prices are likely to be more influenced by non-retailer-specific

[6] Papers that study data underlying the CPI from emerging and developing economies include Gouvea (2007, Brazil), Barros et al. (2009, Brazil), Medina et al. (2007, Chile), Gabriel and Reiff (2008, Hungary), Gagnon (2009, Mexico), Kovanen (2006, Sierra Leone) and Coricelli and Horvath (2006, Slovakia). Julio and Zárate (2008) study price data underlying the Colombian PPI. For evidence on CPI inflation dynamics in emerging and developing economies see, *inter alia*, Backé et al. (2003), Balcilar (2004) and Vašíček (2011).

[7] Two papers focusing on emerging markets that do not use data underlying the official CPI or PPI are Cavallo (2012) and Chaumont et al. (2011). Cavallo (2012) uses online data from retailers in Argentina, Brazil, Chile and Colombia. Chaumont et al. (2011) use scanner price data for Chile.

shocks.

Examination of the cross-sectional distribution of intra-chain prices reveals that retail chains tend to set prices that are largely common across stores. The modal price of a barcode within a chain (referred to in this study as the barcode's "chain price") is an important feature of the cross-sectional distribution of intrachain prices. Between 80 and 90 percent of barcode-level prices coincide with chain prices, and posted prices display a tendency to revolve about chain prices. Thus the evidence is consistent with a price adjustment process characterized by retailers setting prices in a centralized fashion and store managers deviating from the centralized price when changes in local market conditions justify it. Chain prices appear to be more persistent than posted prices but less persistent than reference prices.

Relating chain prices to reference prices provides further insights into the nature of the shocks driving reference price dynamics. The analysis reveals that more than half of nonreference prices are set at the chain level. Thus, deviations from reference prices are not driven solely by idiosyncratic shocks affecting local markets but also respond to shocks affecting all stores in a chain or to retailers' dynamic pricing policies.

Relatedly, I find that price changes of a barcode are substantially more synchronized across stores that are part of a retail chain than across stores from different retail chains. While the probability of a store changing the price of a barcode is increasing in the fraction of other stores changing the price of the barcode in the same week, the likelihood of a price change is orders of magnitude larger when other stores belong to the same chain than when they belong to a different chain. Thus, the evidence is supportive of intra-chain price synchronization, in line with evidence on retailers' price-setting process.

The evidence also favors the hypothesis of *within*-store synchronization. The probability of a price change increases with the fraction of other barcodes changing prices within an individual store. Sheshinski and Weiss (1992) show that prices tend to be synchronized within stores when the technology of price adjustments is characterized by increasing returns and when the prices of different products have positive interactions in the profit function.

The remainder of the paper is organized as follows. Section 2 presents a description of the data. Section 3 examines the evidence on individual price rigidities in posted and reference prices, and presents evidence on heterogeneous price dynamics across retailers. Section 4 studies the behavior of "chain prices" (i.e., modal prices across stores within a chain) and explores the relationship between chain prices and reference prices. Section 5 examines synchronization across stores, chains and within-stores. Section 6 concludes.

2 Description of Data

The data include weekly retail prices and quantities for a large number of product varieties sold by retailers in the Santiago de Chile metropolitan area. The data are at the barcode and store level and were provided to the author by a market research firm. The data include revenue and quantity information on more than 60,000 barcodes for 281 stores belonging to 14 retail chains. Product varieties (at the barcode-level) are classified into 190 categories comprising mainly foodstuffs and drugstore and healthcare products.[8] Table 1 lists the categories included in the data set. These categories correspond to product groups that account for approximately 20 percent of the Chilean CPI.[9]

The set of retailers included in the data is highly representative of the Chilean supermarket industry as a whole. The data cover all major supermarket[10] chains operating in Chile over the period of analysis.[11] This, combined with the fact that the supermarket industry in Chile is highly concentrated (over the period of analysis, the two largest retailers accounted for more than 60 percent of the industry sales nationwide), suggests that a large fraction of

[8] I adopt the taxonomy used by the market research firm that provided the data to classify product varieties.

[9] The categories "'Foodstuffs and Non-Alcoholic Beverages"', "'Alcoholic Beverages, Tobacco and Narcotics"' and "'Health"', represent 18.9 percent, 2 percent, and 5.4 percent, respectively of the cost of the reference basket used in the construction of the CPI in Chile.

[10] For simplicity I use the term "supermarket" to refer to all large-format modern retail (supermarkets, hypermarkets and discount and club stores).

[11] The retail chains included in the data set are the following: Bandera Azul, Economax, Ekono, Jumbo, Las Brisas, Lider, Maicao, Montecarlo, Montserrat, OK Market, Puerto Cristo, Ribeiro, Santa Isabel and Unimarc.

the sales of the categories listed in Table 1 are accounted for in the data. In addition to supermarket chains, the data include a chain of convenience stores and a drugstore.

Data on prices and quantities for all retailers are available for a maximum period of 101 weeks ranging from August 2005 to July 2007. Raw data include the weekly revenue for a given item in a given store and the weekly quantity sold for the item. The weekly price measure I use in the analysis is the ratio of the weekly revenue to the weekly quantity sold.

Measurement Issues. Two measurement issues that are especially relevant in the analysis of scanner data are the following: (i) the large number of missing observations due to stockouts or non-purchase of a product variety, and (ii) the presence of non-round prices due to the use of unit values. Both issues can affect estimated frequencies of price adjustment depending on how one chooses to address them. To address the problem of missing data, I choose to ignore missing observations when computing frequencies of price change.[12] This approach leads to unbiased estimates of price adjustment frequencies as long as the process generating missing observations is independent of the retailer's price adjustment decisions (Konieczny and Skrzypacz, 2006). To limit the prevalence of missing observations, I impose the requirement that the price of a given barcode and store be observed in at least 75 weeks to be included in the analysis.[13]

The second data issue has to do with non-round prices. Because prices are obtained as average weekly revenue, a fraction of the prices are non-round because of price changes occurring in a day of the week different from the one when data are recorded. As Campbell and Eden (2005) note, multiple prices in a given week may lead to an overestimation of the frequency of price adjustment. To address this potential problem, I applied a filter proposed

[12] Nakamura and Steinsson (2008) follow this same strategy.

[13] This requirement reduced the number of price trajectories in the data from 2,141,016 to 433,613. It also reduced the number of retailers in the data, as several retail chains are in the data for short periods of time, primarily because they were acquired by other supermarket chains and started operating under new banners between late 2005 and early 2006. In particular, Las Brisas and Montecarlo were acquired in 2004 by the retailer Cencosud (owner of Jumbo and Santa Isabel) and remained in the sample for 19 weeks. Cencosud also acquired Economax in 2006, which remained in the sample for 65 weeks. The convenience store OK Market and the discounter Ekono entered (in the case of Ekono, *re*-entered) the market in mid-2007 and, hence, remain in the sample for short periods of time –5 and 10 weeks, respectively.

by Campbell and Eden that replaces a non-round price with the immediately preceding price provided that two conditions hold: (i) both the preceding and following price are round prices, and (ii) the price and its neighboring prices form a strictly increasing or decreasing sequence. I also excluded one of the retailers for which the pattern of non-round prices observed in the data suggests the presence of measurement error. [14,15]

3 Evidence on Price Setting Behavior

This section examines the degree of price stickiness observed in individual price trajectories. A price trajectory is defined for a product variety (or barcode) k, store i and chain j.

3.1 Importance of Reference Prices

I start by establishing the importance of reference (or regular) prices in the data. There is substantial evidence in the literature showing that consumer prices are characterized by short-lived departures from more persistent underlying reference prices (e.g., Nakamura and Steinsson, 2008; Kehoe and Midrigan, 2012; Eichenbaum, Jaimovich and Rebelo, 2011; Klenow and Malin, 2011). This section shows that the same phenomenon characterizes retail price dynamics in my data.

I identify reference prices using a filter proposed by Kehoe and Midrigan (2012) (KM, hereafter).[16] In essence, the filter identifies a reference price as the modal price within a rolling window of 13 weeks centered on the current week (see the Appendix in KM for a detailed description of the algorithm). Two desirable properties of the KM filter are that (i)

[14] Approximately 49 percent of all prices are nonround prices in the case of this retailer. In contrast, the average fraction of nonround prices in the rest of the retail chains included in the analysis is approximately 9 percent. According to information provided by an insider, the retailer in question changed its information systems around the time the change in the pattern of nonround prices was observed.

[15] I also imposed the criterion that at least 75 percent of prices in a given price series should be round prices. Although this is admittedly arbitrary, imposing these criteria does not alter the main results reported below.

[16] I thank Virgiliu Midrigan for providing me with the Matlab code that implements the price filter in Kehoe and Midrigan (2012).

it allows reference prices to change within a given time period (something that filters that use fixed temporal windows, such as the filter in EJR, do not permit), and (ii) it ensures that the reference price of a given barcode-store will not change unless the corresponding posted price also changes. Both of these features help avoid identifying spurious reference price changes.

Table 2 presents evidence on the importance of reference prices in the data. It shows estimates of the transitional probabilities of a Markov chain describing the transition of posted prices between three states: "Nonreference", in which the posted price is different from the reference price; "New Reference", in which the posted price is equal to a reference price that has not occurred in any previous week within a given price trajectory; and, "Old Reference", in which the posted price is equal to a reference price that has already been observed at some point in the past within a price trajectory.[17] Each cell (i, j) in Table 2 corresponds to the probability that a posted price that in the current week is in state i moves the next week to state j. The probabilities were computed at the barcode-store level and later aggregated using category level weights.[18]

The evidence presented in Table 2 suggests that posted prices have a tendency to revolve about reference prices. The probability of a nonreference price leaving that state is approximately 0.42. Approximately two-thirds of the time that a nonreference price leaves that state, the posted price returns to a reference price that has been observed in some previous week. Once at a reference price, the posted price tends to remain in that state. The probability of a reference price remaining in that state is equal to 0.90 for old reference prices and to 0.96 for new reference prices. Approximately 80 percent of posted prices are equal to reference prices.

Nonreference vs. Sale Prices. It should be noted that nonreference prices are not necessarily equivalent to sale prices. Sale prices are typically defined as temporary mark-

[17] I thank an anonymous referee for suggesting breaking up a single "‘reference state"’, considered in a previous version of this study, into an "‘old reference"’ state and a "‘new reference"’ state.

[18] In computing the transitional probabilities, I restricted the sample to those price trajectories including at least 84 data points (the median of the distribution of non-missing observations)

downs lasting between one and five weeks before returning to a regular price (e.g. Nakamura and Steinsson, 2008; Midrigan, 2011). In the data, approximately half of all nonreference prices lie above the reference price. Furthermore, the fraction of sale prices in the data is low compared with that of nonreference prices that lie below the reference price.

To characterize sales periods, I construct sale prices using a filter that identifies V-shaped sales as a drop in price, which is followed by a return to the original price after a number of weeks. The filter identifies episodes in which the price remained at some level below the immediately preceding price for a time interval ranging between one and five weeks. The fraction of all prices identified as sale prices equals 2.7 percent. By comparison, Klenow and Kryvtsov (2008) report that approximately 11 percent of the prices in their sample are identified as sale prices by BLS price collectors.

The fraction of sale prices is small (5.7 percent or lower) across all retailers. While this fraction varies across retailers and categories, a simple variance decomposition[19] shows that approximately 43 percent of the variation in the fraction of sale prices is explained by variation across retailers (versus 21 percent explained by variation across categories). In contrast, the fraction of nonreference prices varies more strongly across categories than across retailers (37 percent of the variation of the fraction of nonreference prices is explained by variation across categories versus 24 percent explained by variation across retail chains). This suggests that the frequency of occurrence of sale prices is driven to a larger extent by retailers pricing strategies than that of nonreference prices which appear to be more related to product-level shocks.

[19] I used the following specification to estimate the variance decomposition:

$$s_{cj} = \alpha + \varphi_c + \varphi_j + \varepsilon_{cj}$$

where s_{cj} is the fraction of sale prices in category c and retail chain j; α is a constant term; φ_c and φ_j are category and chain effects, respectively, assumed to be normally distributed with a constant variance; and ε_{cj} is a residual term. The model was estimated by maximum likelihood.

3.2 Frequency and Size of Price Adjustments

This subsection presents evidence of frequencies and the size of price changes for posted and reference prices.

Frequencies of Price Adjustment. The frequency of price adjustment for a product k sold in store i in chain j is defined as follows,

$$fr_{ijk} = \frac{\sum_t \mathcal{I}\{p_{ijk,t} \neq p_{ijk,t-1}\}}{\sum_t \mathcal{I}\{p_{ijk,t} \in \Omega_{ijk}\}}$$

where $\mathcal{I}\{\cdot\}$ is an indicator function and Ω_{ijk} is the set of consecutive non-missing price observations in price trajectory$-ijk$.

The first three rows in Table 3 show the weighted median[20] frequencies of price changes for both posted and reference prices. Retailers change posted prices fairly often. On average, posted prices change every 5.6 weeks; the frequency of posted price adjustments equals 0.178 per week. In contrast, the frequency of reference price adjustment is only 0.04 per week, which implies that the duration of the average reference price spell is approximately 25 weeks (i.e., approximately two quarters). Price increases appear to be more prevalent than price decreases for both posted and reference prices, which is consistent with an economic environment featuring a positive rate of inflation.

There is evidence of heterogeneity in price dynamics both across products and retail

[20] The weighted medians reported in Table 3 are computed as follows. Let X^{50}_{cj} be the sample median of a variable X (observed at the product-store level) for category c and retail chain j. First, a weighted median at the category level is computed as

$$X^{50,w}_c = \sum_j \left(\frac{EXP_{cj}}{\sum_j EXP_{cj}} \right) X^{50}_{cj}$$

where EXP_{cj} is the total expenditure in category c in chain j.

Later, weighted medians at the category level are weighted by the share of total expenditures (across all categories) accounted for by category c. Hence, the weighted medians reported in the paper are computed as

$$X^{50,w} = \sum_c \left(\frac{EXP_c}{\sum_c EXP_c} \right) X^{50,w}_c$$

where $EXP_c = \sum_j EXP_{cj}$.

chains. As previously documented in the literature, frequencies of price adjustment are highly heterogeneous across product categories (see Figure 1).

Table 4 presents the frequencies of price adjustment at the retail chain level. Excluding Chain 3[21], the weighted median frequencies of price changes vary between 0.101 and 0.278 in the case of posted prices. Implied durations of posted price spells vary between 3.6 weeks and 9.9 weeks. Heterogeneity in the frequencies of price adjustment appears to be more modest in the case of reference prices. The weighted median frequency of reference price changes varies between 0.035 and 0.043 (again, excluding Chain 3). The implied durations of reference price spells vary between 23 weeks and 28 weeks. That the heterogeneity in the frequencies of posted price changes appears to be greater than the heterogeneity in the frequencies of reference price changes is consistent with the view that changes in reference prices are likely to be relatively more influenced by non-retailer-specific shocks.

The previous comparisons do not control for the possibility that different retailers sell a different set of product varieties (barcodes). However, variations in frequencies of price adjustment across retailers are similar in magnitude when restricting the sample to a common set of barcodes sold across all retailers.[22] In the next subsection, I use a variance components model to analyze this issue more formally.

Size of Price Adjustment. The price changes are small compared with previously reported results. The weighted median size of a (log) price change is equal to 0.042 for posted prices and 0.065 for reference prices (see Table 3). Approximately 25 percent of reference price changes are smaller than three percent. By comparison, Klenow and Kryvtsov (2008), for instance, find that the average size of price changes in US CPI data is 14 percent in the case of posted prices and 11.3 percent in the case of regular prices. Studies using US scanner data (Kehoe and Midrigan 2012; Eichenbaum et al. 2011) report even larger magnitudes of price adjustment; their figures are 16-17 percent.

[21] Chain 3 is the only non-supermarket/hypermarket chain in the sample and accounts for a small fraction of total expenditure.

[22] Controlling for barcode, frequencies of posted (reference) price changes vary across retail chains between 0.069 (0.034) and 0.264 (0.045).

There is some evidence of heterogeneity in the size of posted price changes across retail chains. The weighted median size of a posted price change varies between 2.6 percent (Chain 6) and 6.7 percent (Chain 4), with a standard deviation of 0.012 and a coefficient of variation equal to 0.303. When restricting the set of barcodes to those sold in all retailers, the variation in the magnitude of posted price changes across retailers is more modest –it varies between 3.7 percent and 6.4 percent, with a coefficient of variation of 0.213.

In contrast, the magnitude of reference price changes is similar across retail chains varying between 5.7 percent and 7.4 percent, with a standard deviation of 0.005 and a coefficient of variation of 0.081.

3.3 Evidence of Heterogeneous Price Dynamics

This subsection conducts a more formal analysis of the way frequencies of price adjustment vary across retail chains, barcodes and stores. I estimate the following variance components model:[23]

$$fr_{ijk} = \beta + \varphi_j + \varphi_k + \varphi_{jk} + \varphi_{ij} + \varepsilon_{ijk} \tag{1}$$

where β is a constant term; φ_j is common across barcodes and stores within a given retail chain; φ_{jk} is common across stores for a specific retail chain and barcode; φ_k is common across stores for a given barcode; φ_{ij} is common across barcodes within a given store; and the residual term ε_{ijk} is idiosyncratic to a given store and barcode. All random components are assumed to be independently normally distributed with zero mean and constant variance.[24] I estimate the model by maximum likelihood at the category level.

Table 5 decomposes the variation in the frequencies of posted and reference price adjustments into their various sources for the average category.[25] Variation that is common across

[23] Nakamura et al. (2011) use a similar specification to study variation in the frequencies of price adjustment in the US.

[24] Note that this is a two-level model in which stores are nested within retail chains. This structure allows one to identify both the variation of level-2 main effects (i.e., retail chain and barcode effects) and their interaction and also the variation at level-1 (i.e., store effects within retail chains).

[25] Results on individual categories are available from the author upon request.

all stores selling a particular barcode account for only 25 percent of the variation in the frequencies of posted price adjustments and 15 percent of the variation in the frequencies of reference price adjustment. In contrast, variation that is common across all stores that are part of a particular retail chain account for 56 percent of the intra-category variation in the frequencies of posted price adjustments and 52 percent of the variation in the frequencies of reference price adjustment. The fraction of total variation that is common across all stores selling the same barcode within a particular retail chain is approximately 29 percent in the case of posted prices and approximately 43 percent in the case of reference prices.

Thus, the evidence suggests that retailer characteristics are important determinants of heterogeneity in both posted and reference price dynamics.[26] Consistent with the view that changes in reference prices are more responsive to non-retailer-specific shocks, variation across retailers explains a higher fraction of the variation in the frequency of posted prices relative to that of reference prices (56 percent versus 52 percent). The fact that a large fraction of the variation in the frequencies of reference price changes is common to stores within chains (but not to stores across retail chains) suggests that other factors, related to retailer characteristics, contribute to explaining reference price dynamics besides aggregate (in the sense of non-retailer-specific) shocks.

There are several alternative explanations to the finding that retailer characteristics are important in explaining heterogeneous price dynamics. One possible explanation is that different retail chains follow different pricing strategies. The marketing literature identifies two types of pricing strategies typically followed by supermarket chains: Every-Day-Low-Prices (EDLP) and High-Low (HL). Retailers that follow EDLP strategies tend to keep low regular prices and to conduct less frequent and less pronounced sales promotions; chains adopting an HL strategy use price promotions more intensively. Nakamura (2008) argues that different dynamic pricing policies across retailers are likely to explain her finding of retail prices varying systematically along a retail chain dimension.

[26] Nakamura et al. (2011) report similar evidence for three product categories in the US.

Another possibility is that shocks to wholesale costs have a chain-specific component. Chain-specific cost shocks would involve manufacturers (or wholesalers, more generally) price discriminating across retailers. Evidence from the costs of the two largest chains suggests that this is unlikely to be the case.[27] Among 31 categories for which wholesale costs are available for both chains, the correlation coefficient between the cost of a given barcode in the two chains is 0.7 for the median category. Considering that one of the cost measures corresponds to historical costs, the correlation between the costs faced by the two retailers appears to be rather high. Wholesale price discrimination is also likely to be limited by the possibility of attracting the scrutiny of competition authorities.

4 Chain Price Behavior

The preceding analysis establishes that retailers play an important role in driving price dynamics. This section provides further evidence regarding retail chains' price setting process. It studies how the cross-sectional price distribution of prices within a chain varies over time. I start by showing that the modal price of a given product across the stores of a chain in a given week is an informative summary measure of the intrachain price distribution.

I refer to the mode of the intra-chain price distribution of barcode k in week t (i.e., the most repeated price for a given barcode across stores belonging to a given retail chain in a given week) as the "chain price". Chain prices are important in the data. The fraction of all prices at the barcode-store level that are equal to the chain price varies between .78 in Chain 6 and .94 in Chain 4.[28] There are no instances of multiple chain prices in the data.

Table 6 presents estimates of the transitional probabilities of a Markov Chain describing the movement of posted prices between the following three states: "Old Chain", in which the posted price is equal to a chain price previously observed within the same price trajectory; "New Chain", in which the posted price is equal to a chain price that has not been observed

[27] See Appendix B for a description of the wholesale cost data.

[28] This excludes retail chains 1 and 3 because the former includes only two stores and the latter corresponds to a drugstore and accounts for a small fraction of total expenditures.

within the same price trajectory; and "Nonchain", in which the posted price is different from the chain price. The estimates indicate that posted prices have a tendency to remain at chain prices once they have visited that state. The probability of a chain price remaining in that state (either as an "old" or a "new" chain price) the following week is equal to .88 for "old" chain prices and to .81 for "new" chain prices. A nonchain price has a high probability of visiting the "chain" state the following week (0.67). With a probability of 0.54, a nonchain price changes the following week to a chain price that has already been observed in some previous week.

Column 3 in Table 3 presents evidence regarding the frequency of chain price adjustment. Chain prices are changed less frequently than posted (barcode/store-level) prices but more frequently than (barcode/store-level) reference prices. The weighted median chain weekly frequency of chain prices is equal to 0.104, which implies a duration of 9.7 weeks for the median chain price spell. Most chain price changes are price increases. The weighted median frequency of chain price increases (decreases) equals 0.056 (0.047).

The magnitude of chain-price changes lies between the magnitude of posted and reference price changes. The weighted median chain price change equals 5.8 percent, which is larger than the (weighted) median size of posted price changes (4.2 percent) but smaller than the (weighted) median size of reference price changes (6.5 percent).

The evidence is consistent with a price adjustment process characterized by retailers setting prices in a centralized fashion but allowing store managers to set a different price when changes in local market conditions justify doing so.[29] The international evidence on chain-wide pricing is mixed and comes primarily (if not entirely) from advanced economies. Levy et al. (1997), Dobson and Waterson (2008) and Eden and Jaremski (2009) find evidence

[29] An alternative explanation is that chains establish different pricing zones depending, among other things, on the amount of competition faced by different stores. Anecdotal evidence indicates that some retail chains in the data do define pricing zones for a subset of products they carry. Under this scheme, all prices are set at the headquarters level for different sets of stores. The data, however, lends little support to the possibility that this type of policy is generalized across barcodes and/or retailers. There are no cases in the data where the second-most repeated price of a product in a given chain and week appears with a frequency greater than one.

consistent with centralized pricing. In contrast, Berck et al. (2009) report that the large US retailer they analyze follows a store-by-store pricing policy. Determining whether uniform pricing policies are more prevalent in emerging economies vis-à-vis advanced economies is a potentially interesting topic for future research.

The above findings have direct implications for the synchronization of price changes, further explored in Section 5 below.

The evidence thus suggests that posted prices have a tendency to revolve both about reference and chain prices. It is instructive to examine the relationship between these two price concepts. The following contingency table summarizes the frequency of occurrence of reference, nonreference, chain and nonchain prices in the data:

$$\begin{array}{ll} & \begin{array}{cc} \text{Nonreference} & \text{Reference} \end{array} \\ \begin{array}{l} \text{Nonchain} \\ \\ \text{Chain} \end{array} & \begin{bmatrix} 0.084 & 0.041 \\ & \\ 0.105 & 0.770 \end{bmatrix} \end{array}$$

As the table above shows, not only are reference prices set at the headquarters level, but a fraction of nonreference prices also appear to be set in a centralized fashion. In approximately half of the deviations from a store's reference price, the posted price is actually aligned with the chain's modal price during the week. This result provides new insights into the nature of reference prices. Deviations from reference prices are not driven solely by idiosyncratic shocks affecting local markets but also respond to shocks affecting all stores in a chain or to retailers' dynamic pricing policies. At the same time, deviations from chain prices are not only due to movements away from a reference price set at the headquarters level. Approximately one-third of non-chain prices $(0.041/0.041 + 0.084)$ set by local managers are also reference prices.

5 Synchronization and Staggering in Price Adjustments

The response of the aggregate price level to a nominal shock depends not only on the degree of price stickiness observed at the individual level but also on the extent to which individual price changes are synchronized or staggered (Fischer, 1977; Taylor, 1979, 1980; Caballero and Engel, 2007). Within the context of multiproduct price setters, aggregate price level dynamics also depend on whether synchronization occurs across firms or within firms. The traditional argument for staggering contributing to a delayed response of the aggregate price level to a nominal shock is based on staggering occurring across as opposed to within price setters (Lach and Tsiddon, 1992).

The empirical literature on price synchronization has, for the most part, focused on narrow sets of products. Lach and Tsiddon (1992), for instance, analyze monthly data for 26 foodstuffs underlying the CPI in Israel. They find that even during periods of high inflation, prices are not synchronized across stores. Lach and Tsiddon (1996) focus on grocery stores selling wine and meat products in Israel and find that price changes tend to be staggered across stores but synchronized within stores. Similar evidence is reported by Fisher and Konieczny (2000), who examine the synchronization of changes in Canadian newspaper prices. Loy and Weiss (2004) study the synchronization of price changes for 10 grocery products in Germany. They find evidence of synchronization within retail chains as well as some evidence of synchronization across chains. They also report evidence of synchronization within stores.[30]

I estimate a conditional logit model to investigate the extent of synchronization in price adjustments across and within stores. The baseline specification is the following:[31]

$$Y_{ik,t}^{(j)} = \alpha^{(j)} + \beta S_{ik,t}^{(j)} + \gamma F_{k,t}^{(j)} + \sum_{m \neq j} \delta_m F_{k,t}^{(m)} + \zeta_i^{(j)} + \zeta_k^{(j)} + \varepsilon_{ik,t}^{(j)} \qquad (2)$$

[30] Other recent papers reporting evidence of within store synchronization are Midrigan (2011) and Cavallo (2012).

[31] Similar specifications are used by Fisher and Konieczny (2000) and Loy and Weiss (2004).

where $Y_{ik,t}^{(j)}$ is a binary response variable that equals 1 if store i in chain j changes the price of barcode k in week t and is zero otherwise; $S_{ik,t}^{(j)}$ is the fraction of other barcodes in store i changing prices in week t; $F_{k,t}^{(j)}$ is the fraction of the remaining stores in chain j that change the price of barcode k in week t; $F_{k,t}^{(m)}$ is the fraction of stores in chain m that change the price of barcode k in week t; $\zeta_i^{(j)}$ and $\zeta_k^{(j)}$ are store and barcode fixed effects; and $\varepsilon_{ik,t}^{(j)}$ is an error term assumed to be distributed extreme value with zero mean and a constant variance.

Table 7 reports the marginal effects from the conditional logit estimation. Estimations are performed for each retail chain in the sample. To keep a consistent number of stores and chains per barcode, I restrict the analysis to the largest four retailers in the data set. The results are consistent with synchronization of price adjustments across stores. Estimated coefficients on the fraction of other stores changing the price of a barcode in the same week are, in most cases, positive and statistically significant. The evidence is weaker for synchronization across chains than for synchronization across stores within chains. The effect of other stores changing prices on the probability of store i changing its price is substantially (even orders of magnitude) larger when the other stores belong to the same chain as store i. In the case of Chain A, for instance, a one percentage point increase in the fraction of other stores in the same chain that change their (posted) price is associated with an increase of approximately three-quarters of a percentage point in the probability of a (posted) price change. The magnitude of the effect is approximately 100 times the effect of an identical increase in the fraction of stores in Chain B changing their price and approximately 87 times the effect of an identical increase in the fraction of stores in Chain C changing their price. The same pattern is observed across other retail chains. The effect of within-chain synchronization is stronger for reference than for posted prices across all chains included in the analysis.

The fact that across-store synchronization is substantially stronger for stores belonging to the same chain suggests that the results are not driven by aggregate shocks affecting all stores in the sample. Further evidence consistent with this view comes from estimating the conditional logit model including time fixed effects.[32] The results of the estimation, presented in Appendix A, reveals that marginal effects associated with the fraction of other stores changing prices are similar –and even larger– when time fixed effects are included in the estimation. Thus, the evidence suggests that the observed synchronization in price changes across stores is related to strategic considerations on the part of price setters rather than to the effect of aggregate shocks. However, it should be stressed that synchronization across stores of different chains is relatively small. In addition, the findings reported in the previous section on retail chain pricing suggest that synchronization across stores belonging to the same chain arises mechanically as a consequence of centralized pricing.

The strength of synchronization of price changes within a store can help discriminate between alternative technologies of price adjustment (Sheshinski an Weiss, 1992). The evidence, reported in Table 7, points to strong within-store synchronization. The coefficient on the fraction of other products in the same store changing prices is statistically significant and positive for all retail chains included in the analysis. Furthermore, the effect is economically relevant compared with the coefficients capturing within-chain synchronization in the price changes of a given barcode.

To examine the extent to which within-store synchronization reflects synchronized price changes within a given product category, Table 8 decomposes the fraction of other barcodes changing prices in the same store into the following two components: (i) the fraction of other barcodes changing prices within the same category (Fr W), and (ii) the fraction of other barcodes changing prices in different categories (Fr O). The results suggest that the observed amount of within-store synchronization reflects primarily within-category synchronization.

[32] Time fixed effects included in the estimation correspond to a full set of 21 monthly dummies. Similar results are obtained when 11 monthly dummies are used.

6 Concluding Remarks

This study has used a unique scanner data set to study price setting behavior in an emerging economy. One remarkable feature of the data set is that it contains price and quantity information for several retail chains. The analysis reveals that price setting behavior varies systematically across retail chains. Most of the variation in the frequencies of both posted and reference price adjustment is common to stores belonging to the same retail chain. Heterogeneity in frequencies of price adjustment is found to be more pronounced for posted than for reference prices. This is consistent with the view that movements in reference prices are likely to be more influenced by non-retailer-specific shocks.

Along the same lines, the amount of synchronization in price changes across stores is substantially larger in the case of stores belonging to a given retail chain. The importance of intrachain synchronization in price adjustments for aggregate price flexibility is compounded by the finding of synchronization of price changes within stores. Not only do stores belonging to a given retail chain tend to simultaneously (i.e., in the same week) change the price of a given barcode, but the prices of several barcodes are also changed at the same time. This type of behavior is consistent with the existence of economies of scope in price adjustment (Sheshinski and Weiss, 1992; Midrigan, 2011).

Analysis of the cross-sectional distribution of barcode-level prices across stores within chains reveals that the modal price, referred to in this study as the "chain price", is a relevant feature of this distribution. This "chain price" is more persistent than posted prices but less persistent than reference prices. The evidence is consistent with retail chains setting prices in a centralized fashion while at the same time allowing store managers to deviate from the chain-wide price conditional on changes in local market conditions. Further research is needed to determine whether this type of pricing scheme is common to other emerging economies. On a purely speculative level, one could conceive of centralized pricing being a more common feature in emerging economies relative to advanced economies because of the conjunction of two factors: (i) price setting being a task that is relatively intensive in managerial time (Levy et al. 1997) and (ii) highly-skilled workers being relatively scarcer in emerging economies.

Interestingly, the analysis reveals that deviations from reference prices cannot be attributed to shocks to local market conditions. If changes in local market conditions were responsible for posted prices deviating from reference prices, then we should expect to see posted prices deviating from chain prices at the same time. Instead, the evidence shows that most nonreference prices are also chain prices and, hence, are set at the headquarters level. This finding is consistent with Klenow and Malin's (2011) result that deviations from reference prices do not seem to wash out with aggregation.

Appendix A

Conditional Logit Estimations including Time Effects

Table A: Synchronization of Posted Price Changes

	Chain A	Chain B	Chain C	Chain D
Fr S (×100)	.417 ***	1.050 ***	.388 ***	.370 ***
	(.023)	(.077)	(.015)	(.016)
Fr A (×100)	.885 ***	.021 ***	.002 **	.002 **
	(.047)	(.004)	(.001)	(.001)
Fr B (×100)	.009 ***	1.200 ***	− .005	.007 ***
	(.002)	(.087)	(.001)	(.002)
Fr C (×100)	.010 ***	.003	.423 ***	.005 ***
	(.002)	(.004)	(.018)	(.001)
Fr D (×100)	− .011 ***	.040 ***	.004 ***	.481 ***
	(.002)	(.006)	(.001)	(.021)
LL	-267,184.2	-36,325.8	-184,936.3	-201,707.9
Wald	149,359.9	46,495.3	97.227.9	58,123.0
Pseudo R-sq	.627	.788	.561	.350
# obs	1,562,299	591,780	912,557	591.163

Notes. Main entries correspond to marginal effects. Model estimated by conditional maximum likelihood. Robust standard errors in parenthesis.

Appendix B

Description of Wholesale Cost Data

A complementary dataset includes wholesale costs for the largest two retailers.[33] The data are available at the barcode level and at a weekly frequency for a subset of product varieties in the primary data set[34] and over the same time period. Retailers provided wholesale cost data that correspond to cost data recorded at one major store for each of these chains. The two cost measures differ in their quality. In one case, the measure of costs is a high quality measure which corresponds to replacement costs. This is the cost paid on the last unit purchased and is viewed by the retailer as the cost of acquiring an additional unit of the product. A measure of replacement costs is particularly useful for studying issues related to price rigidities as the researcher can identify the weeks when retailers faced a change in costs. Most of the literature which has analyzed wholesale cost data has relied on a noisier measure of costs known as average acquisition cost (AAC).[35,36] This is a measure of historical cost calculated as a weighted average cost of units held in inventories. The wholesale cost data provided by the second retailer correspond to this measure of cost. It should be noted that neither measure of cost includes allowance payments made by wholesalers to retailers. Wholesalers pay retailers allowances to be able to display their products in retail outlets, introduce new products or to obtain certain slots within retail outlets. In this sense, the data on wholesale costs are an upper bound to the actual costs paid by the retailer.[37]

[33] It must be noted that the two retailers account for a large fraction of total sales: the combined market share of these two retailers is about 60 percent over the period of analysis.

[34] Cost data are available for 31 product categories included in the primary data set.

[35] The popular *Dominick's* dataset, which contains scanner data for a large supermarket chain from the Chicago area, includes a similar measure of cost.

[36] An exception is Eichenbaum, Jaimovich and Rebelo (2011) who use a measure of replacement costs.

[37] Noton and Elberg (2013) document that allowance payments are between 9.5 percent and 11 percent of the supermarkets' wholesale costs in the coffee category.

References

Aguirregabiria, V. and G. Vicentini (2012). Dynamic spatial competition between multi-store firms. Working Paper, University of Toronto.

Backé, P., J. Fidrmuc, T. Reininger, and F. Schardax (2003, May-June). Price dynamics in central and eastern european eu accession countries. *Emerging Markets Finance and Trade 39*(3), 42–78.

Balcilar, M. (2004, Sep.-Oct.). Persistence in inflation: Does aggregation cause long memory? *Emerging Markets Finance and Trade 40*(5), 25–56.

Barros, R., M. Bonomo, C. Carvalho, and S. Matos (2009). Price setting in a variable macroeconomic environment: Evidence from brazilian cpi. Getulio Vargas Foundation and Federal Reserve Bank of New York.

Berck, P., E. Leibtag, A. Solis, and S. Villas-Boas (2009). Patterns of pass-through of commodity price shocks to retail prices. *American Journal of Agricultural Economics 91*(5), 1456–1461.

Bils, M. and P. J. Klenow (2004). Some Evidence on the Importance of Sticky Prices. *Journal of Political Economy 112*(5), 947–985.

Caballero, R. J. and E. M. R. A. Engel (2007, October). Price stickiness in ss models: New interpretations of old results. *Journal of Monetary Economics 54*(S), 100–121.

Campbell, J. R. and B. Eden (2005). Rigid prices: Evidence from u.s. scanner data. Working Paper Series WP-05-08, Federal Reserve Bank of Chicago.

Cavallo, A. (2012). Scraped data and sticky prices. Mimeo MIT.

Chaumont, G., M. Fuentes, F. Labbé, and A. Naudon (2011). A reassessment of flexible price evidence using scanner data: Evidence from an emerging economy. Central Bank of Chile Working Paper No. 641.

Coricelli, F. and R. Horvath (2006). Price setting behavior: Micro evidence from slovakia. Working Paper CEPR.

Dhyne, E., L. J. Alvarez, H. L. Bihan, G. Veronese, D. Diaz, J. Hoffman, N. Jonker, P. Lünnemann, F. Rumler, and J. Vilmunen (2006). Price changes in the euro area and the united states: Some facts from individual consumer price data. *Journal of Economic Perspectives 20*(2), 171–192.

Dobson, P. W. and M. Waterson (2008). Chain-store competition: Chain-store vs. uniform pricing. Warwick Economic Research Papers No 840, The University of Warwick.

Eden, B. and M. S. Jaremski (2009). The Role of Price Discreteness in Explaining Price Dispersion and Price Changes in a Chain. Working Paper, Vanderbilt.

Eichenbaum, M., N. Jaimovich, and S. Rebelo (2011). Reference prices, costs and nominal rigidities. *American Economic Review 101*(1), 234–262.

Fischer, S. (1977). Long-Term Contracts, Rational Expectations, and the Optimal Money Supply Rule. *Journal of Political Economy 85*, 191–205.

Fisher, T. C. J. and J. D. Konieczny (2000). Own-brand and cross-brand retail pass-through. *Economics Letters 68*(3), 271–277.

Gabriel, P. and A. Reiff (2008). Price Setting in Hungary –A Store Level Analysis. Working Paper, Magyar Nemzeti Bank, Hungary.

Gagnon, E. (2009). Price setting during low and high inflation: Evidence from mexico. *Quarterly Journal of Economics 124*(3), 1221–1263.

Gouvea, S. (2007). Price Rigidity in Brazil: Evidence from CPI Micro Data. Working Paper, Central Bank of Brazil.

Julio, J. M. and H. M. Zárate (2008). The price setting behavior in colombia: Evidence from ppi micro data. Borradores de Economía. Banco de la República. Colombia.

Kehoe, P. and V. Midrigan (2012). Prices are sticky after all. Working Paper Princeton and NYU.

Klenow, P. J. and O. Kryvtsov (2008). State-dependent or time-dependent pricing: Does it matter for recent u.s. inflation? *Quarterly Journal of Economics 123*(3), 863–904.

Klenow, P. J. and B. A. Malin (2011). Microeconomic evidence on price setting. In B. M. Friedman and M. Woodford (Eds.), *Handbook of Monetary Economics, Vol. 3*. Elsevier.

Konieczny, J. D. and A. Skrzypacz (2006). Search, costly price adjustment and the frequency of price changes -theory and evidence. Working Paper, Stanford.

Kovanen, A. (2006). Why Do Prices in Sierra Leone Change So Often. Working Paper, International Monetary Fund.

Lach, S. and D. Tsiddon (1992). The behavior of prices and inflation: An empirical analysis of disaggregated price data. *Journal of Political Economy 100*(2), 349–389.

Lach, S. and D. Tsiddon (1996). Staggering and synchronization in price setting: Evidence from multiproduct firms. *American Economic Review 86*(5), 1175–1196.

Levy, D., M. E. Bergen, S. Dutta, and R. Venable (1997). The magnitude of menu costs: Direct evidence from large us supermarket chains. *Quarterly Journal of Economics 112*(3), 791–825.

Loy, J.-P. and C. R. Weiss (2004). Synchronization due to common shocks? evidence from germany grocery prices. *Economics Letters 85*, 123–127.

Medina, J. P., D. Rappoport, and C. Soto (2007). Dynamics of price adjustments: Evidence from micro level data for chile. Working Papers Central Bank of Chile No. 432.

Midrigan, V. (2011). Menu costs, multi-product firms and aggregate fluctuations. *Econometrica 79*(4), 1139–1180.

Nakamura, A. O., E. Nakamura, and L. I. Nakamura (2011). Price dynamics, retail chains and inflation measurement. *Journal of Econometrics 161*(1), 47–55.

Nakamura, E. (2008). Pass-through in retail and wholesale. *American Economic Review: Papers & Proceedings 98*(2), 430–437.

Nakamura, E. and J. Steinsson (2008a). Five facts about prices: A reevaluation of menu cost models. *Quarterly Journal of Economics 123*(4), 1415–1464.

Nakamura, E. and J. Steinsson (2008b, November). Five facts about prices: A reevaluation of menu cost models. *Quarterly Journal of Economics 123*(4), 1415–1464.

Nakamura, E. and J. Steinsson (2013a). Price Rigidity: Microeconomic Evidence and Macroeconomic Implications. Working Paper, Columbia University.

Nakamura, E. and J. Steinsson (2013b, January). Price rigidity: Microeconomic evidence and macroeconomic implications. Working paper Columbia University.

Noton, C. and A. Elberg (2013). Revealing power through actual wholesale prices. Mimeo Universidad de Chile and Universidad Diego Portales.

Reardon, T., J. Berdegué, and C. P. Timmer (2005). Supermarketization of the "emerging markets" of the pacific rim: Development and trade implications. *Journal of Food Distribution Research 36*(1), 3–12.

Sheshinski, E. and Y. Weiss (1992). Staggered and synchronized price policies under inflation: The multiproduct monopoly case. *Review of Economic Studies 59*(2), 331–359.

Taylor, J. B. (1979, May). Staggered price setting in a macro mod. *American Economic Review 69*(2), 108–113.

Taylor, J. B. (1980). Aggregate dynamics and staggered contracts. *Journal of Political Economy 88*(1), 1–24.

Vasicek, B. (2011). Inflation dynamics and the new keynesian phillips curve in four central european countries. *Emerging Markets Finance and Trade 47*(5), 71–100.

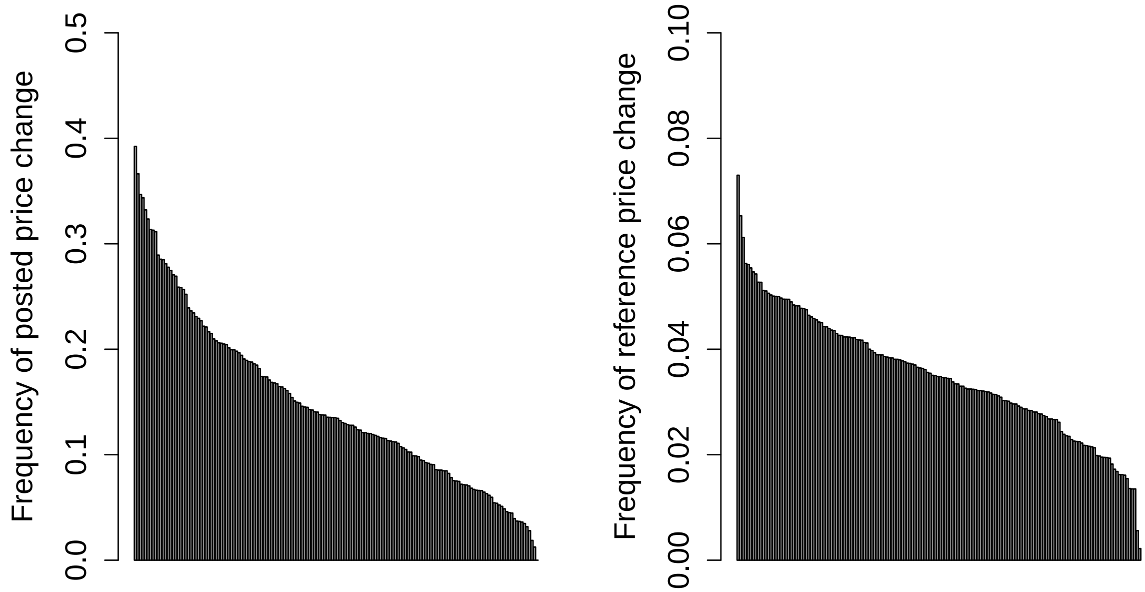

Figure 1: Frequencies of Price Change Across Categories

Note. Frequencies of price change correspond to weighted medians with weights based on expenditure shares.

Table 1: Categories Included in the Data Set

Stain removers	Pet food	Chewing gum	Canned seafood	Dressings and sauces
Baby accessories	Canned food	Synthetic gloves	Frozen pasta	Dental floss
Pet accessories	Prepared food	Frozen hamburgers	Mayonnaise	Paper napkins
Edible oils	Food preservatives	Raw flour	Jelly	Hair shampoos
Agendas	Correction fluids	Ice-cream	Cooking mix	Snacks
Water	Cosmetics	Electrical boilers	Screens	Soups and creams
Chilli sauces	Cotton swabs	Herbs and spices	Mustard	Hair styling products
Alfajores	Coffee creamers	Chlorine	Nectars	Clothes softeners
Light bulbs	Creams	Shaving machines	Frying pans and pots	Nutritional supplements
Clothes stiffener	Facial creams	Microwave ovens	Packed bread	Talcum powder
Packaged rice	Shaving creams	Eggs	Diapers	Prepaid phone cards
Personal care	Baby creams	Printers	Cloths	Tea
Vacuum cleaners	Hands and body creams	Insecticide	Tissues	Tea & coffee ready to drink
Portable audio	Notebooks	Laundry soap	Toilet paper	TV sets
Sugar	Foot care	Toilet soap	Baby powders	Painting
Hair conditioners	Hair removal	Juice powders	Tooth pastes	Hair dyeing
Sodas	Air freshener	Toys	Turkey	Disposable towels
Shoe polishers	Deodorant	Ketchup	Glue	Wet towels
Sponges	Detergents	Washing machines	National newspapers	Kitchen tools
Sketch notebooks	Quince jelly	Dishwasher detergents	Frozen fish	Canned vegetables
Ball pens	Lighters	Condensed milk	Fish	Candles
Kitchen pans	Sweeteners	Milk powder	Fine Fish	Packed frozen vegetables
Trash bags	Energy drinks/nectars	Liquid milk	Batteries	Frozen vegetables
Coffee	Mouthwashes	Pulses	Piscos	Fruits and vegetables
Color pencils	Plastic food containers	Yeast	Iron	Vinegars
Broth	Stereos	Office supplies	Chickens	Wines
Car audio	Various medicines	Cognac	Baking powder	Kitchen scrubbers
Candies	Sponges for shoes	Ginebra	Dessert powder	Floor scrubbers
Sausages	Extracts and essences	Rum	First aid	Whisky
Tooth brushes	Pastas	Vermouth	Automobile care products	Yogurt
Wax	Sun block	Vodka	Feminine care	
Cereal bars	Baby formulas	Home cleaners	Mashed potatoes	
Breakfast cereals	Matches	Floor cleaners	Cheese	
Processed cereals	Women fragrances	Toilet cleaners	Refrigerators	
Beer	Men fragrances	Furniture polishers	DVD players	
Champagne	Baby fragrances	Dulce de leche	Flavored powders for milk	
Chancacas	Frozen fruit	Lard	Juice makers	
Cigarettes	Canned fruit	Butter	Salt	
Kitchenettes	Cookies and chocolates	Margarine	Tomato sauces	
Cocktails	Hangers	Frozen seafood	Sweet sauces	

Table 2: Price Dynamics: Transitional Matrix

		t		
		Old Reference	New Reference	Non-Reference
	Old Reference	.886	.010	.103
t-1	New Reference	.957	.000	.042
	Non-Reference	.275	.141	.584

Notes. Each cell (i,j) corresponds to the probability that a posted price that in the current week is in state i moves the next week to state j. "Old Reference" denotes a state in which the posted price is equal to a reference price that has already been observed in the price trajectory; "New Reference" denotes a state in which the posted price is equal to a reference price that has not been previously observed in the price trajectory; and, "Non-Reference" denotes a state in which the posted price is equal to a non-reference price. The probabilities were computed at the barcode-store level and later aggregated using category level weights.

Table 3: Summary Statistics on Price Dynamics

	Posted (1)	Reference (2)	Chain (3)
Frequency of price change	.178	.040	.104
Frequency of price increases	.094	.021	.056
Frequency of price decreases	.084	.018	.047
Size of price change	.042	.065	.058
Size of price increases	.043	.069	.061
Size of price decreases	.042	.067	.060

Notes. All figures correspond to weighted medians computed across categories. Posted prices correspond to actual retail prices posted by retailers. Reference prices are computed using Kehoe and Midrigan's (2012) algorithm. Chain prices are computed as the modal price across stores within a chain.

Table 4: Frequencies of Price Adjustment by Retail Chain

Retailer	Freq. posted	Imp. dur.	Freq. Reference	Imp. dur.	$\lvert\Delta p^{posted}\rvert$	$\lvert\Delta p^{reference}\rvert$
1	.221	4.53	.035	28.18	.038	.057
2	.168	5.95	.042	23.57	.030	.064
3	.086	11.67	.027	36.64	.038	.062
4	.124	8.06	.036	27.68	.067	.074
5	.101	9.90	.043	23.03	.037	.063
6	.217	4.60	.035	28.37	.026	.063
7	.211	4.74	.040	24.80	.043	.062
8	.278	3.59	.037	26.90	.047	.059
Mean	.176	6.63	.037	27.40	.041	.063
Median	.189	5.35	.037	27.29	.038	.063
St. dev.	.068	2.93	.005	4.27	.012	.005

Notes. Frequencies of price adjustment correspond to weighted medians computed using expenditure weights for categories within chains. Implied durations are computed as the reciprocal of the frequencies of price adjustment. Price changes computed as log differences.

Table 5: Variance Decomposition of the Frequency of Price Adjustment

	Chain (1)	Chain-Barcode (2)	Barcode (3)	Store (4)	Store-Barcode (5)
Posted	.274	.285	.252	.098	.091
Reference	.093	.428	.150	.102	.226

Notes. Entries correspond to the average fraction of total variation in the frequencies of posted price change (first row) and reference price change (second row) attributed to variation across chains (Column 1), variation across chains and barcodes (Column 2), variation across barcodes (Column 3), variation specific to a given store (Column 4) and variation specific to a given store and barcode (Column 5). The model is estimated by maximum likelihood at the category level. Categories including less than 13 barcodes were excluded, as were barcodes sold in less than five retail chains.

Table 6: Chain Price Dynamics: Transitional Matrix

		t		
		Old Chain	New Chain	Nonchain
t-1	Old Chain	.851	.028	.120
	New Chain	.599	.210	.191
	Nonchain	.544	.121	.335

Notes. Each cell (i,j) corresponds to the probability that a posted price that in the current week is in state i moves next week to state j. "Old Chain" denotes a state in which the posted price is equal to a chain price previously observed within the same price trajectory; "New Chain" denotes a state in which the posted price is equal to a chain price that has not been observed within the same price trajectory; and, "Nonchain" denotes a state in which the posted price is different from the chain price. The probabilities were computed at the barcode-store level and later aggregated using category level weights.

Table 7: Synchronization of Price Changes

	Chain A		Chain B		Chain C		Chain D	
	posted	reference	posted	reference	posted	reference	posted	reference
Fr S (×100)	.230 *** (.004)	.807 *** (.064)	.854 *** (.010)	− .094 ** (.010)	.236 *** (.002)	.067 (.113)	.265 *** (.002)	.834 *** (.030)
Fr A (×100)	.745 *** (.006)	1.878 *** (.010)	.015 *** (.003)	− .030 (.022)	.009 [a] (.001)	− .230 *** (.053)	.003 ** (.001)	− .094 *** (.015)
Fr B (×100)	.007 *** (.002)	.006 (.010)	.943 *** (.012)	1.992 *** (.011)	− .002 (.001)	− .025 (.051)	.009 *** (.001)	− .046 *** (.015)
Fr C (×100)	.009 *** (.001)	− .015 (.012)	.000 (.004)	.043 ** (.022)	.282 *** (.005)	.820 *** (.039)	.006 *** (.001)	− .174 *** (.020)
Fr D (×100)	− .019 *** (.002)	.041 *** (.012)	.044 *** (.004)	.163 *** (.022)	.006 *** (.001)	.020 (.063)	.436 *** (.004)	1.855 *** (.011)
Store FE	yes		yes		yes		yes	
Barcode FE	yes		yes		yes		yes	
Time FE	no		no		no		no	
LL	-269,386.0	-87,641.5	-36,764.0	-19,040.0	-185,641.8	-61,388.8	-203,847.0	-44,051.3
Wald	147,926.3	79,519.7	44,843.9	37,056.9	96,757.6	49,664.8	56,600.2	34,888.1
Pseudo R-sq	.624	.649	.785	.765	.559	.566	.343	.503
# obs	1,562,299	1,539,265	591,780	595,128	912,557	889,227	591,163	584,575

Notes. The dependent variable is a dichotomous variable which equals 1 if store i in chain j changes the price of barcode k in week t and zero otherwise. Fr S denotes the fraction of barcodes different from k that change prices in store i, chain j and week t. Fr J (J = A, B, C, D) denotes the fraction of stores (different from i) in chain J that change the price of barcode k in week t. Main entries correspond to marginal effects. Model estimated by conditional maximum likelihood. Robust standard errors in parenthesis.

[a] Marginally significant. The p-value of the z-test equals 0.104.

Table 8: Synchronization of Price Changes within Categories

	Chain A		Chain B		Chain C		Chain D	
	posted	reference	posted	reference	posted	reference	posted	reference
Fr W ($\times$100)	.296 *** (.004)	1.123*** (.016)	.351 *** (.013)	.736 *** (.042)	.137 *** (.003)	1.032*** (.022)	.255 *** (.004)	.785 *** (.023)
Fr O ($\times$100)	−.034 *** (.006)	−.613 *** (.049)	.536 *** (.014)	−.759*** (.050)	.122 *** (.002)	−.967*** (.032)	.039 *** (.004)	.087 ** (.035)
Fr A ($\times$100)	.741 *** (.006)	1.851*** (.008)	.012 *** (.003)	−.025 (.023)	−.001 ** (.001)	−.058 *** (.013)	.000 (.002)	−.098 *** (.015)
Fr B ($\times$100)	.007 *** (.002)	.000 (.011)	.972 *** (.012)	1.925*** (.011)	−.003 *** (.001)	.014 (.012)	.009 *** (.002)	−.048 *** (.016)
Fr C ($\times$100)	.005 *** (.001)	−.037 (.012)	.000 (.004)	.059 *** (.023)	.311 *** (.006)	1.901*** (.009)	.006 *** (.001)	−.142 *** (.019)
Fr D ($\times$100)	−.023 *** (.002)	−.009 (.012)	.042 *** (.004)	.150 *** (.023)	.006 *** (.001)	.044 *** (.015)	.431 *** (.004)	1.756*** (.011)
Store FE	yes		yes		yes		yes	
Barcode FE	yes		yes		yes		yes	
Time FE	no		no		no		no	
LL	-259,090.6	-83,773.3	-35,845.0	-18,501.9	-178,316.8	-58,743.8	-196,975.8	-42,807.5
Wald	152,141.8	79,605.8	43,085.1	36,886.1	97,924.5	47,578.5	55,256.2	33,197.2
Pseudo R-sq	.634	.660	.787	.770	.570	.579	.357	.512
# obs	1,544,141	1,522,477	585,374	588,630	900,545	887,889	583,225	576,478

Notes. The dependent variable is a dichotomous variable which equals 1 if store i in chain j changes the price of barcode k in week t and zero otherwise. Fr W denotes the fraction of barcodes different from k belonging to the same category as k that change prices in store i, chain j and week t. Fr O denotes the fraction of barcodes different from k belonging to other categories that change prices in store i, chain j and week t. Fr J (J = A, B, C, D) denotes the fraction of stores (different from i) in chain J that change the price of barcode k in week t. Main entries correspond to marginal effects. Model estimated by conditional maximum likelihood. Robust standard errors in parenthesis.