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

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January 5, 2012

Abstract

This paper studies nominal rigidities using a novel scanner data set consisting of weekly prices, costs and quantities sold for a cross-section of retailers in Chile. Nominal rigidities are found to take the form of reference price inertia. While posted prices change every 5 weeks (on average), reference prices change every two quarters (29 weeks), on average. Frequencies of reference price adjustment are found to be systematically related to cost volatility and expenditure shares. In addition, the probability of a reference price adjustment is increasing in the markup gap. While frequencies of reference price adjustment vary systematically across chains, markups vary within narrow bounds and pass-through coefficients conditional on a reference price change are high (on the order of 0.86-0.93) suggesting that movements in reference prices are closely related to movements in prices at the previous stage of the distribution chain. Synchronization of price changes across stores appears to be particularly strong across stores belonging to a given chain. Evidence on within-stores and categories synchronization is consistent with a price adjustment technology featuring economies of scope.

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1 Introduction

Recent research on the patterns of micro price adjustment has uncovered a tendency for retail prices to display sales-like behavior.[1] Retail price series are found to be characterized by large and frequent temporary departures (typically falls) from more persistent underlying price series (Hosken and Reiffen, 2004; Nakamura and Steinsson, 2008; Kehoe and Midrigan, 2010; Klenow and Malin, 2010; Eichenbaum, Jaimovich and Rebelo, 2011). Nakamura and Steinsson (2008), analyzing micro data underlying the U.S. CPI, report that a large fraction of posted prices correspond to "sales" (i.e. temporary price markdowns) . Furthermore, they find that price adjustments of a more transitory nature provide an important contribution to overall price flexibility. Removing temporary markdowns or "sales" from the series of posted prices increases the duration of price spells from about 4 months to 8-11 months.[2]

Similar evidence has been uncovered by studies focusing on less comprehensive but deeper scanner data (Kehoe and Midrigan, 2010; Eichenbaum et al. 2011). Eichenbaum et al. (2011), studying a rich scanner data set for a large U.S. retailer, observe that posted prices have a tendency to revolve around reference prices, defined as the most quoted price in a given quarter[3]. They established that reference prices are important according to several different metrics (such as the fraction of the time at which posted prices are equal to reference prices and the fraction of revenues made at reference prices) and that they are substantially more persistent than posted prices. While weekly posted prices are changed every 2-3 weeks, the average implied duration of a reference price is about 1 year.

Theoretical models advanced to account for the phenomenon of posted prices departing for short periods of time from more persistent reference (or regular) prices appeal to features such as (among others): dynamic price discrimination by retailers (Guimaraes and Sheedy, 2011); rational innatention on the part of price setters (Matějka, 2011); the existence of heterogeneous costs of price adjustment (Kehoe and Midrigan, 2010); and, sticky price plans (Eichenbaum et al., 2011).

[1] The seminal paper in the literature on price-setting at the micro level is Bils and Klenow (2004). Klenow and Malin (2010) survey the literature.

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

[3] Hosken and Reiffen (2004) use a similar definition of a regular price: The most quoted price in a year.

The greater price flexibility observed in posted retail prices has potentially important consequences for monetary economics. If "sales" are nonorthogonal to a monetary policy shock, then sticky price models should account for the changes in price flexibility induced by sales activity in the face of a monetary policy shock. The message emerging from the theoretical work is, however, that macroeconomists should focus their attention in reference price behavior. Eichenbaum et al. (2011), for instance, calibrate a sticky plan model to match some of the moments of the price data, and find that even in the presence of highly flexible posted prices, monetary shocks can have persistent effects on economic activity provided that reference prices exhibit a high degree of inertia. Similarly, the model in Guimaraes and Sheedy (2011) implies that sales do not contribute to greater price flexibility in response to monetary policy shocks. This is due to strategic substitutability in sales: The incentives for a firm to use sales are greater the more other firms choose not to use sales. In the face of an aggregate shock, such as a monetary shock, firms find it optimal not to vary sales and hence price responses to the shock are unrelated to changes in sales activity.

This paper aims at providing empirical evidence on the behavior of reference prices by analyzing a unique scanner data set which includes retail prices, wholesale costs and quantities for a large number of product varieties and covers price-setting behavior by several retailers in an emerging economy over a low inflation period.[4] Most of our understanding of the behavior of reference prices comes from the analysis of Eichenbaum et al. (2011) of a single U.S. retail chain. By exploiting the cross-sectional nature of the data, I am able to study issues such as the importance of retail chains in determining reference price inertia, the pass-through of wholesale costs into retail prices across different retailers, and compare the extent of synchronization on reference price changes to that observed in posted prices –an important issue for the persistence of monetary shocks.

The analysis reveals that the reference price phenomenon holds both at the retail and wholesale levels. Posted prices spend most of the time (85 percent, in the case of retail prices) at reference levels and display a tendency to return to a reference price once they have departed from it. Reference prices are substantially more persistent than posted prices. A typical reference price spell has an implied duration of about 2 quarters, versus 5 weeks in the case of posted prices. These patterns are observed

[4] A recent paper by Chaumont et al. (2011) study price-setting behavior by a cross-section of retailers in Chile over the higher inflation period of 2007-2009.

across all retailers in the data.

Retail markups are remarkably stable over time and cost pass-through coefficients from reference costs into reference prices conditional on a price change are high (point estimates are 0.86 and 0.93 for two large supermarket chains for which cost data are available), indicating that retailers tend to pass through most of the accumulated cost changes in between reference price adjustments. In line with this finding, there is strong evidence that retailers adjust reference prices more often the larger is the markup gap (i.e. the difference between the markup of a given product category and its time-series average). The evidence is thus consistent with findings reported by Eichenbaum et al. (2011) and is supportive of the fact that markup variations are not an important source of real rigidities at the retail level.

The data exhibits several other features consistent with state-dependence in reference price adjustment decisions. First, in line with the predictions of menu cost models, frequencies of price adjustment of a given product are increasing in cost volatility.[5] Second, frequencies of price adjustment are positively associated with the share of expenditure devoted to a given product.[6] The effects of these two variables on price rigidities are mostly independent of each other. Point estimates from a logistic regression model indicate that while a one standard deviation increase in the volatility of costs is associated with a fall in the duration of a reference price spell of about 4 weeks, a one standard deviation increase in expenditure shares is associated with a fall in the duration of a reference price spell of about 2.6 weeks.[7] An additional feature of the reference price data consistent with state-dependent pricing models is the presence of a systematic weak negative relationship between the time elapsed since the last price change (i.e. the "age" of a price spell) and the size of a price change. Time-dependent pricing models (Fischer, 1977; Taylor, 1980; Calvo, 1983), in contrast, imply a positive relationship between the age of a price spell and the size of price changes as the longer a price has remained unchanged, the more shocks have accumulated over time and the more the firm will want to adjust its price at the time of a price change.

Regarding synchronization in price adjustment decisions, the evidence is consistent with a non-negligible amount of synchronization across stores which is especially

[5] Eichenbaum et al. (2011) document a similar finding for the U.S. retailer they study.

[6] Studying the same retailer as Eichenbaum et al. (2011), Hong (2011) also documents a positive association between frequencies of price adjustment and expenditure shares.

[7] The estimates assume that a reference price spell is initially at its average duration.

pronounced in the case of reference prices. Across stores synchronization is, however, mostly driven by synchronization in price changes within- (as opposed to between-) chains. Synchronization of price changes within stores and product categories is consistent with the presence of economies of scope in the technology of price adjustment in a multiproduct context. There is a strong negative correlation between the depth of a category (measured by the number of product varieties within a category) and the amount of synchronization, with the timing of price changes in categories including less than 12 items being highly synchronized.

The remainder of the paper is structured as follows. The next section presents a description of the scanner data analyzed in the paper. Section 3 presents evidence on the importance of reference prices for characterizing price dynamics and provides evidence on three features of price adjustment behavior: The frequency of price change, the distribution of the size of price changes, and the shape of hazard functions (i.e. the relationship between the probability of a price adjustment and the time elapsed since the last price change). Section 4 revises data on wholesale costs and provides evidence on wholesale costs rigidities. Section 5 studies the behavior of markups and estimates conditional pass-through regressions from wholesale costs into retail prices. Section 6 provides evidence on state-dependence in price adjustment decisions documenting the importance of some covariates to the frequency of reference price adjustment: Cost volatility and expenditure shares. In addition, it documents a positive relationship between the probability of reference price adjustments and the markup gap and shows that frequencies of posted and reference price adjustment vary systematically along a "retail chain" dimension. Section 7 studies synchronization of price changes across and within stores, as well as synchronization taking place within product categories. Section 8 quantitatively evaluates a standard menu cost model featuring idiosyncratic technology shocks. Section 9 concludes.

2 Data Description

The data include weekly retail prices, quantities sold and wholesale costs for a large number of products at the European Article Number (EAN)[8] level and sold by several retailers in Chile. Data on retail prices and quantities sold were provided by an

[8] EAN-13 is an alternative barcode symbology to the Universal Product Code (UPC) symbology commonly used in the U.S.

international market research firm. They include information on more than 60,000 barcodes for 281 stores belonging to 14 retail chains. Retail chains include the largest supermarket chains in Chile as well as a chain of convenience stores and a drugstore chain.[9]

Product varieties are classified into 190 product groups or categories[10] comprising mainly foodstuffs, drugstore and healthcare products (Table 1 presents a full description of the categories included in the data set). These categories correspond to product groups accounting for roughly 20 percent of the Chilean CPI.[11]

Data on prices and quantities for all retailers are available for a maximum period of 101 weeks ranging between mid-2005 and mid-2007. Data on prices for all retailers and quantities for the largest two retailers (Lider and Jumbo) are available for a longer period of 147 weeks (mid-2005 to mid-2008).[12] Raw data include weekly revenue for a given item in a given store and weekly quantity sold for the item. The weekly price measure that I use in the analysis is obtained as the ratio of weekly revenue over weekly quantity sold.

A complementary dataset includes wholesale costs for the largest two retailers. The data are available at the EAN-level and weekly frequency for a subset of product varieties present in the primary dataset and over the same time period. Wholesale cost data were directly provided by the retailers. They correspond to cost data recorded at one major store in each of these chains. In one case the measure of costs represents replacement cost and is closer to economists' concept of marginal cost.[13] It 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. These are transaction prices paid by retailers to wholesalers which in most cases –according to information provided by industry insiders– correspond to manufacturers.[14] In the other case, the measure

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

[10] I use the same taxonomy employed by the market research firm which provided the data to classify product varieties.

[11] The categories "Foodstuffs and Non-Alcoholic Beverages", "Alcoholic Beverages, Tobacco and Narcotics" and "Health", represent 18.9%, 2%, and 5.38%, respectively of the cost of the reference basket used in the construction of the CPI in Chile.

[12] The longer series are available for a smaller set of product varieties belonging to 33 categories.

[13] The data in Eichenbaum, Jaimovich and Rebelo (2011) include a similar measure of costs.

[14] According to these sources the distribution chain in Chile has evolved in recent decades towards the elimination of middlemen between manufacturers and supermarkets.

of costs represent the average acquisition cost (AAC) and is a measure of historical cost which is potentially affected by movements in inventories.[15] I use the first, high quality, measure of costs to provide evidence on cost stickiness as the timing of costs adjustments is, in this case, not distorted by inventory movements.

It should be pointed out that neither measure of cost includes allowance payments made from the wholesaler to the retailer. These correspond to payments made for the introduction of new products or for obtaining certain slots within outlets. In this sense, the data on wholesale costs represent an upper bound to the actual costs paid by the retailer.[16]

Measurement Issues. One characteristic of scanner data are the large number of missing observations due to stock outs or non-purchase of a product variety in a given week. Missing observations have the potential of biasing estimates of the frequencies of price adjustment. I chose to deal with this problem by keeping missing observations (instead of imputing values) but requiring that a price of a given item (product variety and store pair) is observed in at least 75 weeks (from a maximum of 101 weeks) as a condition to keep the item. Another issue generated by the fact that prices are obtained as average weekly revenue is that a fraction of prices are nonround prices as a consequence of price changes taking place at some point in the middle of a week. As Campbell and Eden (2005) point out, the presence of multiple prices in a given week may lead to an overestimation of the frequency of price adjustment. In most retail chains, the number of round prices is above 90 percent of all prices. In the case of one of the retailers, however, the pattern of nonround prices observed in the data suggested the presence of measurement error.[17] In this case I chose to leave this retailer out of the analysis.[18]

[15] The popular *Dominick's* dataset (consisting of scanner data for a large supermarket chain from the Chicago area) includes a similar measure of cost.

[16] Noton and Elberg (2011) document that in the case of the coffee category allowance payments represent between 9.5 percent and 11 percent of the supermarkets purchases.

[17] According to information provided by an insider, the retailer went through a change in its information systems around the time when the change in the pattern of nonround prices is observed.

[18] I further imposed the criterion that at least 75 percent of prices in a given price series should be round prices. While admittedly arbitrary, the imposition of these criteria did not alter the main results reported below.

3 Facts on Price Rigidities

This section studies some salient features of the data on price rigidities for both posted and reference prices. I start by defining a reference price and showing that reference prices are helpful in characterizing retail price behavior among Chilean retailers. I then move on to examining three features of the data which are relevant for studying price rigidities and that can be helpful in discriminating between alternative pricing models: The frequency of price adjustment, the size of price changes and the hazard function.

3.1 Importance of Reference Prices

Definition. Eichenbaum et al. (2011) define a reference price as the most quoted weekly price in a given calendar quarter. An obvious problem with this definition is that it forces reference price changes to take place at the end of a calendar quarter –in spite of the fact that no evidence supports the notion that price-setters adjust prices on a quarterly basis. This might lead to the identification of spurious reference price changes (Chahrour, 2011). In this paper I adopt a more flexible specification for defining a reference price proposed by Chahrour (2011) which defines a reference price as the most quoted price within a 13-week window centered in the current week. Furthermore, the algorithm employed to filter reference prices is designed to avoid early or late changes in reference prices (see Chahrour's (2011) appendix for a detailed description of the algorithm).

I compute reference prices for each price trajectory, P_{ijk}, defined for a given product variety (or barcode) k sold in store i which belongs to retail chain j. Figure 1 presents some examples of posted and reference price trajectories.

As the charts in Figure 1 suggest, reference prices are important in the data. Pooling across product varieties and stores, 85 percent of all posted prices are equal to a reference price. This pattern holds both across retail chains (Table 2) and across product categories (Figure 2). Note that nonreference prices are not equivalent to "sale" prices as a significant fraction of nonreference prices lies above the reference level. Similarly, a large fraction of retailers' revenues are obtained at reference prices (see Table 2). The median retailer derives 76 percent of its revenues from sales made at reference prices.

The large fraction of posted prices that coincide with reference prices is not a consequence of posted prices remaining constant over time. The standard deviation of (log) reference prices for the average price trajectory is only slightly smaller than the standard deviation for (log) posted prices (0.060 vs. 0.068). As reported by Eichenbaum et al. (2011), posted prices display a tendency to return to a reference price once they have departed from a reference price, and to remain at the reference price once they have arrived at a reference price. This pattern holds across all retailers as can be seen from Figure 3, which presents transition matrices between the states reference (R) and nonreference (NR) for each one of the retailers included in the analysis. The probability that a posted price remains at a reference price next period in the case of the median retailer equals 0.85. The median probability that a posted price will move from a nonreference price to a reference price equals 0.44.

3.2 Frequency of Price Adjustment

The empirical literature on price-setting behavior has followed two approaches to measure the degree of price rigidity at the micro level. The duration approach computes the average duration of price spells directly. While simple, this measure of price rigidity has some drawbacks. In particular, it is sensible to the presence of left- and right- censored spells. An alternative, followed among others by Bils and Klenow (2004), is to compute the frequency of price changes and then obtain the average duration as the average inverted frequency. Frequencies of price change for a given product variety and store are computed as

$$fr_{ijk} = \frac{\sum_{t=1}^{T} \mathcal{I}\left\{P_{ijk,t} \neq P_{ijk,t-1}\right\}}{n_{ijk}} \tag{1}$$

where $\mathcal{I}\left\{P_{ijk,t} \neq P_{ijk,t-1}\right\}$ is an indicator function that takes on the value one if the price in week t is different from the price in week $t-1$ and zero otherwise, T is the length of price trajectory P_{ijk} and n_{ijk} is the number of non-missing observations in price trajectory P_{ijk}.[19,20]

[19] A desirable feature of the frequency approach is that in large samples and in a stationary context, the inverse of the frequency of price changes converges to the mean duration of price spells (Baudry, Le Bihan, Sevestre and Tarrieu, 2004).

[20] The length of a price trajectory is actually trajectory-specific. The formula for the frequency does not explicitly account for this dependence for notational simplicity.

Figure 4 displays the distribution of the frequency of reference and posted price changes. Reference prices are substantially more persistent than posted prices. I use the weighted median frequency of a price change as a summary statistic of the frequency of price adjustment –computed as the median frequency within each product category weighted by the expenditure share of that category over the whole sampling period. The weighted median frequencies of posted and reference price change equal 0.19 and 0.035 respectively. The implied durations (calculated as the reciprocal of the frequency) equal 5.4 weeks and 28.5 weeks, respectively.

By way of contrast, posted prices appear to be more persistent and reference prices less persistent than in the US. Eichenbaum et al. (2011), for example, find that posted prices have an average duration of about 2-3 weeks and reference prices have a duration of about 3-4 quarters. The higher duration of posted prices can be explained by a lower prevalence of temporary price markdowns (or "sales") observed in the Chilean data. Applying a simple "sales" filter which identifies V-shaped sales to the Chilean data reveals than less than 4% of all prices correspond to "sales". In contrast, about 29% of prices in the Dominick's finer foods data set correspond to sale prices (see Guimaraes and Sheedy, 2011). Some candidate explanations to account for the lower duration of reference price spells observed in the Chilean data include the fact that emerging market economies are usually hit by larger shocks and face higher aggregate inflation rates. During the period under study, however, the average annual CPI inflation in Chile was only 3.8%. In addition, the volatility of costs and quantities sold at constant prices (a proxy of demand shocks) are similar to the ones reported by Eichenbaum et al. (2011) for the U.S.[21] A possible explanation for the higher frequency of reference price adjustment observed in the data is that retailers anticipating the higher inflation rates that characterized the period 2008-2009 (where annual CPI inflation rates reached over 8 percent) chose to change prices more often and by small amounts.[22]

Decomposing frequencies of price adjustment into price increases and decreases reveals that while posted price increases are as likely to occur as posted price decreases, reference price increases are more prevalent than reference price decreases.

[21] The standard deviation of (log) costs in the data is about 0.04 (versus 0.12 in Eichenbaum et al.'s (2011) data). The standard deviation of (log) quantities conditional on unchanged prices equals 0.38 (versus 0.42 in Eichenbaum et al.'s (2011) data).

[22] Rotemberg (2005) presents a model in which firms chose to avoid large price changes so as to avoid antagonizing customers.

About 60 percent of reference price changes are price increases. This is consistent with reference prices being driven to a larger extent by aggregate shocks.

As previously documented in the literature (Klenow and Malin, 2010) frequencies of price adjustment are highly heterogeneous across product categories (see Figure 5). Frequencies of reference (posted) price change range between zero (0.01) in the case of "Frozen Seafood" ("Talcum Powder") and 0.07 (0.65) in the case of "Ginebra" ("Hangers"). As Carvahlo (2006) and Nakamura and Steinsson (2010) show, sectoral heterogeneity in price rigidities has the potential to amplify monetary non-neutralities both in time-dependent and state-dependent pricing models. Table 3 documents that heterogeneity is also present across retailers. Implied durations of reference price change among supermarket chains range between 25 weeks and 36 weeks (Chain 3 is the only non-supermarket chain in the group which might explain its idiosyncratic price-setting behavior) with a median of 32 weeks. Section 6 below presents a decomposition of the sources of variation of the frequency of price adjustment into product and chain effects.

3.3 Size of Price Changes

The distribution of the size of price changes is another important feature of price-setting behavior which is helpful in assessing the fit of alternative pricing models to the data. Figure 6 presents the distribution of (log) price changes conditional on a non-zero price change for both posted and reference prices. Both distributions are symmetric around zero and most of the probability mass is concentrated in relatively small price changes. Average size of price changes is 5% for posted prices and 8% for reference prices. About 25% of reference price changes is smaller than 3%.

By way of comparison, the average size of price changes in U.S. CPI data is 14% in the case of posted prices and 11.3% in the case of regular prices (Klenow and Kryvtsov, 2008). Studies that analyze U.S. scanner data (Kehoe and Midrigan (2010); Eichenbaum et al. (2011)) report even larger magnitudes of price adjustment –on the order of 16-17%.

The relatively small size of price changes observed in the data is at odds with the predictions of menu cost models. In menu cost models the firm decides to adjust its price only if the profit loss from leaving the price unchanged outweighs the fixed cost of price adjustment. Thus, if menu costs are large enough to explain price rigidities firms will not find it optimal to make relatively small price adjustments. In section 8 below I show that a standard menu cost model calibrated to match the volatility and persistence of cost shocks faced by retailers is unable to reproduce the large fraction of small price changes observed in the data.

3.4 Hazard Functions

In the price-setting context, hazard rates are defined as the probability of a price change conditional on a price remaining unchanged until a given week. In continuous time, the hazard rate in period t is defined as

$$\lambda(t) = \lim_{\Delta \to 0} \frac{\Pr\{t < D \leq t + \Delta | D \geq t\}}{\Delta t} \tag{2}$$

where D denotes duration of a price spell.

Hazard functions (the mapping between hazard rates and time elapsed since the last price change) are potentially useful for discriminating between alternative pricing models. In Calvo type of models the probability of a firm adjusting its price is constant and hence hazard functions are flat. Menu cost models, on the other hand, admit different shapes for hazard functions depending on the combination of permanent versus temporary shocks affecting price-setters and the volatility of shocks (see Nakamura and Steinsson, 2008). If shocks are highly persistent, hazard functions in menu cost economies are likely to be upward sloping as desired prices tend to deviate from the posted price over time making it more likely for the firm to find it optimal to pay the menu cost and adjust its price.

I estimate hazard functions non-parametrically using the Nelson-Aalen estimator of cumulative hazard rates[23]. Hazard rates are derived from the cumulative hazard function and smoothed out using a kernel smoother (Cavallo, 2010 uses a similar procedure for estimating hazard functions). Hazard rates appear to be initially decreasing and flat afterwards for both posted and reference prices (see Figure 7). It is well known that estimation of hazard functions across heterogeneous individuals is afflicted by a survivor bias which tends to bias estimates of hazard functions downwards (see, for example, Keifer (1988)). Given the large dispersion observed in unconditional probabilities of price adjustment this is potentially a problem that might be biasing

[23] The Nelson-Aalen estimator is known to have better small sample properties than the standard Kaplan-Meier estimator.

hazard function estimates. In order to mitigate this problem I estimate hazard functions at the chain level (Section 6 below reports that frequencies of price adjustment tend to vary systematically over the chain dimension)[24]. Figure 8 presents hazard functions estimated at the chain-level. The figure confirms the finding that hazard functions are roughly flat for almost all chains (chain 1 appears to be an exception in this regard). Evidence on hazard functions is thus consistent with time-dependent pricing models. As shown in Section 8 below, however, a menu cost model calibrated to match the facts on actual replacement costs is able to generate flat hazard functions for the relevant time domain.

4 Facts on Cost Rigidities

This section provides evidence on the extent of cost rigidities. In interpreting the evidence on cost rigidities, a fundamental difference between retail price data and wholesale cost data should be noted. While retail prices correspond to prices posted by retailers, wholesale prices are determined as part of a bargaining process between wholesalers and retailers. In a broad sense, bargaining between wholesalers and supermarkets typically involve, in addition to wholesale price determination, quantities purchased and slotting allowances. If wholesale prices are determined in long-term contracts, then it might be the case that wholesale prices, unlike retail prices, do not respond to current market conditions. In Barro's (1977) terminology, wholesale prices might not be "allocative".

There are several reasons that suggest that wholesale prices (costs from the supermarket perspective) in the data do play an allocative role. First, wholesale price negotiations between wholesalers and Chilean supermarkets are not part of long-term (say annual) negotiations[25]. The high frequency variation observed in wholesale costs is consistent with this fact. Second, allowance payments are negotiated between wholesalers and supermarkets on an annual basis and hence it is safe to assume that movements in wholesale prices at high frequencies are not influenced by movements in allowance payments.

Data on wholesale costs are available for the largest two supermarket chains.

[24] An alternative approach to dealing with the heterogeneity in the data adopted by Klenow and Kryvtsov (2008) yields similar results. This results are available upon request.

[25] Information provided by an industry insider.

This section uses data on replacement costs, available for one of these retailers, to examine cost rigidities as this measure of cost is closer to the concept of marginal cost and is not directly affected by movements in inventories. I use the same procedure for extracting reference costs from weekly cost series employed in the case of retail prices (see Chahrour, 2011). As in the case of retail prices, weekly costs spend a large fraction of the time at reference levels. Pooling across product varieties, weekly costs coincide with reference costs 80% of the time. This pattern is similar across all product categories.

Reference costs are substantially more rigid than weekly costs. The weighted median frequency of reference cost adjustment equals 0.047 per week (implied duration of 21 weeks) versus 0.117 per week (implied duration of 8.5 weeks) in the case of weekly costs. Reference cost increases are significantly more prevalent than reference cost decreases. The frequency of reference cost increases is on average 0.029 compared to 0.018 in the case of cost decreases. Compared to price rigidities, reference costs appear to be as sticky as reference prices[26]. Weekly costs are more persistent than posted prices. This evidence is consistent with posted prices being driven to a larger extent by retailers pricing policies than reference prices which appear to inherit the rigidity present in prices at the previous stage of the distribution chain. As in the case of retail price rigidities there is important heterogeneity in the frequencies of weekly and reference cost changes across product categories.

Cost changes are even smaller in size than price changes and changes in reference costs are slightly larger in size than changes in weekly costs. The average size of a change in weekly costs is equal to 2.8% compared to an average size of 3.7% in the case of reference cost adjustments. As in the case of retail prices, cost increases and decreases are similar in size.

5 Markup Behavior and Pass-through

This section examines the behavior of retail markups –defined as (log) ratio between the retail price and the wholesale cost of a given product variety. Markup behavior can be revealing of the presence of real rigidities and hence are relevant in assessing the size of the contract multiplier. As Gopinath and Itskhoki (2011) point out, prior

[26] The implied duration of reference prices for the same product categories and retailer for which reference costs are computed equals 21.6 weeks.

evidence is consistent with variable wholesale markups and stable retail markups. Thus, variable markups have not been found to be a source of real rigidities at the retail level. Eichenbaum et al. (2011), for example, find that a large U.S. retailer tends to keep markups within narrow bounds. I find similar evidence in the Chilean data.

Figure 9 presents the distribution of markup deviations for the two retailers for which wholesale price data is available[27,28]. Markups appear to be remarkably stable over time. This suggests that the response of retail prices to changes in wholesale costs might be close to complete. I test for the response of retail prices to changes in wholesale costs more formally by estimating the following conditional pass-through regression:

$$\Delta p_k^{t_k - t_k^{-1}} = \alpha + \beta \Delta c_k^{t_k - t_k^{-1}} + \xi_k + \epsilon_k^{t_k} \tag{3}$$

where $\Delta p_k^{t_k - t_k^{-1}}$ denotes the change in the retail price (in logs) of product variety k between the most recent price change and the previous price change, c_k denotes the wholesale cost (in logs) of product variety k, ξ_k are product varieties fixed effects and $\epsilon_k^{t_k}$ is a residual term[29]. The coefficient β captures how much of the accumulated cost increase between price changes is passed-through to retail prices. I estimate pass-through regressions for both retailers for which cost data is available. Estimation by OLS yield point estimates of pass-through coefficients conditional on a posted price change equal of 0.86 and 0.75 (Table 4), indicating that a large fraction of accumulated cost changes is passed-through into retail prices. Conditional pass-through coefficients are even larger when the regression equation is estimated using data on reference prices and costs. Panel B in Table 4 shows that point estimates of conditional pass-through coefficients of reference cost changes into reference price changes are equal to 0.93 and 0.86. Thus, the evidence is consistent with retailers adjusting reference prices so as to limit markup variability.

In the next section I show that the probability of reference price adjustment tends to increase in the gap between the markup of a given product variety and the desired

[27] Due to confidentiality reasons I am not allowed to provide evidence on the levels of markups.

[28] One of the retailers for which cost data are available operates under two different banners considered as different retail chains in the analysis. The markup analysis focuses on only one of these retail chains as the second one was excluded from the analysis due to apparent measurement problems in the retail price data (see Section 2).

[29] Gopinath and Rigobon (2008) and Neiman (2010) use similar specifications to study exchange rate pass-through into U.S. import prices.

markup (proxied by the average markup).

6 Determinants of Reference Price Rigidities and Evidence on State-Dependence

The recent literature on micro price rigidities has identified several covariates of the frequency of price adjustment. In the international price-setting literature, Gopinath and Itskhoki (2010) report a positive association between frequency of price adjustment and long-run exchange rate pass-through coefficients in U.S. import prices. In the closed economy literature, Nakamura et al. (2011) report that frequencies of price adjustment at the retail level are driven to an important extent by the behavior of retail chains (as opposed to product-level shocks[30]). Eichenbaum et al. (2011) find that frequencies of price change are increasing in cost volatility and the gap between markups and average markups.

This section examines the relation between frequencies of price change and some of the covariates identified in the literature. I find evidence consistent with state-dependence in price adjustment behavior. As in Eichenbaum et al. (2011), frequencies of reference price adjustment are increasing in cost volatility. In addition, product varieties that represent a larger fraction of expenditure are more frequently adjusted. Finally, in line with evidence reported by Nakamura et al. (2011), retail chains account for an important fraction of the variation in the frequency of posted and reference price changes. While this finding might appear contradictory with the reported evidence on cost pass-through and markup behavior, I show in Section 8 that different frequencies of reference price change across retailers can be consistent with stable markups in the context of heterogeneous chain-specific menu costs and an economic environment characterized by mild idiosyncratic and aggregate shocks.

6.1 Frequency of Price Adjustment and Retailers Behavior

This subsection investigates the importance of retail chains in determining reference price rigidities. Nakamura (2008) shows that retail price variation is driven to a large extent by variation which is common across stores within chains but not across different chains. This suggests that retailers' dynamic pricing strategies play an important

[30] Similar evidence is reported in Nakamura (2008).

role in shaping retail price dynamics. Similar evidence is reported in Nakamura et al. (2011) who study price rigidities for three product categories in the U.S. They find that a large fraction of the variation in frequencies of price adjustment is explained by variation across retail chains.

I study the importance of Chilean retailers in driving price rigidities using the following variance components model[31]:

$$fr_{ijk} = \beta + \varphi_j + \varphi_{jk} + \varphi_k + \varphi_{ijk} \tag{4}$$

where β is a constant term; φ_j is a random component which captures variation which is common across product varieties and stores within a given retail chain; φ_{jk} is a random component which captures variation common across stores for a specific retail chain and product variety; φ_k is a random component capturing common variation across stores for a given product variety; and φ_{ijk} is a random component capturing variation that is specific to a given store and product variety. All random components are assumed to be distributed normal with zero mean and constant variance ($\varphi_j \sim \mathbb{N}(0, \sigma_1^2)$; $\varphi_{jk} \sim \mathbb{N}(0, \sigma_2^2)$; $\varphi_k \sim \mathbb{N}(0, \sigma_3^2)$; $\varphi_{ijk} \sim \mathbb{N}(0, \sigma_4^2)$). In addition, all components are assumed to be independent of each other. I estimated the model by maximum likelihood at the category level[32].

Table 5 presents the fraction of total variation in frequencies of price adjustment accounted for by each one of the variance components for the average category[33]. The results suggest that retail chains play an important role in determining frequencies of price change of both posted and reference prices. "Chain effects" (adding up the variation explained by chain main effects and the interaction between chain and product variety) explain about 60 percent of total variation in frequencies of price adjustment. This result is somewhat surprising as reference prices, being determined over a longer horizon, are less likely to respond to retailers' dynamic pricing strategies. The previous section showed that in spite of this fact, however, major retail chains tend to pass through most of the accumulated cost shocks into prices when they decide to change their price and this is especially the case for reference prices.

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

[32] For computational purposes, I estimated the model for 31 categories comprising about 70% of total expenditure. I also imposed the requirement that a product variety should be sold in at least five different retail chains.

[33] Results on specific categories are available upon request.

6.2 Frequency of Price Adjustment and Cost Volatility

While time-dependent pricing models predict the absence of a systematic relationship between the magnitude of shocks hitting a price-setter and the frequency of price change, in state-dependent pricing models firms that are hit by larger shocks will find it optimal to adjust their prices more often. This subsection evaluates whether the data supports this particular prediction of state-dependent pricing models.

I estimate the following logistic regression to test for a systematic relationship between the frequency of reference price adjustment of a given product variety, fr_k, and the volatility of (log) costs[34]:

$$\log\left(\frac{fr_k}{1-fr_k}\right) = \alpha + \beta CostVol_k + \xi_c + \epsilon_k \tag{5}$$

where the dependent variable is the natural logarithm of the odds-ratio, $CostVol_k$ is volatility of costs for product variety k (measured by the standard deviation of the log of the cost of product variety k), ξ_c are product-category fixed-effects and ϵ_k is an error term. The results of estimating the above specification by maximum likelihood reveal the existence of a strong positive association between cost volatility and the frequency of reference price change (see Column 1 in Table 6). Eichenbaum et al. (2011) document a similar finding in the case of the large U.S. retailer they analyze. The results are thus consistent with the predictions of menu cost models.

6.3 Frequency of Price Adjustment and Expenditure Shares

I next turn to examining the relationship between frequencies of price adjustment and the share of expenditure devoted to a given item (product variety and store). The literature has been mostly silent about the relationship between expenditure shares and price rigidity. In a recent contribution, Hong (2011), analyzing a scanner data set for a large U.S. retailer[35], finds a negative relationship between the duration of a price spell and expenditure shares. She shows theoretically that bargaining power (proxied by expenditure shares) is positively associated with the frequency of price change.

[34] In the estimations, I use replacement cost data as this measure of cost is not directly affected by movements in inventories.

[35] Her data set include retail and wholesale prices as well as quantities sold for the same retailer studied by Eichenbaum et al. (2011)

I use the same specification of the previous subsection to evaluate the existence of a systematic relationship between frequencies of price adjustment and expenditure shares:

$$\log\left(\frac{fr_k}{1-fr_k}\right) = \alpha + \beta ExpShare_k + \xi_c + \epsilon_k \tag{6}$$

The results of estimating the equation by maximum likelihood confirm the existence of a positive and significant relationship between expenditure shares and frequencies of reference price changes (see Column 2 in Table 6). The positive correlation between expenditure shares and frequencies of price change are also observed within chains. One interpretation of this regularity appeals to rational inattention on the part of retailers. Multiproduct price setters are unable to pay attention to the thousands of product varieties they need to price. Under information capacity constraints, they may be forced to focus their attention on those product varieties representing a larger fraction of consumers' expenditures, which would explain why these products are repriced more often. Anecdotal evidence, gathered through interviews with practitioners, suggests that something along these lines might be at work. According to these sources, supermarkets tend to define baskets of product varieties which they consider particularly important in determining consumers demand, so that they choose to monitor their market conditions (including changes in competitors' strategies) more closely.

As can be seen from Column 3 in Table 6, the effects of cost volatility and expenditure shares on the frequency of price adjustment are mostly independent of each other. The estimated coefficients change only slightly when both variables are included in the logistic regression equation. The results imply that, assuming that the frequency of reference price adjustment is at its mean value, an increase in one standard deviation in cost volatility (expenditure share) lead to a fall in implied duration of a reference price spell by about 4 weeks (2.6 weeks).

6.4 Further Evidence on State-Dependence

Section 5 above documented that retailers tend to pass through most accumulated cost shocks when changing prices. This suggests that the probability of a price adjustment is related to the gap between the markup and the desired markup. In this subsection, I look for evidence of a relation between the markup gap, defined as the difference between the markup for a given product variety and the average markup, and the frequency of reference price adjustment.

Figure 10 shows the relationship between markup gaps and the probability of a reference price change for the two retail chains for which cost data are available. The charts suggest a strong positive association between the two variables. The higher is the markup deviation from the desired markup (proxied by the average markup for a given variety across weeks) the more likely is that the retailer will choose to change a reference price. This pattern is especially pronounced in the case of Chain A, which is consistent with the pass-through evidence reported in Section 5.

The findings in this subsection are in line with previous evidence reported for the U.S. by Eichenbaum et al. (2011). Analyzing the price-setting behavior of a large U.S. retailer. Eichenbaum et al. (2011) find a strong positive association between the probability of price adjustment and the markup gap. They interpret the evidence as suggesting that the retailer chooses the frequency of reference price adjustments so as to limit variations in markups.

One additional piece of evidence of state-dependent pricing is the presence of a weak negative correlation between the size of reference price changes and the time since the last price change (Table 7). Time-dependent pricing models predict a positive relationship between the age of a price and the size of price changes as the longer the time since the last price change the more shocks tend to accumulate inducing the firm to make larger price adjustments. In state-dependent pricing models, in contrast, price longevity is a sign that firms have not been hit by large shocks and hence the relation between age and size of a price change is less clear-cut (Klenow and Malin, 2010).

7 Synchronization of Price Changes

Whether price-setters choose to change prices in a synchronized or staggered fashion has important implications for the persistence of nominal shocks and is potentially revealing of the existence of strategic complementarities.

Prior evidence on the synchronization of price adjustments is mixed. Lach and Tsiddon (1992), analyze a data set consisting of monthly prices for 26 foodstuffs collected by the Central Bureau of Statistics (CBS) in Israel for the purpose of computing the Consumer Price Index (CPI) and report that prices are not synchronized across stores even during periods of high inflation. Lach and Tsiddon (1996) focus on groceries stores selling wines and meat products and find that price changes tend to be staggered across stores but synchronized within stores. It should be pointed out that Lach and Tsiddon's (1992, 1996) data do not include chains of retail stores but only independent grocery stores. Midrigan (forthcoming), examines synchronization in price-setting within a retail chain (Dominick's) using weekly data and finds evidence of within store synchronization. Similar evidence is provided by Cavallo (2010) for online prices.

I evaluate the extent of synchronization of price changes across stores using an index developed by Fisher and Konieczny (2000) . The Fisher-Konieczny index is given by:

$$FK_k = \sqrt{\frac{1}{T}\frac{\sum_{t=1}^{T}\left(f_{kt}-\overline{f}_k\right)^2}{\overline{f}_k\left(1-\overline{f}_k\right)}} = \frac{S_{f_k}}{\sqrt{\overline{f}_k\left(1-\overline{f}_k\right)}}$$

where f_{kt} is the fraction of stores changing the price of product variety k in week t, $\overline{f}_k$ denotes its time-series average and S_f its standard deviation. The FK index lies in the interval $[0,1]$. The intuition underlying the FK index is the following. If price changes are perfectly synchronized, then f_{kt} will take the value one in periods when all stores simultaneously change the price of good k and zero when stores choose not to change the price. Since the variance of a Bernoulli random variable that takes the value one with probability $\overline{f}_k$ and zero with probability $\left(1-\overline{f}_k\right)$ equals $\overline{f}_k\left(1-\overline{f}_k\right)$, the FK index takes the value 1 (its maximum attainable value) in the case of perfect synchronization. In the case of uniform staggering, on the other hand, every period a constant fraction $\overline{f}_k$ of stores chooses to change the price of the good. In this case the FK index takes the value zero. Values of the index between 0 and 1 correspond to intermediate degrees of synchronization.

I examine the degree of synchronization present in the data computing the FK index for all product varieties which are sold in at least five different retail chains. Figure 11 presents the distribution of the FK index across product varieties for both posted and reference prices. Interestingly, changes in reference prices appear to be more synchronized than changes in posted prices. The value of the index in the case of reference (posted) prices ranges between 0.14 (0.18) and 0.68 (0.57) with a median of 0.39 (0.34). One problem with the FK index is that it is difficult to interpret when it takes intermediate values which are not close to zero or one. Compared to previously reported measures of price change synchronization based on the FK index, the degree of price synchronization in reference prices appears to be relatively high. Dhyne and Konieczny (2007), for instance, find an FK index ranging from 0.10 to 0.88 with a median 0.2 in Belgian data underlying the national CPI[36]. The timing of price changes across stores, however, appear to be closer to a situation of uniform staggering than to perfect synchronization.

The distributions of the FK index shown in Figure 11 provide evidence on the degree of synchronization of price changes across stores, but not necessarily across price-setters as prices might be set in a centralized fashion at the chain's headquarters level. In order to evaluate the degree of synchronization across- versus within- chains I estimate the following fixed-effects logit model (Fisher and Konieczny, 2000):

$$Y_{ijt} = \beta_0 + \beta_1 FRACSAME_{ijt} + \beta_2 FRACOTHER_{ijt} + \zeta_i + \zeta_j + \zeta_t + \varepsilon_{ijt}$$

where Y_{ijt} takes on the value one if store i in chain j changes price of a good in period t and zero otherwise, $FRACSAME$ is the fraction of other stores in the same chain changing the price of the good in t, $FRACOTHER$ is fraction of other stores in other chains changing the price of the good in t, the terms ζ_i, ζ_j, and ζ_t are store, chain and time fixed effects, respectively and ε_{ijt} is an error term. Table 8 presents the results of estimating the above specification by conditional maximum likelihood. The results indicate that the probability of price adjustment is increasing both in the fraction of stores in the same or other chains that change prices in the same time period. The magnitude of the effects of the two variables on the probability of price adjustment is, however, strikingly different (especially in the case of reference prices). The effect of an increase in the fraction of price changers within the same chain on the probability of a reference price change at a given store is about 26 times the effect of a similar increase in the fraction of price changers from other chains. The evidence is thus consistent with the fact that synchronization across stores is driven to an important extent by synchronization within chains.

I also examine the degree of intra-store and intra-category synchronization. Prices tend to be synchronized within stores when the technology of price adjustment is characterized by increasing returns as well as when prices have positive interactions in the

[36] One can also get a sense of the degree of synchronization implied by the index by comparing the value of the index with the one obtained from a hypothetical series of f_{kt}. The average value of the index for reference price changes would be obtained, for instance, if the fraction of stores changing the price of the good alternates between 70% and 30%.

profit function (Sheshinski and Weiss, 1992). Sheshinski and Weiss (1992) distinguish between "menu costs" and "decision costs" of price changes. While "menu costs" do not change with the number of prices changed, "decision costs" are increasing in the number of adjusted prices. Thus, when the cost of price change take the form of "menu costs" intra-store price adjustments tend to be bunched together. Midrigan (forthcoming) offers a model of a multiproduct price-setter which exploits this idea to account for the presence of small price changes observed in U.S. data.

Figure 12 shows the distribution of the Fisher-Konieczny index for within-store price change synchronization computed as

$$FK_{i(j)} = \sqrt{\frac{1}{T}\frac{\sum_{t=1}^{T}\left(f_{i(j)t} - \overline{f}_{i(j)}\right)^2}{\overline{f}_{i(j)}\left(1 - \overline{f}_{i(j)}\right)}} = \frac{S_{f_{i(j)}}}{\sqrt{\overline{f}_{i(j)}\left(1 - \overline{f}_{i(j)}\right)}}$$

where $f_{i(j)t}$ is the fraction of prices by store i in chain j in week t. The distribution of the FK index provides little support for within-store synchronization. The index fluctuates between 0.07 (0.1) and 0.31 (0.41) with a mean of 0.11 (0.19) in the case of reference (posted) prices. There is greater evidence of synchronization within stores and categories. As different product varieties within categories are usually located in the proximity of each other within an outlet (usually in the same aisle), it is plausible that stores choose to reprice several products of a category simultaneously in order to economize on resources devoted to price adjustment. The FK index for within store and category synchronization in the case of reference prices ranges between 0.12 and 0.99 with an average of 0.44. By way of contrast, Hong and Li (2011) report values of the FK index ranging between 0.11 and 0.36 within a category for a large retail chain in the US. Consistent with the presence of economies of scope in the technology of price adjustments, the FK index is decreasing in the number of barcodes within a category (see Figure 13). While categories including less than 12 products (corresponding to the 10th percentile of the distribution of products per category) exhibit an average FK index of 0.73, in categories including more than 260 products (corresponding to the 90th percentile of the distribution of products per category) the average value of the FK index is 0.28.

8 Reference Prices and Menu Cost Models: A Quantitative Assessment

Evidence provided in Section 6 suggests the presence of state-dependence in price adjustment decisions. This section studies whether reference price data is consistent with the predictions of menu cost models (Barro, 1972; Sheshinski and Weiss, 1977, 1983; Golosov and Lucas, 2007). Several recent papers (e.g. Kehoe and Midrigan, 2010; Eichenbaum et al., 2011) have suggested that menu cost models should be calibrated to match moments from data on reference prices.

The model is standard in the literature and features a monopolistic firm which chooses the price for its product subject to a fixed cost of price adjustment and an environment characterized by both aggregate inflationary shocks and idiosyncratic technology shocks (Golosov and Lucas, 2007; Nakamura and Steinsson, 2008). The firm faces a Dixit-Stiglitz demand function

$$y_t = Y\left(\frac{p_t}{P_t}\right)^{-\theta},\ \theta > 1$$

where p_t is the nominal price for the firm's product, P_t is an aggregate price index, θ is the price elasticity of demand, and Y is a scale parameter. Real profits, excluding the cost of price adjustment, are given by:

$$\pi_t = Y\left(\frac{p_t}{P_t}\right)^{-\theta}\left[\frac{p_t}{P_t} - z_t\right]$$

where z_t is the marginal cost. The natural logarithm of marginal costs, z_t, follow an AR(1) process:

$$\log(z_{t+1}) = \rho_z \log(z_t) + \epsilon_{t+1},\ \ |\rho_z| < 1$$

where ρ_z is the autoregressive coefficient, and $\epsilon_t \sim \mathbb{N}(0, \sigma_\epsilon^2)$. The natural logarithm of the price level, P_t, is assumed to follow a random-walk with drift:

$$\log(P_{t+1}) = \mu + \log(P_t) + \eta_{t+1}$$

where μ denotes trend inflation and $\eta_t \sim \mathbb{N}\left(0, \sigma_\eta^2\right)$. The firm must pay a fixed cost Ω for making a nominal price change. Thus, the Bellman equation for the firm's problem can be written as:

$$V\left(p_{-1}/P, z\right) = \max_{p}\left\{\pi - \Omega \cdot \mathcal{I}\left\{p \neq p_{-1}\right\} + \beta E\left[V\left(p/P', z'\right)\right]\right\}$$

where $\mathcal{I}\left\{p \neq p_{-1}\right\}$ is an indicator function that takes on the value one if the firm decides to change its nominal price and zero otherwise.

The model includes eight parameters: θ, Ω, ρ_z, σ_ϵ^2, μ, σ_η^2, β and Y. I calibrate the model to match moments of the reference price data observed at the weekly frequency. I estimate the parameters governing the price level dynamics, μ and σ_η, from the series of an aggregate price index constructed as a weighted average price from the data[37]. The point estimates for μ and σ_η are 0.0012 (an implied annual inflation rate of 4.5 percent) and 0.007 respectively[38]. The parameters governing the stochastic process for costs are estimated from data on replacement costs deflated using the constructed price index. Estimation of a dynamic panel by a fixed-effects regression yield the point estimates $\rho_z = 0.84$ and $\sigma_\epsilon = 0.022$. The elasticity of substitution, θ, is chosen so as to be consistent with observed markup behavior and set equal to 4. Parameters β is set to $0.96^{1/52}$ which is standard in the literature and Y is set to one. Finally, the menu cost, Ω, is calibrated so as to match the frequency of reference price change at the retailer level[39]. The model is solved using value function iteration and Tauchen's (1986) method for approximating an AR(1) process through a Markov chain[40,41].

Results. The model is capable of replicating several features of the reference price data. First, the model closely matches the average size of reference price changes. Model simulations yield an average size of reference price changes of about 7 percent (this is true for all retail chains) which is close to the average size of reference price changes observed in the data (about 8 percent). Second, as in the data, hazard functions are roughly flat over the relevant time domain[42]. They appear to be

[37] The price index in week t is computed as a weighted average of the median prices within categories in week t.

[38] In estimating these parameters I excluded those observations outside an interval formed by the 1st and 99th percentiles of the distribution of weekly changes in the (log) price index.

[39] The model is calibrated so as to match the weighted median frequency of reference price change for each retail chain.

[40] I gratefully acknowledge using Matlab codes made publicly available by Emi Nakamura and Jon Steinsson for solving the model.

[41] Knotek and Terry (2008) show that value function iteration dominates over other solution methods such as collocation in the case of dynamic programming problems featuring nonlinearities.

[42] Hazard functions are estimated using the non-parametric Kaplan-Meier estimator.

upward-sloping for the first few weeks and flat afterwards (see Figure 14)[43]. The upward-sloping section is likely to be globally unimportant as the unconditional average duration of reference prices is above 20 weeks. Third, the volatility of markups is similar to the one observed in the data. The standard deviation of markups generated by the model is, in the case of all retailers, on the order of 0.06, which compares to a standard deviation of about 0.08 observed in the data[44,45].

One feature of the data that is inconsistent with the predictions of the model is the large fraction of price changes that are small. In the data, 1/3 of price changes are smaller than 3 percent. As Figure 15 shows, the model does not give rise to such small price changes. This feature of the data is closer to the predictions of time-dependent pricing models and to those of menu cost models for multiproduct retailers featuring economies of scope in the technology of price adjustments (Midrigan (forthcoming)).

9 Concluding Remarks

This paper has documented new evidence on nominal rigidities using a unique data set of scanner data for retailers in Chile. As in the US, nominal rigidities (both at the retail and wholesale levels) take the form of reference price inertia. While posted prices change, on average, every 5 weeks, reference prices change every 2 quarters (29 weeks), on average. Price changes are, however, substantially smaller in size relative to price changes in the U.S., contributing relatively little to the degree of price flexibility in the data.

The evidence on markup behavior and conditional pass-through presented in Section 5 is suggestive of the fact that retailers adjust their prices, in particular reference prices, so as to reflect cost changes accumulated since the last price change. Thus, in spite of frequencies of price adjustment varying systematically across chains (as shown in Section 6), movements in reference prices appear to reflect movements in prices that take place at a previous stage of the distribution chain. As Section 8 showed, varying frequencies of reference price adjustment across retailers are consistent with

[43] An exception is Chain 3 where the hazard function appears to be upward-sloping over the whole time domain.

[44] This corresponds to the standard deviation of markups computed on the basis of replacement costs.

[45] The standard deviation of markups is 0.077 when excluding markups outside an interval formed by the 1st and 99th percentile and 0.089 when no observations are excluded from the computation.

stable markups in an environment characterized by low shock volatility. The evidence is also supportive of the fact that markup variation is not an important source of real rigidities at the retail level.

Although the data exhibit several features consistent with state-dependent pricing (e.g. a positive correlation between the frequency of price adjustment and cost volatility and a weak relationship between age of a price spell and size of price changes), a standard menu cost model is unable to capture the high fraction of price changes that are small in absolute value. One would need to appeal either to time-dependent pricing models or to a multiproduct menu cost model featuring economies of scope in price adjustment (Midrigan, forthcoming) to account for this particular feature of the data. This latter alternative is particularly attractive considering that the evidence on synchronization of price changes within stores and categories is suggestive of the presence of economies of scope in the technology of price adjustments.

Evidence on the synchronization of price changes suggests that most across-stores synchronization takes place within retail chains, as opposed to across price-setters. Staggering of price adjustments across price setters is consistent with more persistent real effects of monetary shocks and inconsistent with the presence of strong strategic complementarities.

Overall, the paper findings are supportive of macroeconomists focus on reference price behavior to investigate issues related to the monetary policy transmission mechanism.

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Table 1. Product Categories included in the Data

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

Table 1. Product Categories included in the Data (cont.)

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

Table 2. Importance of Reference Prices Across Retailers

Chain	Posted Prices			Revenue		
	at reference	below reference	above reference	at reference	below reference	above reference
	(1)	(2)	(3)	(4)	(5)	(6)
1	0.83	0.12	0.04	0.75	0.06	0.19
2	0.86	0.07	0.06	0.77	0.11	0.12
3	0.92	0.04	0.02	0.89	0.03	0.07
4	0.85	0.09	0.04	0.78	0.07	0.15
5	0.89	0.06	0.04	0.83	0.07	0.10
6	0.82	0.12	0.05	0.74	0.07	0.18
7	0.81	0.12	0.06	0.74	0.08	0.18
8	0.80	0.14	0.05	0.72	0.07	0.20
Mean	0.85	0.10	0.05	0.78	0.07	0.15
Median	0.84	0.11	0.05	0.76	0.07	0.16
St. Dev.	0.04	0.03	0.01	0.06	0.02	0.05
Min	0.80	0.04	0.02	0.72	0.03	0.07
Max	0.92	0.14	0.06	0.89	0.11	0.20
# of obs.	36,386,997	36,386,997	36,386,997	36,386,997	36,386,997	36,386,997

Notes. The table presents, for each retail chain, the fraction of posted prices which are equal, below or above reference prices (Columns 1-3) and the fraction of total revenue in each chain that is obtained at prices which are equal, below or above the reference price (Columns 4-6). Reference prices correspond to the most quoted posted price within a 13-week rolling window centered in the current week (see Chahrour (2011) for details).

Table 3. Frequencies of Price Adjustment Across Retail Chains

	Reference		Posted	
Chain	Frequency	Duration	Frequency	Duration
1	0.028	36.0	0.198	5.0
2	0.040	25.3	0.150	6.7
3	0.018	55.6	0.067	14.9
4	0.031	32.3	0.127	7.9
5	0.036	27.4	0.114	8.7
6	0.029	34.1	0.192	5.2
7	0.037	26.9	0.192	5.2
8	0.031	31.8	0.231	4.3
Mean	0.031	33.7	0.159	7.2
Median	0.031	32.0	0.171	5.9
Stdev	0.007	9.6	0.054	3.4
Min	0.018	25.3	0.067	4.3
Max	0.040	55.6	0.231	14.9

Notes. The table presents frequencies of price change for both posted and reference prices. Retail chain level frequencies correspond to weighted median frequencies and are obtained as the weighted average of category-level frequencies (computed, in turn, as the median frequency within a category and retail chain).

Table 4. Conditional Pass-through Regressions

Dependent variable: $\Delta p_k^{t_k - t_k^{-1}}$

Panel A: Posted Prices	*Chain A*	*Chain B*
$\Delta c_k^{t_k - t_k^{-1}}$	0.867	0.743
	(0.001)***	(0.016)***
Product FE	Yes	Yes
No. obs.	598,750	276,923
R-sq	0.71	0.45
Panel B: Reference Prices	*Chain A*	*Chain B*
$\Delta c_k^{t_k - t_k^{-1}}$	0.934	0.858
	(0.001) ***	(0.003) ***
Product FE	Yes	Yes
No. obs.	133,465	60,766
R-sq	0.89	0.61

Notes. The table presents the results of fixed-effects cost pass-through regressions conditional on a price change. The dependent variable is the price difference (in logs) between price observed after the last price change and the price observed after the previous price change. The explanatory variable of interest, $\Delta c_k^{t_k - t_k^{-1}}$, is the accumulated (log) cost change between successive price changes. Standard errors in parenthesis. (***) denotes significant at 1% level.

Table 5. Variance Decomposition of Frequencies of Price Adjustment

	Retailer (1)	Retailer/Product (2)	Product (3)	Store/product (4)
Posted	26.9	35.6	26.0	11.5
Reference	16.3	41.6	21.7	20.3

Notes. The table presents the fraction of total variation in the frequencies of posted and reference price change which is attributed to variation across chains (Column 1), variation across chains and product varieties (Column 2), variation across product varieties (Column 3), and variation specific to a given store and product variety (Column 4). The model is estimated by Maximum Likelihood for each one of 31 product categories which account for about 70% of total expenditures. The first (second) row presents the average fraction of the variation in the frequency of posted (reference) price change accounted for each of the four components.

Table 6. State-dependence in Price Adjustments: Cost Volatility and Expenditure Shares

Dependent variable: $log\left(\frac{fr_k^{ref}}{1-fr_k^{ref}}\right)$

	(1)		(2)		(3)	
	Coeff.	Mg. eff.	Coeff.	Mg. eff.	Coeff.	Mg. eff.
Cost volatility	7.471 (0.598)***	0.271 (0.022)***	___	___	7.515 (0.582)***	0.273 (0.02)***
Exp. share	___		189.6 (36.2)***	6.886 (1.327)***	193.6 (31.2)***	7.022 (1.142)***
FE	Yes		Yes		Yes	
No. of obs.	1,080		1,080		1,080	

Notes. The table presents the results of estimating a logistic regression in which the dependent variable is the log of the ratio between the frequency of reference price change and one minus the frequency of reference price change (odds ratio) and the two explanatory variables of interest are the cost volatility of a product variety, measured by the standard deviation of log costs, and the expenditure share of a given product variety on total expenditure. Product category fixed effects are included and the estimation is carried out by maximum likelihood. Robust standard errors are in parenthesis. (***) denotes significant at the 1% level.

Table 7. Size of Price Changes vs. Time Elapsed Since Last Price Change

Dependent variable: Size of Reference Price Change	
Age	-0.00017
	(0.000004)***
Category FE	Yes
Retailer FE	Yes
Time FE	Yes
No. of obs.	1,339,423
Adj. R-sq.	0.082

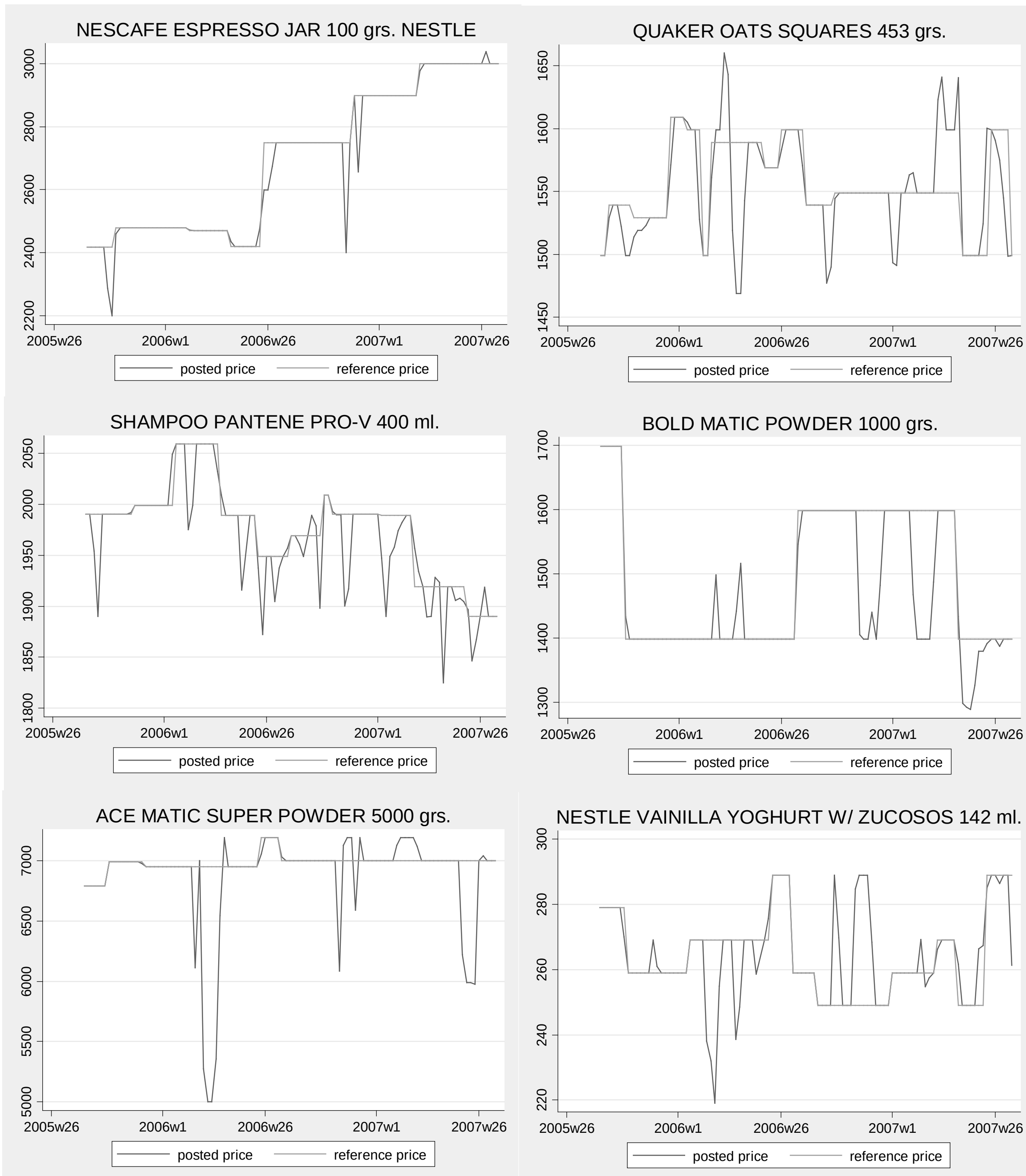
Notes. The table presents the results of a fixed effects regression of the size of reference price changes on the time elapsed since the last reference price change (age of a price spell). Robust standard errors in parenthesis. (***) denotes significant at the 1% level.

Table 8. Synchronization of Price Changes Across and Within Chains

	Coefficient	Marginal Effect
Panel A: Reference Prices		
Fracsame	0.0688	0.0128
	(0.0001)***	(0.00001)***
Fracother	0.0027	0.0005
	(0.0001)***	(0.00001)***
# of obs.	7,064,905	
Panel B: Posted Prices		
Fracsame	0.0718	0.0043
	(0.0001)***	(0.00001)***
Fracother	0.0010	0.0001
	(0.0001)***	(0.00001)***
# of obs.	7,457,493	

Notes. The table presents the results of estimating a fixed-effects logit model in which the dependent variable is the probability of a price change. The explanatory variables Fracsame and Fracother are the fraction of other stores in the same and other chains, respectively, that change the price of a given product variety in a given period. Estimation is performed by conditional maximum likelihood. Standard errors in parenthesis. (***) denote significant at the 1% level.

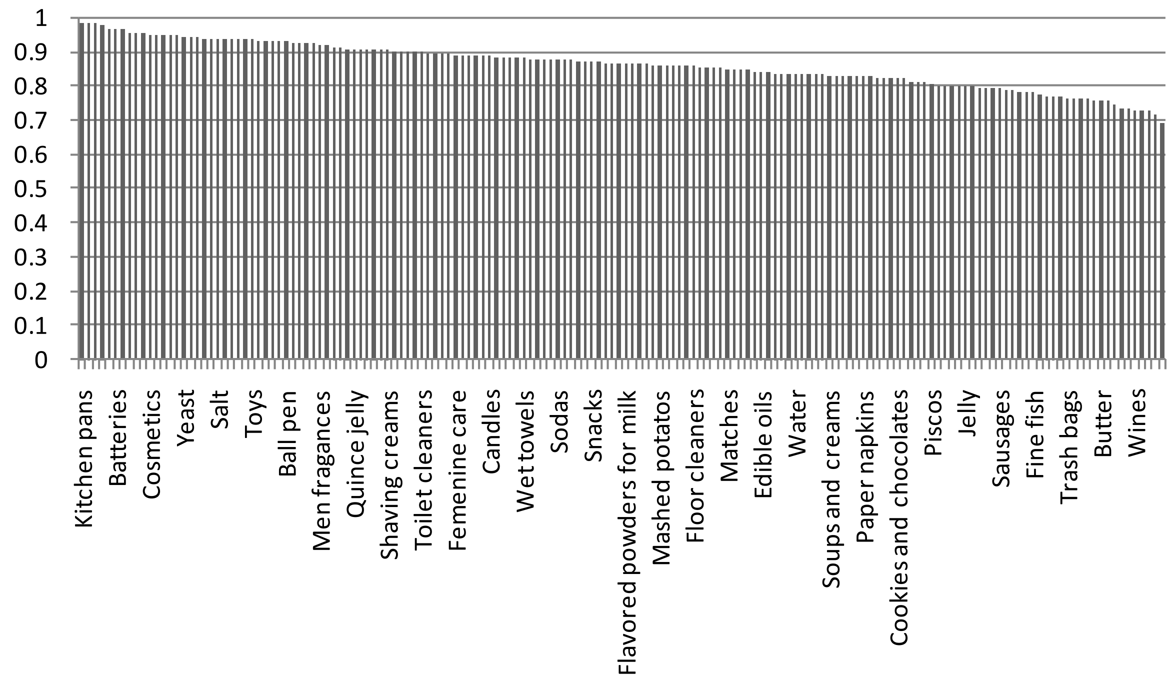
Figure 1. Posted and Reference Price Trajectories for Selected Product Varieties and Stores



Notes. The charts display posted and reference price trajectories of selected product varieties sold at a given outlet. Reference prices correspond to the most quoted posted price within a 13-week rolling window centered in the current week (see Chahrour (2011) for details).

Figure 2. Importance of Reference Prices Across Categories

Fraction of Posted Prices equal to Reference Prices



Notes. The chart displays the fraction of posted prices that coincide with reference prices within each of the 190 product categories included in the analysis. Reference prices correspond to the most quoted posted price within a 13-week rolling window centered in the current week (see Chahrour (2011) for details).

Figure 3. Transitions Between Reference and Non-reference States

Chain 1

	NR	R
NR	0.53	0.47
R	0.18	0.82

Chain 2

	NR	R
NR	0.56	0.44
R	0.12	0.88

Chain 3

	NR	R
NR	0.42	0.58
R	0.16	0.84

Chain 4

	NR	R
NR	0.60	0.40
R	0.12	0.88

Chain 5

	NR	R
NR	0.56	0.44
R	0.11	0.89

Chain 6

	NR	R
NR	0.57	0.43
R	0.19	0.81

Chain 7

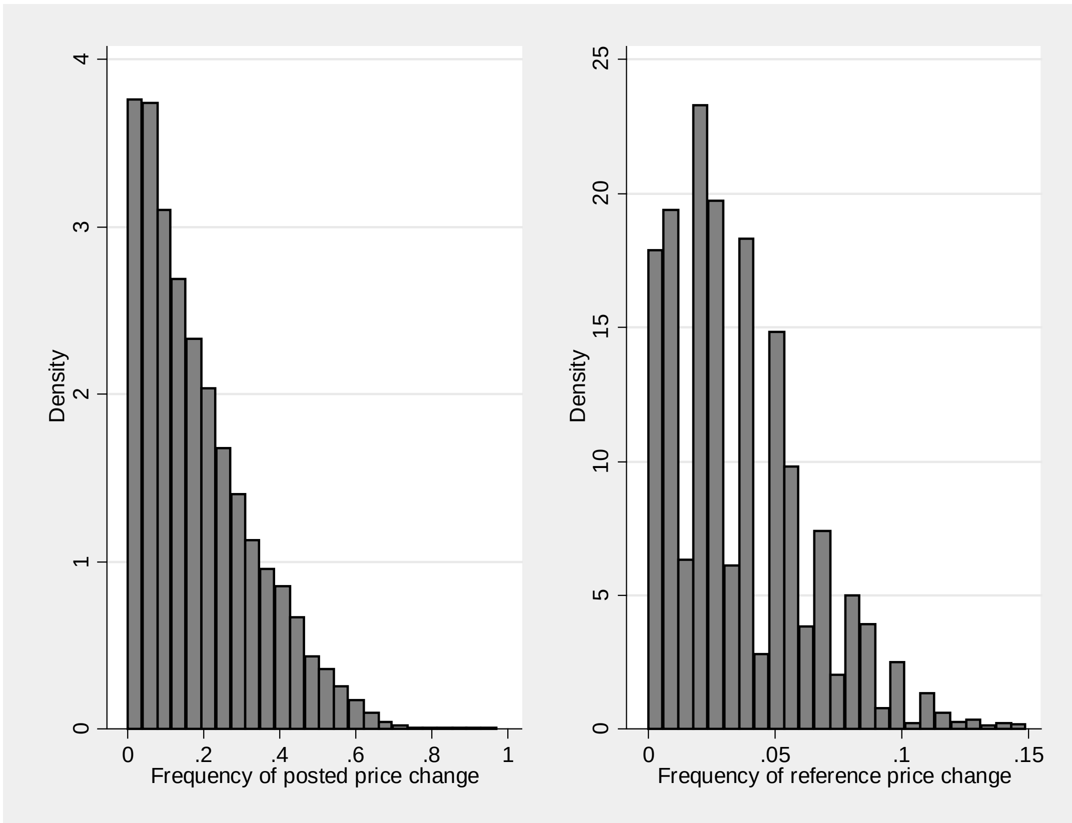
	NR	R
NR	0.61	0.39
R	0.14	0.86

Chain 8

	NR	R
NR	0.52	0.48
R	0.21	0.79

Notes. The figure shows transitional matrices for each retail chain between the states reference (R) attained when a posted price is equal to a reference price and state non-reference (NR) attained when a posted price is either above or below a reference price. A cell (*i*, *j*) in the matrix corresponds to the probability that the price is in state *j* next period conditional on being in state *i* the current period.

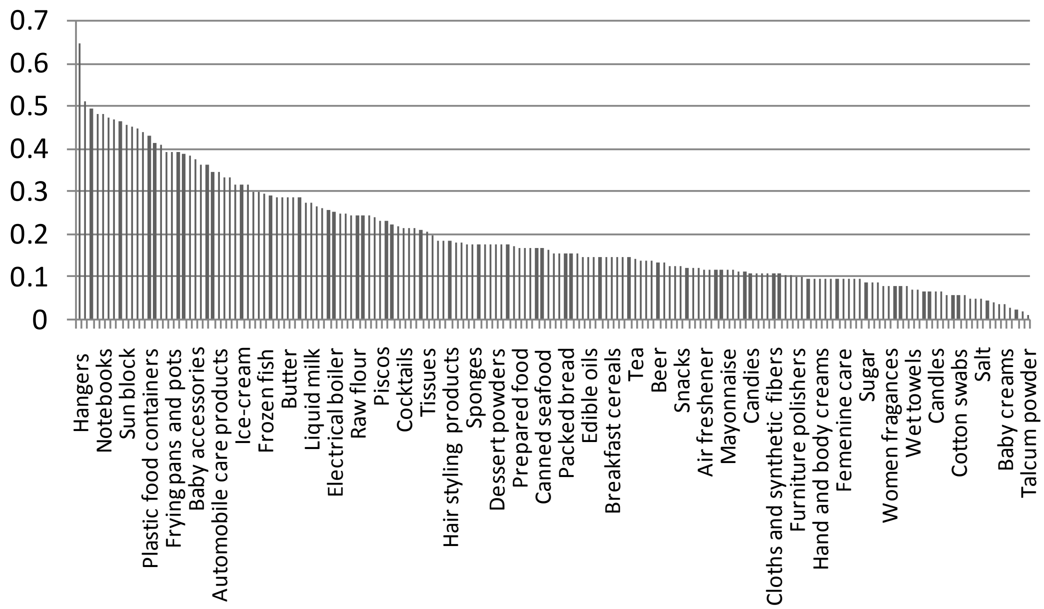
Figure 4. Distribution of the Frequency of Posted and Reference Price Adjustment



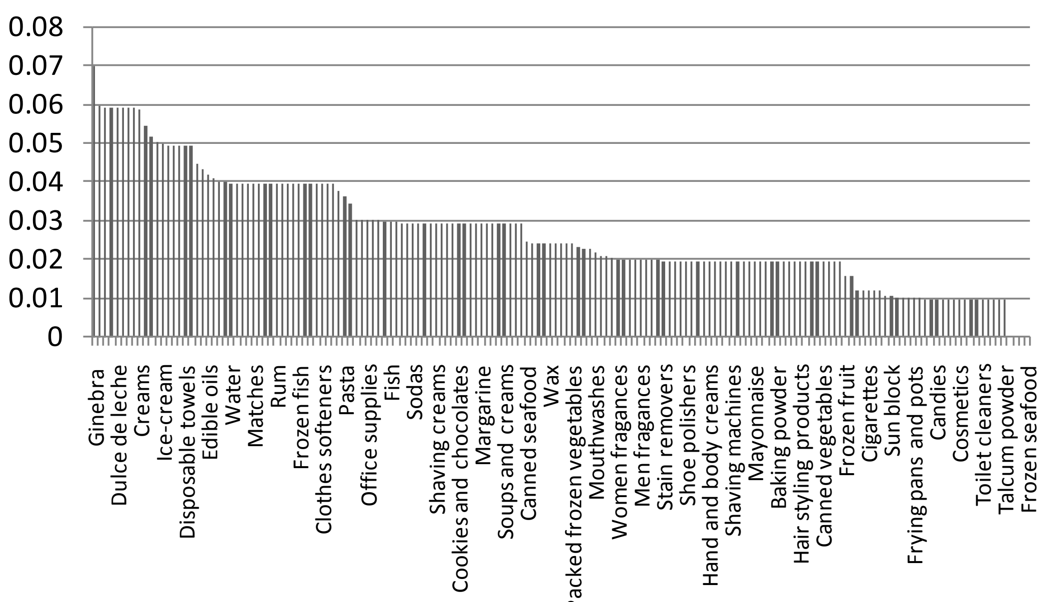
Notes. The figure present the empirical distributions of the frequencies of posted (left-hand side chart) and reference (righ-hand side chart) price adjustment computed at the store and product variety (barcode) level. Reference prices correspond to the most quoted posted price within a 13-week rolling window centered in the current week (see Chahrour (2011) for details).

Figure 5. Frequencies of Price Adjustment Across Product Categories

Panel A. Posted Prices

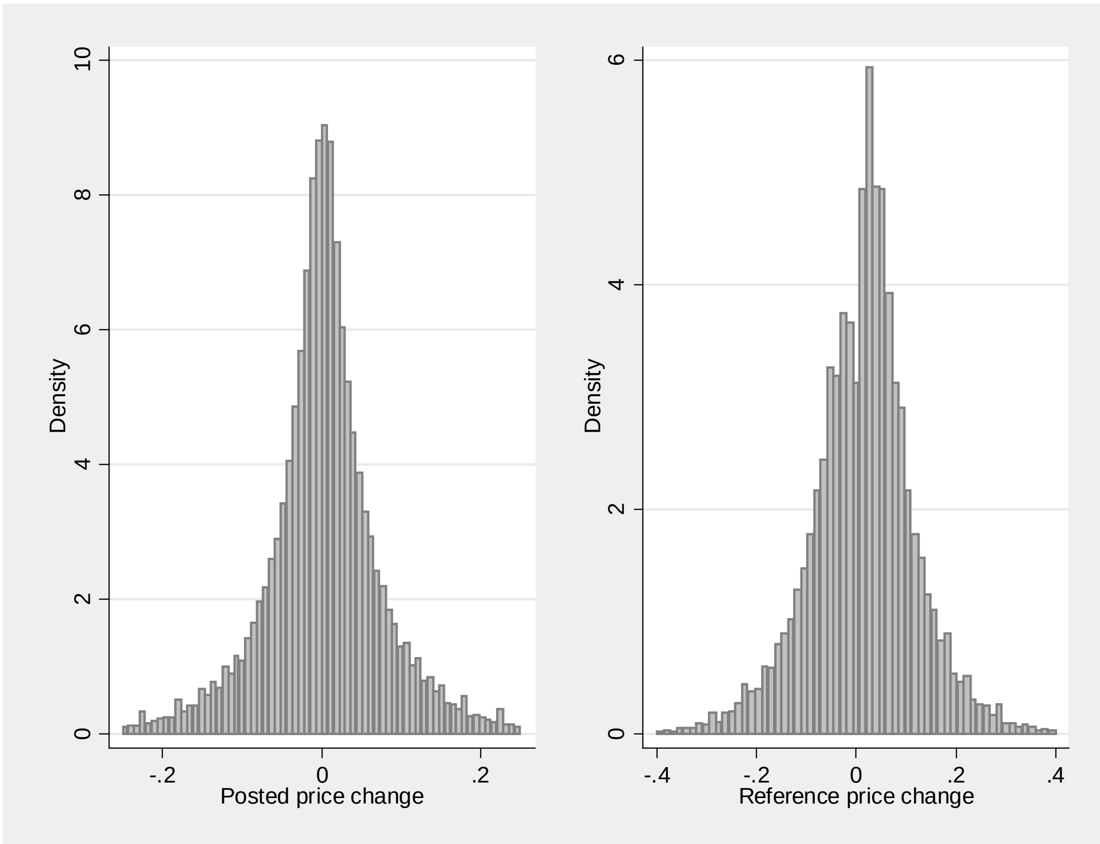


Panel B. Reference Prices



Notes. The figures show the median frequency of price adjustment within each product category. Reference prices correspond to the most quoted posted price within a 13-week rolling window centered in the current week (see Chahrour (2011) for details).

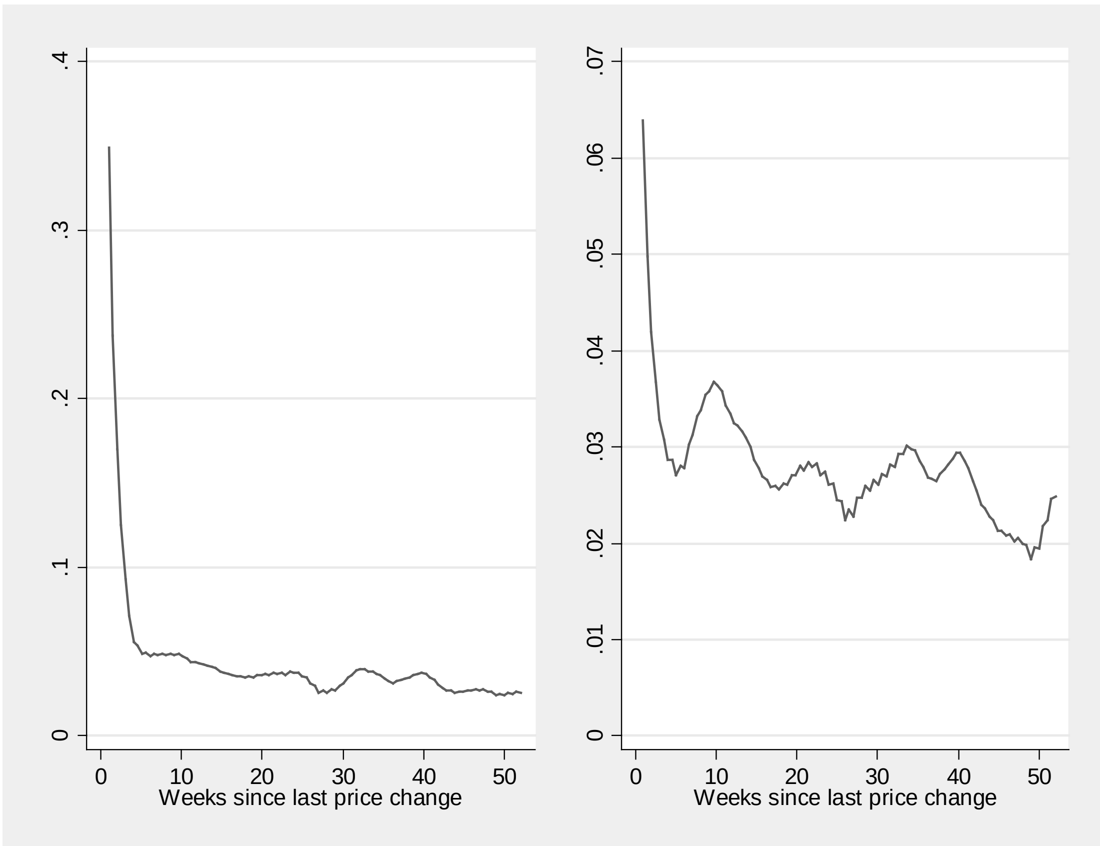
Figure 6. Distribution of the Size of Price Changes



Notes. The figures show the distributions of the size of price changes, conditional on a non-zero price change, where price changes are computed as log differences.

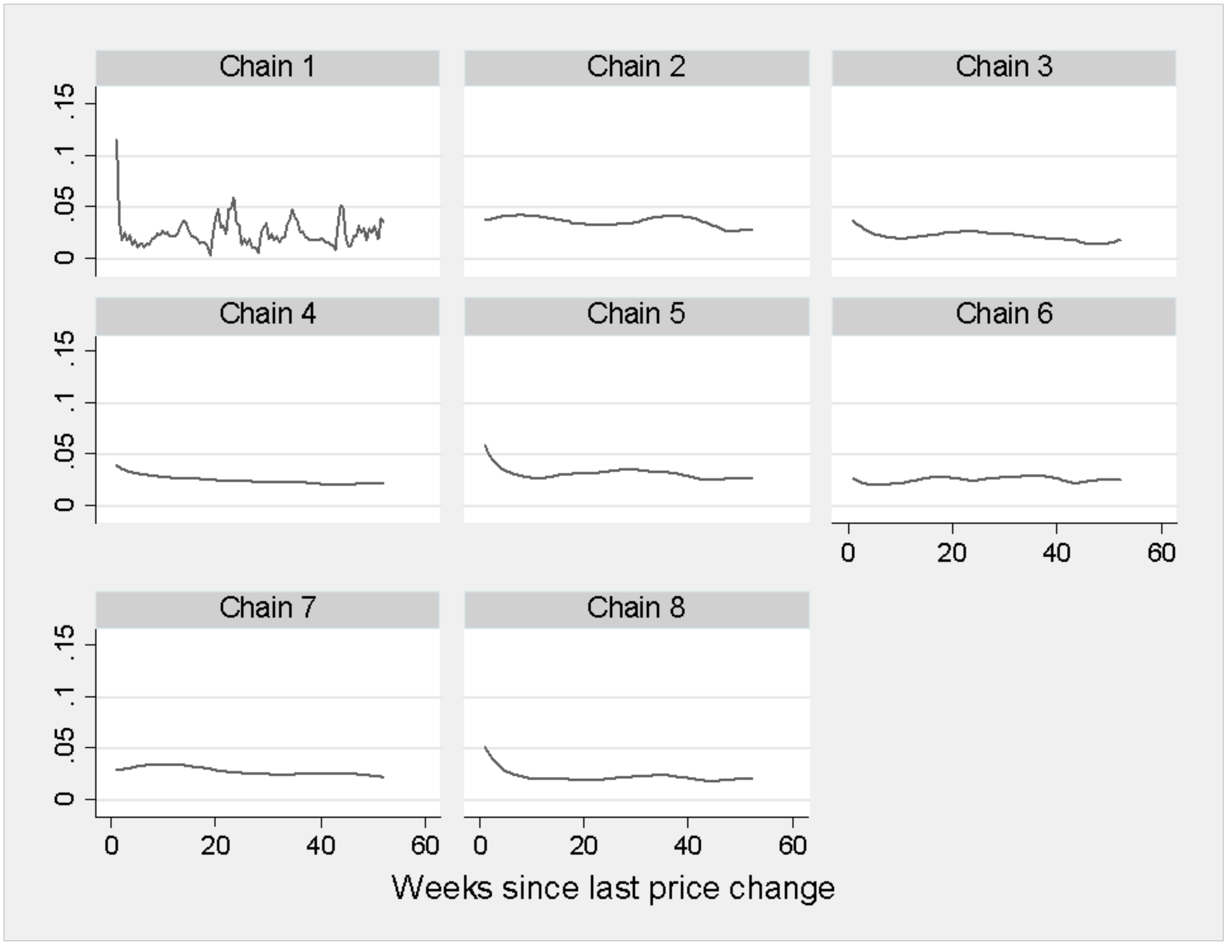
Figure 7. Hazard Functions

a) Posted Prices | b) Reference Prices



Notes. Hazard functions are estimated non-parametrically using the Nelson-Aalen estimator for cumulative hazard functions and smoothed using an Epanechnikov kernel smoother.

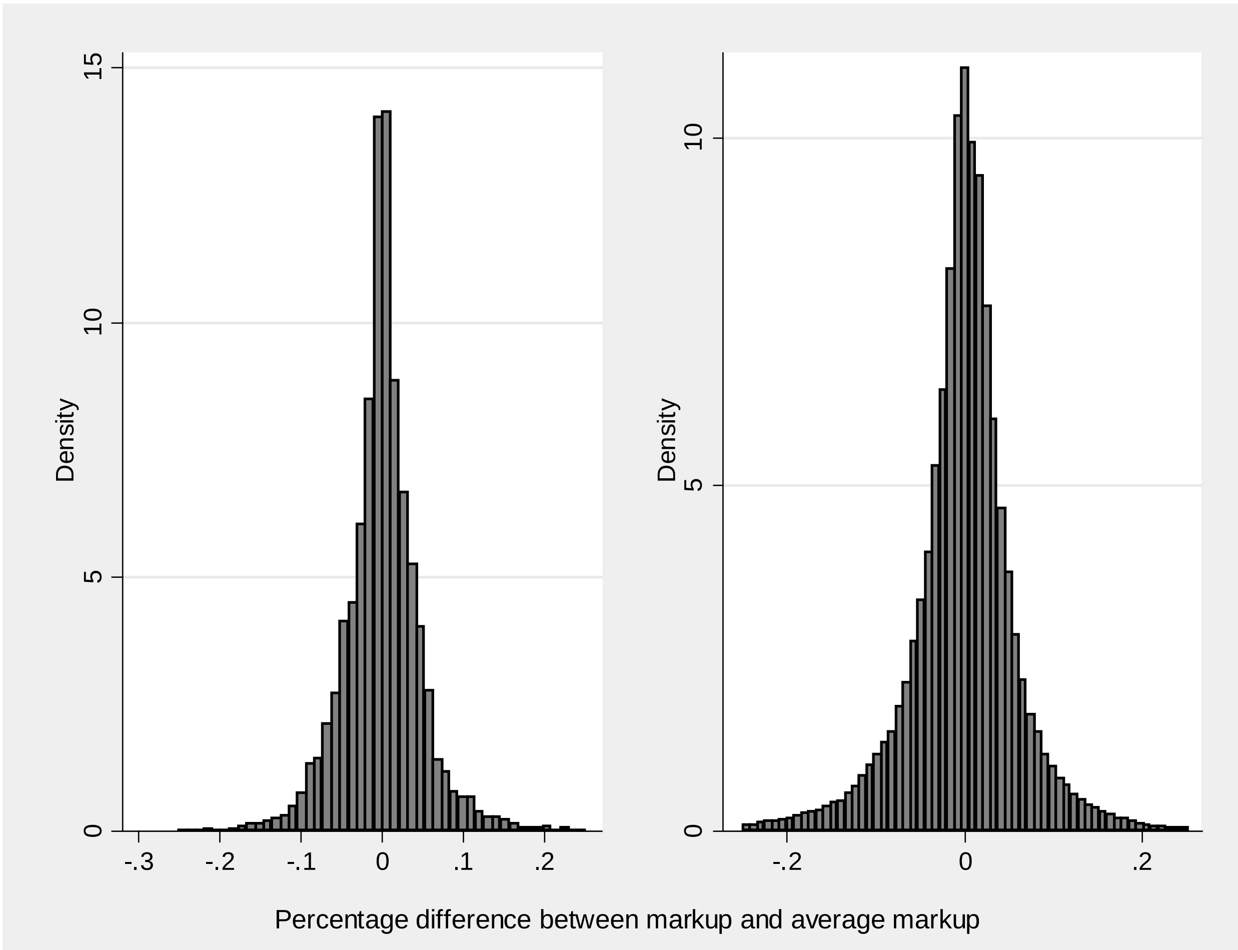
Figure 8. Hazard Functions for Reference Prices by Retail Chain



Notes. Hazard functions are estimated non-parametrically using the Nelson-Aalen estimator for cumulative hazard functions and smoothed using an Epanechnikov kernel smoother.

Figure 9. Distribution of Markup Gaps

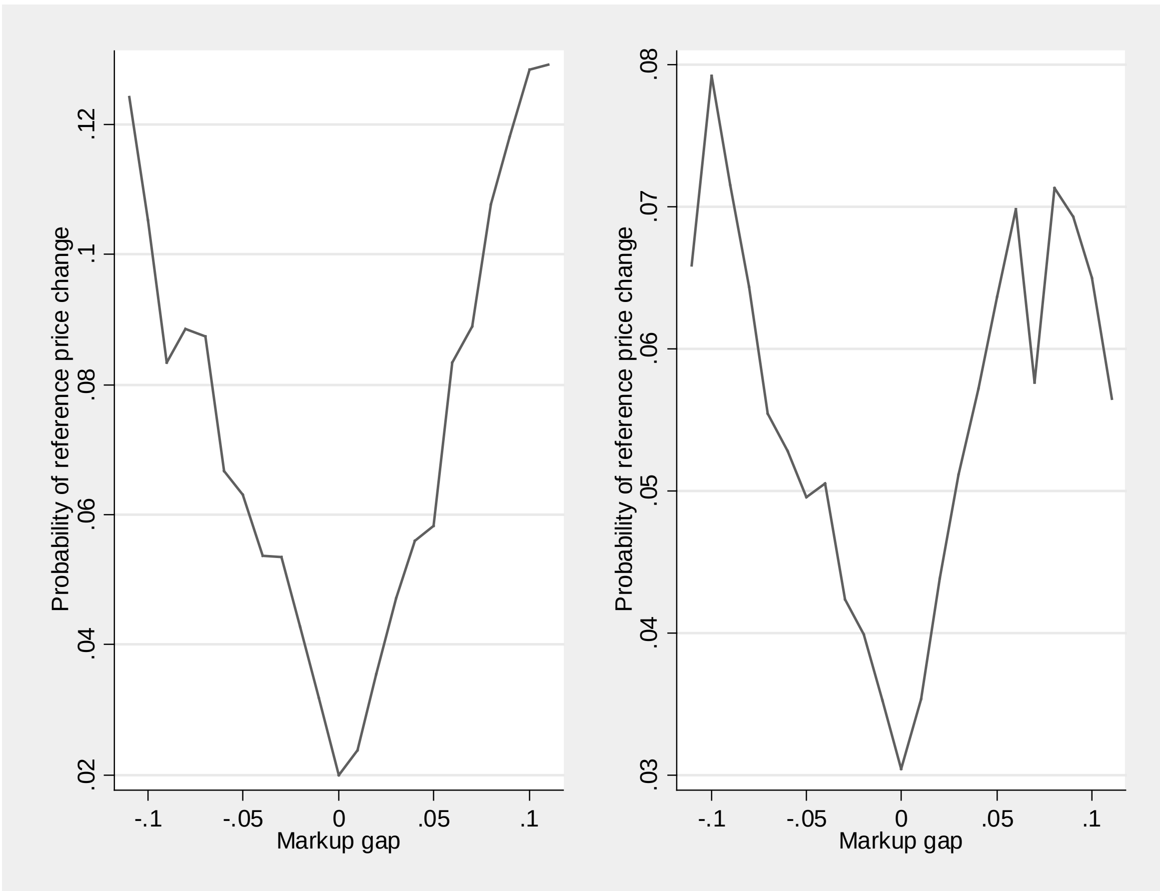
a) Chain A   b) Chain B



Notes. The charts display the distributions of markup deviations of a given product variety from its time-series average for the two retailers for which cost data are available. Markups are computed as the logarithm of the ratio between retail price and wholesale cost. The histogram on the left corresponds to Chain A, for which replacement cost data are available. The histogram on the right corresponds to Chain B, for which average acquisition costs are available. Both distributions are truncated at -0.25 and 0.25 and hence, exclude some outliers. In the case of Chain A the 1st and 99th percentiles of the distribution of markup deviations are -0.141 and 0.155, respectively. In the case of Chain B the 1st and 99th percentiles are -0.185 and 0.183, respectively.

Figure 10. State-Dependence in Reference Price Adjustment: Markup Gap and Probability of Repricing

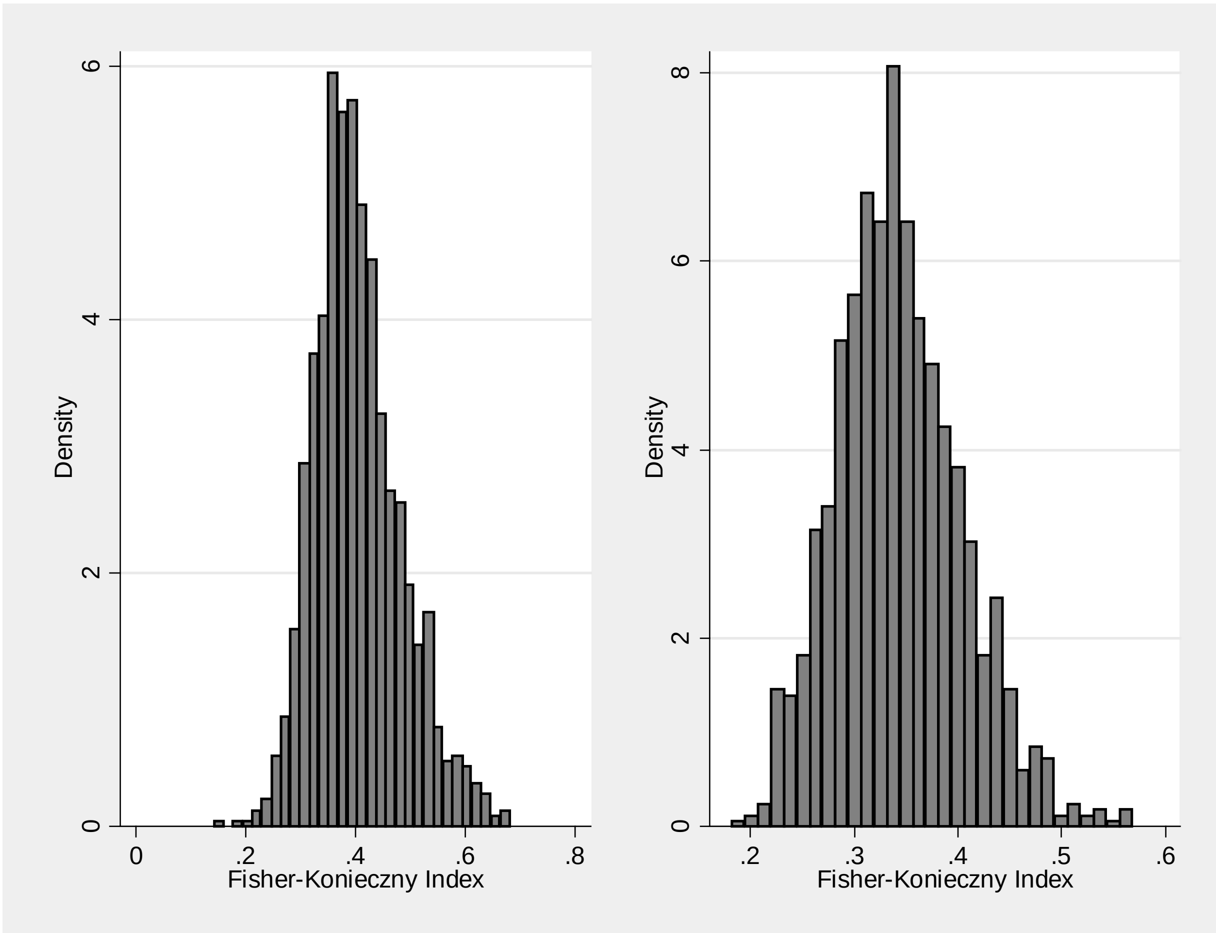
a) Chain A   b) Chain B



Notes. The charts present the relation between the markup gap, defined as the difference between the markup of a given product variety and its average over time and the probability of a reference price change.

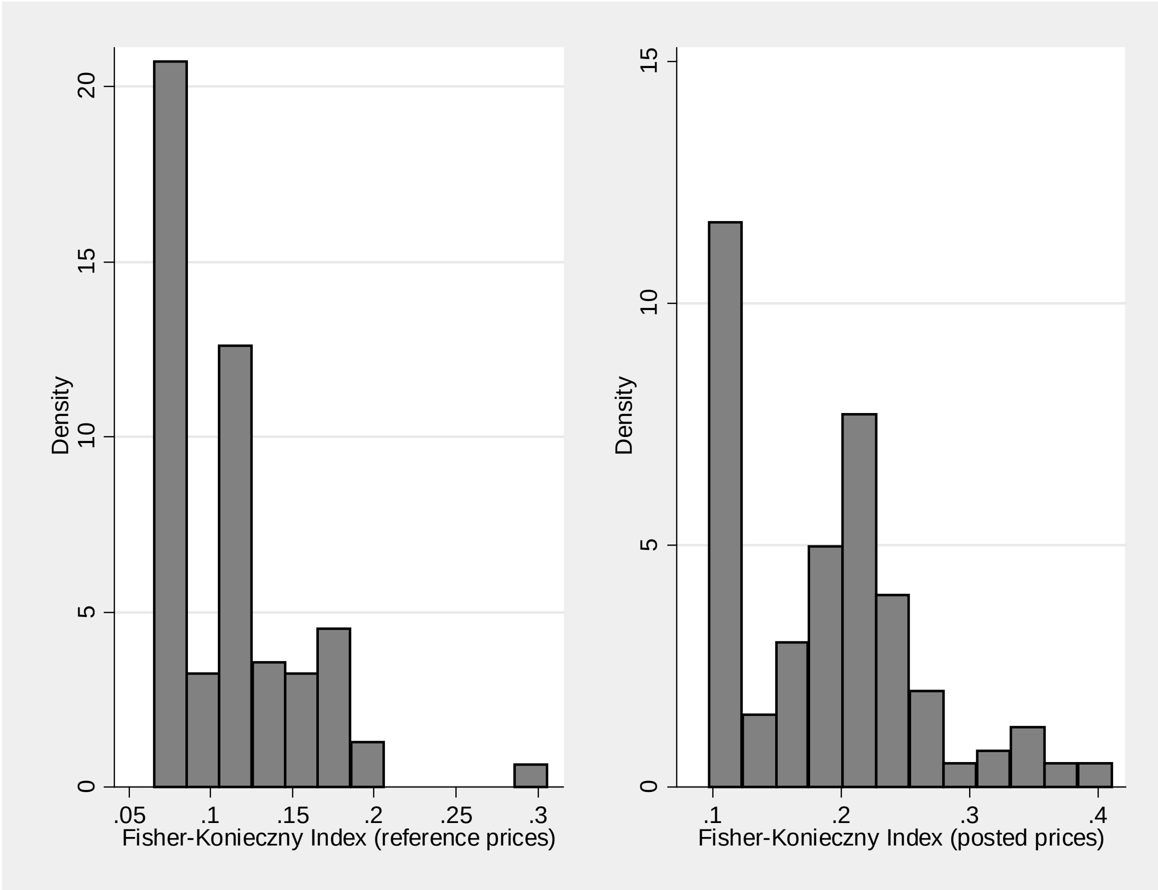
Figure 11. Synchronization of Price Changes Across Stores

a) Reference Prices b) Posted Prices



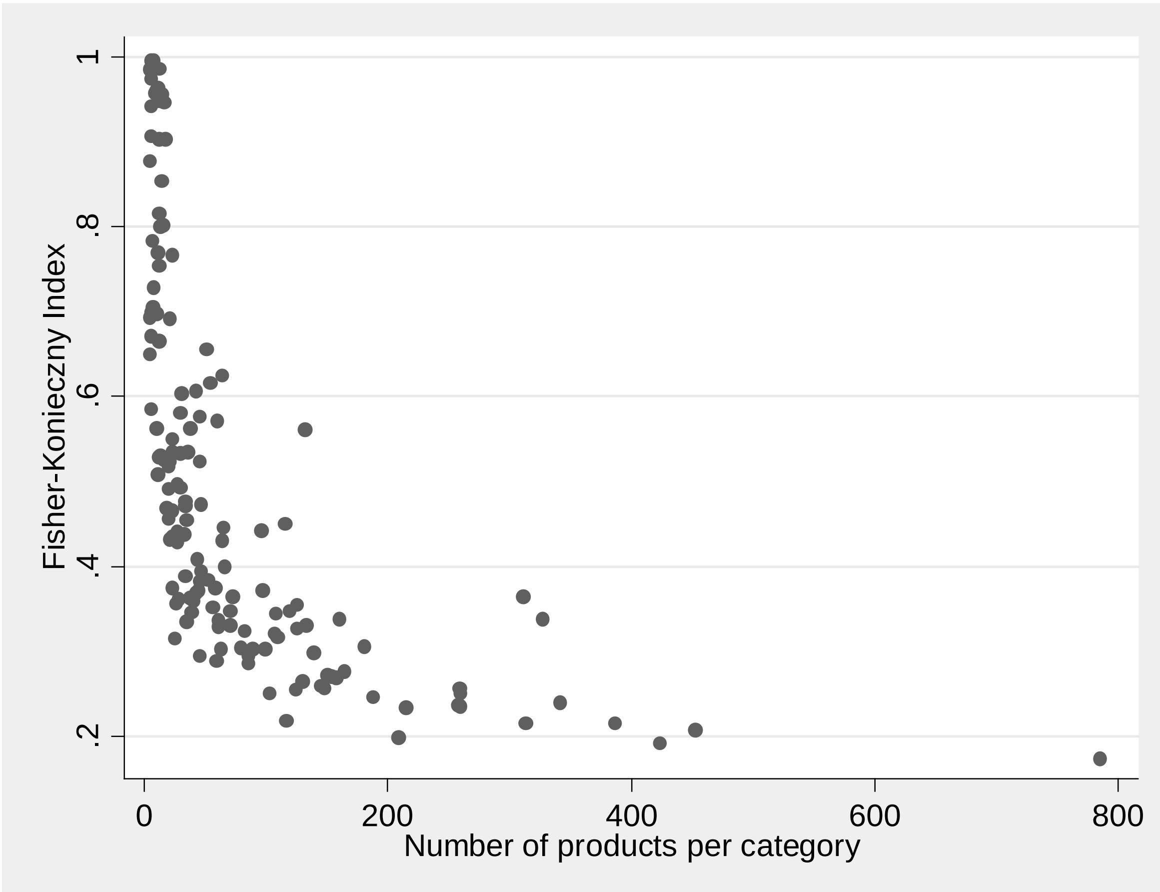
Notes. The figures display the distributions of the Fisher-Konieczny (FK) index of price changes synchronization (Fisher and Konieczny (2000)) across stores for posted and reference prices. The FK index lies in the interval [0, 1]; it takes on the value zero in the case of uniform staggering (the same fraction of stores changes the price of a given product every period) and the value one in the case of perfect synchronization (either all or none of the stores changes the price of the product in a given period).

Figure 12. Synchronization of Price Changes Within Stores



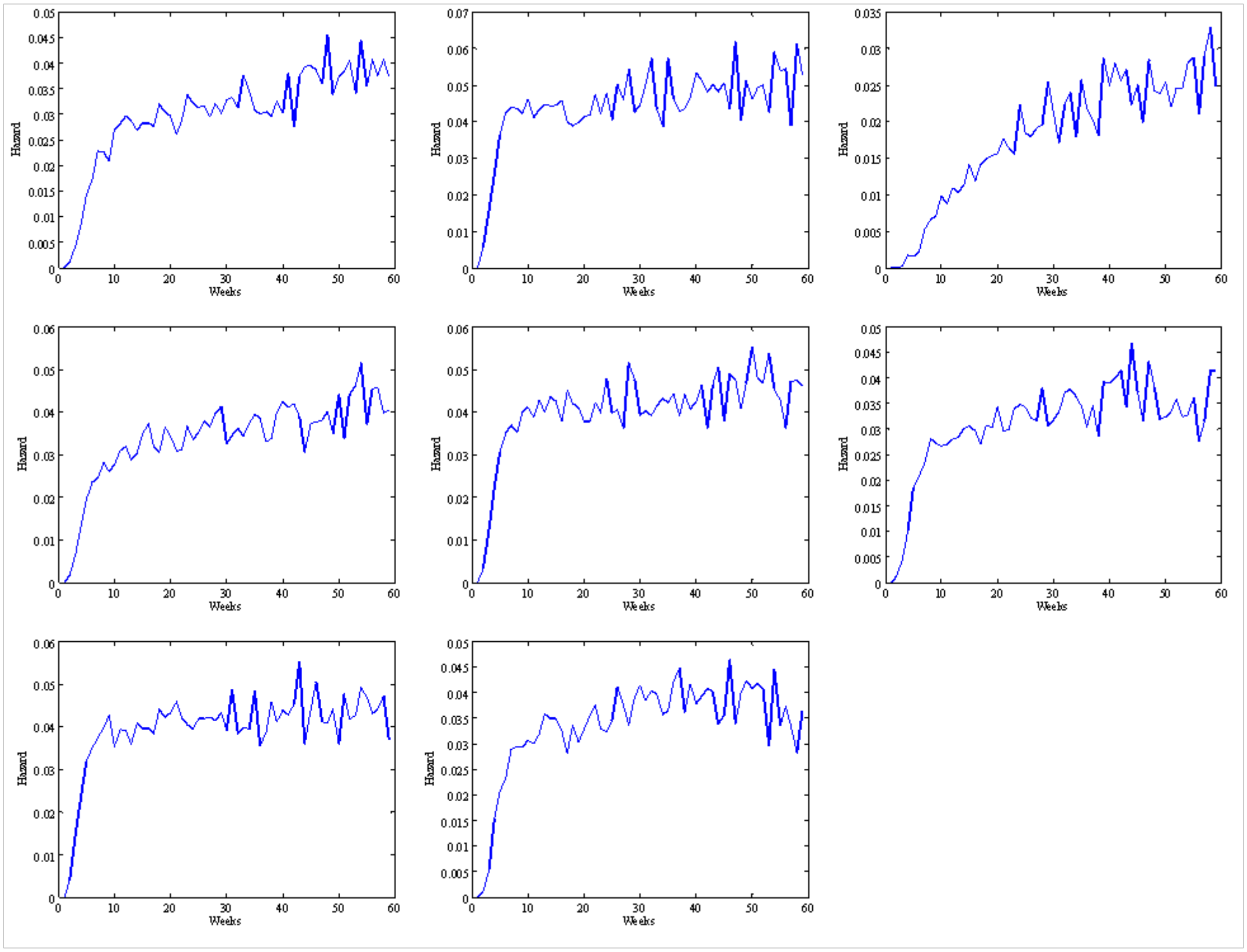
Notes. The figures display the distributions of the Fisher-Konieczny (FK) index of price changes synchronization (Fisher and Konieczny (2000)) within stores for posted and reference prices. The FK index lies in the interval [0, 1]; it takes on the value zero in the case of uniform staggering (the store changes the same fraction of prices every period) and the value one in the case of perfect synchronization (either all or none of the store prices are changed in a given period).

Figure 13. Synchronization within Product Categories and Depth of Product Categories



Notes. The figure displays the relationship between the depth of a product category (measured as the number of products within the category) and the median Fisher-Konieczny index measuring synchronization of price changes within stores and categories, where the median is taken across stores. The FK index lies in the interval [0, 1]; it takes on the value zero in the case of uniform staggering (the store changes the same fraction of prices every period) and the value one in the case of perfect synchronization (either all or none of the store prices are changed in a given period).

Figure 14. Simulated Hazard Functions from Menu Cost Model

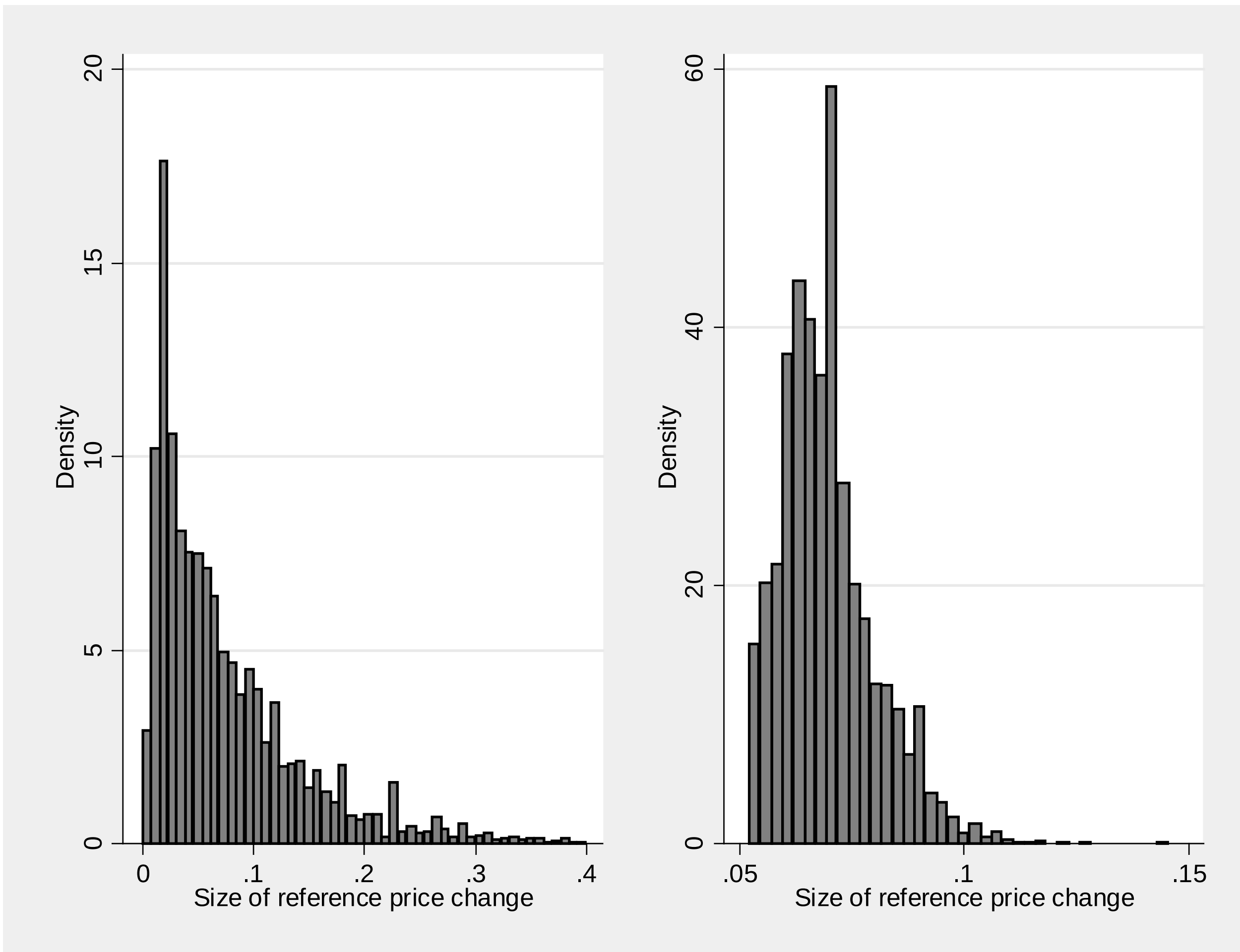


Notes. The figures present hazard functions for simulated price series from a standard menu cost model featuring idiosyncratic shocks. Hazard functions have been estimated using the nonparametric Kaplan-Meier estimator.

Figure 16. Menu Cost Model Unable to Match the Fraction of Small Price Changes in the Data

a) Actual

b) Simulated



Notes. The charts display the distribution of actual and simulated reference price changes for the median retailer. Simulated reference price changes derived from a standard menu cost model featuring idiosyncratic shocks.