MICRO-PRICES AND AGGREGATE STICKINESS: EVIDENCE FOR CHILE

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Micro-prices and Aggregate Stickiness: Evidence for Chile

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Abstract

This research describes price-setting over time and across items in Chile, an emerging market economy. The microeconomic database underlying the consumer price index (CPI) is used to characterize microeconomic pricing behavior, and to study its implications for the transmission of monetary policy to the real economy. Prices are found to be relatively flexible at a microeconomic level, in contrast to macroeconomic findings. Price changes are also mainly small and quite synchronized, and display a decreasing hazard rate. An evaluation of the relevance of microeconomic price data moments for forecasting aggregate inflation finds that the frequency of price increases and decreases, and their respective absolute magnitudes — which can only be computed from disaggregated data — can significantly improve on inflation forecasting based solely on aggregate variables.

Keywords: CPI inflation, micro-price data, price-setting models, forecasting

JEL codes: E30, E31, E37, E50

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1 Introduction

Many theoretical models require a minimum degree of price stickiness for monetary policy to have real effects, at least in the short run; so price-setting behavior is a key element for evaluating the impact of monetary policy on the real economy. Since the relevant data have become available, the study of micro-pricing has provided a powerful insight for understanding macroeconomic pricing phenomena. The purpose of this research is twofold: firstly, to characterize the dynamic of price changes in Chile, an emerging market economy, using the microeconomic data underlying the consumer price index (CPI) for the period 1999-2008. Secondly, to assess the relevance of this data at the macroeconomic level.

Different price measures — posted, regular, and reference prices — are considered in the empirical evaluation so as to consider temporary deviations.[1] An evaluation is made of the frequency of price changes, the magnitude and frequency of increases and decreases, their evolution and relationship with inflation through time, along with price change synchronization and the corresponding hazard rate. The information provided by these calculations is used see the extent to which the data is consistent with time- or state-dependent pricing models (TDP and SDP, respectively). Time-dependent pricing models (Taylor, 1980; Calvo, 1983) assert that the time elapsing between price adjustments is what determines the likelihood of a price change. They assume that the fraction of firms changing their prices in each period — also known as the *extensive* margin — is exogenous and hence independent of the economy's aggregate state. The variation in inflation thus depends on the magnitude of the price changes, or the *intensive* margin. Conversely, state-dependent pricing models (Caplin and Spulber, 1987; Dotsey et al., 1999) invoke sound microeconomic foundations by relating the probability of adjustment to the decisions firms make on changing their prices, depending of the economy's aggregate state and subject to menu costs, which means that the fraction of firms adjusting is also an inflation driver.

Summarizing the key results, it can be stated that prices change on average once a quarter, and that while large changes are observed, small changes predominate. As the first of these findings is not supported by estimations based on aggregate data, which conclude that prices adjust on average every two quarters or longer, an attempt is made to reconcile this discrepancy.[2] The literature frequently explains this situation in terms of the *contract multiplier*, a supposed consequence of strategic complementarities.[3] Moreover, the frequency

[1] Posted prices are the prices actually shown on price labels, while regular prices do not include any sale discount. Reference prices are defined as the most commonly occurring prices in a given time period. These concepts will be reviewed in Section 2.

[2] Data for the case of Chile (Caputo et al., 2006). For the U.S., Klenow and Malin (2010) refer to nominal shocks having effects lasting several years.

[3] Chari et al. (2000).

of price increases — reflecting the extensive margin of price changes — is the main driver of CPI inflation. Also, price changes are synchronized to some extent, even when analyzing seasonal patterns. Lastly, while there is no evidence that the magnitude of price changes varies with the price's age, there is a clear decreasing relation between the probability of adjustment and the time that has elapsed since the previous change.

Finally, disaggregated price data make it possible to compute relevant macroeconomic series that could not otherwise be obtained, such as the frequency of price increases and decreases, and their respective absolute magnitudes for specific groups. As shown below, aggregate inflation can be decomposed using an identity involving these four series; and these newly available data prove their worth in short-term inflation forecasting. In particular, under a real-time forecasting scenario, econometric models including those components outperform exigent benchmarks (based on aggregate inflation) by 3%-12%, in terms of root mean squared prediction error.

2 Previous Literature

2.1 Price Features and the Case of Chile

Goods and services micro-pricing data are registered through quote-lines: every month the Chilean National Institute of Statistics (INE) records the prices of specific product varieties sold in specific establishments (*e.g.* roasted peanuts variety at store X on street Y). The INE then aggregates the data into 483 categories of consumption, which in turn are divided into eight groups (food, housing, home equipment, apparel, transport, health, education and leisure, and others).[4] This research considers data spanning January 1999 to December 2008, which is the most recent and longest period without methodological changes. Since then the groups and weights of the CPI basket were changed in January 2009 and January 2013 (the geographical coverage was also expanded in 2009).

Periods when discounted prices are offered (*i.e.* sales) pose a common dilemma in the relevant literature, as they are seen as a deviation from normal price-setting behavior. While excluding such prices might seem reasonable, this can cause various shortcomings that need to be considered. For instance, if larger discounts reflect a destocking of excess inventory or a low inflation scenario, it could be argued that sales periods bear macroeconomic content. Also, as Mankiw and Reis (2002) note, the omission of price changes which are not macroeconomic-related (*e.g.* those representing idiosyncratic shocks or price discrimination) might risk confusing sticky nominal prices with sticky information.

[4] For further details of the data used, see Appendix A.

Although sale-prices are flagged in the database when collected for most of the countries studied, this is not the case for Chile.[5] To control for sales, an alternative measure proposed by Nakamura and Steinsson (2008) was used, such that whenever a price is lower than its immediate neighbors (*i.e.* exhibiting a V shape), it is replaced by those neighboring values. Nonetheless, those authors conjecture that the implied duration computed from filtered prices (hereinafter referred to as regular or non-sale prices) should not be significantly longer than that computed from posted prices.

Another feature of price-setting is product substitution. When an item is either discontinued or replaced by a new version, Klenow and Kryvtsov (2008) find that their prices differ about 80% of the time. Although this may seem a strong reason for not excluding such price changes, in this case the products' characteristics are changing along with their prices (*i.e.* they are effectively new products at new prices). In one of the scenarios they consider, Nakamura and Steinsson (2008) exclude price changes related to product substitution, arguing they are usually not related to a firm's desire to adjust. As happens with sales, product substitutions are not signaled in the Chilean CPI database: substituted and new items are treated as different products, with no correspondence being indicated between them. The present study maintains Nakamura and Steinsson's (2008) assumption and treats every quote-line as a single item.

2.2 Reference Prices

Eichenbaum et al. (2011) first introduced the concept of "reference price", which they defined as the weekly modal price within a fixed quarter (*i.e.* they obtain four reference prices for a given year). As they used scanner data from a major U.S. retailer instead of nationally representative products and services, the method developed by Klenow and Malin (2010) is more appropriate for handling the database used in this research. In particular, they define the monthly reference price for each quote-line in the CPI, denoted by RP_t, as the most common price within a 13-month window centered at t.[6] An advantage of this method is that it allows the reference price to change each month, unlike that of Eichenbaum et al. (2011).

Reference prices emerge after filtering out a broader set of short-lived prices. As it is impossible to identify sale periods with certainty, owing to the characteristics of the data

[5] For the United States, discount sales are defined by a price that is temporarily lower than the regular one, which is available to all consumers and is usually stated on the price tag. Chile shares a similar definition for its current surveys, but not for the period in study.

[6] When two prices occur equally frequently in a given 13-month window, the current month's posted price is taken as the reference price. Quote-lines that do not allow at least one reference price to be calculated are ignored, which reduces the sample from 468 to 426 products.

Table 1 – Share of reference prices in CPI items, by group

	Median share	Mean share	Std. dev.
Food	47.25%	51.94%	23.34%
Housing	17.47%	35.78%	33.78%
Home equipment	64.54%	66.00%	13.43%
Apparel	58.24%	64.87%	14.05%
Transport	36.36%	43.20%	32.78%
Health	70.96%	71.84%	16.05%
Education and leisure	87.15%	86.34%	13.99%
Others	87.08%	80.95%	24.23%
All items	61.36%	57.55%	28.84%

set, reference prices should be useful for describing features of the price-setting process. The model proposed by Eichenbaum et al. (2011) argues that deviations from reference prices basically reflect idiosyncratic considerations, thereby giving a crucial role in monetary non-neutrality to the frequency of changes in reference prices.[7]

Calculations for CPI-weighted quote-lines show that, on average, posted and reference prices are the same 57.6% of the time (61.4% if measured in weighted-median terms). As Table 1 shows, the share of reference prices varies widely across CPI groups, with housing and transport displaying particularly low values (possibly due to the cyclicality of fuel, which affects both groups), similar to Klenow and Malin's (2010) finding for U.S. CPI data.

Although reference prices seem to be generally valid in the Chilean CPI data, two additional statistics are computed to assess their modeling implications. As Klenow and Malin (2010) point out, long durations of reference prices (see Section 3) and large shares in relation to posted prices, do not imply that price-setters choose prices from a narrow set, or that prices exhibit memory. The fraction of "novel" prices, defined as prices that have not occurred in the previous 12 months, is firstly calculated for each item. As Table 2 shows, the weighted median (mean) attains a level of 31.6% (40.7%) overall, which could be interpreted as considerable novelty shown by deviations in reference prices, as new prices seem to appear every 2.5 - 3 months. Again, more cyclical categories (*i.e.* housing and transport) depart considerably from the general result.

Secondly, "comeback" prices are defined as those that have previously occurred at some

[7] Klenow and Malin (2010).

Table 2 – Share of novel and comeback prices in CPI items, by group

	Novel		Comeback	
	Median share	Mean share	Median share	Mean share
Food	48.90%	47.50%	17.22%	16.98%
Housing	87.44%	62.08%	0.43%	3.67%
Home equipment	26.74%	27.55%	23.76%	22.50%
Apparel	27.27%	26.44%	25.74%	25.62%
Transport	49.18%	56.55%	0.90%	7.33%
Health	24.76%	23.65%	19.09%	17.14%
Education and leisure	19.39%	16.88%	0.00%	8.98%
Others	13.37%	21.28%	0.76%	3.11%
All items	31.60%	40.70%	12.51%	13.48%

point in the last 12 months, with a different price occurring at least once since. The low overall share of comeback prices (weighted median 12.5% and mean 13.5%) suggests a slight memory of monthly CPI-related prices, and a high variation among typical non-reference prices (*i.e.* transition prices occurring between reference prices).[8]

3 Facts about Prices and their Implications

Summarizing the available volume of individual price data has been recognized as a challenge in the related literature. As a starting point, various statistics are calculated for each quote-line, and the variety-weighted averages are taken for those corresponding to a given product. The CPI-weighted means and medians of the estimated product statistics are then used to obtain an aggregate measure. Results are presented for the three relevant aforementioned types of prices, as well as calculations by CPI group.[9] As discussed above, it will not be possible to directly account for discount sales and product substitutions.[10]

[8]Reference price calculations were further validated by comparing the actual economy with a Calvo one. The conclusion was that more complex frictions (given by the actual economy) do not significantly alter the reference price calculations. For more on this, see Appendix D.

[9]For regular prices, results are shown for a filter that removes not only V-shaped sale patterns, but also asymmetric Vs, *i.e.* when a sale price is followed by a change in the regular price. Removing only V-shaped patterns delivers results close to those for posted prices. Nakamura and Steinsson's (2008) algorithm was used in the calculations.

[10]MATLAB code for computations can be requested from the author.

Table 3 – Frequency of price adjustment per month, by category

	Posted		Regular		Reference	
	Median	Mean	Median	Mean	Median	Mean
Food	58.52%	53.59%	53.29%	50.13%	10.55%	10.43%
Housing	56.30%	61.24%	54.96%	60.10%	12.94%	28.67%
Home equipment	27.10%	26.57%	24.09%	24.00%	8.99%	9.01%
Apparel	33.33%	29.86%	28.09%	26.16%	9.06%	8.89%
Transport	68.62%	59.44%	67.04%	58.14%	13.61%	19.12%
Health	28.83%	26.61%	23.79%	23.23%	8.96%	8.87%
Education and leisure	17.72%	16.17%	14.97%	14.69%	7.55%	7.18%
Others	14.45%	22.37%	14.18%	21.67%	6.15%	9.42%
All items	35.80%	43.07%	31.88%	40.63%	9.30%	13.64%

3.1 Frequency of Price Changes

Prices display nominal rigidity worldwide, and Chile is no exception. Yet, it displays one of the highest mean frequencies of price changes (43.1%) relative to both developed countries (U.S., 26.5%; Euro Area, 15.1%) and other developing countries (Brazil, 37.2%; Mexico, 29.4%).[11,12,13] The frequency of price changes is estimated for each product type in the Chilean CPI and then aggregated using CPI-weighted means/medians. Table 3 shows that, between 1999 and 2008, the weighted mean (median) across categories was 43.1% (35.8%) for posted prices. A mean that is above the median reflects the convex distribution of the frequency of price changes across CPI products, as shown in Figure 14 (Appendix C.1). This leads to a longer median implied duration than the corresponding mean (2.3 months compared to 1.8 for posted prices), as Table 4 shows. There is clear heterogeneity in the frequency of adjustment, both across product types and between different subsets of prices (posted, regular, and reference). The implied median price durations range from 0.9 months for transport to 5.1 months for education and leisure.

The results shown in Tables 3 and 4 imply that the filter applied to prices directly modifies their frequency of adjustment. When employing the asymmetric V-shaped filter

[11] This comparison should be interpreted with caution, since the exact dates of the studies and data collection methodology may differ across countries.

[12] Data from Nakamura and Steinsson (2008); Dhyne et al. (2006); Barros et al. (2009); Gagnon (2009). For the U.S., sales are included and substitutions excluded; for the Euro Area, the frequency of price changes for various countries are averaged, while most of them did not consider sales in the data collection (Álvarez et al., 2006); in the case of Brazil, sales are treated as missing values, and for Mexico, the results are inclusive of sales.

[13] For further comparison between countries, see Klenow and Malin (2010).

Table 4 – Monthly implied price durations by category

	Posted		Regular		Reference	
	Median	Mean	Median	Mean	Median	Mean
Food	1.1	1.3	1.3	1.4	9.0	9.1
Housing	1.2	1.1	1.3	1.1	7.2	3.0
Home equipment	3.2	3.2	3.6	3.6	10.6	10.6
Apparel	2.5	2.8	3.0	3.3	10.5	10.7
Transport	0.9	1.1	0.9	1.1	6.8	4.7
Health	2.9	3.2	3.7	3.8	10.7	10.8
Education and leisure	5.1	5.7	6.2	6.3	12.7	13.4
Others	6.4	3.9	6.5	4.1	15.7	10.1
All items	2.3	1.8	2.6	1.9	10.2	6.8

Note: Duration is computed as $-1/ln\,(1-f)$, where f is the aggregate frequency of price change for each category.

(thus obtaining the closest approximation to regular prices), the overall median implied duration increases by 0.3 months. This suggests that, on average, V-shaped patterns are not very common (health, and education and leisure are exceptions, but not by much). Moreover, it is impossible to be sure that every discount sale price is accounted for, as they may or may not exhibit a V shape, and also might not be identifiable from monthly data if sale periods occur in a week other than the registered one.

Reference prices are much stickier than regular prices (nearly five months longer for the mean, and eight for the median implied duration), which could be interpreted as some regular prices actually being temporary deviations from reference prices (Klenow and Malin, 2010). Here, the median duration lengthens for all CPI categories, the longest being education and leisure (12.7 months) and the shortest transport (6.8 months). As noted by Klenow and Malin (2010) and hinted at in Section 2.2, persistent reference prices, together with substantial novelty in their deviations and a low share of previously existing prices (*i.e.* comeback prices), could indicate a sticky plan or sticky information, rather than a menu cost of price changes. If that were to be the case, it would help explain the contract multiplier much better than strategic complementarities combined with heterogeneity: given that each period decisions are made without considering all existing information, a collection of micro price changes is needed to reflect a macro shock (Bils et al., 2012; Klenow and Willis, 2007).

It could be that in indexed economies, indexed prices rather than prices that do not adjust are the prices relevant for monetary policy. In order to obtain a first estimate of the importance of indexation, the fraction of prices that do not adjust,

$$\Theta_t = \{\, \Delta p_{lt} |\, \Delta p_{lt} = 0\}$$

and that are adjusted based on last month's inflation,

$$\Omega_t = \{\, \Delta p_{lt} |\, 100\,(\Delta p_{lt}/p_{lt-1}) \in [\pi_{t-1} - 0.1\%, \pi_{t-1} + 0.1\%]\}$$

are computed. Here, $\Delta \ln p_{lt}$ represents the change in the log-price for each quote-line l and month t, and π_{t-1} corresponds to last month's inflation. It occurs that, for the average month, $\#\Theta_t = 13,359.2$ and $\#\Omega_t = 174.2$, implying a 53% and 0.7%, respectively, of the monthly total number of observations. When removing changes in Ω_t from the calculation of the average frequency of price adjustment, the statistic reduces barely by 1.5 percentage points (pp). Nevertheless, the reduction of the average frequency of price adjustment is the greatest for housing (4.4 pp), which includes main indexed products (*e.g.* mortgages and rent).

3.2 Magnitude of Price Changes

Table 5 – Absolute magnitude of price changes (increases and decreases)

	Posted		Regular		Reference	
	Median	Mean	Median	Mean	Median	Mean
Food	6.33%	7.15%	6.28%	7.21%	10.80%	13.76%
Housing	1.19%	2.76%	1.27%	2.95%	2.24%	5.04%
Home equipment	6.32%	6.59%	6.79%	7.08%	13.78%	14.82%
Apparel	10.46%	11.84%	10.99%	12.74%	19.20%	19.03%
Transport	3.90%	4.91%	3.64%	4.72%	6.60%	8.21%
Health	6.05%	5.50%	5.85%	5.39%	5.64%	8.48%
Education and leisure	6.41%	6.04%	6.43%	6.17%	7.77%	9.88%
Others	2.70%	3.82%	2.71%	3.79%	7.44%	8.65%
All items	5.12%	5.47%	5.12%	5.52%	7.72%	8.43%

Price changes can be further described by their breakdown into the intensive and the extensive margins (IM and EM, respectively). While the former indicates how large price changes are, the latter indicates how often prices change. On average, as Table 5 shows, price changes are relatively large in absolute terms, though smaller than reported for developed countries (according to Klenow and Kryvtsov (2008) for the U.S. CPI, changes in posted prices have a mean magnitude of 14% and a median of 11.5%). The weighted-median price

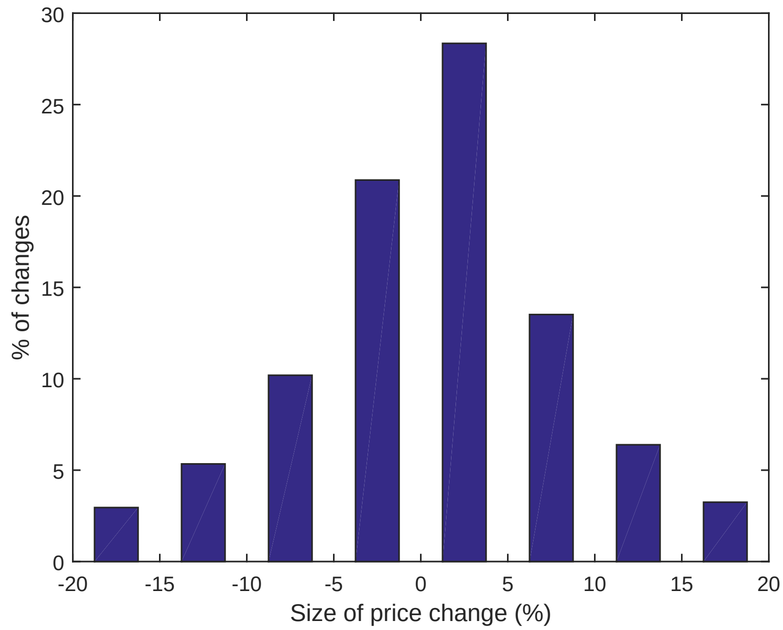

Figure 1 – Magnitude of regular price changes.

Table 6 – Smaller price changes in detail: proportion of total price changes

Prices	$\lvert dp_t \rvert < 5\%$	$\lvert dp_t \rvert < 2.5\%$	$\lvert dp_t \rvert < 1\%$
Posted	49.37%	29.29%	12.94%
Regular	49.22%	29.14%	12.72%
Reference	34.09%	17.68%	7.60%

change across all items (posted and regular prices) is 5.1%, and the weighted mean is 5.5%. Reference prices behave very differently in this regard, displaying median and mean changes of 7.7% and 8.4% respectively. There is also a high degree of heterogeneity between groups, with apparel having a median absolute price change of 10.5% and housing 1.2%.

Tables 19 and 20 (Appendix C.2) show that the absolute magnitude of price decreases tends to be roughly 1 percentage point smaller than increases in the case of posted prices, and 1.5 percentage points smaller in the case of reference prices. The distribution of price changes displayed in Figure 1 also shows that nearly 50% of price changes are less than 5% in absolute value, and that smaller price changes are most frequent. Furthermore, Table 6 shows that around 30% of changes are less than 2.5%, and 13% are below 1%. Small price changes are less frequent among reference prices than among posted or regular prices. The large share of small price changes contradicts the predictions of SDP models with a fixed and large menu cost, where a two-peak distribution would be expected (Klenow and Malin,

Table 7 – EM and IM explaining monthly inflation

		R^2		
η	% of changes	EM	IM	Both
10%	26.79%	39.6%	42.2%	43.2%
15%	14.93%	44.4%	41.0%	44.5%
20%	8.80%	46.0%	39.1%	46.7%
25%	5.48%	46.3%	37.6%	48.1%
30%	3.43%	45.2%	37.0%	48.4%
35%	2.30%	44.0%	36.7%	47.2%
40%	1.61%	41.2%	36.8%	41.9%

Note: R^2 columns refer to the r-squared coefficient of a linear regression of the monthly inflation on N_t for EM, SZ_t for IM, and N_t, SZ_t, for both. N_t is expressed as a monthly total, and SZ_t as a monthly average, thus each regression is based on 120 observations.

2010).

To assess the relevance of EM and IM for explaining inflation, following Doms and Dunne (1998) the EM is defined as the number of changes among quote-lines for each month, N_t, which satisfy $|\triangle p_{it}| > \eta$; η ranges from 0 to 100%, and SZ_t denotes the average absolute size of price changes corresponding to N_t. Then, the monthly inflation is regressed on N_t to study EM, on SZ_t to study IM, and on N_t and SZ_t to control for both margins, where each regression includes monthly seasonal dummies. As Table 7 shows, IM is more relevant than EM for smaller of values of η. The relative importance of the margins reverses starting from $\eta = 15\%$, with EM explaining a higher portion of annual cumulative inflation than IM. In particular, when the highest R^2 is achieved (48.4% when including both margins, at $\eta = 30\%$), the portion of inflation explained by the EM is almost 9 percentage points higher than that explained by the IM. Then, although only a small proportion of absolute price changes are larger than 30% (3.4%), the related number of changes has a greater role in explaining the variation in inflation than the average absolute size of those changes.

3.3 Dynamic Features of Price Changes

3.3.1 Dynamic Relation between Inflation and its Components

Price characteristics that change through time can be described by how the relationship between inflation and the frequency and magnitude of price changes develops. Under nominal stickiness, such as that observed in the Chilean CPI data, price-setters face dynamic decision problems, highlighting the relevance of the dynamic features of prices on the determination of the underlying price-setting model.

A useful way to study dynamic features of prices, and also to distinguish between the TDP and SDP models, is by reviewing the time variation of the frequency of price changes. Consider ω_{it} as CPI weights varying across products (i) and time (t), and $\Delta \ln p_{it}$ as the change in log-prices for each time-product combination. Klenow and Kryvtsov (2008) show that monthly inflation (π_t) can be divided into the weighted-mean price change frequency (fr_t) and magnitude (dp_t) :

$$\pi_t \;=\; \sum_i \omega_{it}\Delta \ln p_{it} = fr_t dp_t. \tag{1}$$

From this definition, it is also possible to derive an identity that relates the frequency of price increases (fr_t^+) and decreases (fr_t^-), and their corresponding absolute sizes $\left(dp_t^+; dp_t^-\right)$ to inflation. For this purpose, recall that price changes are split between increases (Δ^+, weighted by ω_{it}^+) and decreases (Δ^-, weighted by ω_{it}^-) , and there is also a fraction of items whose prices do not change in a given month (Δ^0, weighted by ω_{it}^0) [14]:

$$\begin{aligned}
\pi_t &= \sum_i \omega_{it}\Delta \ln p_{it} \\
&= \sum_i \omega_{it}^+ \Delta^+ \ln p_{it} + \sum_i \omega_{it}^0 \Delta^0 \ln p_{it} + \sum_i \omega_{it}^- \Delta^- \ln p_{it} \\
&= \underbrace{\sum_i \omega_{it}^+}_{fr^+} \underbrace{\frac{\sum_i \omega_{it}^+ \Delta^+ \ln p_{it}}{\sum_i \omega_{it}^+}}_{dp^+} - \underbrace{\sum_i \omega_{it}^-}_{fr^-} \underbrace{\frac{\sum_i \omega_{it}^- \left|\Delta^- \ln p_{it}\right|}{\sum_i \omega_{it}^-}}_{dp^-} \\
&= \underbrace{fr_t^+ dp_t^+}_{pos_t} - \underbrace{fr_t^- dp_t^-}_{neg_t}. \qquad (2)
\end{aligned}$$

Table 8 reports descriptive statistics calculated for regular prices, from January 1999 through December 2008. Inflation in that period averaged 0.29% per month (3.4% annualized). Moreover, the share of quote-lines changing each month is about 40.7%, with a standard deviation of 3.7%; while the absolute size of price changes averages 0.64%, with a 0.83% standard deviation which is higher in relative terms. The table also shows that price increases are far more common than decreases (62.9% against 37.1% of total price changes). The magnitude of price changes, or intensive margin, has the highest correlation with inflation when considering regular prices (0.94). This is confirmed by further analysis based on the variance of inflation, presented in Appendix B.

The frequencies of price increases and decreases are highly correlated with inflation (0.7 and -0.6, respectively), while the absolute size of increases is more weakly correlated (0.3), and the absolute size of decreases is hardly correlated at all (0.05). Regressions of these

[14] The correlation between official inflation, π_t and the inflation predicted by the identity presented is 0.961, is even higher than that obtained by Wulfsberg (2009). Further details can be found in Appendix A.

Table 8 – Time series moments, regular prices

Variable	Mean (%)	Std. dev. (%)	Corr. w/π	Regression on π	
				Coef.	Std. error
π	0.287	0.391	-	-	-
fr	40.741	3.652	0.269	2.506	0.841
dp	0.642	0.833	0.936	1.980	0.070
fr^+	25.625	4.333	0.669	7.424	0.773
fr^-	15.117	3.333	-0.591	-4.918	0.628
dp^+	4.808	0.788	0.318	0.643	0.179
dp^-	6.522	1.463	0.048	0.179	0.352
pos	1.235	0.315	0.665	0.538	0.057
neg	0.966	0.235	-0.512	-0.302	0.048

Note: Each variable represents the monthly weighted mean, for the CPI products. The results obtained by regressing a variable on inflation are shown in the last two columns.

variables on inflation show that a 1 percentage point (pp) rise in inflation is associated with a 7.4 pp change in the frequency of price increases, and -4.9 pp for decreases. Moreover, a 1 pp uptick in inflation implies a 0.6 pp change in the size of increases, and a 0.2 pp change in the magnitude of decreases. Only the coefficients on fr_t^+, fr_t^- and dp_t^+ are statistically significant, although the first two are the only ones with a meaningful correlation with inflation.[15] Price increases (pos_t) have a slightly higher correlation with inflation than price decreases (neg_t); and regressing these variables on inflation returns coefficients of 0.54 and -0.3 respectively, both statistically significant. These findings are similar to those reported by Klenow and Kryvtsov (2008).

Table 9 reports the same exercise but using reference instead of regular prices. A key difference is that, while the correlation between inflation and fr_t^+ decreases by approximately 75%, the correlation between inflation and the other components (fr_t^-, dp_t^+ and dp_t^-) becomes negligible. Regressions of such components on inflation demonstrate that, when deviations from the most common prices are removed, only the frequency of price increases displays a statistically and economically significant link with inflation. Moreover, as the statistics on the pos_t variable show, inflation movements are only correlated with price increases. Unlike the results for posted and regular prices, these findings are consistent with those of Nakamura and Steinsson (2008).

Figures 2 and 3 illustrate the results derived in Tables 8 and 9. The annual averages

[15]The results for posted prices, which are very similar to those of regular prices, are presented in Appendix C.3.

Table 9 – Time series moments, reference prices

Variable	Mean (%)	Std. dev. (%)	Corr. w/π	Regression on π	
				Coef.	Std. error
π	0.276	0.388	-	-	-
fr	13.783	3.506	0.389	3.496	0.801
dp	2.391	1.515	0.396	1.540	0.345
fr^+	10.992	3.404	0.416	3.630	0.768
fr^-	2.790	0.813	-0.064	-0.134	0.201
dp^+	6.633	1.889	-0.004	-0.018	0.468
dp^-	12.994	2.634	0.014	0.092	0.653
pos	0.705	0.261	0.433	0.290	0.058
neg	0.351	0.083	-0.129	-0.027	0.020

Note: Each variable represents the monthly weighted mean, for the CPI products. The results obtained by regressing a variable on inflation are shown in the last two columns.

Table 10 – Inflation and the contribution of the components

Prices	Correlation with π			
	fr^+	fr^-	dp^+	dp^-
Posted	0.655	0.604	0.287	0.082
Regular	0.669	0.591	0.318	-0.048
Reference	0.416	0.064	-0.004	-0.014

Note: Each column represents the correlation of inflation with the outcome of equation 2 when replacing each variable with its mean, other than that indicated in the column heading.

for monthly inflation rates varied considerably throughout the period, with the average size of price changes tracking inflation rates closely for the period 1999-2008 (less closely in the case of reference prices). Meanwhile, the average frequency of price changes fluctuated but only within a narrow range, appearing almost constant and only mildly related to inflation (correlation of 0.27 in Table 8). On the other hand, the frequency of price increases remains the most important component, for all types of prices.[16]

Another useful way to measure the contribution of the different margins to the variation in inflation — similar to that developed by Wulfsberg (2009) — is to compute equation (2) but replacing most variables with their means and allowing only one of them to vary. As can be seen in Table 10, the frequency of price increases remains the most relevant component of inflation among price types.

[16] For the figures relating inflation to the absolute magnitude of price increases and decreases, see Appendix C.4.

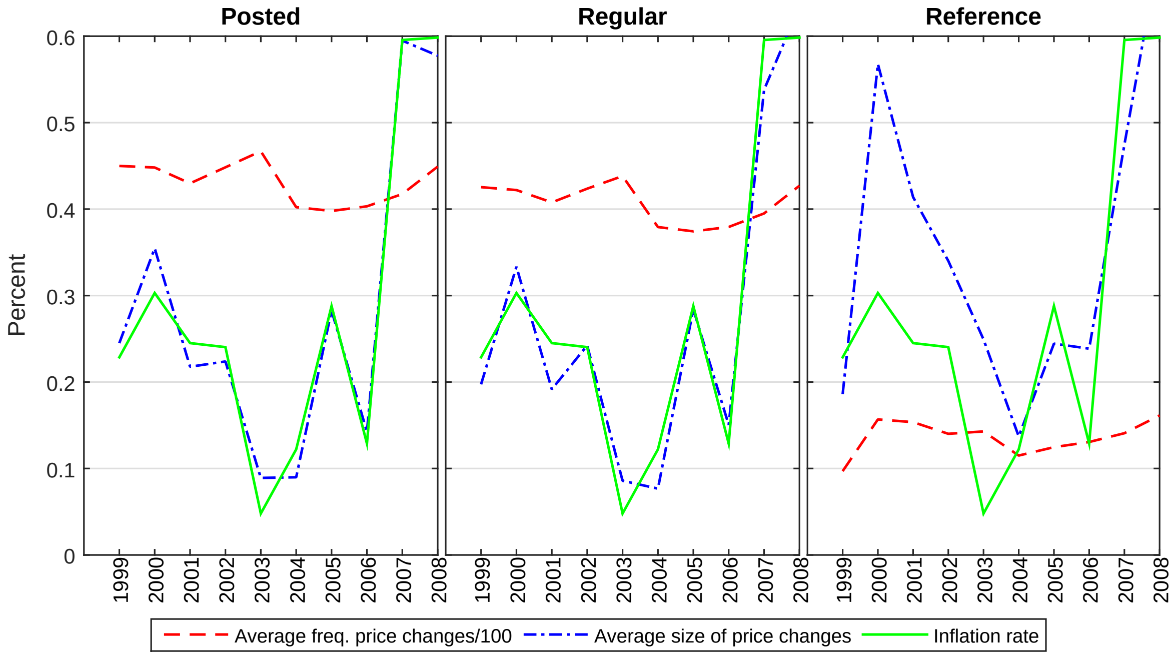

Figure 2 – Inflation and its extensive and intensive margins. Each series represents the annual average of monthly weighted means for different types of prices.

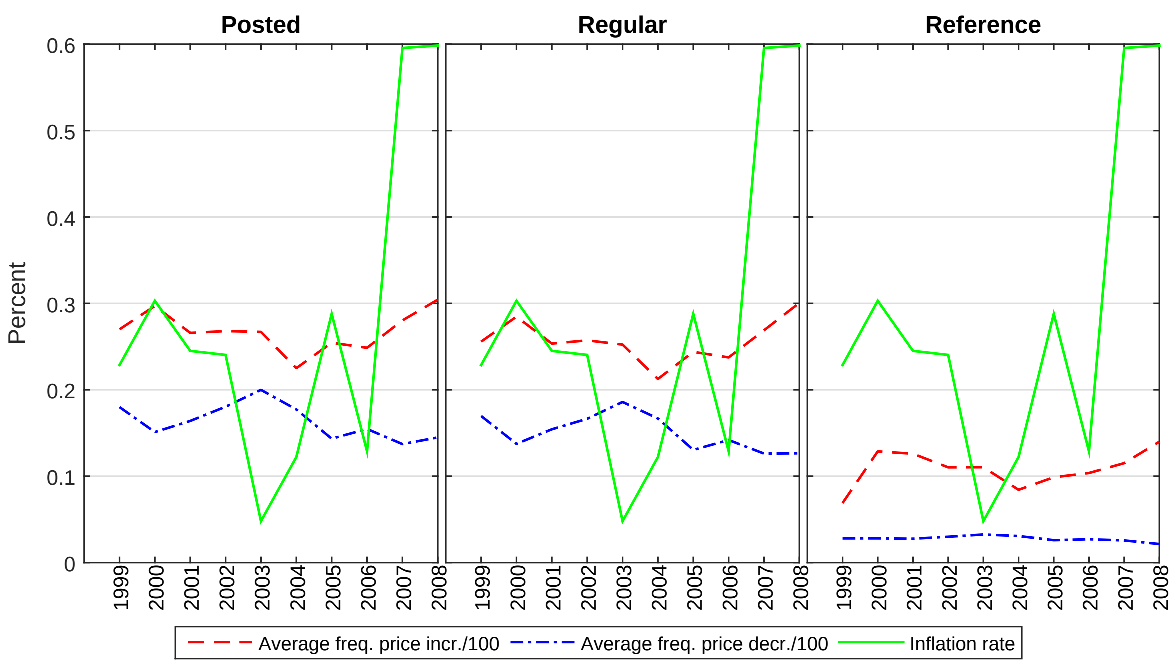

Figure 3 – Inflation and the frequency of price increases and decreases. Each series represents the annual average of monthly weighted means for different types of prices.

3.3.2 Synchronization

Staggered price adjustment has played a crucial role in modeling the persistent real effects of monetary shocks, since not all prices change at the same time. Synchronization among price changes, *i.e.* how different establishments and products react to different shocks, has been studied at the product level using the Fisher-Konieczny (FK)(2000) measure, which indicates the degree to which price changes occur simultaneously (Dhyne et al., 2006). Taking fr_i as the average frequency of adjustment for a particular product i and fr_{it} as its average frequency of adjustment in a given month, the measure is defined as $FK_i = \frac{SD_i}{SDMAX_i}$, where $SD_i = \sqrt{\frac{1}{T-1}\sum_{t=2}^{T}\left(fr_{it} - fr_i\right)^2}$ and $SDMAX_i = \sqrt{fr_i\left(1 - fr_i\right)}$. The measure is computed for each product, in which a value of 1 implies perfect synchronization while 0 stands for uniform staggering of price changes, and then the weighted average within CPI groups is calculated.

Table 11 – Fisher-Konieczny ratio, by group

Ratio	Food	Housing	H. equip.	Apparel	Transp.	Health	Ed./leisure	Others	All
Mean	0.264	0.733	0.371	0.382	0.492	0.447	0.635	0.713	0.463
Median	0.249	0.895	0.354	0.309	0.415	0.330	0.550	0.717	0.357

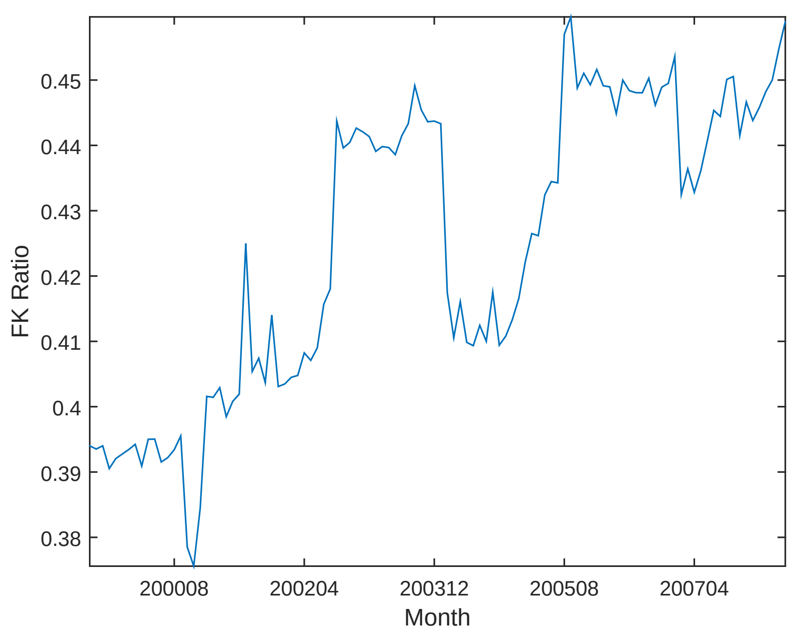

Figure 4 – Fisher-Konieczny (FK) ratio for all items, weighted monthly mean.

Table 11 reports that price changes generally tend to be unsynchronized (with a mean FK ratio of 0.46, and a median of 0.36), especially in products belonging to the food category (mean ratio of 0.26). Moreover, items in the housing, others, and education and leisure groups display higher than average levels of synchronization (0.73, 0.71, and 0.64 respectively). Despite the low overall synchronization ratio between 1999-2008, price changes have been trending towards greater synchronization (see Figure 4).[17]

Nakamura and Steinsson (2008) explore seasonality as a distinct form of synchronization. Figure 5 depicts the weighted-median frequency of price changes, increases, and decreases in regular prices by month. A quarterly pattern is not apparent from the figure.[18] Nonetheless, it can be argued that the frequency of price increases is the main component driving the seasonal behavior of the frequency of price changes; and that a peak occurs in March. Possible explanations could be linked to the fact that, in Chile, March is considered as the *real* start of the year. The reasons are primarily related to the fact that various public and private institutions close for summer vacations in January and February and resume their activities in March.

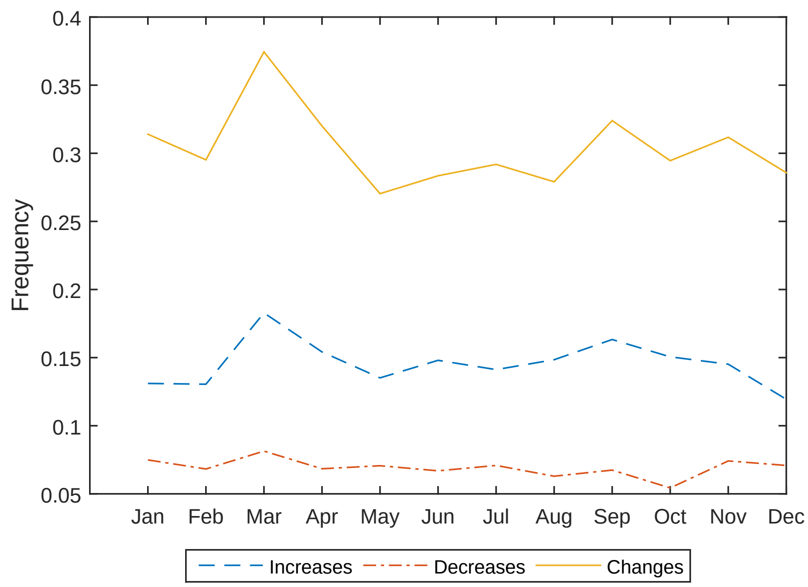

Figure 5 – Weighted-median frequency of price changes, increases, and decreases in regular prices by month.

[17]For a monthly measure, FK_{it} was computed considering a 12-month rolling window, and then averaged across products.

[18]Nakamura and Steinsson (2008) find a local-peak pattern within each quarter, for the U.S. economy.

3.3.3 Hazard Function of Price Changes

By computing the hazard function of price changes, it is possible to show how the probability of adjustment depends on a price's age. A basic reason for evaluating this feature is that the characteristics of the hazard function vary sharply depending on the price-setting model being used. For instance, and following Klenow and Malin (2010), the hazard function predicted for the Calvo (1983) model is flat; for the Taylor (1980) model with deterministic adjustment it is zero (with the exception of a single age), and for menu cost models it is usually increasing.

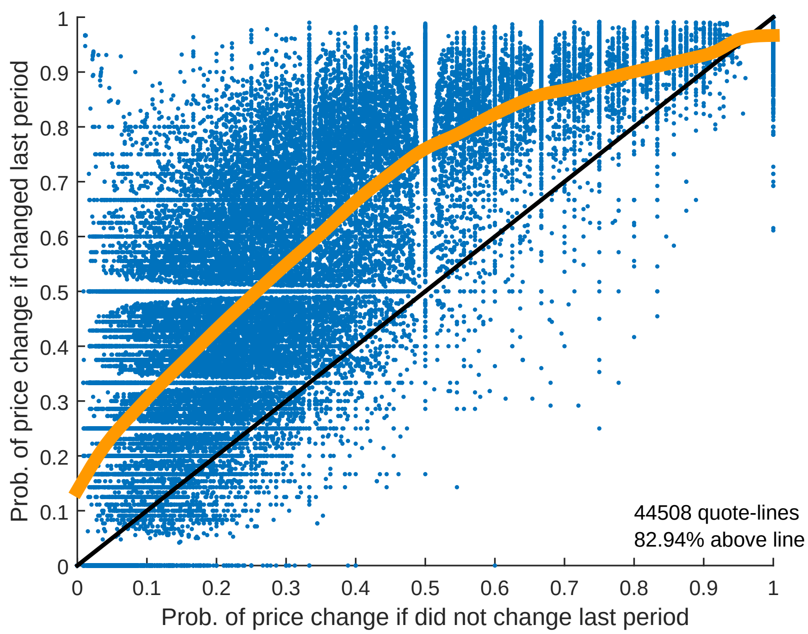

Figure 6 – Relation between the probabilities of a price change after one period and at all other times, for each quote-line in the CPI.

The heterogeneity of adjustment speeds among items and survivor bias have posed challenges for estimating the hazard function, as they bias estimates towards a decreasing hazard rate. Vavra (2010) proposes a novel strategy to address this problem, which involves empirically testing the assumption that items face a constant probability of adjustment. This entails calculating the probability of adjustment if the price changed in the last period, and the probability of adjustment if it did not, and seeing if they are equal. In other words, the author tests whether $\Pr(I_t = 1 \,|\, I_{t-1} = 1) = \Pr(I_t = 1 \,|\, I_{t-1} = 0)$, where I_t is a binary variable that takes the value 1 if a price adjustment for a given item occurs at t and zero otherwise. Even though items have different probabilities of price adjustment, these must be the same for each item in the case of a constant hazard rate, so their graphical representation

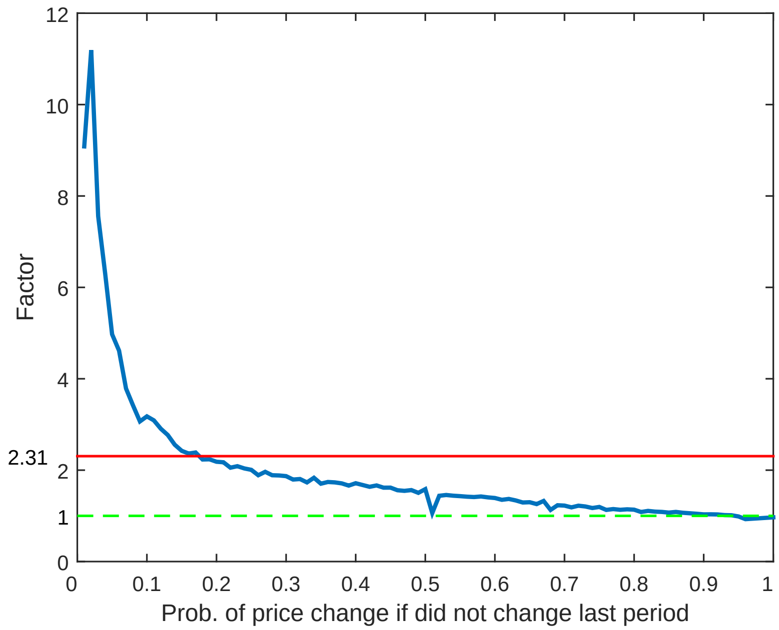

Figure 7 – Factor for each probability of price change conditional on no adjustment in the previous period.

should correspond to a 45 degree line. The consideration of each quote-line in the plot is what corrects the heterogeneity problem in the estimation of the hazard rate.

Figure 6 plots a point for each quote-line in the CPI data (considering regular prices), which represents the relations between the probability of a price change after one period, and the probability of a change if the price has not been adjusted in the last period. As can be clearly seen, the vast majority (83%) are above the 45 degree line and not on it, which means that prices are prone to change if they have just been altered, rather than if they have not. The kernel smoothing non-parametric curve fitted to the data, and plotted in the figure, shows this directly. Figure 7 shows the average factor, defined as $\Pr\left(I_t = 1 \,|\, I_{t-1} = 1\right) / \Pr\left(I_t = 1 \,|\, I_{t-1} = 0\right)$, for each probability of a price change conditional on no adjustment in the previous period. On average, $\Pr\left(I_t = 1 \,|\, I_{t-1} = 1\right)$ is 2.3 times greater than $\Pr\left(I_t = 1 \,|\, I_{t-1} = 0\right)$, reaching a maximum of 11. The finding of a decreasing hazard rate for CPI items is aligned to that of Nakamura and Steinsson (2008), and contrasts with the flat hazard rate reported by Klenow and Kryvtsov (2008).

3.3.4 Magnitude of Price Changes and Price Age

Some models predict that the older the price, the larger will be the absolute size of the change at the time of adjustment. An example is the Calvo model (1983), where exogenous adjustment timing mandates the accumulation of shocks.

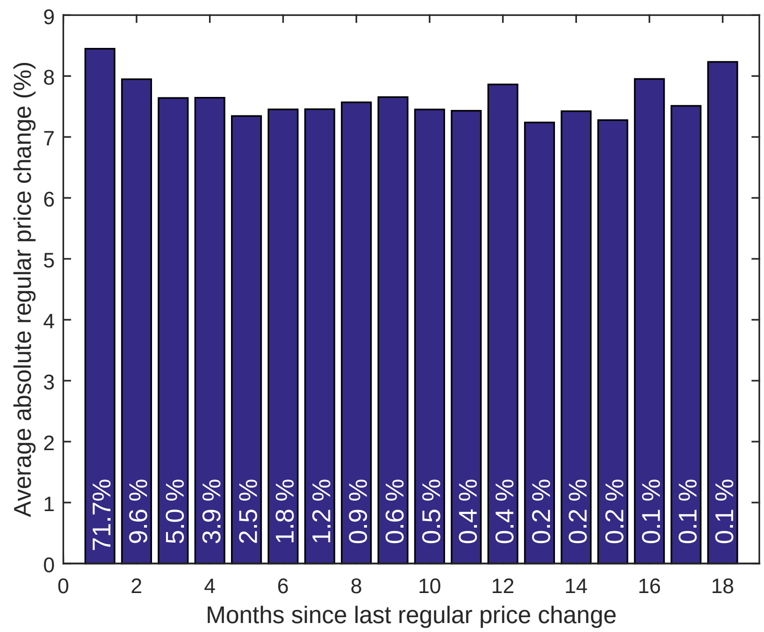

Figure 8 – Weighted-average magnitude of regular price changes, by age.

Figure 8 shows, for each price age between 1-12 months, a bar indicating the weighted average of absolute changes in regular prices (the proportion of price changes corresponding to a certain age, relative to the total among quote-lines and months, is indicated at the base of each bar). Prices with an age of one month (71.7% of the sample) change on average by 8.5%, while those twelve months old (0.4% of the sample) do so by 8%. The remainder of the price ages tend to cluster around 7.5%. The results suggest no correlation between the absolute magnitude of a price change and the age of the price at the time of adjustment, a common finding in the literature supporting SDP models (Klenow and Malin, 2010). This conclusion holds for changes in reference prices, and also for increases/decreases of both regular and reference prices.

4 Application to Inflation Forecasting

4.1 Motivation

The results reported in the previous sections suggest that the prices used to calculate the Chilean CPI exhibit nominal rigidities, at least in the short term, thus underpinning the concern for long-term economic commitments. The Central Bank of Chile bases its monetary policy on inflation targeting, aiming at an annual rate of 3% bounded between 2% and 4%

(Central Bank of Chile, 2003). In this context, idiosyncratic and aggregate external shocks that could pass through to domestic prices should be monitored carefully as they could jeopardize fulfillment of the target.

For instance, the prices of basic goods, such as food and fuel, rose sharply between 2007 and 2009 worldwide; and, as can be seen in Figure 9, inflation deviated considerably from its target in that period. Pedersen (2011) noted how the duration and propagation of those shocks to domestic prices was comparatively greater in Chile than in other economies, both developed and emerging. This motivates evaluating how the inclusion of disaggregated information, specially of inflation components, improves short-term inflation forecasting.

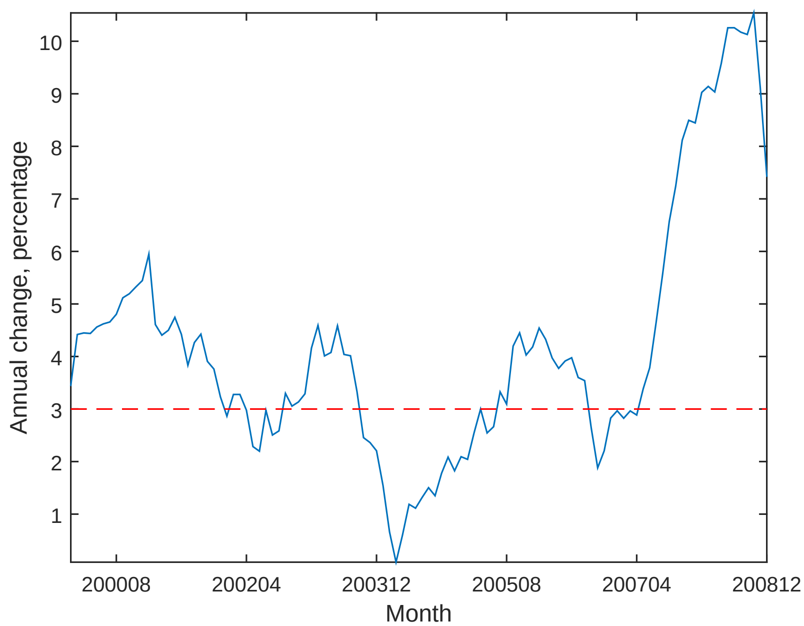

Figure 9 – CPI inflation, annual change.

4.2 Official and Conventional Forecasting Methods

Central banks regularly use a wide range of models to forecast short- to long-term inflation; in a constantly changing economy, no single model is sufficient on its own to determine monetary policy decisions. In the case of Chile, the Board of the Central Bank draws on its own economic judgment as well as forecasts produced by economic models. According to Central Bank of Chile (2003), economic models structure monetary policy transmission mechanisms; and those mechanisms are used to forecast inflation and, hence, support the Board's monetary policy decision making.

Short-term inflation forecasting through vector auto-regressive (VAR) models — in conjunction with short-term growth prospects — provide a background to the policy discussion, and more importantly, feed into and complement the bank's structural model for macroeconomic projections (*Modelo Estructural de Proyecciones* – MEP).[19] The VAR models used by the Central Bank include endogenous variables (domestic product, prices, monetary policy rate, nominal money and real bilateral exchange rate against the dollar), as well as exogenous ones (inflation target, external GDP, the LIBOR rate, and various commodity prices), at a monthly frequency. These are arranged in several specifications including series in levels, first differences, and annual differences, with a different number of lags; the variables are seasonally adjusted with X-12 ARIMA in the first two models.[20] An inflation forecast is calculated for each specification, and the model chosen is the one that delivers the lowest out-of-sample mean squared error (MSE). The projections in question are not publicly available.

4.3 Inflation Components Method

The VARs used by the Central Bank include the main macroeconomic variables, which may relate to the general price level, to achieve the best possible inflation forecast. As noted in Section 3.3.1, inflation can be decomposed into an identity involving the frequency of price increases and decreases, and their respective sizes, so the data required are the same as used to construct CPI inflation.

According to Stock and Watson (2001), the value-added of VARs is that they can capture dynamics among multiple time series, in contrast to univariate auto-regressions. Reduced form VARs are considered "powerful and reliable tools", and are widely used particularly in forecasting. The authors prove the usefulness of VARs in this regard by comparing their out-of-sample forecast performance with those of a univariate auto-regression and a random walk, using quarterly U.S. data for inflation, unemployment and interest rates. They find that the VAR for the three variables matches or improves forecasting accuracy compared to the other specifications.

The standard pseudo out-of-sample procedure follows that developed by West (1996) and Clark and McCracken (2001): the data is split between a pseudo-in-sample period for estimation, and a pseudo-out-of-sample period for forecast evaluation. The models are estimated using the pseudo-in-sample period, and an initial forecast is obtained. Subsequently,

[19] This general equilibrium model makes it possible to simulate the reactions of variables to different policies and assess their short-term dynamics and long-term convergence; it is therefore central to the determination of monetary policy.

[20] The cited document dates from 2003 and is the latest published. It states that the Central Bank of Chile continuously updates its estimation methods, so X-13 ARIMA is probably the method currently used to make seasonal adjustments.

the in-sample period is expanded by reducing the out-of-sample period by one observation, and the models are recursively estimated. This yields out-of-sample forecasts of the same length as the out-of-sample data.

The strategy used in this study consists of estimating VAR models with various lags, where the vector of variables initially corresponds to the components of inflation (frequency and absolute magnitude of increases and decreases in prices). The specification can be represented as

$$\Pi_t = \Lambda + \sum_{j=1}^{p} \Phi_j \Pi_{t-j} + \epsilon_t \tag{3}$$

where vector variables are defined as

$$\Pi_t = \begin{bmatrix} dp_t^+ \\ fr_t^+ \\ dp_t^- \\ fr_t^- \end{bmatrix}, \Lambda = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{bmatrix}, \Phi_j = \begin{bmatrix} \phi_j^{1,1} & \phi_j^{1,2} & \phi_j^{1,3} & \phi_j^{1,4} \\ \phi_j^{2,1} & \phi_j^{2,2} & \phi_j^{2,3} & \phi_j^{2,4} \\ \phi_j^{3,1} & \phi_j^{3,2} & \phi_j^{3,3} & \phi_j^{3,4} \\ \phi_j^{4,1} & \phi_j^{4,2} & \phi_j^{4,3} & \phi_j^{4,4} \end{bmatrix}, \epsilon_t = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \end{bmatrix}.$$

This makes it possible to capture the influence and feedback between prices that rise and fall through time, while including the absolute amount by which they change. To assess the accuracy gains of the forecast when including disaggregated information, the following pseudo out-of-sample procedure is used:

1. Cut the 119-month sample after observation number 84 (which corresponds to January 2006), discarding the remaining 35 observations, and dividing the $T = 84$ observations between an estimation set of $N = 78$ and a testing set of $S = 6$ months (the choice of this length reflects the horizon used by the Central Bank of Chile in their time series projections).[21]

2. The 78 observations in the estimation set are seasonally adjusted using X-13 ARIMA, which removes the seasonal components of the series.[22] These are saved for a subsequent seasonal correction of forecasts.

3. The seasonally adjusted data serve as an input for VAR models (from 1 to 3 lags so as to limit parameter uncertainty), which are estimated using maximum likelihood. Using the estimated parameters and the seasonally adjusted estimation set, a forecast up to 6-steps-ahead is obtained for each variable.

[21] The official value for January 1999 inflation cannot be computed with the available data, so the 120-month sample is reduced to 119.

[22] See U.S. Census Bureau (2015) for further details on the procedure.

4. To forecast the seasonal component of each variable, two approaches are followed: (i) the *naive forecast* approach, which corresponds to the average of the seasonal components, by month of the year (*e.g.* January, February, etc.), for the previous six years; and (ii) the *seasonal model forecast*, where the procedure of the previous step is repeated for the seasonal components data, but considering a set of monthly seasonal dummies for each variable.

5. To seasonally correct or *reseasonalize* the forecast obtained for each component of inflation, their respective forecasted seasonal components are added. Reseasonalized forecasts of components are then assembled according to the identity expressed in equation (2) to obtain the inflation forecast. For instance, $\hat{\pi}_t = \hat{dp}_t^+ \hat{fr}_t^+ - \hat{dp}_t^- \hat{fr}_t^-$.

6. Steps 1 to 5 of the procedure are repeated, but an observation is added to the sample (*i.e.* $T = 85, N = 79, S = 6$) to obtain 41 1-step-ahead forecasts, 40 2-step-ahead forecasts, and so on up to 36 6-step-ahead forecasts, for each specification and number of lags. Another variation used was estimation with a rolling origin, in which an observation is added and the first observation is eliminated (so the parameters remain at $T = 84, N = 78, S = 6$). The first sampling method is referred to as "fixed origin", and the second as "rolling origin".

7. The estimated series, again, for each specification m, number of lags j, and step-ahead forecast period s, is compared to that of the testing set of aggregate inflation through the root mean squared error (RMSE), defined as

$$RMSE_{m,j,s} = \sqrt{\frac{\sum_{t=78+s}^{119} \left(\pi_t - \hat{\pi}_{t|t-s}\right)^2}{119 - (78 + s) + 1}}.$$

Models are also considered in which the variables vector in the VAR is broken down into CPI groups. Considering the four components of inflation for each of the eight groups in the CPI would generate so many parameters that the estimation might be unstable; so the groups are selected according to their contribution to the variation in inflation.

To that end, inflation variance is first calculated when excluding a certain group, $var\left(\pi_t^{-G}\right)$; this involves adjusting the CPI weights accordingly, and subtracting it from the inflation variance, $var\left(\pi_t\right)$. The group that displays the greatest difference is deemed to contribute most to the variation of inflation. Table 12 shows that, unsurprisingly, the group in question is food. This exercise is repeated recursively (*i.e.* starting from inflation calculated without food), to find the second most important group in the terms described above, which turned out to be transport. Further repetitions of the exercise, considering additional groups, did not prove useful for the accuracy of the forecast estimation reviewed in the next section.

Table 12 – Inflation variance: contribution of different CPI groups

Group (G)	$var(\pi_t) - var\left(\pi_t^{-G}\right)$	$var\left(\pi_t^{-Food}\right) - var\left(\pi_t^{-Food,G}\right)$
Food	**1.896E-07**	-
Housing	-2.377E-06	-5.146E-06
Home equipment	-3.844E-06	-6.379E-06
Apparel	-6.431E-09	-9.140E-07
Transport	-3.742E-07	**2.938E-06**
Health	-2.825E-06	-2.324E-06
Education and leisure	-3.307E-06	-4.135E-06
Others	-5.561E-07	-5.406E-07

Note: The $-G$ superscript denotes inflation calculation excluding group G. This includes a weight adjustment for the omitted items.

Consequently, vector variable Π_t is replaced with

$$\Pi_t^A = \left[dp_t^{+(-F)}, fr_t^{+(-F)}, dp_t^{-(-F)}, fr_t^{-(-F)}, dp_t^{+(F)}, fr_t^{+(F)}, dp_t^{-(F)}, fr_t^{-(F)}\right]^T,$$

$$\Pi_t^B = \left[dp_t^{+(-F,Tr)}, fr_t^{+(-F,Tr)}, dp_t^{-(-F,Tr)}, fr_t^{-(-F,Tr)}, dp_t^{+(F)}, fr_t^{+(F)}, dp_t^{-(F)}, fr_t^{-(F)},\right.$$
$$\left. dp_t^{+(Tr)}, fr_t^{+(Tr)}, dp_t^{-(Tr)}, fr_t^{-(Tr)}\right]^T$$

as alternate specifications. Superscripts $(-F)$ and $(-F, Tr)$ indicate calculations excluding food, and food and transport, while (F) and (Tr) represent series for food and transport, respectively. Four-dimensional VAR models separating food from the rest are also included, which requires replacing the vector of variables in equation (3) with

$$\Pi_t^{(F)} = \begin{bmatrix} dp_t^{+(F)} \\ fr_t^{+(F)} \\ dp_t^{-(F)} \\ fr_t^{-(F)} \end{bmatrix} \quad \wedge \quad \Pi_t^{(-F)} = \begin{bmatrix} dp_t^{+(-F)} \\ fr_t^{+(-F)} \\ dp_t^{-(-F)} \\ fr_t^{-(-F)} \end{bmatrix}.$$

The inflation forecasts obtained for each group are then averaged according to the CPI weights, *i.e.* $\hat{\pi}_t' = \omega^{(F)}\hat{\pi}_t^{(F)} + \omega^{(-F)}\hat{\pi}_t^{(-F)}$. For the case which considers food and transport individually, the procedure is the same; so $\hat{\pi}_t'' = \omega^{(F)}\hat{\pi}_t^{(F)} + \omega^{(Tr)}\hat{\pi}_t^{(Tr)} + \omega^{(-F,Tr)}\hat{\pi}_t^{(-F,Tr)}$.

As a fair benchmark for the previous inflation components (IC) family of models, the forecast procedure is repeated with aggregate inflation (AI) specifications. This means replacing Π_t with $\Pi_t^X = \pi_t$ (univariate inflation specification), $\Pi_t^Y = \left[\pi_t^{-F}, \pi_t^F\right]$, and $\Pi_t^Z = \left[\pi_t^{-F,Tr}, \pi_t^F, \pi_t^{Tr}\right]$ (multivariate inflation specifications disaggregating by groups).

4.4 Results and Comparative Analysis

Tables 13 and 22 (Appendix C.5) report the RMSEs for the AI and IC specifications as described above, each table representing a different way of forecasting seasonal components.[23] The first result is that the best out-of-sample forecasts, from 1 to 6 steps-ahead, are delivered by the IC specifications.[24] Second, both for naive and seasonal model forecast of seasonal components, the best average out-of-sample forecast is given by the specification that considers the inflation components of food and transport separately. This finding is consistent with the facts that, firstly, both groups contain basic items which contribute the most to inflation variance; and, secondly, those groups suffered large shocks during the period studied (Central Bank of Chile, 2010).

According to Table 14, comparisons of the AI versus IC specifications show that the RMSE is always lower when forecasting inflation from its components than from inflation itself. Reductions in RMSE obtained by using inflation components range from 2.2% to 9.9% when considering a naive forecast for the seasonal component, and from 3.1% to 11.6% when they are forecasted through a seasonal model. The contrast between the minimum RMSE specifications of AI and IC also suggests that forecasting inflation through its components will always be preferable.

An interesting question is which of the four, eight or twelve inflation components, depending on the groups considered, contributes the most to predictive gains. Table 23 (Appendix C.6) shows RMSEs of forecasts repeating the evaluation procedure of the previous section, but keeping an inflation component constant on the average of its past values (which requires removing the constant parameter from the model). It turns out that, when only four components are considered, the absolute magnitude of price increases (dp^{+}) has the highest average RMSE, thus showing its relevance on predictive gains. When eight or twelve components are taken into account, the frequency of price increases and decreases in the food category ($fr^{+(F)}; fr^{-(F)}$) , and the absolute magnitude of price decreases for the remaining items ($dp^{-(-F)}; dp^{-(-F,Tr)}$) turn into the relevant components.

4.5 A More Demanding Approach

The forecasting evaluation procedure described in Section 4.3 has a minor shortcoming: the best specification is chosen on the basis of calculations for the whole sample rather than on a real-time basis. Namely, the analysis indicates the best "out-of-sample" model to forecast

[23] Results with rolling and fixed origin in the out-of-sample forecast evaluation are similar, therefore only the former are presented.

[24] IC specifications also outperform naive forecasts of aggregate inflation, such as the average of the last twelve months and a random walk, *i.e.* the last month's value.

Table 13 – RMSE of out-of-sample forecasts, from August 2005 to December 2008 (naive forecast for seasonal components)

		h-steps-ahead						
Specification	Lags	1	2	3	4	5	6	Average
Π_t^X	1	0.396%	0.436%	0.434%	0.456%	0.465%	0.472%	0.443%
	2	0.403%	0.439%	0.427%	0.452%	0.463%	0.471%	0.443%
	3	0.389%	0.426%	0.411%	0.449%	0.459%	0.456%	0.432%
Π_t^Y	1	0.378%	0.434%	0.415%	0.429%	0.459%	0.468%	0.430%
	2	0.396%	0.459%	0.437%	0.450%	0.474%	0.472%	0.448%
	3	0.375%	0.445%	0.436%	0.455%	0.483%	0.481%	0.446%
Π_t^Z	1	0.381%	0.442%	0.425%	0.439%	0.468%	0.478%	0.439%
	2	0.398%	0.471%	0.445%	0.459%	0.485%	0.486%	0.457%
	3	0.378%	0.458%	0.436%	0.464%	0.495%	0.494%	0.454%
Π_t	1	0.379%	0.425%	0.422%	0.444%	0.468%	0.479%	0.436%
	2	0.388%	0.435%	0.422%	0.437%	0.463%	0.473%	0.436%
	3	0.385%	0.414%	**0.390%**	0.410%	0.436%	**0.446%**	0.414%
Π_t^A	1	0.360%	0.425%	0.442%	0.443%	0.472%	0.493%	0.439%
	2	**0.360%**	0.416%	0.415%	**0.396%**	**0.413%**	0.448%	**0.408%**
	3	0.394%	0.438%	0.412%	0.417%	0.420%	0.452%	0.422%
Π_t^B	1	0.384%	0.427%	0.439%	0.443%	0.471%	0.491%	0.443%
	2	0.362%	**0.409%**	0.426%	0.425%	0.417%	0.468%	0.418%
	3	0.432%	0.466%	0.450%	0.455%	0.430%	0.469%	0.450%
$\hat{\pi}_t'$	1	0.367%	0.428%	0.429%	0.446%	0.475%	0.488%	0.439%
	2	0.360%	0.418%	0.414%	0.425%	0.449%	0.461%	0.421%
	3	0.370%	0.412%	0.409%	0.437%	0.458%	0.470%	0.426%
$\hat{\pi}_t''$	1	0.376%	0.426%	0.427%	0.446%	0.476%	0.488%	0.440%
	2	0.366%	0.417%	0.421%	0.431%	0.455%	0.465%	0.426%
	3	0.377%	0.423%	0.424%	0.448%	0.472%	0.484%	0.438%
Number of observations		41	40	39	38	37	36	-

Note: As described in Section 4.3, the first three specifications only consider aggregate inflation, and the last five are based on inflation components. The last column shows the average of steps-ahead for each specification-lag pair. The model with the lowest RMSE for each h-step-ahead is highlighted in bold. Rolling origin used in the the out-of-sample forecast evaluation.

Table 14 – Comparison of best RMSE of out-of-sample forecasts, AI vs. IC, percentage improvement (from August 2005 to December 2008)

Seasonal comp. forecast		h-steps-ahead						
		1	2	3	4	5	6	Average
Naive	Min AI	0.360%	0.409%	0.390%	0.396%	0.413%	0.446%	0.408%
	Min IC	0.375%	0.426%	0.411%	0.429%	0.459%	0.456%	0.430%
	Improvement	4.21%	3.87%	5.03%	7.61%	9.87%	2.18%	5.21%
Seasonal model	Min AI	0.352%	0.407%	0.391%	0.392%	0.405%	0.441%	0.404%
	Min IC	0.364%	0.431%	0.413%	0.429%	0.458%	0.456%	0.428%
	Improvement	3.10%	5.45%	5.37%	8.76%	11.62%	3.29%	5.55%

Note: For each sample type and h-step-ahead, AI and IC specifications are compared considering the number of lags that gives the lowest RMSE. The row labeled "Improvement" compares the lowest RMSE aggregate inflation specification against the lowest inflation components specification.

inflation, but does not assess its particular forecasting performance. A real-time scenario is now simulated to evaluate how the method would work if used to forecast tomorrow's inflation. Firstly, the 119-month sample is assumed to end at month 95, which makes it possible to replicate the tables in Section 4.4 by applying the procedure described in 4.3 (rolling-origin sampling is used). This makes it possible to determine the best 1-step-ahead (month 90) inflation forecast model by choosing the specification with the smallest RMSE for the 1-step-ahead forecasts for months 78 to 89, and then forecast month 90 inflation in (pseudo) "real time" using the best model.

The process is repeated by adding a month (hence, months 78-90 are considered in the evaluation) to get the real-time 1-step-ahead forecast for month 91, and so on until month 119. Thus, a series of 30 real-time 1-step-ahead forecasts is obtained by estimating inflation with the best specification to date. The same logic is followed to forecast 2 to 6 steps-ahead, obtaining series of 29 to 25 real-time forecasts, respectively.

Table 15 reports the RMSEs of real-time forecasts for the period studied (months 90 — instead of 79 — to 119) for both the AI and the IC specifications following the procedure described above. It can be seen that, despite the reduction of the sample used for comparison, the previous section's results hold for both ways of forecasting the seasonal component.

Forecasts are usually compared through a Diebold-Mariano (DM) test of predictive accuracy, using a mean squared error (MSE) loss differential function (Hansen and Timmermann, 2015).[25] Diebold (2015) states that, under small parameter estimation uncertainty, loss differential would be approximately stationary as forecast errors would have a small non-

[25]See Appendix E for details about the DM test statistic.

Table 15 – Comparison of best RMSE of out-of-sample real-time forecasts, percentage improvement using rolling origin (from July 2006 to December 2008)

Seasonal comp. forecast		h-steps-ahead 1	2	3	4	5	6	Average
Naive	Min AI	0.393%	0.448%	0.453%	0.490%	0.519%	0.529%	0.386%
	Min IC	0.370%	0.411%	0.419%	0.460%	0.463%	0.488%	0.347%
	Improvement	6.02%	8.26%**	7.48%	6.05%	10.76%**	7.73%*	9.97%
Seasonal model	Min AI	0.389%	0.445%	0.454%	0.488%	0.518%	0.527%	0.389%
	Min IC	0.379%	0.416%	0.422%	0.437%	0.456%	0.486%	0.344%
	Improvement	2.57%	6.62%*	7.03%	10.48%	12.10%**	7.82%	11.56%
Number of observations		30	29	28	27	26	25	30

Note: The first two pairs of rows consider the best h-step-ahead specifications for IC and AI sets. The last row compares the results for each seasonal component forecast method. The last column shows RMSE for the average of the 6-steps-ahead. The Diebold-Mariano test for non-nested models, using Newey-West corrected standard errors, is applied to compare the forecast accuracy of both specifications, from 1 to 6 steps-ahead (Diebold and Mariano, 1995). ***, **, * denote significance levels of 1%, 5%, and 10%.

stationary component. Moreover, the validity of the DM test can be assessed by examining the loss differential. For both ways of forecasting the seasonal components, loss differential series obtained from comparing the AI and IC specifications prove stationary, according to the Dickey-Fuller (DF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests.[26] Therefore, for 2 and 5-steps-ahead and considering a naive forecast for seasonal components, IC specifications outperform AI ones at a significance level of 5%, as they also do at 10% for 6-steps-ahead.

As a double-check on these results, the real-time scenario simulation is repeated while changing the model selection method: instead of choosing the best model for each step-ahead, the model with the minimum average RMSE, among steps-ahead, is used to predict each step-ahead in "real time". Then, for each of the 30 iterations, the average RMSE among the six steps-ahead is computed, and the average of the 30 RMSEs is displayed in the last column of Table 15. IC models are, on average, between 9.97% and 11.56% better than AI models for predicting inflation.

According to Faust and Wright (2013), survey-based forecasts of inflation tend to largely outperform model-based ones. Nowadays for inflation forecasting, the Central Bank of Chile supplements its macroeconometric models by monthly surveying a group of academics, consultants, and executives or advisors of financial institutions. Nonetheless, for the 1999-2008

[26]The Dickey-Fuller (DF) test rejects the null hypothesis of a unit root for the steps-ahead and model selection cases, while the KPSS test cannot reject the null hypothesis of stationarity. See Dickey and Fuller (1979); Kwiatkowski et al. (1992).

period, the Economic Expectations Survey (EES) is the only one available. It delivers information on expectations for different macroeconomic variables, and is published at the end of the first fortnight of each month. In particular, the publicly available series are those that report inflation expectations for the same month and for the average of the two following months. This study uses the latter series as an additional benchmark to assess the accuracy of inflation forecasting under IC specifications.

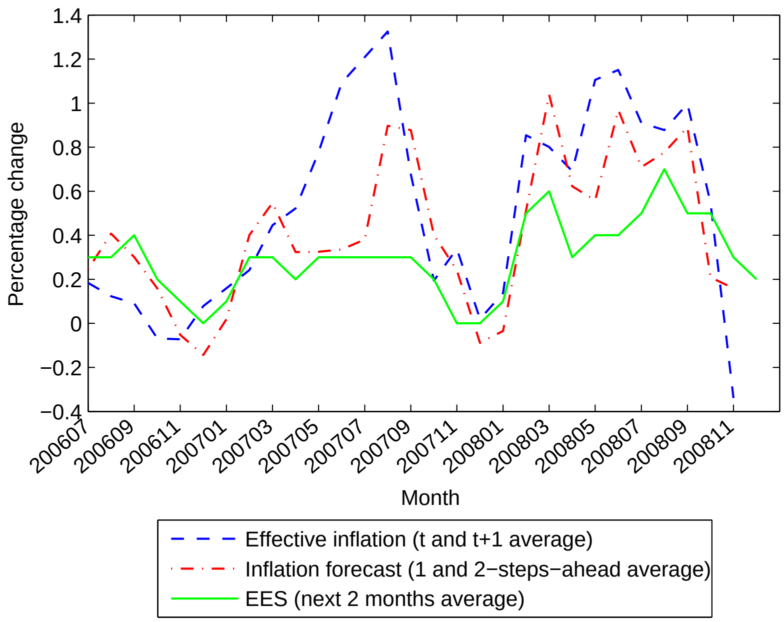

Figure 10 – CPI monthly inflation and comparison with forecasts.

For the period July 2006 to November 2008, Figure 10 shows the average of current and next month effective inflation (*e.g.* the data for November 2008 represent average inflation for November and December 2008). The averages of 1- and 2-step-ahead inflation forecasts obtained through best IC specifications (using the rolling-origin sample procedure and a naive forecast for seasonal components) are plotted in the figure, along with the EES series that gives expected average inflation for the next two months. It is clear that the IC specification captures macroeconomic fluctuations better than the EES series, particularly between March and October 2007. In fact, the RMSE of effective inflation with the former specification is 0.32%, compared to 0.44% with the latter, implying a 27.8% improvement (at 1.1% significance level) in forecasting accuracy.[27]

As a final benchmark analysis, the out-of-sample inflation forecasts made by Pincheira and García (2009) for the same period are considered. In their search for a predictive bench-

[27]The use of a seasonal model to forecast seasonal components preserves the results.

mark for inflation, they conducted a variety of tests and concluded that extended seasonal ARIMA (ESARIMA) on aggregate inflation can contribute by enhancing its forecasting. When comparing their results to those of this study, there are improvements of at least 7.9%.

4.6 The Reasons behind the Improvements

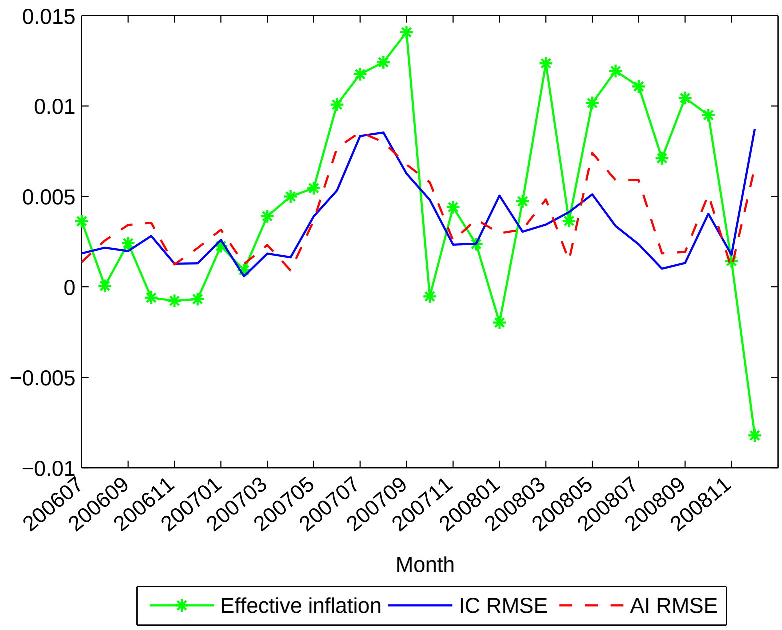

Figure 11 – CPI monthly inflation and RMSEs for different specifications.

Figure 11 shows effective inflation and forecasts obtained using the minimum average RMSEs, among steps-ahead, for the AI and IC specifications as computed in Section 4.5 (using seasonal models to forecast seasonal components). A closer look at the predictions of both families of models reveals that, on average, IC specifications have lower RMSE than AI ones when inflation rises with respect to the last period.

Minimum average RMSEs forecasts for both specifications are plotted against the first difference of inflation (Figure 12), and against the difference between inflation and its average for the evaluation period (Figure 13) to assess the previous statement. A kernel smoother of the same bandwidth is used to fit the curves to the data. The black dotted line represents a smooth version, via kernel estimation, of the density of observations. It can be seen from the figures that the main gains in forecasting accuracy of IC over AI specifications are due to better performance of the former when facing increases in inflation, which happen more often than decreases. In other words, the density of observations is high when IC specifications

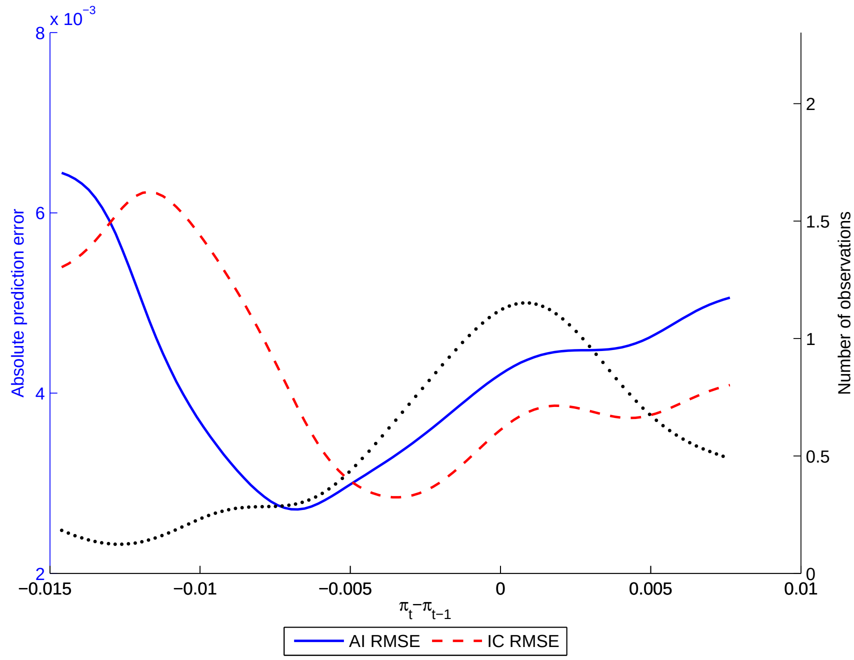

Figure 12 – Prediction error and inflation changes.

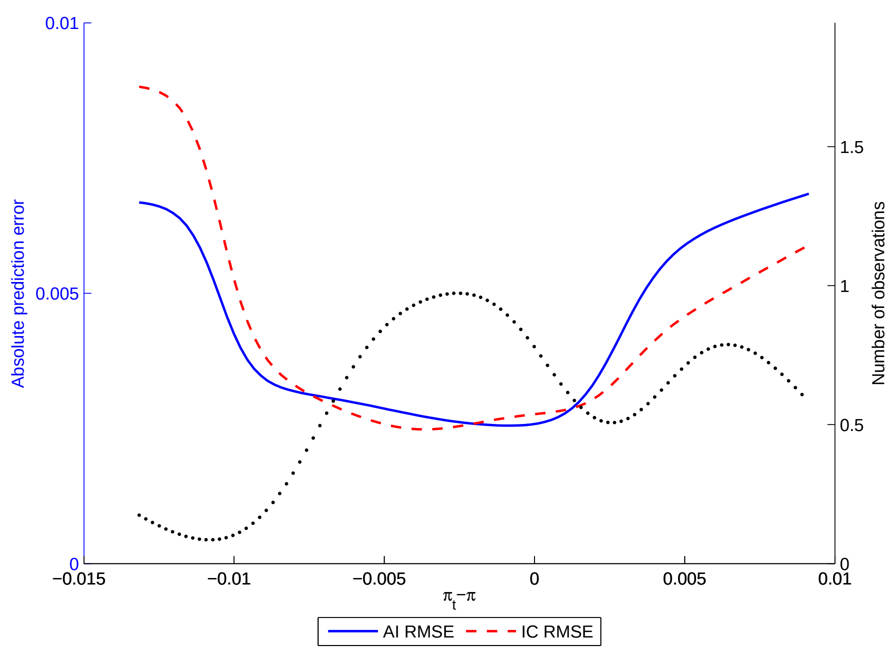

Figure 13 – Prediction error and inflation changes around its mean.

outperform AI ones (*i.e.* when inflation increases), and low in the contrary case, what explains the overall gains. Predictive improvements might be related to the fact that IC specifications consider a broader data set, capturing the behavior of the IM and EM of price changes for different product groups in detail.

5 Concluding Remarks

This research used microeconomic price data from the Chilean CPI basket to describe the economy's price-adjustment dynamics. Calculations were made to summarize the database and study price-setting behavior. The main findings do not significantly depart from those usually found in the literature: prices adjust on average every quarter, displaying a large difference with respect to aggregate estimations, and a high level of heterogeneity among groups of products. An analysis performed for reference prices sheds light on the factors underlying the contract multiplier: slight memory in CPI-related prices and considerable novelty in transition (non-reference) prices, alongside persistent reference prices, suggest the presence of sticky plans or sticky information.

The distribution of price changes also reveals a "missing middle", as a large proportion of them are small. Most of the variance in inflation can be attributed to the intensive margin. Also, no sign of an increasing hazard rate is found. These facts provide evidence supporting TDP rather than SDP models. On the other hand, the lack of association between the magnitude of price changes and their age and the presence of synchronization in price changes, tilt the balance in favor of SDP models.

The identity formed by decomposing inflation into the frequency of increases and decreases, and their respective absolute sizes, is also explored in depth; and the frequency of price increases is found to be the most relevant driver of inflation. With the aim of exploiting the previous series, which can only be obtained through disaggregated data, their usefulness for inflation forecasting was tested. The results show that short-term inflation forecasts are considerably improved — between 3% and 12% — when performed through VAR specifications consisting of inflation components, compared to those done using aggregate inflation series only. Accuracy gains seem to be related to the fact that IC specifications account for increases in inflation better than AI ones.

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A Data Considerations

The INE is only allowed to disclose data that does not violate statistical confidentiality (items such as financial services and telecommunications do so). Hence, from the 483 products (the equivalent for entry level items – ELIs – in the U.S.) comprising the CPI, this research had access to 468. Each product is composed of a number of varieties, which are usually weighted differently (weights at the variety level were used in the calculations). To estimate CPI inflation, the INE computes price variation indices at the quote-line level, which are then geometrically weighted to obtain price variation indices at the variety or product level.

Restrictions imposed for reference price calculations reduce the sample to 426 products (as described in Section 2.2), representing around 83% of the CPI. Table 16 describes the eight groups forming the CPI basket. The most important of these is food (31.4%) followed by housing (17.6%); while others (2.2%) — encompassing items such as professional services, tobacco and financial expenses — is the least important group. Likewise, food is the group with the largest number of products (151), followed by home equipment (83), and education and leisure (53).

Table 16 – CPI groups characteristics

	CPI weight	Products	Quote-lines
Food	31.4%	151	21880
Housing	17.6%	27	1389
Home equipment	10.3%	83	6531
Apparel	6.0%	45	2784
Transport	9.6%	21	720
Health	10.5%	39	8171
Education and leisure	12.4%	53	2888
Others	2.2%	7	145
All items	100%	426	44508

Before doing the calculations, an evaluation was made of the extent to which the disaggregated information provided by the INE makes it possible to replicate official aggregate figures. Aggregate inflation was calculated for each of the 426 products (using official weights): (i) as the weighted-average of official aggregate series by product, and (ii) as the weighted-average of the log of price changes obtained from disaggregated data, *i.e.* $\pi_t = \sum_i \omega_{it} \Delta \ln p_{it}$. As Table 17 shows, the overall correlation is high (0.96), with that of housing and home equipment being the lowest (0.76). Despite this, it was decided to include every available and relevant quote-line in this research, as calculations excluding them did not yield significantly different results, and doing so could endanger the representativeness of the sample.

Table 17 – Correlation between official and estimated CPI inflation

	Correlation
Food	0.99
Housing	0.79
Home equipment	0.76
Apparel	0.94
Transport	0.98
Health	0.98
Education and leisure	0.99
Others	0.97
All items	0.96

B EM, IM and the Variance of Inflation

According to Klenow and Kryvtsov (2008), the variance of inflation can be split between IM and EM terms (from equation (1)), and also between positive (POS) and negative (NEG) terms (from equation (2)), as follows:

$$var(\pi_t) = \underbrace{var(dp_t)\,\overline{fr}^2}_{IM\ term} + \underbrace{var(fr_t)\,\overline{dp}^2 + 2\cdot\overline{fr}\cdot\overline{dp}\cdot cov(fr_t, dp_t) + O_t}_{EM\ terms},$$

$$var(\pi_t) = \underbrace{var(pos_t) - cov(pos_t, neg_t)}_{POS\ term} + \underbrace{var(neg_t) - cov(pos_t, neg_t)}_{NEG\ term}.$$

Both decompositions are useful for assessing the relevance of the variables in question for inflation movements, and thus for evaluating the feasibility of different pricing models. The first decomposition makes it possible to distinguish between staggered TDP models — in which the IM term explains most of the variance — and SDP models — where the EM terms usually play a greater role. Klenow and Kryvtsov (2008) show that key terms are the variances, as the covariance and high order terms (O_t) are small. In the second case, where the covariance is evenly distributed between terms (Klenow and Kryvtsov, 2008), it becomes possible to further measure the relevance of positive and negative terms on inflation variance. As Table 18 shows, for posted and regular prices, the intensive margin term accounts for a high proportion of inflation variance (84% and 76%, respectively), while the extensive margin term does so for reference prices.

Table 18 – Variance decompositions

	IM vs. EM		POS vs. NEG	
Prices	IM term	EM term	POS term	NEG term
Posted	0.842	0.158	0.571	0.429
Regular	0.755	0.245	0.548	0.452
Reference	0.289	0.711	0.456	0.544

Consequently, the magnitude of price changes (reflected in the IM term) is less important when deviations from the most common prices are excluded, with the fraction of items that change price playing a key role in inflation movements (hence entailing greater synchronization of price changes and a lower contract multiplier). From Table 18 it can also be deduced that the positive term accounts for a larger share of inflation variance (57.1% for posted and 54.8% for regular prices) than the negative term, at least when larger deviations from reference prices are not excluded. Thus, for reference prices, the negative term explains a larger portion of inflation variance than the positive term.

C Additional Tables and Figures

C.1 Frequency of Changes in Posted Prices by Product

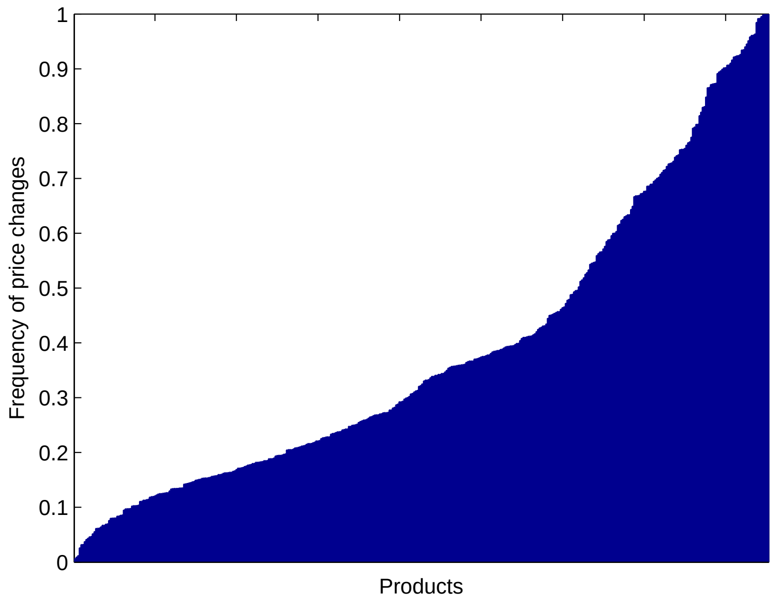

Figure 14 – Frequency of changes in posted prices by product. The bars represent the price change frequency for each product, calculated as the weighted-average across the quote-lines for each product.

C.2 Absolute Magnitude of Price Increases and Decreases

Table 19 – Absolute magnitude of price increases

	Posted		Regular		Reference	
	Median	Mean	Median	Mean	Median	Mean
Food	5.90%	6.55%	5.89%	6.56%	10.29%	13.72%
Housing	1.42%	3.73%	1.36%	4.49%	1.93%	6.10%
Home equipment	5.98%	6.32%	6.22%	6.74%	15.13%	15.96%
Apparel	10.04%	13.58%	11.03%	14.37%	19.68%	19.05%
Transport	3.12%	4.13%	3.13%	4.06%	5.89%	7.43%
Health	5.10%	4.75%	4.90%	4.68%	3.86%	6.77%
Education and leisure	6.47%	5.95%	6.48%	6.59%	7.13%	8.87%
Others	2.81%	3.89%	2.69%	3.85%	6.92%	7.53%
All items	4.48%	5.19%	4.39%	5.52%	6.64%	8.20%

Table 20 – Absolute magnitude of price decreases

	Posted		Regular		Reference	
	Median	Mean	Median	Mean	Median	Mean
Food	6.44%	6.98%	6.51%	7.12%	10.96%	13.98%
Housing	0.67%	1.39%	0.68%	1.35%	3.77%	3.21%
Home equipment	6.47%	6.87%	7.27%	7.65%	13.54%	14.82%
Apparel	10.53%	12.33%	11.52%	13.21%	22.32%	20.28%
Transport	3.17%	4.22%	2.70%	4.02%	9.60%	13.14%
Health	6.15%	6.97%	6.39%	7.13%	18.25%	17.45%
Education and leisure	4.55%	6.08%	4.72%	6.05%	12.49%	14.45%
Others	3.95%	4.80%	4.19%	4.85%	14.66%	15.54%
All items	3.17%	4.37%	2.69%	4.35%	4.88%	9.51%

C.3 Time Series Moments, Posted Prices

Table 21 – Time series moments, posted prices

				Regression on π	
Variable	Mean (%)	Std. dev. (%)	Corr. w/π	Coef.	Std. error
π	0.282	0.404	-	-	-
fr	43.197	3.863	0.238	2.283	0.862
dp	0.629	0.857	0.956	2.018	0.057
fr^+	26.865	4.418	0.655	7.166	0.764
fr^-	16.333	3.304	-0.604	-4.883	0.596
dp^+	4.862	0.840	0.287	0.596	0.184
dp^-	6.389	1.439	-0.082	-0.292	0.330
pos	1.311	0.340	0.622	0.526	0.061
neg	1.029	0.275	-0.563	-0.379	0.051

Note: Each variable represents the monthly weighted mean of the CPI products. The results obtained from regressing a variable on inflation are shown in the last two columns.

C.4 Inflation and the Absolute Size of Price Increases and Decreases

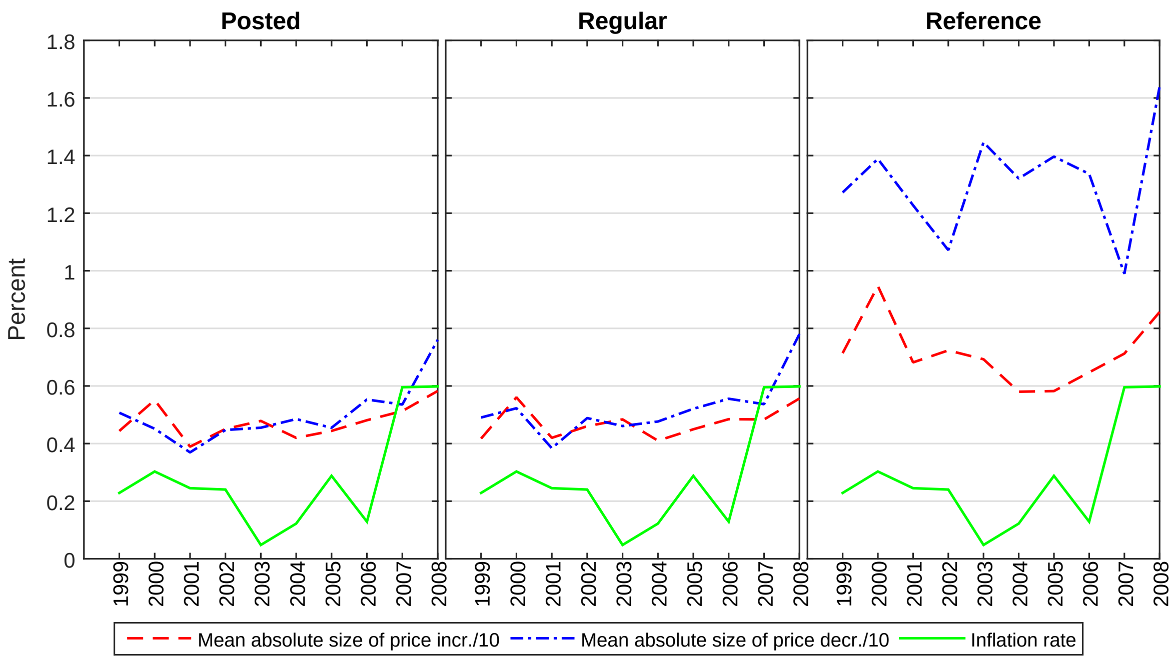

Figure 15 – Inflation and the absolute magnitude of price increases and decreases. Each series represents the annual average of monthly weighted means for different types of prices.

C.5 RMSE of Out-of-Sample Forecasts (seasonal model forecast for seasonal components)

Table 22 – RMSE of out-of-sample forecasts, from August 2005 to December 2008 (seasonal model forecast for seasonal components)

		h-steps-ahead						
Specification	Lags	1	2	3	4	5	6	Average
Π_t^X	1	0.391%	0.435%	0.434%	0.456%	0.465%	0.472%	0.442%
	2	0.402%	0.443%	0.428%	0.452%	0.463%	0.471%	0.443%
	3	0.390%	0.432%	0.413%	0.450%	0.458%	0.456%	0.433%
Π_t^Y	1	0.366%	0.431%	0.416%	0.429%	0.459%	0.468%	0.428%
	2	0.386%	0.454%	0.435%	0.451%	0.475%	0.471%	0.445%
	3	0.369%	0.451%	0.433%	0.455%	0.484%	0.479%	0.445%
Π_t^Z	1	0.366%	0.440%	0.426%	0.440%	0.468%	0.477%	0.436%
	2	0.391%	0.474%	0.445%	0.459%	0.485%	0.485%	0.457%
	3	0.364%	0.460%	0.435%	0.467%	0.495%	0.495%	0.453%
Π_t	1	0.378%	0.423%	0.421%	0.446%	0.467%	0.479%	0.436%
	2	0.378%	0.439%	0.428%	0.440%	0.465%	0.470%	0.437%
	3	0.377%	0.416%	**0.391%**	0.410%	0.425%	**0.441%**	0.410%
Π_t^A	1	**0.352%**	0.427%	0.441%	0.439%	0.468%	0.491%	0.436%
	2	0.358%	0.416%	0.410%	**0.392%**	**0.405%**	0.446%	**0.404%**
	3	0.394%	0.442%	0.416%	0.416%	0.418%	0.454%	0.423%
Π_t^B	1	0.387%	0.429%	0.435%	0.437%	0.467%	0.487%	0.440%
	2	0.359%	**0.407%**	0.424%	0.418%	0.416%	0.467%	0.415%
	3	0.433%	0.463%	0.449%	0.449%	0.432%	0.474%	0.450%
$\hat{\pi}_t'$	1	0.365%	0.426%	0.428%	0.447%	0.475%	0.487%	0.438%
	2	0.358%	0.428%	0.415%	0.426%	0.454%	0.460%	0.424%
	3	0.379%	0.417%	0.405%	0.440%	0.461%	0.471%	0.429%
$\hat{\pi}_t''$	1	0.369%	0.422%	0.425%	0.445%	0.476%	0.488%	0.437%
	2	0.366%	0.414%	0.418%	0.431%	0.462%	0.464%	0.426%
	3	0.389%	0.436%	0.422%	0.447%	0.474%	0.486%	0.442%
Number of observations		41	40	39	38	37	36	-

Note: As described in Section 4.3, the first three specifications only consider aggregate inflation, and the last five are based on inflation components. The last column shows the average of steps-ahead for each specification-lag pair. The model with the lowest RMSE for each h-step-ahead is highlighted in bold. Rolling origin used in the the out-of-sample forecast evaluation.

C.6 Relevance of Inflation Components on Predictive Gains

Table 23 – Predictive gains and inflation components

	h-steps-ahead						
Variable	1	2	3	4	5	6	Average
fr^{+}	0.432%	0.469%	0.464%	0.491%	0.509%	0.513%	0.480%
fr^{-}	0.419%	0.436%	0.431%	0.441%	0.458%	0.469%	0.442%
dp^{+}	0.450%	0.471%	0.479%	0.493%	0.500%	0.498%	**0.482%**
dp^{-}	0.450%	0.487%	0.454%	0.474%	0.500%	0.509%	0.479%
$fr^{+(F)}$	0.406%	0.452%	0.458%	0.463%	0.475%	0.491%	**0.458%**
$fr^{-(F)}$	0.398%	0.446%	0.440%	0.454%	0.479%	0.495%	**0.452%**
$dp^{+(F)}$	0.395%	0.421%	0.423%	0.441%	0.461%	0.480%	0.437%
$dp^{-(F)}$	0.390%	0.441%	0.428%	0.440%	0.468%	0.488%	0.443%
$fr^{+(-F)}$	0.357%	0.426%	0.433%	0.443%	0.461%	0.478%	0.433%
$fr^{-(-F)}$	0.386%	0.424%	0.428%	0.441%	0.462%	0.477%	0.436%
$dp^{+(-F)}$	0.391%	0.440%	0.444%	0.448%	0.460%	0.475%	0.443%
$dp^{-(-F)}$	0.396%	0.462%	0.450%	0.468%	0.492%	0.514%	**0.464%**
$fr^{+(F)}$	0.416%	0.459%	0.465%	0.474%	0.481%	0.497%	**0.465%**
$fr^{-(F)}$	0.406%	0.451%	0.447%	0.475%	0.493%	0.506%	**0.463%**
$dp^{+(F)}$	0.410%	0.432%	0.435%	0.457%	0.470%	0.488%	0.449%
$dp^{-(F)}$	0.395%	0.442%	0.429%	0.449%	0.474%	0.494%	0.447%
$fr^{+(Tr)}$	0.392%	0.441%	0.445%	0.452%	0.460%	0.481%	0.445%
$fr^{-(Tr)}$	0.396%	0.446%	0.448%	0.450%	0.459%	0.482%	0.447%
$dp^{+(Tr)}$	0.374%	0.425%	0.427%	0.441%	0.457%	0.480%	0.434%
$dp^{-(Tr)}$	0.374%	0.430%	0.432%	0.445%	0.457%	0.488%	0.438%
$fr^{+(-F,Tr)}$	0.358%	0.422%	0.425%	0.449%	0.463%	0.481%	0.433%
$fr^{-(-F,Tr)}$	0.393%	0.424%	0.428%	0.456%	0.473%	0.482%	0.443%
$dp^{+(-F,Tr)}$	0.402%	0.440%	0.437%	0.465%	0.462%	0.478%	0.447%
$dp^{-(-F,Tr)}$	0.403%	0.445%	0.444%	0.472%	0.496%	0.512%	**0.462%**

Note: Each row represents RMSE of inflation forecast computed as in Section 4.3 (rolling origin sample and naive forecast for seasonal components), but keeping the correponding variable constant on the average of its past values, The superscripts $(-F)$ and $(-F, Tr)$ indicate calculations excluding food, and food and transport, while (F) and (Tr) represent series for food and transport, respectively.

D Reference Prices in a Calvo Economy

To assess the extent to which reference price calculations change depending on the economy's frictions, a Calvo economy (2,000 items, 120 periods) is simulated, with the same overall mean probability of a change in regular prices as actually occurred (*i.e.* 0.41). Then the mean probability of reference price changes for different window sizes, ranging from 1 to 7, is computed, both for the actual and the Calvo economy.

As shown in Figure 16, the calculations for reference prices are always lower than those for regular prices; and the mean probability of a change in reference price is decreasing on window size. Also, the probability of reference price change in the actual and Calvo economies coincide at a window size of 4 and differ for the other window sizes. Nevertheless, the differences do not exceed 0.015 points, so it can be concluded that a real economy, versus a similar Calvo one, does not pose great concerns regarding reference price calculations.

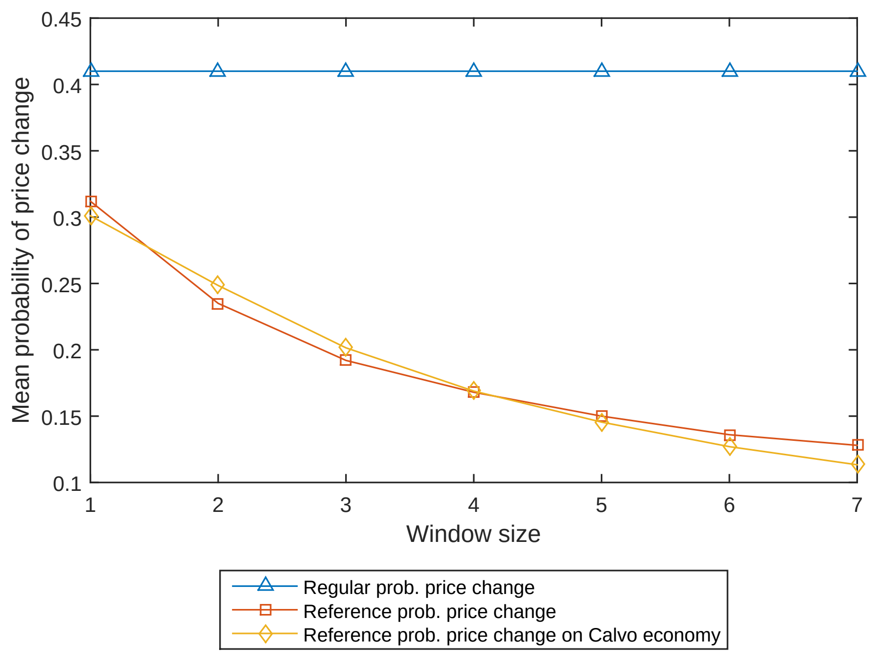

Figure 16 – Overall mean probability of price change, actual versus Calvo economy.

E Diebold-Mariano Test of Predictive Accuracy

Let $\left\{\hat{e}_{1,t+s|t}\right\}_{t=T+1}^{T+N}$ and $\left\{\hat{e}_{2,t+s|t}\right\}_{t=T+1}^{T+N}$ denote forecast errors from two different models, and $d_{t+s} = \left(\hat{e}_{1,t+s|t}\right)^2 - \left(\hat{e}_{2,t+s|t}\right)^2$, the squared error loss differential. The Diebold-Mariano test statistic will be given by

$$DM = \frac{\bar{d}}{\sqrt{\widehat{avar}\left(\bar{d}\right)}}$$

where $\bar{d} = N^{-1}\sum_{t=T+1}^{T+N} d_{t+s}$, and $\widehat{avar}\left(\bar{d}\right)$ is a consistent estimate of the asymptotic variance of $\sqrt{N}\bar{d}$ (Andersen et al., 2009). It can be estimated using the Newey-West kernel-based estimator, such that

$$\widehat{avar}\left(\bar{d}\right) = N^{-1}\left[\hat{\gamma}_0 + 2\sum_{j=1}^{q-1}\left(1 - \frac{j}{q}\right)\hat{\gamma}_j\right]$$

where j represents the lag length of the autocovariance term of d_{t+s}, $\hat{\gamma}_j$, and q represents the total number of significant autocovariances terms included (Newey and West, 1987).