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The Dynamics of Individual Consumer Price Data for Austria [1]

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Abstract

In this paper a data set with price records collected for the computation of the Austrian CPI is used to estimate the average frequency of price changes and the duration of price spells to provide empirical evidence on the degree and characteristics of price rigidity in Austria. Depending on the estimation method, on average, prices are unchanged for 11 to 14 months. We find a strong heterogeneity across sectors and products. Price increases occur only slightly more often than price decreases. For both cases the typical size of the weighted average price change is quite large (11% and 15%, respectively). Like in related contributions we find that the aggregate hazard function is decreasing with time. Apart from

[1] We thank Statistics Austria for providing the data and especially Paul Haschka and Alexandra Beisteiner for valuable information on the data. This study has been conducted in the context of the 'Eurosystem Inflation Persistence Network (IPN)'. We are indebted to the members of this network, especially to Steve Cecchetti, Emmanuel Dhyne and Johannes Hoffmann. We also thank Jerzy Konieczny, Michael Pfaffermaier, Thomas Url, Christoph Weiss, the participants of the Annual Meeting of the Austrian Economic Association 2005 and an anonymous referee for valuable comments. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Oesterreichische Nationalbank (OeNB) or the Eurosystem. All remaining errors and shortcomings are our responsibility alone

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heterogeneity across products and price setters, this is due to oversampling of products with a high frequency of price changes. Accounting for the unobserved heterogeneity in estimating the probability of a price change with a panel logit model (with fixed elementary product effects), we find a small but positive effect of the duration of a price spell on the probability of a price change. We also find that during the euro cash changeover period the probability of price changes was higher.

JEL classification: C41, D21, E31, L11
Keywords: Consumer prices, sticky prices, frequency and synchronization of price changes, duration of price spells

1. Introduction

The frequency of price changes or its counterpart the duration for which prices remain unchanged, play a major role in the assessment of the impact of various shocks on the economy. Most macroeconomic models assume sluggish price and/or wage adjustment to generate real effects of monetary policy at least in the short run. The literature on the microeconomic foundation of price stickiness is vast (see Ball and Mankiw, (1995), Taylor, (1999) for an overview). However, due to the lack of individual price data and/or a restrictive practice of Statistical offices with respect to the use of the data for academic research, the empirical evidence on the relevance and patterns of price stickiness is sparse.

Several papers have shown that for some products or product groups prices remain unchanged for many months. Cecchetti (1986), who looked at 38 U.S. news-stand magazine prices from 1953 to 1979, reported 1.8 to 14 years (!) since the last price change. Kashyap (1995), who studied the price changes of 12 mail order catalogue goods, found that on average prices were unchanged for 14.7 months. A series of papers by Lach and Tsiddon (1992, 1996) analyzes the price-setting behavior of firms by looking at the prices of 26 food products at grocery stores. However, all these studies faced the problem of small samples including only a (very) limited number of products and one has to make extremely strong assumptions on the sectoral (or product group) homogeneity for economy wide generalizations of their results.

Bils and Klenow (2004) used a much broader set of unpublished individual price data collected by the Bureau of Labor Statistics (BLS) for the calculation of the U.S. consumer price index (CPI). They found much more frequent price changes of consumer prices in the U.S.A. than the studies mentioned above. For about half of the consumption goods, prices remain constant for less than 4.3 months. They also found that the frequency of price changes differs dramatically across goods.

For euro area countries until recently very limited evidence on this issue was available, notable exceptions being Campiglio (2002) on Italy, Suvanto and Hukkinen (2002) on Finland, and Aucremanne et al. (2002) on Belgium. Thanks to the initiative of the Eurosystem Inflation Persistence Network (IPN) for 10 of the 12 euro area countries micro data evidence on frequencies of price changes and the duration of prices based on CPI data is now available. Dhyne et al. (2005) provide a summary of the research efforts in the analysis of individual consumer price data within the IPN.[3]

In this paper we examine the frequency of consumer price changes in Austria, using a unique data set of individual price quotes collected for the calculation of the Austrian consumer price index. The major aim is to analyze the degree and characteristics of the nominal rigidity present in Austrian consumer prices and trying to explain some factors influencing this rigidity.

We find that the average (median) duration of price spells is 14 (11) months, but that the duration varies considerably across sectors and products. Like in similar studies, we find that the aggregate hazard function for all price spells is decreasing with time which is at odds with all relevant price-setting theories. However, apart from heterogeneity across products and price setters, one important reason for this is aggregating over product types with different spell duration. We show that – using an appropriate weighting scheme – the aggregate hazard function has its most marked spike at the duration of one year. Kaplan-Meier estimates of hazard functions display substantial heterogeneity across goods and product types. Taking into account the unobserved heterogeneity in estimating the probability of a price change with a panel fixed effects logit model, we find a small positive but highly significant effect of the duration of a price spell on the probability of a price change. We also find that in the months before and after the euro cash changeover the probability of price changes is higher than in other periods.

The paper is organized as follows. In section 2 we introduce the micro dataset on which our analysis is based. The methodology of our analysis and the empirical results which summarize the vast information in the data are presented in section 3. There we present estimates for the frequency of price changes and the duration of price spells and additionally address the issue of the synchronization of price changes within product categories. To describe and explain the stylized facts of price setting in Austria we present hazard rates and run panel logit regressions in section 4. The paper concludes with a summary of the main results.

[3] For detailed country results see Aucremanne and Dhyne, (2004A) for Belgium, Dias et al. (2004) for Portugal, Baudry et al. (2004) for France, Álvarez and Hernando (2004) for Spain, Fabiani et al. (2004) for Italy, Jonker et al. (2004) for The Netherlands, Vilmunen and Paloviita (2004) for Finland and Hoffmann and Kurz-Kim (2005) for Germany.

2. The Data

For investigating individual price dynamics in Austria, we use a longitudinal micro data set of monthly price quotes collected by Statistics Austria which is used to compute the national index of consumer price (CPI). The sample spans over the period from January 1996 to December 2003 (96 months) and contains between 33,800 (1996) and 40,700 (2003) elementary price records per month. The first half of our observation period coincides with the sample of goods included in CPI 1996 goods basket. In the period from 2000 to 2003 our data are based on a revised goods basket (CPI 2000). Overall, our dataset contains about 3.6 million individual price quotes which cover roughly 90% of the total Austrian CPI.[4] The main portion of price quotes is collected in 20 major Austrian cities.

Each price quote consists of information on the product category, the date, an outlet identifier as well as on the packaging (quantity) of an item. As the product category we define the products at the elementary level which are contained in the CPI basket (e.g. milk). Our original dataset includes a total of 639 such products categories. For each product category the product variety denotes the specific variety and brand of the product. For confidentiality reasons the dataset has been made anonymous with respect to the variety and brand of the product, i.e. we do not have any information on the brand.

With the information on the date (t), the outlet (k) and the product category (j) we can construct a *price trajectory* $P_{jk,t}$, that is a sequence of price quotes for a specific product belonging to a product category in a specific outlet over time. A *price spell* is defined as the sequence of price quotes (for a specific product in a specific outlet) with the same price.

For the calculation of the descriptive statistics all price quotes are converted into prices per unit in order to account for package changes and temporary quantity promotions. The prices around the cash changeover to the euro have been converted into common currency to make them comparable over the cash changeover.

Concerning the price changes associated with promotions or (seasonal) sales we decided to follow a dual approach: In the baseline version of the results we treat promotions and sales as regular price changes which terminate a price spell. However, it can be argued that these price changes merely reflect noise in the price

[4] Tobacco products, cars, daily newspapers and mobile phone fees were not included in our data set for confidentiality reasons by Statistics Austria. After some data manipulations and exclusions the coverage of our data set reduces to about 80% of the total Austrian CPI. A detailed description of some data issues and manipulations that are required prior to the statistical analysis can be found in Annex I. There we discuss the temporal unavailability of price observations, imputed prices, outliers, aggregate products, the revision of the CPI goods basket in January 2000, sales, product replacements, product weights and censoring of price spells.

setting process and are not due to changes in fundamental price determining factors (as e.g. monetary policy and business cycle developments) and therefore they should be ignored from the viewpoint of monetary policy analysis. Therefore, we also provide an alternative set of results in section 3 without taking into account the price changes induced by temporary promotions and sales.

3. Methodology and Descriptive Empirical Results

3.1 The Frequency of Price Changes and the Duration of Price Spells

As measures to assess the degree of price rigidity or flexibility at the micro level we use the average frequency of all price changes and the implied duration of price spells. For each product category *j*, the frequency of price changes (F_j) is computed as the ratio of observed price changes to all valid price records.[5] Thus, the measure F_j is an average incorporating price changes of all firms where the product *j* has been recorded and over all periods of time. The implied duration of price spells could be calculated as the inverse of the frequency of price changes $T = \frac{1}{F}$.

However, for this estimator to be consistent homogenous observations in the cross-sectional dimension are required. Another issue to be considered for the derivation of the implied duration of price spells is the discrete timing of observations: We observe only one price per month and implicitly assume, if we observe a price change, that the price change occurred at the end of the month and the price remained unchanged for the rest of the month. Relaxing this assumption and allowing for continuous timing and assuming that the durations of price spells follow an exponential distribution, the *implied average duration* of price spells can be estimated as

$$T_j^{F,avg} = \frac{-1}{\ln\left(1 - F_j\right)} \tag{1}$$

[5] Here the frequency of price changes (F) is computed directly from the data and the duration of price spells (T) is derived indirectly from the frequency. Alternatively, the duration of price spells could be calculated directly from the price trajectories and the frequency could be derived implicitly. We decided to use the first approach (which could be called "frequency approach") because it uses the maximum amount of information possible, implying that it can be used even if the observation period is very short and if specific events, such as the revision of the CPI basket or the euro cash changeover, need to be excluded from the analysis. In addition, it does not require an explicit treatment of the censoring of price spells. For a robustness check we also calculated the frequencies and durations following an alternative method ("duration approach"). The results, which are included in the working paper version of this paper, are quite similar (see Baumgartner et al., (2005)).

and the *implied median duration* as

$$T_j^{F,med} = \frac{\ln(0.5)}{\ln(1-F_j)}. \tag{2}$$

These expressions are unbiased estimates of the mean and median duration of price spells in continuous time under the assumption of a constant hazard rate within a month (see Baudry et al., (2004), and Bils and Klenow, (2004)). In tables 1 and 2 the results aggregated on the COICOP[6] and product type level are presented.

Price rigidity varies considerably: On average, 15% of all prices are changed every month, which implies an average (median) duration of price spells of 14 (11) months (see table 1). Unprocessed food and energy products display a rather high frequency of price changes (24% and 40%) and thus a short implied duration (6.5 and 8.3 months, respectively). Within these categories seasonal food products and fuels of different types show the highest frequency of price changes.[7] Due to the continuous time assumption to derive formula (1) and (2), for these products the implied durations are smaller than one month, although the observation frequency is monthly. However, this is not unreasonable since fuel prices are indeed changed with a very high frequency – sometimes even on a daily basis. In contrast, some service items as well as products with administered prices display a (very) low frequency of price changes and, on average, a duration which is almost three times as long as for unprocessed food. For example, banking, parking and postal fees show an estimated average duration of 50 months or longer.

The patterns of price adjustment in Austria across product groups are consistent with those found for other European countries. Also for the aggregate, the duration of price spells and the frequency of price changes are similar to the other countries as they are close to the average of all euro area countries considered (see Dhyne et al., (2005)).

If we analyze price increases and decreases separately, we realize that prices increase slightly more often than they decrease: the frequency of price increases is 8.2% compared to 6.6% for price decreases. Exceptions from this pattern can be found in the category communication (especially personal computers), where price decreases appear much more frequent than price increases.

[6] COICOP stands for "Classification Of Individual COnsumption by Purpose" (see Statistics Austria, (2001B)).

[7] Results on individual products are available from the authors upon request.

Table 1: Frequency of Price Changes by COICOP Classification and Product Type (Weighted Average of the Entire CPI Basket)

	Frequency of price changes	Average duration of price spells	Median duration of price spells	Frequency of price increases	Frequency of price decreases	Average price increase	Average price decrease
By COICOP							
COICOP 01: Food and non-alcoholic beverages	17,3%	7,9	7,9	9,1%	7,9%	16,9%	18,7%
COICOP 02: Alcoholic beverages and tobacco	14,6%	6,5	5,9	7,4%	7,0%	14,6%	14,9%
COICOP 03: Clothing and footwear	12,0%	9,4	7,9	6,4%	5,0%	23,1%	33,7%
COICOP 04: Housing, water, gas and electricity	11,2%	14,7	11,3	6,9%	4,0%	6,6%	8,7%
COICOP 05: Furnishing & maintenance of housing	6,9%	17,8	16,0	4,1%	2,5%	9,3%	13,6%
COICOP 06: Health care expenses	5,6%	18,8	19,7	4,4%	1,1%	4,0%	6,7%
COICOP 07: Transport	36,5%	11,2	9,6	18,8%	17,7%	8,3%	8,8%
COICOP 08: Communications	8,9%	16,0	10,5	1,8%	6,9%	15,5%	26,0%
COICOP 09: Leisure and culture	24,2%	15,8	11,2	12,3%	11,2%	11,1%	12,3%
COICOP 10: Education	4,5%	23,2	20,2	4,1%	0,4%	4,9%	0,5%
COICOP 11: Hotels, cafés and restaurants	8,3%	19,3	21,3	5,4%	2,6%	7,3%	8,4%
COICOP 12: Miscellaneous goods and services	7,1%	18,7	15,2	4,9%	2,0%	7,6%	11,4%
By Product type							
Unprocessed food	24,0%	6,5	7,5	12,6%	11,1%	19,6%	22,0%
Processed food	12,8%	8,5	7,9	6,8%	5,8%	14,8%	16,1%
Energy	40,1%	8,3	4,8	20,7%	19,3%	5,1%	4,4%
Non energy industrial goods	10,2%	13,7	11,5	5,4%	4,3%	13,2%	18,6%
Services	12,6%	19,4	18,5	7,4%	5,0%	8,1%	10,9%
Total	15,1%	14,1	11,1	8,2%	6,6%	11,4%	14,7%

Frequency: Average proportion of prices changes per month, in % - Duration: in months.
Sample period: January 1996 – December 2003.

Concerning the size of price changes, price increases and decreases appear to be quite sizeable when they occur. The average price increase is 11% whereas prices are reduced on average by 15%. Especially for clothing and footwear (due to seasonal sales) and again for communication and electronic items (personal computers) price decreases are very pronounced.

As has been mentioned before, the results on the frequencies of price changes and the implied duration of price spells are also computed *without sales and promotions*. Corresponding results are shown in table 2. For all product groups the frequencies of price changes have to be smaller (or equal) compared to the figures in table 1. It also turns out that the average size of price changes is smaller without sales and promotions reflecting the fact that price cuts due to seasonal sales especially in the clothing sector are usually quite sizeable. As expected, these effects are most pronounced for food and alcoholic beverages where temporary promotions are a common practice to attract new customers, as well as for clothing and footwear where end of season sales are usual to clear inventories. For the latter category the average price decrease (in absolute terms) is almost 15 percentage points lower if sales are disregarded.

3.2 The Frequency and Magnitude of Price Changes over Time

When looking at the frequency of price changes over time we can see that there is a clear seasonal pattern visible in chart 1: The spikes in January 1998, 1999, 2001, 2002 and 2003 indicate that most prices are changed in January.[8] Starting with the year 2000 price changes have been more frequent than before which coincides with higher aggregate inflation in the period 2000–2003 than in the period 1996–1999. However, one must bear in mind that from 2000 on a new CPI basket forms the basis of our data set.

Apart from this shift in 2000, there is no trend in the frequency of price changes visible over the period considered. Furthermore, price increases and decreases show a marked seasonal pattern and their frequencies appear to be closely related.

We have calculated not only the frequency of price changes but also the size of the price changes for each period in time. Chart 2 plots the weighted average of the absolute size of all price changes as well as the magnitudes of price increases and decreases over time. The graph reveals a strong seasonal pattern especially for price decreases: These appear to be more pronounced in January and February as well as in July and August which reflects end-of-season sales usually taking place in that period of the year.

[8] Note that price changes in January 2000 have been excluded from the analysis (see Annex 1).

Table 2: Frequency of Price Changes by COICOP Classification and Product Type (Weighted Average of the entire CPI basket – without Sales and Promotions)

	Frequency of price changes	Average duration of price spells	Median duration of price spells	Frequency of price increases	Frequency of price decreases	Average price increase	Average price decrease
By COICOP							
COICOP 01: Food and non-alcoholic beverages	11,3%	13,0	13,9	6,1%	4,8%	12,3%	13,3%
COICOP 02: Alcoholic beverages and tobacco	8,0%	12,1	11,9	4,1%	3,6%	10,3%	10,0%
COICOP 03: Clothing and footwear	8,5%	12,5	11,1	4,7%	2,9%	16,3%	19,2%
COICOP 04: Housing, water, gas and electricity	10,5%	15,2	11,3	6,6%	3,7%	6,5%	8,5%
COICOP 05: Furnishing & maintenance of housing	5,9%	19,5	17,1	3,5%	2,0%	7,8%	11,1%
COICOP 06: Health care expenses	5,5%	19,1	19,7	4,4%	1,0%	4,0%	6,9%
COICOP 07: Transport	34,4%	11,5	10,4	17,7%	16,6%	8,2%	8,5%
COICOP 08: Communications	8,1%	16,4	10,5	1,5%	6,5%	21,4%	26,2%
COICOP 09: Leisure and culture	21,3%	17,2	11,7	10,8%	9,7%	10,7%	11,6%
COICOP 10: Education	4,5%	23,2	20,4	4,0%	0,4%	4,9%	0,5%
COICOP 11: Hotels, cafés and restaurants	7,7%	19,7	21,9	5,1%	2,3%	7,3%	7,8%
COICOP 12: Miscellaneous goods and services	6,4%	21,1	15,5	4,6%	1,7%	6,5%	8,7%
By Product type							
Unprocessed food	17,4%	10,6	12,5	9,2%	7,7%	15,0%	16,4%
Processed food	7,1%	14,3	14,0	4,0%	2,8%	10,4%	10,8%
Energy	37,9%	8,6	5,5	19,6%	18,2%	5,1%	4,5%
Non energy industrial goods	8,4%	15,7	13,7	4,5%	3,2%	10,6%	13,5%
Services	11,6%	20,2	19,3	6,9%	4,5%	8,2%	10,5%
Total	12,8%	16,1	14,0	7,0%	5,3%	9,6%	11,5%

Frequency: average proportion of prices changes per month, in % - Duration: in months.
Sample period: January 1996 – December 2003.

Consequently, also price increases display a seasonal pattern as the price decreases due to sales are usually reversed in the following period implying higher price increases in March and September, but this pattern appears to be less clear-cut than that of price decreases. The most striking observation from the figure is the decrease in the size of price changes in the second half of 2001 reaching a low of less than 10% in January 2002 and increasing again thereafter. This development is clearly attributable to the euro cash changeover which obviously induced many small price changes when prices had to be converted from the old to the new currency. In addition, the size of price increases and the size of price decreases turned out to be roughly equal in January 2002 which is in contrast to the seasonal regularity of larger decreases than increases normally observed in January. Disregarding the smaller than average price changes in 2001 and 2002, there is no upward or downward trend visible in the development of the size of price changes in chart 2 with the average magnitude of price changes fluctuating around 15% most of the time.

Taking together, the evidence for the frequency and the size of price changes in charts 1 and 2 we find that in the period surrounding the cash changeover (from about mid 2001 to mid 2002) consumer prices were adjusted more frequently but by smaller amounts than in other times. In addition, price adjustment with respect to both the frequency and the size of price changes was quite symmetric during the cash changeover period. This implies that our dataset – to the extent that it is representative for the total CPI – does neither suggest a sizeable positive nor negative impact of the cash changeover on aggregate inflation.

3.3 Synchronization of Price Changes

For each product the *synchronization of price changes* ($SYNC_j$) is measured by the index proposed by Fisher and Konieczny (2000) which is given as the ratio of the empirical standard deviation of the frequency of price changes for product category j to the theoretical maximum standard deviation in the case of perfect synchronization of price changes

$$SYNC_j = \frac{\sqrt{\frac{1}{\tau - 1}\sum_{t=2}^{\tau}\left(F_{jt} - F_j\right)^2}}{\sqrt{F_j\left(1 - F_j\right)}} \tag{3}$$

where τ is the total number of periods for which the ratio is calculated. Perfect synchronization of price changes occurs when either all stores change their price at the same time or none of them changes a price. Consequently, synchronization of price changes is high if the synchronization ratio is close to 1 and low if it is near 0. Separate synchronization ratios for price increases and decreases are also computed.

Chart 1: Frequency of Price Changes over Time, Weighted Average (in %), and Aggregate Inflation (Right Axis)

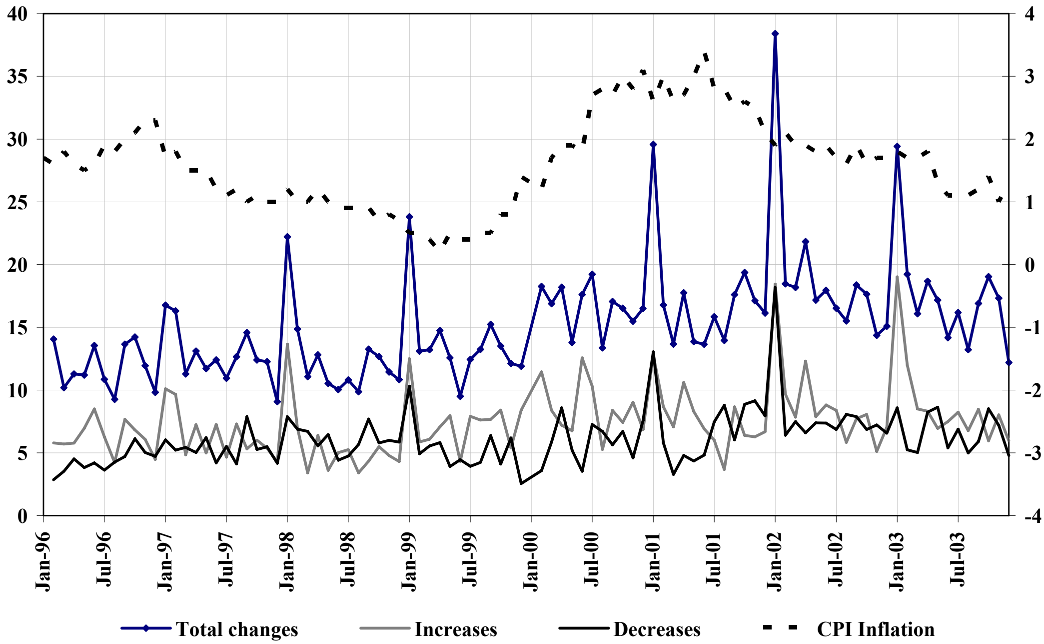
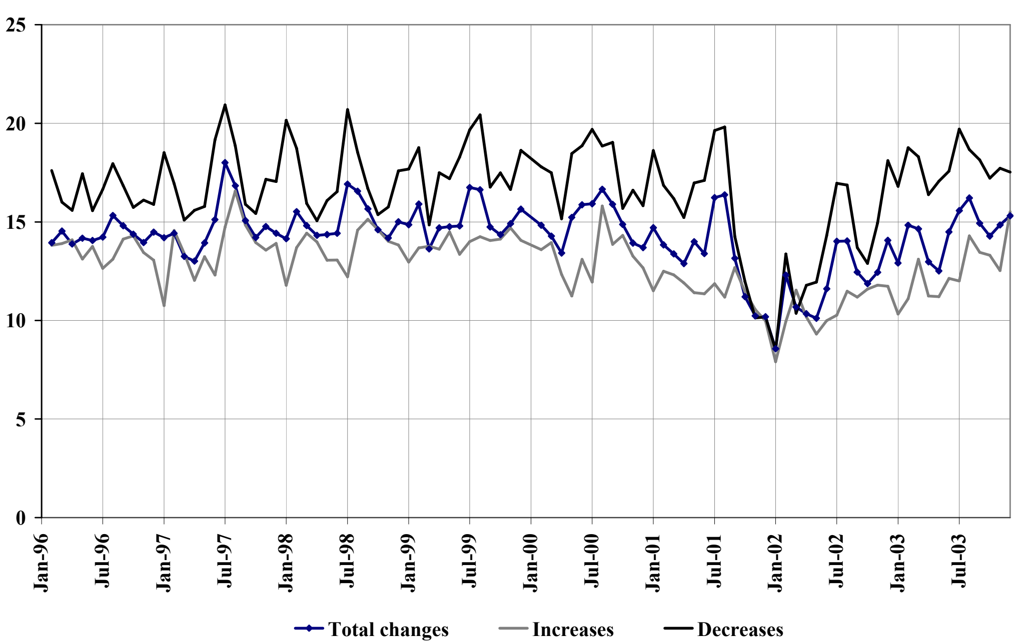


Chart 2: Size of Price Changes Over Time, Weighted Average (in %)



The results in table 3 show that the average synchronization ratio of price changes for all products amounts to 42% which constitutes an intermediary degree of price synchronization. However, this number masks the substantial heterogeneity across sectors and products: There is a wide range from 20% for alcoholic beverages to 87 and 94% for health care and communication items, respectively. Prices in education and health care are regulated to a large extent, and in most cases these changes are price increases.[9]For food items the synchronization ratios are also very low, with an average of 21%. Furthermore, we observe that the synchronization ratio is generally higher for price increases than for decreases. This could reflect price changes that are triggered mainly by supply shocks, as the observed asymmetry is especially pronounced for energy products.

With the exception of alcoholic beverages and clothing and footwear the results calculated without the price changes induced by sales and promotions are very similar. As expected, for these products the exclusion of promotions and seasonal sales results in a synchronization ratio for price decreases which is considerably lower (by 4 and 7 percentage points, respectively) compared to the results including sales and promotions.

4. The Probability of Price Changes

As is shown in the previous section price setting is very heterogeneous among products and also within a product group. To gain further insight in the determination of the frequency of price changes we present estimates of hazard functions and regression results of a panel logit model for the probability of a price change. For similar studies for other euro area countries see Álvarez and Hernando (2004) for Spain, Baudry et al., (2004) and Fougère et al. (2004) for France, Aucremanne and Dhyne (2004B) for Belgium, Dias et al. (2005) for Portugal and Jonker et al. (2004) for the Netherlands.

[9] The synchronization ratios for price increases and decreases are based on calculations without accounting for product replacements because price changes cannot seriously be divided into price increases and decreases in this case. As a consequence, the value for all changes (with replacements) need not necessarily lie within the range given by ratios for increases and decreases for each product category.

Table 3: Synchronisation Ratios by COICOP Classification and Product Type (Weighted Average of the Entire CPI Basket)

	Synchronisation ratio of price changes		Synchronisation ratio of price increases		Synchronisation ratio of price decreases	
By COICOP	all prices	without sales	all prices	without sales	all prices	without sales
COICOP 01: Food and non-alcoholic beverages	21,1%	21,8%	21,2%	22,6%	19,9%	19,5%
COICOP 02: Alcoholic beverages and tobacco	20,3%	22,2%	16,6%	18,1%	23,5%	27,3%
COICOP 03: Clothing and footwear	26,0%	26,5%	18,9%	17,4%	22,8%	15,9%
COICOP 04: Housing, water, gas and electricity	53,6%	53,7%	58,3%	58,6%	39,9%	39,1%
COICOP 05: Furnishing & maintenance of housing	27,7%	28,3%	25,5%	25,8%	21,2%	21,4%
COICOP 06: Health care expenses	86,7%	86,4%	84,0%	83,6%	54,6%	55,2%
COICOP 07: Transport	51,4%	52,0%	54,9%	54,5%	56,5%	56,8%
COICOP 08: Communications	93,8%	93,9%	85,3%	79,8%	91,7%	91,8%
COICOP 09: Leisure and culture	51,1%	49,3%	51,3%	49,9%	42,9%	41,4%
COICOP 10: Education	80,8%	80,7%	81,7%	81,6%	44,7%	44,7%
COICOP 11: Hotels, cafés and restaurants	30,9%	31,0%	29,0%	28,9%	25,4%	25,2%
COICOP 12: Miscellaneous goods and services	50,1%	50,3%	47,6%	47,8%	36,5%	36,2%
By Product type						
Unprocessed food	20,5%	20,9%	22,7%	23,8%	22,4%	21,0%
Processed food	21,3%	22,4%	19,6%	21,2%	18,9%	19,8%
Energy	51,6%	51,9%	62,7%	62,7%	49,1%	47,9%
Non energy industrial goods	34,2%	34,6%	30,8%	30,4%	28,3%	26,6%
Services	58,6%	58,1%	55,8%	54,6%	45,4%	44,9%
Total	41,9%	42,0%	40,4%	40,0%	34,2%	33,2%

Sample period: January 1996 – December 2003.

4.1 Kaplan-Meier Estimates of Survivor and Hazard Functions

In the following, we present Kaplan-Meier estimates of the survivor and hazard functions for all products and separately for product groups. Particular emphasis is given to the question how the weighting of spell observations influences the results. The Kaplan-Meier estimator is a non-parametric estimate of the survivor function *S(t)*, the probability of "survival" of a price spell until time *t*. For a dataset with observed spell lengths $t_1,\ldots,t_k$ where *k* is the number of distinct failure times (time until a price change) observed in the data, the Kaplan-Meier estimate at any time *t* is given by

$$\hat{S}(t) = \prod_{j|t_j \le t} \left(\frac{n_j - d_j}{n_j} \right) \tag{4}$$

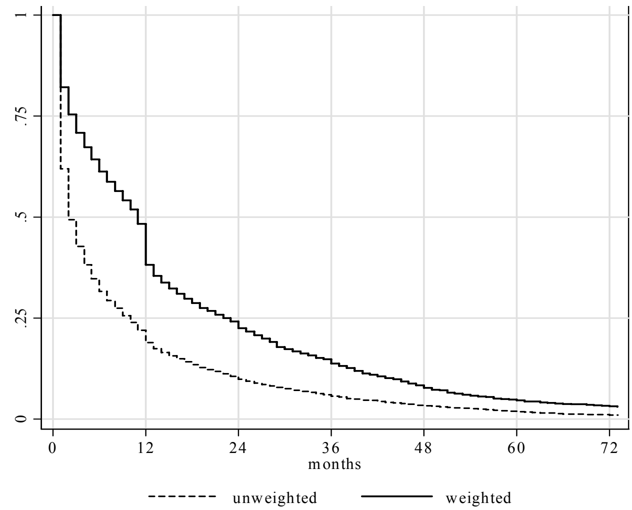
where n_j is the number of price spells "at risk" of exhibiting a price change at time t_j and d_j is the number of price changes at time t_j. The product is calculated over all observed spell durations less than or equal to *t* (see, for example, Cleves et al., 2002). The interpretation of the survivor function is as follows: For each analysis time *t*, the step function gives the fraction of price spells which have durations of *t* months or more.

Chart 3 shows two versions the Kaplan-Meier estimate of the survivor function for all price spells of all elementary products in our data. The dashed line is the "unweighted" survivor function whereas the solid line is "weighted" in a sense that will be explained in a moment. Note that the dashed line in chart 3 decreases very quickly during the first months which means that most price spells have a low duration.

The survivor function shown by the dashed line gives equal weight to each price spell. This implies that its shape is dominated by elementary products exhibiting a high number of spells, i. e. which have short durations.

Table 4 gives values for quantiles (25^{th} percentile, the median and 75^{th} percentile of the spell durations, respectively) for COICOP categories and product types separately. The table also shows the number of spells per category and compares the share of spells to the weights in the CPI baskets. Both classifications indicate clearly that COICOP food items have a much higher share of spells (59%) than indicated by their CPI weight (17%). Non-energy industrial goods and services, on the other hand, contribute a comparably small share of spells but much higher CPI weights.

Chart 3: Aggregate Survivor Function



Dias et al. (2005) show formally how the relatively higher share of spells of product categories with higher frequencies of price changes creates a bias when estimating the duration of price spells. They suggest, as one way to solve this problem, to use only a fixed number of spells per product category. As the authors note themselves such a sampling scheme does not use all the available information and will hence not be efficient. As an alternative, we apply a weighting scheme where (1) each product category is weighted with the inverse of the total number of price spells for that product category which ensures that each product category has the same weight in the results; (2) in addition, we attach to each product category its CPI weight. This is the basis for our "weighted" Kaplan-Meier estimates of survivor and hazard functions. Adjustment (1) makes a big difference because the enormous weight of food products is reduced whereas step (2) changes the picture not very much.

The solid line in chart 3 shows the survivor function where each spell was re-weighted as described. Compared to the previous version this new survivor function is shifted upwards. Moreover, it has a marked drop at a duration of twelve months which indicates that prices that change every year are an important phenomenon. Table 4 shows that the unweighted median duration over all spells is merely 2 months which is mainly due to the short duration of food item price spells. The weighted median over all products categories is 11 months which is approximately the same result as obtained by the frequency approach in section 3. According to the weighted survivor function, for almost half of all products (adjusted for different CPI weights), prices are adjusted at a frequency of less than once a year.

The hazard rate based on the Kaplan-Meier estimator is displayed in chart 4.[10]Panel (a) represents the unweighted version. As expected, its overall shape is decreasing with time. But it also displays peaks, for example at durations of 12, 24, and 36 months, respectively which suggests that a substantial portion of firms change their prices at fixed intervals. Unconditional aggregate hazards which are decreasing with analysis time are a typical result of duration studies on micro CPI data (see Fougère et al., (2005), Álvarez et al., (2004) and Dhyne et al., (2005)). At first sight, this result is puzzling in the light of price-setting theories, as it could be interpreted that a firm will have a lower probability to change its price the longer it has been kept unchanged.

However, there are several explanations for the decreasing shape of the hazard function. All focus on the heterogeneity of price setters or products. Apparently, a major reason for the decreasing hazard function is the oversampling problem described above, namely that product categories with a high frequency of price changes and thus a higher number of spells wrongly suggest that the probability of a price change is highest after 1, 2, or 3 months (such as in panel (a) of the figure). Panel (b), however, shows that after re-weighting the likelihood of a price change is highest 12 months after the last price change.

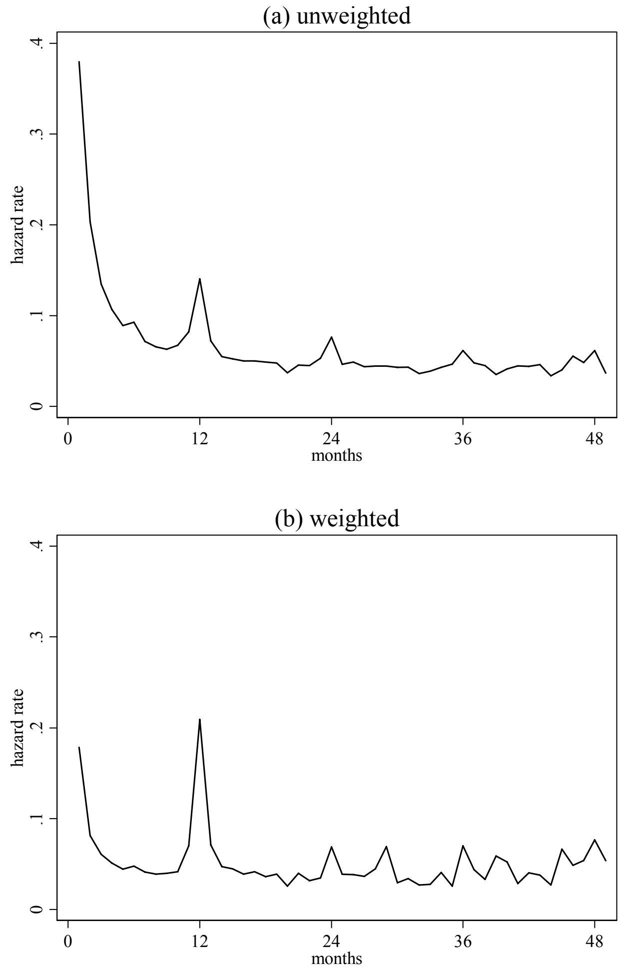
[10] The hazard rate is estimated as d_j / n_j, i. e. the rate at which spells are completed after duration t.

Table 4: Spell Durations – Kaplan-Meier Estimates (Weighted and Unweigthed)

	no. of spells (completed or right-censored)	share of spells	share of product categories	Average CPI weight	unweighted			weighted		
					25p	median	75p	25p	median	75p
By COICOP										
COICOP 01: Food and non-alcoholic beverages	214.650	58,6%	20,7%	16,9%	1	2	5	1	3	10
COICOP 02: Alcoholic beverages and tobacco	12.000	3,3%	1,7%	1,7%	1	3	9	1	3	9
COICOP 03: Clothing and footwear	26.049	7,1%	8,9%	9,2%	2	7	24	4	10	29
COICOP 04: Housing, water, gas and electricity	10.005	2,7%	6,4%	12,6%	1	2	7	4	11	20
COICOP 05: Furnishing & maintenance of housing	17.019	4,6%	11,7%	11,4%	3	9	22	6	12	32
COICOP 06: Health care expenses	1.478	0,4%	4,1%	3,3%	9	12	24	12	12	26
COICOP 07: Transport	34.283	9,4%	9,7%	9,9%	1	1	10	1	5	13
COICOP 08: Communications	462	0,1%	2,5%	3,5%	2	4	11	10	11	n. def.
COICOP 09: Leisure and culture	18.234	5,0%	15,2%	13,0%	1	5	18	2	10	28
COICOP 10: Education	299	0,1%	1,7%	0,7%	12	12	24	12	12	24
COICOP 11: Hotels, cafés and restaurants	16.819	4,6%	6,1%	8,7%	2	8	22	7	15	29
COICOP 12: Miscellaneous goods and services	15.043	4,1%	11,3%	9,1%	3	11	19	11	12	24
By Product type										
Unprocessed food	140.953	38,5%	9,4%	7,1%	1	2	3	1	2	7
Processed food	85.697	23,4%	13,0%	11,6%	1	3	10	1	4	12
Energy	29.348	8,0%	2,8%	9,4%	1	1	2	1	2	9
Non energy industrial goods	68.768	18,8%	41,5%	37,0%	2	8	20	4	12	25
Services	41.575	11,4%	33,3%	34,9%	3	11	22	8	12	28
Total	366.102	100,0%	100,0%	100,0%	1	2	10	3	11	22

Note: Left-censored spells and spells with gaps have been dropped.

Chart 4: Aggregate Unconditional Hazard Function

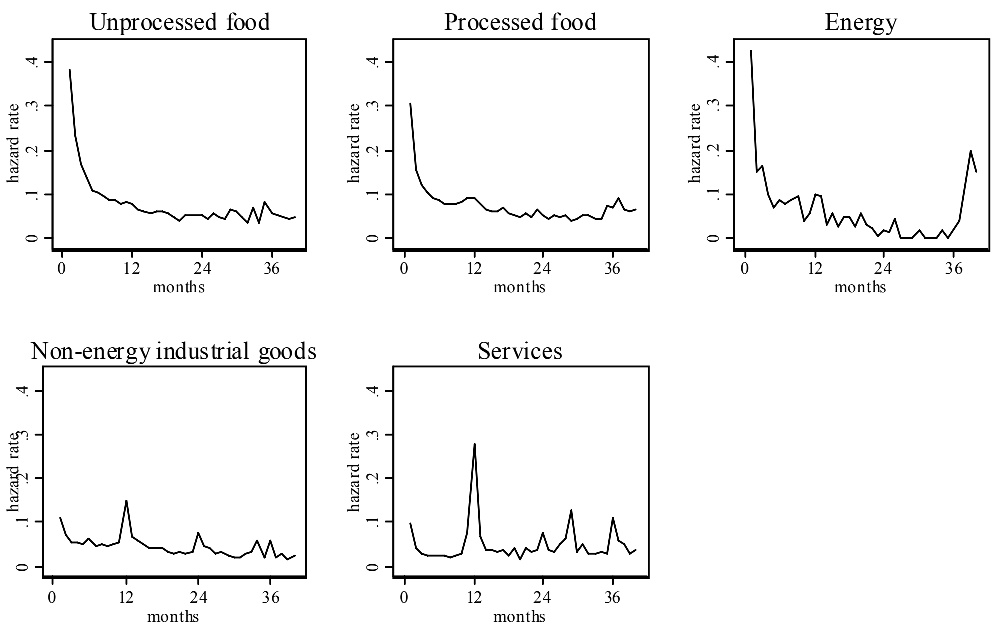


An additional reason for downward sloping hazard functions comes from aggregating firms with different (time-dependent) price-setting behavior. As Álvarez et al. (2004) point out, the aggregation of different types of time dependent price setters almost always leads to a decreasing aggregate hazard function. Another related rationale for falling hazards is that the CPI is the result of the aggregation of heterogeneous products: For some products, prices are adjusted infrequently (e. g. services) whereas for others many price changes are observed (e. g. energy). Even if there is no oversampling of products categories, the hazard function may still be decreasing. For example, Dias et al. (2005) and Fougère et al.

(2005) only use one spell per product in the estimation of hazard functions, but in both cases the hazard functions are still declining.

Hazard rate estimates for different product groups (chart 5) show some interesting patterns: For example, for services the hazard is highest when the duration is approximately 1 year. The corresponding hazard function also displays noticeable spikes at 24, 36, and 48, months, respectively. Energy items, on the other hand, have a very high hazard when the spell duration is low. Non-energy industrial goods have high probabilities of price changes both at short durations and after one year whereas, for both unprocessed and processed food, the hazard rates are highest at short durations.

Chart 5: Aggregate Hazard Functions by Procuct Type



Weighted estimates (see text).

4.2 Logit Estimates

In order to control for unobserved characteristics of individual units (i) we estimate a panel logit model with fixed elementary product effects, where an elementary product is the combination of the product category (j) and the outlet code (k), taking into account product and store replacements (see Annex I.2). The cross-section dimension (j*k) is indexed by (i). This allows us to control for the fact that within the same product category firm A can adjust its price more or less frequently than firm B. For the estimation all left-censored price spells (as well as spells with gaps) are excluded because some explanatory variables like the duration of a price spell and the accumulated inflation for a product category since the last price change are not defined when the starting date of the spell is unknown.

As in Cecchetti (1986) and Aucremanne and Dhyne (2004B), we specify the following fixed effects conditional logit model.[11] The dependent variable is binary indicating the occurrence of a price change *next month* (or at the end of the current period t, Y_{it}=1),

$$\Pr(Y_{it} = 1 \mid \mathbf{x}_{it}) = F(\boldsymbol{\beta}'\mathbf{x}_{it} + \alpha_i) \tag{5}$$

with

$$\begin{aligned}\boldsymbol{\beta}'\mathbf{x}_{it} = {} & \beta_0 + \beta_1 * TAU_{it} + \beta_2 * INF\_ACC\_J_{it} + \beta_3 * ATTR_{it} + \beta_4 * LDW_{it} \\ & + \beta_5 * LSIZE\_UP_{it} + \beta_6 * LSIZE\_DW_{it} + \sum\nolimits_{h=1}^{5} \beta_{6+h} * DURh_{it} \\ & + \sum\nolimits_{h=1}^{2} \beta_{11+h} * EUROh_{it} + \sum\nolimits_{h=1}^{11} \beta_{13+h} * MONTH\_h_{it} \\ & + \sum\nolimits_{h=2}^{7} \beta_{23+h} * YEAR\_h_{it} + \beta_{31} * DUM\_12\_99_{it} + \beta_{32} * DUM\_00\_03_{it}\end{aligned} \tag{6}$$

and i = 1,...,N is the cross-section dimension (the number of elementary products), t = 1,...,T_i is the time-series dimension, α_i are the fixed effects and F represents the cumulative logistic distribution function

$$F(z) = \frac{\exp(z)}{1 - \exp(z)}. \tag{7}$$

As explanatory variables we included several state and time dependent variables described below. The duration of price spells (TAU) gained a lot of attention in related studies, as the sign of its coefficient reflects the panel data estimate of the direct time effect which was described by the hazard functions in the previous section. We argued there that the downward sloping hazard functions are a consequence of aggregating over (very) heterogeneous products. After controlling for unobserved heterogeneity with a fixed effects model we therefore expect a positive sign for the coefficient of the duration of price spells.

As another state dependent explanatory variable we included the absolute value of the accumulated sectoral rate of inflation for the product category (j) to which the elementary product (i) belongs (INF_ACC_J). For each elementary product at time (t) the sectoral inflation rate is accumulated over the period since its last price change. This variable is a proxy for the relative price position of outlet (k) selling product (j) to the average of all other outlets selling a product of the same category. Therefore, if the accumulated inflation increases, on average the competitors already increased their prices, whereas outlet (k) held its price unchanged, which

[11] See Baltagi (2001, chapter 11) for a discussion of the properties of panel logit models.

puts it in a better position to increase its price without losing customers. Consequently, for this variable our expectation is also a positive coefficient.

We consider the impact of common commercial practices (as psychological pricing, sales and promotions) on the price-setting behavior by including dummy variables reflecting that a price was set in attractive terms[12] (ATTR) and the direction of the last price change (LDW = 1, if the last price change was a price decrease), respectively. For attractive prices we expect a dampening effect on the probability of a price change, i. e. a negative sign for this coefficient. If the last price change was a price reduction a reversion of this action with the next price adjustment becomes more likely therefore a positive sign for the coefficient of LDW is expected.

In addition, two variables reflecting the impact of the magnitude of a price change, defined as the absolute value of the last price change (LSIZE), are included: LSIZE_UP (defined as LSIZE*(1-LDW)) contains the size of price increases and LSIZE_DW (defined as LSIZE*LDW) measures the size of price reductions. If the last price change was a large price increase we expect that more time will elapse till the next price change, so the coefficient for LSIZE_UP should be negative. For a large price decrease, usually due to a promotion or a sale, we expect that this action is soon reversed, which should increase the probability of the occurrence of a price change in the next period, i. e. the coefficient of LSIZE_DW should be positive.

The hazard functions in charts 4 and 5 highlight the fact that there are local modes at specific durations, noteworthy 1, 6, 12, 24 and 36 months. We interpret this fact as some kind of truncated Calvo or Taylor pricing behavior and try to capture this with a set of dummy variables (DUR_*h*).

Two variables capture the effects of the euro cash changeover: one dummy for the direct effect in January 2002 (EURO1), and a second defined over the period 6 months before and 5 months after the month of the changeover in January 2002 (EURO2). In addition, several indicator variables for time dependent aspects as the seasonal pattern (monthly dummies MONTH_*h*) and yearly dummies (YEAR_*h*) to control for structural and/or cyclical economic effects not captured by other variables are included. To control for effects due to the revision of the CPI basket

[12] Attractive prices are defined for ranges of prices in order to take account of different attractive prices at different price levels: (i) from 0 to 10 ATS (Austrian Schilling) all prices ending at x.00, x.50 and x.90, (ii) from 10 to 100 ATS all prices ending at xx0.00, xx5.00 and xx.90, (iii) from 100 to 1,000 ATS prices ending at xx0.00, xx5.00 and xx9.00 and xxx.90 ATS and (iv) exceeding 1,000 ATS all 10, 100, 1,000 multiples of the prices in the previous range have been defined as attractive. If this definition is met, ATTR = 1, otherwise ATTR = 0. An equivalent rule has been defined to identify attractive prices in euro after the cash changeover.

in January 2000 dummy variables are included (DUM_12_99 = 1 in December 1999 and DUM_00_03 = 1 for the period January 2000 to November 2003).[13]

The estimation results are reported in table 5. We present the estimated marginal effects (slope) defined as the first derivatives of the probability function with respect to the explanatory variables, evaluated at the mean of the variables ($\overline{X}$) and its significance levels (p-value). The reference probability is a price change in January 1996.

The probability of a price change slightly increases the longer a price quote has been unchanged. An increase in the duration of a price spell (TAU) by one month increases the probability of a price change by roughly 0.6 percentage points. We interpret this result as evidence that, after controlling for unobserved heterogeneity at the elementary product level, (slightly) increasing hazard rates are obtained through a direct duration impact.

In addition, there is an indirect duration effect working through the role of the accumulated inflation variable as the sign of the coefficient for the accumulated inflation (INF_ACC) is positive as one would expect, i. e. the probability of a price change increases as inflation in the same product category rises. An increase in the accumulated monthly rate of inflation (of the same product category) by 1 percentage point increases the probability for a price change by 0.3 percentage points.

Attractive prices (ATTR) reduce the probability to change prices and the opposite is true for the dummy indicating that the last price change was a price reduction (LDW). Both results are in line with commercial practices, especially with promotions and seasonal sales. The size of the last price increase (LSIZE_UP) has no effect on the probability of a price change, where as the probability of a price change is higher the larger the last price decrease (LSIZE_DW) was: if the last price decrease was (in absolute terms) 1 (10) percentage points larger the probability of a price change to occur next period is 0.4 (4) percentage points higher. This finding is consistent with the practice of promotions and sales, as large temporal price reductions are usually quickly reversed by (large) price increases.

[13] In addition to the variables discussed, we experimented with other state dependent variables as the industrial production index, the aggregate consumer price index (both variables included either as month-on-month or year-on-year rates of change) and a tax variable. But none of these variables showed any significant effect.

Table 5: Probability of Price Change – Conditional Fixed Effects Logit Model

	Slope	p value	$\overline{X}$
TAU	0.006	0.00	8.26
INF_ACC_J	0.003	0.00	1.08
ATTR	-0.047	0.00	0.64
LDW	0.063	0.00	0.35
LSIZE_UP	0.000	0.82	8.83
LSIZE_DW	0.004	0.00	5.49
DUR1	0.110	0.00	0.20
DUR6	0.019	0.00	0.05
DUR12	0.225	0.00	0.02
DUR24	0.136	0.00	0.01
DUR36	0.094	0.00	0.00
EURO1	0.215	0.00	0.01
EURO2	0.036	0.00	0.14
MONTH_1	-0.056	0.00	0.08
MONTH_2	-0.105	0.00	0.08
MONTH_3	-0.076	0.00	0.08
MONTH_4	-0.107	0.00	0.08
MONTH_5	-0.109	0.00	0.08
MONTH_6	-0.105	0.00	0.09
MONTH_7	-0.135	0.00	0.09
MONTH_8	-0.078	0.00	0.09
MONTH_9	-0.099	0.00	0.09
MONTH_10	-0.100	0.00	0.09
MONTH_11	-0.150	0.00	0.09
YEAR_2	-0.042	0.00	0.10
YEAR_3	-0.065	0.00	0.13
YEAR_4	-0.090	0.00	0.13
YEAR_5	-0.019	0.00	0.13
YEAR_6	0.002	0.40	0.14
YEAR_7	0.014	0.00	0.16
D_12_99	0.058	0.00	0.01
D_00_03	-0.070	0.00	0.58

Dependent variable: Y = 1 if a price change occurs in the next month
No. of observations: 1,579,553 LR (*b*=0, p-value)= 0.000, log likelihood = -470,488
No. of groups: 44,192 elementary products, LR (pooling, p-value) = 0.000
Slope: dy/dx at the mean of the explanatory variable
Reference: January 1996 (MONTH_12, YEAR_1)

Concerning the time-dependent and Taylortype phenomena mentioned above, our logit estimates reinforce this evidence: especially for the duration of 12 months and to a lesser extent for durations of 1 month, 2 and 3 years we find a higher probability of a price change. For the euro cash changeover the time dummies are indicating a higher probability of a price change in January 2002 (EURO1), and less so in the 6 months before and 5 months after the month of the euro introduction as a physical means of payment (EURO2).

There is a strong seasonal pattern in the price-setting process. The probability that prices change next month is highest in December (the reference month) as the coefficients for all monthly dummies are negative and highly significant. Aucremanne and Dyhne (2004A,B), Baudry et al. (2004), Jonker et al. (2004), Dias et al. (2004) report similar results for other euro area countries. Furthermore, the seasonal dummies are also jointly highly significant, further indicating the importance of time-dependent elements in the price-setting process.

The establishment of a new CPI basket in January 2000 and the thereby introduced new definitions and reporting practices had a significant impact on the probability of a price change. It resulted in an almost 6 percentage points higher price change probability in January 2000 (D_12_99) whereas for the whole period January 2000 to December 2003 (D_12_99 + D_00_03) this probability was 1.2 percentage points lower compared to the first four years in the sample.[14]

To summarize: although some time dependent aspects can be observed in the data, our evidence does not support pure time dependent representations of the price-setting process (as Calvo, truncated Calvo or Taylor contracts) at the micro CPI level, as some of the state dependent variables have a significant effect on the probability of a price change.

5. Conclusions

In this paper we analyze the patterns and determinants of price rigidity present in the individual price quotes collected to compute the Austrian CPI. We calculated estimates for the average frequency of price changes and the duration of price spells for 639 product categories.

We find that consumer prices change quite infrequently in Austria. The weighted average (median) duration of price spells for all products is 14 (11) months. The sectoral heterogeneity is quite pronounced: Prices for services, health care and education change rarely, typically approximately once per year. For the product types food, energy (transport) and communication prices are adjusted on average every 6 to 8 months. Promotions and sales have a considerable impact on

[14] One has also to take into account that the effects due to different business cycle conditions as well as the average annual rate of inflation are captured by the yearly dummies.

the frequency of price adjustments for food, clothing and footwear, where temporal promotions and end-of-season sales are a common practice. With respect to the synchronization of price changes a similar sectoral pattern occurs as for the durations of price spells: The prices of products with a longer duration are also adjusted in a more synchronous way.

Price increases occur slightly more often than price decreases. Price increases and decreases are quite sizeable when they occur: on average, prices increase by 11% whereas prices are reduced on average by 15%. Especially for clothing and footwear (due to seasonal sales) and for communication and electronic items price decreases are very pronounced (34% and 26%, respectively).

Like in similar studies, we find that the aggregate hazard function for all price spells is decreasing with time (i.e. the duration of a price spell) which would be at odds with most price-setting theories. However, this is to a large extent a consequence of aggregating over product types with different spell durations. A re-weighted version of the hazard function which ensures that each product category basically has the same weight (and adjusted for CPI weights) is not monotonously decreasing, but has its most marked spike at a duration of 1 year which indicates that for a substantial proportion of all goods infrequent price adjustment occurs. Using Kaplan-Meier estimates of hazard functions, we show that there is substantial heterogeneity across goods and product types: Energy and unprocessed food show high hazards during the first months. For services, on the other hand, the hazard is highest after one year.

In contrast to other European studies, we find a positive and significant effect of the duration of a price spell on the probability of a price change if we account for unobserved heterogeneity in a panel logit model with fixed elementary product effects. We observe also a positive link between the probability of a price change and the accumulated inflation at the product level. Additionally, we find a pronounced seasonal pattern and a negative impact on the probability to change a price if it is currently set as an attractive price. During the period associated with the euro cash changeover the probability to change prices was higher.

Although some time dependent aspects have a significant impact on the probability of a price change, our evidence does not support pure time dependent representations of the price-setting process at the outlet level, as some of the state dependent variables also show a significant influence on the probability to observe a price change.

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Annex: Data Issues

1. Imputations, Exclusions, Outlier Adjustment and Revision of the CPI Goods Basket

In the case of temporal unavailability of a price quote the price has been imputed with the previous price quote for at most one month. Filling the (one-month) gaps of missing observations mitigates the problem induced by censored price spells (see next sub-section). In case the price quote was unavailable for more than one month it has not been imputed, because the chance of missing an unobserved price change becomes more and more likely with the duration of missing observations.

On the other hand, individual prices quotes which were imputed by the statistical office due to temporal and seasonal unavailability of an item were excluded from our data set, however with the disadvantage of creating additional censored spells. We do not regard them as true price observations but as "pseudo observations", which unintentionally would introduce an upward bias in the estimation of the duration of price spells.

Some products which display systematically unrealistic price movements were removed as outliers from the data set mainly on a judgmental basis. The nature of these products as outliers was reflected by the fact that they all displayed *average* price increases or decreases of more than 60%, some of them considerably more (according to the log price difference, $\ln\left(P_{jk,t}\right)-\ln\left(P_{jk,t-1}\right)$). On this basis, 14 products (e.g. kindergarten fees, public swimming pool, refuse collection, public transport day ticket) have been excluded representing a weight of 1.4% in the total CPI. In addition, very large individual price changes exceeding a pre-defined threshold value have been identified as outliers and disregarded in the analysis. We applied a combined rule specifying an absolute value for the log price change and a distribution dependent upper and lower bound as the threshold for outliers. Specifically, all individual price changes with $\left|\ln\left(P_{jk,t}\right)-\ln\left(P_{jk,t-1}\right)\right| \geq 1$ as well as those exceeding the upper and lower quartile of the distribution of price changes plus 3 times the interquartile range have been defined as outliers. This rule turned out to be a rather conservative way of outlier detection such that only a few observations had to be excluded.

In addition, based on information from Statistics Austria, 14 products whose price quotes already contain aggregated information have been removed for the purpose of our analysis as they do not represent price quotes on the micro level (e.g. rents and operating costs for houses are derived from the microcensus of Austrian households, and a few medical services are obtained from the social insurance institution). After the exclusion of these products together with the outlier products, individual price quotes for 639 product categories are included in our data consisting of a total of 1,888 product varieties and 49,766 combinations of product categories (j) and outlet codes (k), covering 80% of the Austrian CPI.

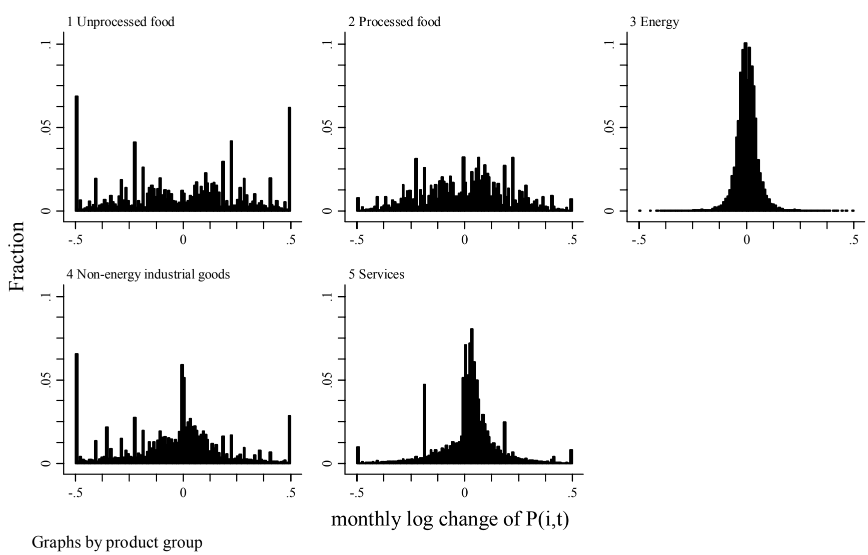
The chart shows the price change distribution where observations of zero price changes (which would produce very large spikes of 70% or more) were dropped. The five histograms differ considerably: Goods in the unprocessed food and processed food categories have a comparably large dispersion of price changes with especially unprocessed food items being characterized by many large price changes. A similar observation can be made for non-energy industrial goods.

Services and energy goods have a much smaller variance of price changes. The distribution for energy is almost symmetric, whereas for services it is markedly skewed towards positive price changes.

With the introduction of a *revised goods basket* for the CPI data collection in January 2000 (see Statistics Austria, 2000A, 2000B, 2001B), definitions and reporting practices were changed for many products. This makes a comparison of prices reported in December 1999 and January 2000 unfeasible for many products. As a consequence, all price changes from December 1999 to January 2000 have been disregarded in the computation of the descriptive statistics, given the large number of products affected by the revision of the Austrian CPI basket. In the econometric analysis in section 4 these price changes have not been excluded but have been accounted for by a dummy variable.

As regards the panel structure of the data, the most common case is that the records span the full period from January 1996 to December 2003 (46.1% of all combinations of product categories and outlets). Because our data contain two CPI baskets, many such combinations show up only from Jan. 1996 to Dec. 1999 (1996 CPI basket; 10.8% of all products-outlet combinations) or from Jan. 2000 to Dec. 2003 (2000 CPI basket, 14.1% of all combinations). Other patterns (including price trajectories with gaps) account for the rest.

Chart : Price Change Distribution within Product Groups



Note: Price changes with absolute values of more than 0.5 were replaced by -0.5 and +0.5, respectively. Bin width 0.01. 374,143 total observations (zero values are excluded).

2. Sales, Censoring, Product Replacement and Weighting

The information in our data set allows us to identify observations that are flagged as sales. In order to exclude price changes induced by flagged sales from our analysis, we replaced all flagged sales prices with the last regular price, i.e. the price before the sale or promotion started. As the reporting of sales and promotions is generally up to the interviewer and therefore cannot be expected to be complete and consistent across all products, we additionally tried to identify also those temporary price promotions which have not been coded as sales. We define "unflagged" temporary promotions and sales as a price sequence $P_{jk,t-1}$, $P_{jk,t}$, $P_{jk,t+1}$, where $P_{jk,t-1} = P_{jk,t+1}$, and $P_{jk,t-1} \neq P_{jk,t}$, i.e. price changes that are reversed in the following period. As in the case of flagged sales, the price changes induced by unflagged promotions and sales have been excluded from the analysis by replacing all identified prices ($P_{jk,t}$) with the preceding regular prices ($P_{jk,t-1}$).[15]

At the beginning and at the end of the sample period all price trajectories are *censored*, as we do not know the true starting date of the first price spell and the ending date of the last price spell. A price spell is left (right)-censored if the date of the beginning (end) of the spell is not observed, and double-censored if both the start and the end date of the spell are unknown. Censoring entails a downward bias in the estimation of the duration of price spells, as longer spells are more likely to be censored.

The products underlying the price observations are sometimes *replaced* in the database by others for two reasons: When a product is no longer available in a particular outlet (attrition), it is usually replaced by another product of the same product category which terminates the price spell (and the trajectory). However, products are sometimes also replaced due to the sampling strategy, e.g. when Statistics Austria defines another elementary product to be more representative for the product category. Unfortunately, we have no information on the nature of the product replacements, in particular not if they are forced or voluntary. According to Statistics Austria, the major part of product replacements in our database are forced replacements due to attrition, therefore we count the end of each price spell associated with a product replacement as a price change.

For the estimation of the hazard functions and the panel logit regression in section 4 left-censoring constitutes a serious problem as the starting date of the spell is not defined. For each elementary product, the first observed price spell is

[15] Flagged and unflagged sales and promotions are a quite common feature in the data, in particular in the food and clothing sectors. Overall, about 4% of all prices in our data set are flagged as sales prices while the share of prices identified as unflagged sales and promotions amounts to about 1.5% of the total number of observations. The effect of excluding all price changes that are due to (flagged and unflagged) sales and promotions can be assessed by comparing the results in tables 4 and 5 (see section 3.1).

left-censored because we cannot know for how long the price has been unchanged. For the same reason every spell after a product replacement is also regarded as left-censored. This comes close to "stock sampling" which constitutes a sample selection problem. A way to overcome this bias is to omit all left-censored spells from the estimation. Then only those spells are considered where we know exactly when the spell started. This is also called "flow sampling" and does not constitute a selection problem if at least one price change for every elementary product is observed (see Dias et al., (2005)). After dropping left-censored spells, we are left with a dataset that consists of 42,832 product-outlet combinations, contributing to 366,102 price spells or 1,879,929 monthly price observations.

Product-outlet combinations, however, are not identical to "elementary products" as defined in section 2 because they do not consider product and store replacements which occur quite often. For the panel logit regressions below we construct a subject variable which should correspond closely to the definition of an elementary product over time: In any case where a product or a store replacement is observed we change the identifier of the product-outlet combination. This results in 72,892 elementary products which is considerably higher than 42,832, the number of different product-outlet combinations.

In order to compute aggregate measures of the statistics described in section 3 and for the weighted hazard rates in section 4, we applied the same *weighting scheme* that is used to calculate the CPI. As these weights are not defined at the individual store level, we use an unweighted average over price records within a product category. All statistics at the elementary products level are then aggregated to 12 COICOP groups and 5 product types based on the CPI weights. As our data set spans over two goods baskets (1996, 2000) and the products included do not completely coincide, the average weights of the two weighting schemes are used, with a weight of zero at times when an elementary product was not included in the respective CPI basket. The individual weights which initially do not sum to one as not 100% of the CPI is covered in our sample, are then rescaled such that the sum of the weights equals 1 and the relative weights among the goods are preserved.

For a more in-depth discussion of some of the data issues the reader is referred to the working paper version of this paper (Baumgartner et al., (2005)) downloadable from the ECB homepage www.ecb.int.