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PATTERNS AND DETERMINANTS OF PRICE CHANGES: ANALYSING INDIVIDUAL CONSUMER PRICES IN AUSTRIA

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Abstract

We provide empirical evidence on the degree and characteristics of price rigidity in Austria by estimating the average frequency of price changes and the duration of price spells from a large data set of individual price records collected for the computation of the Austrian CPI. On average, prices in Austria are unchanged for about 11 months. We find strong heterogeneity across sectors and products. Price increases occur only slightly more often than price decreases. For both directions the typical size of the weighted average price change is quite large (11% and 14%, respectively). Accounting for the unobserved heterogeneity in estimating the probability of a price change with a panel logit model, 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 the product-specific inflation, the size and the sign of the last price change and the period of the euro cash changeover significantly affect the probability of a price change.

JEL classification: C41, D21, E31, L11

Keywords: Consumer prices, sticky prices, frequency and size of price changes, duration of price spells.

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1. Introduction

The principles of price setting are at the heart of macroeconomic modelling. The empirical evidence indicates that prices only react with a certain delay to changing economic conditions. Most macroeconomic models assume sluggish price and/or wage adjustment which inter alia generates real effects of monetary policy in the short run. More generally, the degree of price stickiness determines how long inflation and real economic variables take to return to their initial values after a shock.

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. Although the literature on the microeconomic foundation of price stickiness is vast (see Ball and Mankiw, 1995; Taylor, 1999, for an overview), the empirical evidence on the relevance and patterns of price stickiness is sparse. This is due to the lack of appropriate individual price data and/or to the restrictive stance of statistical offices with respect to the use of their data for academic research.

Several papers have thus confined their analysis of price stickiness to some products or product groups only. They have shown that prices may remain unchanged for many months: Cecchetti (1986), who analyzed 38 U.S. news-stand magazine prices from 1953 to 1979, reported durations of 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) analyses the price-setting behaviour 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 limited number of products such that strong (and implausible) assumptions on the sectoral (or product group) homogeneity are needed for economy wide generalizations to hold.

Bils and Klenow (2004) were the first to use 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 considerably more frequent price changes of consumer prices 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) micro data evidence on frequencies of price changes and the duration of prices based on CPI data is now available. Dhyne et al. (2006) provide a summary of the research efforts in the analysis of individual consumer price data within the IPN.

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 analyse the degree and characteristics of the nominal rigidity present in Austrian consumer prices and trying to identify some factors influencing this rigidity.

We find that the median duration of price spells is 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 durations. We show that – using an appropriate weighting scheme – the aggregate hazard function has its most marked spike at the duration of one year. 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 but significant positive effect of the duration of price spells 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. Section 3 presents descriptive results on the frequency and magnitude of price changes. To further describe and investigate 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.

2. The data

We use a longitudinal micro data set of monthly price quotes collected by Statistics Austria to compute the national index of consumer prices (CPI). We shortly describe the structure of the data and the most important steps in their preparation for the analysis.[1]

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 more than 3.5 million individual price quotes which

[1] A detailed description of some data issues and manipulations which have been carried out prior to the statistical analysis can be found in the appendix. These issues are the temporal unavailability of price observations, imputed prices, outliers, aggregate products, the revision of the CPI goods basket in January 2000, product replacements, product weights and censoring of price spells.

cover roughly 90% of the total Austrian CPI expenditure weights.[2] 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. potatoes, milk, gasoline, light bulbs, and parking fees). Our dataset includes a total of 639 such products categories.

With the information on the date *i*, 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. We shall call such a product-outlet combination *elementary product.* A *price spell* is defined as the sequence of price quotes (for a specific elementary product) 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. Concerning the price changes associated with promotions or (seasonal) sales we decided to treat promotions and sales as regular price changes.[3]

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 divided by all valid price records.[4] Thus, the measure F_j is an average incorporating price

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[2] 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 weight.

[3] However, it can be argued that these price changes merely reflect noise in the price 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. In the working paper version (Baumgartner et al., 2005) we also report the results without taking into account the price changes induced by temporary promotions and sales.

[4] 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 ("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

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 median duration* of price spells can be estimated as

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

This expression is an unbiased estimate of the 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 Table 1 the results on the frequency, duration and size of price changes aggregated at the COICOP[5] and product type[6] levels are reported. The results for each aggregate are weighted by the CPI expenditure shares.

Price rigidity varies considerably: On average, 15% of all prices are changed every month, which implies a median duration of price spells of 11 months. Unprocessed food and energy products display a rather high frequency of price changes (24% and 40%) and thus a short implied duration (7.5 and 4.8 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), for these products the implied durations are smaller than one month. However, this is not unreasonable since fuel prices are indeed changed with a very high frequency – sometimes even daily. In contrast, some service items display a (very) low frequency of price changes and, on average, a duration which is almost three times as long as for unprocessed food.

approach"). The results, which are included in the working paper version of this paper, are quite similar (see Baumgartner et al., 2005).

5 COICOP denotes "Classification Of Individual COnsumption by Purpose" (see Statistics Austria, 2001).

6 The five product types are defined by the ECB to analyse inflation dynamics in the euro area: unprocessed food, processed food, energy, non-energy industrial goods and services.

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	Median duration of price spells	Frequency of		Average size of	
			price increases	price decreases	price increases	price decreases
By COICOP						
COICOP 01: Food and non-alcoholic beverages	17.3%	7.9	9.1%	7.9%	16.9%	18.7%
COICOP 02: Alcoholic beverages and tobacco	14.6%	5.9	7.4%	7.0%	14.6%	14.9%
COICOP 03: Clothing and footwear	12.0%	7.9	6.4%	5.0%	23.0%	33.7%
COICOP 04: Housing, water, gas and electricity	11.2%	11.3	6.9%	4.0%	6.6%	8.7%
COICOP 05: Furnishing & maintenance of housing	6.9%	16.0	4.1%	2.5%	9.3%	13.6%
COICOP 06: Health care expenses	5.6%	19.7	4.4%	1.1%	4.0%	6.8%
COICOP 07: Transport	34.0%	9.9	17.6%	16.4%	9.6%	8.6%
COICOP 08: Communications	8.9%	10.5	2.6%	6.1%	15.5%	13.2%
COICOP 09: Leisure and culture	23.8%	11.3	12.2%	11.0%	11.1%	12.1%
COICOP 10: Education	4.5%	20.2	4.1%	0.4%	4.8%	0.5%
COICOP 11: Hotels, cafés and restaurants	8.3%	21.3	5.4%	2.6%	7.3%	8.4%
COICOP 12: Miscellaneous goods and services	7.4%	13.6	5.2%	2.0%	7.0%	10.3%
By Product type						
Unprocessed food	24.1%	7.5	12.6%	11.1%	19.6%	22.0%
Processed food	12.8%	7.9	6.8%	5.8%	14.8%	16.1%
Energy	40.1%	4.8	20.7%	19.3%	5.1%	4.4%
Non energy industrial goods	10.2%	11.5	5.4%	4.3%	13.2%	18.6%
Services	12.3%	18.5	7.5%	4.6%	8.4%	9.3%
Market-based services	*16.9%*	*15.5*	*10.0%*	*6.7%*	*7.7%*	*10.1%*
Services subject to regulation	*5.2%*	*22.2*	*3.6%*	*1.5%*	*9.4%*	*7.8%*
Total	15.0%	11.3	8.2%	6.4%	11.4%	14.1%

Notes: Frequency: average proportion of price changes per month, in percent - Duration: in months. Sample period: January 1996 - December 2003.

Within the group of services there is a strong difference between services whose prices are determined by market forces and services that are subject to some form of regulation.[8] The sub-group of market-based services (e.g. services in the tourism sector) shows an above-average frequency of price changes of 17%, whereas the services which are regulated by public authorities (e.g. educational services, public fees) are characterized by a rather low frequency of price changes of 5%.

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., 2006).

If we analyse price increases and decreases separately (columns 3 and 4 in Table 1), we realise that prices increase slightly more often than they decrease: the frequency of price increases is 8.2% compared to 6.4% for price decreases. Exceptions from this pattern can be found in the category

communication (especially personal computers), where price decreases occur much more frequently than price increases. Concerning the size of price changes (last two columns of the table), 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 14%. Especially for clothing and footwear (due to seasonal sales) and again for communication and electronic items (personal computers) price decreases are very pronounced.[9]

3.2 The frequency and magnitude of price changes over time

Figure 1 shows the weighted average of the frequency of price changes computed for each period in time which is characterized by a clear seasonal pattern: The spikes in January 1998, 1999, 2001, 2002 and 2003 indicate that most prices are changed in January.[10] In addition, 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, it has also to be borne in mind that from 2000 on our data set is based on a new CPI basket.

[8] The information which service items are subject to regulation has been provided by Statistics Austria.

[9] When disregarding all price changes induced by *sales and temporary promotions*, the frequencies of price changes are smaller or equal than the numbers in Table 1 for all product groups. 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. These effects are most pronounced for food and alcoholic beverages where temporary promotions are very common, as well as for clothing and footwear where end of season sales are introduced to clear inventories.

[10] Note that price changes in January 2000 have been excluded from the analysis (see the appendix).

Figure 1: Monthly frequency of price changes over time, weighted average (in %), and aggregate inflation (right axis)

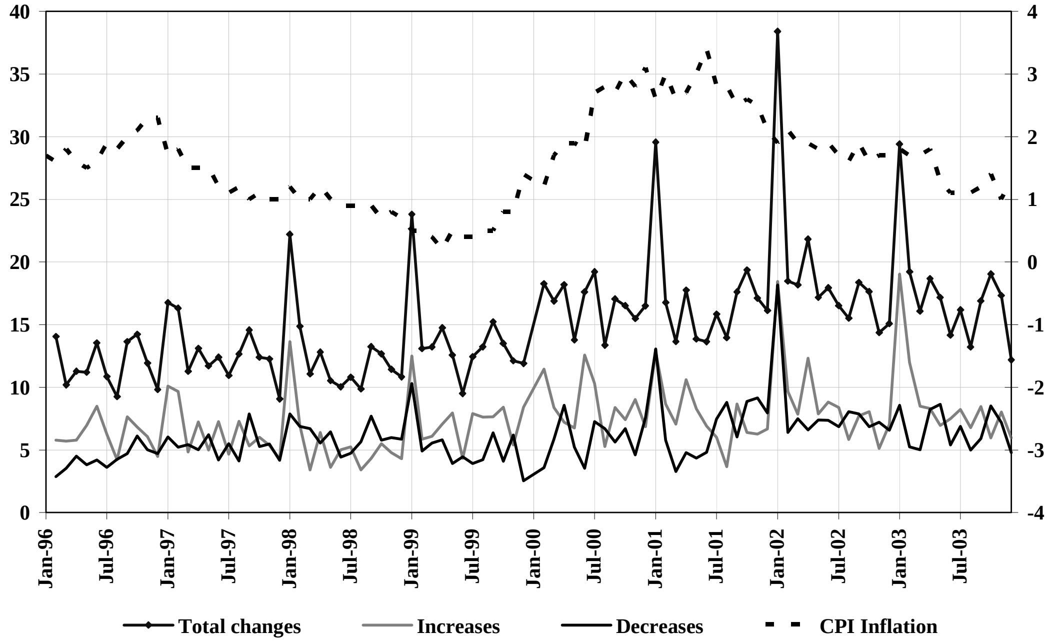
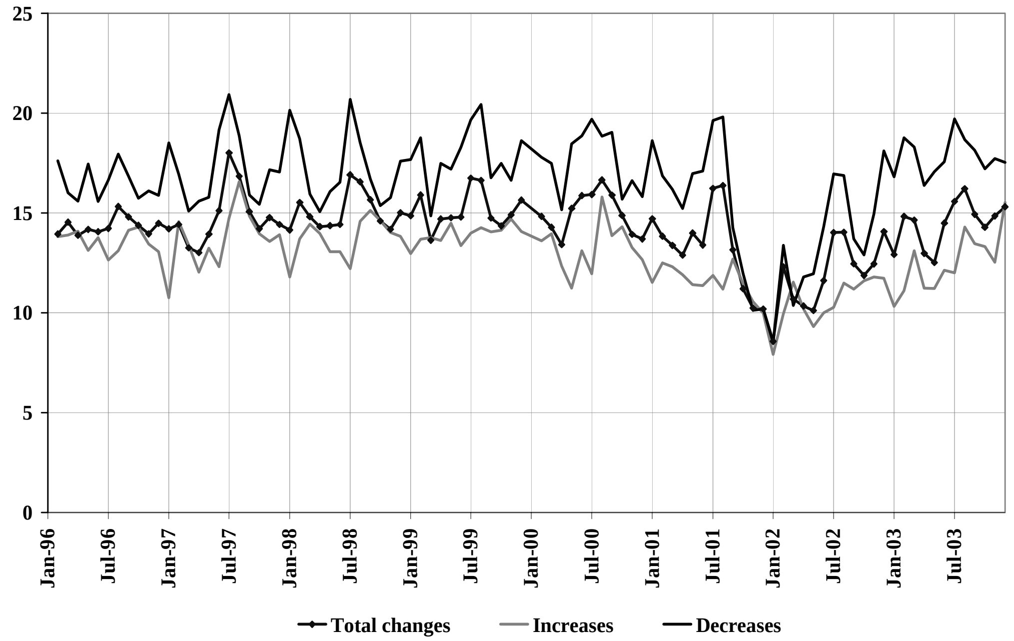


Figure 2: Size of price changes over time, weighted average (in %)



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.

Figure 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 are 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. 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 attributable to the euro cash changeover which induced many small price changes when prices had to be converted to the new currency.

In addition, the size of price increases and the size of price decreases in January 2002 turned out to be roughly equal 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 Figure 2 with the average magnitude of price changes fluctuating around 15% most of the time.

Taken together the evidence for the frequency and the size of price changes in Figures 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.

4. The probability of price changes

As shown in the previous section price setting is very heterogeneous across products and also within product groups. 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 these analyses, we use only price spells which are either completed or right-censored, i. e. we drop all observations of price spells which are left-censored because the hazard functions and certain variables in the regression are not defined for left-censored spells.

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

$$\hat{S}(t) = \prod_{j \mid t_j \leq t} \left(\frac{n_j - d_j}{n_j} \right) \tag{2}$$

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*. For each analysis time *t*, the survivor function gives the fraction of price spells which have durations of *t* months or more.

Figure 3 shows two versions of the estimated 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 below. Note that the dashed line in Figure 3 decreases very quickly during the first months which means that most price spells have a short 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.

Figure 3: Aggregate survivor function (weighted and unweighted)

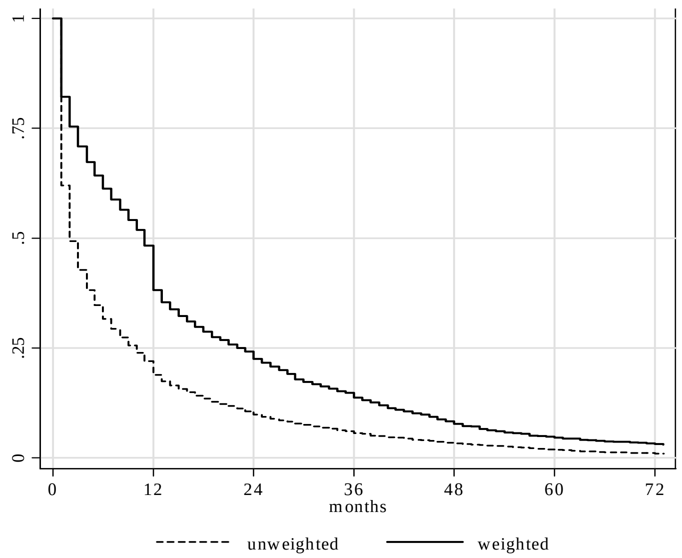


Table 2 indicates the number of spells per category and compares the share of spells to the weights in the CPI baskets. Food items have a much higher share of spells than indicated by their CPI weight. Non-energy industrial goods and services, on the other hand, contribute to a comparably small share of spells but have much higher CPI weights.

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 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, first, 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. Second, we attach to each product category its CPI weight. This is the basis for our "weighted" Kaplan-Meier estimates of survivor and hazard functions.

Table 2: Analysis of spells: number and share of price spells and product weights

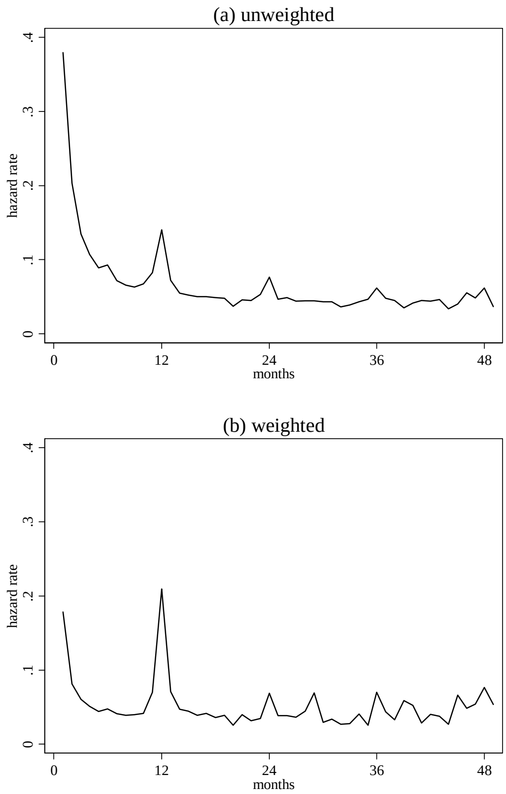
	no. of spells (completed or right-censored)	share of spells	share of product categories	Average CPI weight
By COICOP				
COICOP 01: Food and non-alcoholic beverages	214,650	58.6%	20.7%	16.9%
COICOP 02: Alcoholic beverages and tobacco	12,000	3.3%	1.7%	1.7%
COICOP 03: Clothing and footwear	26,049	7.1%	8.9%	9.2%
COICOP 04: Housing, water, gas and electricity	10,005	2.7%	6.4%	12.6%
COICOP 05: Furnishing & maintenance of housing	17,019	4.6%	11.7%	11.4%
COICOP 06: Health care expenses	1,478	0.4%	4.1%	3.3%
COICOP 07: Transport	34,283	9.4%	9.7%	9.9%
COICOP 08: Communications	462	0.1%	2.5%	3.5%
COICOP 09: Leisure and culture	18,234	5.0%	15.2%	13.0%
COICOP 10: Education	299	0.1%	1.7%	0.7%
COICOP 11: Hotels, cafés and restaurants	16,819	4.6%	6.1%	8.7%
COICOP 12: Miscellaneous goods and services	15,043	4.1%	11.3%	9.1%
By Product type				
Unprocessed food	140,953	38.5%	9.4%	7.1%
Processed food	85,697	23.4%	13.0%	11.6%
Energy	29,348	8.0%	2.8%	9.4%
Non energy industrial goods	68,768	18.8%	41.5%	37.0%
Services	41,575	11.4%	33.3%	34.9%
Total	366,102	100.0%	100.0%	100.0%

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

The solid line in Figure 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. 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 Figure 4.[11] 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 Dhyne et al., 2006). 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.

Figure 4: Aggregate unconditional hazard function



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 overrepresented product categories with a high frequency of price changes and thus a higher

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

number of spells spuriously 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 conditional likelihood of a price change is highest 12 months after the last price change.

An additional reason for downward sloping hazard functions comes from aggregating firms with different price setting behaviour. 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 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.

4.2 Explaining price changes with a conditional fixed effects logit model

4.2.1 Model

In this section we provide evidence on factors which may drive the adjustment of consumer prices in Austria. Cecchetti (1986) provides a price adjustment rule based on a target-threshold model, where the probability of a price change depends on the magnitude of the disequilibrium $\sigma = \log\left(P_t^* / P_t\right)$, where P^* is the short-term optimal price that would be set if price changes where costless and continuous, and P is the actual price. If σ exceeds a threshold h^c, a firm decides to adjust its price as the adjustment gains outweigh the adjustment costs. Cecchetti derives an empirically implementable formulation of this model, where the probability of a price change is related to the time elapsed and the accumulated inflation since the last price change and the size of the last price change.[12] Following Aucremanne and Dhyne (2004) we extend Cecchetti's state-dependent pricing rule by two aspects: first, we disaggregate the empirical specification and estimate the model with individual firm (outlet) level data, and second, we include also several time-dependent variables to capture aspects found in the data and discussed in sections 3 and 4.1.

To control for unobserved characteristics of individual units (i) the extended Cecchetti price adjustment model is formulated as a Chamberlain (1980) 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 2). The cross-

[12] In Cecchetti's model a variable capturing demand conditions (the cumulative change in industry sales) is also included. However, as we do not observe demand conditions at the individual firm or product category level we could not include a demand indicator.

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.

We specify the following fixed effects conditional logit model, where the binary dependent variable indicates the occurrence of a price change (at the end of the current period t, $Y_{it} = 1$),

$$\Pr(Y_{it} = 1 \mid \mathbf{x}_{it}) = \Pr\left(\log\left(\frac{P_{it}^{*}}{P_{it}}\right) \geq h^{c} \mid \mathbf{x}_{it}\right) = F(\boldsymbol{\beta}'\mathbf{x}_{it} + \alpha_i) \tag{3}$$

where $i = 1,...,N$ is the cross-sectional dimension (the number of elementary products), $t = 1,...,T_i$ is the time-series dimension, $\boldsymbol{\beta}$ are coefficients to be estimated, $\mathbf{x}_{it}$ is a vector of covariates described below, α_i are the fixed effects and

F represents the cumulative logistic distribution function

$$F(z) = \frac{\exp(z)}{1 - \exp(z)}. \tag{4}$$

For the estimation all left-censored price spells are excluded because some explanatory variables (like the duration of a price spell and the product-specific accumulated rate of inflation since the last price change) are not defined when the starting date of the spell is unknown. Some of the explanatory variables in $\mathbf{x}_{it}$ can be characterised as either state- or time-dependent.

4.2.2 Explanatory variables

The time elapsed since the last price change (the duration of price spells) 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 that the downward sloping hazard functions are a consequence of aggregating over heterogeneous products. After controlling for unobserved heterogeneity with a fixed effects model, we expect – in line with Cecchetti's model – a positive sign for the coefficient on the duration of price spells.

As another state dependent variable we include the absolute value of the accumulated sectoral rate of inflation for the product category j which the elementary product i belongs to. For each elementary product at time t the sectoral inflation rate is accumulated over the period since its last price change. This variable is an indicator for the relative price position of outlet k selling product j to the average price of all other outlets selling the same product. Therefore, the higher is accumulated inflation, the larger is the deviation of outlet k's price for product j from the average (supposedly optimal) price of product j. Consequently, for this variable we also expect a positive coefficient.

We also consider the impact of common commercial practices (as psychological pricing, sales and promotions) on the price setting behaviour by including dummy variables reflecting that a price was set in attractive terms[13], respectively. For attractive prices we expect a dampening effect on the probability of a price change as a move from one attractive price to a new one is usually associated with larger and less frequent price changes.

The direction of the *previous* price change may contain information about the next price adjustment. A large number of price reductions are due to (short-term) promotions or sales, which are reversed in the consecutive price adjustment. Consequently, if the last price change was a price decrease, it becomes more likely that this price is changed again in the next period and therefore a positive sign for the coefficient of the associated dummy variable is expected. In addition, two variables reflecting the impact of the magnitude of the last price change, defined as the absolute magnitude as well as the interaction of the direction and the magnitude of the last price change, are included. A large previous price change may indicate rather high costs of price adjustment such that more time will elapse until the next price change. In turn, a small previous price change may indicate small adjustment costs, leading to more frequent price changes. Thus, the probability of a price change in the next period should depend negatively on the size of the previous price change. For a large price decrease, usually due to a promotion or a sale, we expect that this action is reversed soon, which should increase the probability of the occurrence of a price change in the next period. Thus, the coefficient for the interaction effect of the size and the direction of the last price change should be positive.

The hazard functions in Figure 4 highlight the fact that there are local modes at specific durations, noteworthy 1, 6, 12, 24 and 36 months. Our interpretation of this fact is that firms also follow some kind of time-dependent price setting rules characterized e. g. by (truncated) Calvo or Taylor pricing behaviour. We try to account for these effects with a set of dummy variables.

Our descriptive evidence in section 3 indicates more frequent price changes around the euro cash changeover. Two dummy variables are included to capture the effects of the cash changeover: one dummy for the month where the changeover actually occurred (price changes in January 2002), and a second dummy variable over the period 6 months before and 5 months after January 2002 (i. e. the dummy is set to 1 for price changes from July to December 2001 and from February to June 2002). In addition, several indicator variables for the seasonal pattern (monthly dummies) and yearly dummies to control for structural and/or cyclical economic effects not captured by other variables are included. To control for the effects of the revision of

[13] 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. An equivalent rule has been defined to identify attractive prices in euro after the cash changeover.

the CPI basket in January 2000 which induced many spurious price changes, a dummy variable capturing all price changes in that month is included in our specification.

4.2.4 Results

The estimation results are reported in Table 3. We present estimated coefficients, marginal effects (slope) defined as the first derivatives of the probability function with respect to the explanatory variables, evaluated at the respective mean of the variables ($\overline{X}$) and significance levels (p-value) for the marginal effects. In order to infer about the sensitivity of our results with respect to the interaction of the elapsed duration of price spells and the time dummies for specific durations (at 1, 6, 12, 24, and 36 months) as well as the interaction of the magnitude and the direction of the previous price changes we present four different specifications of our model where include all these variables in specification (1). The other specifications are either without the magnitude-size interaction of the last price change (2), without the dummies for specific durations (3) or without both (4). We discuss the results for specification (1), which is the most general specification, and only point to major deviations in the results for the other specifications.

As discussed in Ai and Norton (2003) the computation of the magnitude, sign and significance of the marginal effects for interactions terms in non-linear models is quite complicated and is not implemented by most standard software in the correct way.[14] In the context of Chamberlain's fixed effects logit model this problem is even more severe. As a consequence we do not report marginal effects and p-values ("na" in Table 3) for the interaction term of the absolute magnitude and the direction of the previous price change in the specifications (1) and (3).

The probability of a price change increases slightly the longer a price quote has been unchanged. An increase in the elapsed duration of a price spell by one month increases the probability of a price change by roughly 0.5 percentage points. Thus, we find 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 operating through the accumulated inflation variable as the sign of the coefficient for the accumulated sector-specific inflation 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 by 1 percentage point increases the probability for a price change by 0.3 percentage points.

[14] An exception is Stata for which Norton et al. (2004) suggest a program code for ordinary logit and probit models.

Table 3: Explaining the probability of a price change – conditional fixed effects logit regressions

	Specification (1)			Specification (2)			Specification (3)			Specification (4)			Mean
Variable	**Coeff.**	**Slope**	**p-value**	**Coeff.**	**Slope**	**p-value**	**Coeff.**	**Slope**	**p-value**	**Coeff.**	**Slope**	**p-value**	$\overline{\mathbf{X}}$
Elapsed spell duration	0.022	0.005	0.000	0.023	0.006	0.000	0.015	0.003	0.000	0.015	0.003	0.000	8.26
Accumulated product-specific inflation	0.011	0.003	0.000	0.007	0.002	0.000	0.011	0.003	0.000	0.007	0.002	0.000	1.08
Attractive price	-0.194	-0.047	0.000	-0.181	-0.044	0.000	-0.192	-0.044	0.000	-0.177	-0.042	0.000	0.64
Previous price change:													
Absolute magnitude	0.004	0.001	0.893	0.751	0.184	0.000	0.004	0.001	0.886	0.803	0.190	0.000	0.14
Was a price decrease	0.255	0.062	0.000	0.547	0.135	0.000	0.267	0.062	0.000	0.581	0.139	0.000	0.35
Magnitude * decrease	1.685	na	na	–	–	–	1.805	na	na	–	–	–	0.05
Dummies for specific durations:													
1 month	0.442	0.108	0.000	0.455	0.113	0.000	–	–	–	–	–	–	0.20
6 months	0.077	0.019	0.000	0.076	0.019	0.000	–	–	–	–	–	–	0.05
1 year	0.923	0.227	0.000	0.923	0.225	0.000	–	–	–	–	–	–	0.02
2 years	0.544	0.135	0.000	0.545	0.135	0.000	–	–	–	–	–	–	0.01
3 years	0.369	0.091	0.000	0.372	0.093	0.000	–	–	–	–	–	–	0.00
Euro cash changeover:													
Month of changeover (January 2002)	0.786	0.194	0.000	0.786	0.193	0.000	0.812	0.198	0.000	0.813	0.200	0.000	0.01
Time interval around changeover (July-Dec. 2001; Feb.-June 2002)	0.158	0.038	0.000	0.151	0.037	0.000	0.161	0.037	0.000	0.154	0.037	0.000	0.14
Other time controls:													
February	-0.290	-0.068	0.000	-0.287	-0.069	0.000	-0.267	-0.059	0.000	-0.262	-0.060	0.000	0.08
March	-0.504	-0.115	0.000	-0.500	-0.118	0.000	-0.502	-0.106	0.000	-0.497	-0.110	0.000	0.08
April	-0.377	-0.087	0.000	-0.375	-0.089	0.000	-0.395	-0.085	0.000	-0.392	-0.088	0.000	0.08
May	-0.516	-0.117	0.000	-0.514	-0.121	0.000	-0.532	-0.112	0.000	-0.529	-0.117	0.000	0.08
June	-0.522	-0.118	0.000	-0.521	-0.122	0.000	-0.545	-0.115	0.000	-0.543	-0.120	0.000	0.08
July	-0.505	-0.115	0.000	-0.502	-0.118	0.000	-0.532	-0.112	0.000	-0.528	-0.117	0.000	0.09
August	-0.644	-0.143	0.000	-0.633	-0.146	0.000	-0.663	-0.137	0.000	-0.651	-0.141	0.000	0.09
September	-0.390	-0.090	0.000	-0.380	-0.091	0.000	-0.421	-0.090	0.000	-0.410	-0.092	0.000	0.09
October	-0.481	-0.110	0.000	-0.475	-0.112	0.000	-0.495	-0.105	0.000	-0.488	-0.109	0.000	0.09
November	-0.486	-0.111	0.000	-0.483	-0.114	0.000	-0.505	-0.107	0.000	-0.501	-0.111	0.000	0.09
December	-0.712	-0.157	0.000	-0.710	-0.163	0.000	-0.732	-0.149	0.000	-0.729	-0.156	0.000	0.09
1997	-0.253	-0.059	0.000	-0.258	-0.062	0.000	-0.284	-0.062	0.000	-0.291	-0.067	0.000	0.10
1998	-0.395	-0.091	0.000	-0.400	-0.095	0.000	-0.423	-0.091	0.000	-0.429	-0.097	0.000	0.13
1999	-0.424	-0.098	0.000	-0.429	-0.102	0.000	-0.451	-0.097	0.000	-0.457	-0.103	0.000	0.13
2000	-0.456	-0.105	0.000	-0.458	-0.109	0.000	-0.480	-0.103	0.000	-0.483	-0.108	0.000	0.12
2001	-0.360	-0.084	0.000	-0.356	-0.085	0.000	-0.381	-0.083	0.000	-0.377	-0.086	0.000	0.14
2002	-0.322	-0.075	0.000	-0.329	-0.079	0.000	-0.352	-0.077	0.000	-0.361	-0.083	0.000	0.16
2003	-0.354	-0.083	0.000	-0.353	-0.085	0.000	-0.372	-0.081	0.000	-0.372	-0.085	0.000	0.16
Month of CPI goods basket revision (Jan. 2000)	0.172	0.042	0.000	0.168	0.042	0.000	0.193	0.045	0.000	0.191	0.046	0.000	0.01
Log likelihood		-470,365			-471,461			-474,537			-475,800		
LR (β=0, p-value)		0.000			0.000			0.000			0.000		

Notes: Dependent variable: Y = 1 if a price change occurs; Slope: marginal effect dy/dx at the mean of the explanatory variable; Reference: January 1996.
Number of observations: 1,579,553; number of groups: 44,192

If the current price is an attractive price, the probability of a price change is reduced, and the opposite is true for the dummy indicating that the previous price change was a price reduction. Both results are in line with commercial practices, especially with promotions and seasonal sales. The absolute magnitude of the last price change has virtually no effect on the probability of a price change, whereas the probability of a price change is higher the larger the last price decrease was, given that it was a price decrease. This finding is consistent with the practice of promotions and sales, as large temporal price reductions are usually reversed quickly by (large) price increases. The exclusion of the interaction term (specification 2) has only an effect on the coefficients of the magnitude and the direction of the previous price change, respectively, but not on the other variables included. As the log likelihood drops and the (implausible) positive sign of the absolute magnitude of the price change becomes significant it seems that the interaction term is of importance, but as discussed above, we cannot say how strong its effect is on the probability of a price change.

Concerning the time-dependent and Taylor-type phenomena mentioned above, our logit estimates reinforce the evidence of section 4.1: especially for the duration of 12 months and less so for durations of 1 month, 2 and 3 years we find a higher probability of a price change. An exclusion of these duration dummies (specifications 3 and 4) reduces the estimated effect of the elapsed price-spell duration, but it is still positive and significant.

The time dummies for the euro cash changeover indicate (as expected) a higher probability of a price change in January 2002, and also but to a lesser extent in the 12-month period surrounding the introduction of the euro.

There is a strong seasonal pattern in the price setting process. The probability that prices are changed is highest in January as the coefficients for all other monthly dummy variables are negative. Furthermore, the seasonal dummies are also jointly highly significant, further indicating the importance of time-dependent elements in the price setting process.

Finally, the introduction 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 observed in our data. It resulted in an almost 4 percentage points higher price change probability in January 2000.

Summing up, our evidence does not support a pure time dependent representation of the price setting process (as Calvo, truncated Calvo or Taylor contracts) at the micro CPI level, but also indicates strong elements of state-dependence as the elapsed duration and the accumulated inflation have a significant effect on the probability of a price change.

5. Conclusions

In this paper we analyse the patterns and determinants of price rigidity present in the individual price quotes collected to compute the Austrian CPI. We calculate 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 median duration of price spells for all products is 11 months. The sectoral heterogeneity is quite pronounced: Prices for services, health care and education change rarely, typically less than once per year. For the product types food, energy (transport) and communication prices are adjusted on average every 5 to 8 months.

These results have at least two implications for macroeconomic modelling of the Austrian economy. First, the finding that prices are unchanged on average for about one year in Austria provides a guideline for the appropriate calibration of the parameters governing sluggish price adjustment in models with nominal rigidities. Second, the strong heterogeneity in adjustment frequencies across sectors calls for models that takes into account this heterogeneity by modelling two or more sectors (assuming different degrees of price rigidity).

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 by 14%. Especially for clothing and footwear (due to 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 the duration of 1 year which indicates that for a substantial proportion of all goods infrequent price adjustment occurs.

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 at an attractive level. 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 a pure time dependent representation 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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Appendix: Data issues

A.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 price 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, $\ln[P_{jk,t}] - \ln[P_{jk,t-1}]$). 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 $\left|\ln[P_{jk,t}] - \ln[P_{jk,t-1}]\right| \geq 1$ 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 micro census survey of Austrian households, and price indices for a number of 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. Altogether, the data consist of 3,548,010 monthly price observations

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.

Figure A.1 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 products is almost symmetric, whereas for services it is markedly skewed towards positive price changes.

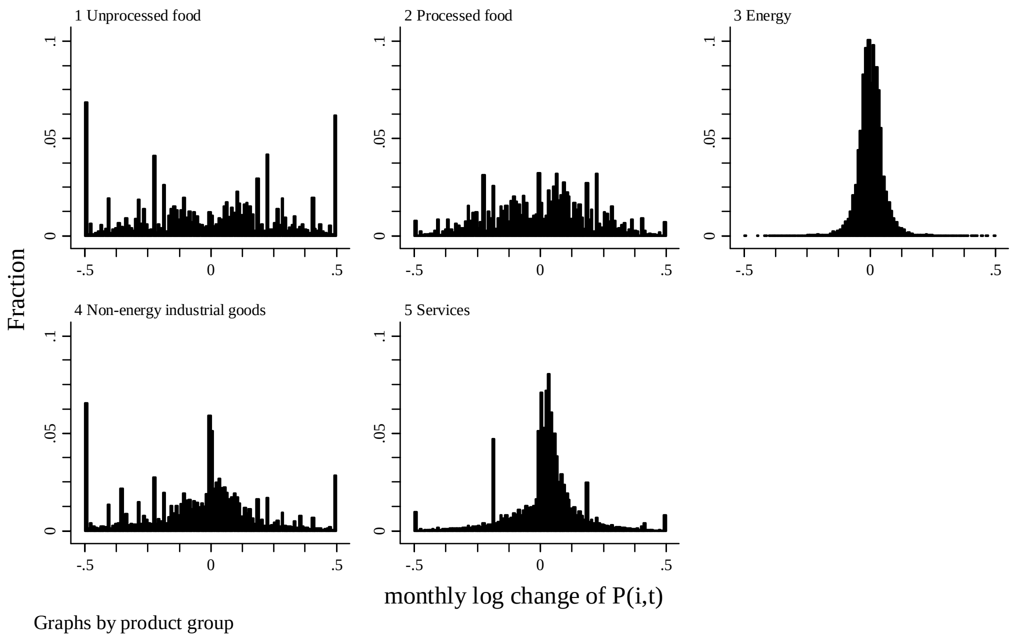
With the introduction of a *revised goods basket* for the CPI data collection in January 2000 (see Statistics Austria, 2001), definitions and reporting practices were changed for many products. This makes a comparison of prices reported in December 1999 and January 2000 unfeasible for many products. 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.

A.2 Censoring, product replacement and weighting

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. However, the frequency approach, which we chose to calculate the descriptive statistics in Section 3, does not require an explicit treatment of censoring as it derives the duration of price spells only indirectly.

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.

Figure A1: 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).

For the estimation of the hazard functions and the panel logit regressions 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 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 equivalent to "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 1 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 further data issues the reader is referred to the working paper version of this paper (Baumgartner et al., 2005).

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