How Frequently Do Consumer Prices Change in Austria?

Evidence from Micro CPI Data [a]

Josef Baumgartner[b], Ernst Glatzer[c], Fabio Rumler[d], Alfred Stiglbauer[e]

1. DRAFT, COMMENTS ARE HIGHLY WELCOME

November 2004

---

[a] We thank Statistics Austria (ST.AT) for providing the data and especially Paul Haschka for valuable information on data properties and data deficiencies.

This study has been conducted in the context of the 'Eurosystem Inflation Persistence Network (IPN)'. We are indebted to the members in this network, especially to IPN – RG2 members, the participants of the Workshop 'Empirical Industrial Organization', held on June 18, 2004 at the Vienna University of Economics and Business Administration, and an internal seminar at the OeNB for valuable comments.

[b] Austrian Institute of Economic Research (WIFO), P.O. Box 91, 1103 Vienna, Austria,+43 1 798 26 0, ext. 230, Josef.Baumgartner@wifo.ac.at. Josef Baumgartner acknowledges the financial support of the 'Jubilaeumsfonds der Oesterreichischen Nationalbank' (Grant no. 10265).

[c] Oesterreichische Nationalbank (OeNB), Otto Wagner Platz 3, P.O. Box 61, 1010 Vienna.

[d] Oesterreichische Nationalbank (OeNB), Otto Wagner Platz 3, P.O. Box 61, 1010 Vienna, +43 1 40420, ext. 7444, Fabio.Rumler@oenb.at.

[e] Oesterreichische Nationalbank (OeNB), Otto Wagner Platz 3, P.O. Box 61, 1010 Vienna, +43 1 40420, ext. 7435, Alfred.Stiglbauer@oenb.at.

How Frequently Do Consumer Prices Change in Austria?

Evidence from Micro CPI Data

Josef Baumgartner, Ernst Glatzer, Fabio Rumler, Alfred Stiglbauer

Summary

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 applied, on average prices are unchanged for 11 to 14 month. We find a strong heterogeneity among 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 percent, respectively). Like others, we find that the aggregate hazard function is decreasing with time. However, breakdowns by product categories show that this is the result of considerable product heterogeneity. We also find that the period of the Euro cash changeover increases the probability of price changes and the hazards of price spells.

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, when assessing the impact of various shocks to 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 an restrictive practice of Statistical agencies with respect to its use 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) analyse 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 for 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 (2002) 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 US than the studies mentioned above. For about half of 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 European 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 are now available.

Dhyne et al. (2004) provide a summary of the research efforts in the analysis of individual consumer price data. [1]

In this paper we examine the frequency of consumer price changes and its counterpart the duration of price spells 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 nominal rigidity present in Austrian consumer prices and trying to explain the factors influencing nominal rigidity.

We find that (depending on the estimation method), the average duration of price spells is 11 to 15 month, but that the duration varies considerably among sectors and products. For various fuel types and seasonal food products the average (median) duration is less than one month, whereas for several services as banking, parking or postal fees it is 50 (34) months and above. Like in similar studies, we find that the aggregate hazard function for all price spells is decreasing with analysis time which is somewhat at odds with theories of firm price-setting behaviour. However, this is the results of aggregating over product types with different spell durations. Using Kaplan-Meier estimates of survivor and hazard functions and Cox regressions, we show that there is substantial heterogeneity across goods and product types. We also find that in the months before and after the Euro cash changeover probabilities of price changes as well as hazards of price spells are higher than in the other periods.

The paper is organized as follows. In Section 2 the data base and data manipulations like imputation of missing observations, outlier detection and correction, and other data issues as e.g. the problem of censored price spells are discussed. The methodology of our analysis and the empirical results which summarize the vast information in the data are presented in Section 3. We compute direct and indirect estimates for the frequency of price changes and its counterpart the duration of price spells. We also address the issue of how synchronous price changes are within product categories. In the further sections the focus is on explaining the stylized facts of Section 3: In Section 4 we run logit regressions, and adopt methods of survival analysis. In the present version of the paper, the analyses in Sections 4 are confined to a common sample of 48 products which can be identified in all the micro CPI data sets used in the corresponding subproject of the IPN. The paper concludes with a summary of the main results.

---

[1] For detailed results on each country see; Aucremanne and Dhyne, (2004A) for Belgium, Dias et al. (2004) for Portugal, Baudry et al. (2004) for France, Alvarez and Hernando (2004) for Spain, Fabiani et al. (2004) for Italy, Jonker et al. (2004) for The Netherlands and Vilmunen and Paloviita (2004) for Finland. For Germany and Luxembourg some empirical results are also available. Ireland and Greece did not participate in this research group (RG 2) of the IPN.

2. Data

2.1 Data set and definitions

For investigating individual price dynamics in Austria, we use a longitudinal micro data set of monthly price quotes collected by Statistics Austria (ST.AT) in order to compute the national index of consumer prices CPI.[2] The sample spans over the time period from January 1996 to December 2003 (96 month) and contains between 33,800 (1996) and 40,700 (2003) elementary price records per month. As can be seen form Table 1, overall around 3.6 million price quotes which cover roughly 90% of the total CPI are included in the *raw data set*. Only the COICOP groups 2 and 7 (alcoholic beverages and tobacco and transport) are underrepresented in our sample. [3] Table 1 also reveals that most observations in our sample can be attributed to the food and clothing sectors (COICOP groups 1 and 3).[4] About 40 percent of the product categories are centrally collected (e.g. regulated services, energy, housing), which account for only 7 percent of the observations in our data set. The main portion of price quotes is collected in a decentralized way in 20 major Austrian cities.

Insert Table 1 around here

Each individual price quote consists of information on the product category, the date, the outlet and the packaging (quantity) of the item (see table 2). As the product category we define the products at the elementary level which are contained in the CPI basket (e.g. milk). The raw dataset contains a total of 668 products categories. For each product category the product variety denotes the specific variety and brand of the product. For confidentiality reasons the raw dataset has been anonymized with respect to the variety and brand of the product, i.e. we have no verbal information on the brand.

Insert Table 2 around here

[2] See Statistics Austria (2001A). We distinguish between the 'raw data set' (the data set we received from ST.AT) and 'our data set' (the data set after some manipulations as exclusions, imputations etc. – see below for details) in the text.

[3] Classification Of Individual COnsumption by Purpose (COICOP), see Statistics Austria (2001B)

[4] Tobacco products, cars, daily newspapers and mobile phone fees were not included in the raw data set for confidentiality reasons by Statistics Austria.

With the information on the date (t), the outlet (i) and the product code (j) we can construct a *price trajectory* $P_{ij,t}$, that is a sequence of price quotes for a specific product belonging to a product category in a specific outlet over time. To be more specific, two consecutive price quotes belong to the same elementary product if the following conditions are fulfilled:

(i) the time difference between the records is one month,

(ii) the outlet[5] and the product codes are equal for t and t+1 and,

(iii) no product replacement and no outlet replacement occurred in t or t+1.

A *price spell* is defined as the sequence of price quotes (for a specific product in a specific outlet) with the same price.

2.2 Data manipulations: imputations, outliers and sales

For the calculation of the descriptive statistics the raw data set has been modified and data manipulations have been carried with the aim of bringing them in an appropriate form for our numerical analysis. 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). On the other hand, prices which were imputed by the statistical office due to temporal and seasonal unavailability of an item (code F, G and V in table 3) were excluded form our data set. 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. Additionally, 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.

Insert Table 3 around here

[5] According to Statistics Austria the outlet codes in the Austrian CPI database cannot identify a store, which is usually defined as a location where different kinds of products are sold. In our data set a store (for which we do not have a code) is split up in different sectors (or product types), according to different kinds of products. Every sector of a store is coded as an individual outlet. E.g. if bread and stationery are sold in the same store both products get a different outlet code as these products belong to different sectors.

Products which display systematically unrealistic price movements, which we defined to be all products with more than 50 percent average price increase or decrease (according to the log difference formula of price changes $\ln(P_t)-\ln(P_{t-1})$) were removed as outliers from the data set (e.g. kindergarten fees, public swimming pool, refuse collection, public transport day ticket). 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 price changes with $\ln\left(P_t\right)-\ln\left(P_{t-1}\right)\geq 1$ as well as 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 an information from Statistics Austria, 14 products whose price quotes already contain already aggregated information (e.g. rents and operating costs for houses are derived from the micro-census of Austrian households, and a few medical services are obtained from the social insurance institution) have been removed for the purpose of our analysis as they do not represent price quotes on the micro level. After the exclusion of these products together with the outlier products, individual price quotes for 639 products are included in our data, covering 80 percent of the CPI.

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.

Concerning the price changes associated to 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 pure noise in the price setting process and are not due to changes in fundamental price determining factors (as e.g. monetary 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 of price changes induced by temporary promotions and sales. The information in our data set allows us to identify observations that are flagged as sales (code A in Table 3). 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. Because the data collection practice with respect to sales was changed over the years (especially with the introduction of the new goods basket in January 2000 - see Table 3) we also tried to identify unflagged sales prices and replaced them with the last regular price. Unflagged sales are defined as a price sequence $P_{ij,t-1}$, $P_{ij,t}$, $P_{ij,t+1}$, where $P_{ij,t-1} = P_{ij,t+1}$, and $P_{ij,t-1} \neq P_{ij,t}$, i.e. price changes that are reversed in the following period.

2.3 Censoring, attrition 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 of 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.

Attrition denotes the fact that some observed products disappear from the database due to the sampling strategy: When a product is no longer available in a particular outlet it is usually replaced by another product of the same product category which terminates the price spell (and the trajectory). Due to this forced nature of the replacement, we count the end of each price spell associated with attrition as a price change.

In order to compute aggregate measures of the statistics described in Section 3, 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 is used, with a weight of zero at times when an elementary product was not included in the 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. [6]

[6] See Table A1 in the Annex II for the weights of all 639 products categories included in our analysis.

3. Methodology and empirical results

The descriptive analysis of the degree of price rigidity at the micro level using individual price quotes is either based on the frequency of price changes or on the duration of price spells. Prices are considered as rigid if they show a low frequency of price changes and therefore a long duration of price spells. In this Section we briefly describe the applied methodologies for both approaches and discuss the results. In Section 3.1 we describe how the frequency of price changes (with and without taking sales into account) is calculated and the implied duration of price spells is derived from these numbers. In Section 3.2 we present the results for the synchronization of price changes and price increases and decreases separately. Finally, we also present a direct computation of the duration of prices and derive its counterpart, an implied frequency measure, in Section 3.3.

3.1 The Frequency Approach

According to the frequency approach 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 by

$$T = \frac{1}{F} \cdot \tag{1}$$

An advantage of the frequency approach is that 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 censoring of price spells. The frequency approach and the duration approach are equivalent only if all spells are uncensored.

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. Since this measure is only a biased estimate of the true frequency of price changes due to the existence of censored price spells, for the calculation of the implied duration of price spells $E(T) = \frac{1}{E(F)}$ we have to invoke an assumption on the distribution of the frequencies of price changes (which in our case is the exponential distribution) in order to get an unbiased estimate of the mean (and median) duration. With these assumptions, the *implied average duration* of price spells is given by

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

and the *implied median duration* by

$$T_j^{F,med} = \frac{\ln(0.5)}{\ln(1-F_j)}. \tag{3}$$

In other words, these expressions display a "continuous time versions" of an unbiased estimate of the duration of price spells with the assumption of a constant hazard function, i.e. assuming that the probability of a price change is constant over time (see Baudry et al, 2004).

In tables 4 to 6 the results aggregated on the COICOP and product type level are presented. If not otherwise stated, all statistics in these tables are computed by accounting for attrition. Detailed results of all product categories are presented in Table A1 in the Annex II.

Insert Table 4 around here

Price rigidity as measured by the implied duration based on the frequency of price changes varies considerably (see Table 4). On average 15 percent of all prices are changed every month, which implies an average (median) duration of price spells of 14 (11) months. Unprocessed food and energy products display a rather high frequency of price changes (24 and 40 percent) 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 flexibility. Due to the continuous time approximation applied to derive formula (2) and (3), for these products the implied durations are smaller than one month, although the observation frequency is monthly. However, this is not very surprising since in real life fuel prices are changed with a very high frequency – sometimes even on a daily or weekly basis, so estimates of a duration of less then one month are not unreasonable.

On the contrary, some service items and 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. So, e.g. banking, parking and postal fees show an estimated average duration of 50 months or longer.

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 percent compared to 6.6 percent for price decreases. The exception form this pattern is in the category communication items (especially computers), where price decreases appeared much more frequent than increases. Concerning the size of price changes, price increases and decreases appear to be quite sizeable when they occur. The average price increase is 11 percent whereas prices are reduced on average by 15 percent. Especially for cloth and footwear (due to seasonal sales) and again for communication and electronic items (computers) price decreases are very pronounced.

Insert Table 5 and 6 around here

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. For all product groups the frequencies and the size of the price changes are smaller compared to the figures in Table 5. 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 cloth and footwear where end of season sales are a common practice to clear inventories. For the latter category the average price decrease would be almost 15 percentage points lower if sales are disregarded.

When looking at the frequency of price changes over time we can see that there is a clear seasonal pattern visible in Figure 1: The spikes in January 1998, 1999 and 2001 indicate that most prices are changed in January.[7] During the year 2000 price changes have been more frequent than before and afterwards which also corresponds with rising aggregate inflation in that year. Apart from this short period, there is no trend in the frequency of price changes visible over the period considered. Furthermore, price increases and decreases show a similar seasonal pattern.

Insert Figure 1 around here

3.2 Synchronization of price changes

For each product the *synchronization of price changes* ($SYNC_j$) is measured by the approach 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 (numerator) to the theoretical maximum standard deviation in the case of perfect synchronization of price changes (denominator)

$$SYNC_j = \frac{\sqrt{\frac{1}{T-1}\sum_{t=2}^{T}\left(F_{jt}-F_j\right)^2}}{\sqrt{F_j\left(1-F_j\right)}} \tag{4}$$

[7] Price changes in January 2000 has been excluded from the analysis, see section 2.2.

where T 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 near 1 and low if it is near 0. Analogous expressions are applied for price increases and decreases, with the only difference that in the calculation of the frequencies of price increases and decrease we did not account for attrition because price changes cannot seriously be divided into price increases and decreases as the new price corresponds to a different product in the case of attrition.

Insert Table 7 around here

The results in Table 7 show that the average synchronization ratio of price changes for all products amount to 42 percent which constitutes an intermediary degree of price synchronization. However, this number greatly masks the heterogeneity across sector and products: There is a wide range from 20 percent for alcoholic beverages to 87 and 94 percent 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.[8] For food items the synchronization ratios are also very low, with an average of 21 percent.

With the exception of alcoholic beverages and cloth and footwear the results calculated without the price changes induced by sales 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, resp.) compared to the results including sales (see Table 8).

Insert Table 8 around here

3.3 The Duration Approach

According to the *duration approach* the duration of price spells is directly computed from the price trajectories in the data and prices are considered rigid if the durations are long and flexible if they are short. The implied frequency of price changes is then derived from the duration of

[8] The synchronization ratios for price increases and decreases are based on calculations without accounting for attrition. Therefore, the value for all changes (with attrition) must no necessarily lie within the range given by ratios for increases and decreases for each product category.

spells using the formulas (5) and (6). In the duration approach one has to directly address the issue of censoring of price spells which has a high influence the results.

From Table 9 it can be seen, that a majority of 61 percent of the price spells is not censored, and that left censored spells are twice as frequent as right censored spells (10.3%). The asymmetry between left censored and right censored spells has to do with attrition: when a (forced) replacement occurs, the ending spell is considered to be non-censored while the new spell is typically left censored. Among all spells the double-censored spells tend to be the longest (16.4 month) while the non-censored spells are shorter on average (8 month), which shows the downward bias that would be introduced if only non-censored spells would be analyzed.

Insert Table 9 around here

In the period January 1996 to December 2001 a total of 317,815 price spells are observed (see Table 10). Most price spells are observed in the food and clothing sectors. The weighted mean (median) duration of a price spell is about 10.6 (9) months. The longest price spells can be found in the service sector, whereas durations are relatively short for food and energy items. Compared with the results of Table 4, the direct computation of spell durations yields a similar pattern across COICOP groups and products types, but the durations are shorter, in several cases considerably shorter (services, education, health care), where prices are rather sticky and therefore the downward bias mentioned before becomes more severe. Apart from that, part of the difference in spell durations between the two approaches is also explainable by the non-linear transformation of frequencies into durations in the frequency approach where low frequency products yield very long implied durations by the transformations shown in equations (2) and (3).

Insert Table 10 around here

The implied frequencies of price changes (F^{imp}_j) in the last two columns of Table 10 are calculated with and without accounting for attrition. Equation (5) shows an unbiased estimator for the frequency of price changes only if the number of left censored and right censored spells is equal, i.e. not taking attrition into account would induce an asymmetry between left censored and right censored spells

$$F_j^{imp} = \frac{n_{j,nc} + n_{j,lc}}{n_{j,nc}T_{j,nc} + n_{j,lc}T_{j,lc} + n_{j,rc}T_{j,rc} + n_{j,dc}T_{j,dc}}, \qquad (5)$$

where $n_{j,nc(lc)[rc]\{dc\}}$ is the number of non-censored (left censored), [right censored] and {double censored} spells

and $T_{j,nc(lc)[rc]\{dc\}}$ is the corresponding duration of non-censored (left censored), [right censored] and {double censored} spells for product category j.

In the case of attrition, an unbiased estimator of the implied frequency of price changes is given by

$$F_j^{imp,att} = \frac{n_{j,nc} + n_{j,lc}}{n_{j,nc}T_{j,nc} + n_{j,lc}T_{j,lc} + n_{j,lc}T_{j,rc} + n_{j,lc}\dfrac{n_{j,dc}}{n_{j,rc}}T_{j,dc}} . \qquad (6)$$

As can be seen from Table 10, the differences between these two estimates are negligible. When comparing the results with those from the direct estimation of the frequency of price changes (see Table 4), we observe the same pattern, but the implied frequencies are higher across COICOP groups or product types.

As a result, depending on the estimation method, the duration of price spells last on average 11 (14) month with a considerable variation among products. Compared with other European countries prices in Austria depict similar patterns among product groups. But overall, the duration of price spells tend to be longer than in most other Euro area members.

4. Further Analysis of the Probability of Price Changes - Logit Estimates and Survival Analysis

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 logit models for the probability of a price change (Section 4.2) and estimates of hazard functions and cox regressions (Section 4.3) For similar studies for other Euro Area countries see Alvarez and Hernando (2004) for Spain, Baudry et al. (2004) and Fougere et al. (2004) for France, Aucremanne and Dyhne (2004B) for Belgium, Dias et al. (2004) for Portugal and Jonker et al. (2004) for the Nehterlands.

4.1 Data and sample selection

Our full sample of products contains 639 product categories and almost 49,800 elementary products (i. e. combinations of goods categories and outlet codes). As regards the panel structure of the data, the most common case is that the records span the full period of Jan. 1996 to Dec. 2003 (46.1% of all elementary product observations).[9] Because our data contain two CPI baskets, many elementary products show up only from Jan. 1996 to Dec. 1999 (1996 CPI basket; 10.8% of all elementary products) or from Jan. 2000 to Dec. 2003 (2000 CPI basket, 14.1% of all observations). Other patterns make up for the rest.

In the current version of our analysis we restricted the number of products included in the sample to those 48 products which match with the IPN-RG2 common sample definition (see Dhyne et al. 2004).[10] This restriction was necessary to reduce the amount of data to a manageable size given the available computer capacity. The data set includes 5,059 elementary products. The total number of price spells exceeds 60,000. Hence, the average number of observations per individual price spell is about 12. However these figures do not take censoring into account.

As already explained in Section 2 censoring constitutes a problem for the estimation of the average length of price spells. Whereas to deal with right-censored spells is rather easy, left-censoring is a more serious problem for the survival analysis. For each elementary product, the first price spell is left-censored because we cannot know for how long the price has been unchanged. Furthermore every spell after a product change is probably also left-censored.[11] This is a form of "stock sampling" which tends to over-represent long spells, and constitutes a sample selection problem.

A simple way to overcome this bias is to omit all left-censored spells from the analysis. Then only those spells are regarded where we know exactly when the spell started. This is also called "flow sampling" and does not constitute a sample selection problem if at least one price change for every elementary product is observed (see Dias et al. 2004). Other studies within the IPN also follow this approach (e. g. Aucremanne and Dhyne, 2004A, B, and Fougère et al., 2004).

---

[9] However, there may be gaps in the price trajectory where there is no valid price observation.

[10] For Austria, only for 48 of the 50 products defined as the common sample, a useful match is possible. The products "Balancing of wheels" and "Video tape hiring" are not included in the Austrian CPI baskets, neither are close substitutes. In addition, the product category "Fresh fish" was not included in the 1996 CPI basket.

[11] Only a product change too a product newly introduced to the market is not left-censored. But this information is not available. So we treated the first spell after a product change also as left-censored spell.

4.2 Logit Estimates

To analyze the determinants of a price change in a first step we estimate a pooled logit model. The dependent variable is binary indicating the occurrence of a price change at the beginning of next month (or at the end of period t) (PD_=1).[12]

As explanatory variables we included the duration of the price spell (TAU), the accumulated inflation for the product category since the last price change (INF_ACC_J), the magnitude of the last price change (LDLNP) as well as a dummy variable reflecting the fact that a price was set in attractive terms (ATTR) and a dummy to indicate if the last price change was a price decrease (LDPDW). In addition, several dummy variables indicating the product group (COICOP), the month (to uncover seasonal patterns, MONTH) and the year (to control for structural and cyclical effects, YEAR) are included. Three dummies capture the effects of the Euro cash changeover: one dummy for the direct effect in January 2002 (EURO1), another for the time of double product pricing (October 2001to March 2002) and a third dummy for the period of three month before and after the period of double product pricing (EURO3). We also experimented with a dummy to indicate changes in product taxes and fees for products and services administered by the public authorities (TAX).[13]

As mentioned above, all left censored price spells are excluded, as 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 is unknown. In total this left us with a sub-sample of 53,745 price spells with 232,791 price quotes.[14]

The unweighted estimation results are reported in Table 11. We present the estimated coefficient (β), the standard error (S.E.), the significance level of the estimated coefficient (p-value), the significance level of a likelihood ratio test for a variable or a group of variables (LR), the odds ratio (e^{β}), and the marginal effect (slope) evaluated on the mean of the explanatory

---

[12] See Annex I for details on the definition of the variables included.

[13] In the sample period 1996 to 2003 no changes in value added taxes occurred. Therefore only tax changes related to some specific products as e.g. alcohol and petroleum taxes and fees administered by public authorities like the passport fee, driving license fee and the change in the highway toll fee are included.

[14] The difference in the number of observations included for the logit estimates (Tables 11 and 12) and in the survival analysis (hazard rates and Cox regressions, see Table 13) in the following sub-section is due to the variables LDLNP and LDPDW in the logit model.

variables.[15] The reference is the price change for a product in the COICOP classification 07 (transport) in January 1996, with an estimated price change probability of 11.7 percent.

Insert Table 11 around here

As can be seen from Table 11, with the exception of the dummies for the years 1999 to 2001, for August and some COICOP groups all included variables are highly significant.

As observed for other countries (see e. g. Baudry et al 2004, Alvarez and Hernando 2004, and Aucremanne and Dyhne 2004), also for Austria the counterintuitive result holds, that the probability of a price change decreases the longer a price quote has been unchanged. An increase in the duration of a price spell by one month decreases the probability of a price change by 1.2 percent. The sign of the coefficient for the accumulated inflation is positive, as one would expect that the probability of a price change increases as inflation in the same product category increases. However the magnitude of the slope coefficient is (implausibly) high.

The use of attractive prices reduces the probability to change prices, as the opposite is true for the dummy indicating that the last price change was a price reduction. Both results are in line with commercial practices, especially with promotions and seasonal sales. The positive effect of the size of the last price change on the probability of a price change is also due to the practice of temporal promotions: large price reductions during a promotion are quickly off set by a (large) price increase.

The impact of the product group is only weakly concordant with the findings reported in Section 3 for all 639 products. As the COICOP group 7 (transport including fuel products) show a high frequency to change prices (see Tables 4 and 10), one would expect, that the conditional frequencies of a price change for other product groups is (much) lower and therefore shows a negative sign. However, one has to keep in mind the different coverage and weighting structure between the 48 products sample and the weighted results based on the much larger sample for the frequency and duration analysis in Section 3.

According to our estimates, there is a clear seasonal pattern in the price setting process. The probability to change prices in January (the reference month) is much larger, as the coefficients for the other months are all negative. Aucremanne Dyhne (2004A), Baudry et al. (2004); Jonker et al. (2004), Dias et al. (2004) report similar results for other Euro Area countries. Furthermore,

[15] The odds or risk ratio is equal to exp (β_i) and reflects how the relative probability to observe a price change in the next period is influenced by a right hand side variable.

the seasonal dummies are jointly highly significant, pointing out some time dependency in the pricing setting process. With respect to the Euro cash changeover two of our time dummies (EURO1 and EURO3) are highly significant, indicating a higher probability of a price change in January 2002 and in the three month before and after the period of double product pricing. For the period October 2001 to March 2002 when double product pricing was introduced (except for January) no significant effect was found. The introduction of a tax dummy was not significant, since no major product tax changes and no VAT change occurred during the sample period. However, one should keep in mind that several taxes and fees had to be changed with the introduction of the Euro. So it seems that same of the tax effects are covered by the variable EURO1.

Insert Table 12 around here

In order to control for unobserved characteristics of individual units and to take into account the heterogeneity of the price setting behavior not only across products, but also within product categories, we estimated a panel logit model with random elementary product effects. An elementary product is the combination of the product category and the outlet code. This allows us to control for the fact that within the same product group firm A can more or less frequently adjust its price than firm B. The results of these estimates are given in Table 12.

With respect to the sign of the estimates the same results hold as for the pooled logit model. Thus the counterintuitive result for the duration of a price spell still holds. The estimated coefficient for the accumulated inflation is now much lower and more in line with prior expectations.

4.3 Survival analysis

In the survival analysis, the time until an event occurs (in our case, a price change) is the variable of particular interest. Its advantage for the topic of price setting behaviour is that the duration of price spells and the shape of the hazard function are treated more explicitly. First, we present Kaplan-Meier estimates of the survivor and hazard functions for all products and separately for product groups. Second, a set of preliminary survival (Cox) regressions is presented.

4.3.1 Descriptive results – Kaplan-Meier estimates

Figure 2 shows the Kaplan-Meier estimate of the survivor function for all price spells of all elementary products in our data. This estimator is a nonparametric estimate of the survivor function *S(t)*, the probability of "survival" of a price spell past time *t*. For a dataset with observed spell lengths $t_1,\ldots t_k$ where *k* is the number of distinct failure times observed in the data, the Kaplan-Meier estimate at any time *t* is given by

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

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 a duration of *t* months or less. Note that the function in Figure 2 decreases quickly when *t* is low which means that most price spell have a low duration.

Insert Figure 2 around her

The smoothed hazard rate based on the Kaplan-Meier estimator is displayed in Figure 3. As expected, its overall shape is decreasing with time. But it also displays peaks, for example at a duration of approximately 1 year. Unconditional hazards that are decreasing with analysis time are a typical result of duration studies of micro CPI data (see Fougère et al., 2004 and the references in Dhyne et al., 2004). At first sight, this result is puzzling in the light of price-setting theories. It could be interpreted as that a firm will have a lower probability of changing its price the longer it has been kept unchanged.

Insert Figure 3 around her

But there are several reasons for a decreasing hazard function none of which is at odds with prevailing theories of price setting behaviour. One explanation focuses on the heterogeneity of price setters. Álvarez et al. (2004) show that the aggregation of different firms with different (time-dependent) price setting behavior almost always leads to a decreasing aggregate hazard function. Another reason is that a typical CPI sample consists of different products: For some products, prices are adjusted infrequently (e. g. services) whereas for others many price changes may be observed (e. g. energy). Goods with more frequent price changes contribute to a higher number of price spells in the data. Hence, they shift the aggregate hazard function upwards for short durations (Dias et al., 2004). In the following, we concentrate on the second aspect, product heterogeneity.

Figure 4 shows survivor functions for the five different product types.[16] Even this broad categorization reveals considerable heterogeneity across products. The solid line (product group #1 - unprocessed food) shows that price spell durations for this product group are rather short. Even shorter spells are indicated by the dotted line (product group #3 (energy): The corresponding survivor function decreases very quickly towards zero which means that almost all price spells have a duration of just a few months at most. The short-dashed line (product group #2 - processed food) implies price spells of intermediate length for that product category. At the other end of the spectrum, price spells of non-energy industrial goods (product group #4, dashed-dotted line) and especially the services (product group #5, long-dashed line) are relatively long-lived.

Insert Figure 4 around her

Hazard rate estimates for different product groups (Figure 5) show some interesting patterns: First, with this breakdown, the hazard function need not be a decreasing function of analysis time. For example, for services (product group #5) the hazard, i. e. the probability of a price change, is highest when the duration is approximately 1 year. Energy items (product group #3), on the other hand, have a high hazard when the spell duration is low, but there is also a higher hazard after 1 year.[17] Non-energy industrial goods (product group #4) have high hazards both at short durations and about after one year whereas for both unprocessed and processed food (product groups #1 and #2, respectively) the hazard rates are more or less decreasing monotonously with time.

Insert Figure 5 around her

---

[16] A remarkably similar picture can be found in Fabiani et al. (2004).

[17] Note also the different scales in Figure 5.

4.3.2 Survival regressions

In Table 13 regression results from the Cox proportional hazards model are presented.[18] The Cox model specifies the hazard function *h(t)* as:

$$h(t) = h(0)\, exp\left(X'\beta\right)$$

The hazard rate *h(t)* is the rate of a price spell at *t*, given that it existed up to *t*-1, with which it will be terminated in the next period. The baseline function *h(0)* specifies the hazard function when all covariates are set to zero, X is the vector of covariates and β is the vector of coefficients, which are to be estimated. This regression model allows to take the influence of several explanatory variables on duration into account. The Cox model is "semi-parametric": It is parametric in the sense the effect of the covariates on the hazard is assumed to have a certain form. On the other hand it does not require any assumptions regarding the shape of the baseline hazard which is left in fact unspecified (Cleves et al., 2002).

In the table, we present exponentiated coefficients which eases interpretation: The direction of the influence of a variable on the baseline hazard can be inferred from whether the coefficients are smaller or greater than unity. If, for example, the coefficient of a variable is 1.2 this means that a unit increase of this variable (or when a dummy variable takes on value of one) increases the hazard rate by 20% relative to the baseline. If it is lower than one, then an increase of the corresponding variable decreases the hazard.

Insert Table 13 around here

The table presents the results of three simple regressions where the hazard rate is estimated as a function product characteristics and the period of the Euro cash changeover.[19] They are intended to give a descriptive impression which complements the previous results. Estimations (1), (2), and (3) differ in the choice of product characteristics: Regression (1) uses the five product groups discussed above. Alternatively, regression (2) uses the COICOP classification and regression (3) uses the single good classifications in the common sample. All three estimations are based on almost 300,000 monthly price spell observations of our elementary products. The

[18] See Jonker et al. (2004) for a similar approach.

[19] Experiments with other explanatory variables in these regressions have not been successful so far: We considered the level of the aggregate inflation rate as well as tax dummies for certain products where we recorded a change in the estimation period (i. e. beer tax, alcohol tax and fuel taxes). (There was no major change in a sales tax like a variation of the VAT rate.) We also tried – unsuccessfully - lagged values.

cash changeover is represented by a dummy variable which takes the value of 1 for price changes in the period from July 2001 to June 2002 (EURO).[20] It is highly significant in all three specifications. The coefficients which vary from 1.11 to 1.18 imply that, all else equal, the "risk" of a price change in the months immediately before and after the changeover was by 11 to 18% higher than in the other months.

The results of estimation (1) suggest that the hazards of price spells of processed food are substantially (by approximately 40%) lower than those of processed food (which is the reference category). The rate of price changes of energy items is almost 38% higher than in the reference category whereas non-energy industrial goods and services have a significantly lower hazard.

Estimation (2) uses COICOP 01 (food and non-alcoholic beverages) as the reference category. Relative to this type of goods, most other categories show lower hazards. The results of the likelihood ratio test for estimations (1) and (2) suggest that the five product types better capture the heterogeneity of price-spell durations than the COICOP classes. The reason is probably the considerably heterogeneity within COICOP classes. For example, COICOP 07 (transport) encompasses both fuel (where prices are short-lived) and services and industrial goods related to transport (which exhibit longer durations). Finally, estimation (3) considers the single goods types: Some goods have substantially higher hazards than the reference good (steaks), e. g. unprocessed food items like bananas and lettuce or fuel types. Price spells of services like photo development and taxis or manufacturing goods like electric bulbs, on the other hand, have substantially longer durations.

4.4 Planned further analysis

We consider the results above as a first step in the analysis of price changes, using the duration of price spell as an explanatory variables. In a further version of this paper, we plan to extend the analysis. First, we want to consider all the 639 products (or a random sample of all spells) which are in our data. Moreover, we will add further explanatory variables.

---

[20] The results are qualitatively unchanged if narrower definitions of the cash changeover period are used.

5. Summary

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 direct and implied estimates for the average frequency of price changes and the duration of price spells for 639 products.

We found that consumer prices are quite sticky in Austria. The weighted average (implied) duration of price spells for all products is 10.6 (14) months. The sectoral heterogeneity is quite pronounced: prices for services, health care and education change rarely, typically around once per year (or even less according to the implied duration measure). In the product groups food, energy (transport) and communication prices are adjusted on average every 6 to 8 month. Promotions and sales have a considerable impact on 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. This reflects the fact that the prices of many of these products are in some way either directly administered or highly influenced by public authorities (including social security agencies).

Price increases occur slightly more often than price decrease, except for communication items, where due to the technical progress and high competition in the electronic equipment sector price decreases appear much more frequent than increases. Price increases and decreases are quite sizeable when they occur: on average prices increase by 11 percent whereas prices are reduced on average by 15 percent. Especially for cloth and footwear (due to seasonal sales) and again for communication and electronic items (computers) price decreases are very pronounced (34 and 26 percent, respectively).

Like in similar studies conducted within the inflation persistence network, we find that the aggregate hazard function for all price spells or the probability of a price change is decreasing with analysis time (i.e. the duration of a price spell) which is somewhat at odds with theories of firm price-setting behaviour. However, this is the results of aggregating over product types with different spell durations.. Using Kaplan-Meier estimates of survivor and hazard functions and Cox regressions, we show that there is substantial heterogeneity across goods and product types: Energy and unprocessed food show high hazards during the first months of price spells. For services, on the other hand, the hazard is highest after approximately one year. Based on logit estimates we observe a positive link between the probability of a price change and the accumulated inflation at the product level. We also find a strong seasonal (January) effect and a negative influence to change a price if it is currently set as an attractive price. The Euro cash changeover seems to have increased the probability to change a price.

6. References

Álvarez, L. J., Burriel, P., Hernando, I.: Do decreasing empirical hazard functions make any sense? Banco de España, September 2004.

Alvarez, L. J., Hernando, I., (2004), Price Setting Behaviour in Spain: Stylised Facts Using Consumer Price Micro Data, Bank of Spain, mimeo.

Aucremanne, L., Brys, G., Hubert, M., Rousseeuw, P.J., Struyf, A., (2002), "Inflation, Relative Prices and Nominal Rigidities", NBB Working Paper No. 20.

Aucremanne, L., Dhyne,E., (2004A), How Frequently do prices Change? Evidence Based on the Micro Data Underlying the Belgian CPI, ECB Working paper 331 April 2004, Frankfurt.

Aucremanne, L., Dyhne, E., (2004B), "The Frequency of Price Changes: A Panel Data Approach to the Determinants of Price Changes", National Bank of Belgium, Brussels, mimeo.

Ball, L., Mankiw, N. G., (1995), A Sticky Price Manifesto, NBER Working Paper 4677

Baudry, L., Le Bihan, H., Sevestre, P., Tarrieu, S., (2004), Price rigidity. Evidence from the French CPI micro-data, ECB Working Paper 384, August 2004, Frankfurt.

Bils, M., Klenow, P., (2002), "Some Evidence on the Importance of Sticky Prices", NBER Working Paper No. 9069.

Campiglio, L., (2002), "Issues in the Measurement of Price Indices: A New Measure of Inflation", Istituto di Politica Economica Working Paper No. 35, January 2002.

Cecchetti, S., (1986): "The Frequency of Price Adjustment. A Study of the Newsstand Prices of Magazines", Journal of Econometrics, 31, 255-274.

Cleves, M. A., Gould, W. W., Gutierrez, R. G., (2002): An Introduction to Survival Analysis Using Stata, Stata Press, College Station, Texas 2002.

Dhyne, E., Alvares, L., Le Bihan, H., Veronese, G., Dias, D., Hoffman, J., Jonker, N., Mathä, T., Rumler, F., Vulminen J., (2004), Price Setting in the Euro area : Some Stylized Facts from Micro Consumer Price Data, mimeo.

Dias, D. A., Neves, P. D., Santos Silva, J. M. C.: Hazard functions are not that decreasing after all. Banco de Portugal, 15 September, 2004.

Dias, M., Dias, D., Neves, P. D., (2004), Stylised features of price setting behaviour in Portugal: 1992-2001, ECB Working paper 332 April 2004, Frankfurt.

Fabiani, S., Gattulli,, A., Sabbatini, R., Veronese, G., (2004), Consumer price behaviour in Italy: Evidence from micro CPI data, Banca d'Italia, April 2004, mimeo.

Fischer, T., Konieczny, J. D., (2000): "Synchronization of Price Changes by Multiproduct Firms: Evidence from Canadian Newspaper Prices", *Economic Letters*, 271-277.

Fougère, D., Le Bihan, H. Sevestre, P.: Calvo, Taylor and the estimated hazard function for price changes. Banque de France, June 2004.

Jonker, N., Folkertsma, C., Blijenberg, H.: An empiricial analysis of price setting behaviour in the Netherlands in the period 1998-2003 using micro data. De Nederlandsche Bank, September 2004.

Kashyap, A., (1995), "Sticky Prices: New Evidence from Retail Catalogs", Quarterly Journal of Economics, 245-274.

Lach, S., Tsiddon, D., (1992), The Behavior of Prices and Inflation: An Empirical Analysis of Disaggregated Price Data", Journal of Political Economy, 100, pp. 349-389.

Lach, S., Tsiddon,D., (1996), "Staggering and Synchronization in Price Setting: Evidence from Multiproduct Firms", American Economic Review 86, 1175-1196.

Statistics Austria, (2000A), VPI/HVPI-Revision 2000 - Übersicht, Statistische Nachrichten, 3/2000, pp. 220 - .

Statistics Austria, (2000B), VPI/HVPI-Revision 2000 - Umsetzung, Statistische Nachrichten, 5/2000, pp. 360 - .

Statistics Austria, (2001A), Der neue Verbraucherpreisindex 2000. Nationaler und Harmonisierter Verbraucherpreisindex, 2001, Vienna,

Statistics Austria, (2001B), VPI/HVPI-Revision 2000 – Fertigstellung und Gewichtung, Statistische Nachrichten, ?/2001, pp. ? - .

Suvanto, A., Hukkinen, J., (2002): “Stable Price Level and Changing Prices”, mimeo, Bank of Finland.

Taylor, J. B., (1999), “Staggered Price and Wage Setting in Macroeconomics”, in J. Taylor and M. Woodford (eds.), Handbook of Macroeconomics, Volume 1b, Amsterdam, North-Holland, pp. 1009-1050.

Vilmunen, J., Paloviita, M., (2004), How Often do Prices Change in Finland? Micro-level Evidence from the CPI, Bank of Finland, mimeo.

Annex I: List of variables

Identifier of an observation :

PCODE	Product identifier (j)
LCODE	Outlet code (i)
TIME	Time identifier (t)
ID	Elementary product code
SPELLID	Identifier of a price spell for an elementary product (s).
P_{ijt}	Price quote for product (j) in store (i) at time (t).

Dependent variable:

P_D_{ijt}	Binary variable for price change: if a price change occurs in t+1, i.e. $[\ln(P_{ijt+1}) - \ln(P_{ijt}) \neq 0]$ than P_D = 1, otherwise = 0

Explanatory variables:

TAU_{ijt}	Duration of a price spell: number of month since the price P_{ijt} is unchanged.
$INF\_ACC\_J_{ijt}$	Accumulated inflation for product category (j) since the outlet (i) selling product (j) had the last time changed its price.
$LDLNP_{ijt}$	Magnitude of the last price change of product (j) in outlet (i) if P_D=1, otherwise 0.
ATTRijt	Dummy to indicate an attractive price. Attractive price have been defined for ranges of the mean absolute price in order to take account for different attractive price at different absolute prices. For products with a mean of valid prices • from 0 to 100 ATS all prices ending at 0.00, 0.50 and 0.90 ATS • from 100 to 1000 ATS prices ending at 00.00, 5.00 and 9.00 ATS have been defined as attractive (where prices have been rounded up to the *x.00 digit) • exceeding 1000 ATS prices ending at 000.00, 50.00 and 90.00 (where prices have been up rounded to the *x0.00) have been defined as attractive. If this definition is met, ATTR = 1, otherwise ATTR = 0
$LDPDW_{ijt}$	Dummy variable indicating that the last price change was a price decrease:
$MONTH\_k_{ijt}$	k=1 to 12, Seasonal dummy variables; if modulus of (t / 12) = k $MONTH\_{k}$ =1, otherwise $MONTH\_{k}$ = 0.
$YEAR\_k_{ijt}$	k= 1 to 7, yearly dummies for 1996 to 2003 if k is a specific year $YEAR\_{k}$ =1, otherwise $YEAR\_{k}$ =0.

$COICOP\_k_{ijt}$	k=1 to 12, COICOP classification; see Table 4 for a description. if j is a specific product belonging to k, $COICOP_{\_k}$ =1, otherwise $COICOP_{\_k}$ =0
$EURO1_{ijt}$	Dummy variable for the Euro cash changeover: if t = December 2001 EURO1 = 1, otherwise EURO1 = 0 (P_D indicates a price change in the next month. Thus, EURO1 indicates that a price change occurred in January 2002).
$EURO2_{ijt}$	Dummy variable for the period double product pricing in Austria: for t = Sepember 2001 to February 2002 (except Dec. 2001) EURO2 =1, otherwise EURO2 = 0. (P_D indicates a price change in the next month. The period defined above, therefore represents the time interval October 2001 till March 2002, the period for which double product pricing was compulsory).
$EURO3_{ijt}$	Dummy variable for a period of 3 month before and after double product pricing in Austria: for t = June to August 2001 and March to May 2002 EURO3 =1, otherwise EURO3 = 0. (P_D indicates a price change in the next month, therefore the period defined above represents the the time intervals July to September 2001 and April to June 2002).
$EURO_{ijt}$	Dummy variable for the period of 6 month before and after the cash change-over: for t = July 2001 to June 2002) EURO = 1, otherwise EURO = 0 (this variable is used in the Cox regression in Section 4.3)
TAX_{ijt}	Dummy variable that a change in product tax or a fee administered by public authorities occurred at time (t).

Table 1: Classification of elementary price quotes by COICOP groups and type of product

	Price records		Weights of products included in our sample		Weights in CPI basket
	# of observations	in %	actual weights	weights rescaled	
By COICOP					
COICOP 01: Food and non-alcoholic beverages	1343690	37.38%	13.45%	14.95%	13.80%
COICOP 02: Alcoholic beverages and tobacco	93101	2.59%	1.38%	1.53%	3.33%
COICOP 03: Clothing and footwear	547013	15.22%	7.30%	8.12%	7.30%
COICOP 04: Housing, water, gas and electricity	92769	2.58%	19.26%	21.42%	19.26%
COICOP 05: Furnishing & maintenance of housing	348748	9.70%	9.07%	10.09%	9.07%
COICOP 06: Health care expenses	31998	0.89%	2.92%	3.25%	2.92%
COICOP 07: Transport	255449	7.11%	7.96%	8.85%	13.56%
COICOP 08: Communications	4504	0.13%	2.76%	3.07%	2.60%
COICOP 09: Leisure and culture	304548	8.47%	10.63%	11.82%	11.60%
COICOP 10: Education	12307	0.34%	0.74%	0.82%	0.74%
COICOP 11: Hotels, cafés and restaurants	294974	8.21%	7.22%	8.03%	6.95%
COICOP 12: Miscellaneous goods and services	265202	7.38%	7.23%	8.04%	8.86%
By Product type					
Unprocessed food	627972	17.47%	5.63%	6.26%	5.74%
Processed food	808819	22.50%	9.19%	10.22%	11.47%
Energy	73177	2.04%	7.70%	8.57%	7.74%
Non energy industrial goods	1314899	36.58%	29.58%	32.90%	35.29%
Services	769436	21.41%	37.81%	42.05%	39.76%
Total	3594351	100.00%	89.91%	100.00%	100.00%

Table 2: Information available for each elementary price quote

Date of the price quote	Month and year of the quote
Store code	Each outlet can be identified by a specific code (anonymized)
Product category code (incl. a sub-code for the variety)	668 product categories (no direct information on the brand of the product)
Packaging of the item	Weight of or number of items in the package
Price of the item	in Austrian Schilling (till Dec. 2001) or Euro (from Jan. 2002)
Addition al information	
Sales prices	Code indicating a sales price (Codes A, N)
Temporal unavailability	Code indicating seasonal and other temporal unavailability of the item (Codes F, G, V, X,)
Product replacements	Code indicating that a product variety has been replaced by another (no information on the nature of the replacement, i.e. whether it is forced or voluntary; Code S)
Quality adjustment	Code for quality adjustment (for hedonic prices; Code Q)
Store replacements	Code indicating the replacement of a specific store by another (Code W)

Table 3: Repartition of the records: occurrence of informational codes by year

Year	1996	1997	1998	1999	2000	2001	2002	2003
Total observations	405427	412771	416465	424690	480452	480379	486102	488065
Code								
A	11761	14473	14967	16081	19583	20318	23299	26167
N	2562	2203	4007	4804	4858	4465	4793	5508
F	4	28	1667	4084	4489	2537	2615	2626
G	3993	5316	5493	5629	12823	20428	22218	22276
V	0	0	0	0	6	3140	4087	3260
X	5422	11065	13906	26410	16619	11248	13511	14464
S	0	0	0	0	6005	6067	7677	7413
QZ	0	0	0	0	732	1224	1169	1243
Q0	0	0	0	0	104	296	476	804
Q1	0	0	0	0	54	172	253	189
Q2	0	0	0	0	97	504	767	681
Q3	0	0	0	0	25	159	286	189
Q4	12324	4860	4219	5540	3652	2780	1675	572
W0	0	0	0	0	30	485	776	106
W1	0	0	0	0	3	1	5	0
W2	0	0	0	0	6	4	68	5
W3	0	0	0	0	0	11	0	1
W4	0	0	0	0	2145	1154	916	8

Codes:		
	A	sales price
	N	normal price - end of sales price
	F, G	seasonal unavailability
	V	temporal unavailability
	X	longer unavailability
	S	replacement of product
	QZ,Q0-Q4	quality adjustment - equivalent to product replacement
	W0-W4	store replacement

Table 4: Frequency of price changes by COICOP classification and product type
Weighted average of the entire 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	17,30%	7,87	7,87	9,14%	7,90%	16,9%	18,7%
COICOP 02: Alcoholic beverages and tobacco	14,58%	6,48	5,95	7,40%	6,99%	14,6%	14,9%
COICOP 03: Clothing and footwear	12,03%	9,40	7,90	6,41%	5,04%	23,1%	33,7%
COICOP 04: Housing, water, gas and electricity	11,16%	14,70	11,25	6,91%	3,99%	6,6%	8,7%
COICOP 05: Furnishing & maintenance of housing	6,89%	17,85	15,97	4,07%	2,51%	9,3%	13,6%
COICOP 06: Health care expenses	5,62%	18,80	19,70	4,41%	1,10%	4,0%	6,7%
COICOP 07: Transport	36,53%	11,16	9,56	18,75%	17,65%	8,3%	8,8%
COICOP 08: Communications	8,92%	15,97	10,49	1,84%	6,91%	15,5%	26,0%
COICOP 09: Leisure and culture	24,16%	15,84	11,17	12,34%	11,15%	11,1%	12,3%
COICOP 10: Education	4,53%	23,16	20,22	4,14%	0,38%	4,9%	0,5%
COICOP 11: Hotels, cafés and restaurants	8,29%	19,30	21,32	5,41%	2,59%	7,3%	8,4%
COICOP 12: Miscellaneous goods and services	7,10%	18,68	15,23	4,90%	2,02%	7,6%	11,4%
By Product type							
Unprocessed food	24,02%	6,52	7,47	12,56%	11,13%	19,6%	22,0%
Processed food	12,77%	8,48	7,94	6,78%	5,79%	14,8%	16,1%
Energy	40,11%	8,34	4,78	20,69%	19,31%	5,1%	4,4%
Non energy industrial goods	10,20%	13,66	11,50	5,39%	4,25%	13,2%	18,6%
Services	12,58%	19,45	18,50	7,43%	5,01%	8,1%	10,9%
Total	15,13%	14,07	11,14	8,21%	6,60%	11,4%	14,7%

Sample period: January 1996 - December 2003

Table 5: Frequency of price changes by COICOP classification and product type
Weighted average of the entire basket - without sales

	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	11,32%	13,00	13,91	6,14%	4,79%	12,31%	13,26%
COICOP 02: Alcoholic beverages and tobacco	7,97%	12,11	11,94	4,11%	3,57%	10,31%	10,04%
COICOP 03: Clothing and footwear	8,53%	12,49	11,11	4,72%	2,91%	16,28%	19,15%
COICOP 04: Housing, water, gas and electricity	10,50%	15,18	11,25	6,56%	3,65%	6,53%	8,50%
COICOP 05: Furnishing & maintenance of housing	5,88%	19,54	17,07	3,54%	1,96%	7,78%	11,09%
COICOP 06: Health care expenses	5,51%	19,08	19,70	4,36%	1,04%	4,00%	6,94%
COICOP 07: Transport	34,40%	11,53	10,37	17,69%	16,56%	8,16%	8,51%
COICOP 08: Communications	8,14%	16,42	10,49	1,46%	6,51%	21,39%	26,23%
COICOP 09: Leisure and culture	21,33%	17,17	11,69	10,75%	9,67%	10,66%	11,61%
COICOP 10: Education	4,52%	23,19	20,41	4,02%	0,38%	4,86%	0,51%
COICOP 11: Hotels, cafés and restaurants	7,75%	19,69	21,90	5,12%	2,31%	7,26%	7,84%
COICOP 12: Miscellaneous goods and services	6,44%	21,11	15,50	4,58%	1,67%	6,50%	8,74%
By Product type							
Unprocessed food	17,37%	10,64	12,53	9,16%	7,68%	15,00%	16,41%
Processed food	7,11%	14,31	13,99	3,98%	2,84%	10,35%	10,84%
Energy	37,86%	8,63	5,54	19,56%	18,19%	5,14%	4,45%
Non energy industrial goods	8,40%	15,68	13,65	4,46%	3,19%	10,58%	13,45%
Services	11,57%	20,17	19,33	6,89%	4,51%	8,16%	10,49%
Total	12,77%	16,07	13,99	7,01%	5,34%	9,55%	11,52%

Table 6: Distribution of price increases and decreases by COICOP classification and product type
Median, 1. Quartile and 3. Quartile

	Median Increase	1. Quartile Increase	3. Quartile Increase	Median Decrease	1. Quartile Decrease	3. Quartile Decrease
By COICOP						
COICOP 01: Food and non-alcoholic beverages	16,89%	12,44%	20,38%	18,42%	14,20%	22,38%
COICOP 02: Alcoholic beverages and tobacco	13,96%	12,39%	17,09%	14,15%	13,29%	16,63%
COICOP 03: Clothing and footwear	22,58%	19,54%	26,72%	34,77%	28,10%	39,96%
COICOP 04: Housing, water, gas and electricity	6,12%	4,76%	7,91%	6,68%	3,90%	11,40%
COICOP 05: Furnishing & maintenance of housing	8,53%	7,23%	10,34%	13,03%	9,74%	17,57%
COICOP 06: Health care expenses	2,50%	0,92%	7,43%	5,44%	0,83%	12,08%
COICOP 07: Transport	6,83%	3,10%	9,09%	8,03%	2,67%	16,24%
COICOP 08: Communications	21,09%	0,39%	24,90%	32,80%	3,24%	33,95%
COICOP 09: Leisure and culture	11,01%	7,15%	12,51%	10,70%	6,97%	15,50%
COICOP 10: Education	4,88%	4,25%	5,18%	0,29%	0,29%	0,84%
COICOP 11: Hotels, cafés and restaurants	6,59%	5,38%	7,61%	6,74%	5,59%	9,40%
COICOP 12: Miscellaneous goods and services	6,41%	3,59%	10,20%	10,47%	5,56%	14,65%
By Product type						
Unprocessed food	17,59%	16,07%	22,48%	22,00%	17,47%	24,82%
Processed food	14,30%	11,18%	17,93%	15,91%	13,29%	18,96%
Energy	3,77%	3,10%	6,38%	3,41%	2,67%	5,13%
Non energy industrial goods	10,22%	7,37%	19,02%	14,82%	10,29%	24,76%
Services	6,59%	4,69%	10,17%	7,79%	5,07%	12,78%
Total	8,80%	6,19%	15,61%	12,64%	6,50%	19,48%

Table 7: 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			
COICOP 01: Food and non-alcoholic beverages	21,05%	21,23%	19,91%
COICOP 02: Alcoholic beverages and tobacco	20,31%	16,61%	23,45%
COICOP 03: Clothing and footwear	26,04%	18,93%	22,79%
COICOP 04: Housing, water, gas and electricity	53,64%	58,28%	39,86%
COICOP 05: Furnishing & maintenance of housing	27,70%	25,45%	21,19%
COICOP 06: Health care expenses	86,70%	84,00%	54,57%
COICOP 07: Transport	51,43%	54,91%	56,50%
COICOP 08: Communications	93,76%	85,33%	91,73%
COICOP 09: Leisure and culture	51,07%	51,29%	42,89%
COICOP 10: Education	80,79%	81,71%	44,66%
COICOP 11: Hotels, cafés and restaurants	30,92%	28,99%	25,38%
COICOP 12: Miscellaneous goods and services	50,08%	47,61%	36,54%
By Product type			
Unprocessed food	20,48%	22,72%	22,44%
Processed food	21,29%	19,62%	18,89%
Energy	51,63%	62,74%	49,11%
Non energy industrial goods	34,20%	30,81%	28,34%
Services	58,62%	55,84%	45,41%
Total	41,88%	40,37%	34,20%

Table 8: Synchronisation ratios by COICOP classification and product type
Weighted average of the entire CPI basket - without sales

	Synchronisation ratio of price changes	Synchronisation ratio of price increases	Synchronisation ratio of price decreases
By COICOP			
COICOP 01: Food and non-alcoholic beverages	21,76%	22,61%	19,50%
COICOP 02: Alcoholic beverages and tobacco	22,22%	18,10%	27,30%
COICOP 03: Clothing and footwear	26,52%	17,35%	15,87%
COICOP 04: Housing, water, gas and electricity	53,72%	58,55%	39,11%
COICOP 05: Furnishing & maintenance of housing	28,34%	25,80%	21,41%
COICOP 06: Health care expenses	86,45%	83,64%	55,15%
COICOP 07: Transport	52,05%	54,49%	56,79%
COICOP 08: Communications	93,85%	79,79%	91,77%
COICOP 09: Leisure and culture	49,26%	49,85%	41,40%
COICOP 10: Education	80,68%	81,60%	44,66%
COICOP 11: Hotels, cafés and restaurants	31,00%	28,89%	25,17%
COICOP 12: Miscellaneous goods and services	50,33%	47,76%	36,22%
By Product type			
Unprocessed food	20,91%	23,79%	20,97%
Processed food	22,35%	21,21%	19,78%
Energy	51,89%	62,73%	47,94%
Non energy industrial goods	34,58%	30,44%	26,64%
Services	58,07%	54,60%	44,90%
Total	42,01%	40,00%	33,24%

Table 9: Number of spells and duration by type of censoring (taking into account for attrition)

Left censored	Right censored	Number of spells		Duration of spells	
		observations	in %	mean	median
0	**0**	194671	61.25%	8.01	6
0	**1**	32630	10.27%	11.19	10
1	**0**	66702	20.99%	10.78	10
1	**1**	23812	7.49%	16.42	12
Total		317815	100.00%	10.60	9

Table 10: Statistics on price spells – duration and implied frequency of price changes

	Price spells				**Implied frequency of price changes**	
	Number of spells	in %	duration of spells - weighted mean	duration of spells - weighted median	F_j	F_j^{att}
By COICOP						
COICOP 01: Food and non-alcoholic beverages	164634	51.80%	7.72	8	13.73%	13.52%
COICOP 02: Alcoholic beverages and tobacco	8824	2.78%	6.32	5	11.88%	11.71%
COICOP 03: Clothing and footwear	37430	11.78%	7.71	8	6.53%	5.97%
COICOP 04: Housing, water, gas and electricity	8915	2.81%	6.58	6	40.94%	40.96%
COICOP 05: Furnishing & maintenance of housing	20705	6.51%	11.28	12	4.91%	4.83%
COICOP 06: Health care expenses	1343	0.42%	12.24	15	4.57%	4.63%
COICOP 07: Transport	24448	7.69%	7.38	12	33.37%	33.41%
COICOP 08: Communications	498	0.16%	8.22	6	8.92%	9.49%
COICOP 09: Leisure and culture	20892	6.57%	9.48	9	19.61%	19.54%
COICOP 10: Education	572	0.18%	8.86	7	6.09%	6.60%
COICOP 11: Hotels, cafés and restaurants	15920	5.01%	13.77	15	6.92%	6.87%
COICOP 12: Miscellaneous goods and services	13628	4.29%	12.83	12	4.82%	4.85%
By Product type						
Unprocessed food	105806	33.29%	7.14	8	18.90%	18.68%
Processed food	67652	21.29%	7.84	8	10.29%	10.10%
Energy	18769	5.91%	6.79	5	35.94%	35.93%
Non energy industrial goods	85154	26.79%	9.63	9	6.67%	6.45%
Services	40428	12.72%	9.59	12	27.21%	27.32%
Total	317815	100.00%	10.60	9	18.80%	18.74%

Table 11: Conditional probability of a price change -Pooled logit estimates

Variables (X)	β	S.E	p-value	LR-Test	Odds ratio	Slope
TAU	-0.119	0.001	0.000	0.000	0.888	-0.012
INF_ACC_J	3.624	0.080	0.000	0.000	37.500	0.375
LDLNP	0.684	0.047	0.000	0.000	1.982	0.071
ATTR	-0.518	0.015	0.000	0.000	0.596	-0.056
LDPDW	0.473	0.013	0.000	0.000	1.605	0.052
MONTH_2	-0.175	0.029	0.000	0.000	0.839	-0.017
MONTH_3	-0.078	0.029	0.007		0.925	-0.008
MONTH_4	-0.309	0.030	0.000		0.734	-0.029
MONTH_5	-0.387	0.030	0.000		0.679	-0.035
MONTH_6	-0.335	0.030	0.000		0.715	-0.031
MONTH_7	-0.375	0.030	0.000		0.687	-0.035
MONTH_8	-0.046	0.029	0.114		0.955	-0.005
MONTH_9	-0.079	0.029	0.006		0.924	-0.008
MONTH_10	-0.209	0.029	0.000		0.812	-0.020
MONTH_11	-0.349	0.030	0.000		0.705	-0.032
MONTH_12	-0.183	0.031	0.000		0.833	-0.018
YEAR_2	-0.044	0.026	0.098	0.000	0.957	-0.004
YEAR_3	-0.096	0.027	0.000		0.909	-0.010
YEAR_4	0.002	0.026	0.929		1.002	0.000
YEAR_5	0.013	0.027	0.615		1.013	0.001
YEAR_6	0.003	0.029	0.923		1.003	0.000
YEAR_7	-0.575	0.029	0.000		0.563	-0.051
YEAR_8	-0.523	0.028	0.000		0.593	-0.047
COICOP_1	1.089	0.126	0.000	0.000	2.972	0.137
COICOP_2	0.533	0.128	0.000		1.705	0.066
COICOP_3	0.064	0.128	0.618		1.066	0.007
COICOP_4	0.466	0.128	0.000		1.594	0.056
COICOP_5	-1.083	0.136	0.000		0.339	-0.078
COICOP_6	1.650	0.127	0.000		5.206	0.260
COICOP_8	0.021	0.128	0.871		1.021	0.002
COICOP_9	0.013	0.127	0.919		1.013	0.001
COICOP_10	-0.099	0.130	0.445		0.906	-0.010
EURO1	0.794	0.056	0.000	0.000	2.213	0.109
EURO3	0.060	0.028	0.032		1.061	0.006
Intercept	-1.078	0.131	0.000	-	-	

Notes:
Number of obs = 232791, LR (β=0) = 0.000, Log likelihood = -91066.088 Pseudo R2 = 0.2127
Odds ratio = exp(β); Slope: dy/dx at the mean of the explanatory variables
Reference: COICOP: 7 , MONTH: January, YEAR 1996.
Dependent variable: P_D=1 if price change

Table 12: Conditional probability of a price change - Panel logit estimates
Random elementary product effects

Variables (X)	β	S.E	p-value	LR-Test	Odds ratio
TAU	-0.020	0.001	0.000	0.000	0.980
INF_ACC_J	0.852	0.122	0.000	0.000	2.344
LDLNP	0.458	0.049	0.000	0.000	1.581
ATTR	-0.237	0.021	0.000	0.000	0.789
LDPDW	0.353	0.016	0.000		1.423
MONTH_2	-0.248	0.033	0.000		0.781
MONTH_3	-0.129	0.033	0.000		0.879
MONTH_4	-0.406	0.033	0.000		0.666
MONTH_5	-0.508	0.034	0.000		0.601
MONTH_6	-0.487	0.034	0.000		0.614
MONTH_7	-0.563	0.034	0.000	0.000	0.569
MONTH_8	-0.191	0.033	0.000		0.826
MONTH_9	-0.247	0.032	0.000		0.781
MONTH_10	-0.417	0.033	0.000		0.659
MONTH_11	-0.542	0.033	0.000		0.582
MONTH_12	-0.381	0.034	0.000		0.683
YEAR_2	0.057	0.031	0.065		1.058
YEAR_3	-0.129	0.031	0.000		0.879
YEAR_4	-0.042	0.031	0.169		0.959
YEAR_5	0.012	0.031	0.695	0.000	1.012
YEAR_6	0.066	0.035	0.058		1.068
YEAR_7	-0.268	0.035	0.000		0.765
YEAR_8	-0.379	0.034	0.000		0.685
COICOP_1	1.149	0.240	0.000		3.155
COICOP_2	0.417	0.243	0.086		1.518
COICOP_3	-0.456	0.248	0.066		0.634
COICOP_4	0.214	0.242	0.375		1.239
COICOP_5	-1.179	0.254	0.000	0.000	0.308
COICOP_5	1.899	0.246	0.000		6.679
COICOP_6	-0.550	0.243	0.024		0.577
COICOP_8	-0.434	0.244	0.075		0.648
COICOP_10	-0.585	0.249	0.019		0.557
EURO1	1.258	0.061	0.000	0.000	3.519
EURO3	0.141	0.032	0.000		1.152
Intercept	-1.927	0.243	0.000	-	-

Notes:
Number of obs = 232791, WALD (β=0) = 0.000, Log likelihood =-79356.088
Random effects - group variable: ID (PCODE*LCODE), Number of groups: 4520
Odds ratio = exp(β); Slope: dy/dx at the mean of the explanatory variables
Reference: COICOP: 7 , MONTH: January, YEAR 1996.
Dependent variable: P_D=1 if price change

Table 13: Cox regression results for the duration of individual price spells 1996-2003

	(1)		(2)		(3)	
	hazard ratio	std. error	hazard ratio	std. error	hazard ratio	std. error
Euro cash changeover (EURO)	1.148*	0.010	1.111*	0.010	1.181*	0.010
Product types						
(reference: pgroup #1 (unprocessed food))						
pgroup #2 (processed food)	0.593*	0.008				
pgroup #3 (energy)	1.376*	0.012				
pgroup #4 (non-energy industrial goods)	0.358*	0.005				
pgroup #5 (services)	0.289*	0.004				
COICOP						
(reference: COICOP 01 (food and non-alcoholic beverages)						
COICOP 02 (alcoholic beverages, tobacco)			0.706*	0.012		
COICOP 03 (clothing and foothwear)			0.466*	0.007		
COICOP 04 (housing, water, gas, electricity)			0.708*	0.013		
COICOP 05 (furnishing, maintenance of housing)			0.310*	0.008		
COICOP 07 (transport)			1.258*	0.012		
COICOP 08 (communications)			0.630*	0.032		
COICOP 09 (leisure and culture)			0.457*	0.008		
COICOP 11 (hotels, cafés, restaurants)			0.435*	0.007		
COICOP 12 (mics. goods and services)			0.375*	0.009		
Product category (reference: steaks)						
frozen spinach					1.225*	0.064
milk					2.963*	0.375
sugar					1.222*	0.065
fresh fish					1.357*	0.073
beer in a shop					1.960*	0.097
whisky					1.688*	0.085
mineral water					2.004*	0.100
coffee					2.742*	0.123
bananas					4.389*	0.189
lettuce					4.719*	0.198
hot dog					0.715*	0.051
meal in restaurant					0.641*	0.034
beer in a cafe					0.652*	0.031
coke					0.594*	0.033
plumber, hourly rate					0.748*	0.043
electrician, hourly rate					0.693*	0.046
gasoline (heating)					3.181*	0.153
1 type of furtniture					0.783*	0.052
towel					0.623*	0.041
electric bulb					0.494*	0.044
hand mixer					0.748*	0.044
trousers (men)					0.739*	0.039

(Continued on the next page)

	(1)	(2)	(3)	
			hazard s ratio	std. error
shirt (men)			1.282*	0.065
socks (men)			1.837*	0.103
sports shoes			1.069	0.056
tennis ball			0.906	0.059
suitcase			0.529*	0.046
toothpaste			1.398*	0.075
dog food			1.411*	0.081
dry cleaning			0.439*	0.030
hairdresser (women)			0.572*	0.035
haircut (men)			0.502*	0.031
movie			0.893	0.070
photo development			0.407*	0.039
TV set			1.247*	0.061
fuel type1			5.601*	0.233
fuelfuel type2 (diesel)			5.606*	0.233
car wash			0.642*	0.047
garage, hourly rate			1.042	0.050
car tyre			1.120*	0.059
construction game			0.944	0.070
taxi			0.494*	0.059
cement			1.295	0.141
acrylic paint			0.695	0.112
domestic services			0.715*	0.090
hotel room			2.585*	0.119
comfort telephone			1.669*	0.123
Observations	299,873	299,873	299,873	
LR test (d. f.)	16,711.48 (5)	9,476.91 (5)	28,345.70 (5)	

Notes:
Exponentiated coefficients. Robust standard errors. Asterisks denote significane at the 99% level.

Figure 1: Frequency of price changes over time, weighted average (in p.c.), and aggregate inflation (right axis)

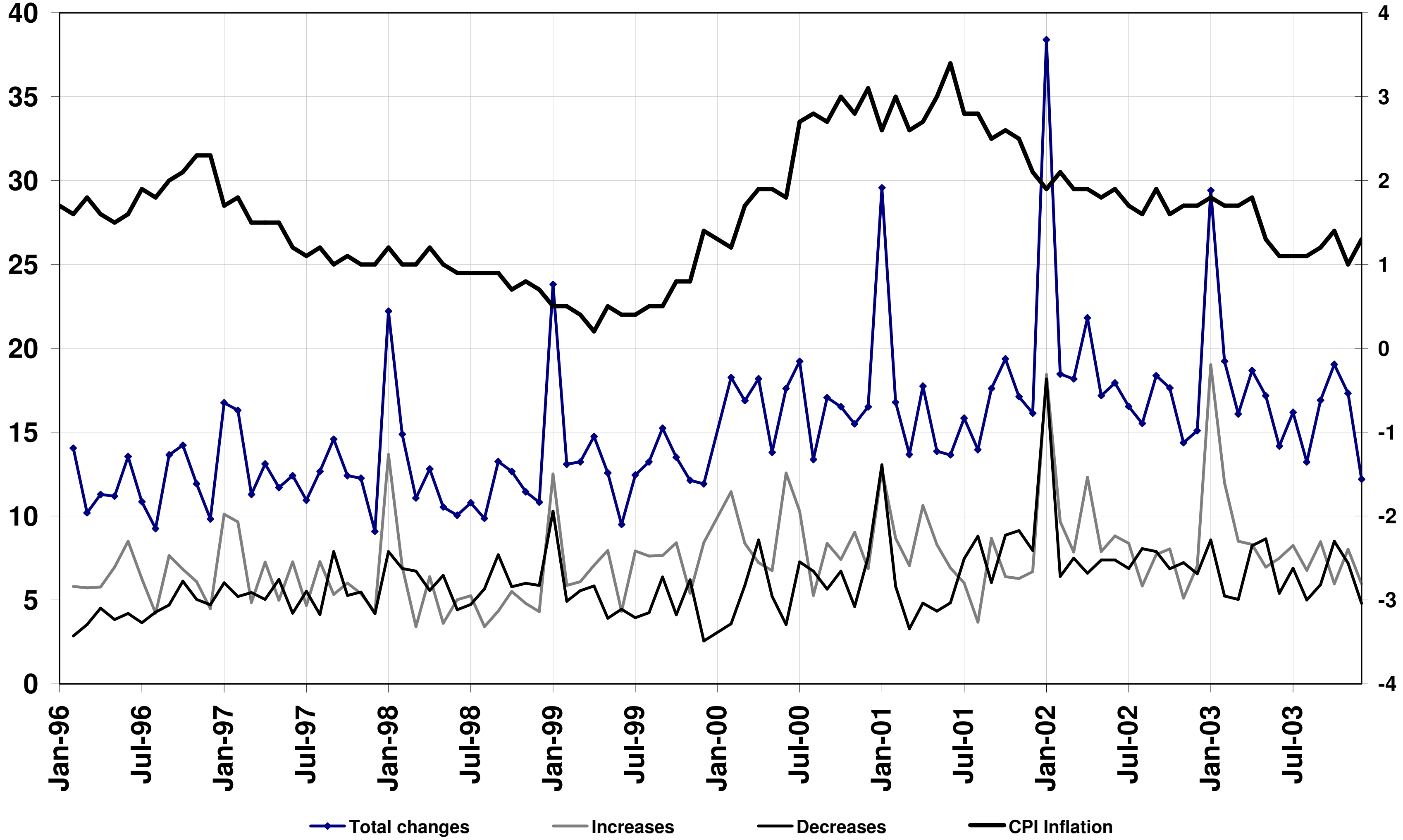
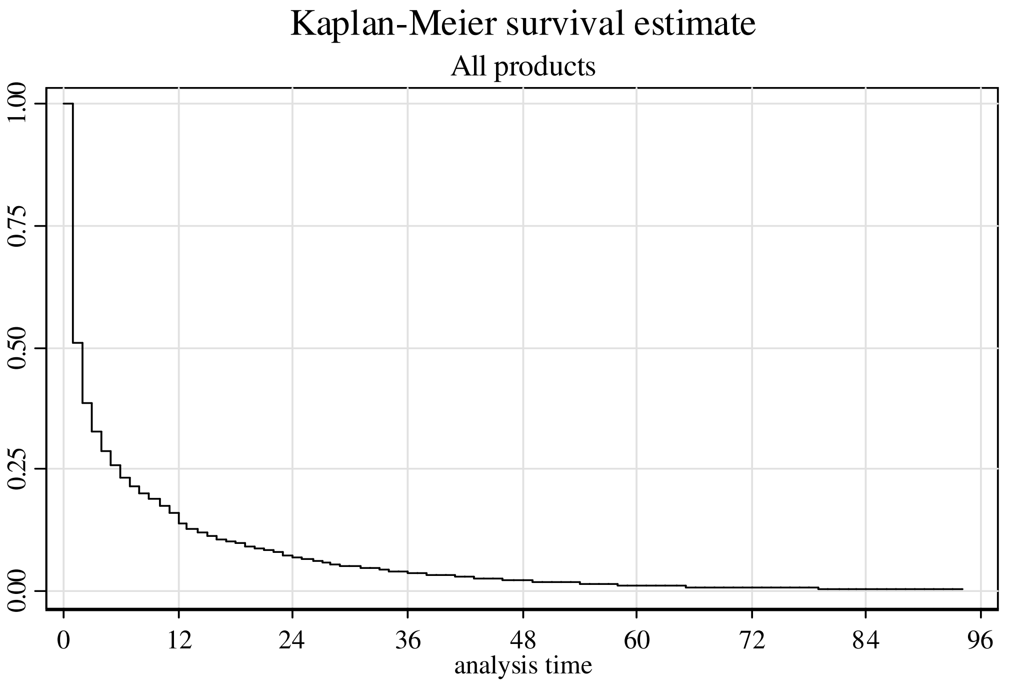
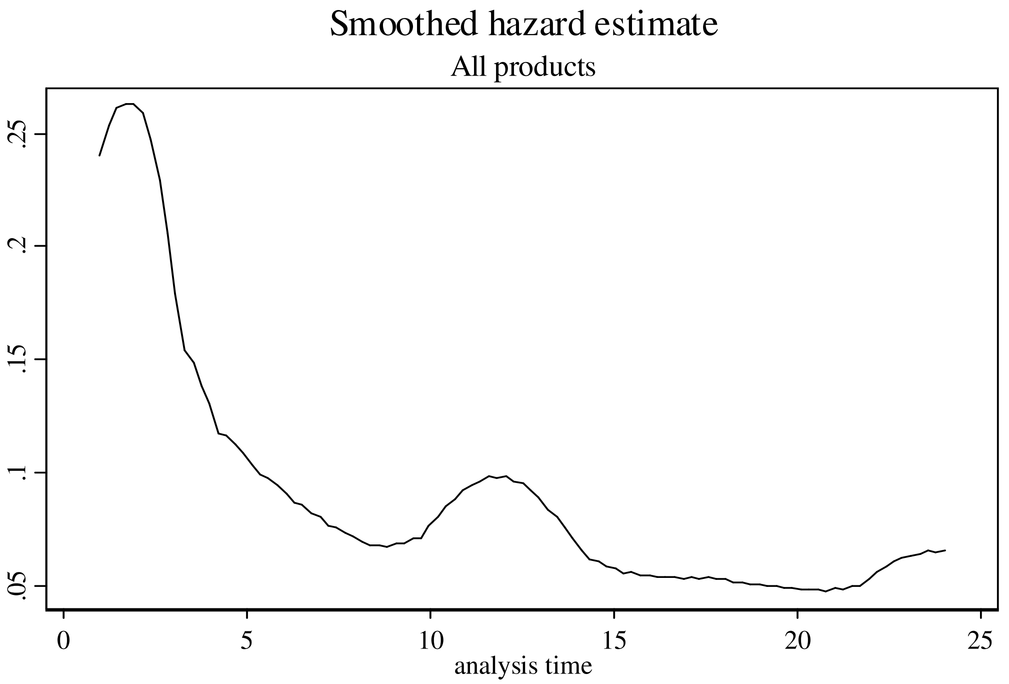


Figure 2



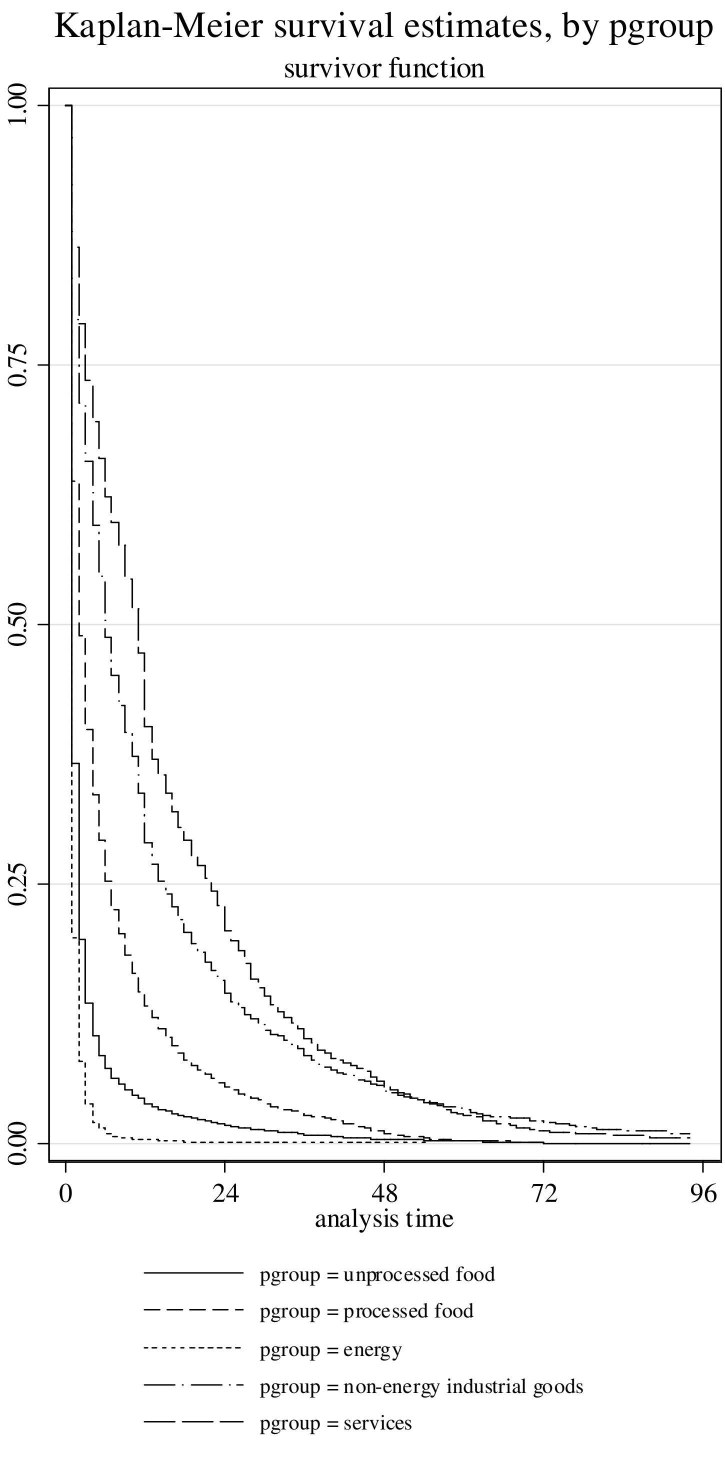
Note: Products in common sample.

Figure 3



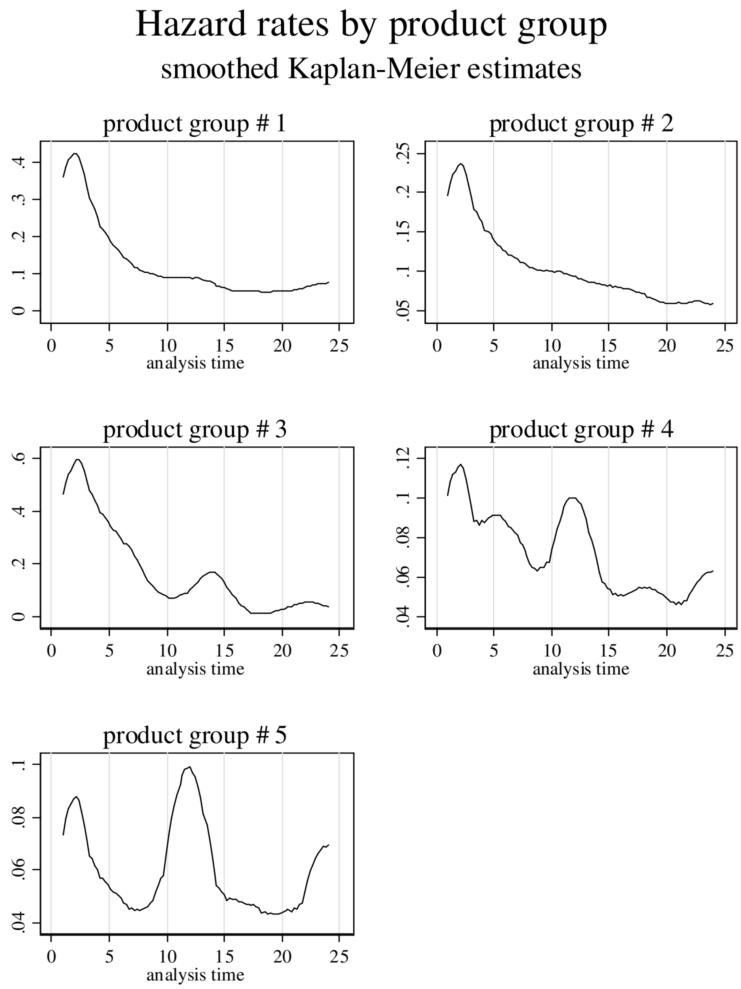
Note: Products in common sample.

Figure 4



Note: Products in common sample.

Figure 5



Note: Products in common sample.