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June 2004 (first version: february 2004)[3]

PRICE RIGIDITY. EVIDENCE FROM THE FRENCH CPI MICRO-DATA

Abstract

Based upon a large fraction of the price records used for computing the French CPI, we document consumer price rigidity in France. We first provide a methodological discussion of issues involved in estimating average price duration with micro-data. The average duration of prices in the sectors covered by the database (65% of CPI) is then found to be around 8 months. A strong heterogeneity across sectors both in the average duration of prices and in the pattern of price setting is reported. There is no clear evidence of downward nominal rigidity, since price cuts are almost as frequent as price rises. Moreover, the average size of a change in price is quite large in both cases. Overall, while our results do not entail a clear conclusion about the existence of menu costs, there is evidence of both time-dependent and state-dependent price setting behaviors by retailers.

Keywords: Price stickiness, duration of prices, consumer price index, frequency of price change.
JEL codes: E31,D43, L11

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[3]This study has been developped in the context of the Eurosystem Inflation Persistence Network. We are grateful to the INSEE (Direction des Statistiques Démographiques et Sociales) for providing access to the data, and in particular to Dominique Guédès for discussion and advice. We thank an anonymous referee of the ECB working paper series, as well as many colleagues and participants at seminars at the Banque de France, the European Central Bank and the INSEE, in particular Luis Alvarez, Ignazio Angeloni, Emmanuel Dhyne, Denis Fougère, Jordi Gali, Ignacio Hernando, Andrew Levin, Pedro Neves, Philip Vermeulen, for heplful remarks and discussions. The views expressed in this paper do not necessarily reflect the opinion of the Banque de France.
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Price stickiness is a major issue when assessing the potential impact of various kinds of shocks to the economy. Indeed, the response of output, inflation and employment to a shock on e.g. interest rates or energy prices, is highly dependent on the flexibility of prices (and wages). However, while a number of microeconomic theoretical models of price stickiness have been developed (e.g. Taylor, 1980, Rotemberg, 1982, Calvo, 1983) and used in empirical and theoretical macroeconomic models, their empirical assessment at the micro-economic level has remained relatively limited, as can be infered from the surveys by Weiss (1993), or Wolman (2000). This lack of micro-economic empirical evidence reflects the scarcity of available statistical information on prices at the microeconomic level. Indeed, most existing micro-studies are quite partial, focusing on very specific products or markets (e.g. the seminal contributions by Cecchetti 1986, on magazine prices, by Lach and Tsiddon 1992 on food product prices, by Kashyap, 1995, on goods sold through catalogs, or the more recent one by Genesove, 2003, on apartment rents). However more comprehensive empirical evidence has very recently been provided about consumer prices stickiness in the US (Bils and Klenow, 2004 and Klenow and Kryvtsov, 2003) as well as in some european countries such as Belgium and Portugal (Aucremanne and Dhyne, 2004, and Dias, Dias and Neves, 2004).[4]

The purpose of the present paper is to add a piece to this sparse, although growing, evidence using a large and comprehensive dataset containing more than 13 Millions observations of price records collected in order to compute the French CPI. Those data cover a large part of the economy and allow to provide indicators of price rigidity that are representative of the whole non-farm business economy. The dataset is of very large size in the cross-section dimension (more than 750000 individual products identified at the outlet level) and fairly large in the time dimension (the sample of monthly prices going from July 1994 to February 2003).

These data are used to characterize the flexibility of prices both in terms of the time duration between two price changes and in terms of the frequency of price changes over a given period. These two complementary approaches enable one to thoroughly investigate the heterogeneity of

[4]Those two papers as well as the present one are part of a Eurosystem research project.

price rigidity across goods, type of outlets and time. Moreover in order to investigate possible duration dependence, we report the hazard function for price changes. Among others, three questions of macroeconomic interest are addressed: how long is the average duration between two price changes in the economy? Do the data suggest state-dependent or time-dependent price-setting by retailers? Is there nominal downward price rigidity?

The outline of the paper is as follows. A description of the dataset is provided in Section 1. Section 2 discusses how to measure an average duration of prices, and provides some estimates. Section 3 and 4 investigate the determinants of the probability of a price change, focusing respectively on heterogeneity and duration-dependence. Section 5 presents evidence on the sign and size of variations in prices. Section 6 presents some robustness checks. Finally Section 7 summarizes the stylized facts and draws some indications for future research.

1 The dataset: over 13 millions price quotes.

1. 1. Overview

The data is a longitudinal dataset of monthly price quotes collected by the INSEE (Institut National de la Statistique et des Etudes Economiques) in order to compute the French CPI (Consumer Price Index). The methodology of data collection is described in INSEE (1998), and is also discussed in Lequiller (1997).

The sample contains CPI records from 1994:7 to 2003:2; each record relating to a precisely defined product sold in a particular outlet. With each individual price quote (i.e. the exact price level of the product), the following additional information is recorded : the year and month of record, an individual product identification number, a qualitative "type of record" code and (when relevant) the quantity sold.[5] By "individual product", we mean a particular product, of a particular brand and quality, sold in a particular outlet. The individual product identification number allows us to follow the price of a product through time, as well as to recover information

[5] When relevant, the price is divided by the indicator of the quantity sold in order to recover a consistent price per unit.

on the type of outlet, the category of product and the regional area.[6] The sequence of records corresponding to one individual product is referred to as a price trajectory. Importantly, if in a given outlet a given product is permanently replaced by a similar product of another brand or of a different quality, a new identification number is created, and a new price trajectory is started. The "type of record" code indicates into which of the following categories the record falls: regular price record, sales or rebates, or "pseudo-observation" (see below).

On the whole, the raw dataset contains around 13.2 Millions price quotes and covers around 65% of the CPI.[7] The breakdown of the available records by sectors, and the coverage rate by sub-component are presented in Table 1. The coverage rate is above 70% for food and non-energy industrial goods; close to 50% in the services, since a large part of services prices are centrally collected. Indeed some categories of goods and services are not available in our sample: centrally collected prices - major items being purchases of cars and administered prices- as well as other types of products such as fresh foods and rents.[8]

Insert Table 1 around here

1.2 Specific data issues

"Pseudo-observations".

For the purpose of computing the CPI, the INSEE cannot allow for missing values in its recording of prices of the individual products in the CPI basket. However, in some instances the price of a product cannot be actually observed. The value recorded in the datafile is then the outcome of an estimation procedure (or, following the terminology summarized in Turvey, 1999 , an imputation procedure), and is labelled a "pseudo-observation" in the present paper. For the purpose of our study, we have chosen, for some categories of pseudo-observations, to depart from the INSEE imputation procedure.

[6] Three alternative breakdowns by category of product are actually used in the paper: the COICOP classification by consumption purpose, the HICP sub-components used by the Eurosystem, and a sectoral classification that allows to separate sub-sectors with specific pricing patterns (energy, clothes, durable goods).

[7] Tables A1 to A4 in the appendix provide detailed information on the contents of the dataset.

[8] See Table A1 in the appendix.

Failure to observe a price can result from a variety of actual causes (see Table A3 in the Appendix for a breakdown of records by "type of record"), calling for a different procedure for computing a pseudo-price. First, some prices fail to be observed because the prices of some products are collected only at a quarterly frequency (5.6% of records). These products are mainly durable goods. The proportion of prices collected quarterly has sharply declined along the sample period : from 15.3% in 1994 to 7.63% in 1995 and 1.24% in 2002. Secondly, some products are seasonal by nature and their price is not posted all year round: for instance some hotels are closed in winter times; while ski gloves may not be sold during summer. These kinds of pseudo-observations account for 7.2% of price quotes, and appear mainly in the clothing sector. For these two categories of missing observations, the INSEE generally uses the "carry forward" procedure: the unobserved price of the item is assumed to be the same as when it was last observed. We remind that fresh foods, which are a kind of seasonal product, undergo a different statistical treatment based on a rolling basket but, as previously mentioned, they are not included in our dataset.

A third cause for the non-observation of prices is that the product is temporarily absent from an outlet, or that the outlet is temporarily closed or, more rarely, that the collector was absent (summing up to 4.5% of price quotes). In that case, the INSEE evaluates the missing price according either to the carry forward procedure, or by using extrapolation, or by computing a replacement price. The extrapolation procedure relies on adjusting the previous price by using the rate of change of an index of the product price index in the same geographical area. The replacement procedure implies recording the observed price of a similar product in the same outlet, or in another outlet. Although this procedure is fully appropriate for producing a real-time unbiased aggregate CPI, it is not so in our context. Indeed, if for instance, the outlet was closed in a given month, we do not want to record a price change as it would result from any kind of imputation. Therefore, our choice is to replace most of the pseudo-observations of prices using the carry forward procedure. Our assumption can be illustrated as follows. If a price P was observed at date t-1 and a price P' observed at date t+1, we assume that the price change occurred at date t+1, and that the virtual price at date t was P. The only instance in which our procedure might create a downward bias in the estimate of the frequency of price changes (and thus an upward bias in the estimated duration of prices) would be the case where the product was unavailable (or the outlet closed) on the precise day the collector visited the outlet, but present on other days in the month with a price different from P, say P", and that thereafter the price moved to P' on next month. We can however reasonably think that this type of instance is not very frequent and thus, the possible bias in our computation of price change frequencies should be quite small. Moreover, our strategy is partly supported by the observation that when P_t is a "pseudo-observation" $P_{t+1} = P_{t-1}$ is a posteriori the most often observed event. An exception to our use of the carry-forward procedure is the following: when at date t the item was transitorily absent, and when it turns out at date $t+1$ or $t+2$ that the product had been permanently replaced, we discard the observations from date t from the database (reflecting the fact that the price was actually last observed at date $t-1$).[9] Note that one major reason that allows for our treatment to be different from that adopted by INSEE, is that the INSEE has to evaluate prices in "real time" (at date t) and by definition cannot use information dated $t+1$.

The euro cash change-over

The euro cash-changeover took place in January 2002. All prices in the economy did change due to the conversion into euros at the exchange rate of 1 euro=6.55957 French Francs. We deal with that numéraire issue by dividing all prices prior to 2002:1 by 6.55957, the official Franc/euro exchange rate, without rounding (notice that, had we rounded prices over the first subperiod, then some subsequent but different prices expressed in French Francs would have been rounded up to the same price in euros, thus spuriously merging different price spells). At the time of the euro cash changeover (January 2002) however, all prices were set in euro rounded up to the second decimal (so virtually all prices changed due to mere rounding from, say, 8 to 2 digits). In order to build consistent price spells we have adopted the following rule: if the price (in euro) in December 2001 rounded up to the second decimal is equal to the price observed in January 2002, then the two prices are considered as part of the same spell, and no price change

[9] Note that following the EC regulation 1749/96, three subsequent prices observations cannot be "estimated" prices. If an item is missing for more than two months, it is automatically replaced by another item in the CPI basket.

is recorded.

Even when adjusting for the change in numéraire, many prices did change around the time of the changeover because retailers were targeting rounded prices in euro prior to the changeover, or psychological prices in euro after the changeover. This has created a moderate increase in the frequency of price changes or, equivalently, an interruption of many price spells (see INSEE, 2003 and the discussion below). The increase in the frequency of price changes actually started prior to the cash changeover date. However restricting the sample to the period 1994:7 to 2000:12, i.e. to the period ending one year before the changeover, does not affect our results in any significant way (see section 6). Therefore, the tables presented in this paper mainly relate to the whole period 1994:7 to 2003:2, with prices converted into euros.

Sales, rebates, changes in taxes.

In the data we can identify whether the observed price corresponds to sales or temporary rebates. The proportion of price quotes that are sales is 0.76% and temporary discounts amount to 1.92%. Also note that two major specific events occurred during the observed sample: in August 1995 the normal VAT rate was raised from 18.6% to 20.6% and in April 2000 this rate was lowered to 19.6%. In the baseline analysis, we considered all price changes as regular ones as outlets could nevertheless choose not to change their prices. The influence of sales is investigated in the robustness analysis section.

Weighting

For the purpose of producing aggregate measures of the frequency of price changes and of price durations, we compute weigthed averages using CPI weights. Since these weights are not defined at the store level, our procedure for computing aggregate quantities is as follows. In a first step we perform unweighted average over price records (or price spells) and outlets for each elementary product level of the CPI. Elementary products ("variétés") are the lowest level for which CPI weights are defined.[10] There are around 1300 categories of elementary products in the database, the contents of which is subject to statistical confidentiality. This level is used for

[10] Note that intermediate aggregation by regional areas is also used in the computation of the CPI. This information is not incorporated here.

aggregation purpose, and results at this level are not reported. In a second step we compute an aggregate statistic by averaging over elementary products using weights. Those weights are the averaged (consumer expenditure based) CPI weights over the period 1994-2003 (with weight set to zero at times when an elementary product is not included in the CPI basket). We note ω_j the weight of product j in the overall CPI basket. Preliminary experiments indicated that our results are not significantly changed when first averaging by outlet before averaging by elementary product.

2 How long does the average price spell last?

A straightforward way to describe prices stickiness is to compute the (average) duration between two price changes for a given product in a given outlet. Prices will be considered as sticky when this duration is long while they will be considered as flexible in the opposite case.[11] One particular motivation for focusing on such an indicator is that the average duration of a price is a key "structural" parameter in many macroeconomic models featuring price stickiness (e.g. see Gali and Gertler 1999, Taylor 1999). For instance, Rotemberg and Woodford (1997), in a model that relies on the Calvo specification, calibrate the probability of price change using various micro-data estimates of average price duration. Also, in the Taylor staggered contracts model, the contract length is one parameter to be calibrated.

2.1 Direct estimates of the duration of price spells.

In order to allow a clear reading of results, we first provide a set of definitions and notations.

2.1.1 Definitions and notations.

The raw observations in our database are made of sequences of **prices quotes** $P_{j,k,t}$, where $j = 1, ..., J$ is an index for elementary products, k is an index (specific to product j, with $k = 1, ..., K_j$) for outlets selling product j, and t is a (calendar) time index, $t = 1, ..., \Gamma$. An individual good/service, identified in our data by an identification number, is a product j sold

[11] Although being "natural", such an approach is not exempt of drawbacks. In particular, prices may be flexible but still remain unchanged if their driving factors are themselves constant.

in outlet k, and is thus defined by the (j,k) pair. Note that for simplicity of exposition, in the following we may omit the index k, when convenient.

A **price spell** is an episode of fixed price for a specific product j in a particular outlet k. Let i be the index of price episodes $i = 1, ..., N_{j,k}$ where $N_{j,k}$ denotes the number of observed episodes of fixed price for this specific couple (j,k). The **price spell duration** $T_{j,k,i}$ is the time between two price changes of that product j in outlet k ($T_{j,k,i} \geqq 1$).[12] Then, the i^{th} price spell can be characterized by its observed duration $T_{j,k,i}$, by the price level prevailing during that price spell ($P_{j,k,i}$), and by $t_{j,k,i}$ the calendar time of the i^{th} price change.[13]

A **price trajectory** is a succession of several episodes with fixed prices. It can be defined by the date of the first observation and the set of successive price spells. Figure A1 provides an illustration of a typical price trajectory. **The trajectory length** $L_{j,k}$ is the number of periods for which a product (j,k) and its price are continuously observed. The number of price quotes in the dataset is clearly the sum of all trajectories length $Q = \sum_{j=1}^{J} \sum_{k=1}^{K_j} L_{j,k}$. The number of observed price spells wil be noted as $N = \sum_{j=1}^{J} \sum_{k=1}^{K_j} N_{j,k}$.

As we aim at computing a macroeconomic estimate of the duration of prices, aggregation is an important issue. There are alternative ways of aggregating durations into an aggregate duration of prices. A first measure is the **average unweighted duration of all price spells**

$$\overline{T} = \sum_{j=1}^{J} \sum_{k=1}^{K_j} \sum_{i=1}^{N_{j,k}} \left[\frac{1}{N}\right] T_{j,k,i} = \frac{Q}{N}$$

In this first measure, all price spells have the same weight. The average unweighted duration is just the number of observations divided by the number of price spells. However, given that different products are likely to behave differently with respect to price rigidity, it seems preferable to compute durations by homogeneous sub-groups and then aggregate durations than to estimate

[12] The data collection scheme imply that infra-monthly durations of prices are not observed. For instance, when $0 < T \leq 1$ month, we observe a duration of 1 month, inducing an upward bias in the measured spells duration. This bias is relatively more harmul for short durations. In addition, one type of occurence of price changes may not be observed : when within the period between two records the price moves and them comes back to its initial level.

[13] Appendix 1 provides define formal definitions of the duration and of other relevant quantities.

a single overall duration. We then consider the **average duration for one individual good (product** j), which is obtained by averaging over spells and outlets :

$$\overline{T}_j = \sum_{k=1}^{K_j} \sum_{i=1}^{N_{j,k}} \left[\frac{1}{\sum_{k=1}^{K_j} N_{j,k}} \right] T_{j,k,i}. \tag{1}$$

From the latter we can define the **average unweighted duration of price spells (averaged by product).**
$\overline{T}^P = \sum_{j=1}^{J} \frac{1}{J} \overline{T}_j = \sum_{j=1}^{J} \sum_{k=1}^{K_j} \sum_{i=1}^{N_{j,k}} \left[\frac{1}{J.\sum_{k=1}^{K_j} N_{j,k}} \right] T_{j,k,i}$

An important remark is that definition this statistic gives less weight than $\overline{T}$ to products that have frequent price changes. Indeed, the latter ($\overline{T}$) tends to undervalue the average duration (because more price spells are observed).

Last, the CPI weights can be incorporated in order to compute the **average weighted duration of price spells,** defined as follows:

$$\overline{T}^W = \sum_{j=1}^{J} \omega_j \overline{T}_j = \sum_{j=1}^{J} \sum_{k=1}^{K_j} \sum_{i=1}^{N_{j,k}} \alpha_{i,j,k} T_{j,k,i} \tag{2}$$

Our first purpose being to provide measures that are relevant macroeconomic proxies we mainly focus on this last indicator. This amounts to weighting each individual spell $T_{j,k,i}$ by the weight $\alpha_{j,k,i} = \omega_j / (\sum_{k=1}^{K_j} N_{j,k})$, that is the CPI weight of the category divided by the number of spells in the given category. These weights $\alpha_{j,k,i}$ are also used when computing the weighted median duration, or other quantiles. Note that, as is standard with duration data, we expect the distribution to be asymetric, and median duration to be lower than mean duration. If durations follow an exponential distribution homogenous across goods (as assumed in the Calvo constant hazard model), then median duration is $Median(T) = -\ln(0.5)E(T) \simeq 0.69E(T)$ where $E(T)$ is the expectation of duration.

2.1.2 The duration of price spells: a first set of estimates.

A first set of results about price trajectories and price spells are reported in tables 2 and 3 below.

Insert tables 2 and 3 around here

The number of observed trajectories (one trajectory is a sequence of prices of one product in one given outlet) is $K = 754,220$. The average length of an observed trajectory is $\overline{L} = 16.65$ months. The average number of spells per trajectory is 3.15 so the overall average unweigthted duration over all price spells is evaluated to be $\overline{T} = 5.28$ months (consistent with Table 3). The distribution around this mean is unsurprisingly very asymmetric : the median duration of spells is 3 months. The distribution is plotted in Figure 1. There is a very high mode at duration 1 month. Also a very long right-side tail is apparent, with 25% of spells lasting more than 7 months, and around 2% of spells lasting more than 2 years. Some very long durations are observed in every category of goods, but services prices are over-represented in the tail.[14]

The basic unweighted average duration $\overline{T}$ clearly over-weights the products with short durations (since for a given trajectory length, a larger number of spells is observed). Table 3 also provides results based on alternative aggregation procedures. When averaging durations by individual trajectories first, the unweighted average duration rises to 6.83 months. Indeed, the overall distribution is moved to the right (the first quartile is 3 months). The third line of the Table reports characteristics of the distribution of durations at the elementary group level (the T_j's) using the CPI weights. The weighted average duration of price spells ($\overline{T}^W$) is 7.24 months, while the weighted median is equal to 5.88 months. Finally the last line of Table 3 provides summary statistics about the distribution of spells at the individual level, those statistics being computed using the weights $\alpha_{j,k,i}$ defined above. The average duration is, as implied by equation (2), identical to $\overline{T}^W$. The weighted median duration of price spells (the median of $T_{j,k,i}$) is found to be 4 months. This weighted median is farther away from the mean than the previous one (the median of the T_j 's) indicating a dispersion of durations within each elementary category.

2.1.3 Truncation, censoring and the product replacement (attrition) issue

An important issue to be addressed when measuring durations of price spells is that of truncation and censoring. Censoring and attrition are important phenomena in our database

[14] Entrance to a show or a museum is an example of item for which long durations are found. We also conjecture that coin-operated machines is a motive for some items to have long price durations (e.g. car-wash).

since, as shown in Table 4, only 58.59% of observed price spells are uncensored (figures for censoring use CPI weights). Typically, the first and last spells of a price trajectory are truncated (the dotted lines in Figure A1 figure the unobserved part of truncated spells).

The terminology on truncation and censoring does not seem to be harmonized across authors, so we find it worthwhile to present the definition adopted in the present paper. **Left-censoring** is the fact that the (calendar) time of beginning of the first price spell of an individual product in the database, is not observed. Indeed it cannot be assumed that the price was set on the precise month when a product was actually included in the CPI basket, or when an individual product started to be observed in a particular outlet. This is the most frequent case of censoring in our dataset as 27.95% of spells are left-censored.

Right-truncation is the fact that the end-date of the last price spell is not observed. Right-truncation may be due to three kinds of causes. A first cause is the interruption of the observation process, which corresponds to the usual right-censoring phenomenon in duration analysis. For individual products included in the CPI basket at the last period of the sample, the observation was interrupted while the process was still on-going, i.e. the last price observation does not correspond to the end of a price spell. A second case of right-truncation is that the statistical institute can no more record the price of a given product in a given outlet, because the product is no more sold by the outlet (or more rarely, because the outlet itself closes). Following the duration data literature we refer to this phenomenon, i.e. the disappearance of the individual from the database, as "attrition". In general, the statistical institute does replace the missing product by selecting another item in the same shop or in another outlet. This kind of replacement is termed "forced replacement" by some statistical agencies (Turvey, 1999). A third source of right-truncation is that, for statistical representativeness reasons, the statistical institute may decide to discard a product or an outlet from the set of recorded price quotes. Such a case is called "voluntary" or "optional product replacement" (Turvey, 1999). The product may continue to be sold, but its price is no more collected.

In our data, the information is available to distinguish among these three different kinds of right-truncation. Around 60% of right-truncated spells are associated with forced replacement, 20% are presumably voluntary replacements and 20 % correspond to the end of the observation process (price quotes dated 2003:2). We use this information to treat differently the various cases of right-truncation in analyzing durations. Our maintained assumption throughout the analysis is that any price spell ending with a forced replacement can be considered as complete (uncensored). Such an assumption can be motivated by considering the example of clothes. Due to the winter/summer collection pattern, the life-cycle of those products is very short. When the collection changes, items (say shirts) are typically replaced by items with different characteristics. In the dataset, the trajectory for the previous individual product is stopped, without a change in price being recorded. As a results, only few price changes are actually observed and thus, not accounting for this particular type of attrition would lead to estimating a very low frequency of price changes and hence, very long durations. Therefore, our baseline approach is to consider each case of forced replacement as indicating the end of a spell, i.e. to treat it as "equivalent" to a change in price. This assumption has a major impact on our results, as will be seen from the comparison between figures accounting and not accounting for this particular type of attrition. It is to be stressed that, even under our preferred assumption on attrition, a large number of price spells remain right-censored (those corresponding to other forms of right-truncations than attrition). Also note that a price spell may be both left-and right truncated. Such types of prices spells are not negligible in our database (around 4% of spells): a product that has recently been incorporated in the CPI basket may stop to be sold before its price was observed to change. In such cases the trajectory is made of only one price spell.

Insert table 4 around here

The consequences of censoring upon measured durations of prices are as follows. First, censoring truncates some of the price spells so that *ceteribus paribus*, the duration of a censored price spell will be shorter. If censoring is quantitatively important, discarding censored spells is not a satisfactory option since it may give rise to a selection effect. The price spells that are long-lasting are indeed more likely to be censored. Ignoring censored spells will typically lead to understating the true average duration.

In our data, the selection effect of discarding censored data is apparent: restricting to uncensored spells leads to an average duration of prices of 5.97, compared to 7.24 months for all spells. At the opposite, the average duration of spells that are both left and right censored is 12.29. The extent of censoring suggests that the average duration of 7.24 months is likely to be downward-biased.

One relevant treatment of truncation involves the estimation of duration models. For instance, a simple correction for censoring is as follows. If $\overline{T}$ is average duration over both censored and uncensored, then an estimate of average duration is $T^{*}=\overline{T}\frac{N}{N^{U}}$ where N is total number of spells and N^{U} is the number of uncensored spells. It corresponds to the ML estimate of a constant hazard model, assuming all censoring is right censoring. (e.g. Kiefer, 1988, pp 662). Using such a simple procedure, one may get a tentative idea of the magnitude of the correction that should be applied to the average duration estimate. A rough estimate of the weighted average duration along these line would be to multiply the average weighted duration ($\overline{T}^{W}=7.24$) by $\frac{N}{N^{U}}$, yielding around twelve months. This estimate is however too rough to be reliable because, to compute the correcting factor one should also take into account for left-censoring, check the constant hazard assumption, and consistently incorporate weights. Indeed in our context however, designing an adequate treatment of censoring raises some complex issues. First, left-truncated and right-truncated spells should not be treated in a similar way (except in the case of constant hazard and stationarity of the DGP). The presence of doubly-truncated spells should also be acknowledged for. Another issue to be investigated is how to treat attrition, as compared to standard right-truncation. Investigating these issues will be the purpose of future work. In the present paper, we stick to reporting observed durations as well as evidence on censoring, and use as a cross-check an alternative approach relying on the frequency of price change.

2.2. Indirect estimates of the duration of price spells: the frequency approach

2.2.1 Definitions and notations

The frequency of price changes, computed from the cross section dimension of the data, can be used to provide an indirect measure of the average duration of price spells. It has also an interest per se in characterizing price rigidity.

The frequency of price changes is defined as follows (for convenience outlet indexes are dropped here). Let $I_{j,t}$ is an indicator function for a price change, defined by $I_{j,t} = 0$ if $P_{j,t} = P_{j,t-1}$ and $I_{j,t} = 1$ if $P_{j,t} \neq P_{j,t-1}$. Denote as Γ the calendar date of the last observation and assume for simplicity of exposition that the data are balanced (the number of observations is J at each date), so that Q the total number of observations, is equal to ΓJ. The average frequency of price changes at date t is defined as $F_t = \frac{1}{J}\sum_{j=1}^{J} I_{j,t}$. Assuming that there is no left-censoring (i.e. the first price observation of each spell corresponds to a "fresh" price, i.e. is associated with a price change), the average frequency of price changes for product j is $F_j^{nlc} = \frac{1}{\Gamma}\sum_{t=1}^{\Gamma} I_{j,t} = N_j/\Gamma$.[15] Similarly, the average frequency of price changes over the whole sample is defined as $F = \frac{1}{Q}\sum_{t=1}^{\Gamma}\sum_{j=1}^{J} I_{j,t}$, and the weighted average frequency of price changes is defined as $F^W = \frac{1}{Q}\sum_{t=1}^{\Gamma}\sum_{j=1}^{J} \omega_j I_{j,t}$.

2.2.2 From the frequency of price changes to the duration of price spells.

The average implied duration is computed from observed frequency is computed as

$$\overline{T}^F = \frac{1}{F}. \tag{3}$$

A simple property rationalizing this formula is that, *when there is no censoring*, and *if the data are unweighted*, the average of observed durations is equivalent to the inverse of the average frequency. Indeed, when price records belong to uncensored spells, each price spell is associated to one value of $I_{j,t}$ being equal to one. The numerator of F is then $\sum_{t=1}^{\Gamma}\sum_{j=1}^{J} I_{j,t} = \sum_{j=1}^{J} N_j = N$. Then, Q being the total number of observations, the estimator based on the inverse frequency is thus $\frac{Q}{N}$ (the average number of observations per spell) which is equivalent to the simple average of observed durations $\overline{T}^F = \overline{T}$.

[15] This definition assumes for the sake of simplicity that the price spells are not left-censored. With left-censored data, the relevant formula is $F_j = \frac{1}{\Gamma-1}\sum_{t=2}^{\Gamma} I_{j,t} = (N_j - 1)/(\Gamma - 1)$, reflecting ignorance of whether or not the first observation recorded corresponds to a change in price. Moreover, relaxing the assumption of balanced data, one gets $F_j = (N_j - 1)/(\Gamma_j - 1)$, where Γ_j is the number of observations for product j.

A deeper, more general motivation for using this approach is that in a stationary context, and in a large sample, the inverse of the frequency of price changes converges to the mean duration (or, if $\widehat{p}$ is an estimator of the unconditional probability of a price change then $Plim\ \widehat{p}=1/E(T)$). This relationship is obtained asymptotically under general conditions in a renewal process (see Lancaster, 1990, p.90). We underline that this property does not rely on the distribution of durations, but requires stationarity, together with the homogeneity of price change behavior in the cross-section dimension. Under those conditions, the computation of price changes frequencies in either the time or the cross-section dimension allows an indirect estimation of the average duration of prices. Note that the relationship $E(T) = 1/p = 1/E(F)$ holds exactly in a constant hazard model (in which p is the constant probability of price change). Furthermore, under the constant hazard assumption, the median duration between two subsequent changes of price is $Median(T^F) = -\ln(0.5)/F$. Note also that equation (3) above assumes discrete time : retailers implicitly change prices, when they do so, once in a month, and at the end of the month. In the empirical estimates, following Bils and Klenow (2004), we relax that assumption assuming a constant hazard, i.e. assuming the probability of a price change is constant within a month. One can estimate the "continuous time" average duration by $\overline{T}^F = -\frac{1}{\ln(1-F)}$.[16] To some extent, this addresses one caveat of direct measures of durations noted above (see footnote 13).

The frequency approach, employed among others by Bils and Klenow (2004) offers several practical advantages. First, a long span of time series is not needed, as long as homogeneity and stationarity is a valid assumption. One may estimate durations even if the observation window is very short (for instance, shorter than the average duration of a price spell). Secondly, this approach is likely to be more robust to any specific event (one can for instance ignore one specific month characterized by an exceptional event such as an increase in the VAT rate, ot the euro cash changeover). Third, this approach allows to compute durations without access to the individual records. For instance Bils and Klenow (2004) have used data on monthly frequency at a disaggregated sectoral level. Fourth, this approach does not require an explicit treatment of censoring. Provided censoring is independent from the duration process, the inverse frequency

[16] This amount to substracting half a month to the former measure of average durations. The corresponding measure of median duration is $\overline{T}^{med,F} = \ln(0.5)/\ln(1-F)$.

estimator of average duration is consistent.

2.2.3 Estimating frequencies: practical issues

Before presenting results, some remarks are in order as regards the implementation of the frequency approach.

Firstly, for the homogeneity and stationarity assumptions to be fulfilled, is important that the analysis is performed both a disaggregated level, and for homogeneous sub-periods.

Secondly, proper acknowledgment of attrition remains crucial. It is indeed our prior that attrition (product replacement) is a kind of truncation that is not independent from price setting. In the following, we keep considering any replacement as ending a price spell, i.e. equivalent to a change in price (setting $I_{j,t} = 1$ if a forced replacement is observed at date t).

Thirdly, aggregation raises some issues. Assuming uncensored data, one simple indicator of the overall duration is the inverse of the weighted average frequency of price changes $\overline{T}^{F,H} = 1/F^W$. However, acknowledging that homogeneity is likely to be fulfilled at the product level only, a more relevant approach is to compute the weighted average of inverse frequencies, as follows. For a given good j the average duration can be estimated as $\overline{T}_j = 1/\overline{F}_j$. Then, averaging over all products and using weights ω_j, one gets $\overline{T}^{F,W} = \sum_{j=1}^{J} \omega_j (1/\overline{F}_j) = \overline{T}^W$. Thus, in case of no censoring, the direct measure of weighted duration is equal to the weighted average of inverse frequencies. Under the assumption of independent censoring (and identical distribution within products), the weighted average of inverse frequencies is a measure of average duration presumably less affected by censoring than the direct measurement of durations. A noteworthy property is that the first approach, computing the inverse of weighted average frequency to estimate an average duration provides a different result.[17] Indeed $\overline{T}^{\overline{F},H} = 1/\overline{F}^W = \frac{1}{\sum_{j=1}^{J} \omega_j \overline{F}_j,} = \frac{1}{\sum_{j=1}^{J} \omega_j \frac{1}{\overline{T}_j},}$ which is an harmonic mean of the individual goods duration. By a property of the harmonic mean we have:

$$\overline{T}^{\overline{F},H} < \overline{T}^{F,W}.$$

Another statistic of interest (used e.g. by Bils and Klenow, 2004) is the weighted median of

[17] This point is also emphasized by Baharad and Eden (2004).

inverse frequencies. This measure is particularly interesting given that for some sectors the frequency $\overline{F}_j$ is close to zero, leading to very large values of implied duration $(1/\overline{F}_j)$ which strongly influence the mean. The weighted median cannot, however, be interpreted as an estimator for the average duration of prices. It is also important to remind that using frequencies does allow one to characterize the average duration, but not the full distribution of price durations. In particular, the shape of the hazard function, i.e. the conditional probability of a price change, cannot be derived from frequencies of price changes.

2.2.4 The average duration of a price spell: further results

The weighted average frequency of price changes over the baseline period, reported in Table 5, is 0.189. The estimator based on inverting this weighted average frequency is $\overline{T}^{\overline{F},H} = (1/\overline{F}^W) =$ 5.29, or under the "continuous -time assumption" $\overline{T}^{\overline{F},H} = -1/\ln(1-\overline{F}^W) = 4.77$. The weighted average of implied durations (continuous time) is $T^{\overline{F},W} = 8.38$. As expected $T^{\overline{F},W}$ is larger than the inverse of the aggregate frequency ($\overline{T}^{\overline{F},H}$). The order of magnitude of the difference between the two indicators is similar to that obtained by Baharad and Eden (2004) on Israeli data (7.9 versus 4.1). The estimate based on inverse frequencies is also larger than the direct average of durations. The latter inequality results from censoring (note that the discrete time assumption used in the direct measurement of durations tends to attenuate the discrepancy). The weighted median of inverse frequencies is 6.20. The difference between the median and the weighted average is due to some frequencies of price changes F_j being close to zero for a few elementary groups. The distribution of frequencies across elementary products is represented in Figure 2.

Insert Table 5 around here

Overall, our best estimate for the average duration of prices is thus around 8 months. This estimate is very close to the value found by Bils and Klenow (2004) for the US. Moreover the median implied duration is 6.20 months, which falls in the middle of estimates found in recent similar studies (see Aucremanne and Dhyne, 2004, Dias, Dias and Neves, 2004, Bils and Klenow, 2004).

The distribution of frequencies across elementary products, represented in Table 5 and in Figure 2, is very asymmetric. While a few group of products have frequencies close to one, most of the distribution is concentrated in the range 0.05 to 0.25. Roughly 25% of the products have implied average durations equal to or greater than 12 months.The next sections provides evidence that there is considerable heterogeneity across sectors, and that the distribution of price durations, unlike in the constant hazard model, cannot be characterized by one single parameter.

3 Heterogeneity in the frequency of price change

3.1.The price changes pattern strongly depends on the product category

Tables 6 and 7 provide basic results on sectoral patterns of durations.[18]

Insert tables 6 and 7 around here

Price rigidity, as measured by the direct estimate of the average duration of price spells, strongly varies across sectors (Table 6). The main relevant contrast seems to be between services and other types of goods. The weighted average duration of a price is twice larger in the services sector (11.43 months) than in the manufacturing sectors (durable goods, clothing, other manufactured goods) and in the food sector (around 5 months). Note that the contrast between categories of good defined by purpose (as reported in Table A6 in the Table Appendix) seems to be less relevant.

The importance of attrition and censoring also considerably varies across categories of products. The strong impact of the assumption about attrition is documented in Table 7. The first column reports the average frequency of price changes by category taking attrition into account, while the last column reports the same figure not accounting for attrition. For clothes in particular, the latter indicator, i.e. the frequency of actually observed price changes is very low (0.098 using our breakdown by sector). This reflects the fact that such a basic measure of frequency

[18] See also table A5 to A7 in Table Appendix for additionnal results.

does not capture price changes that are implemented through changes in clothes collections. When assuming that each replacement indicates the end of a price spell and, as such, can be treated as if a price change occurred, we obtain a frequency equal to 0.178, and recover a more plausible average implied duration of 5.978 month in this sector.

It is intuitive that our treatment of attrition, i.e. assimilating any forced replacement to a price spell end, raises the frequency of price changes, particularly in sectors with short life-cycle. More formally, the impact of the assumption about attrition can be rationalized as follows. Since the first spell of each price trajectory is left-censored, the observed frequency of price changes is $F_j = (\sum_{t=2}^{\Gamma_j} I_{j,t})/(\Gamma_j - 1) = (N_j - 1)/(\Gamma_j - 1)$.[19] As mentioned above, the number of observed price changes is exactly the number of observed spells (N_j) minus one. The first observation of $I_{j,t}$ is indeed a missing value as we do not know whether or not it corresponds to a price change.[20] Now, consider that attrition induces the end of a price spell. This can be accounted for by assuming that, posterior to the last observation of each trajectory subject to attrition, an additional change in price occurs. Then, with left-censoring, the frequency estimate becomes $F_j^a = (\sum_{t=2}^{\Gamma_j} I_{j,t} + 1)/\Gamma_j = (N_j/\Gamma_j) = F_j(1 - 1/\Gamma_j)/(1 - 1/N_j) = kF_j$ with $k > 1$ (because $\Gamma_j > N_j$).[21] As a consequence, the indirect estimator of average duration accounting for attrition will provide a lower duration than the frequency estimator unadjusted for attrition. The difference between the two estimators will be particularly large when the number of spells per trajectory is small, which is particularly the case in the clothing sector.

Besides attrition, the importance of censoring (other than forced replacement) also varies considerably across categories of products. Only 55% of price spells are uncensored in the non-energy industrial goods (table A7 in the Appendix). Censoring is less an issue for Food (with around 72% of spells uncensored) and Energy (around 91% of spells uncensored).

Table 7 presents the breakdown by sub-components of implied durations derived from the

[19] where $I_{j,t}$ is the indicator of a price change and we assume for convenience that all observed trajectories start at the same date.

[20] Without left censoring and not accounting for attrition, the frequency of price changes for product j would be evaluated by $F_j = (\sum_{t=1}^{\Gamma_j} I_{j,t})/\Gamma_j = N_j/\Gamma_j$.

[21] Without left-censoring the frequency estimate would then be $(\sum_{t=1}^{\Gamma_j} I_{j,t} + 1)/(\Gamma_j + 1) = (N_j + 1)/(\Gamma_j + 1)$.

indirect (frequency) approach, arguably less sensitive to censoring. We observe a strong heterogeneity across categories of good, and sub-components. The component with the lowest price rigidity is energy: prices last for 1.38 month on average (recall that the sample does not include gas nor electricity prices, which are centrally collected, so this component is mainly gasoline and fuel). Prices of unprocessed food products (i.e. mainly meat given that the available sample does not include seasonal fresh food products) last for 4.6 months on average. The services sector contrasts sharply with other sectors, with an average duration of 14.53 months.

3.2 The frequency of price changes also differs over outlets and varies over time.

To illustrate in a simple manner the determinants of the frequency of price change, we have estimated a logit model. The model is intended as a reduced form -"analysis-of-variance" type-estimate rather than a structural model. The dependent variable is the dichotomous variable indicating the occurrence of a change in price. The right-hand-side variables are the sector, the type of outlet, the month (to investigate seasonalities in price changes), the year (to investigate structural change and cycle effects) and dummies that capture specific events (dummy variables for the two months with a VAT tax change, the month of euro cash changeover, and the "euro cash change over period" corresponding to 6 months prior and six months posterior to the euro cash changeover of January 2002).

Results are presented in Table 8. Observations are not weighted in this analysis. In the last column of the table, we report the impact of the each factor, other things being equal, on the probability of changing price. The reference is the price of a manufactured good sold in a supermarket, in December of year 1998. The estimated probability of a change in price for the reference category is 11.9 percent.

Insert table 8 around here

Given the very large number of observations, the regression is unsurprisingly very significant, and all variables have some explanatory power. The impact of the sector is much in line with that observed in the previous section. The conditional frequency of a price change is 3.5 percentage point higher in the food sector, and 3.7 percentage point lower in the services sector than in the manufacturing good sector. Note that in the services case one should also decrease the probability by an additional 4.1 percentage point, because services are typically not sold in supermarkets but in services outlets. The type of outlet also matters, when controlling for the type of good sold. Prices are more flexible in hypermarkets (the conditional probability of a price change is 0.144 versus 0.119), while they are much stickier in hard discount stores and traditional corner shops (probabilities are respectively 6.9 and 7.9 percent). The time dummies for major events are very significant. The instantaneous probability of a price change was seemingly more affected by the year 2000 VAT decrease than by the VAT raise of 1995 (note that this analysis is not informative about the size of the VAT pass-through). There is a clear seasonal pattern in price setting. January and September are months with numerous price changes. There seem to be some signs of increased frequency of price changes over time. Note that the dummies for year 2001 and 2002 are significant in spite of the presence of a one month indicator for the euro cash change over and of a "euro-change-over" period. This may suggest that the impact of the euro cash change-over was spread out over more than twelve months, or may indicate a recent shift in the overall price rigidity.

Some of these patterns are illustrated in Figure 3, which represent the time series of the average frequency of price changes (computed in the cross-section dimension as a weighted average of frequencies of price changes across elementary products). The seasonal pattern with peaks in January and September is evident. The spikes in the frequency of price changes at the time of VAT changes and of the euro cash changeover are also very apparent.

4 Are long-lasting prices more likely to be changed ?

This section investigates the probability of a change in price conditional on the elapsed duration of a price spell, i.e. the hazard function of a price spell. The hazard function is a convenient tool to analyze economic duration data (see Kiefer, 1988). In addition, some theories of price-setting have direct predictions about the shape of the hazard function. For instance the widely used Calvo model relies on a constant hazard (see Wolman, 1999, for other examples).

We report hazard functions by sector in Figures 4 to 8, computed using the life-table method (see e.g. Kalbfleisch and Prentice, 2002 for a description). Note that censoring is acknowledged for in this approach. Strong contrasts across sectors in the shape of the hazard function are manifest. For the manufacturing and food sectors, the hazard has a rapidly decreasing shape, with a very marked spike at one month. This reflects that a large number of prices are reset every month. For clothes there is also a large spike at one month: this peak is explained by spells of sales, and virtually disappears when sales and temporary rebate price spells are removed from the dataset. There is also a peak at 6 months for clothes, reflecting the succession of summer/winter collections. In the durable goods sector, the overall shape is decreasing but there are peaks in the hazard function every three months. This pattern is mainly a reflection of the data collection process, for in this sector many prices were early in the sample collected at the quarterly frequency. Hazard function is not reported for the energy sector: in this sector, less than 10% of spells last more than 2 months. Finally, in the services sector, the main feature is a very marked peak at 12 months, and to a less extent, at 24 and 36 months. Otherwise, the hazard is quit flat and, as expected, lower than in other sectors. This suggest, that a typical price-setting scheme is in this sector is to re-settle prices with twelve months intervals. The hazard shape suggests that should a producer "fail" to adjust prices after a one year spell, he would wait for an additional year before changing his price. These figures suggest that, for services, the constant hazard model does not match the micro evidence. The truncated Calvo model might more likely be rationalized with the evidence on the hazard function. Dotsey, King and Wolman (1999) have proposed a model that generalizes the truncated Calvo model, allowing for a richer pattern of the hazard function. It is to be noted that in Dotsey et al. as in other theoretical set-ups, the hazard rate is expected to be increasing. That the empirical hazard functions are found to be decreasing (in sectors other than services) thus stands as a puzzle. While solving this puzzle is out of the scope of the present paper, we suggest that one way to reconcile theory and evidence would be to account for heterogeneity (see Fougère, Le Bihan, Sevestre, 2004).

5 Do long-lasting prices increase/decrease more ?

This section investigates the size of price changes for each product category and in particular its relation to the frequency of price changes. One prediction of the menu cost model is that, in sectors where the menu cost is higher, price changes will be less frequent and the average size of the absolute price variations will be higher.

Insert table 9 around here

Results on the size of price increases and decreases are presented in Table 9. Note that in this exercise, we are not able to deal with attrition in the same way as in the previous frequency analysis. Indeed when a product disappears from an outlet due to replacement by a new product, the price spell is complete, which we take into account in frequency through recoding a virtual price change. But whether the virtual change in price is a price increase or a price decrease is not known. While the dataset includes information on the replacing product price, providing a correct breakdown would imply to engage into controlling for quality change or matching product models, which is out of our scope. We thus report the average rises and decreases figures observed for strictly identical items in the same outlet. As is clear from figure 3 the overall frequency of price change is the sum of the frequency of price increases, decreases, and of (forced) product replacements. One consequence is that even adjusting for coverage, the weighted average of increases and decreases that we report cannot straightforwardly be matched with the aggregate inflation rate, which incorporates quality change.

On the whole, price decreases are rather frequent in the economy, as apparent from the distribution of price changes (Figure 9).[22] Around 40% of observed price changes are decreases, suggesting the absence of downward nominal rigidity.[23] We again observe a strong contrast between services and other sectors. Price changes in services are less frequent, and they are most

[22]The plotted distribution is truncated at -50 and +50 percentage decrease and increases, and is conditional on a price change (the spike at zero would obviously dominate the distribution otherwise).

[23]For a recent micro-data investigation of nominal rigidity in French wages, see Biscourp and Fourcade (2003).

often rises (20% only of price changes are decreases). In other sectors, prices decrease nearly as often as they increase. The data suggest that both large and moderate price changes are common in the economy. The weighted average size of a price increase is 12.46% and the average size of a price decrease is 9.98%. The weighted median is 4.15%, while the weighted median decrease is 5.31%. In the energy sector, average price change are modest (4.71% for increases) but frequent (monthly probability of upward and downward change being respectively around 40% and 30%) suggesting no menu cost. For some manufactured goods such as clothes, price changes are both quite frequent and of a large magnitude (the average increase in clothes price is 39.42%, and the average decrease is 26.06%).[24] This feature obviously reflects the incidence of sales.

Insert table 10 around here

A correlation matrix of the frequency of price increases/decreases with the size of price changes across elementary products is presented in Table 10. Of course, a correlation coefficient is a rough measure of association as a structural model would probably not predict a linear relation between these quantities. It nevertheless clearly emerges that the products with frequent price increases are also those products with frequent price decreases (the correlation is as strong as 0.936). We also observe a significant positive correlation between the size of average increases and the absolute average size of price decreases (|-0.126|, with p-value lower than 0.001). Thus, products that experience high price increases also experience large decreases. It is worth being noticed that this pattern still holds when sales and temporary rebates are excluded from the sample (see the next section).

The probably most interesting correlation to look at is that between the frequency of price changes and the average size of those price changes. Indeed, the menu cost theory would predict a negative correlation between those quantities, provided the relevant distribution of menu cost is across sectors. Prices which change less frequently because of the existence of menu costs, should do so by a larger amount than less “sticky prices”. Although we observe a significant

[24] The size of large price increases and decreases is obviously expected to be asymetric around zero, recalling that after a temporary, say 50% price decrease, the price has to raise by 100% to return to previous, say regular, price.

correlation between the frequency of price decreases and their magnitude, this correlation is not significant for price increases. The nonsignificant correlation is inconsistent with a menu cost model in which elementary products differ by the size of menu cost. It is nevertheless difficult to conclude to a clear rejection of the menu costs theory per se. For instance, the absence of a significant correlation may result from menu costs differing across outlets or outlet types rather than across elementary goods.

6 Some robustness experiments

In order to assess the robustness of our results to some specific data features or assumptions, some additional computations are reported in Tables A8 to A10 in the Appendix . The experiments were carried, for computational time and space reasons on a random subsample of 2% of the price trajectories, containing over over 47,000 price spells. The information loss seems to be unimportant: for instance unweighted average duration in the subsample is 5.33 months as compared to 5.28 months on the full dataset of 2.3 millions observations.

One first issue is that the introduction of the euro is an exceptional event that could bias downward the estimated average duration of spells, since it has led to interruption of many price spells. Table A8 documents the impact of the euro cash changeover, by reporting summary statistics on durations when truncating the database at the end of year 2000. We intentionally truncate the database one year prior to the introduction of the euro, to account for the fact that prices have started to be implicitly set in euros some months in advance. As indicated in the second panel of Table A8, the estimated average duration is 7.89 month in the "pre-euro" sample. As expected, the mean duration is larger than with full period data (7.59 months) but the difference is marginal, corresponding to one and a half week. This finding is confirmed by analysis of the frequency of price changes presented in Table A9. The weighted average frequency is 0.193 on the whole period, against 0.184 on the pre-euro period (we recall that the average frequency is 0.189 for full dataset over the whole period).

Another concern is that some price quotes are collected at a quarterly frequency only, mainly in the durable goods sector. This obviously creates an upward bias in the measurement of price durations. One way to assess this bias is to compute durations excluding all price trajectories that contain some observations collected on a quarterly basis. This computation is arguably approximate, since the spells collected at quarterly frequency are likely not to be homogenous to the rest of the spells. Furthermore, the statistical institute may choose to collect prices quarterly when it has information suggesting that price typically change at a quarterly frequency. The average weighted duration of prices excluding such trajectories, reported in the last panel of Table A8, is 7.24 months (compared to 7.59 using all trajectories) so that the difference is minor. From Table A9, we observe that the main difference in the frequency of price changes indeed occurs in the durable goods sector: the frequency of price change is 0.209 when excluding trajectories with quarterly collected prices, against 0.180 for all trajectories in that sector.

A last concern is the impact of sales and temporary promotions. Table A10 reports results on the frequency and size of price changes when excluding price observations that correspond to the start or end of a sales or rebate episode.[25] As a result, the frequency of both price raises and decreases is lower for all sectors. Unsurprisingly, the impact is very marked for clothes where frequency of raises and decreases excluding sales is 0.016 and 0.008 (against 0.041 and 0.054 respectively using all price changes). Most price decreases in the clothes sector are thus sales or temporary rebates. Also, the large median size of price decreases and increases in this sector appears to be a reflection of sales and rebates epidodes. However, the impact of sales and rebates is moderate in other sectors. On the whole, excluding sales and rebates, average frequency of price increases is lowered from 0.097 to 0.089, while average frequency of price decreases is lowered from 0.065 to 0.051. This moderate impact of sales and temporary rebates is similar to that reported by Bils and Klenow (2004). Interestingly, the ratio of the frequency of price decreases in the total observed price changes, excluding sales and temporary rebates is still rather high at 36.4% (against 40.1% including all price changes). That price decreases are frequent in the economy is not a mere reflection of sales episodes, and can be viewed as a robust stylised fact.

[25] This table is to be compared with Table 9 which reports results for all price changes.

7 Conclusion

Several stylized patterns emerge from our analysis. First, consumer prices are rather sticky. Based on our preferred assumptions, the weighted average duration is around 8 months (recalling that our data cover roughly non fresh food business sector).[26] Second, there is a strong heterogeneity across outlet types and sectors: prices in services sector change more rarely (typically once a year) than price of manufactured goods (typically twice a year). Third, while nominal prices are sticky, there are few signs of downward rigidity. Except in the services sector, price decreases are almost as frequent as price increases. On average, four price changes out of ten are price decreases. Fourth, the average size of a price change is large (around plus or minus 10 percent) but there exists an important fraction of small changes (median price increase/decrease is around 5 percent). These patterns are consistent with those observed in other european countries (see Aucremanne and Dhyne, 2004, and Dias, Dias and Neves, 2004) and in the US (Bils and Klenow, 2004, Klenow and Kryvtsov, 2003). In addition, we point to strong a heterogeneity in the shape of the hazard function.

It is however to be stressed that the analysis performed in this paper is not structural. Lacking relevant explanatory variables, we do not provide a formal structural test of pricing schemes used in sticky price models. In particular, part of the observed price stickiness may just reflect stickiness of marginal costs (which are not observed at the item level) under flexible prices. Nevertheless, the stylized facts we obtain provide some hints to discriminate across some price-setting theories. First, it is evident that, as found in other micro studies, price changes are discrete by nature. Also, there is both evidence of time-dependence and state-dependence in consumer price-setting. In the services sector, the Taylor or the truncated Calvo models seem to be closest to matching the data than other familiar price stickiness models. One stylized fact obtained for other sectors is that the unconditional hazard function for price change is decreasing. This fact stands as a puzzle in view of most models of price setting under nominal rigidity. One avenue to reconcile theory and micro-data evidence ould be to incorporate

[26] Extending analysis to the whole field of the CPI would result incorporating items with short price durations (fresh food) together with items with long price duration of typically one year (rents, medical services, tobacco). Overall, given the weight of the latter categories, our guess is that the average duration might raise a little.

unobserved or cross-outlet heterogeneity. In this line, the next steps of research will consist in testing alternative schemes of price rigidity by specifying and estimating conditional hazard functions, and in analyzing the relation between the duration and the size of price changes.

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Appendix 1 : Some definitions and notations

Price observations

The raw observations are sequences of prices quotes $P_{j,k,t}$.where :

-j is an index for products (defined by product category), $j = 1, ..., J$

-t is a (calendar) time index, $t = 1, ..., \Gamma$.

- k an index (specific to product j) for outlets selling product j: $k = 1, ..., K_j$

An individual good/service is a product j sold in outlet k, and is thus defined by the (j, k) pair.

We note ω_j the weight of product j in the overall CPI basket. We underline that CPI weights are not defined at the outlet level but at the product level only.

Price trajectories and durations

If a new price is set at time t ($P_{j,k,t} \neq P_{j,k,t-1}$), the **price spell duration** is the integer $T_{j,k}$ such that $P_{j,k,t} = P_{j,k,t+1} = ... = P_{j,k,t+T_{j,k}-1}$, and $P_{j,k,t+T_{j,k}-1} \neq P_{j,k,t+T_{j,k}}$, or :

$$T_{j,k} = \inf \{\tau | \tau \geqslant 1,\ P_{j,k,t+\tau-1} \neq P_{j,k,t+\tau}\}$$

Price trajectories

For product j, k, let $N_{j,k}$ denote the number of observed episodes of fixed price.

Let index i describe price episodes $i = 1, ..., N_{j,k}$. We define

$T_{j,k,i}$ as the observed duration of price spell i ($T_{j,k,i} \geqq 1$),

$P_{j,k,i}$ as the price level prevailing during price spell i,

$t_{j,k,i}$ as the calendar time of the i^{th} price change

We will also note for convenience : $t_{N_{j,k}+1}$ the calendar time of the last price observation (i.e. the end of the last observed price spell)

A **price spell** is an episode of fixed price for one item, characterized by the pair $(P_{j,k,i}, T_{j,k,i})$.

Duration and date of the price change are related by :

$$\begin{aligned} T_{j,k,i} &= (t_{j,k,i+1} - t_{j,k,i}) \text{ for } i = 1, ..., N_{j,k-1}, \\ T_{j,k,N_{j,k}} &= (t_{j,k,N_{j,k}+1} - t_{j,k,N_{j,k}} + 1). \end{aligned}$$

The observed trajectory (or sample path) $\Omega_{j,k}$ is defined by the date of the first observation and the set of successive price spells :

$\left\{t_{j,k,1},(P_{j,k,1},T_{j,k,1}),(P_{j,k,2},T_{j,k,2}),...,(P_{j,k,N_{j,k}-1},T_{j,k,N_{j,k}-1})(P_{j,k,N_{j,k}},T_n)\right\}$, or:

$$\Omega_{j,k} = \left(t_{j,k,1},\ \{(P_{j,k,i},T_{j,k,i})\}_{i=1,...,N_{j,k}}\right)$$

where $t_{j,k,1}$ is the (calendar) time of the first price observation.

Alternatively the trajectory can be defined by the sequence of dates of the price changes, together with the duration of the last price spell:

$$\widetilde{\Omega}_{j,k} = \left(\{(t_{j,k,i},P_{j,k,i})\}_{i=1,...,N_{j,k}},T_{N_{j,k}+1}\right)$$

The trajectory length $L_{j,k}$ is the number of periods for which a product j,k and its price are observed:

$$L_{j,k} = (t_{N_{j,k}+1} - t_1 + 1) = \sum_{i=1}^{N_{j,k}} T_{j,k,i}$$

Summary statistics of interest

Number of price quotes in the data set $Q = \sum_{j=1}^{J}\sum_{k=1}^{K_j} L_{j,k}$

Number of observed trajectories $K=\sum_{j=1}^{J} K_j$

Number of observed price spells $N = \sum_{j=1}^{J}\sum_{k=1}^{K_j} N_{j,k}$.

Average trajectory length $\overline{L} = \frac{\sum_{j=1}^{J}\sum_{k=1}^{K_j} L_{j,k}}{\sum_{j=1}^{J} K_j}$

Average number of price spells by trajectory $\overline{N} = \frac{\sum_{j=1}^{J}\sum_{k=1}^{K_j} N_{j,k}}{\sum_{j=1}^{J} K_j}$

Average unweighted duration of price spells

$\overline{T} = \frac{\sum_{j=1}^{J}\sum_{k=1}^{K_j}\sum_{i=1}^{N_j} T_{j,k,i}}{\sum_{j=1}^{J}\sum_{k=1}^{K_j} N_{j,k}} = \sum_{j=1}^{J}\sum_{k=1}^{K_j}\sum_{i=1}^{N_j}\left[\frac{1}{N}\right] T_{j,k;i} = \frac{\overline{L}}{\overline{N}} = \frac{Q}{N}$

Average duration for one individual good (j,k) **(product** j **in outlet** k)

$\overline{T}_{j,k} = \sum_{i=1}^{N_{j,k}}\left[\frac{1}{N_{j,k}}\right] T_{j,k,i}$

Average duration for elementary product j

$\overline{T}_j = \sum_{k=1}^{K_j}\sum_{i=1}^{N_{j,k}}\left[\frac{1}{\sum_{k=1}^{K_j} N_{j,k}}\right] T_{j,k,i}$

Average unweighted duration of price spells averaged by elementary product

$\overline{T}^P = \sum_{j=1}^{J}\frac{1}{J}\overline{T}_j$

Average weighted duration of price spells averaged by individual product

$\overline{T}^W = \sum_{j=1}^J \omega_j \overline{T}_j = \sum_{j=1}^J \sum_{k=1}^{K_j} \sum_{i=1}^{N_{j,k}} \alpha_{i,j,k} T_{j,k,i}$

with $\alpha_{i,j,k} = \omega_j / (\sum_{k=1}^{K_j} N_{j,k})$

We rely on the latter measure. Computations were also performed with the alternative measure average weighted duration of price spells first averaged by outlet, then by elementary product:

$\overline{T}^{W,K} = \sum_{j=1}^J \omega_j \left[\sum_{k=1}^{K_j} \frac{1}{K_j} \overline{T}_{j,k} \right]$

Summary statistics for frequencies

Average frequency of price changes for product j (with no left-censored spells, no attrition)

Denote $I_{k,j,t}$ is an indicator function for a price change of product j in outlet k at date t.Then $\overline{F}_j^{nlc} = \frac{1}{K_j} \frac{1}{\Gamma_j} \sum_{k=1}^{K_j} \sum_{t=1}^{\Gamma_j} I_{k,j,t} = (\sum_{k=1}^{K_j} N_{j,k}) / (\Gamma_j . K_j)$

Notice that we have assumed that, at the product level, data are balanced across outlets, all price observations starting and ending at the same date. For convenience, in the following we in addition ignore the outlet index (equivalently, we assume that one product j is sold in only one outlet).

$F_j^{nlc} = \frac{1}{\Gamma_j} \sum_{t=1}^{\Gamma_j} I_{j,t} = N_j / \Gamma_j$where $I_{j,t}$ is an indicator function for a price change

Average frequency of price changes for product j (with left-censored spells, no attrition)

$F_j = \frac{1}{\Gamma_j - 1} \sum_{t=2}^{\Gamma_j} I_{j,t} = (N_j - 1)/(\Gamma_j - 1)$

Average frequency of price changes for product j (with left-censored spells and attrition)

$F_j^a = (\sum_{t=2}^{\Gamma_j} I_{j,t} + 1)/(\Gamma_j) = (N_j / \Gamma_j) = F_j (1 - 1/\Gamma_j)/(1 - 1/N_j)$

Average frequency of price changes

$F = \frac{1}{J} \sum_{j=1}^J F_j$ or $F^a = \frac{1}{J} \sum_{j=1}^J F_j^a$

Weighted average frequency of price changes

$F^W = \frac{1}{J} \sum_{j=1}^J \omega_j F_j$ or $F^{a,W} = \frac{1}{J} \sum_{j=1}^J \omega_j F_j^a$.

Table 1 : Database coverage and repartition of records by sector
(1994:7 - 2003:2)

	Sector	Number of observations	Percentage in database	Coverage (3)	Weight in database	Weight in CPI
AB -	Food	4098940	30.99	79.13	25.38	20.62
C1 -	Durable goods	1491576	11.27	57.36	8.22	9.21
C2 -	Clothing, textile	2408063	18.20	100.00	9.34	6.00
C3 -	Other manufactured goods	2596920	19.63	72.98	19.19	16.91
D -	Energy	345512	2.61	60.35	7.87	8.39
E -	Services	2246977	16.98	49.60	30.00	38.87
N -	Unidentified (out of CPI)	42351	0.32	-	-	-
	Total	13230339	100.00	64.28	100.00	100.00

Note : column (3) reports the cumulated weight of elementary groups covered in the database, as a percentage of weight of all elementary group in each category.

Table 2 : Price trajectories

(unweighted average, baseline period 1994:7 - 2003:2)

	Number of obs.	Mean	Median	Standard deviation	Minimum	Maximum
Duration of trajectories	754220	16.65	11.00	19.58	1.00	104.00
Number of spells per trajectories	754220	3.15	2.00	5.31	1.00	102.00

Note : Number of price quotes used is 12556879.

Table 3 : Duration of price spells

Population	Number of obs.	Mean	Median	Standard deviation	Minimum	Maximum	25th percent	75th percent
Baseline period 1994:7 - 2003:2								
All price spells	2377682	5.28	3.00	6.73	1.00	104.00	1.00	7.00
Price spells averaged by individual trajectory	754220	6.83	4.60	6.81	1.00	104.00	3.00	9.00
Price spells averaged by elementary group weighted by averaged weight in CPI	1328	7.24	5.88	4.35	1.10	37.53	4.44	9.55
Price spells weighted (*)	2371681	7.24	4.00	9.16	1.00	104.00	2.00	10.00

Notes (*) : number of observations for weighted means is different from total number of observations because some observations are out of the CPI.
Spell weight is (period average) elementary group weight in CPI divided by number of spells in each elementary group.

Table 4 : Number of spells and duration by type of censoring
(weighted, 1994:7 - 2003:2)

Left-censor	Right-censor	Number of obs.	Percentage	Mean	Median	Standard deviation	Minimum	Maximum
0	0	1454983	58.59	5.97	3.00	7.73	1.00	98.00
0	1	164586	9.62	8.83	6.00	8.96	1.00	103.00
1	0	662952	27.28	8.57	5.00	10.48	1.00	103.00
1	1	89160	4.52	12.29	7.00	13.63	1.00	104.00
All spells		2371681	100.00	7.24	4.00	9.16	1.00	104.00

Note : weight is average weight in CPI divided by number of spells in each elementary group.
Percentage is breakdown by censoring category using weights.

Table 5 : Distribution of frequency and implied duration
(1994:7 - 2003:2)

Frequency of price changes	
Mean	0.189
Median	0.149
5th percent	0.048
25th percent	0.083
75th percent	0.208
95th percent	0.758
Duration of price	
Mean	8.38
Median	6.20
5th percent	0.71
25th percent	4.30
75th percent	11.60
95th percent	20.31

Note : Frequency estimated with taking into account for attrition

Table 6 : Duration of price spells by sector
(weighted, 1994:7 - 2003:2)

Sector	Trajectories length Mean	Trajectories length Median	Number of obs.	Mean	Median	Standard deviation	Min.	Max.	25th percent	75th percent
Food	29.34	19.00	847566	5.27	3.00	6.84	1.00	104.00	1.00	6.00
Durable goods	11.83	8.00	256854	5.53	3.00	6.01	1.00	104.00	2.00	7.00
Clothing, textile	10.29	9.00	438144	5.46	4.00	5.94	1.00	104.00	1.00	7.00
Other manufactured goods	23.68	15.00	395496	7.10	5.00	8.09	1.00	104.00	2.00	9.00
Energy	42.50	34.00	220369	1.87	1.00	2.91	1.00	103.00	1.00	2.00
Services	36.64	27.00	213252	11.43	9.00	12.05	1.00	104.00	4.00	14.00
Total	28.26	18.00	2371681	7.24	4.00	9.16	1.00	104.00	2.00	10.00

Table 7 : Frequency of price changes : implied durations by COICOP category, HICP sub-component and sector

(weighted average, 1994:7 - 2003:2)

	Frequency of price change	Implied average duration	Median implied duration	Frequency without taking into account for attrition
COICOP category				
01 - Food and non-alcoholic beverage	0.192	5.653	4.843	0.179
02 - Alcoholic bev., tobacco	0.215	4.363	4.294	0.181
03 - Clothing and footwear	0.175	6.484	4.878	0.096
04 - Housing, water, electricity, etc	0.241	7.937	8.100	0.235
05 - Furnishings, household equipment, etc	0.159	6.771	5.671	0.113
06 - Health	0.080	12.840	12.734	0.063
07 - Transport	0.357	6.129	6.946	0.349
08 - Communication	0.233	3.860	4.014	0.143
09 - Recreation and culture	0.130	11.809	8.460	0.084
10 - Education	0.061	15.961	15.387	0.052
11 - Restaurants and hotels	0.082	14.023	14.273	0.068
12 - Other goods and services	0.120	11.720	9.403	0.093
HICP sub-component				
A - Unprocessed food	0.210	4.615	4.373	0.197
B - Processed food	0.185	6.051	4.843	0.167
C - Non-energy industrial goods	0.161	6.857	5.837	0.109
D - Energy	0.707	1.378	0.633	0.705
E - Services	0.083	14.536	13.511	0.072
Sector				
AB - Food	0.195	5.493	4.697	0.179
C1 - Durable goods	0.184	5.541	5.065	0.112
C2 - Clothing, textile	0.178	5.978	4.855	0.098
C3 - Other manufactured goods	0.143	7.848	6.946	0.112
D - Energy	0.707	1.378	0.633	0.705
E - Services	0.083	14.536	13.511	0.072
Total	0.189	8.382	6.195	0.162

Table 8 : Conditional probability of price change - Logit estimate

Variable category	Variable	Parameter estimate	s.e.	p_val	Impact on probability of price change
	Intercept	-2.002	0.004	***	0.119
Type of good	Food	0.299	0.002	***	0.035
	Durable goods	0.280	0.003	***	0.033
	Clothing, textile	0.405	0.003	***	0.049
	Energy	2.444	0.004	***	0.490
	Services	-0.414	0.004	***	-0.037
Year	1994	-0.227	0.004	***	-0.022
	1995	-0.057	0.003	***	-0.006
	1996	-0.053	0.003	***	-0.005
	1997	-0.006	0.003	0.08	-0.001
	1999	-0.002	0.003	0.59	-0.0002
	2000	0.112	0.003	***	0.012
	2001	0.261	0.004	***	0.030
	2002	0.094	0.004	***	0.010
	2003	0.080	0.006	***	0.009
Time dummies	VAT 1995	0.451	0.008	***	0.056
	VAT 2000	0.641	0.008	***	0.085
	Euro Cash changeover	0.537	0.008	***	0.069
	Euro period	0.053	0.003	***	0.006
Month	1	0.612	0.004	***	0.081
	2	0.489	0.004	***	0.062
	3	0.504	0.004	***	0.064
	4	0.270	0.004	***	0.031
	5	0.218	0.004	***	0.025
	6	0.117	0.004	***	0.013
	7	0.295	0.004	***	0.035
	8	0.324	0.004	***	0.038
	9	0.604	0.004	***	0.079
	10	0.315	0.004	***	0.037
	11	0.136	0.004	***	0.015
Type of outlet	hypermarket	0.216	0.003	***	0.025
	hard discount store	-0.600	0.008	***	-0.050
	convenience store	-0.440	0.006	***	-0.039
	general store	0.003	0.004	0.46	0.0003
	department store	-0.179	0.005	***	-0.018
	large-area specialist	-0.037	0.003	***	-0.004
	traditional corner shop	-0.449	0.003	***	-0.040
	market	-0.824	0.014	***	-0.063
	service	-0.465	0.005	***	-0.041
	others	-0.201	0.009	***	-0.020

Note:
Number of observations: 12,429,686. Average of dependent variable : 0.181
log-likelihood : ln L =-5,491,344; LR (beta=0) 778,883.9 ; p_val(39 d.f.)<.0001
Reference is : sector= manufactured goods (excl. textile, durable and energy)
Outlet= Supermarket, Month= December , Year= 1998
*** indicates p_value is <.0001

Table 9 : Frequency and size of price increases and decreases

(weighted average, 1994:7 - 2003:2)

		Frequency of price increases	Frequency of price decreases	Average price increases	Average price decreases	Median price increases	Median price decreases
	COICOP category						
01 -	Food and non-alcoholic beverage	0.105	0.073	17.29	-10.30	4.86	-6.29
02 -	Alcoholic bev., tobacco	0.106	0.073	4.97	-5.22	2.81	-2.85
03 -	Clothing and footwear	0.041	0.053	38.57	-25.77	25.80	-25.62
04 -	Housing, water, electricity, etc	0.152	0.083	7.14	-6.74	3.00	-4.76
05 -	Furnishings, household equipment, etc	0.061	0.050	10.45	-11.27	5.38	-8.21
06 -	Health	0.046	0.017	5.27	-5.62	2.75	-2.70
07 -	Transport	0.210	0.138	4.25	-4.71	2.15	-1.41
08 -	Communication	0.025	0.116	11.46	-10.87	8.59	-10.10
09 -	Recreation and culture	0.042	0.041	10.30	-10.63	5.14	-6.90
10 -	Education	0.047	0.006	3.67	-4.63	2.65	-2.00
11 -	Restaurants and hotels	0.054	0.014	6.08	-6.60	3.91	-4.41
12 -	Other goods and services	0.061	0.031	8.62	-9.13	3.68	-4.81
	HICP sub-component						
A -	Unprocessed food	0.112	0.085	15.07	-13.25	6.85	-9.09
B -	Processed food	0.101	0.066	16.20	-7.39	3.62	-4.48
C -	Non-energy industrial goods	0.057	0.050	16.59	-13.83	5.71	-9.31
D -	Energy	0.404	0.300	4.71	-2.77	2.09	-1.71
E -	Services	0.058	0.014	6.66	-7.40	3.52	-4.17
	Sector						
AB -	Food	0.105	0.073	15.76	-9.67	4.55	-5.75
C1 -	Durable goods	0.046	0.063	10.62	-11.51	6.08	-9.28
C2 -	Clothing, textile	0.041	0.054	39.42	-26.06	27.95	-26.58
C3 -	Other manufactured goods	0.069	0.042	8.04	-8.87	3.50	-4.27
D -	Energy	0.404	0.300	4.71	-2.77	2.09	-1.71
E -	Services	0.058	0.014	6.66	-7.40	3.52	-4.17
	Total	0.097	0.065	12.46	-9.98	4.15	-5.31

Table 10 : Correlation of frequencies and magnitudes of price increase / decrease
(weighted average, 1994:7 - 2003:2)

	Frequency of price increase	Average price increase	Frequency of price decrease	Average price decrease
Frequency of price increase	1	-	-	-
Average price increase	-0.028 *0.306*	1	-	-
Frequency of price decrease	0.936 *<0.0001*	-0.007 *0.810*	1	-
Average price decrease	0.350 *<0.0001*	-0.126 *<0.0001*	0.162 *<0.0001*	1

Note : p_value in italics.
The table reports correlations across elementary products.

APPENDIX

Table A1 : CPI (COICOP) categories not included in price records database

	COICOP category	Average CPI weight 1994-2003 (percent)
011311	Fresh fish	0.40
011312	Fresh seafood	0.13
011611	Fresh fruit	0.89
011711	Fresh vegetable	0.99
022111	Tobacco	1.95
041111	Actual rental paid by tenants	5.68
041121	Rentals for secondary residences	0.26
044121	Refuse collection	0.49
045111	Electricity	2.33
045211	Town gas	0.81
045511	Hot water and steam purchased from district heating plants	0.16
056211	Employment of paid staff in private domestic service	1.05
061111	Pharmaceutical products	3.33
062111	Medical services	2.78
062211	Dental services	1.02
062311	Services of medical analysis laboratories	0.49
062312	Services of medical auxiliaries	0.77
071111	Purchase of new motor cars	3.32
071121	Purchase of second hand motor cars	0.86
072411	Toll facilities	0.46
072423	Driving licences	0.01
073111	Passenger transport by railway	0.59
073311	Passenger transport by air	0.64
081111	Postal services	0.23
081221	Telephone and telefax services	1.90
093311	Flowers and plants	0.43
094231	Licence fees and subscriptions to private television networks	0.60
095221	Magazines	0.54
112131	Accomodation services of holiday establishments	0.15
125311	Insurance connected with health	0.70
126111	Financial services	0.78
127121	Fees for administrative formalities	0.14
127122	Legal services	0.70
TOTAL		35.59

Table A2 : Coverage rate by COICOP category and HICP sub-component
(1994:7 - 2003:2)

		Coverage (1)	Weight in database	Weight in CPI
	COICOP category			
01	Food and non-alcoholic beverages	85.90	22.23	16.63
02	Alcoholic beverages and tobacco	50.85	3.15	3.98
03	Clothing and footwear	100.00	9.62	6.18
04	Housing, water, electricity, gas and other fuels	25.49	5.20	13.12
05	Furnishings, household equipment, etc…	87.01	8.93	6.60
06	Health	9.90	1.44	9.35
07	Transport	64.17	16.65	16.68
08	Communication	2.22	0.08	2.20
09	Recreation and culture	76.54	10.15	8.52
10	Education	90.61	0.23	0.16
11	Restaurants and hotels	97.47	12.47	8.22
12	Miscellaneous goods and services	76.03	9.86	8.34
	HICP sub-component			
A	Unprocessed food	73.01	9.87	8.69
B	Processed food	83.59	15.51	11.93
C	Non-energy industrial goods	73.56	36.75	32.12
D	Energy	60.35	7.87	8.39
E	Services	49.60	30.00	38.87
N	Centrally collected prices	-	-	-
	Total	64.28	100.00	100.00

Note : column (1) reports the cumulated weight of elementary groups covered in the database, as a percentage of weight of all elementary group in each category.

Table A3 : Repartition of records by "type of records"
(1994:7 - 2003:2)

Month	Code = O	Code = %	Code = +	Code = N	Code = P, R	Codes = F,Z,H,T,S	Codes = A, B	Codes = D, E	Codes = I, M	Total
1	799462	36387	19451	47007	10673	123828	173	34620	34651	1106252
	8.45	*36.18*	*7.64*	*6.3*	*8.23*	*8.81*	*0.14*	*6.80*	*6.94*	*8.36*
2	787365	20545	20527	49009	9805	137642	670	46686	46500	1118749
	8.32	*20.43*	*8.06*	*6.57*	*7.56*	*9.79*	*0.55*	*9.17*	*9.32*	*8.46*
3	714842	203	19439	50233	8601	109211	561	56243	55953	1015286
	7.55	*0.2*	*7.64*	*6.73*	*6.63*	*7.77*	*0.46*	*11.04*	*11.21*	*7.67*
4	744322	11	19920	44648	10056	99088	511	41504	41388	1001448
	7.86	*0.01*	*7.83*	*5.98*	*7.75*	*7.05*	*0.42*	*8.15*	*8.29*	*7.57*
5	748388	3	20010	47196	10416	99900	673	34119	34113	994818
	7.91	*0*	*7.86*	*6.32*	*8.03*	*7.11*	*0.55*	*6.70*	*6.84*	*7.52*
6	746174	875	20321	49829	10306	102195	1019	31083	31094	992896
	7.88	*0.87*	*7.98*	*6.68*	*7.95*	*7.27*	*0.84*	*6.10*	*6.23*	*7.50*
7	782281	30757	19120	76056	11104	141822	1330	27212	23970	1113652
	8.27	*30.58*	*7.51*	*10.19*	*8.56*	*10.09*	*1.09*	*5.34*	*4.80*	*8.42*
8	729784	11625	20643	74902	11402	205267	1027	37682	36021	1128353
	7.71	*11.56*	*8.11*	*10.04*	*8.79*	*14.60*	*0.84*	*7.40*	*7.22*	*8.53*
9	798256	165	22834	75555	11485	112283	1830	75198	71623	1169229
	8.43	*0.16*	*8.97*	*10.12*	*8.86*	*7.99*	*1.51*	*14.77*	*14.35*	*8.84*
10	841213	11	23678	76697	11533	93689	5563	51870	50869	1155123
	8.89	*0.01*	*9.3*	*10.28*	*8.89*	*6.67*	*4.58*	*10.19*	*10.19*	*8.73*
11	861561	2	25171	75748	12851	90326	44571	38825	38669	1187724
	9.1	*0*	*9.89*	*10.15*	*9.91*	*6.43*	*36.67*	*7.62*	*7.75*	*8.98*
12	910201	0	23428	79438	11455	90328	63621	34181	34157	1246809
	9.62	*0*	*9.2*	*10.64*	*8.83*	*6.43*	*52.34*	*6.71*	*6.84*	*9.42*
Total	9463849	100584	254542	746318	129687	1405579	121549	509223	499008	13230339
	71.53	*0.76*	*1.92*	*5.64*	*0.98*	*10.62*	*0.92*	*3.85*	*3.77*	*100.00*

<u>Codes</u> :

O	normal observation
%	sales
+	temporary promotion
N	quarterly observation
P, R	temporary replacement
F, Z, H, T, S	price not observed (outlet closed, field agent absent, others…)
A, B	new product / outlet
D, E	product replacing previous
I, M	product replaced

<u>Note</u> : repartition across months of each type of records in italics (percentage)

Table A4 : Repartition of price records

		Number of observations	Percentage in database
	COICOP category		
01	Food and non-alcoholic beverages	3569352	26.98
02	Alcoholic beverages and tobacco	529588	4.00
03	Clothing and footwear	2437036	18.42
04	Housing, water, electricity, gas and other fuels	322959	2.44
05	Furnishings, household equipment, etc…	1661697	12.56
06	Health	158093	1.19
07	Transport	1053859	7.97
08	Communication	11725	0.09
09	Recreation and culture	1431545	10.82
10	Education	7185	0.05
11	Restaurants and hotels	892653	6.75
12	Miscellaneous goods and services	1112296	8.41
99	Out of CPI	42351	0.32
	HICP sub-component		
A	Unprocessed food	1655484	12.51
B	Processed food	2443456	18.47
C	Non-energy industrial goods	6496559	49.10
D	Energy	345512	2.62
E	Services	2246977	16.98
N	Unidentified (out of CPI)	42351	0.32
	Sector		
AB	Food	4098940	30.99
C1	Durable goods	1491576	11.27
C2	Clothing, textile	2408063	18.20
C3	Other manufactured goods	2596920	19.63
D	Energy	345512	2.61
E	Services	2246977	16.98
N	Unidentified (out of CPI)	42351	0.32

Table A4 (continued) : Repartition of price records

		Number of observations	Percentage in database
	Type of outlet		
10	hypermarket	2629270	19.87
20	supermarket	1802583	13.62
25	hard discount store	155483	1.18
30	convenience store	317233	2.41
40	general store	483165	3.65
50	department store	483981	3.66
60	large-area specialist	1679584	12.69
70	traditional corner shop	3611926	27.30
80	market	62257	0.47
90	service	1896128	14.33
99	others	108729	0.82
	Year		
	1994 (July to December)	822784	6.22
	1995	1676898	12.67
	1996	1619574	12.24
	1997	1635650	12.36
	1998	1448188	10.95
	1999	1441687	10.90
	2000	1445527	10.93
	2001	1455231	11.00
	2002	1447790	10.94
	2003 (January to February)	237010	1.79
	Total	13230339	100.00

Table A5 : Duration of trajectories by COICOP category and HICP sub-component

(weighted, 1994:7 - 2003:2)

		Number of obs.	Mean	Median	Standard deviation	Minimum	Maximum
	COICOP category						
01	Food and non-alcoholic bev.	129932	30.11	20.00	27.54	1.00	104.00
02	Alcoholic bev., tobacco	29221	23.87	14.00	25.46	1.00	104.00
03	Clothing and footwear	242980	11.09	9.00	12.51	1.00	104.00
04	Housing, water, electricity, etc	10631	38.41	31.00	30.32	1.00	104.00
05	Furnishings, household equipment, etc	109632	16.91	11.00	18.53	1.00	104.00
06	Health	5915	32.27	25.00	27.80	1.00	104.00
07	Transport	35028	37.21	28.00	29.96	1.00	104.00
08	Communication	1281	8.48	6.00	7.31	1.00	57.00
09	Recreation and culture	100361	24.68	13.00	27.36	1.00	104.00
10	Education	221	34.49	42.00	18.27	1.00	54.00
11	Restaurants and hotels	30328	34.05	25.00	30.06	1.00	104.00
12	Other goods and services	56582	27.83	17.00	27.46	1.00	104.00
	HICP sub-component						
A -	Unprocessed food	61494	29.94	20.00	27.51	1.00	104.00
B -	Processed food	97659	28.95	18.00	27.27	1.00	104.00
C -	Non-energy industrial goods	511485	17.63	11.00	19.91	1.00	104.00
D -	Energy	8931	42.50	34.00	31.80	1.00	104.00
E -	Services	72543	36.64	27.00	30.48	1.00	104.00
	Total	752112	28.26	18.00	27.80	1.00	104.00

Table A6 : Duration of price spells by COICOP category and HICP sub-component
(weighted, 1994:7 - 2003:2)

		Number of obs.	Mean	Median	Standard deviation	Minimum	Maximum
	COICOP category						
01	Food and non-alcoholic bev.	738482	5.38	3.00	7.06	1.00	104.00
02	Alcoholic bev., tobacco	109084	4.50	3.00	4.87	1.00	102.00
03	Clothing and footwear	440050	5.72	4.00	6.59	1.00	104.00
04	Housing, water, electricity, etc	75321	6.88	4.00	8.00	1.00	103.00
05	Furnishings, household equipment, etc	270211	6.30	4.00	7.24	1.00	104.00
06	Health	15619	10.84	8.00	9.86	1.00	104.00
07	Transport	283261	5.48	3.00	6.80	1.00	97.00
08	Communication	2733	4.18	3.00	3.84	1.00	31.00
09	Recreation and culture	203652	9.45	6.00	11.59	1.00	104.00
10	Education	592	12.32	12.00	9.18	1.00	54.00
11	Restaurants and hotels	80254	11.47	8.00	12.02	1.00	104.00
12	Other goods and services	152422	9.55	6.00	11.76	1.00	104.00
	HICP sub-component						
A -	Unprocessed food	360666	4.66	2.00	6.59	1.00	104.00
B -	Processed food	486900	5.65	3.00	6.96	1.00	104.00
C -	Non-energy industrial goods	1090494	6.33	4.00	7.20	1.00	104.00
D -	Energy	220369	1.87	1.00	2.91	1.00	103.00
E -	Services	213252	11.43	9.00	12.05	1.00	104.00
	Total	2371681	7.24	4.00	9.16	1.00	104.00

Table A7 : Duration of spells and duration by sector and censoring
(weighted, 1994:7 - 2003:2)

Sector	Left-censor	Right-censor	Percentage	Number of obs.	Mean	Median
AB - Food	0	0	71.58	621854	4.45	2.00
	0	1	8.48	66559	7.10	5.00
	1	0	17.51	140950	6.82	4.00
	1	1	2.42	18203	11.71	7.00
C1 - Durable goods	0	0	46.65	119942	4.40	3.00
	0	1	4.33	10613	6.61	4.00
	1	0	44.37	115020	6.38	4.00
	1	1	4.64	11279	7.67	5.00
C2 - Clothing, textile	0	0	40.20	179394	4.13	2.00
	0	1	4.35	16561	6.32	4.00
	1	0	48.85	214881	6.30	4.00
	1	1	6.61	27308	6.69	5.00
C3 - Other manufactured goods	0	0	55.35	220199	6.25	4.00
	0	1	9.41	32300	8.52	6.00
	1	0	30.61	123868	7.70	5.00
	1	1	4.91	19129	10.22	6.00
D - Energy	0	0	91.41	205098	1.65	1.00
	0	1	3.48	6340	3.23	1.00
	1	0	4.78	8567	4.38	2.00
	1	1	0.33	364	11.82	9.00
E - Services	0	0	50.05	108496	10.53	9.00
	0	1	15.58	32213	10.47	8.00
	1	0	27.91	59666	12.48	8.00
	1	1	6.45	12877	16.18	11.00

Table A8: Robustness analysis - Durations

	Number of obs.	Mean	Median	Standard deviation	Minimum	Maximum	25th percent	75th percent
Baseline period 1994:7-2003:2								
All price spells (full data set)	2377682	5.28	3.00	6.73	1.00	104.00	1.00	7.00
All price spells (sub-sample)	47387	5.33	3.00	6.90	1.00	104.00	1.00	7.00
Price spells averaged by elementary group weighted by averaged weight in CPI (sub-sample)	1239	7.59	6.00	5.56	1.00	54.00	4.15	9.91
"Pre-euro" period 1994:7-2000:12								
All price spells (sub-sample)	35576	5.44	3.00	6.99	1.00	78.00	1.00	7.00
Price spells averaged by elementary group weighted by averaged weight in CPI (sub-sample)	1164	7.89	6.10	6.46	1.00	78.00	4.17	10.11
Excluding trajectories with quarterly collected records Baseline period 1994:7-2003:2								
All price spells (sub-sample)	43507	4.99	3.00	6.51	1.00	104.00	1.00	6.00
Price spells averaged by elementary group weighted by averaged weight in CPI (sub-sample)	1196	7.24	5.55	5.53	1.00	54.00	3.98	9.14

Table A9 : Robustness analysis - Frequency of price change by sector

(weighted average, sub-sample)

Sector	Frequency of price change 1994:7-2003:2	Frequency of price change 1994:7-2000:12	Frequency of price change without quarterly collected items 1994:7-2003:12
Food	0.201	0.192	0.201
Durable goods	0.180	0.167	0.209
Clothing, textile	0.190	0.182	0.195
Other manufactured goods	0.141	0.131	0.152
Energy	0.704	0.690	0.704
Services	0.083	0.073	0.084
Total	0.193	0.184	0.200

Table A10 : Robustness analysis - Frequency and size of price increases and decreases Excluding sales and temporary rebates (sub-sample)

Sector	Frequency of price increases	Frequency of price decreases	Average price increases	Average price decreases	Median price increases	Median price decreases
Food	0.092	0.053	13.03	-5.38	3.69	-3.77
Durable goods	0.033	0.034	7.44	-6.90	4.17	-5.16
Clothing, textile	0.016	0.008	22.54	-6.67	7.72	-3.72
Other manufactured goods	0.061	0.033	6.01	-5.50	3.45	-2.94
Energy	0.406	0.295	2.76	-2.40	1.94	-1.67
Services	0.055	0.014	5.73	-5.94	3.41	-3.60
Total	0.089	0.051	9.04	-5.51	3.54	-3.33

Figure 1 : Distribution of observed durations (unweighted)

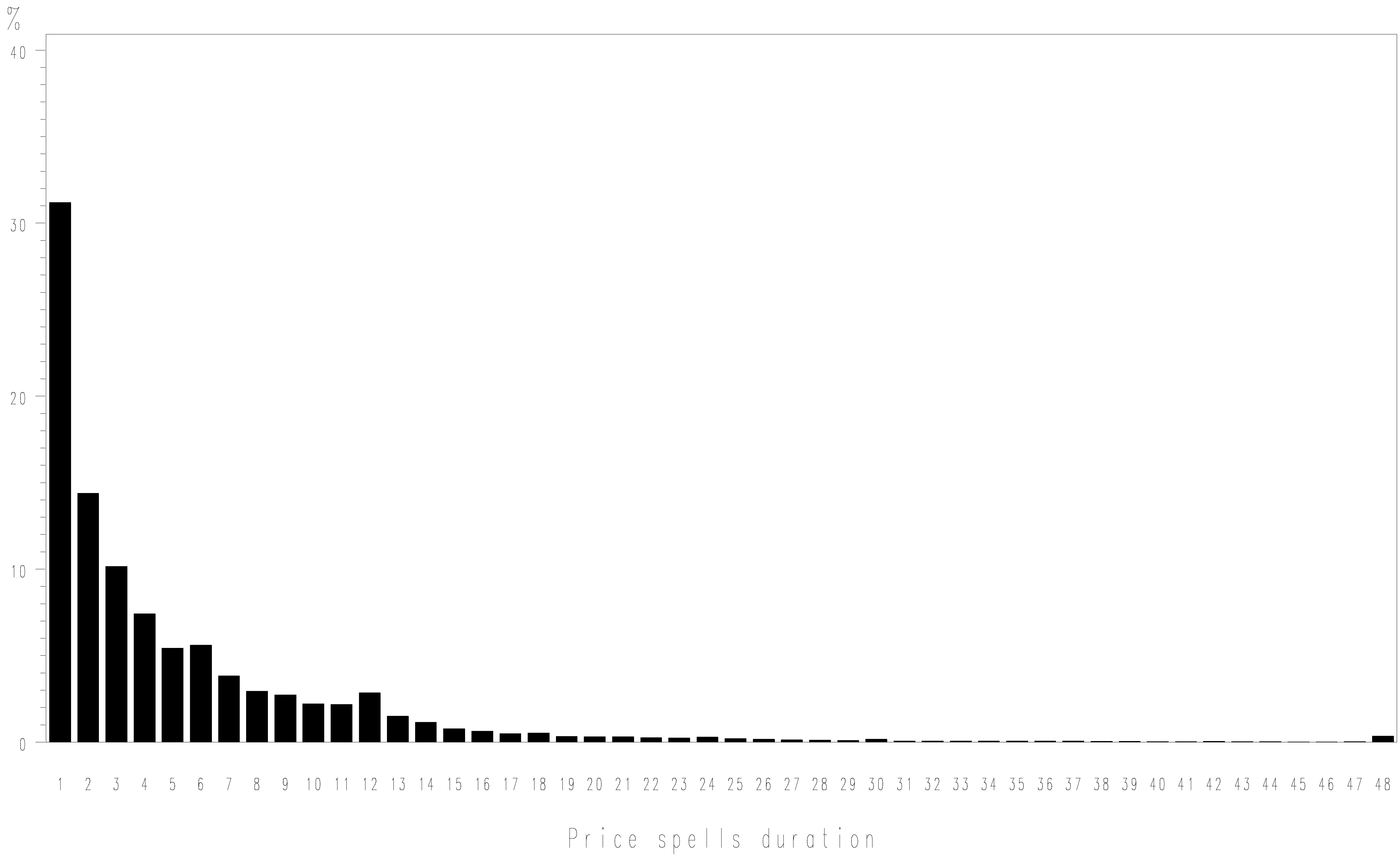

Figure 2 : Distribution of frequencies of price change across elementary items (unweighted)

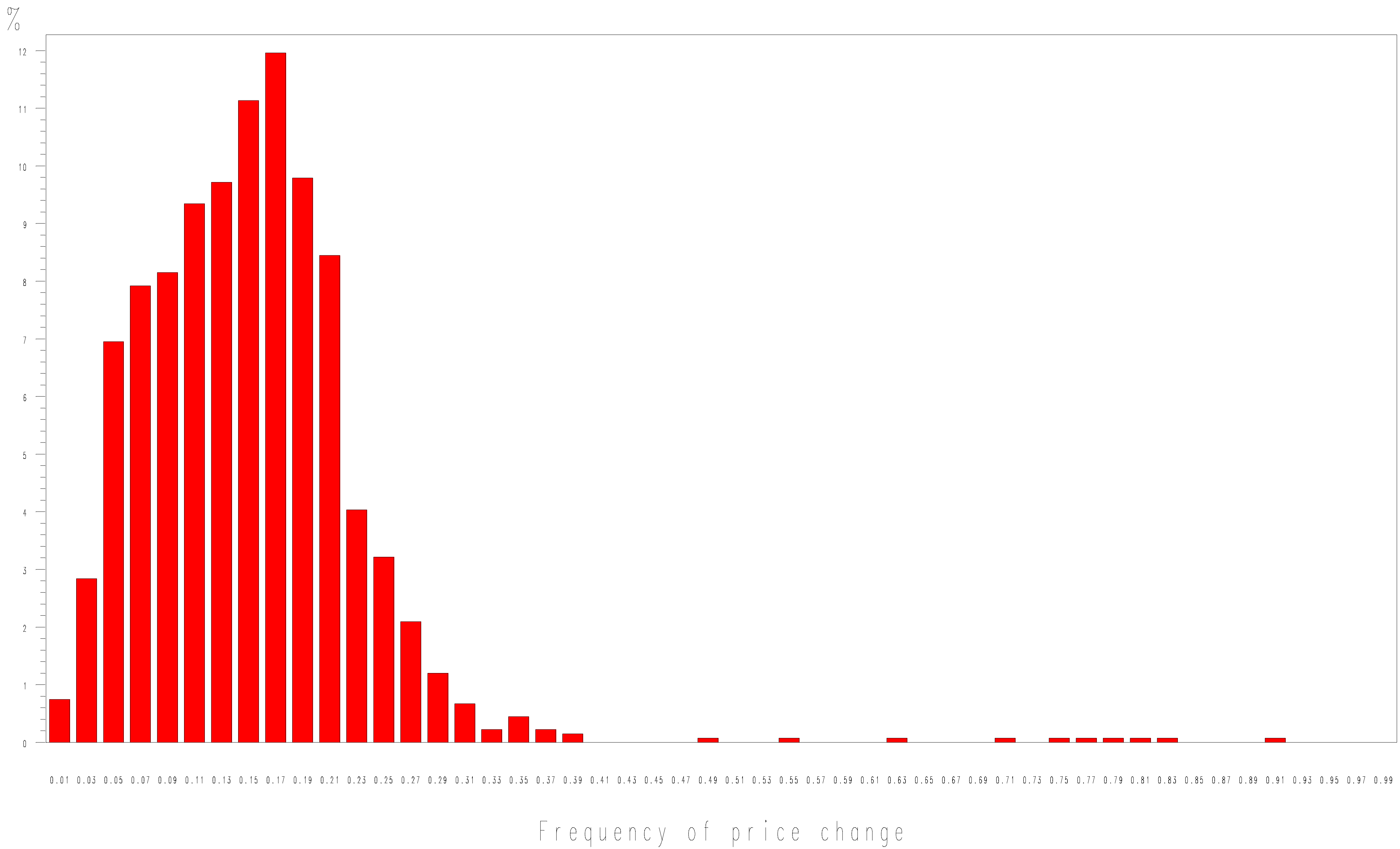

Figure 3 : Frequency of price change over time - All sectors

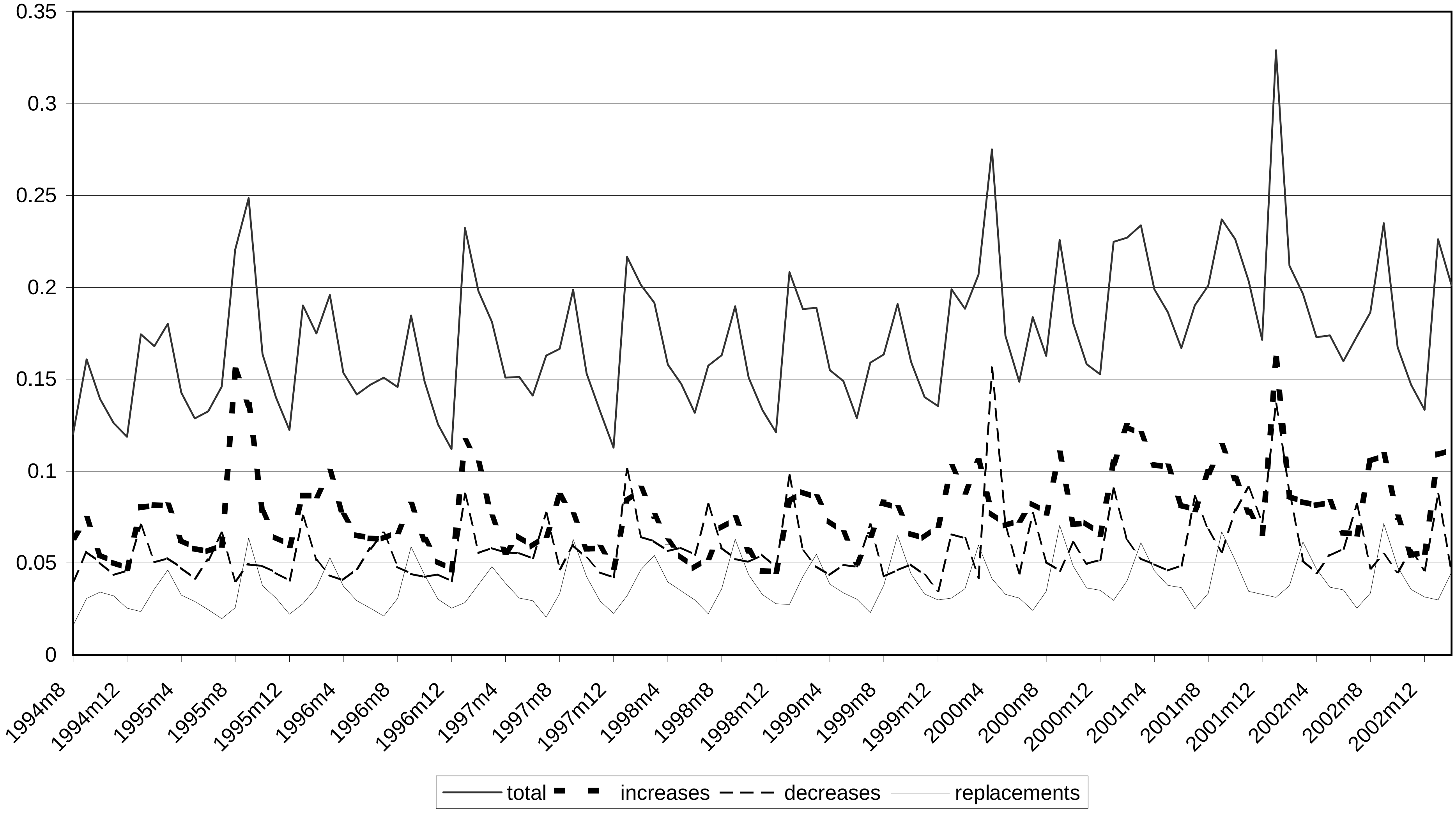

Figure 4 : Hazard function - Food

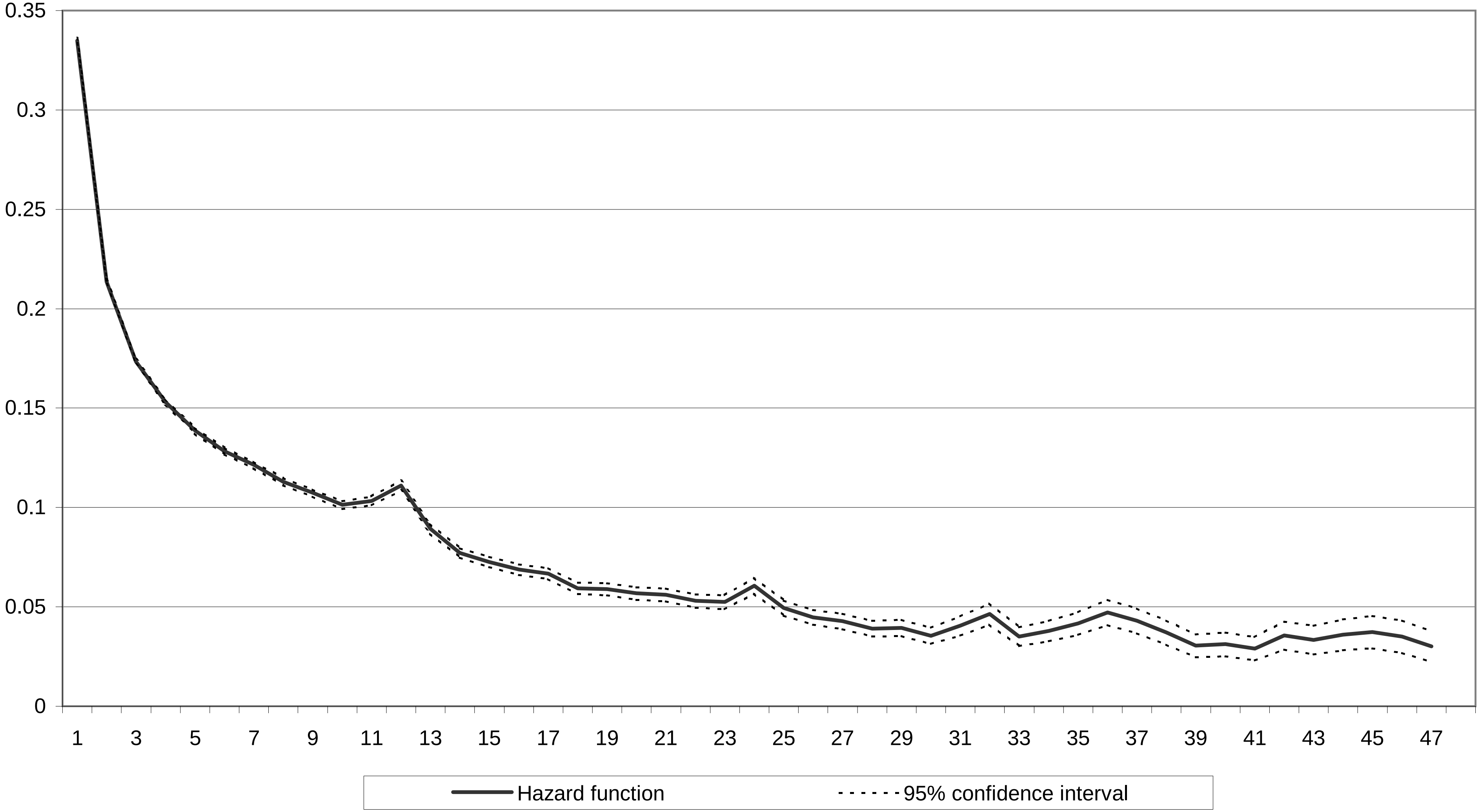

Figure 5 : Hazard function - Durable goods

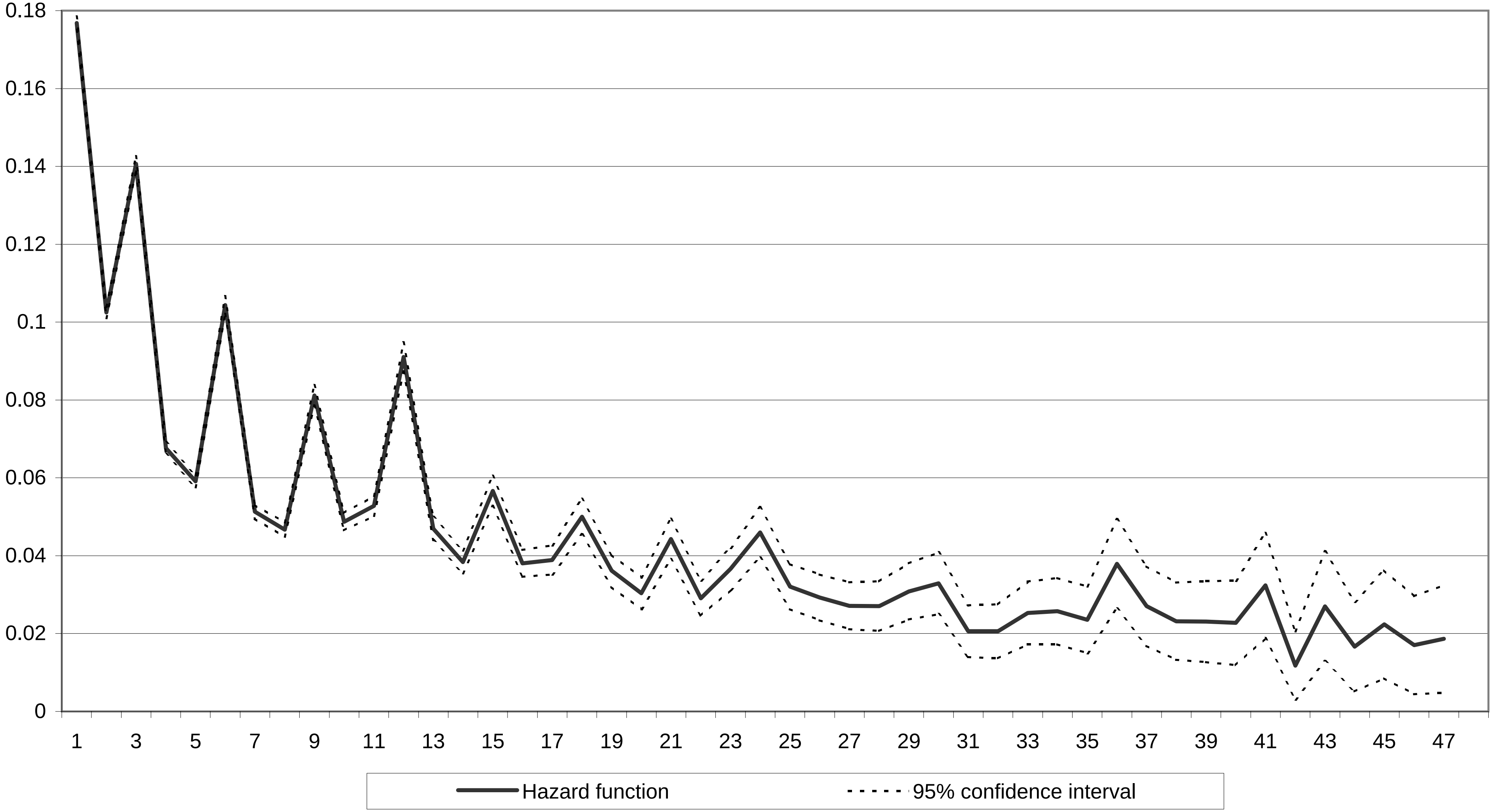

Figure 6 : Hazard function - Clothing, textile

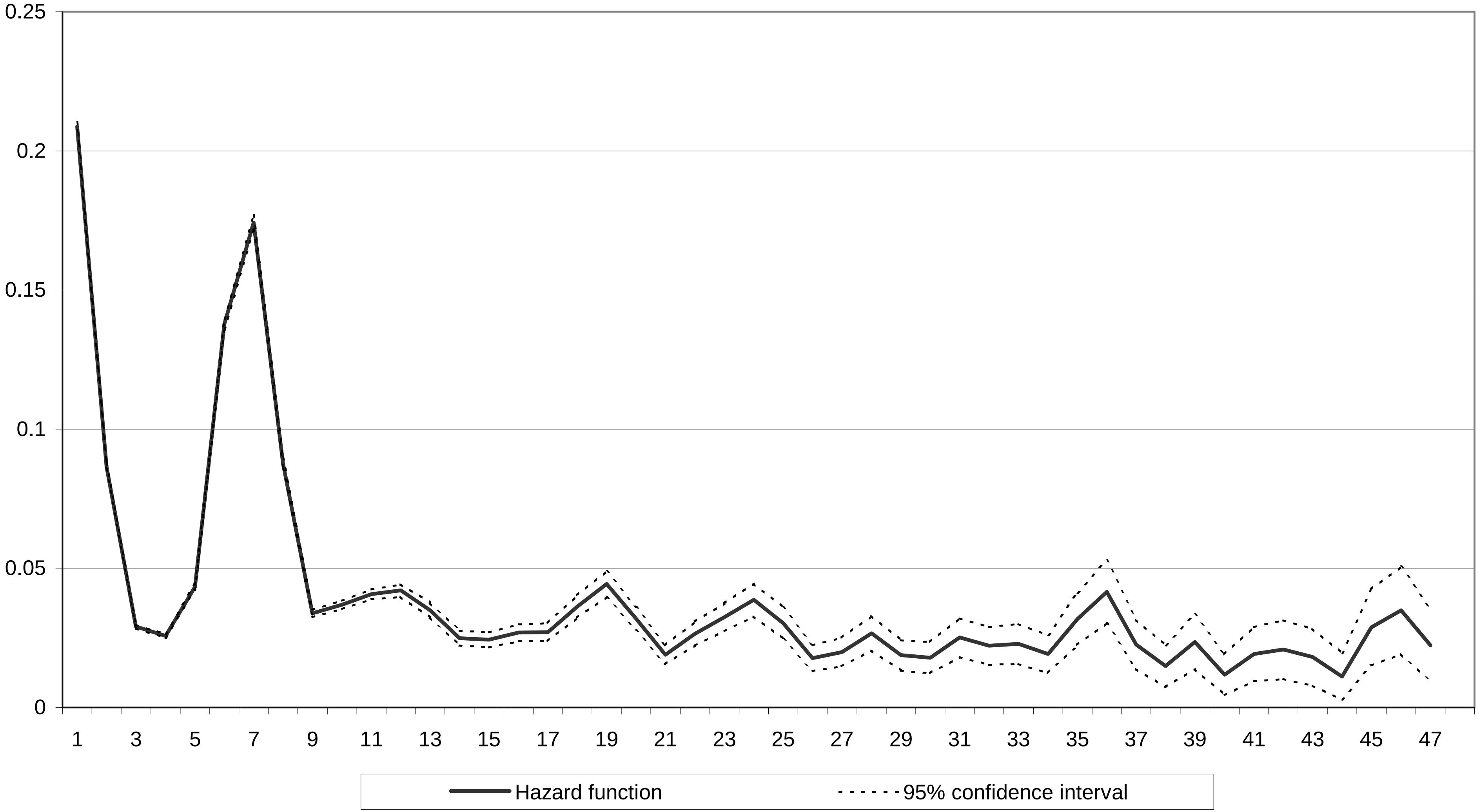

Figure 7 : Hazard function - Other manufactured goods

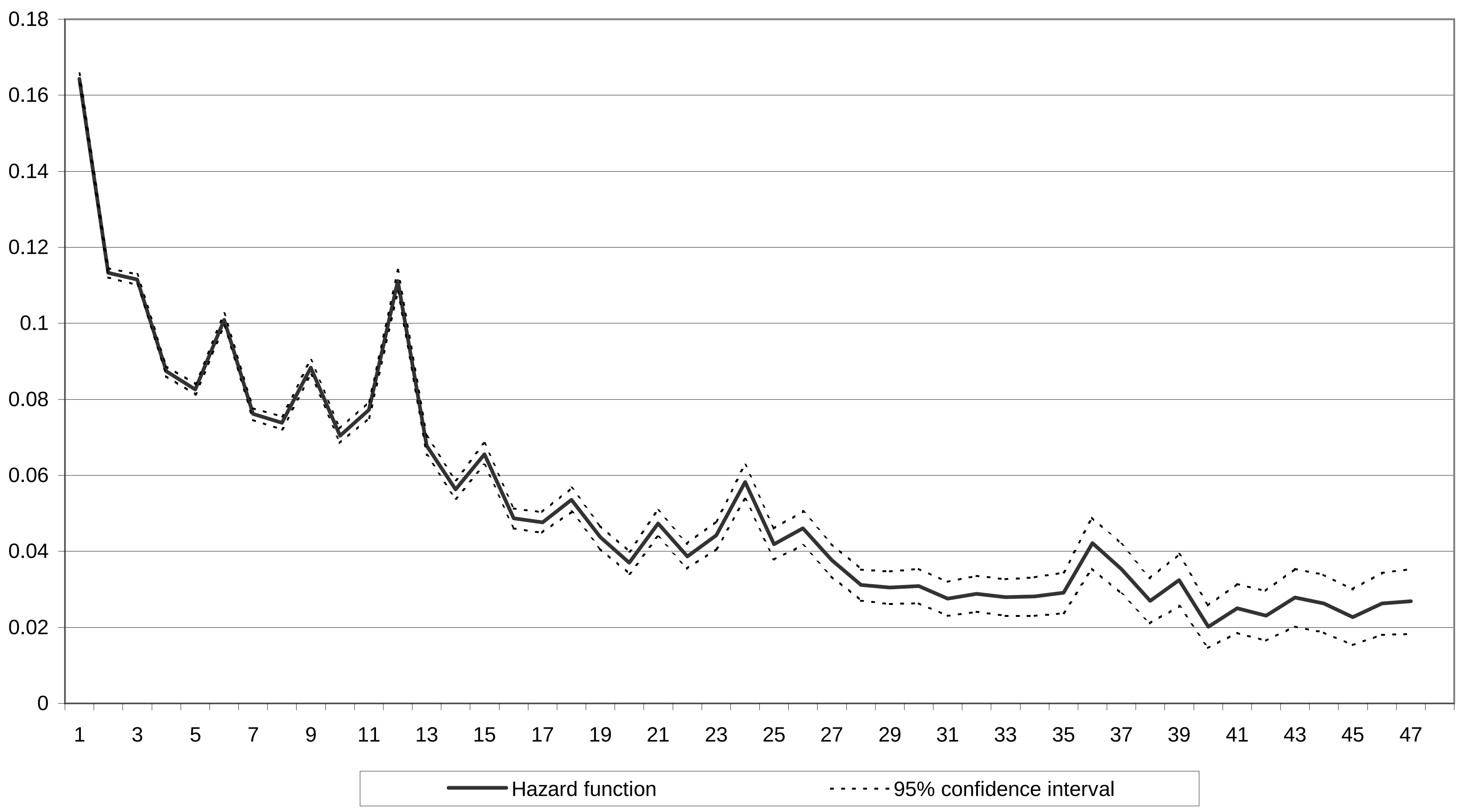

Figure 8 : Hazard function - Services

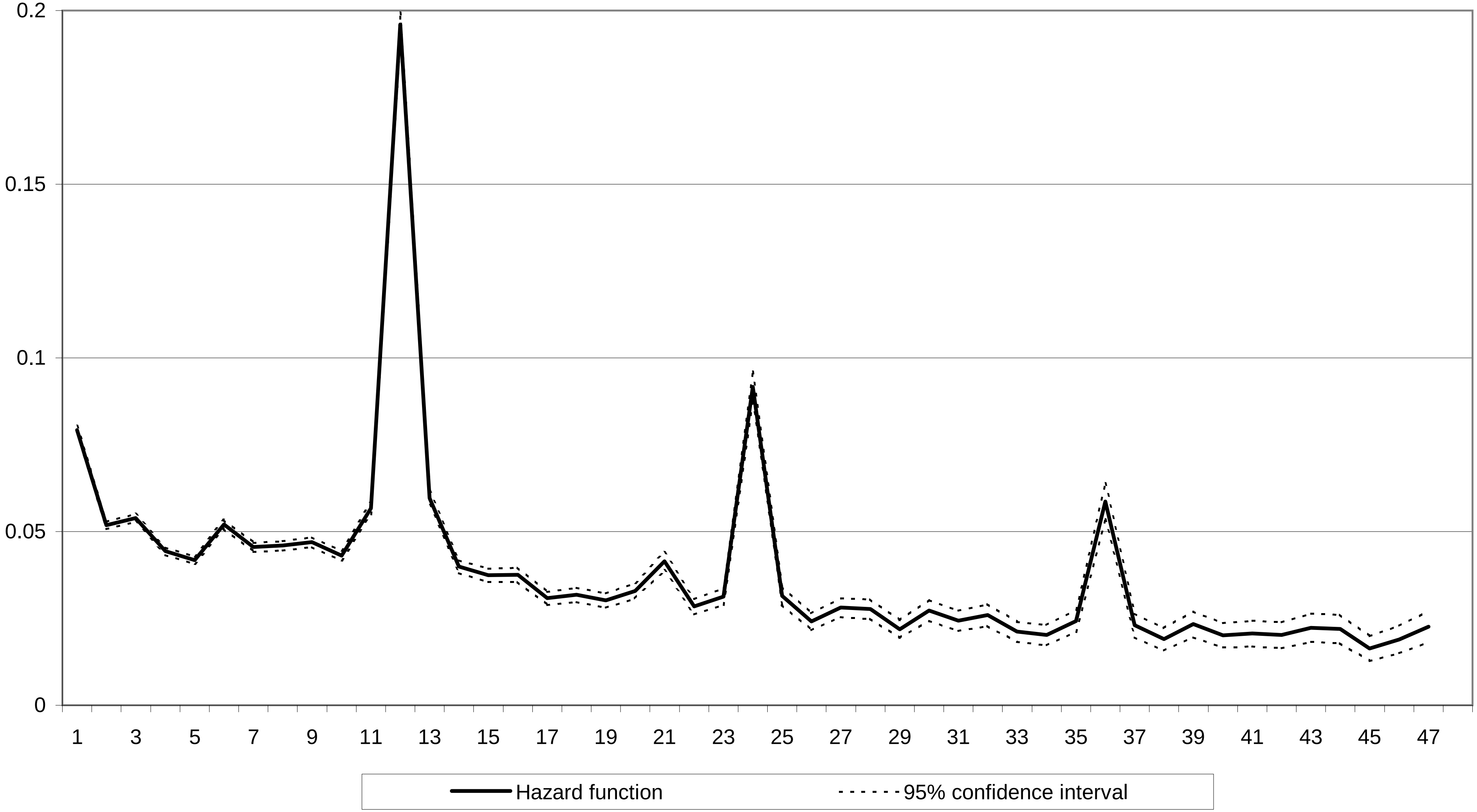

Figure 9 : Distribution of price changes (unweighted)

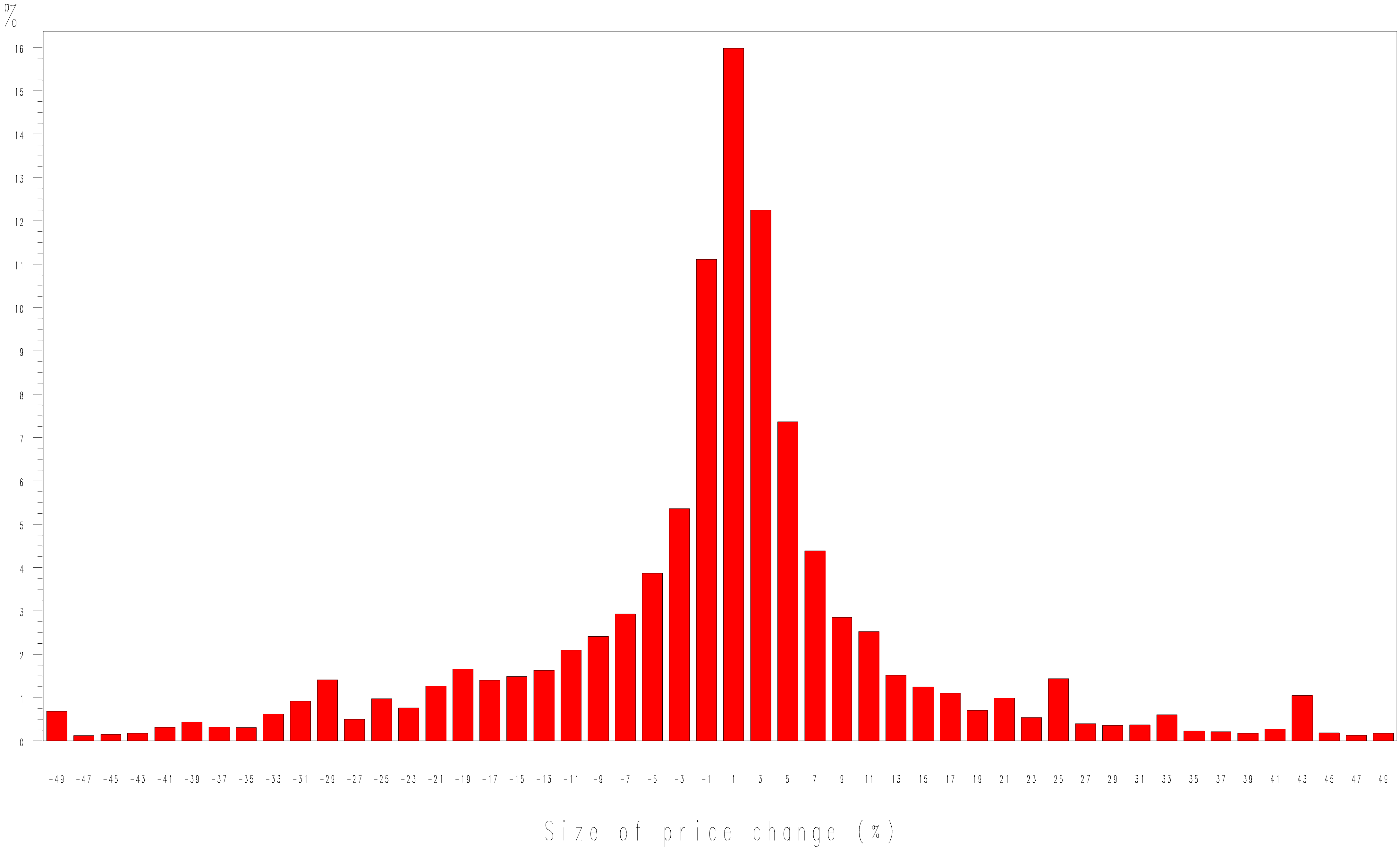

Figure A1 : A typical price trajectory

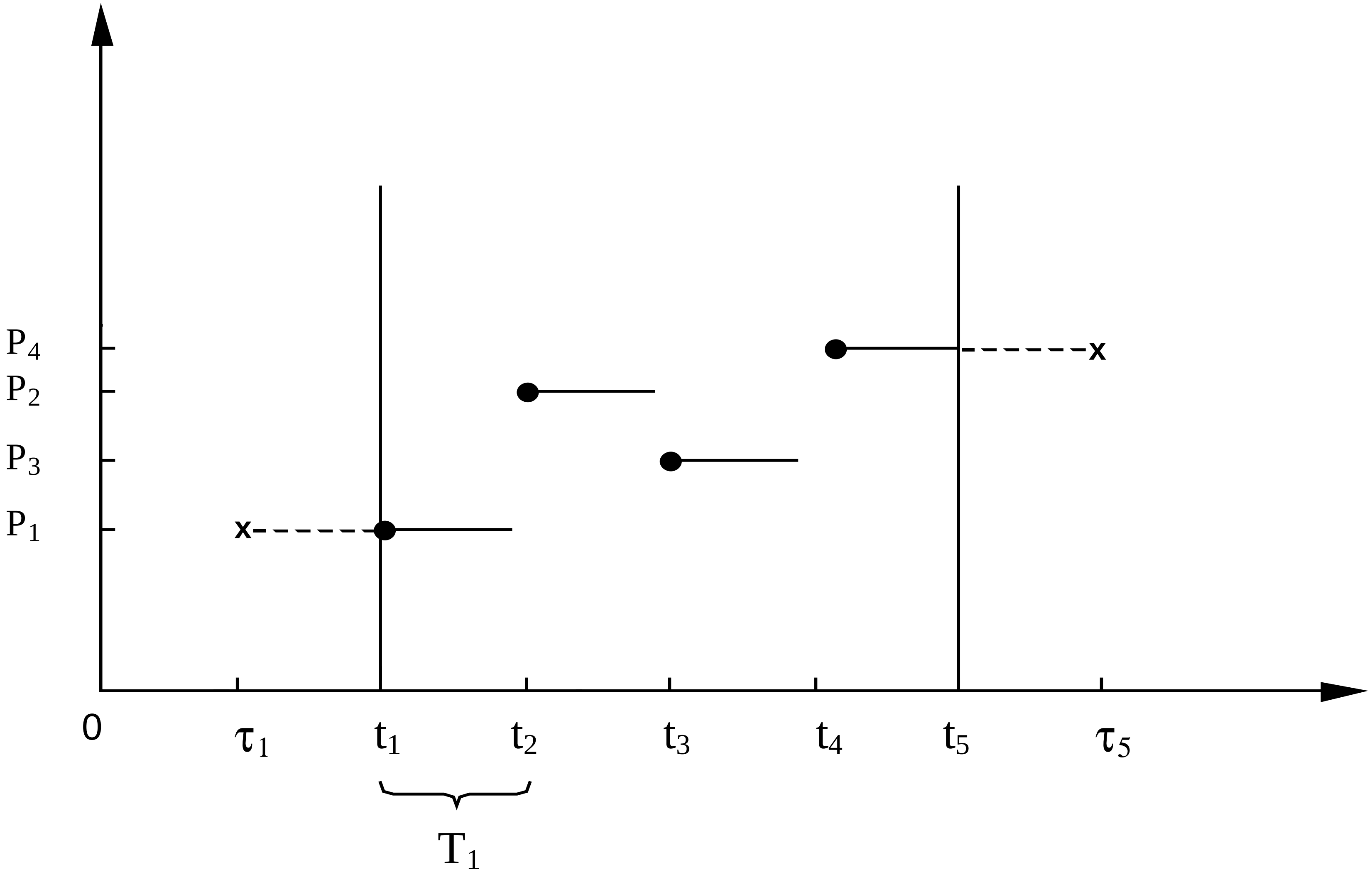

Figure A2 : Hazard function - Clothing, textile

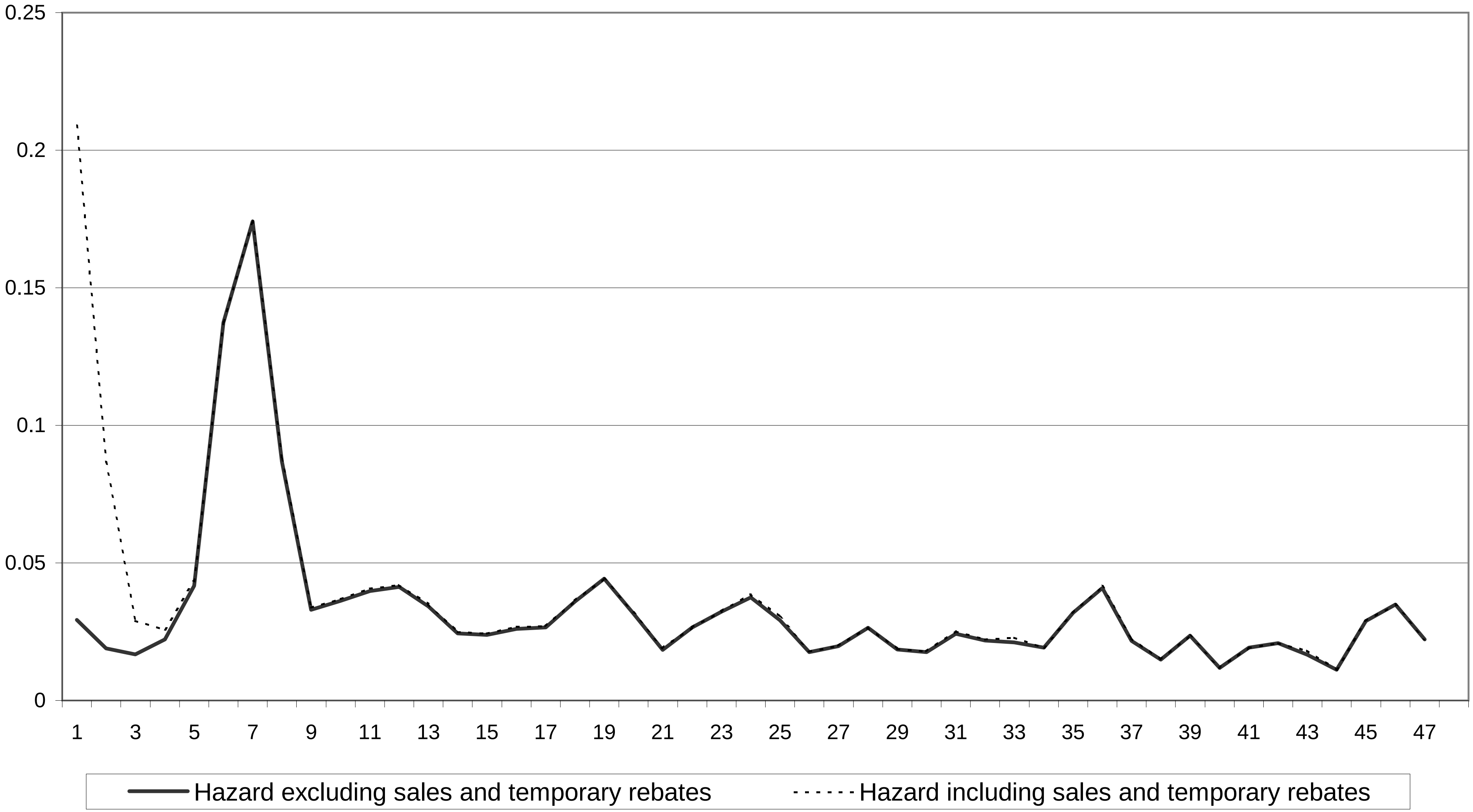

Figure A3 : Hazard function - Other manufactured goods