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ABSTRACT

Heterogeneity in Consumer Price Stickiness: A Microeconometric Investigation*

This paper examines heterogeneity in price stickiness using a large, original, set of individual price data collected at the retail level for the computation of the French CPI. For that purpose, we estimate at a very high level of disaggregation competing-risks duration models that distinguish between price increases, price decreases and product replacements. The main findings are the following: i) cross-product and cross-outlet-type heterogeneity is pervasive, both in the shape of the hazard function and in the impact of covariates; ii) at the product-outlet type level, the baseline hazard function of a price spell is non-decreasing; iii) there is strong evidence of state dependence, especially for price increases.

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1 Introduction

Assessing price rigidity is a notoriously crucial issue from a macroeconomic perspective, in particular for monetary policy. While a typical approach to this issue is to investigate time-series of aggregate price indices, there are several motivations for adopting a microeconometric approach. First, many models of price rigidity that have been proposed in the macroeconomic literature are explicitly based on microeconomic behavior (see for instance Taylor 1998 for a survey, and Taylor 1980, Calvo 1983, Sheshinski and Weiss 1983, or Dotsey, King and Wolman 1999, for important contributions). Moreover, the use of microdata may overcome the problem of observational equivalence of models that emerge at the aggregate level (in the case of the New Keynesian Phillips curve, see Rotemberg 1987). Finally, such data shed light on the heterogeneous patterns of price setting behaviors that do coexist in the economy. Heterogeneity in average price durations has recently been documented using individual consumer price data by Bils and Klenow (2004) for the U.S., and by Dhyne et al. (2005) for the euro area (see also the references therein).

Our paper uses duration models to investigate heterogeneity in price stickiness. Though rarely applied so far to price data, the hazard function approach is a relevant framework since it allows to test for duration-dependence and state-dependence in price-setting. The test results allow to assess some predictions of sticky price models. In this approach, controlling for heterogeneity is an important concern. Inadequate treatment of heterogeneity can bias the estimates of the hazard function (see Heckman and Singer 1984, or in the context of prices Alvarez et al. 2005).

The data we use consist of a large, original, database of individual consumer price quotes collected in French outlets for the computation of the Consumer Price Index. Taking advantage of the wide coverage and of the very large size of the dataset, we estimate duration models at a very high level of disaggregation, namely at the product-outlet type level. To take into account the type of event terminating a price spell, we adopt a competing risks duration framework: a distinction is made between price increases, price decreases and product replacements. On the whole, more than seven hundred duration models are estimated. Parameter estimates are used to document heterogeneity in the shape of the hazard function and in state-dependence. In each model, several covariates, in particular the cumulative sectoral inflation, do provide an indication on the degree of state-dependence in price setting.[1]

First, we find that cross-product as well as cross-outlet-type heterogeneity is pervasive, both in the shape of the hazard function and in the extent of state-dependence. Second, when accounting for heterogeneity, the hypothesis of a declining hazard function for price change can in general be rejected. Third, we provide evidence of some state-dependence: in many cases, the cumulated sectoral inflation raises the probability of a price increase. Our results suggest that elements of different price setting models can be found at the product/outlet

[1] This approach follows the seminal microeconometric analysis of nominal rigidities by Cecchetti (1986).

type level. Overall, at the product and type of outlet level, the price change behavior appears to be consistent with either Calvo's model or a mixture of state-dependent, Taylor and Calvo behaviors.

The outline of the paper is as follows. Predictions of theoretical models in terms of state- and duration-dependence in price setting are briefly reviewed in the next section. Section 3 presents the econometric framework. Section 4 describes the dataset, and section 5 comments the results. Section 6 concludes.

2 Duration- and state-dependence in price setting: theoretical background

This section motivates our investigation by reviewing the implications of the main models of price setting behavior used in monetary economics for the hazard function of a price change. A more detailed survey can be found in e.g. Taylor (1998). In our context, the hazard function is the instantaneous conditional probability of adjusting the price of an item, given the elapsed duration since the last price change.

Models of price rigidity can broadly be classified into two categories: time-dependent and state-dependent models (see e.g. Blanchard and Fisher 1989, pages 388-389). Time-dependent models assume that price changes take place at fixed or random intervals. Time-dependent models differ with respect to their predictions about the hazard function. One prominent model is Taylor's staggered contracts model (Taylor 1980) which has been used to describe both the price and wage adjustment patterns. This model assumes that prices and wages are negotiated for fixed periods, say one year. As a consequence, the probability of a price change should be zero for the first periods and exhibit one spike with value one at the contract renewal. If contracts of different lengths coexist in the economy, one may expect several modes in the hazard function for a sample of price spells. In the monetary policy literature, a widespread alternative is Calvo's model (Calvo 1983). In this model, each firm has a constant instantaneous probability of changing its price. As a consequence, the hazard function is flat. A variant that encompasses both Taylor's and Calvo's schemes is the truncated Calvo model, in which there is a maximum duration for price spells. Thus, the hazard function should be flat up to this maximum value, and then equal to one for this maximal duration (see Wolman 1999). Rotemberg's quadratic adjustment cost model (Rotemberg 1982) is often used in the monetary policy literature, but does not appear to be appropriate for micro data. Indeed, this model predicts frequent price adjustments with small magnitude. Such a pattern is at odds with the evidence of lumpy adjustment typically found with micro data in most sectors. It is however noticeable that, using macro data, Calvo's and Rotemberg's models lead to observationally equivalent "new Keynesian Phillips curves", as discussed by Rotemberg (1987). One prediction of such time-dependent models is that the probability of a price change does not depend on the firm's environment (costs, demand), though its magnitude in

general does.

State-dependent models predict on the contrary that the probability of a price change varies according to the state of the economy. State-dependence with infrequent price changes typically emerges from menu cost models. Such models imply that a firm will not change its price if the foregone profit due to deviation of its current price from the optimal price is smaller than the menu cost, i.e. the fixed cost of changing price. Sheshinski and Weiss (1983) have proposed such a model. The probability of a price change is predicted to decrease with the size of the menu cost, while the size of the price change will increase with that of the menu cost. Generally, the probability of a price increase is predicted to raise with the trend inflation rate. More recently, Dotsey, King, and Wolman (1999) have proposed a model that generalizes Calvo's model by incorporating state-dependent pricing into a truncated Calvo model. In their model, firms face a random menu cost. Only the firms with relatively low menu costs choose to adjust. The hazard rate increases with the time elapsed since the previous price change, since firms that set their prices a long time ago are more likely to observe relative price in excess of the menu cost. A higher steady state inflation leads then to a more rapid erosion of relative prices and hence to a steeper unconditional hazard function.

One important feature of all price models reviewed in this section is that the hazard function is a non-decreasing function of the elapsed duration since the previous price change (except perhaps for spikes in the hazard function). This is at odds with the available estimates of hazard functions for price changes (see e.g. Alvarez et al. 2005, or Dias et al. 2005). As already emphasized in the literature, this is a consequence of the population heterogeneity (see Kiefer 1988, Heckman and Singer 1984, and, in a price-setting context, Alvarez et al. 2005).

3 Modelling price spells: econometric framework

Duration models are relevant tools to characterize duration as well as state-dependence in price-setting. This section describes the statistical framework, and derives the likelihood function for duration models.[2]

3.1 The econometric analysis of durations: a reminder

Let us consider a price spell, beginning at time $t_0 = 0$ and lasting until time T. The date T is not known exactly, although it is observed to be located between dates $t-1$ and t. For convenience, we shall consider that dates $t-1$ and t correspond to the end of months $t-1$ and t respectively: then we know only that the price spell has lasted more than $t-1$ months and at most t months. We aim at characterizing the probability for a price change to occur after some time has elapsed since the previous price change.

[2] See Kiefer (1988) and Lancaster (1997) for comprehensive presentations of the econometric analysis of durations.

Let us first consider that there is no right-censoring[3]. As usually the survivor function $S(t)$ at $T = t$ is the probability for a spell to last at least t months:

$$S(t) = \Pr(T \geq t) = 1 - F(t) \tag{1}$$

where $F(.)$ and $S(.)$ are the cumulative density function and the survivor function of the duration T of a price spell, respectively. Because our duration data are grouped on a monthly basis, the typical likelihood contribution $l(t)$ is the probability for a spell to terminate between the end of month $t-1$ and the end of month t. This probability is given by

$$\begin{aligned} l(t) &= \Pr(t-1 \leq T < t) \\ &= F(t) - F(t-1) \\ &= S(t-1) - S(t) \\ &= \exp[-H(t-1)] - \exp[-H(t)] \end{aligned} \tag{2}$$

the last equality resulting from the relationship between the survivor function and the cumulated hazard, namely $\ln S(t) = -H(t)$ (see e.g. Kalbfleisch and Prentice 2002). Let us recall that the cumulated hazard function $H(t)$ is defined by:

$$H(t) = \int_0^t h(\tau)\ d\tau \tag{3}$$

where $h(\tau)$ is the hazard function of the duration T defined as :

$$h(\tau) = \lim_{\Delta \downarrow 0} \frac{1}{\Delta} \Pr(\tau \leq T < \tau + \Delta \mid T \geq \tau) \tag{4}$$

Under this observation scheme, the baseline hazard h is not identified, unless we make some parametric assumption about over the interval $[t-1, t[$. The simplest assumption is to consider that this baseline hazard is constant over this interval, namely $h(\tau) = h_t, \forall\ t-1 \leq \tau < t$, although it can vary over different intervals indexed by t.[4] Then,

$$\int_{t-1}^{t} h(\tau)\ d\tau = h_t \tag{5}$$

Accounting for time discretization, the probability for a spell to end during month t is then given by

$$\begin{aligned} l(t) &= \Pr(t-1 \leq T < t) \\ &= \exp[-H(t-1)] - \exp[-H(t)] \\ &= \exp\left[-\sum_{s=1}^{t-1} h_s\right] - \exp\left[-\sum_{s=1}^{t} h_s\right] \end{aligned} \tag{6}$$

[3] The censoring issue is adressed in the next section.

[4] This assumption generates the well-known piecewise constant hazard model (see e.g. Meyer 1990).

The likelihood contribution of a price spell that is right-censored in month t is:

$$l(t) = S(t) = \exp\left[-\sum_{s=1}^{t-1} h_s\right] \tag{7}$$

Consequently, if we denote c_i the dummy variable taking value 1 if the i-th price spell is not right-censored, and 0 otherwise, the log-likelihood function for a sample of N i.i.d. price spells is given by:

$$\ln L = \sum\nolimits_{i=1}^{N} \left[c_i \ln\left[1 - \exp\left(-h_{t_i}\right)\right] - \sum_{s=1}^{t_i-1} h_s\right] \tag{8}$$

However, it may be unduly restrictive to assume that the hazard function is constant across price spells. One has indeed to worry about the possible existence of heterogeneity across spells.

3.2 Accounting for time-varying covariates

Price spell durations may vary across products (e.g. food, gasoline, clothes, services, etc.), outlets (hypermarkets, general stores, traditional "corner shops", etc.) and over time. Indeed, outlets have their own pricing policy, depending on the type of product they sell, on the characteristics of their customers and on the competition with other retailers. Differences in the evolution of costs across sectors and in the production and merchandising technologies may also contribute to explain differences in the pricing behavior across different types of goods. The approach followed hereafter to account for these differences is to stratify the sample by products and outlet types.

Once the stratification is done, remaining covariates are mainly time-varying. When the covariates are time-varying, their whole path over the price spell matters. Inflation is a relevant example. At each point in time during the spell, accumulated inflation creates an increasing gap between the unchanged price of the product in a given outlet and the overall price level (and/or the average price of the same product set by other outlets as a whole or by direct competitors). Defining the covariate as the accumulated inflation evaluated only at the end of the spell would indeed lead to biased estimates since longer spells would be systematically associated with higher inflation. The other time-varying covariates we consider include dummies for changes in the VAT rate as well as for the Euro cash change-over.

Thus we assume that the hazard function of the i-th price spell is specified as:

$$h_i(\tau) = h_\tau \exp(z_{i\tau}\alpha) \tag{9}$$

where h_t is a baseline hazard function that is assumed to be constant over the interval $[t-1, t[$, z_{it} is the value at time t of a vector of time-varying covariates, and α is a vector of (unknown) parameters associated with the vector of covariates $z_{i\tau}$. If we assume that the variables $z_{i\tau}$ do not vary over the time interval

$[t-1, t[$, namely $z_{i\tau} = z_{it}$, $\forall\ t-1 \leq \tau < t$, the likelihood contribution of the i-th (complete) price spell is:

$$\begin{aligned} l\left(t_i | \{z_{is}\}_0^{t_i}, \alpha\right) &= \exp\left[-\sum_{s=1}^{t_i-1} h_s \exp(z_{is}\alpha)\right] - \exp\left[-\sum_{s=1}^{t_i} h_s \exp(z_{is}\alpha)\right] \\ &= (1 - \exp\left[-h_{t_i} \exp(z_{it_i}\alpha)\right]) \\ &\quad \times \exp\left[-\sum_{s=1}^{t_i-1} h_s \exp(z_{is}\alpha)\right] \end{aligned} \tag{10}$$

and the log-likelihood function for a sample of N i.i.d. price spells (potentially right-censored) is given by:

$$\ln L = \sum\nolimits_{i=1}^{N} \left[c_i \ln\left(1 - \exp\left[-h_{t_i} \exp(z_{it_i}\alpha)\right]\right) - \sum_{s=1}^{t_i-1} h_s \exp(z_{is}\alpha)\right] \tag{11}$$

3.3 Multiple outcomes as competing risks

The last observation of a price spell may correspond to different events:

1. an increase in the price of the item,
2. a decrease in the price of the item,
3. a product replacement: the item ceases to be sold and is replaced in the dataset by another equivalent item,
4. right-censoring: the spell is ongoing beyond the end of the observation period.

A relevant question is whether it is reasonable to consider that both the baseline hazard function and the impact of covariates are similar whatever the event terminating the observed spell. If they are, a dummy accounting for the particular type of event can be added to the set of covariates. If not, which we argue below is the case, it is preferable to opt for a competing risks model. In such a framework, the hazard function as well as the covariates coefficients are then allowed to differ according to the outcome.

3.3.1 Price increases vs. price decreases

The hazard functions may possibly differ for price decreases and price increases. For instance, recent specific surveys about firms pricing behaviors that have been conducted in the euro area (see Fabiani et al. 2004, as well as, for evidence on France, Loupias and Ricart 2004,) suggest that, as regards price adjustments, firms react differently when their production costs (or the demand for their

product) rise or decrease. Indeed, firms react faster to a rising cost and a lowering demand than to changes going the other way round. Moreover, the impact of some covariates on the probability of price change clearly differs in these two cases. Indeed, (positive) accumulated inflation since the last price change is expected to *lower* the probability of a price decrease while it is assumed to have the opposite effect for a price increase. Pooling spells ending with a price increase together with those ending with a decrease will then produce biased estimates of the coefficients. Consequently, the hazard function may depend on the type of outcome.

3.3.2 Attrition

Individual price data are also affected by attrition, corresponding to statistical units "leaving" the sample before the end of the observation period. Two sources of attrition in price records are the following :

1. first, products have life-cycles: "old" products disappear from the market and "new" ones appear. The time series of prices observations for a specific product is very likely to be interrupted at some point during the observation period;

2. second, outlets or firms may close, which obviously interrupts the time series of price observations for all products sold by the outlet or the firm.

Product replacement is quite common in some sectors (in particular in the clothing sector) and is not uncommon in general. Indeed, replacements represent about 20% of the price spell endings in our dataset. They induce attrition and cannot be left out of our analysis as product replacement indeed provide an opportunity to change prices. However, while the data at hand allow to identify product replacements, we cannot assess whether a given product replacement is associated with a price increase or a price decrease.

3.3.3 Censoring

Censoring is a major issue when analyzing durations in general, and in our context in particular. Indeed, several reasons may cause price spells to be censored:

1. First, the observation period is restricted by the database availability. Thus it is very likely that the first spell in a price trajectory is left-censored, and that the last one is right-censored.

2. Second, the sampling of products and outlets by the statistical institute is also likely to generate some censoring. Indeed, the statistical institute may decide to discard a specific product from the "representative" CPI basket due to changes in consumer behaviors that shrink demand for certain products types, although those products may still be sold in outlets (e.g. Video Cassette Recorders with the advent of DVD players). Then, the last price spell of such a product will be right-censored. Conversely, when

a new product is included in the CPI basket, it is likely that its price will start to be recorded in a given outlet after the product was actually made available for consumers, thus during the course of one price spell. This will generate left-censoring of the first price spell.

3. Third, outlets and firms may decide to stop selling a product while its price path is followed up by the statistical agency. In such a case, the procedure most often adopted by statistical agencies consists of replacing the "old product" by either a close substitute in the same outlet or by the same product sold in another outlet. It is then very likely that the price of the "replacing" item is set before the first price observation for this product. Then the price spell of this new product is left-censored.

3.3.4 The competing risks model

Formally, let us denote by T_1 the latent duration associated with a price increase, $h_1(T_1)$ its hazard function, $f_1(T_1)$ its density function and $S_1(T_1)$ its survivor function. Analogously, let us denote T_2 the latent duration associated with a price decrease, $h_2(T_2)$, $f_2(T_2)$ and $S_2(T_2)$ being its hazard, density and survivor functions, respectively. Finally, let us denote T_3 the latent duration associated with a product replacement, $h_3(T_3)$, $f_3(T_3)$ and $S_3(T_3)$ being its hazard, density and survivor functions, respectively.

- a spell termination corresponding to a price increase. In this case, we know that the duration of the spell ending by this price increase is shorter than the latent durations corresponding to either a price decrease or a product replacement: $T_1 \leq T_2$ and $T_1 \leq T_3$;
- a spell termination corresponding to a price decrease. In this case, we know that the duration of the spell ending by this price decrease is shorter than the latent durations corresponding to either a price increase or a product replacement: $T_2 \leq T_1$ and $T_2 \leq T_3$;
- a spell termination corresponding to a product replacement. In this case, we know that the duration of the spell ending by this product replacement is shorter than the latent durations corresponding to either a price increase or a price decrease: $T_3 \leq T_1$ and $T_3 \leq T_2$;
- a right-censored spell, corresponding either to the end of the observation period or by a decision of the statistical office to stop observing this particular item. Then, if we denote C the latent duration associated with right-censoring, we have in this case $\min(C, T_1, T_2, T_3) = C$.

Let us define the *joint survivor function* of the first three latent durations as:

$$S(t_1, t_2, t_3) = \Pr\left(T_1 > t_1, T_2 > t_2, T_3 > t_3\right) \tag{12}$$

If (T_1, T_2, T_3) are *stochastically independent,* then :

$$S(t_1, t_2, t_3) = \prod_{k=1}^{3} S_k(t_k) \tag{13}$$

$S_k(t_k)$ being the marginal survivor function of the k-th latent duration. In the sequel, our *maintained assumption* is that (T_1, T_2, T_3) are *conditionally independent* given the covariates, namely:

$$T_k \amalg T_{k'} \mid \{z_{it}\}_{t>0} \quad \forall k' \neq k \tag{14}$$

The initial dataset contains right-censored spells, left-censored spells as well as both right- and left-censored spells. The case of exogenous right-censoring, is rather straightforward. Indeed, what is known about a spell that is right-censored in month t_i is that its complete (latent) duration is equal to or higher than t_i months. In other words, the spell is still ongoing at the end of the t_i-th month. Its contribution to the likelihood function is then:

$$l_c(t_i) = S(t_i, t_i, t_i) = \prod_{k=1}^{3} S_k(t_i) \tag{15}$$

Many spells in the sample however are either left-censored or both right and left-censored. In general, the statistical treatment of left-censored spells induces more difficulties than the right-censored spells. However, since the sample is made of thousands of spells for each product type and outlet type, we are able to discard the left-censored spells without substantial information loss. As left-censoring is independent of the duration of price spells, it does not produce a selection bias. In the present context, contrarily to what often occurs in unemployment duration studies, left-censoring does not concern a particular subpopulation with specific characteristics.[5] We checked the absence of bias when disregarding left-censored spells by performing a simulation study, based on a data-generating process approximating the generation of a longitudinal price dataset. Accordingly, left-censored (including both right- and left-censored) spells have been discarded from the sample used for estimation.

Under these assumptions, if the hazard function is piecewise constant and if there is no unobserved heterogeneity, the likelihood contribution of a spell

[5] The only exception is the category of clothes where there are very specific pricing and renewing strategies that are not independent from each other: changes in prices are not necessarily frequent but changes in the items often occur every 6 months (the "winter/summer" collection pattern is important for this particular group of products).

ending in month t_i with a type k event is

$$\begin{aligned} l_k\left(t_i;\alpha\right) &= \left[S_k(t_i-1 \mid \{z_{is}\}_0^{t_i-1}) - S_k(t_i \mid \{z_{is}\}_0^{t_i})\right] \\ &\quad \times \prod\nolimits_{k'\neq k} S_{k'}\left(t_i \mid \{z_{is}\}_0^{t_i}\right) \\ &= \{1-\exp[-h_{k,t_i}\exp(z_{it}\alpha_k)]\} \\ &\quad \times \exp[-\sum_{s=1}^{t_i-1} h_{k,s}\exp(z_{is}\alpha_k)] \\ &\quad \times \prod\nolimits_{k'\neq k} \exp[-\sum_{s=1}^{t_i} h_{k's}\exp(z_{is}\alpha_{k'})] \end{aligned} \tag{16}$$

For a spell ending in month t_i with a type$-j$ event ($j \neq k$), the likelihood contribution is

$$\begin{aligned} l_j\left(t_i;\alpha\right) &= \{1-\exp[-h_{j,t_i}\exp(z_{it}\alpha_j)]\} \\ &\quad \times \exp[-\sum_{s=1}^{t_i-1} h_{j,s}\exp(z_{is}\alpha_j)] \\ &\quad \times \exp[-\sum_{s=1}^{t_i} h_{k,s}\exp(z_{is}\alpha_k)] \\ &\quad \times \prod\nolimits_{\substack{k'\neq k;\\ k'\neq j}} \exp[-\sum_{s=1}^{t_i} h_{k',s}\exp(z_{is}\alpha_{k'})] \end{aligned} \tag{17}$$

In this second type of contribution, parameters depending on the destination indicator k, namely $h_{k,s}$ and α_k, appear only in the marginal survivor function

$$S_k(t_i \mid \{z_{is}\}_0^{t_i}, \alpha_k) = \exp[-\sum_{s=1}^{t_i} h_{k,s}\exp(z_{is}\alpha_k)] \tag{18}$$

This is also the case for right-censored-spells because:

$$\begin{aligned} l_c\left(t_i;\alpha\right) &= \exp[-\sum_{s=1}^{t_i} h_{k,s}\exp(z_{is}\alpha_k)] \\ &\quad \times \prod\nolimits_{k'\neq k} \exp[-\sum_{s=1}^{t_i} h_{k',s}\exp(z_{is}\alpha_{k'})] \end{aligned} \tag{19}$$

Consequently:

1. as we have three possible terminating events (except right-censoring denoted by $c_i = 0$), we get $K = 3$ additively separable log-likelihood subfunctions with expressions:

$$
\begin{aligned}
\ln L_k = \sum\nolimits_{i=1}^{N} c_i \mathbf{1}\left(k_i = k\right) \times \{\ln\left(1 - \exp[-h_{k,t_i} \exp(z_{it}\alpha_k)]\right) \\
- \sum\nolimits_{s=1}^{t_i-1} h_{k,s} \exp(z_{is}\alpha_k)\Big\} \\
- \sum\nolimits_{i=1}^{N} \sum\nolimits_{k' \neq k} c_i \mathbf{1}\left(k_i = k'\right) \times \left[\sum\nolimits_{s=1}^{t_i} h_{k',s} \exp(z_{is}\alpha_{k'})\right] \\
- \sum\nolimits_{i=1}^{N} \sum\nolimits_{k'=1}^{3} \left(1 - c_i\right) \left[\sum\nolimits_{s}^{t_i} h_{k',s} \exp(z_{is}\alpha_{k'})\right]
\end{aligned}
\tag{20}
$$

where $\mathbf{1}(.)$ is an indicator function equal to 1 if the expression in parentheses is true, 0 otherwise;

2. thus the total likelihood function may be written as:

$$
\max_{\theta} \ln L = \sum\nolimits_{k=1}^{3} \max_{h_{k,s},\alpha_k} \ln L_k \tag{21}
$$

3. when maximizing the k-th subfunction $\ln L_k$ with respect to $[h_{k,s}, \alpha_k]$, price spells terminated by events $k' \neq k$ contribute only through their marginal survivor function $S_{k'}(t_i \mid \{z_{is}\}_0^{t_i}, \alpha_{k'})$. Thus they can be treated as right-censored spells.

4 The data

The data used for our econometric analysis are the individual price records collected by INSEE (Institut National de la Statistique et des Etudes Economiques, Paris) for the computation of the French CPI.[6] This is an original dataset, both as regards its contents and its size. In this section, we briefly document these data.

4.1 The original dataset and the sample design

The sample contains monthly CPI records from July 1994 to February 2003. These data cover around 65% of the overall weight of the CPI. Individual price data for fresh foods, rents, purchase of cars, and administered prices such as electricity or telephone (when still regulated) are not included in the dataset made available to us. The number of price quotes in the initial database is around 13 millions price observations, and around 2.3 millions price spells. With each individual record the information recorded includes the price level, an individual product code (outlet and product category), the year and month of the record, a "type of record" code (indicating whether the price record is a regular one, a sales price, an "imputed" price due to stockout, etc.).

[6] The methodology used for data collection is described in INSEE (1998).

Some specific data issues have been dealt with prior to estimation. For instance, due to temporary stock-outs or holidays, "missing" prices are not uncommon. Those unobserved prices are most often replaced by INSEE using an imputation procedure. For our purpose, it was found more relevant to replace any unobserved price by the previous price observed for the same item. This avoids to create "artificial" price changes due to the very likely discrepancy between the missing price and its average over other outlets as imputed by INSEE in its computation of the CPI. As the observation period goes from 1994:7 to 2003:2 (prices being set in euros from 2002:1 onwards), we also take the euro cash change-over into account. Consequently, we divide all prices recorded before 2002:1 by 6.55957, the official French Franc/euro exchange rate. We ensure that price spells are unaffected prior to the cash change-over, and that in January 2002 price changes corresponding to a simple rounding up to 2 digit are not counted as price spell terminations (see Baudry et al. 2004, for details on these issues and other aspects of data treatment).

Some trimming of the original dataset proved to be necessary. First, all left-censored spell were discarded. This exclusion avoids to make non-testable assumptions on the price setting behavior before the beginning of our observation period (see Heckman and Singer 1984). Second, price spells corresponding to sales or temporary rebates were removed (these spells were identified using the "type of observation" code).[7] Indeed, spells corresponding to such events are very likely to be short, typically less than 3 months. Moreover, the impact of covariates such as the cumulative inflation over the spell do not play the same role for such spells: "sales price" spells do not end because the cumulated inflation has reached a threshold during the spell but because sales are temporary by nature. We also discard price trajectories for which price quotes are collected quarterly, to avoid spurious spikes in the hazard function. Third, for each outlet, we have randomly selected one price spell by product category. This results in a more manageable database without substantial information loss, and also corrects for over-representation of items with short spell durations. The sample is thus representative of economic units (see Dias et al. 2005, for a discussion on this issue). Note however that sampling should not be an issue as long as the econometric model is correctly specified and provides a relevant representation of homogeneous behaviors at the very microeconomic level.

The number of observations left in the subsample is 164,626, out from around 2.3 millions in the original dataset. To understand this significant reduction of the sample size, note first that removing left-censored spells typically suppresses one spell out of three. More importantly, selecting one spell per product and outlet amounts to select one spell out of 10 to 20, the number typically available in each outlet/product type cell.[8]

The distribution of the number of spells according to various criteria (sector, outlet type, destination) is presented in the first column of Table 1. Note that the

[7] The overall proportion of price records corresponding to sales is equal to 0.76%, while temporary reductions represent 1.92% of all observations.

[8] In some cases with short durations like oil products, as many as 100 spells are available for one outlet, of which we keep one only.

coverage of the "services" outlet type and the "services" sector do not match exactly, and are not included in each other. For instance, restaurants fall in the outlet type category "traditional outlet" while belonging to the "services" sector. Conversely, gasoline sold in gas stations appears in the "services" cell for outlet type, but in the "energy" sector. The adopted sectoral breakdown is more detailed than in many studies of prices, since the manufacturing sector is disaggregated into durable goods, clothing, and other manufactured goods. This finer disaggregation is adopted because of the very specific pattern of price setting in clothes and durable goods. Given the coverage restriction noted above, the "food" sector in the following tables refer to processed food and meat, while "energy" refers essentially to oil-related energy. In some of the tables, we weight results using CPI weights. CPI weights are available in our database for products at the 6 digit level of the Coicop (Classification of individual consumption by purpose) nomenclature. We have in addition used the number of price records by type of outlet (at the 6 digit level) to create a weighting scheme by outlet type within each type of product.[9] While food products and large outlets appear to be over-represented in the sample of spells, the sample is representative of the CPI in terms of breakdown by broad sectors, once weights are taken into account.

4.2 Price durations: some stylized facts

The distribution of spell durations and the average spell durations are reported in Table 1 and Figure 1. The average duration of price spells, a standard indicator of price stickiness, is 7.44 months, and 8.22 months when using CPI weights. Note this indicator is obviously affected by right-censoring (as indicated in the lower panel, 26.8% of spells are right-censored). Average duration strongly varies across sectors. The main relevant contrast is between services and other types of goods. The average duration of a price spell is about twice larger in the services sector (11.86 months) than in the manufacturing sectors (around 7 months)[10] and in the food sector (6.62 months). Heterogeneity across outlet types is significant as well: the average price spell duration is 4.59 months in supermarkets, while it is 9.12 months in traditional outlets. The contrast in average durations corresponding to different outcomes (price increases, price decreases, product replacements) is not as sharp, although right-censored spells last longer than the average spell (9.73 months), which may reflect a selection effect.

The unconditional hazard function for price changes of manufactured goods is represented in Figure 1. It has a strongly decreasing pattern, and there are marked peaks at 1 and 12 months. These peaks may suggest the presence of both flexible price-setters and price-setters with a "Taylor type" behavior. Similar patterns are obtained for other sectors as well as other countries (see Baudry

[9] The motivation for this is that the collection of price records by INSEE aims at reflecting the market share of each outlet type.

[10] The manufacturing sectors include durable goods, clothing, and other manufactured goods.

et al. 2005, and Dhyne et al. 2005). The probable cause of the decrease of the hazard function lies in the heterogeneity of price-setters' behaviors (see e.g. Kiefer 1988, Heckman and Singer 1984, and, in a price-setting context, Alvarez et al. 2005). Our main challenge is then to assess whether a better account for heterogeneity will allow to identify patterns in better accordance with the theoretical models.

5 Heterogeneity in pricing behaviors: empirical results

5.1 Empirical strategy and specification

Our empirical strategy aims at controlling as much as possible for heterogeneity. To that end, we stratify the data at the highest available level of disaggregation, simultaneously in terms of the type of good and of the type of outlet. For each price spell, the item type is available through the Coicop nomenclature at the 6 digit level. There are 271 Coicop categories of products in our sample. The type of outlet is also available through an indicator variable.[11] Eleven types of outlets are observed. Overall there are 1,775 strata with at least one price spell. In addition, we consider different spell outcomes by distinguishing between price increases, price decreases and product replacements.

For each stratum, we have estimated a model including both a piecewise constant baseline hazard and time-varying covariates.[12] In order to minimize numerical difficulties, we imposed constraints both on the minimum number of observations (spells) in each stratum and on the model itself. More precisely, we require that each stratum contains at least 120 observations. In addition since we consider multiple outcomes, at least 30 exits towards the relevant destination are required to get a sufficiently precise estimate of the corresponding specific hazard function. Under these criteria, the number of estimated models is 734. Table 2 provides an overview of the estimated models. The number of estimated models is $N = 309$ models for spells ending with a price increase, $N = 229$ models for spells ending with a price decrease, and $N = 197$ models for those ending with a product replacement. The average number of spells per model is 362.2. For instance, 108,428 spells were used in the analysis for price increases. Note that we have performed a similar analysis at the Coicop 5 digit level (leading to a

[11] The dataset classification distinguishes between eleven outlet types. We use this to define strata. For convenience, when reporting the results we regroup them into 5 categories only.

[12] We tried to estimate piecewise constant hazard models with a Gamma-distributed unobserved heterogeneity term (see the likelihood in the appendix). However, as it is documented in the literature, the flexibility of the piecewise hazard makes it difficult to allow simultaneously for unobserved heterogeneity (on these issues, see Baker and Melino 2000). Indeed, we faced important numerical problems that prevented us from getting a sufficient set of estimates. We alternatively estimated a set of Weibull models allowing for unobserved heterogeneity; the results were less satisfactory due to the rather restrictive shape of the Weibull hazard. This is why we focus on the estimates obtained from the piecewise constant hazard without unobserved heterogeneity. Indeed, given the very high level of disaggregation at which we estimate our models, we do expect that the remaining unobserved heterogeneity is not important.

lower number of models and to a larger number of spells per model): results were essentially unchanged.

In each model, the following time-varying covariates are included:

- a dummy variable for the Euro cash change-over which occurred in January 2002. The impact on the frequency of price changes is well documented (INSEE 2003, Baudry et al. 2005). This dummy is expected to raise both the probability of a price increase and of a price decrease, e.g. if the retailer decided to set psychological prices in euros,

- two dummy variables for the increase in the VAT rate increase in August 1995 (from 18.6 % to 20.6 %), one in August and one in September. Indeed, many outlets are closed in August and the VAT rate change may have been postponed to September for those outlets. The expected coefficients are obviously positive for price increases and negative for decreases,

- a dummy variable for the VAT rate decrease in April 2000 (from 20.6 % to 19.6 %), with coefficients of the opposite sign to those above,

- the inflation rate over the course of the spell for the product sector at the Coicop 5 level of aggregation. Accumulated inflation is defined as the growth rate in the sectoral (Coicop 5 digit level) price index from the month preceding the beginning of the spell to the month preceding the current month.[13] This variable can have two alternative interpretations: the first one is that it is a proxy to the inflation in production costs or wholesale prices in the sector under consideration. The associated coefficient would then represent the impact of the average evolution of production costs for this particular product. Starting from a constant mark-up, the larger the rise in real costs, the more likely is a price change.[14] An alternative interpretation is that sectoral inflation is a proxy for the evolution of the competitors' prices for the same product: everything else being equal, an increase in competitors' prices is an incentive for a price increase. With both interpretations, a positive inflation is expected to increase the probability of a price increase and to lower the probability of a price decrease.[15]

Note that VAT and euro cash change-over dummies are time-varying covariates, which provide insight on the issue of state-dependence. Estimation is

[13] Price indices are not available at the 6 digit Coicop level.

[14] Note however that sticky price models typically predict the aggregate mark-up to fluctuate over time.

[15] There exist obviously other potentially relevant time-varying covariates, e.g. the aggregate rate of inflation, inflation variability, cyclical indicators such as sectoral or aggregate industrial production, etc. Some of these covariates (e.g., output or demand indicators at the product level) are simply not available in our dataset. Including other available covariates, such as the aggregate rate of inflation and the inflation variability would create some difficulties, because these covariates are potentially correlated with the sectorial accumulated inflation rates. In addition our systematic approach would make specification search quite complex and strongly time consuming.

performed by maximizing the likelihood function given by equation (20). In the estimation of the piecewise constant model, we impose the constraint that the baseline hazard is constant from a duration of 14 months onward (namely, $h_s = h_{14}$ for $s \geqq 14$).[16] For each piecewise constant hazard model, we perform tests on the shape of the hazard function. In particular, testing for a constant baseline hazard function, one of Calvo's model prediction, is performed by conducting Wald tests of the null hypothesis $H_0 : h_1 = h_2 = h_3 = ... = h_T$.

5.2 Three examples

In order to illustrate the main features of the statistical models and some typical results, we start by presenting three examples.

A first example is pastry. The estimated baseline hazard function, obtained under the assumption of a piecewise constant hazard specification, is reported in Figure 2 for two alternative outlet types: supermarkets and traditional outlets (bakeries). As Figure 2 makes clear, the shapes of the hazard functions sharply differ across different types of outlets. For bakeries, the slope of the overall hazard function is positive. A striking feature is the peak of the hazard function at 12 months. For supermarkets, the hazard function is decreasing, suggesting some remaining heterogeneity. This example clearly indicates that a proportional hazard specification (i.e. treating outlet type as a covariate having a proportional effect on the hazard) would not be relevant.

Another example is haircut for women. Figure 3 presents the hazard functions for price increases and for price decreases for this item. The corresponding estimation results are reported in Table 3. From Figure 3 the baseline hazard is seen to be different for price increases and price decreases. Concerning price increases, a Wald test of the assumption of a constant baseline hazard is rejected at the 5% level. However, when allowing for one peak in the baseline hazard function at 12 months, the Wald test p-value is 0.147, so that the hazard constancy is not rejected. Turning to parameter estimates, the estimated parameter of cumulative inflation is positive but not significant for price increases, while it is negative and significant at the 10% level for price decreases. In addition, the dummy for the euro cash change-over has a massive impact for both price increases and price decreases. The two dummies for VAT increases have also a marked impact on the instantaneous probability of a price increase, while the dummy for the VAT decrease fails to be significant in the model for price decreases.

The third and last example is intended to illustrate product replacement. Figure 4 presents the baseline hazard function for the product replacement of jackets for men in traditional outlets. The hazard function is close to zero in the first months while it has a peak in months 6, 7 and 8. Thus price change,

[16] Estimation is performed using the GAUSS constrained maximum likelihood procedure. The hazard is constrained to be zero when there are no exits at a given duration. We also implement the constraint that hazard parameters are positive by specifying $h_i = \exp(b_i)$ and optimizing over b_i . The delta method is used to compute standard errors.

which for this type of goods operates mainly through product replacement, has a specific pattern of duration dependence.[17]

5.3 Estimation results

The first question concerns the shape of the hazard function for price changes, when estimated at a highly disaggregated level. As noted in section 2, price setting models have predictions in terms of the hazard function for price changes. To evaluate theses predictions, we examine Wald tests using the estimated coefficients of the piecewise hazard function.

5.3.1 Heterogeneity in the baseline hazard function for price spells

The results of the tests conducted about the shape of the hazard are reported in Table 4. Table 4 provides the percentage of strata for which the null hypothesis of baseline hazard constancy is not rejected. Results can be summarized as follows:

1. The first striking result is the rather low rate of non-rejection of the hypothesis of a time-constant hazard. For more than two thirds of the 734 estimated models, this assumption cannot be rejected and changing the significance level of the test does not alter this result substantially. Although the overall non-rejection rate using CPI weights is lower than the non-weighted one, it is still larger than 60% for spells ending with a price decrease (61,4%) or with a product replacement (68.8 %). For price increases the weighted frequency of non-rejection is 34.5% As outlined below, this higher rejection rate is essentially due to increasing hazards, not to decreasing ones (see Table 6 below). Moreover, the last line of the first panel in Table 4 indicates that allowing for peaks at 1 and 12 months leads to quite high rates of acceptance of the hypothesis of a time-constant hazard (excluding the peaks), whatever the outcome.

2. There is significant heterogeneity both across sectors and across outlets. As far as spells ending with a price increase are concerned, the assumption of a constant baseline hazard is relevant in a majority of cases for manufactured goods and processed food (e.g., using weighted results, 51.6% for food, 74.2% for durable goods and 47.4% for other manufactured goods) It is most often rejected for energy and services (non rejection rates are respectively 18.9% and 10.4%). As already mentioned, the assumption of a time-constant hazard is less frequently rejected for spells ending with a price decrease or a product replacement. In addition, a constant hazard is not rejected for large outlets, while the opposite is true for traditional corner shops and service providers. The non-rejection rate is for instance 59.6% for hypermarkets against 10.5% for service providers. A possible

[17] Few models are estimated for price decreases, since we distinguish sales ending with regular price decrease from those ending with sales.

explanation might be the pricing strategy of those large outlets where price changes and the availability of products are part of the marketing policy.

3. When the null gypothesis of a constant hazard is rejected, it is often the case that the hazard is increasing or that there are peaks in the hazard rate. A first informal assessment is that in such cases, many of the hazard functions have an overall increasing pattern, as in Figure 3. The second column of Tables 5A and 5B report the percentage of cases for which the slope of an OLS line fitted through the hazard function is positive.[18] This is particularly striking as regards other manufactured products and services for spells ending with a price increase: the hazard rates can be classified as broadly increasing in respectively 77.8% and 86.1% of cases. Here again, there is a clear distinction between food and energy products on the one hand, and manufactured products and services on the other hand. The rejection of the hazard constancy for the latter group mainly corresponds to an increasing shape while the reverse is true for the former group of products.

   To capture the impact of specific peaks, we first implemented a test inspired by Taylor's model with contracts durations either at 6 months (or between 5 and 7 months) or with a one-year duration (or between 11 and 13 months); implying a theoretical zero hazard for other durations. The restrictions implied by those models were all rejected, due to the strictly positive estimated value of the hazard function outside the peaks, which appeared to be significantly different from zero. We then implemented a less restrictive test, by testing for hazard constancy except at some given durations (1, 6 and 12 months). A possible interpretation of this test is the coexistence of several types of price setting behaviors, including in particular various Taylor models associated with different contracts durations. The results of this test are presented in last two columns of Tables 5A and 5B. Each column gives the percentage of models for which the assumption of a constant baseline hazard is not rejected, when allowing for one (or several) spikes in specific months (an obvious caveat is that the number of estimated models is rather limited for some subgroups). The main conclusion of this exercise is that allowing for such particular peaks makes the constancy of the hazard an acceptable assumption, at least for spells ending with price increases or decreases. As regards product replacements in the clothes' sector, contrary to what one would expect through visual inspection of the hazard functions (see Figure 4), tests do not lead to accept the assumption of a constant hazard away from the peak at 6 months. This result comes from the rather high precision of the estimated hazard for other durations, as well as from the fact that many replacements occur indeed after 7 or 8 months (as in the example of Figure 4).

[18] Fitting a hazard curve slope from the Weibull distribution, using minimum distance estimation, provided qualitatively similar results.

Finally, the shape of the hazard function (the localization of peaks) exhibits sectoral-specific patterns. Most types of energy exhibit short spells (such as gasoline) and other "almost annual" changes (such as solid fuels: coke, etc., mainly used for heating). It appears that the rejection for food and energy products is due to a significant flexible component (that translates into a peak at 1 month). For services, the occurrence of a peak around 12 months is frequent. Then, an acceptable characterization of the behavior of price setters in services can be seen as a mix of Calvo's units and Taylor's 12 months contracts. For clothes, the low acceptance rate results from the seasonal pattern for those items with a peak around 6 months.

4. When the assumption of a time-constant hazard is accepted, there is considerable heterogeneity in the level of the hazard function. This is shown in Figure 5 which plots the distribution of the baseline hazard rates across strata. In accordance with the descriptive evidence, the hazard is highest for energy products and lowest for services. Moreover the estimated hazard vary substantially across types of outcomes and types of outlets, but also within each of those groups. In particular, prices are much more flexible in hyper- and supermarkets than in the other types of outlets. Indeed, the fraction of "flexible" prices in those outlets is significant in 80 % of our estimated models.[19]

Overall, the above results show that estimating models at a highly disaggregated level allows to solve the decreasing hazard "puzzle" and to recover estimates in better accordance with theoretical models. Indeed, using the results in Tables 4 and 5A, the proportion of non-decreasing estimated hazard rates equals about 80% for both price increases and decreases and 95% for product replacements, leading to a ratio of 85% when all estimated models are grouped together.[20] The corresponding ratios are respectively 76%, 68% and 84% when CPI weights are used. Allowing for peaks still improves the acceptance rates, which become 87% (resp. 69%), 96% (resp. 89%) and 76% (resp. 76%) for price increases, prices decreases and product replacements (resp. for weighted results).

These results highlight the strong degree of heterogeneity that exist in the baseline hazard function for price changes. Moreover, such a high level of heterogeneity also appears to characterize the impact of covariates.

5.3.2 Heterogeneity in the impact of covariates

A. The impact of the sector specific cumulative inflation

Estimation results for the impact of the accumulated inflation on the probability of a price change are summarized in Table 6 and Figure 6. These provide

[19] For brevity, the exact numerical results are not reported here but are available from the authors.

[20] For instance, for price increases the total share of non-rejection is computed adding "constant" and "increasing" cases, as $0.625 + (1 - 0.625) \times 0.491$.

two complementary ways to look at the results. The first one is to look at the significance and sign of the estimated coefficients, which provide an indication of the importance of state-dependence in price-setting behaviors. Table 6 shows that as regards price increases, the estimated inflation coefficient is frequently positive, as expected, and is statistically significant in about 45% of cases. State-dependence, although not clearly dominant, thus appears to be important to explain price rises. On the contrary, the coefficient of accumulated inflation is rarely significant for price decreases and product replacements. Thus price reductions and product replacements are not driven by this variable.

Processed food products and energy appear to be largely sensitive to inflation in their sector, in contrast with other products. This result should not be taken to imply that inflation does not affect price changes in other sectors. Although their revision schedule does not heavily depend on the inflation rate, the magnitude of price revisions is likely to depend on the prevailing or expected inflation rate (as it is, for instance, predicted by Calvo's model). Another interesting result is that the response of price changes to inflation is more systematic for hyper- and supermarkets than it is for traditional outlets. The proportion of significantly positive coefficients is larger in the former groups.

The other way to look at our estimation results is to analyze the magnitude of the impact of the accumulated inflation on the likelihood of a price change. This magnitude is clearly strongly heterogeneous, as indicated by Figure 6. While the average impact of the accumulated inflation on the probability of a price increase is clearly positive, this impact varies a lot and can even be negative (though often not statistically significant) in a non negligible fraction of cases.

B. The impact of the euro cash change-over

The first striking result from Table 7 is that, on the whole, the euro cash change-over has had a quite symmetric impact on price increases and decreases. The proportion of significant coefficients is not much different: respectively 58.5% and 45.4% for increases and decreases, considering weighted figures. The magnitudes of average effects (not reported) are also very close. However, some differences emerge at a lower level of disaggregation. First, increases in prices have been more frequent for clothes and services than for other types of goods. Second, those price increases seem to have occurred mainly in traditional outlets, for which we get most of the significant estimated coefficients and a larger magnitude of the impact. It must be noticed that the frequency of price decreases has also been increased in those outlets. This might reflect the search for psychological prices, leading to both increases and decreases in prices expressed in euros. At the opposite, the coefficients are almost never significant for hyper- and supermarkets. For instance in hypermarkets the cash-change-over indicator is significant in 7.8% of estimated models for price increases and 13.9% of models for price decreases. This can be seen as a confirmation that, at least at the very time of the euro cash change-over, hyper- and supermarkets fulfilled their commitment not to change their prices during the three months before and the three months after the change of numeraire.

C. The impact of VAT changes

As documented in Table 8 the main VAT rate changes also appear to have an impact on the occurrence of price changes. As expected, the coefficients of the dummies associated with the 1995 increase of the VAT rate are most often significant for explaining price increases (56.4% of cases). Results for the dummy characterizing the subsequent month, which captures muted effects of a VAT increase, are also often significant. Symmetrically, the dummy for the VAT rate decrease that occurred in April 2000 is significant in a majority of models for price decreases, namely 54.1% of cases. Note that the effect of a VAT increase on the probability of a price decrease, and of the VAT decrease on the probability of a price increase, not reported for brevity, are in general not statistically significant. It is also striking that the VAT decreases are generally more often transmitted to prices in large outlets than in smaller ones, thus confirming the lower importance of state-dependence in the price setting behaviors of the latter group of outlets.

5.3.3 Crossing evidence on state- and duration-dependence

Macroeconomic models emphasize the importance of the price-setting behavior of economic agents for evaluating the impact of monetary policy on macro aggregates. State-dependent agents are more likely to react promptly to a (large) shock while time-dependent agents react with some lag, inducing a delay in the impact of the monetary policy. Table 9 summarizes the results of the Wald tests for duration- and state-dependence, thus providing an insight into the relative importance of the different behaviors.

As noted previously, there are significant discrepancies across outcomes: state-dependence is infrequent as long as we consider product replacements and price decreases, while it is much more important for price increases (around 45% of cases). As a consequence, it is difficult to characterize the price-setting behavior of agents in a simple way as they react differently to different shocks, positive or negative. Such an asymmetry echoes the findings of Fabiani et al. (2005) based on survey data.

The absence of both duration- and state-dependence may be associated with a "Calvo"-type behavior. Thus, with respect to product replacements and price decreases, Table 9 indicates that such a pattern is dominant for these outcomes (52.1% of cases for price decreases and 54.4% of cases for product replacements). As regards price decreases, a possible interpretation of this behavior might be that randomization of prices is an optimal marketing strategy (as predicted e.g. by Varian 1980). It is noticeable that such a pattern is much more frequent for hyper- and supermarkets than it is for traditional outlets (see Tables 4 and 6). The availability of a particular product and the turnover of products is also likely to be part of such marketing practices, at least in large outlets, leading to "Calvo"-type behavior in product replacements. The conclusion is different for price increases: a "Calvo" behavior is less frequent while, symmetrically state-dependence is much more important.

There is thus cross-outcomes heterogeneity in behaviors. Table 9 also indicates that there is a large number of cases with both duration- and state-dependence (32.2 percent in the weighted sample). On the whole, the price setting behavior should probably be characterized by a mixture of various theoretical models.

6 Conclusion

This paper has analyzed price stickiness by estimating duration models at a very disaggregated level. Three main original results stand out.

First, at the outlet type-product level, the assumption of a non-decreasing baseline hazard function for price changes cannot be rejected in about 80% of cases. The decreasing pattern that emerges with pooled data is thus a consequence of imperfectly accounting for heterogeneity in pricing behaviors.

Second, the shape of the hazard function for price changes is found to vary across sectors and types of outlets. Two typical patterns are the fully constant baseline hazard (especially for price decreases and product replacements) and the partially constant hazard function with modes located at durations 1, 6 and 12 months. In particular, the hazard functions for energy products exhibit marked peaks at one month, while those for services exhibit peaks around 12 months.

Third, there is evidence of state-dependence in a large number of cases, primarily for price increases. For approximately 50 per cent of the estimated models for price increases, state-dependence plays a significant role. In addition, the coefficients of covariates, when statistically significant, vary across sectors and outlet types.

Overall these results raise some issues for macroeconomic modelling and monetary policy evaluation. First the extent of heterogeneity in price stickiness suggests that pricing behavior should be modelled as a mixture of flexible, Taylor, Calvo and state-dependent behaviors. The evaluation of monetary policy should acknowledge this heterogeneity. State-dependent agents are for instance more likely to react promptly to a (large) shock, while time-dependent agents react with some lag, inducing a delay in the impact of the monetary policy.

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Table 1 : Price spell durations

	# spells	Proportion spells	Proportion spells (weighted)	Sectoral CPI weights(*)	Average duration	Average duration (weighted)
All spells	164626	1.000	1.000	1.00	7.44	8.22
By sector						
Food	65525	0.398	0.271	0.206	6.31	6.62
Energy	6591	0.04	0.093	0.084	2.60	2.01
Clothes	18216	0.111	0.060	0.092	7.00	7.32
Durable	10371	0.063	0.062	0.060	6.55	6.46
Other manuf. goods	33917	0.206	0.189	0.169	7.49	8.11
Services	30006	0.182	0.326	0.389	11.48	11.86
By outlet type						
Hypermarkets	34359	0.209	0.167	0.199	4.97	4.59
Supermarkets	29882	0.182	0.124	0.136	5.74	5.59
Traditional corner shops	39364	0.239	0.254	0.278	9.07	9.12
Services	23883	0.145	0.284	0.143	11.38	11.46
Others	37138	0.226	0.012	0.244	6.81	6.91
By outcome						
Price increases	51284	0.312	0.356	-	7.40	8.43
Price decreases (exc. sales)	32046	0.195	0.185	-	4.92	4.99
Price decreases (sales only)	1842	0.011	0.008	-	6.21	6.70
Product replacement	35333	0.215	0.178	-	7.81	8.86
Right-censored spells	44121	0.268	0.273	-	9.06	9.73

Notes: Average duration is in months.
The coverage of "service" outlet type and of the "service" sector are distinct.
The column weight report the CPI weight of components for sectors.
In the case of outlets, it reports the proportion of price quotes by type of outlet

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Table 2 : Descriptive statistics for estimated models

	All outcomes	Price increases	Price decreases	Product replacements
# models	734	309	228	197
# spells used per model	362.18	350.85	360.86	381.49
By type of good				
Food	343	158	131	54
Energy	26	14	12	0
Durable goods	57	15	18	24
Clothes	55	8	0	47
Other manuf. goods	169	64	51	54
Services	84	50	16	18
By type of outlet				
Hypermarkets	204	79	79	46
Supermarkets	183	76	70	37
Traditional corner shops	149	61	27	61
Services	73	41	17	15
Others	125	52	35	38

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Table 3. Estimated parameters of a competing-risks piecewise constant hazard model
Item: Haircut for women

	Hazard for price increases		Hazard for price decreases	
Parameters	Estimates	St. errors	Estimates	St. errors
Baseline hazard (log)				
b_1	-5.1399	0.463	-4.9263	0.4853
b_2	-4.7192	0.3855	-5.631	0.6431
b_3	-4.1872	0.336	-	.
b_4	-4.0376	0.3216	-5.3919	0.7383
b_5	-3.6239	0.2826	-4.4517	0.5417
b_6	-4.0041	0.3395	-	.
b_7	-3.6818	0.3228	-4.8021	0.7441
b_8	-3.7113	0.3396	-	.
b_9	-3.998	0.3832	-5.4186	1.0469
b_{10}	-3.6379	0.3416	-5.1609	1.0439
b_{11}	-3.8749	0.3879	-4.4184	0.7838
b_{12}	-2.988	0.2723	-4.8801	1.0592
b_{13}	-3.17	0.3261	-3.3345	0.6313
b_{14}	-3.3877	0.1856	-4.533	0.7054
Time-varying covariates				
Cumulated inflation	3.7282	3.7607	-35.5123	20.5645
January 2002 (Euro changeover)	3.1075	0.265	4.0545	0.6251
August 1995 (VAT)	1.6127	0.4644	1.3325	1.0354
September 1995 (VAT)	1.8886	0.3615	1.1493	1.0698
April 2000 (VAT)	0.1701	0.6456	1.0739	1.0272
Wald test for constant hazard				
	Wald stat.	p-value	Wald stat.	p-value
$b_1 = ... = b_{12}$	31.93	0.002	10.313	0.413
$b_2 = … = b_{12}$	17.88	0.057	3.285	0.857
$b_1 = … = b_5 = b_7 = ... = b_{12}$	26.353	0.003	3.314	0.913
$b_1 = … = b_{11}$	14.618	0.147	3.313	0.855
$b_2 = … = b_{11}$	7.805	0.554	3.285	0.772
Number of spells:	563		563	
Log-likelihood at the maximum:	-946.79		-191.75	

Notes:
Coicop code (6 digit) is 121112
St. error: standard error
The estimated parameter is the logarithm of the baseline hazard $h_s = exp(b_s)$

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Table 4. Wald tests for the assumption of a constant hazard: % of non rejection across strata

	Price increases	Price increases *weighted*	Price decreases	Price decreases *weighted*	Product replacements	Product replacements *weighted*
Overall						
% of non-rejection at 5%	0.625	0.345	0.785	0.614	0.721	0.688
% of non-rejection at 1%	0.706	0.443	0.842	0.675	0.751	0.731
% of non-rejection at 10%	0.563	0.307	0.702	0.554	0.69	0.669
% of non-rejection: h2=…=h11	0.861	0.690	0.947	0.876	0.741	0.748
By type of good						
Food	0.684	0.516	0.763	0.657	0.963	0.957.
Energy	0.429	0.189	0.5	0.206	-	-
Durable goods	0.800	0.742	0.889	0.809	0.875	0.826
Clothes	0.875	0.858	-	-	0.106	0.059
Other manuf. goods	0.719	0.474	0.902	0.716	0.907	0.882
Services	0.280	0.104	0.688	0.647	0.833	0.589
By type of outlet						
Hypermarkets	0.759	0.596	0.772	0.647	0.761	0.744
Supermarkets	0.684	0.547	0.829	0.722	0.973	0.970
Traditional corner shops	0.459	0.220	0.593	0.402	0.508	0.551
Services	0.244	0.105	0.647	0.586	0.867	0.622
Others	0.827	0.687	0.943	0.810	0.711	0.818

Note:
Figures are percentages of cases for which a Wald test at the 5% level does not reject H_0: *h1=…=h14*

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Table 5: Shape of the hazard in strata in which the assumption of a constant hazard is rejected
Panel A: by sector

	# strata	% of increasing hazards	% of increasing hazards *weighted*	% with peaks at 1, 6 or 12	% with peaks at 1, 6 or 12 *weighted*
Price Increases					
All sectors	116	0.491	0.634	0.647	0.533
Food	50	0.160	0.198	0.660	0.567
Energy	8	0.125	0.049	0.625	0.784
Durable goods	3	0.667	0.266	1.000	1.000
Clothes	1	1.000	1.000	0.000	0.000
Other manuf. Goods	18	0.778	0.851	0.667	0.428
Services	36	0.861	0.922	0.611	0.468
Price Decreases					
All sectors	49	0.082	0.178	0.837	0.718
Food	31	0.000	0.000	0.935	0.900
Energy	6	0.000	0.000	1.000	1.000
Durable goods	2	0.000	0.000	1.000	1.000
Clothes	-	-	-	-	-
Other manuf. Goods	5	0.400	0.652	0.200	0.034
Services	5	0.400	0.408	0.600	0.475
Product Replacements					
All sectors	55	0.836	0.486	0.145	0.224
Food	2	0.000	0.000	0.500	0.561
Energy	-	-	-	-	-
Durable goods	3	0.667	0.220	0.667	0.932
Clothes	42	0.929	0.898	0.000	0.000
Other manuf. goods	5	0.800	0.663	0.600	0.621
Services	3	0.333	0.095	0.667	0.238

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Table 5: Shape of the hazard in strata in which the assumption of a constant hazard is rejected
Panel B: by outlet type

	# strata	% of increasing hazards	% of increasing hazards *weighted*	% with peaks at 1, 6 or 12	% with peaks at 1, 6 or 12 *weighted*
Price Increases					
All sectors	116	0.491	0.634	0.647	0.533
Hypermarkets	19	0.000	0.000	0.684	0.805
Supermarkets	24	0.170	0.112	0.625	0.583
Traditional corner shop	33	0.670	0.600	0.667	0.525
Services	31	0.840	0.925	0.613	0.481
Others	9	0.560	0.793	0.667	0.292
Price Decreases					
All sectors	49	0.082	0.178	0.837	0.718
Hypermarkets	18	0.056	0.087	0.833	0.777
Supermarkets	12	0.000	0.000	1.000	1.000
Traditional corner shops	11	0.091	0.248	0.818	0.746
Services	6	0.333	0.354	0.667	0.544
Others	2	0.000	0.000	-	-
Product Replacements					
All sectors	55	0.836	0.486	0.145	0.224
Hypermarkets	11	0.818	0.647	0.091	0.252
Supermarkets	1	1.000	1.000	1.000	1.000
Traditional corner shops	30	0.800	0.639	0.167	0.314
Services	2	0.500	0.111	0.500	0.111
Others	11	1.000	1.000	0.000	0.000

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Table 6: Student test results on estimated parameters associated with accumulated inflation

	Price Increases		Price Decreases		Product Replacements	
	% *positive* and significant parameter	% *positive* and significant parameter *weighted*	% *negative* and significant parameter	% *negative* and significant parameter *weighted*	% *positive* and significant parameter	% *positive* and significant parameter *weighted*
All sectors	0.453	0.435	0.122	0.198	0.137	0.214
By type of good						
Food	0.601	0.602	0.099	0.117	0.111	0.119
Energy	0.571	0.758	0.167	0.358	-	-
Durable goods	0.200	0.259	0.056	0.102	0.208	0.248
Clothes	0.000	0.000	-	-	0.170	0.176
Other manuf. goods	0.297	0.207	0.154	0.131	0.093	0.063
Services	0.300	0.371	0.250	0.352	0.167	0.404
By type of outlet						
Hypermarkets	0.456	0.481	0.100	0.116	0.043	0.025
Supermarkets	0.566	0.569	0.100	0.103	0.135	0.137
Traditional corner shops	0.426	0.500	0.185	0.293	0.230	0.266
Services	0.293	0.348	0.235	0.359	0.067	0.336
Others	0.442	0.259	0.114	0.115	0.132	0.110

Note: Models are estimated with a piecewise constant hazard function

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Table 7: Average value of estimated parameters associated with the euro cash changeover dummy

	Price Increases		Price Decreases		Product Replacements	
	% *positive* and significant parameter	% *positive* and significant parameter *weighted*	% *positive* and significant parameter	% *positive* and significant parameter *weighted*	% *positive* and significant parameter	% *positive* and significant parameter *weighted*
All sectors	0.447	0.585	0.374	0.454	0.275	0.439
By type of good						
Food	0.260	0.284	0.318	0.310	0.167	0.122
Energy	0.222	0.175	0.100	0.134	0.286	0.331
Durable goods	0.571	0.641	0.500	0.562	0.107	0.088
Clothes	0.833	0.838	-	-		-
Other manuf. goods	0.375	0.507	0.378	0.572	0.412	0.495
Services	0.857	0.877	0.750	0.745	0.444	0.677
By type of outlet						
Hypermarkets	0.104	0.078	0.163	0.139	0.360	0.383
Supermarkets	0.160	0.122	0.319	0.271	0.125	0.054
Traditional corner shops	0.797	0.782	0.667	0.627	0.238	0.418
Services	0.789	0.812	0.667	0.694	0.467	0.665
Others	0.355	0.536	0.400	0.506	0.280	0.221

Note: Models are estimated with a piecewise constant hazard function

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Table 8: Average value of estimated parameters associated with the VAT change dummy variables

	VAT increase (1995:8) dummy Impact on Price Increases		VAT decrease (2000:4) dummy Impact on Price Decreases	
	% *positive* and significant parameter	% *positive* and significant parameter *weighted*	% *positive* and significant parameter	% *positive* and significant parameter *weighted*
All sectors	0.563	0.564	0.679	0.541
By type of good				
Food	n.c.	n.c.	n.c.	n.c.
Energy	0.429	0.370	0.111	0.026
Durable goods	0.000	0.000	0.588	0.552
Clothes	0.500	0.489	-	-
Other manuf. goods	0.696	0.734	0.889	0.883
Services	0.525	0.582	0.714	0.563
By type of outlet				
Hypermarkets	0.591	0.413	0.792	0.555
Supermarkets	0.769	0.613	0.800	0.632
Traditional corner shops	0.613	0.623	0.471	0.457
Services	0.441	0.559	0.571	0.571
Others	0.526	0.596	0.750	0.803

Note: Models are estimated with a piecewise constant hazard function . Results do not include food items since they are not covered by the main VAT rate. n.c. : not concerned

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Table 9: Crossing evidence on duration and state dependence

	Price increases N=309		Price decreases N=228		Product replacements N=197	
	Non state-dependence	State-dependence	Non state-dependence	State-dependence	Non state-dependence	State-dependence
Panel A:Proportion of models (%)						
Non duration-dependence	37.9	24.6	69.7	8.8	56.9	15.2
Duration-dependence	16.8	20.7	18.0	3.5	17.8	10.2
Panel B: Proportion of models (%, weighted)						
Non duration-dependence	23.2	11.2	52.1	9.3	54.4	14.3
Duration-dependence	33.3	32.2	28.1	10.5	12.9	18.4

Note: Each panel for each destination reports the cross-tabulation of models according to two tests results. The first row of each panel ("non-duration dependence") reports the breakdown of models for which the null of non-duration dependence (i.e. h1=...=h14) is not rejected at the 5 percent level. The first column of each panel ("non state-dependence") reports the breakdown of models for which the null of non-state dependence (i.e. α_1=0, where α_1 is the parameter on cumulative inflation) is not rejected at the 5 percent level. "N=" reports the number of estimated models.

Source: individual price records used for the calculation of the French CPI (INSEE, 1994-2003)

Fig 1. Hazard function for price changes of manufactured goods

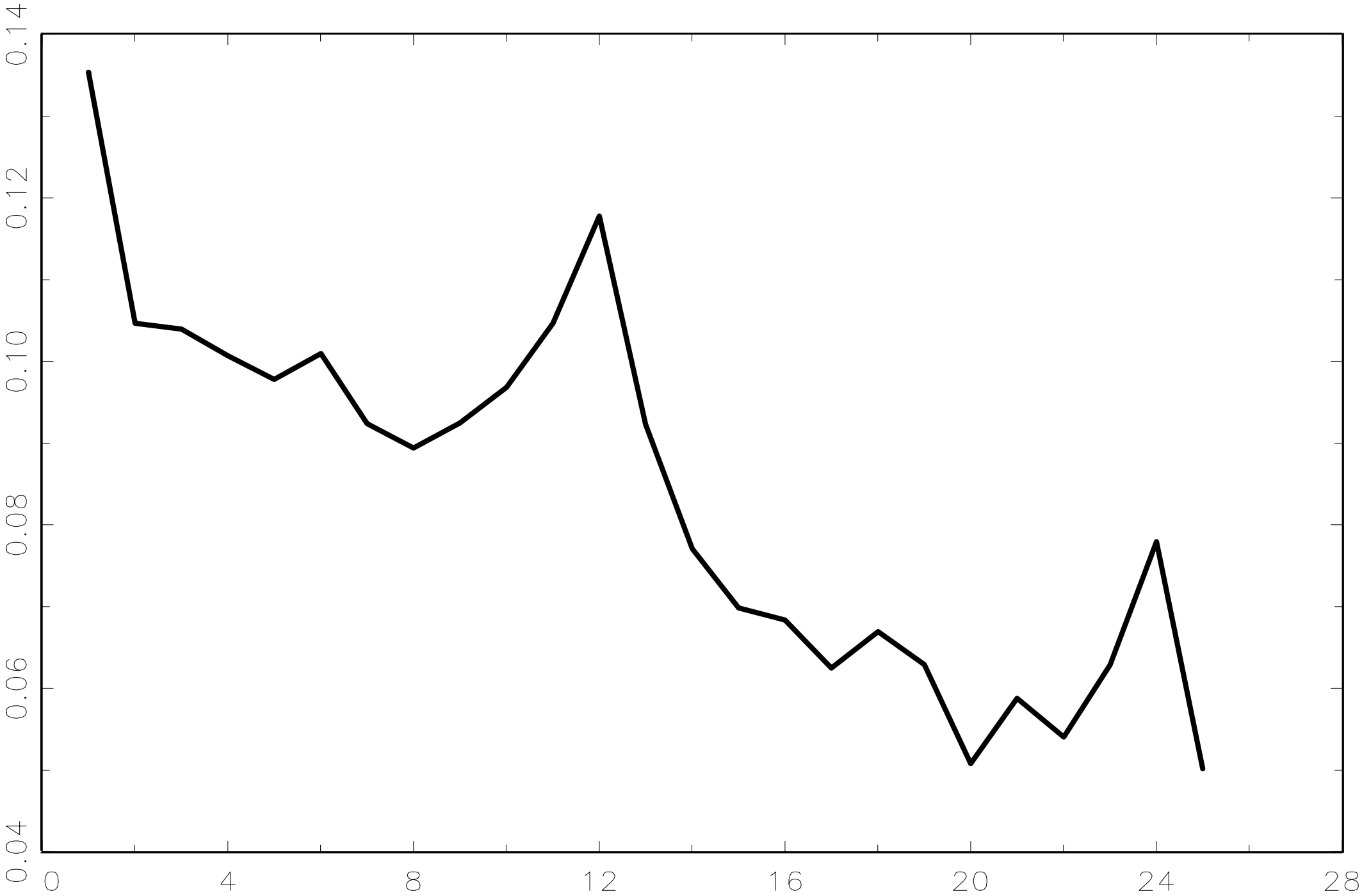
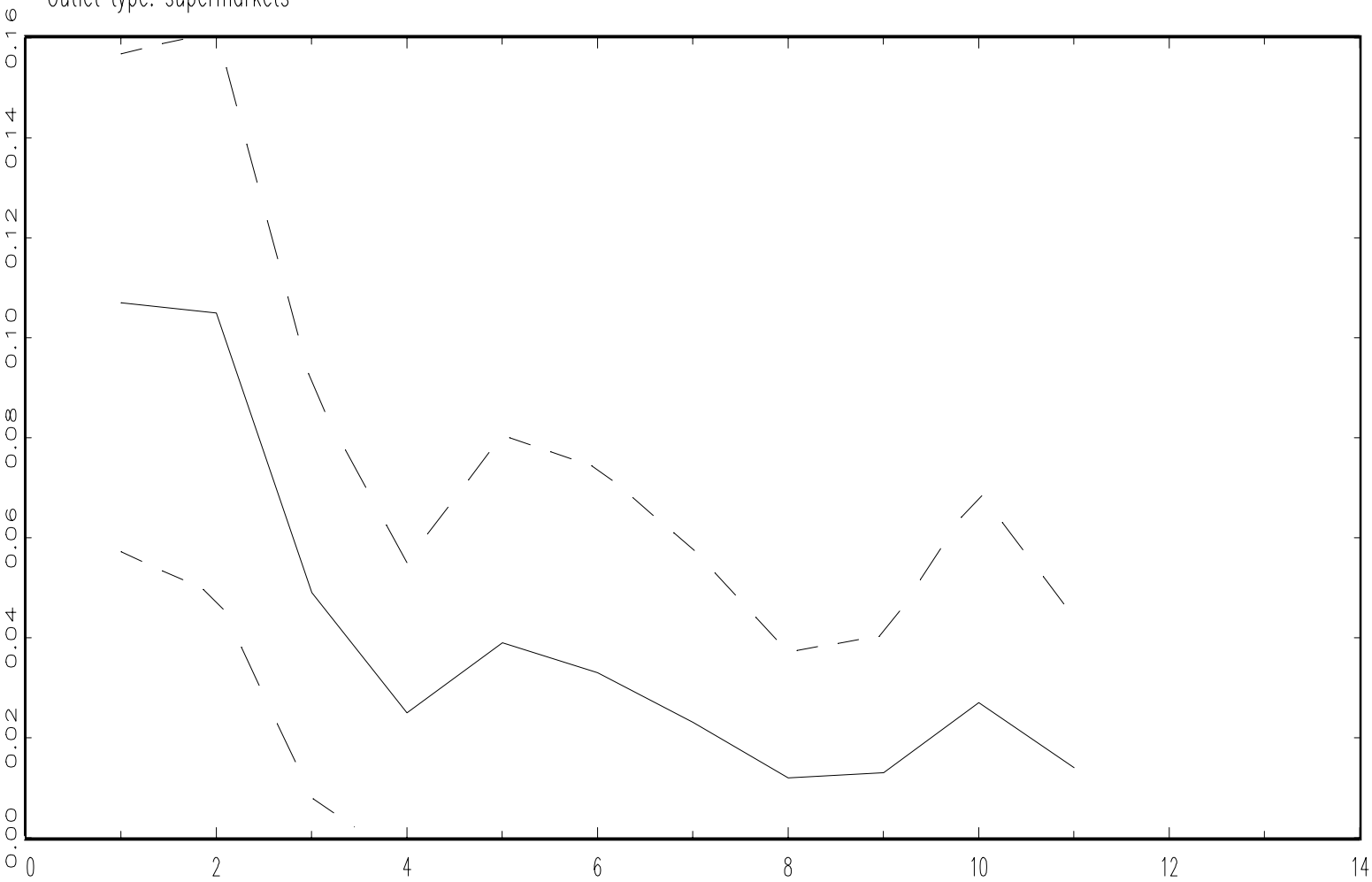


Fig. 2 Hazard Functions (example: Pastry – Price increases)

Outlet type: supermarkets



Outlet type: traditional outlets

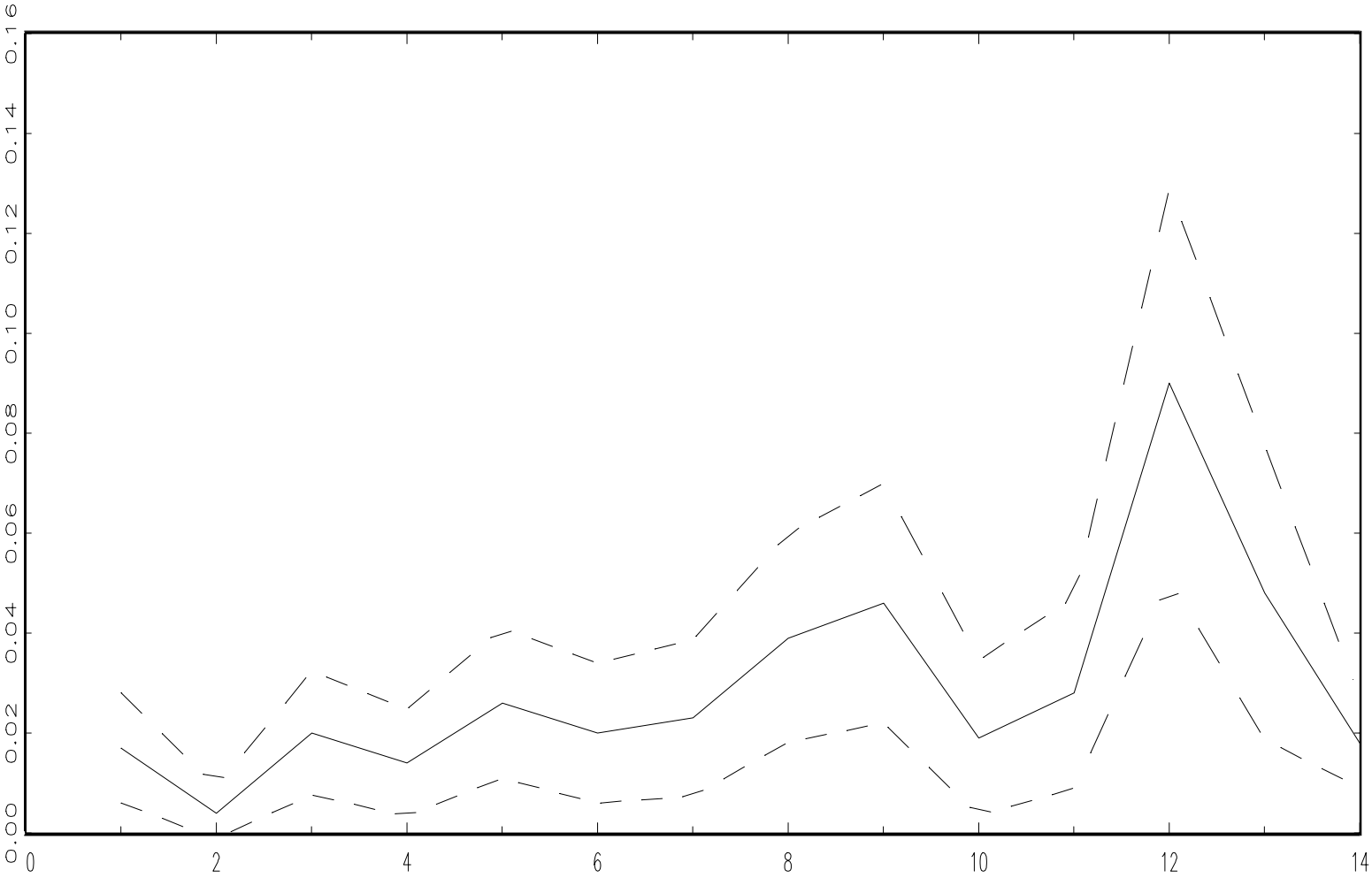
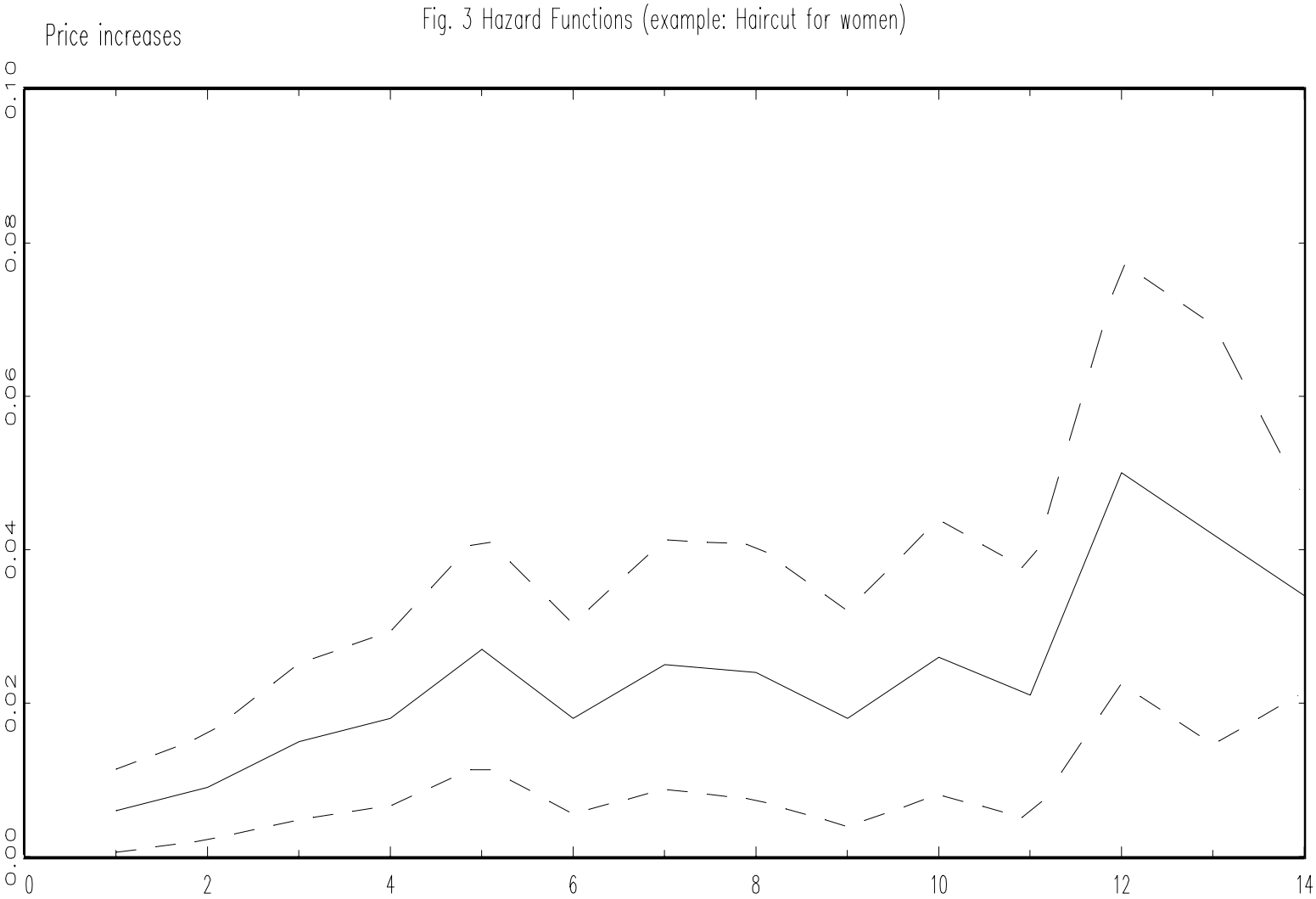


Fig. 3 Hazard Functions (example: Haircut for women)



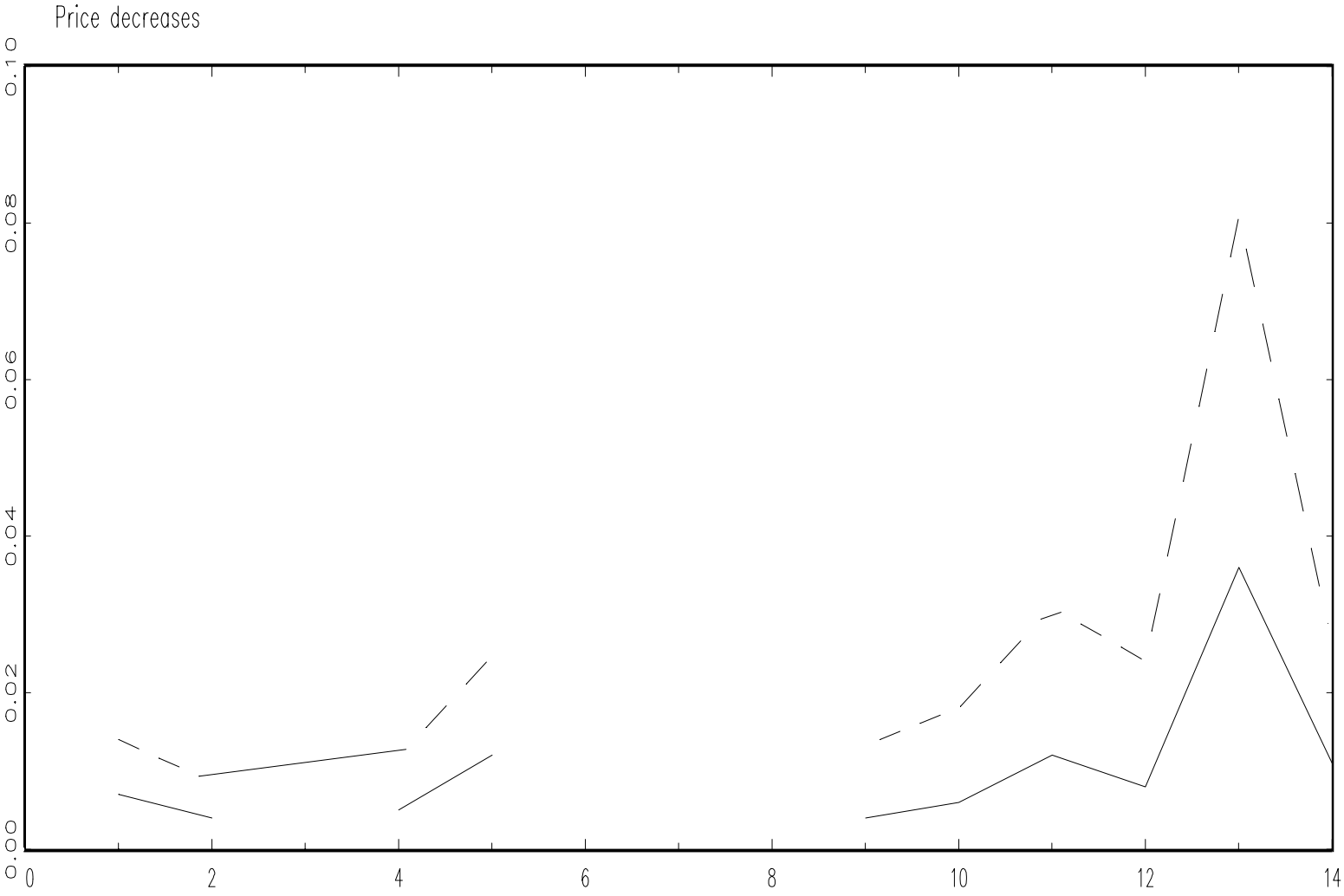


Fig. 4 Hazard function for product replacement
(Example: jackets for men)

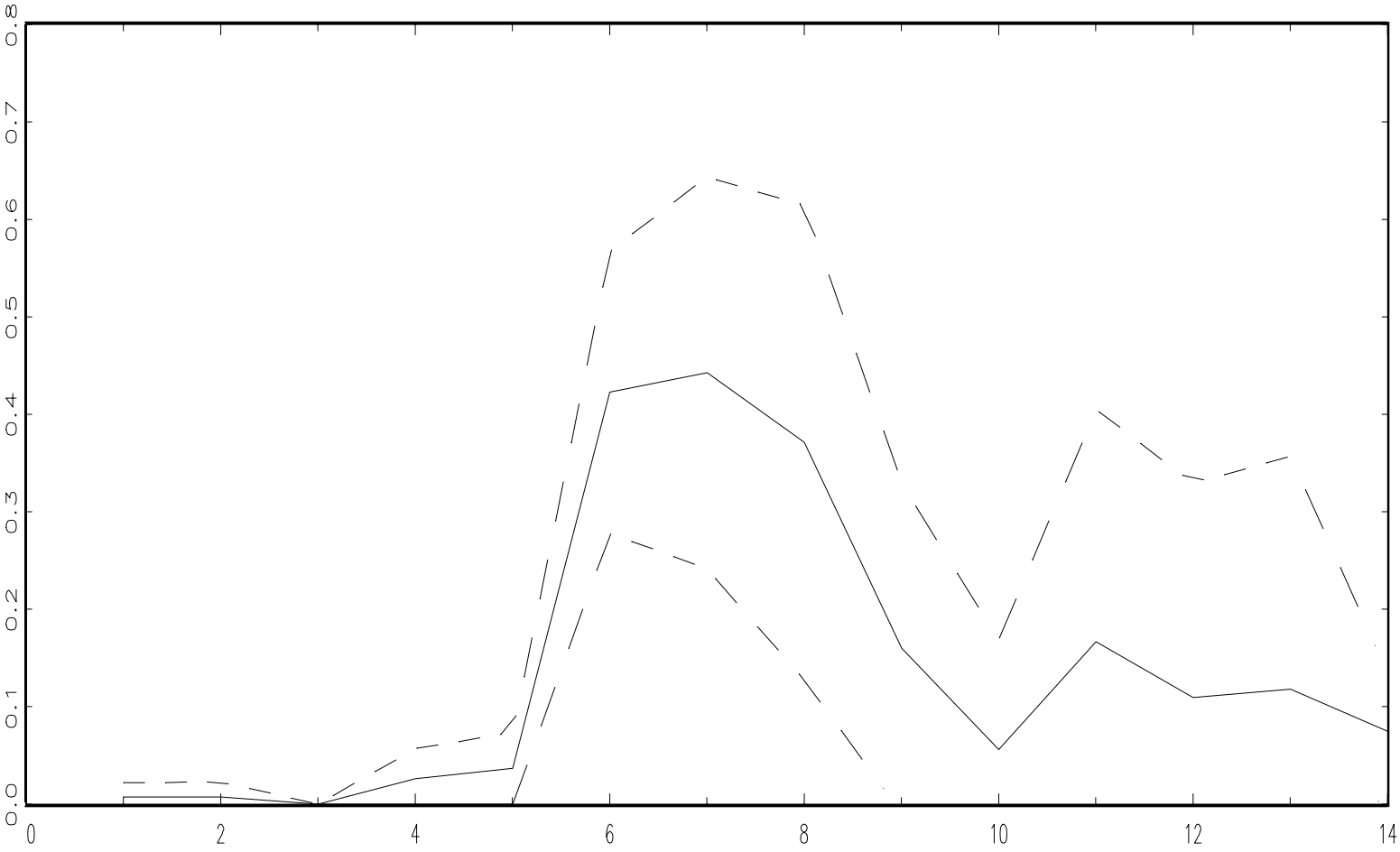


Fig. 5 Distribution of hazard level for price increases
(when hazard is constant)

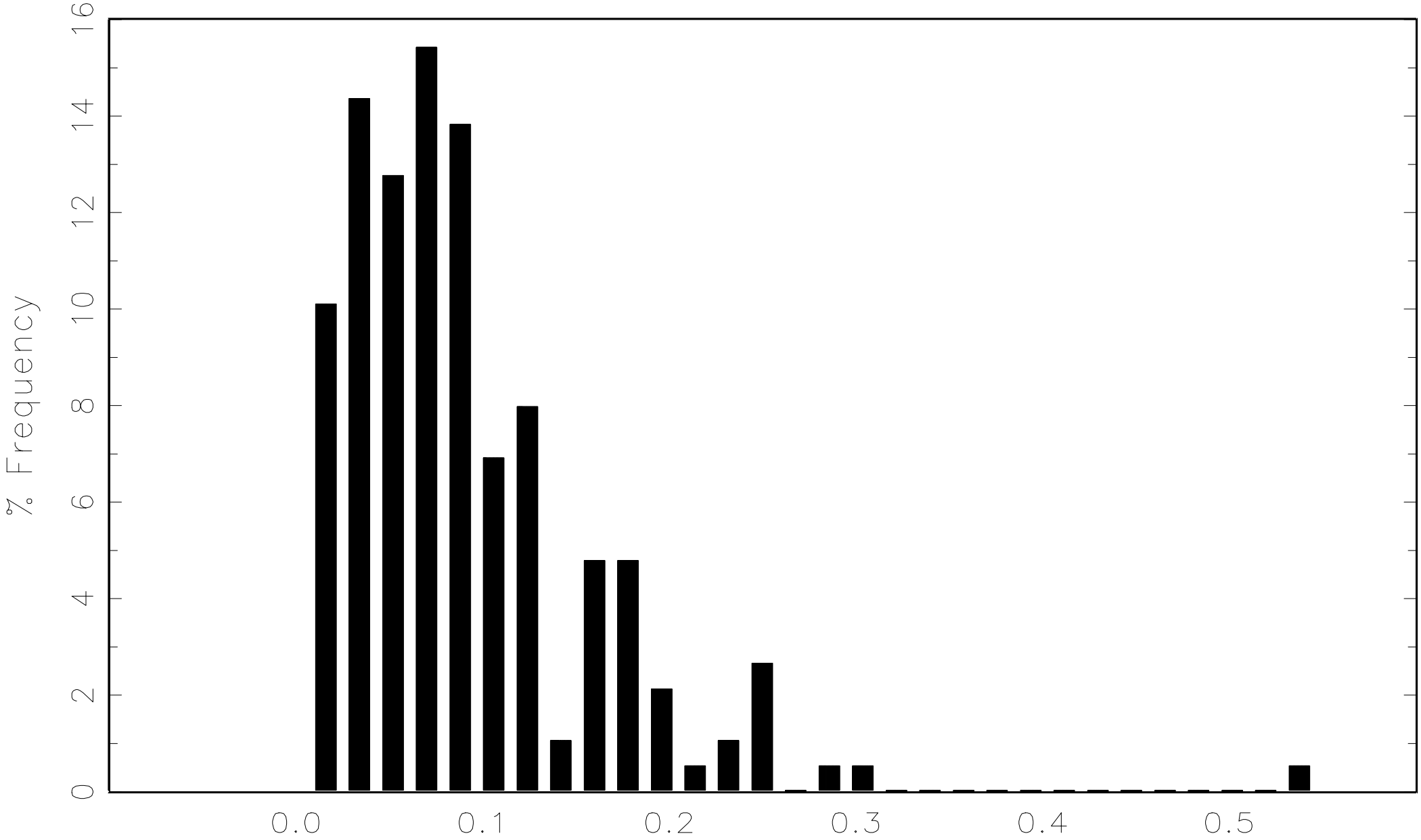


Fig.6 Distribution of inflation coefficients
(Models for price increases)