Lumpy Price Adjustments: A Microeconometric Analysis*

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Abstract

Based on a state-dependent pricing model, we specify and estimate a non-linear factor model allowing us to identify the relative importance of the degree of price rigidity that is inherent to the price setting mechanism (intrinsic) and that which is due to cost and/or demand factors (extrinsic). We find that intrinsic price stickiness, related to price adjustment costs, is indeed an important determinant of the frequency of price changes. However, the volatility of the shocks affecting optimal prices also plays a significant role in the determination of the frequency of price changes. We also find that this volatility is the major determining factor of the magnitude of price changes.

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1 Introduction

Following the contributions of Cecchetti (1986) on newspaper prices, Kashyap (1995) on catalog prices (both using US data), and Lach and Tsiddon (1992) on meat and wine prices in Israel, a recent wave of empirical research has provided new evidence on the nature and sources of consumer and producer price stickiness at the micro level. These studies include Bils and Klenow (2004), Klenow and Kryvstov (2008) and Nakamura and Steinson (2008) who study consumer prices in the US, and Dhyne et al. (2006) who give a synthesis of recent empirical analyses carried out for the euro area countries. Studies of producer prices include Vermeulen et al. (2007), Cornille and Dossche (2008), Loupias and Sevestre (2008), among others.

One of the main conclusions of these studies is the existence of a significant degree of heterogeneity in the frequency of price changes across different product categories. Some products are characterized by a high frequency of price changes, with outlets resetting their prices almost on a continuous basis (for instance, oil products and perishable food), whilst other product categories are characterized by a very low frequency of price changes (for instance, some durable goods and many services). Aucremanne and Dhyne (2004) also document a high degree of heterogeneity in the duration of price spells (and hence in the frequency of price changes) even within relatively homogeneous product categories. Indeed, several studies have shown that the frequency of consumer price changes not only differs across product categories, but also varies across categories of retailers.[1] Hyper and super-markets also tend to change their prices more frequently than local corner shops.

A vast majority of these studies is, however, silent as to the reasons for such infrequent price changes. A low frequency of price change has sometimes been taken as evidence of intrinsic price rigidity, namely price rigidity that is inherent to the price-setting mechanism, such as the presence of menu costs. This, however, ignores the role of extrinsic price rigidity that originates from the sluggishness of costs and mark-ups.[2] Indeed, infrequent price changes are not necessarily due to high menu costs and could arise when marginal costs or other market conditions do not vary. In such situations firms will have little or no incentive to change their prices even if menu costs are negligible. The aim of this paper is to provide an empirical assessment of the relative importance of these two sources of price rigidities across a large number of product categories. To this end

[1] See Baudry *et al.* (2007), Fougère, Le Bihan and Sevestre (2007), Jonker, Blijenberg and Folkertsma (2004), and Veronese *et al.* (2005).

[2] Here we are adopting a terminology used in Altissimo, Ehrmann and Smets (2006) to characterize the different sources of inflation persistence.

we begin with the theoretical contribution of Dixit (1999) and develop an (S, s) state dependent price-setting model that relates price changes to the variations in an optimal price reflecting common and idiosyncratic variations in marginal costs and/or in the desired mark-up, but where price changes are subject to price adjustment costs. Since the optimal price targeted by outlets is unobserved, we decompose it into three components: first, a component that is shared across all outlets selling a given fairly homogeneous product. From an economic point of view, this component reflects the average marginal cost augmented with the average desired mark-up associated with this particular product. From an econometric point of view, we model this as a common factor which is estimated by aggregating the non-linear pricing equations across the outlets. The second component of the unobserved optimal price is an outlet specific effect, which accounts for price differences due to product differentiation, local competition conditions, etc. The third component of the optimal price is an idiosyncratic term, reflecting shocks that may affect the outlet specific optimal price in a given period (possibly due to outlet specific demand shocks or unexpected changes in costs). This set up allows us to decompose price stickiness into intrinsic and extrinsic components, the latter being associated with the variability of the various components of the unobserved optimal price.

From the perspective of econometric modelling, the (S, s) model represents a non-linear extension of the factor models used extensively in the empirical finance and macroeconomic literature (e. g. Bai and Ng, 2002, 2006, Connor and Korajczyk, 1986, 1988, Forni et al., 2000 and Stock and Watson, 1998, 2002). Making use of two large data sets composed of consumer price records used to compute the CPI in Belgium and France, the model is estimated for more than 180 narrowly defined product categories where we have a relatively large number of outlets supplying fairly homogeneous products. Our results show that the now well-documented differences across products in the frequency of price changes do not strictly correspond to differences in terms of adjustment costs; i.e. intrinsic rigidity does not suffice to explain the frequency of price changes. This frequency also depends, in a significant way, on the magnitude of the shocks, common and/or idiosyncratic, to the unobserved optimal price. We also show that idiosyncratic shocks strongly contribute to the occurrence of price changes as they appear to be of a larger magnitude than common shocks affecting all the outlets selling a given product.

The outline of the rest of the paper is as follows. Section 2 presents the (S, s) model and discusses the identification of intrinsic and extrinsic sources of price rigidities. Section 3 considers alternative approaches to the estimation of the model. Section 4 describes the micro price data sets, presents the estimation results, and discusses the main findings in relation to the observed frequency and the magnitude of price changes by product categories. Section 5 offers some concluding remarks.

2 (S, s) Models of Sticky Prices

It is now a well-established stylized fact that most consumer prices remain unchanged for periods that can last several months (see, for example, Bils and Klenow, 2004, Dhyne et al., 2006). Presence of physical menu costs, fear of customer anger, existence of implicit or explicit contracts might deter retailers from immediately adjusting their prices to changes in their market conditions such as changes in costs and demand factors, or variations in local competition. This behavior can be modelled assuming fixed price adjustment costs that do not depend on the size of the price change,[3] leading to an optimal price strategy of the (S, s) variety (see, for example, Sheshinski and Weiss, 1977, 1983, Cecchetti, 1986, Dixit, 1991, Hansen, 1999, and Gertler and Leahy, 2006).

A simple representation of the (S, s) model can be written as:

$$p_{jit} = \begin{cases} p_{ji,t-1}, & \text{if } \left|p^*_{jit} - p_{ji,t-1}\right| \leq s_{jit}, \\ p^*_{jit}, & \text{if } \left|p^*_{jit} - p_{ji,t-1}\right| > s_{jit}, \end{cases} \tag{1}$$

where p_{jit} is the (log) observed price of a product j in outlet i at time t, p^*_{jit} is the (log) optimal price that would be set in the absence of any adjustment costs, and s_{jit} denotes the thresholds beyond which outlets find it profitable to adjust their prices in response to a shock. In what follows, to simplify the notation, we drop the subscript j and refer to s_{it} as the adjustment threshold (or band of inaction) for outlet i in period t. We refer to

$$|p^*_{it} - p_{i,t-1}| \geq s_{it}, \tag{2}$$

as the 'price change trigger' condition.

Assuming monopolistic competition prevails, the optimal price, p^*_{it}, is specified as a product-specific mark up over marginal costs. The threshold, s_{it}, typically depends on three parameters: the size of the fixed menu cost, c_{mi}, which is paid every time the price is changed; the coefficient on the flow costs of being out of equilibrium between two

[3]Several papers have found evidence of fixed physical menu costs of price adjustment (Levy *et al.*, 1997, Zbaracki *et al.*, 2004). However, Zbaracki *et al.* (2004) argue that, in addition to these fixed physical menu costs, managerial and customer-related costs are convex in the price change, while survey responses discussed in Blinder *et al.* (1998) suggest that price adjustment costs might be fixed.

successive price changes, c_{ei},[4] and the variance of the innovations to the optimal price. In the case where $p^*_{it} - p_{it}$ follows a Brownian motion with a constant variance, σ_i^2, Dixit (1991) and Hansen (1999) show that $s_{it} = s_i = (6c_{mi}\sigma_i^2/c_{ei})^{1/4}$. In cases where $p^*_{it} - p_{it}$ follows a more general stochastic process, the adjustment threshold could be time varying, and its relationship to c_{mi}/c_{ei} and the parameters of the underlying stochastic process is likely to be more complicated. Nevertheless, Dixit's theoretical derivation provides a simple, yet useful, link between the reduced form parameters characterizing s_i, and the structural parameters, c_{mi}/c_{ei} and σ_i. Clearly the magnitude of the menu cost can not be inferred from the size of the band of inaction alone but also depends on the volatility of the optimal price. Increased uncertainty widens the band of inaction but also induces more frequent price changes in the long run. As Hansen (1999, p.1066) points out, higher volatility whilst increasing the band also at the same time increases the probability of observing large changes in the optimal price which makes it more likely for the band to be breached. However, a rise in the menu cost increases the band of inaction without inducing changes in the volatility of the optimal price. It is these independent sources of variations of s that can be used to distinguish the intrinsic (menu cost changes) from the extrinsic (volatility changes) sources of price rigidities and the average size of price changes.

In our empirical analysis, for each product category, we estimate the mean and the variance of s_{it} which we denote by s and σ_s. We also estimate σ_i^2, which we assume to be constant over time and across outlets by $\sigma^2 = Var(p^*_{it} | \mathcal{I}_{t-1})$, where $\mathcal{I}_{t-1}$ denotes the publicly available information. We then recover an estimate of the menu cost parameter, $c = \sqrt{c_m/c_e}$, from Dixit's formula. See Section 4 for further details.

Let $I(A)$ denote an indicator function that takes the value of unity if $A > 0$ and zero otherwise. Then model (1), can be written as:

$$\begin{aligned} p_{it} &= p_{i,t-1} + (p^*_{it} - p_{i,t-1})I(p^*_{it} - p_{i,t-1} - s_{it}) \\ &\quad + (p^*_{it} - p_{i,t-1})I(p_{i,t-1} - p^*_{it} - s_{it}). \end{aligned} \tag{3}$$

This formulation is reasonably general and allows the adjustment threshold to vary both over time and across outlets. Assuming a constant and identical threshold might be considered as a too strong assumption since price setting may be strongly heterogeneous

[4] In other words, when the observed price, p_{it}, deviates from its optimal level, p^*_{it}, firm i faces a quadratic inaction cost given by $c_{ei}\left(p_{it} - p^*_{it}\right)^2$. If firm i decides to set its price p_{it} to its optimal level, p^*_{it}, it then faces a fixed menu cost of c_{mi}. See, for example, Dixit (1991). Note that in this framework only the ratio c_{mi}/c_{ei} enters the optimal solution, and hence can be identified.

across outlets, even within relatively homogeneous product categories (Aucremanne and Dhyne, 2004, and Fougère, Le Bihan and Sevestre, 2007). At the outlet level, some price trajectories are characterized by very frequent price changes, while others are characterized by infrequent price changes. Moreover, as described in Campbell and Eden (2007), some price trajectories at the micro level exhibit long periods of price stability followed by periods of frenetic price changes. As noted by Caballero and Engel (2007), this pattern of price changes suggests that s_{it} is best modelled as a stochastic process. Another argument for adopting such an approach lies in the synchronization of price changes within stores. Midrigan (2006) documents that a lot of price changes are particularly small compared to the average magnitude of price changes.[5] Following Lach and Tsiddon (2007), he rationalizes these small price changes by the existence of economies of scales in price setting behavior for multi-product sellers.

Now, the question arises as to whether such a framework also allows us to identify extrinsic rigidities, i.e. those corresponding to the low variability of the fundamentals underlying prices such as changes in marginal costs caused by input price variations or demand variations, changes in the mark-up caused by varying market competition, etc. Unfortunately, despite their size and coverage, the data sets on consumer prices do not provide any information on costs and demand conditions faced by outlets. In spite of this, it is possible, as we shall show below, to extract information on the probability distribution of p^*_{it}, using a non-linear unobserved common factor model. To this end, we consider the following decomposition of the (unobserved) optimal price:

$$p^*_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + f_t + v_i + \varepsilon_{it}, \tag{4}$$

where $\mathbf{x}_{it}$ is a vector of observable retail-specific variables with the associated coefficients, $\boldsymbol{\beta}$, and f_t represents the unobserved common cost or demand component of p^*_{it}. The remaining terms in (4) are intended to capture the retail-specific, v_i, or purely random differences, ε_{it}, in optimal prices across the outlets. The variables in $\mathbf{x}_{it}$ are introduced to control for possible effects of store types (such as hyper or supermarket versus corner shop) or geographical location (city centre or suburbs), and other observable characteristics that might affect the price setting behavior of the outlets. The retail-specific unobservable effects, v_i, account for the heterogeneity in the level of observed prices at the product category level that cannot be traced to observables (product differentiation and/or the

[5] Using US data, Midrigan (2006) indicates that 30% of the observed price changes are smaller than half of the average absolute size of price changes. This figure is 34% for Belgium and close to 50% in France.

ability of retailer i to consistently price above or below the common component f_t, e.g. because of local competitive demand conditions).

The optimal price can be further decomposed into a component which is known to the outlet, namely $x_{it}'\beta + E\left(f_t \left|\mathcal{I}_{t-1}\right.\right) + v_i$, and the unpredictable component given by $\omega_t + \varepsilon_{it}$, where $\omega_t = f_t - E\left(f_t \left|\mathcal{I}_{t-1}\right.\right)$, and $\mathcal{I}_{t-1}$ is the information which is common across the outlets. Without loss of generality we will assume that ω_t and ε_{it} are independently distributed. Within Dixit model the variance of $\omega_t + \varepsilon_{it}$ captures the degree of extrinsic price rigidities, which together with an estimate of the mean of s_{it}, namely s, allows us to estimate the mean of c_i, namely c, which measures the degree of intrinsic price rigidities. A low value of $Var(\omega_t+\varepsilon_{it})$ indicates that costs and/or mark-up variations are expected to be infrequent and/or of a small magnitude. It is also worth noticing that the retail-specific random effect, v_i, and time-invariant regressors x_{it}, if any, have a priori no impact on the price dynamics but only on the price level, as both are embodied in the optimal price p_{it}^* and in $p_{i,t-1}$. Therefore, these elements do not constitute a source of price rigidity, either intrinsic or extrinsic. Should we have included time varying regressors x_{it} in our model, they might be considered as a supplementary source of extrinsic price rigidity if, for instance, x_{it} were capturing the evolution of marginal costs over time. However, since in this paper, the only x_{it} variable included in our model is a time invariant dummy variable that indicates whether outlet i is a supermarket or not, this is not an issue here.

Although our model is relatively close to the one presented for instance by Rosett (1959) for the analysis of frictions in yield changes and more recently, by Tsiddon (1993) or Ratfai (2006), we depart from the existing empirical literature in several ways. First, instead of using a producer price index to proxy the common movements in consumer price trajectories as in Ratfai (2006), we rely on an unobserved common component. This allows us to conduct our analysis of the relative importance of intrinsic and extrinsic price stickiness for products for which there is no directly observable or not easily identified common variables. One important advantage of proceeding in this way is to ensure the coherency of this common component with the dynamics of micro price decisions as stated by our model. Further we avoid the drawback that if the observed variable fails to capture the common factor, part of the common variation will be relegated in the error term, which will therefore violate the condition of cross-sectional independence.

Second, we also depart from the existing empirical literature in the information used in our estimation procedure. Most of the literature estimates state-dependent pricing model using binary response or duration models (Cecchetti, 1986, Aucremanne and Dhyne, 2005, Campbell and Eden, 2007, Fougère, Le Bihan and Sevestre, 2007, Ratfai, 2006) and therefore neglects the information contained in the magnitude of price changes. However, this information is crucial in order to identify the volatility of the idiosyncratic component and for disentangling the idiosyncratic component of the optimal prices from the idiosyncratic threshold parameter, s_{it}.

Third, our approach does not impose any restrictions on the dynamics of the common factors, but assumes, for ease of estimation, that the idiosyncratic shocks are serially uncorrelated. The latter may be viewed as unduly restrictive, but given the Monte Carlo results reported in Appendix B, we find that neglecting (positive) serial correlation in the idiosyncratic shocks tends to result in over-estimation of the range of inaction. This indirectly reinforces our main conclusion that, besides intrinsic (or nominal) rigidities, extrinsic price rigidity plays an important role in explaining the observed price stickiness.

3 Alternative Approaches to Estimation of (S, s) Model

One can combine equations (3) and (4) to obtain the following econometric representation:

$$\begin{aligned} p_{it} - p_{i,t-1} &= (f_t + \mathbf{x}_{it}'\boldsymbol{\beta} + v_i + \varepsilon_{it} - p_{i,t-1})I(f_t + \mathbf{x}_{it}'\boldsymbol{\beta} + v_i + \varepsilon_{it} - p_{i,t-1} - s_{it}) \\ &\quad +(f_t + \mathbf{x}_{it}'\boldsymbol{\beta} + v_i + \varepsilon_{it} - p_{i,t-1})I(p_{i,t-1} - f_t - \mathbf{x}_{it}'\boldsymbol{\beta} - v_i - \varepsilon_{it} - s_{it}). \end{aligned} \tag{5}$$

There are essentially two groups of parameters to be estimated. First, the unobserved common components, f_t, which can also be viewed as unobserved time effects. Second, the parameters that do not vary over time, namely s and σ_s which respectively denote the mean and standard deviation of s_{it}, σ_ε, the standard deviation of the idiosyncratic component ε_{it}, σ_v, the standard deviation of the firm specific random effect, v_i, and $\boldsymbol{\beta}$, the parameters associated with the observed explanatory variables, $\mathbf{x}_{it}$.

The estimation of the baseline model can be carried out in two ways. One can use an iterative procedure that combines the estimation of the f_t's using the cross-sectional dimension of the data with the maximum likelihood estimation of the remaining parameters, conditional on the first-stage estimate of f_t. Alternatively, one can use a standard maximum likelihood procedure, where the f_t's are estimated simultaneously with the other parameters. The two procedures lead to consistent estimates, provided N and T are sufficiently large. It is worthwhile noting that if N is small, one would face the well-known incidental parameters problem: the bias in estimating f_t, due to the limited size of the cross-sectional dimension, would contaminate the other parameter estimates. In the alternative situation where T happens to be small, the problem of the initial observation would become an important issue. Therefore, our estimation procedure is essentially valid for relatively large N and T. Fortunately, in our context, prices of most of the products we consider have been observed monthly over the period 1994:7 - 2003:2 (i.e. more than 100 months), and the number of outlets selling the various products we consider are also relatively large, being, on average, only slightly less than 300, both in Belgium and in France.

3.1 Estimation of f_t using cross-sectional averages

As mentioned above, f_t is in practice an unobserved time effect that needs to be estimated along with the other unknown parameters. It reflects the common component in the optimal prices for each particular product for which we estimate the model. Moreover, because we are able to consider precisely defined types of products sold in a particular outlet, it is reasonable to assume that any remaining cross-sectional heterogeneity in the price level can be modelled through the observable outlet-specific characteristics, $\mathbf{x}_{it}$, and through random specific effects (accounting for outlets unobserved characteristics).

Accordingly, we assume that, conditional on $\mathbf{h}_{it} = (f_t, \mathbf{x}'_{it}, p_{i,t-1})'$, $(s_{it},\ v_i, \varepsilon_{it})'$ are distributed independently across i, and that s_{it} and ε_{it} are serially uncorrelated. Due to the non-linear nature of the pricing process and to make the analysis tractable, we shall also assume that

$$\begin{pmatrix} s_{it} \\ v_i \\ \varepsilon_{it} \end{pmatrix} |\mathbf{h}_{it} \backsim i.i.d.N\left(\begin{pmatrix} s \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_v^2 & 0 \\ 0 & 0 & \sigma_\varepsilon^2 \end{pmatrix}\right).$$

The assumption of zero covariances across the errors is made for convenience and can be relaxed.

Before discussing the derivation of f_t we state the following lemma, established in the Appendix, which provides a few results needed below.

Lemma 3.1 Suppose that $y \backsim N(\mu, \sigma^2)$ then

$$E\left[yI(y+a)\right] = \sigma\phi\left(\frac{a+\mu}{\sigma}\right) + \mu\Phi\left(\frac{a+\mu}{\sigma}\right),$$

$$E\left[\phi\left(\frac{y+a}{b}\right)\right] = \frac{b}{\sqrt{b^2+\sigma^2}}\phi\left(\frac{a+\mu}{\sqrt{b^2+\sigma^2}}\right),$$

$$E_y\left[\Phi\left(\frac{y+a}{b}\right)\right] = \Phi\left(\frac{a+\mu}{\sqrt{b^2+\sigma^2}}\right),$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are, respectively, the density and the cumulative distribution function of the standard normal variate, and $I(A)$ is the indicator function defined above.

Let

$$d_{it} = f_t + \mathbf{x}_{it}'\boldsymbol{\beta} - p_{i,t-1}, \quad \xi_{it} = v_i + \varepsilon_{it} \backsim N(0, \sigma_\xi^2),$$

and note that $\sigma_\xi^2 = \sigma_v^2 + \sigma_\varepsilon^2$. Consider now the baseline model, (5), and using the above, write it as

$$\Delta p_{it} = (d_{it} + \xi_{it})I(d_{it} + \xi_{it} - s_{it}) + (d_{it} + \xi_{it})I(-d_{it} - \xi_{it} - s_{it}),$$

or

$$\Delta p_{it} = (d_{it} + \xi_{it}) + (d_{it} + \xi_{it})\left[I(d_{it} + \xi_{it} - s_{it}) - I(d_{it} + \xi_{it} + s_{it})\right].$$

Denote the unknown parameters of the model by $\boldsymbol{\theta} = (s, \boldsymbol{\beta}', \sigma_s^2, \sigma_v^2, \sigma_\varepsilon^2)'$, and note that

$$E\left(\Delta p_{it} \left| \mathbf{h}_{it}, \boldsymbol{\theta}\right.\right) = d_{it} + g_{it},$$

where $g_{it} = g_{1,it} + g_{2,it}$, with

$$g_{1,it} = d_{it} E\left[I(d_{it} + \xi_{it} - s_{it}) - I(d_{it} + \xi_{it} + s_{it}) \left| \mathbf{h}_{it}, \boldsymbol{\theta}\right.\right],$$

and

$$g_{2,it} = E\left[\xi_{it} I(d_{it} + \xi_{it} - s_{it}) - \xi_{it} I(d_{it} + \xi_{it} + s_{it}) \left| \mathbf{h}_{it}, \boldsymbol{\theta}\right.\right].$$

Also, under our assumptions

$$\begin{pmatrix} s_{it} \\ \xi_{it} \end{pmatrix} \left| \mathbf{h}_{it} \backsim i.i.d.N\left(\begin{pmatrix} s \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_s^2 & 0 \\ 0 & \sigma_v^2 + \sigma_\varepsilon^2 \end{pmatrix} \right)\right..$$

It is easily seen that

$$\begin{aligned} & E\left[I(d_{it} + \xi_{it} - s_{it}) - I(d_{it} + \xi_{it} + s_{it}) \left| \mathbf{h}_{it}, \boldsymbol{\theta}\right.\right] \\ = \ & \Phi\left(\frac{d_{it} - s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\right) - \Phi\left(\frac{d_{it} + s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\right). \end{aligned}$$

Using the results in Lemma 3.1 and noting that $\xi_{it} \, |\mathbf{h}_{it}, \boldsymbol{\theta} \backsim N(0, \sigma_\xi^2)$, then

$$E\left[\xi_{it} I(d_{it} + \xi_{it} - s_{it}) \, |\mathbf{h}_{it}, s_{it}, \boldsymbol{\theta}\right] = \sigma_\xi \phi\left(\frac{d_{it} - s_{it}}{\sigma_\xi}\right).$$

Hence, taking expectations with respect to s_{it}, we have

$$E\left[\xi_{it} I(d_{it} + \xi_{it} - s_{it}) \, |\mathbf{h}_{it}, \boldsymbol{\theta}\right] = \sigma_\xi E\left[\phi\left(\frac{d_{it} - s_{it}}{\sigma_\xi}\right) |\mathbf{h}_{it}, \boldsymbol{\theta}\right].$$

Again using the results in Lemma 3.1 we have

$$E\left[\phi\left(\frac{d_{it} - s_{it}}{\sigma_\xi}\right) |\mathbf{h}_{it}, \boldsymbol{\theta}\right] = \frac{\sigma_\xi}{\sqrt{\sigma_s^2 + \sigma_\xi^2}} \phi\left(\frac{d_{it} - s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\right),$$

and therefore,

$$E\left[\xi_{it} I(d_{it} + \xi_{it} - s_{it}) \, |\mathbf{h}_{it}, \boldsymbol{\theta}\right] = \frac{\sigma_\xi^2}{\sqrt{\sigma_s^2 + \sigma_\xi^2}} \phi\left(\frac{d_{it} - s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\right).$$

Similarly,

$$E\left[\xi_{it} I(d_{it} + \xi_{it} + s_{it}) \, |\mathbf{h}_{it}, \boldsymbol{\theta}\right] = \frac{\sigma_\xi^2}{\sqrt{\sigma_s^2 + \sigma_\xi^2}} \phi\left(\frac{d_{it} + s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\right).$$

Collecting the various results we obtain

$$g_{1,it} = d_{it}\left[\Phi\left(\frac{d_{it} - s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\right) - \Phi\left(\frac{d_{it} + s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\right)\right],$$

and

$$g_{2,it} = \frac{\sigma_\xi^2}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\left[\phi\left(\frac{d_{it} - s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\right) - \phi\left(\frac{d_{it} + s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}}\right)\right].$$

Note that $g_{1,it}$ and $g_{2,it}$ are non-linear functions of f_t and depend on i only through the observable, $p_{i,t-1}$ and $\mathbf{x}_{it}$. It is therefore possible to compute f_t for each t in terms of $p_{i,t-1}$, $\mathbf{x}_{it}$ and $\boldsymbol{\theta}$. Then, following Pesaran (2006), the cross-sectional average estimator of

f_t, denoted by $\tilde{f}_t$, can be obtained as the solution to the following non-linear equation

$$\bar{p}_t = \tilde{f}_t + \bar{\mathbf{x}}_t' \boldsymbol{\beta} + \bar{g}_t(\tilde{f}_t), \tag{6}$$

where

$$\bar{p}_t = \sum_{i=1}^{N} w_{it}\ p_{it},\ \bar{\mathbf{x}}_t = \sum_{i=1}^{N} w_{it}\ \mathbf{x}_{it},\ \text{and}\ \bar{g}_t(f_t) = \sum_{i=1}^{N} w_{it}\ g_{it},$$

and $\{w_{it}, i = 1, 2, .., N\}$ represent a predetermined set of weights such that

$$w_{it} = O(N^{-1}),\ \text{and} \sum_{i=1}^{N} w_{it}^2 = O(N^{-1}).$$

For a given value of $\boldsymbol{\theta}$ and each t, (6) provides a non-linear function in $\tilde{f}_t$. This equation clearly shows that unlike the linear models considered in Pesaran (2006), here the solution to the common component f_t does not reduce to an average of (log) prices. In particular, $\tilde{f}_t$ also accounts for the dynamic feature of the price-setting behavior through the $\bar{g}_t$ component, which depends on $p_{i,t-1}$. Equation (6) has a unique solution as long as $s > 0$. A proof is provided in Appendix A. It is also easily seen that under the cross-sectional independence of v_i and ε_{it}, $\bar{g}_t(f_t) \to E(g_{it})$ and $\tilde{f}_t - f_t \xrightarrow{p} 0$, as $N \to \infty$.[6]

3.2 Conditional likelihood estimation with no individual effects

In this section, we derive the maximum likelihood estimation of the structural parameters, $\boldsymbol{\theta}$, conditional on f_t and assuming there are no firm-specific effects, so that $\sigma_v^2 = 0$, and hence in this case $\boldsymbol{\theta} = (s, \boldsymbol{\beta}', \sigma_s^2, \sigma_\varepsilon^2)'$. Given the distributional assumptions stated in Section 3.1, and defining ζ_{it} as $s_{it} - s$, our baseline model can be rewritten as

$$\Delta p_{it} = d_{it} + \varepsilon_{it} + (d_{it} + \varepsilon_{it}) \left\{ I\left[d_{it} + \varepsilon_{it} - \zeta_{it} - s\right] - I\left[d_{it} + \varepsilon_{it} + \zeta_{it} + s\right] \right\},$$

where

$$\begin{pmatrix} \zeta_{it} \\ \varepsilon_{it} \end{pmatrix} \backsim iid\ N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_s^2 & 0 \\ 0 & \sigma_\varepsilon^2 \end{pmatrix} \right),\ \text{for}\ i = 1, 2, ..., N;\ t = 1, 2, ..., T.$$

[6] For the sake of simplicity, we assume here that the panel data sample is balanced. This is not the case in practice. However, the result can be easily generalized to unbalanced panels assuming that $N_t \to \infty$ for each t (see the Appendix A).

Equivalently

$$\Delta p_{it} = d_{it} + \varepsilon_{it} + (d_{it} + \varepsilon_{it}) \left\{ I\left[d_{it} - s + \varepsilon_{1it}\right] - I\left[d_{it} + s + \varepsilon_{2it}\right] \right\},$$

where

$$\varepsilon_{1it} = \varepsilon_{it} - \zeta_{it},\ \varepsilon_{2it} = \varepsilon_{it} + \zeta_{it},$$

with

$$\begin{pmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \\ \varepsilon_{it} \end{pmatrix} \sim iidN \left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2 + \sigma_s^2 & \sigma_\varepsilon^2 - \sigma_s^2 & \sigma_\varepsilon^2 \\ . & \sigma_\varepsilon^2 + \sigma_s^2 & \sigma_\varepsilon^2 \\ . & . & \sigma_\varepsilon^2 \end{pmatrix} \right), \text{for } i = 1, 2, ..., N;\ t = 1, 2, ..., T.$$

Let

$$\begin{aligned} \tau_{1it} &= \begin{cases} 1 \text{ if } \Delta p_{it} = 0 \text{ for } i = 1, 2, ..., N \text{ and } t = 1, 2, ..., T, \\ 0 \text{ otherwise} \end{cases} \\ \tau_{2it} &= \begin{cases} 1 \text{ if } \Delta p_{it} > 0 \text{ for } i = 1, 2, ..., N \text{ and } t = 1, 2, ..., T, \\ 0 \text{ otherwise} \end{cases} \\ \tau_{3it} &= \begin{cases} 1 \text{ if } \Delta p_{it} < 0 \text{ for } i = 1, 2, ..., N \text{ and } t = 1, 2, ..., T, \\ 0 \text{ otherwise} \end{cases} \end{aligned}$$

Then conditional on $f_t, t = 1, 2, ..., T$ and the initial value p_{i0}, the log-likelihood function of the model for each i can be written as

$$\begin{aligned} L_i(\boldsymbol{\theta} \,|\mathbf{f}\,) &= \Pr\left(\Delta p_{i1} \,|p_{i0}\right) \Pr\left(\Delta p_{i2} \,|p_{i0}, p_{i1}\right) \\ &\quad \times \Pr\left(\Delta p_{i,T} \,|p_{i0}, p_{i1}, ..., p_{i,T-1}\right) \times \Pr\left(p_{i0}\right) \end{aligned}$$

where $\mathbf{f} = (f_1, f_2, ..., f_T)'$. In view of the first-order Markovian property of the model we have

$$\begin{aligned} L_i(\boldsymbol{\theta} \,|\mathbf{f}\,) &= \Pr\left(\Delta p_{i1} \,|p_{i0}\right) \Pr\left(\Delta p_{i2} \,|p_{i1}\right) \\ &\quad \times \Pr\left(\Delta p_{i,T} \,|p_{i,T-1}\right) \times \Pr\left(p_{i0}\right). \end{aligned}$$

When T is small, the contribution of $\Pr\left(p_{i0}\right)$ could be important. In what follows we assume that p_{i0} is given and T reasonably large so that the contribution of the initial observations to the log-likelihood function can be ignored.

To derive $\Pr\left(\Delta p_{it}\,|p_{i,t-1}, f_t\right)$ we distinguish between cases where $\Delta p_{it} = 0$, $\Delta p_{it} > 0$ and $\Delta p_{it} < 0$, noting that

$$\begin{aligned}
& \Pr\left(\Delta p_{it} = 0\,|, p_{i,t-1}, f_t\right) = \Pr\left(\varepsilon_{1it} \le s - d_{it}\ ;\ \varepsilon_{2it} \ge -s - d_{it}\right) \\
= \ & \Pr\left(\varepsilon_{1it} \le s - d_{it}\right) - \Pr\left(\varepsilon_{1it} \le s - d_{it}\ ;\ \varepsilon_{2it} \le -s - d_{it}\right) \\
= \ & \Phi\left(\frac{s - d_{it}}{\sqrt{\sigma_\varepsilon^2 + \sigma_s^2}}\right) - \Phi_2\left(\frac{s - d_{it}}{\sqrt{\sigma_\varepsilon^2 + \sigma_s^2}}; \frac{-s - d_{it}}{\sqrt{\sigma_\varepsilon^2 + \sigma_s^2}}; \frac{\sigma_\varepsilon^2 - \sigma_s^2}{\sigma_\varepsilon^2 + \sigma_s^2}\right) = \pi_{1it},
\end{aligned}$$

where $\Phi_2\left(x; y; \rho\right)$ is the cumulative distribution function of the standard bivariate normal. Similarly

$$\begin{aligned}
& \Pr\left(\Delta p_{it} > 0\,|, p_{i,t-1}, f_t\right) = \Pr\left(\varepsilon_{it} = \Delta p_{it} - d_{it}\right) \Pr\left(\varepsilon_{1it} \ge s - d_{it}\ ;\ \varepsilon_{2it} > -s - d_{it}\,|\varepsilon_{it}\right) \\
= \ & \frac{1}{\sigma_\varepsilon}\phi\left(\frac{\Delta p_{it} - d_{it}}{\sigma_\varepsilon}\right)\left[\Phi\left(\frac{-s + \Delta p_{it}}{\sigma_s}\right) - \Phi\left(\frac{-s - \Delta p_{it}}{\sigma_s}\right)\right] = \pi_{2it},
\end{aligned}$$

and

$$\begin{aligned}
& \Pr\left(\Delta p_{it} < 0\,|, p_{i,t-1}, f_t\right) = \Pr\left(\varepsilon_{it} = \Delta p_{it} - d_{it}\right) \Pr\left(\varepsilon_{1it} < s - d_{it}\ ;\ \varepsilon_{2it} \le -s - d_{it}\,|\varepsilon_{it}\right) \\
= \ & \frac{1}{\sigma_\varepsilon}\phi\left(\frac{\Delta p_{it} - d_{it}}{\sigma_\varepsilon}\right)\left[\Phi\left(\frac{-s - \Delta p_{it}}{\sigma_s}\right) - \Phi\left(\frac{-s + \Delta p_{it}}{\sigma_s}\right)\right] = \pi_{3it}.
\end{aligned}$$

Hence

$$\ell\left(\boldsymbol{\theta}, \mathbf{f}\right) = \sum_{i=1}^{N} \ln L_i(\boldsymbol{\theta}, \mathbf{f}) = \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\tau_{1it}\ln(\pi_{1it}) + \tau_{2it}\ln(\pi_{2it}) + \tau_{3it}\ln(\pi_{3it})\right]. \tag{7}$$

The ML estimator of $\boldsymbol{\theta}$ is given by

$$\hat{\boldsymbol{\theta}}_{ML}(\mathbf{f}) = \arg\max_{\boldsymbol{\theta}} \ell\left(\boldsymbol{\theta}, \mathbf{f}\right)$$

and for N and T sufficiently large we have:

$$\sqrt{NT}\left(\hat{\boldsymbol{\theta}}_{ML}(\mathbf{f}) - \boldsymbol{\theta}\right) \overset{a}{\backsim} N(0, \mathbf{V}_{\boldsymbol{\theta}}),$$

where $\mathbf{V}_{\boldsymbol{\theta}}$ is the asymptotic variance of the ML estimator and can be estimated consistently using the second derivatives of the log likelihood function.

Remark 1 *In the case where f_t, $t = 1, 2, ..., T$, are estimated, the ML estimator will continue to be consistent as both N and T tend to infinity. However, the asymptotic* *distribution of the ML estimator is likely to be subject to the generated regressor problem. The importance of the generated regressor problem in the present application could be investigated using a bootstrap procedure.*

3.3 Conditional likelihood estimation with random effects

Consider now the random effects specification where $p_{it}^* = f_t + \mathbf{x}_{it}'\boldsymbol{\beta} + v_i + \varepsilon_{it}$, and note that

$$Cov(p_{it}^*, p_{it'}^* \,|\mathbf{h}_{it}, \mathbf{h}_{it'}) = \sigma_v^2 \text{ for all } t \text{ and } t',\ t \neq t'.$$

Under this model, the probability of no price change in a given period, conditional on the previous price, $p_{i,t-1}$, will not be independent of episodes of no price changes in the past. So we need to consider the joint probability distribution of successive unchanged prices. For example, suppose that prices for outlet i have remained unchanged over the period t and $t+1$, then the relevant joint events of interest are

$$\mathcal{A}_{it} : \{-s - \zeta_{it} - d_{it} \leq \varepsilon_{it} + v_i \leq s + \zeta_{it} - d_{it}\}\,,$$

and

$$\mathcal{A}_{i,t+1} : \left\{-s - \zeta_{i,t+1} - d_{i,t+1} \leq \varepsilon_{i,t+1} + v_i \leq s + \zeta_{it} - d_{i,t+1}\right\}.$$

An explicit derivation of the joint distribution of A_{it} and A_{it+1} would seem rather difficult. An alternative strategy is to use the conditional independence property of successive price changes, and note that for each i, and conditional on $\mathbf{v} = (v_1, v_2, ..., v_N)'$ and $\mathbf{f}$, the likelihood function will be given by

$$L(\boldsymbol{\theta}, \mathbf{v}, \mathbf{f}) = \prod_{i=1}^{N}\prod_{t=1}^{T} [\pi_{1it}(v_i)]^{\tau_{1it}}\,[\pi_{2it}(v_i)]^{\tau_{2it}}\,[\pi_{3it}(v_i)]^{\tau_{2it}}\,,$$

where

$$\begin{aligned}
\pi_{1it}(v_i, f_t) &= \Phi\left(\frac{s - v_i - d_{it}}{\sqrt{\sigma_\varepsilon^2 + \sigma_s^2}}\right) - \Phi_2\left(\frac{s - v_i - d_{it}}{\sqrt{\sigma_\varepsilon^2 + \sigma_s^2}}; \frac{-s - v_i - d_{it}}{\sqrt{\sigma_\varepsilon^2 + \sigma_s^2}}; \frac{\sigma_\varepsilon^2 - \sigma_s^2}{\sigma_\varepsilon^2 + \sigma_s^2}\right), \\
\pi_{2it}(v_i, f_t) &= \frac{1}{\sigma_\varepsilon}\phi\left(\frac{\Delta p_{it} - v_i - d_{it}}{\sigma_\varepsilon}\right)\left[\Phi\left(\frac{-s + \Delta p_{it}}{\sigma_s}\right) - \Phi\left(\frac{-s - \Delta p_{it}}{\sigma_s}\right)\right]
\end{aligned}$$

and

$$\pi_{3it}(v_i, f_t) = \frac{1}{\sigma_\varepsilon}\phi\left(\frac{\Delta p_{it} - v_i - d_{it}}{\sigma_\varepsilon}\right)\left[\Phi\left(\frac{-s - \Delta p_{it}}{\sigma_s}\right) - \Phi\left(\frac{-s + \Delta p_{it}}{\sigma_s}\right)\right].$$

The random effects can now be integrated out with respect to the distribution of v_i [assuming $v_i \sim N\left(0, \sigma_v^2\right)$, for example] and then the integrated log-likelihood function, $E_{\mathbf{v}}\left[\ell(\boldsymbol{\theta}, \mathbf{v}, \mathbf{f})\right]$, maximized with respect to $\boldsymbol{\theta}$.[7]

3.4 Full maximum likelihood estimation

In the case where N and T are sufficiently large, the incidental parameters problem does not arise and the effects of the initial distributions, $\Pr\left(p_{i0}\right)$, on the likelihood function can be ignored. Then, the maximum likelihood estimators of $\boldsymbol{\theta}$ and $\mathbf{f}$ can be obtained as the solution to the following maximization problem:

$$\left(\hat{\mathbf{f}}_{ML}, \widehat{\boldsymbol{\theta}}_{ML}\right) = \arg\max_{\mathbf{f}, \boldsymbol{\theta}} \sum_{t=1}^{T}\sum_{i=1}^{N}\left[\tau_{1it}\ln(\pi_{1it}) + \tau_{2it}\ln(\pi_{2it}) + \tau_{3it}\ln(\pi_{3it})\right]. \qquad (8)$$

Note that for a given value of $\boldsymbol{\theta}$ the ML estimator of f_t can be obtained as

$$\hat{f}_t(\boldsymbol{\theta}) = \arg\max_{f_t} \sum_{i=1}^{N}\left[\tau_{1it}\ln(\pi_{1it}) + \tau_{2it}\ln(\pi_{2it}) + \tau_{3it}\ln(\pi_{3it})\right],$$

and will be consistent as $N \to \infty$, since conditional on $\boldsymbol{\theta}$ and f_t, the elements in the above sum are independently distributed. Also for a given estimate of $\mathbf{f}$, the optimization problem defined by (8) will yield a consistent estimate of $\boldsymbol{\theta}$ as N and $T \to \infty$. Iterating between the solutions of the two optimization problems will deliver consistent estimates of $\boldsymbol{\theta}$ and $f_1, f_2, ..., f_T$, even though the number of incidental parameters, $f_t, t = 1, 2, ..., T$, is rising without bounds as $T \to \infty$. This is analogous to the problem of estimating time and individual fixed effects in standard linear panel data models. Individual fixed effects can be consistently estimated from the time dimension and time effects from the cross section dimension.

In order to evaluate the performance of these estimation methods, a number of Monte Carlo simulations are reported in Appendix B. We evaluate the ML estimation with and without random effects. These roughly leads to qualitatively similar results. We also

[7] A further extension of the model would consist of including also a firm specific effect into the menu cost. However, the estimation of this model would then requires a double integration with respect to the distribution of the two individual effects.

report a set of ML estimations for alternative values of the parameters and frequency of price changes. We then perform a set of Monte Carlo simulations to evaluate the robustness of the model under deviations from the underlying assumptions. We first examine the small sample properties of our estimator. We then consider the case of serially correlated idiosyncratic shocks. Lastly we investigate the impact of cross-sectional dependence on the estimates of the model's parameters.

The results of these simulations may be briefly summarized as follows. The estimation of the common component is adversely affected only if the cross-section dimension is relatively small. Ignoring serial correlation of the idiosyncratic component leads to a positive bias in the estimates of s and σ_s. However, the bias becomes substantial only as one approaches the unit root case. For the level of serial correlation estimated by Ratfai (2006) for meat (0.34), our simulations suggest that the upward bias in the estimates of s should be below 8 percent. Lastly, as is the case with linear factor models, estimates of the common components are not adversely affected by the presence of weak cross-sectional dependence in the idiosyncratic shocks.[8]

4 Empirical Results

The model discussed in Section 2 has been estimated using individual consumer price quotes compiled by the Belgian and French statistical institutes for the computation of their respective consumer price indices. Each data set contains more than 10 millions observations referring to monthly price quotes of individual products sold in a particular outlet. For each product category price in a given outlet is computed as logarithm of sales per unit of product so that promotions in quantities are captured in our analysis. The period covered has been restricted to the intersection of the two databases, that is July 1994 - February 2003.[9] Since one of the aims of our approach is the identification of the common factors affecting the price of a given product in different outlets, price series have been grouped into narrowly defined product categories (368 for Belgium and 305 for France). However, as the estimation procedure is particularly time consuming,[10] the estimation has been conducted on a subset of randomly selected product categories,

[8]Results not reported for the sake of brevity indicate that the same conclusions hold in the presence of serial correlation or cross-sectional dependance of s_{it}.

[9]Further details of the two data sets are given in Appendix C, with a more thorough description provided in Aucremanne and Dhyne (2004) and Baudry *et al.* (2007).

[10]The estimation of our model for a typical product category, using S.A.S. 8.02 on a 1.6 Ghz P4 computer takes between 3 to 5 days.

restricting ourselves to those price trajectories that are at least 20 months long.[11] As a result, we end up estimating our baseline model for 94 product categories in Belgium and 88 categories in France.

All estimates reported below are computed by the full maximum likelihood method where for each product category the unobserved common components, f_t, for $t = 1, 2, ..., T$, as well as the other parameters, namely, the average level of the adjustment threshold, s, and its variability, σ_s, the variability of the idiosyncratic component, σ_ε, and the variability of firms specific random effects, σ_v are estimated simultaneously. Also to allow for possible differences in the price setting behavior by supermarkets and by corner shops, x_{it} is chosen to be a dummy variable that takes the value of 1 whenever the outlet where the product is sold is a supermarket and 0 otherwise.

The full set of estimation results for all the 182 product categories (94 for Belgium and 88 for France) is given in Appendix D. The results for Belgium are given in Table D.1 and for France in Table D.2. Each table provides ML estimates of the reduced form parameters ($\hat{s}$, $\hat{\sigma}_s$, $\hat{\sigma}_v$, $\hat{\sigma}_\varepsilon$), the unobserved common factors, $\hat{f}_t$, as well as the estimates of the structural parameters, $\widehat{\sigma} = \sqrt{\widehat{\sigma}_\varepsilon^2 + \widehat{\sigma}_\omega^2}$, and $\widehat{c} = \widehat{s}^2/(\widehat{\sigma}\sqrt{6})$, where $\widehat{\sigma}_\omega^2$ is the variance of the shock to the estimated common factors, $\widehat{f}_t$. To compute $\hat{\sigma}_\omega^2$, we assume that f_t follows a general autoregressive process possibly with a linear trend. Therefore, for each product category, the estimates $\widehat{f}_1, \widehat{f}_2, ..., \widehat{f}_T$ are used to fit an $AR(K)$ model defined as $\widehat{f}_t = \beta_0 + \beta_1 t + \sum_{k=1}^{K} \rho_k \widehat{f}_{t-k} + \omega_t, \quad \omega_t \backsim i.i.d.\,(0, \sigma_\omega^2)$.[12] As shown in Section 2, the estimated threshold parameter, $\hat{s}$, cannot be directly interpreted as reflecting the only intrinsic component of price rigidity, i.e. the nominal rigidity. This parameter also incorporates an extrinsic rigidity component, corresponding to the volatility of the underlying costs and mark-ups. As discussed earlier, $\hat{c}$ and $\hat{\sigma}$ will be interpreted as measures of intrinsic and extrinsic price rigidities, respectively.

In addition to the estimated parameters, Tables D.1 and D.2 also give a number of summary statistics such as the average number of observations per month, the correlation coefficient of $\hat{f}_t$ and the corresponding product category price index, the frequency and the average size (in absolute terms) of price changes.[13] The latter two statistics are then compared with those obtained from simulation of the estimated models by product

[11] A price trajectory is a continuous sequence of price reports referring to one particular product sold in store i.

[12] For each product category, K is selected using AIC applied to autoregressions with the maximum value of K set to 12.

[13] We have also computed standard errors for the parameter estimates reported in Tables D.1 and D.2. They all tend to be very small suggesting highly significant estimates. To save space these are not included in the result tables but are available on request.

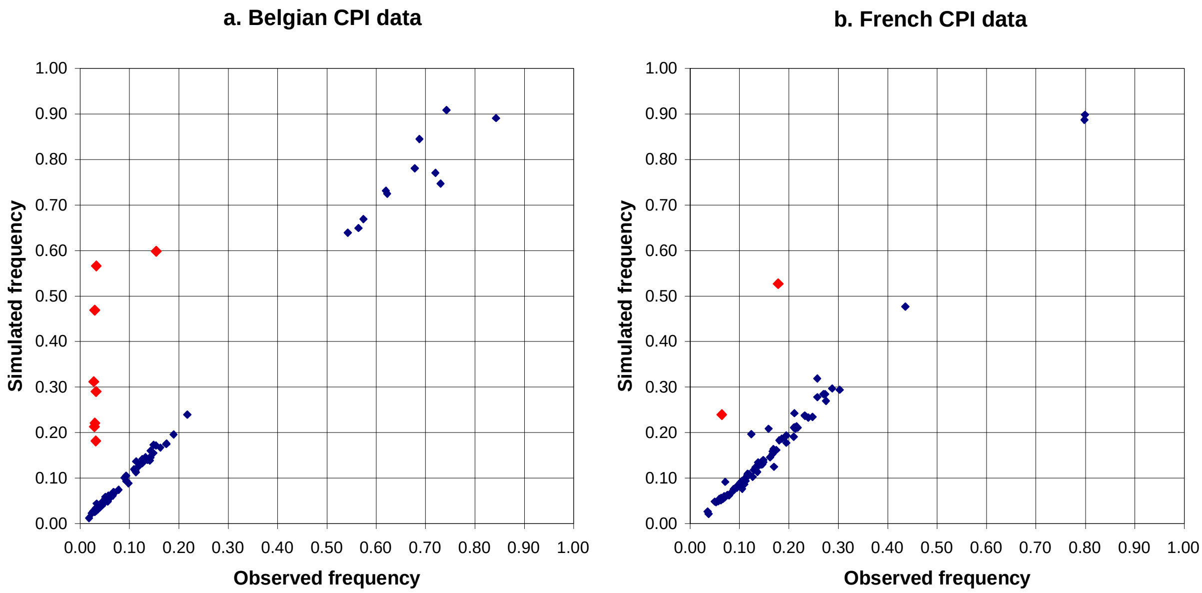

Figure 1: Observed versus simulated frequencies of price changes

categories. The details of the simulation exercise are provided in Appendix E. The results are generally supportive of the model. Estimates of s are all positive and tend to take plausible values. The estimated error variances also seem plausible although difficult to evaluate individually. With a few exceptions the correlation between $\hat{f}_t$ and the associated (log) price index is positive and often quite high, falling in the range of 0.85-0.98 in the case of the majority of product categories.

Most importantly, for each product category, the simulated frequency of price changes matches quite well the observed one. Scatter plots of the realized and simulated frequencies for the 94 product categories in the Belgian CPI and the 88 product categories in the French CPI are presented in Figure 1.

This figure shows that, except for a small number of products (8 out of the 94 product categories of the Belgian CPI, 2 out of the 88 product categories of the French CPI), the observed frequencies of price changes match the simulated ones quite well. The few cases where the simulations do not match the realizations are confined to product categories with relatively rigid prices.[14] For these 10 products, our simulations over-estimate the frequency and under-estimate the average size of price changes. In what follows we

[14]The 8 product categories with poor fit for Belgium were, "Dining room oak furniture", "Cup and saucer", "Parking spot in a garage", "Fabric for dress", "Wallet", "Small anorak"; "Men T Shirt" and "Hair spray 400 ml", and the two product category with poor fit for France, were "Classic lunch in a restaurant" and "Pasta".

exclude these products and focus on the remaining 172 products that seem to fit the observed price changes reasonably well.

Table 1 provides a summary of the CPI weighted average estimates of the main parameters of interest for six broad product categories: energy, perishable food, non-perishable food, non-durable manufactured goods, durable manufactured goods and services, for Belgium and France separately. This table also includes the estimates of the structural parameters c and σ, that characterize the intrinsic and extrinsic components of price rigidity.

Table 1: Parameter Estimates by Broad product categories - CPI Weighted Averages

	Energy	Perishable food	Non perishable food	Non durable goods	Durable goods	Services
			Belgium			
$\widehat{s}$	0.013	0.219	0.304	0.367	0.522	0.378
$\widehat{\sigma}_\varepsilon$	0.020	0.108	0.080	0.076	0.074	0.046
$\widehat{\sigma}_\omega$	0.032	0.036	0.016	0.018	0.016	0.009
$\widehat{c}$	0.002	0.401	0.479	0.947	1.540	1.245
$\widehat{\sigma}$	0.038	0.115	0.082	0.079	0.095	0.048
$Freq$	0.723	0.315	0.127	0.145	0.056	0.041
$\overline{\lvert\Delta p\rvert}$	0.039	0.139	0.102	0.083	0.072	0.056
			France			
$\widehat{s}$	0.004	0.215	0.203	0.396	0.304	0.308
$\widehat{\sigma}_\varepsilon$	0.023	0.106	0.074	0.104	0.074	0.053
$\widehat{\sigma}_\omega$	0.017	0.015	0.063	0.037	0.028	0.015
$\widehat{c}$	0.000	0.181	0.226	0.601	0.486	0.780
$\widehat{\sigma}$	0.029	0.107	0.076	0.112	0.081	0.057
$Freq$	0.799	0.247	0.204	0.124	0.134	0.077
$\overline{\lvert\Delta p\rvert}$	0.022	0.119	0.064	0.166	0.083	0.047

Notes: $\widehat{s}$ is the estimated size of the price inaction band. $\widehat{\sigma}_\varepsilon$ is the estimated standard deviation of the idiosyncratic component. $\widehat{\sigma}_\omega$ is the estimated standard deviation of the common shock. $Freq$ is the observed frequency of price changes. $\overline{\lvert\Delta p\rvert}$ is the observed average absolute value of price changes. $\widehat{c}$ is estimated as $\widehat{s}^2/(\widehat{\sigma}\sqrt{6})$, and $\widehat{\sigma} = \sqrt{\widehat{\sigma}_\varepsilon^2 + \widehat{\sigma}_\omega^2}$.

The detailed results in Tables D.1 and D.2 and the average estimates in Table 1, allow us to draw a number of important conclusions. First, the size of the inaction band, as measured by $\hat{s}$, clearly depends on the magnitude of both parameters of the intrinsic and extrinsic price rigidities. The service sector provides a good example where both of these two components contribute to the overall observed price stickiness in an important way. For this sector we obtain relatively high values of $\hat{c}$ and relatively low values of $\hat{\sigma}$. For Belgium these estimates are 1.245 and 0.048, respectively, whilst for France we obtain the estimates 0.780 and 0.057. In other words, service prices do not change very frequently not only because of the existence of strong nominal rigidities (possibly due to high menu costs and/or costs of consumers reaction to price changes) but also because their production costs are not subject to frequent and/or large changes.

Indeed, considering that wages are the most important cost component for the production of services, the variations of this cost component are not very frequent and appear to be of a rather small magnitude (e.g. see Heckel *et al.*, 2008). This also explains why, despite the existence of large menu costs, service prices change by rather limited amounts: the magnitude of the variations in the underlying costs is indeed quite small. It is worth mentioning here what might be considered as a rather puzzling result: for services, but also for other products except oil products, the average size of price changes is smaller than the average estimated inaction band parameters s. In fact, this result can be rationalized noting the stochastic nature of the bound, s_{it}. Since the distribution of s_{it} is assumed to be symmetric around its mean, s, the likelihood of a price change is larger when the menu cost, c_{mi}, is temporarily small or when the parameter of the quadratic cost of inaction, c_{ei}, is larger than usual. Such situations would correspond for instance to multi-product retailers, for which the menu cost associated to a price change of a particular product may be smaller whenever prices of other products are also changed (e.g. see Lach and Tsiddon, 2007, Midrigan, 2006), or in situations where competitors of an outlet decrease their price, thus increasing the cost of price inaction for this particular outlet. The randomness of the inaction band is a way to allow for small price changes that are observed in the data. One of its consequences is that small price changes are more likely than large ones, thus lowering the average size of price changes.

Let us now consider energy prices, which tend to exhibit opposite characteristics to those of service prices. The estimated intrinsic rigidity appears to be negligible, pointing to very small menu costs and/or very large costs of inaction. Moreover, the estimate of σ is quite low, showing that shocks affecting energy prices are of a relatively small magnitude, at least during our observation period and as compared to the other product categories. On the whole, these results are consistent with the observation that energy prices change often and do so by small amounts and imply that energy prices are flexible and extrinsic price rigidities do not seem to play an important role in energy price changes. However, an alternative explanation of the observed pattern of energy price changes (high frequency, small magnitude) might be that the structure of adjustment costs differs from the one assumed here. Indeed, quadratic adjustment costs may also explain this pattern of price changes. Such a pattern might be due to the highly homogenous nature of energy products and the high degree of competition that exists in this sector. As a consequence, one may tentatively make the conjecture that customers' anger stemming from large price increases would be quite high so that energy retailers are more likely to adopt a strategy of frequent small price changes. However, the frequent price changes of oil products at the wholesale level leads us to believe the former explanation to be more likely.

The contribution of both the intrinsic and extrinsic price rigidities to the observed price stickiness as measured by the magnitude of the inaction band (the s parameter) can be observed for the other broad categories of products, both for Belgium and France. For a given level of intrinsic rigidity (price adjustment costs), a larger magnitude of the shocks is associated with a wider band of inaction: firms/outlets react to shocks that are important, relative to the "usual" costs variations as measured by $\widehat{\sigma}$. This explains why, despite the higher level of intrinsic rigidity of service prices as compared to that associated with non-durable goods, the inaction band for this last group of products is, in Belgium, quite similar to that of services: the larger volatility of the shocks to non-durable goods prices contributes to increasing the magnitude of the inaction band for these products. Similar observations can be made as regards perishable food and non-perishable food products in France as well as for durable goods and services.[15]

A second important feature of the results is that intrinsic/nominal rigidities (as measured by the size of $\widehat{c}$) seem to be the main determining factor of the observed differences in the frequencies of price changes across products, whilst the size of shocks ($\widehat{\sigma}$) seems to largely explain the differences in the magnitude of price changes. This would explain why despite the fact that energy products and services exhibit strongly different degrees of nominal rigidities and frequencies of price changes, the sizes of observed price changes are relatively small for both products. This conclusion seems to hold also for the other products we consider. Indeed, the ranking of products we get from the frequency of price changes and from the estimated $\widehat{c}$ measuring the intrinsic price rigidity are quite similar.

[15] Our evaluation of the relative importance of extrinsic and intrinsic rigidities for explaining the magnitude of the inaction band may be affected by our assumptions regarding the idiosyncratic component. Indeed, assuming these to be uncorrelated if in fact they are serially correlated is likely to induce a bias in our estimates. We have run some Monte Carlo simulations to check the possible magnitude of such biases (see Appendix B). It appears that unless ε_{it} is highly serially correlated, the biases introduced by neglecting such serial correlation do not seem to be not be too serious.

Moreover, the ranking obtained from the magnitude of price changes on the one hand and from the estimated variance of shocks on the other hand appear to be close to each other too. In order to evaluate the strength of these correlations, we have run a number of cross section regressions of the frequency and the size of price changes on $\hat{c}$ and $\hat{\sigma}$ across the 172 product categories that pass our initial diagnostic test explained above. The results are presented in Table 2. First, we have estimated a simple equation relating the observed frequency of price changes to $\widehat{c}$ either alone or together with $\widehat{\sigma}$, plus the interaction term, $\hat{c} \times \hat{\sigma}$.[16] Because the frequency of price changes lie between 0 and 1, this first equation is estimated by the quasi maximum likelihood (QML) estimation procedure proposed by Papke and Wooldridge (1996). Second, we have run a linear regression explaining the observed magnitude of price changes by $\widehat{\sigma}$ alone, and together with $\widehat{c}$ and the interaction term. All the regressions include a country dummy which takes the value of unity for France.

Table 2: Cross Section Regressions of the frequency and the magnitude of price changes on measures of intrinsic ($\hat{c}$) and extrinsic rigidities ($\hat{\sigma}$)

	Frequency			Magnitude		
$Constant$	−0.080	−2.525	−0.307	−0.017	−0.024	0.102
	(−0.23)	(−4.59)	(−1.06)	(−1.68)	(−3.94)	(9.37)
D_France	−0.393	−0.006	−0.388	0.002	0.005	0.015
	(−3.09)	(−0.02)	(−2.88)	(0.44)	(0.98)	(1.41)
$\widehat{c}$	−3.471	–	−2.229	−0.011	–	−0.010
	(−6.84)		(−10.32)	(−0.93)		(−1.18)
$\widehat{\sigma}$	7.677	9.136	–	1.391	1.437	–
	(2.93)	(1.99)		(16.15)	(23.08)	
$\widehat{c} \times \widehat{\sigma}$	1.792	–	–	0.090	–	–
	(0.38)			(0.72)		
$\bar{R}^2$	0.72	0.13	0.63	0.76	0.76	0.02

Note: The figures in bracket are t-ratios. D_France is a dummy variable equal to one for France. $\widehat{c}$ is estimated as $\widehat{s}^2/(\widehat{\sigma}\sqrt{6})$, where $\widehat{s}$ is the estimated size of the price inaction band, $\widehat{\sigma} = \sqrt{\widehat{\sigma}_\varepsilon^2 + \widehat{\sigma}_\omega^2}$, $\widehat{\sigma}_\varepsilon$ is the estimated standard deviation of the idiosyncratic component, and $\widehat{\sigma}_\omega$ is the estimated standard deviation of the common shock.

The first set of regressions support the existence a strong negative link between the frequency of price changes and the estimates of the degree of intrinsic price rigidities.

[16] The regression also includes a constant and a dummy variable for France.

The coefficient of $\hat{c}$ in this regression has a t-ratio of -10.32 which is highly significant statistically. Comparing the regression where this component is included alone with the one where the extrinsic rigidity and an interaction term are also included shows that, though the influence of the extrinsic rigidity on the frequency of price changes cannot be denied, most of the explanatory power comes from the intrinsic rigidity. The variations in $\hat{c}$ explains as much as 63% of the observed frequency of price changes. In contrast, the regressions aimed at explaining the magnitude of price changes show that these are essentially related to the size of the shocks, $\widehat{\sigma}$. The coefficient of $\widehat{\sigma}$ in these regressions have t-ratios in excess of 16 and explain around 76% of the cross section variations of the size of price changes. These results suggest that smaller observed price changes mainly result from smaller variations of the underlying optimal price rather than from a low level of intrinsic rigidity that would allow outlets to adjust their prices frequently and by small magnitudes.

Returning to the results presented in Tables D.1 and D.2 and summarized in Table 1, it is worth noting that $\widehat{\sigma}_{\varepsilon}$ is larger than $\widehat{\sigma}_{\omega}$ in almost all cases, i.e. idiosyncratic shocks seem to be of a larger magnitude than common shocks affecting all the outlets selling a given product. Indeed, one may observe from the results provided in appendix D that with very few exceptions (mainly energy products), the volatility of the idiosyncratic component is generally larger than the variability of the shocks affecting common component $\widehat{f_t}$. Over our set of 172 products, the ratio of $\widehat{\sigma}_{\varepsilon}$ to $\widehat{\sigma}_{\omega}$ takes values above one for 165 product categories (84 in Belgium and 81 in France). This result is in line with the conclusion of Golosov and Lucas (2007) who state that price trajectories at the micro level are largely affected by idiosyncratic shocks.

Finally, this set of results, and in particular the strong correlation obtained between the intrinsic price rigidity and the frequency of price changes on the one hand, and that between the extrinsic price rigidity and the magnitude of price changes on the other hand, has interesting implications for the modelling of price rigidities in macroeconomic models. First, these results can be considered to validate to a certain extent the use of the frequency of price changes as an indicator of nominal rigidity in these models. Indeed, the correlation between the (log of) $\hat{c}$ and the (log) of the frequency of price changes is quite high but not perfect. Second, nominal rigidity is indeed not sufficient for explaining the observed price stickiness: the extrinsic rigidity also plays an important role. A large part of the rigidity of service prices stem from this extrinsic component of price rigidity. Given that, in models with (often implicitly) heterogenous sectors, the stickiness of the aggregate basically comes from its more rigid component, this shows the importance of the extrinsic rigidity in explaining price rigidity at the macroeconomic level. Finally, the results in Table 2 also indicate that magnitude of price changes could be a good proxy for the extent of "extrinsic" price rigidity.

5 Conclusion

Modern macroeconomics has emphasized the role of price rigidity in the impact of monetary policy on economic activity and inflation dynamics. The slope of the New Keynesian Phillips curve typically depends on nominal (intrinsic) price rigidity. Most previous empirical literature approximated these intrinsic rigidities by the frequency of price changes. However, in the case of state dependent rules, the frequency of price changes does not only depend on the size of the adjustment costs (intrinsic rigidity), but it is also affected by the distribution of shocks that affect outlets (extrinsic rigidity).

Following this new strand in theoretical models (see Dotsey, King and Wolman, 1999, and Gertler and Leahy, 2006), we specify a state-dependent (S,s) type model. Since the optimal price targeted by outlets is unobserved, we decompose it into three components: a common factor, an idiosyncratic component, and a random outlet-specific effect. This setup involves modeling of the price changes as a non-linear dynamic panel model with unobserved common effects and allows us to decompose price stickiness into intrinsic and extrinsic rigidities. Assuming fixed cost of price adjustment and quadratic costs of inaction, intrinsic rigidity is derived from our estimates of the average range of price inaction, $\widehat{s}$, using Dixit (1991) characterization of the (S, s) model. Extrinsic rigidity is associated with the variability of the various components of the (unobserved) optimal price.

Making use of two large data sets composed of consumer price records used to compute the CPI in Belgium and France, the (S, s) model is estimated for more than 180 narrowly defined product categories where we have a relatively large number of outlets supplying relatively homogeneous products. Our results show that the now well-documented differences across products in the frequency of price changes do not strictly correspond to differences in terms of intrinsic rigidities. Intrinsic price rigidity alone is not enough to explain the sectoral heterogeneity in the frequency of price changes. These frequencies also depend in a significant way on the magnitude of the shocks, common and/or idiosyncratic, to the unobserved optimal prices. For instance, a large part of the rigidity of service prices stem from the extrinsic component of price rigidity.

Our results also strongly favor the introduction of heterogenous price behaviors in macroeconomic models. Two recent papers examine the implications of heterogeneity of (Calvo) pricing for the New Keynesian Phillips Curve. Using sectoral data on prices and marginal costs, Imbs *et al.* (2007) show that estimates of the NKPC that do not account for industry-level heterogeneity substantially overestimate the backward looking component, and slightly underestimate the role of marginal costs on inflation. In a multi-sector general equilibrium model, Carvalho (2006) shows that under heterogeneous pricing, monetary policy has larger and more persistent real effects than those predicted by single-firm models. Our results indicate that to take account of the observed heterogeneity across firms (or product categories) would require paying attention to both sources of price rigidities. Differences in extrinsic rigidities are important not only in capturing part of the heterogeneity in the overall degree of price stickiness measured by the frequency of price changes, but also to capture the sectoral heterogeneity in the magnitude of price changes.

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Appendix A: Mathematical Proofs

Proof of the first part of Lemma 3.1.

$$E\left[yI(y+a)\right] = \sigma\phi\left(\frac{a+\mu}{\sigma}\right) + \mu\Phi\left(\frac{a+\mu}{\sigma}\right).$$

■

$$\begin{aligned} E\left[yI\left(y+a\right)\right] &= \int_{-a}^{+\infty} y\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}dy \\ &= \int_{-a}^{+\infty} \frac{y-\mu}{\sigma}\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}dy + \int_{-a}^{+\infty} \frac{\mu}{\sigma}\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}dy \end{aligned}$$

Letting $z = (y-\mu)/\sigma$, the above expression becomes

$$\begin{aligned} E\left[yI\left(y+a\right)\right] &= \sigma\int_{-\frac{a+\mu}{\sigma}}^{+\infty} z\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}z^2}dz + \mu\int_{-\frac{a+\mu}{\sigma}}^{+\infty} \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}z^2}dz \\ &= \sigma\left[-\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}z^2}\right]_{-\frac{a+\mu}{\sigma}}^{+\infty} + \mu\int_{-\infty}^{\frac{a+\mu}{b}} \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}z^2}dz \\ &= \sigma\phi\left(\frac{a+\mu}{\sigma}\right) + \mu\Phi\left(\frac{a+\mu}{\sigma}\right) \end{aligned}$$

Proof of the second part of Lemma 3.1.

$$E\left[\phi\left(\frac{y+a}{b}\right)\right] = \frac{b}{\sqrt{b^2+\sigma^2}}\phi\left(\frac{a+\mu}{\sqrt{b^2+\sigma^2}}\right)$$

■

$$
\begin{aligned}
E\left[\phi\left(\frac{y+a}{b}\right)\right] &= \int\limits_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y+a}{b}\right)^2} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2} dy \\
&= \frac{1}{\sigma^2\pi} \int\limits_{-\infty}^{+\infty} e^{-\frac{1}{2}\left(\frac{\left(\sigma^2+b^2\right)y^2+\left(2a\sigma^2-2b^2\mu\right)y+a^2\sigma^2+b^2\mu^2}{b^2\sigma^2}\right)} dy \\
&= \frac{1}{\sigma^2\pi} \int\limits_{-\infty}^{+\infty} e^{-\frac{1}{2}\left(\frac{\left(\sqrt{\sigma^2+b^2}y+A\right)^2-A^2+a^2\sigma^2+b^2\mu^2}{b^2\sigma^2}\right)} dy
\end{aligned}
$$

where $A = \left(a\sigma^2 - \mu b^2\right)/\sqrt{b^2+\sigma^2}$. Let $B = \frac{1}{2}\left(\frac{A^2-a^2\sigma^2-b^2\mu^2}{b^2\sigma^2}\right) = -\frac{1}{2}\frac{(a+\mu)^2}{b^2+\sigma^2}$,

$$
\begin{aligned}
E\left[\phi\left(\frac{y+a}{b}\right)\right] &= \frac{1}{\sigma^2\pi} e^B \int\limits_{-\infty}^{+\infty} e^{-\frac{1}{2}\left(\frac{\left(\sqrt{\sigma^2+b^2}y+A\right)^2}{b^2\sigma^2}\right)} dy \\
&= \frac{1}{\sigma^2\pi} e^B \int\limits_{-\infty}^{+\infty} e^{-\frac{1}{2}\frac{\sigma^2+b^2}{b^2\sigma^2}\left(y+\frac{a\sigma^2-\mu b^2}{b^2+\sigma^2}\right)^2} dy
\end{aligned}
$$

Setting $\omega = b\sigma/\sqrt{b^2+\sigma^2}$ and $\widetilde{\mu} = -\left(a\sigma^2 - \mu b^2\right)/\left(b^2+\sigma^2\right)$, we now have

$$
\begin{aligned}
E\left[\phi\left(\frac{y+a}{b}\right)\right] &= \frac{1}{\sigma^2\pi} e^B \int\limits_{-\infty}^{+\infty} e^{-\frac{1}{2\omega^2}(y-\widetilde{\mu})^2} dy \\
&= \frac{1}{\sigma^2\pi} e^B \omega\sqrt{2\pi} = \frac{b}{\sqrt{b^2+\sigma^2}} \frac{1}{\sqrt{2\pi}} e^B \\
&= \frac{b}{\sqrt{b^2+\sigma^2}} \phi\left(\frac{a+\mu}{\sqrt{b^2+\sigma^2}}\right)
\end{aligned}
$$

Proof of the third part of Lemma 3.1.

$$
E\left(\Phi\left(\frac{y+a}{b}\right)\right) = \Phi\left(\frac{a+\mu}{\sqrt{b^2+\sigma^2}}\right)
$$

■

$$
E\left[\Phi\left(\frac{y+a}{b}\right)\right] = \int\limits_{-\infty}^{+\infty} \int\limits_{-\infty}^{\frac{y+a}{b}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}w} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2} dw dy
$$

Stating that $\frac{z+y+a}{b} = w$, the expression above becomes

$$
\begin{aligned}
E\left[\Phi\left(\frac{y+a}{b}\right)\right] &= \int_{-\infty}^{+\infty}\int_{-\infty}^{0} \frac{1}{b\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{z+y+a}{b}\right)^2} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2} dz dy \\
&= \int_{-\infty}^{0} \frac{1}{b} \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{z+y+a}{b}\right)^2} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2} dy dz \\
&= \int_{-\infty}^{0} \frac{1}{b} E\left[\phi\left(\frac{y+a+z}{b}\right)\right] dz
\end{aligned}
$$

Using the second part of Lemma 1,

$$
\begin{aligned}
E\left[\Phi\left(\frac{y+a}{b}\right)\right] &= \int_{-\infty}^{0} \frac{1}{b} \frac{b}{\sqrt{b^2+\sigma^2}} \phi\left(\frac{z+a+\mu}{\sqrt{b^2+\sigma^2}}\right) dz \\
&= \frac{1}{\sqrt{b^2+\sigma^2}} \int_{-\infty}^{0} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{z+a+\mu}{\sqrt{b^2+\sigma^2}}\right)^2} dz
\end{aligned}
$$

Setting $(z+a+\mu)/\sqrt{b^2+\sigma^2} = \widetilde{z}$,

$$
\begin{aligned}
E\left[\Phi\left(\frac{y+a}{b}\right)\right] &= \frac{1}{\sqrt{b^2+\sigma^2}} \int_{-\infty}^{\frac{a+\mu}{\sqrt{b^2+\sigma^2}}} \frac{\sqrt{b^2+\sigma^2}}{\sqrt{2\pi}} e^{-\frac{1}{2}\widetilde{z}^2} d\widetilde{z} \\
&= \Phi\left(\frac{a+\mu}{\sqrt{b^2+\sigma^2}}\right)
\end{aligned}
$$

Proof of the uniqueness of $\tilde{f}_t$ (the non-linear cross section average estimator of f_t). Let

$$
z_{it}(f_t) = \frac{d_{it}}{\sqrt{\sigma_s^2+\sigma_\xi^2}},
$$

and

$$
\begin{aligned}
\widetilde{\Delta p}_{it} &= \frac{\Delta p_{it}}{\sqrt{\sigma_s^2+\sigma_\xi^2}},\ \tilde{\eta}_{it} = \frac{\eta_{it}}{\sqrt{\sigma_s^2+\sigma_\xi^2}}, \\
\widetilde{s} &= \frac{s}{\sqrt{\sigma_s^2+\sigma_\xi^2}} \geq 0,\ \delta^2 = \frac{\sigma_\xi^2}{\sigma_s^2+\sigma_\xi^2} < 1,
\end{aligned}
$$

and note that we have

$$
\begin{aligned}
\widetilde{\Delta p}_{it} &= z_{it}(f_t) + z_{it}(f_t)\left[\Phi\left(z_{it}(f_t) - \widetilde{s}\right) - \Phi\left(z_{it}(f_t) + \widetilde{s}\right)\right] && (9)\\
&\quad + \delta^2\left[\phi\left(z_{it}(f_t) - \widetilde{s}\right) - \phi\left(z_{it}(f_t) + \widetilde{s}\right)\right] + \tilde{\eta}_{it}. && (10)
\end{aligned}
$$

The cross-sectional average estimate of f_t is now given by the solution of the non-linear equation

$$
\begin{aligned}
\Psi(\tilde{f}_t) &= \sum_{i=1}^{N} w_{it}\{z_{it}(\tilde{f}_t) + z_{it}(\tilde{f}_t)\left[\Phi\left(z_{it}(\tilde{f}_t) - \widetilde{s}\right) - \Phi\left(z_{it}(\tilde{f}_t) + \widetilde{s}\right)\right] && (11)\\
&\quad + \delta^2\left[\phi\left(z_{it}(\tilde{f}_t) - \widetilde{s}\right) - \phi\left(z_{it}(\tilde{f}_t) + \widetilde{s}\right)\right]\} - a_{Nt} && (12)\\
&= 0, && (13)
\end{aligned}
$$

where $a_{Nt} = \sum_{i=1}^{N} w_{it}\widetilde{\Delta p}_{it}$.

First it is clear that $\Psi(\tilde{f}_t)$ is a continuous and differentiable function of f_t, and it is now easily seen that

$$
\lim_{f_t \to +\infty} \Psi(\tilde{f}_t) \to +\infty \quad \text{and} \quad \lim_{f_t \to -\infty} \Psi(\tilde{f}_t) \to -\infty.
$$

Also the first derivative of $\Psi(f_t)$ is given by[17]

$$
\Psi'(\tilde{f}_t) = \frac{1}{\sqrt{\sigma_s^2 + \sigma_\xi^2}} \sum_{i=1}^{N} w_{it} q_{it},
$$

where

$$
q_{it} = 1 + \Phi\left(z_{it}(\tilde{f}_t) - \widetilde{s}\right) - \Phi\left(z_{it}(\tilde{f}_t) + \widetilde{s}\right) + (1 - \delta^2) h(z_{it}(\tilde{f}_t)),
$$

and

$$
h(z_{it}(\tilde{f}_t)) = z_{it}(\tilde{f}_t)\left[\phi\left(z_{it}(\tilde{f}_t) - \widetilde{s}\right) - \phi\left(z_{it}(\tilde{f}_t) + \widetilde{s}\right)\right].
$$

But since $1 - \Phi\left(z_{it}(\tilde{f}_t) + \widetilde{s}\right) = \Phi\left(-z_{it}(\tilde{f}_t) - \widetilde{s}\right)$, then

$$
1 + \Phi\left(z_{it}(\tilde{f}_t) - \widetilde{s}\right) - \Phi\left(z_{it}(\tilde{f}_t) + \widetilde{s}\right) = \Phi\left(z_{it}(\tilde{f}_t) - \widetilde{s}\right) + \Phi\left(-z_{it}(\tilde{f}_t) - \widetilde{s}\right) > 0,
$$

and it is easily seen that $h(z_{it}(\tilde{f}_t))$ is symmetric, namely $h(z_{it}(\tilde{f}_t)) = h(-z_{it}(\tilde{f}_t))$. Focusing

[17] Recall that the weights, w_{it}, are non-zero pre-determined constants, and in particular do not depend on f_t.

on the non-negative values of $z_{it}(\tilde{f}_t)$ it is easily seen that

$$h(z_{it})) = \frac{z_{it}}{\sqrt{2\pi}}\left[e^{-0.5(z_{it}-\widetilde{s})^2} - e^{-0.5(z_{it}+\widetilde{s})^2}\right] > 0 \text{ for } \widetilde{s} > 0,$$

and by symmetry $h(z_{it})) \geq 0$, for all $\widetilde{s} \geq 0$. Hence, $q_{it} > 0$ for all i and t, and $\widetilde{s} \geq 0$. Therefore, it also follows that $\Psi'(f_t) > 0$, for all value of $w_{it} \geq 0$ and $s \geq 0$. Thus, by the fixed point theorem, $\Psi(f_t)$ must cut the horizontal axis but only once.

Proof of the consistency of $\tilde{f}_t$ as an estimator of f_t as $N \to \infty$.

Let

$$\begin{aligned}\Psi(f_t) &= \sum_{i=1}^{N} w_{it}\left\{z_{it}(f_t) + z_{it}(f_t)\left[\Phi\left(z_{it}(f_t) - \widetilde{s}\right) - \Phi\left(z_{it}(f_t) + \widetilde{s}\right)\right]\right. \\ &\qquad \left. +\delta^2\left[\phi\left(z_{it}(f_t) - \widetilde{s}\right) - \phi\left(z_{it}(f_t) + \widetilde{s}\right)\right]\right\} - a_{Nt},\end{aligned}$$

and note that

$$\Psi(f_t) = -\sum_{i=1}^{N} w_{it}\eta_{it}.$$

Consider now the mean-value expansion of $\Psi(f_t)$ around $\tilde{f}_t$

$$\Psi(f_t) - \Psi(\tilde{f}_t) = \Psi'(\bar{f}_t)(f_t - \tilde{f}_t),$$

where $\bar{f}_t$ lies on the line segment between f_t and $\tilde{f}_t$. Since $\Psi(\tilde{f}_t) = 0$ and $\Psi'(\bar{f}_t) > 0$ for all $\bar{f}_t$ (as established above) we have

$$\tilde{f}_t - f_t = \frac{-\sum_{i=1}^{N} w_{it}\tilde{\eta}_{it}}{\Psi'(\bar{f}_t)}.$$

Recall that $\tilde{\eta}_{it} = \left(\sigma_s^2 + \sigma_\xi^2\right)^{-1/2}\left[\Delta p_{it} - E\left(\Delta p_{it}\left|\mathbf{h}_{it}\right.\right)\right]$, where $\mathbf{h}_{it} = (f_t, \mathbf{x}_{it}, p_{i,t-1})$, and hence $E\left(\tilde{\eta}_{it}\right) = 0$. Further, conditional on f_t and $\mathbf{x}_{it}$, price changes, Δp_{it}, being functions of independent shocks v_i and ε_{it} over i, will be cross sectionally independent. Therefore, η_{it} will also be cross sectionally independent; although they need not be identically distributed even if the underlying shocks, v_i and ε_{it}, are identically distributed over i.

Given the above results we now have (for each t and as $N \to \infty$)

$$\left(\sum_{i=1}^{N} w_{it}^2\right)^{-1/2}\left(\tilde{f}_t - f_t\right) \backsim N\left(0, \vartheta_{\tilde{f}}^2\right),$$

where

$$\vartheta_{\tilde{f}}^2 = \lim_{N\to\infty} \left\{ \frac{\left(\sum_{i=1}^N w_{it}^2\right)^{-1} \sum_{i=1}^N w_{it}^2 Var(\tilde{\eta}_{it})}{[\Psi'(f_t)]^2} \right\}.$$

Note that as $N \to \infty$, $\sum_{i=1}^N w_{it}\tilde{\eta}_{it} \xrightarrow{p} 0$, and hence $\tilde{f}_t \xrightarrow{p} f_t$, since $\Psi'(f_t) > 0$ for all f_t.It must also be that $\bar{f}_t \xrightarrow{p} f_t$.

In the case where $w_{it} = 1/N$, we have

$$\vartheta_{\tilde{f}}^2 = \lim_{N\to\infty} \left\{ \frac{N^{-1} \sum_{i=1}^N Var(\tilde{\eta}_{it})}{[\Psi'(f_t)]^2} \right\}.$$

It also follows that $\tilde{f}_t - f_t = O_p\left(N^{-1/2}\right)$. ■

Appendix B: Monte Carlo Simulations

We generated the log price series according to the baseline model, (5), and simulating the common factors as [a] first order autoregressive process. In our reference case, the sample size is set at $N = 50$, $T = 50$. In Table B.1, we report the average (across 1000 replications) of the point estimates of s, σ_ε, σ_s and σ_v and their average standard errors in different setups. Concerning the estimation of f_t, we compute the RMSE with respect to the true f_t and compare the standard deviation of the true f_t with that of the estimated f_t. Initial values for the estimation of f_t are set to $\overline{p}_t$. The standard errors of the parameter estimates are computed from the second derivatives of the full log-likelihood function. This table also reports the value of c computed from the point estimates of s, σ_ε and $\sigma_\omega = \sigma_f\sqrt{1-\rho^2}$, where σ_f is the standard deviation of the estimated f_t and ρ is the true autoregressive coefficient of the AR(1) process assumed for f_t.

Results reported in Table B.1 allow a comparison of the following cases: (i) with and without random effects, (ii) panels with N small, $N = 25$ versus $N = 50$, (iii) cases where the average frequency of price changes is 0.27 versus 0.12, (iv) the case of a small idiosyncratic component and a large common factor versus the case of a large idiosyncratic component and a relatively small common component, which corresponds to parameter values close to the estimates based on observed data. In general, estimated parameters are close to their true values. Our simulations show that the range of inaction is estimated with high precision. The estimate of the variance of the idiosyncratic component is closer to its theoretical value in the model with random effects. This drives the c above its true value, as it is related to the ratio of s to the size of the idiosyncratic and common shocks. Not surprisingly, the estimation of the common factor improves as the cross-section dimension increases. The results in Table B.1 also suggest that the estimation of f_t deteriorates as the frequency of price changes and the size of the common shock diminishes.

Table B.1 - Monte Carlo Simulations

Average frequency of price changes $\sim$ 0.27 with random effects							
	s	σ_ε	σ_s	σ_v			c
True values	0.15	0.05	0.01	0.025			0.082
	$\widehat{s}$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_s$	$\widehat{\sigma}_v$	$RMSE(\widehat{f}_t)$	$\frac{RMSE(\widehat{f}_t)}{RMSE(f_t)}$	$\widehat{c}$
$N = 50, T = 50$	0.151 (0.0014)	0.049 (0.0011)	0.011 (0.0013)	0.027 (0.0030)	0.00019	1.0018	0.096
Average frequency of price changes $\sim$ 0.27 without random effect							
	s	σ_ε	σ_s	σ_v			c
True values	0.15	0.05	0.01	0			0.082
	$\widehat{s}$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_s$		$RMSE(\widehat{f}_t)$	$\frac{RMSE(\widehat{f}_t)}{RMSE(f_t)}$	$\widehat{c}$
$N = 50, T = 50$	0.150 (0.0013)	0.049 (0.0011)	0.007 (0.0013)		0.00014	1.0018	0.099
$N = 25, T = 50$	0.150 (0.0019)	0.048 (0.0015)	0.006 (0.0018)		0.00029	1.0052	0.099
Average frequency of price changes $\sim$ 0.12 with random effect - large common component							
	s	σ_ε	σ_s	σ_v			c
True values	0.300	0.050	0.100	0.025			0.329
	$\widehat{s}$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_s$	$\widehat{\sigma}_v$	$RMSE(\widehat{f}_t)$	$\frac{RMSE(\widehat{f}_t)}{RMSE(f_t)}$	$\widehat{c}$
$N = 50, T = 50$	0.302 (0.0071)	0.047 (0.0017)	0.103 (0.0055)	0.029 (0.0036)	0.00049	1.0052	0.430
Average frequency of price changes $\sim$ 0.12 with random effect - large common component							
	s	σ_ε	σ_s	σ_v			c
True values	0.300	0.100	0.125	0.250			0.260
	$\widehat{s}$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_s$	$\widehat{\sigma}_v$	$RMSE(\widehat{f}_t)$	$\frac{RMSE(\widehat{f}_t)}{RMSE(f_t)}$	$\widehat{c}$
$N = 100, T = 100$	0.307 (0.0108)	0.099 (0.0027)	0.131 (0.0080)	0.247 (0.0246)	0.00593	1.1841	0.380

Notes: 1000 replications, estimation by full ML. The figures in brackets are standard errors. f_t is simulated as a first order autoregressive process with intercept equal to 0.05 and slope equal to 0.90. $\sigma_f = 1$, except in the last simulation exercise (large idiosyncratic component) where $\sigma_f = 0.00625$. s is the size of the price inaction band, σ_ε^2 is the variance of the idiosyncratic component, σ_s^2 is the variance of s_{it} the threshold parameter for price changes. $\widehat{c}$ is estimated as $\widehat{s}^2/(\widehat{\sigma}\sqrt{6})$, where $\widehat{s}$ is the estimated size of the price inaction band, $\widehat{\sigma} = \sqrt{\widehat{\sigma}_\varepsilon^2 + \widehat{\sigma}_\omega^2}$, $\widehat{\sigma}_\varepsilon$ is the estimated standard deviation of the idiosyncratic component, and $\widehat{\sigma}_\omega$ is the estimated standard deviation of the common shock. $RMSE(\widehat{f}_t)/RMSE(f_t)$ stands for the ratio of the standard deviation of the estimated f_t over the standard deviation of the true f_t.

Our second set of Monte Carlo simulations consider the case of serial correlation of the idiosyncratic component. We model it as an AR(1) process where the variance of ε_{it} is identical to that of the base case. The results indicate that serial correlation in the idiosyncratic component introduces an upward bias in the estimated $\widehat{s}$ and $\widehat{\sigma}_s$.and a small downward bias in the estimates of $\widehat{\sigma}_\varepsilon$. The results are summarized in table B.2. The bias is negligible for low values of the serial correlation coefficient. It remains limited for small values of ρ (for $\rho = 0.50$, the estimate of s is only 0.03 higher than the true value). The bias becomes important only as serial correlation approaches the unit root case. However, because our measure of intrinsic price rigidity c is a function of $s/\sqrt{\sigma_\varepsilon{}^2 + \sigma_\omega{}^2}$, its computed value involves an upward bias that increases with the degree of serial correlation of ε_{it}. For $\rho = 0.50$, the bias amounts to 0.08.

Table B.2 - Monte Carlo Simulations with serially correlated idiosyncratic component

	s	σ_ε^2	σ_s^2			c
True values	0.35	0.005625	0.010			0.54
	$\widehat{s}$	$\widehat{\sigma_\varepsilon^2}$	$\widehat{\sigma_s^2}$	$RMSE(\widehat{f_t})$	$\frac{RMSE(\widehat{f_t})}{RMSE(f_t)}$	$\widehat{c}$
ρ=0	0.357 (0.020)	0.0038 (0.005)	0.0011 (0.002)	0.0021	1.343	0.55
ρ=0.10	0.359 (0.021)	0.007 (0.0004)	0.011 (0.002)	0.0021	1.356	0.56
ρ=0.50	0.379 (0.024)	0.0033 (0.0004)	0.013 (0.003)	0.0024	1.400	0.63
ρ=0.90	0.464 (0.042)	0.0022 (0.0004)	0.023 (0.006)	0.0030	1.425	1.00
ρ=0.95	0.510 (0.054)	0.0017 (0.0003)	0.029 (0.009)	0.0031	1.376	1.28
ρ=0.99	0.574 (0.087)	0.0012 (0.0003)	0.038 (0.015)	0.0029	1.162	2.00

Notes: 1000 replications, $N = 50$, $T = 50$, estimation by full ML. The figures in bracket are standard errors. f_t is simulated as a first order autoregressive process with intercept equal to 0.05 and slope equal to 0.75. ε_{it} is simulated as a first order autoregressive process with zero intercept and the serial correlation coefficient given by ρ. $\sigma_f = 0.057$ and $\sigma_\varepsilon = 0.075$. See also the notes to Table B.1.

The third set of Monte Carlo simulations examines the case of cross-sectional dependence. Cross-sectional dependence may be motivated on two grounds. First, local competition may lead outlets to be influenced by their neighbor pricing policies. Evidence on this can be found in Pinske et al. (2002) for US wholesale gasoline markets. Second, outlets of the same chain may have a common pricing policy, when pricing decision are centralized. In order to investigate this, two alternative specifications are chosen. The first is a Spatial Moving Average Model. *The second is factor error structure where the* *cross-section dependence is generated according to a finite number of unobserved common factors. We include 10 factors for the 50 outlets considered in the experiments. The results are summarized in Table B.3.*

As is well known in the literature on the linear factor model, "weak" cross sectional dependence (in the sense defined in Pesaran and Tosetti, 2007) does not affect the consistency of the estimates of the common factors using cross section averages or principle component approaches.[18] The Monte Carlo experiments suggest that this property also holds in the case of our non linear factor model. Whether this result holds more generally clearly require further investigation.

TABLE B.3 - MONTE CARLO SIMULATIONS WITH CROSS SECTIONALLY DEPENDENT IDIOSYNCRATIC COMPONENT

	s	σ_ε^2	σ_s^2			c
True values	0.35	0.005625	0.010			0.54
	$\widehat{s}$	$\widehat{\sigma_\varepsilon^2}$	$\widehat{\sigma_s^2}$	$RMSE(\widehat{f}_t)$	$\frac{RMSE(\widehat{f}_t)}{RMSE(f_t)}$	$\widehat{c}$
no cross-sectional dependence	0.357 (0.020)	0.0038 (0.0005)	0.011 (0.011)	0.0021	1.343	0.55
SMA$^{(1)}$	0.357 (0.020)	0.0035 (0.0004)	0.011 (0.002)	0.0024	1.369	0.55
10 factors$^{(2)}$	0.357 (0.020)	0.0036 (0.0004)	0.011 (0.002)	0.0024	1.375	0.55

Notes: Simulations are based on 1000 replications with $N = 50$ and $T = 50$. Estimation is by full ML. The figures in bracket are standard errors. f_t is simulated as $f_t = 0.05 + 0.75 f_{t-1} + \omega_t$, ω_t~iid $N(0, \sigma_\omega^2)$, with $\sigma_\omega^2 = 0.0002734$. See also the notes to Table B.1

$^{(1)}$ stands for the Spatial Moving Average model $\varepsilon_{it} = x_{it} + x_{i-1,t} + x_{i+1,t}$ with x_{it}~iid $N(0, \sigma_x^2)$. The value of σ_x is set so that $\sigma_\varepsilon = 0.075$, the same value used in the experiments summarized in Table B.2.

$^{(2)}$ stands for the multifactor error structure $\varepsilon_{it} = \sum_{j=1}^{10} \gamma_{ij} z_{jt} + x_{it}$, where z_{jt}~iid $N(0, \sigma_j^2)$ and x_{it}~iid $N(0, \sigma_x^2)$ are drawn independently, with $\sigma_j^2 = \sigma_x^2$ =0.0028125. $\gamma_{i1} = 1$ for i=1, ...,5, and 0 otherwise, $\gamma_{i2} = 1$ for i=6, ...,10, and 0 otherwise, γ_{i3}=1, for $i = 11, ..., 15$, and so on.

[18] Stock and Watson (1998) show that their estimator is robust with limited serial and cross-sectionnally correlated idiosyncratic component and time varying factor loadings. Consistency if obtains as N and T go to infinity with T/N going to zero (for large N small T panels). Pesaran and Tosetti (2007) derive the conditions under which the Pesaran (2006) Common Correlated Effect estimator is robust to cross-sectionally weakly dependant processes such as SMA and multifactor structures. Consistency is obtained in N alone.

Appendix C: Data Sources

The Belgian CPI data set :

The Belgian CPI data set contains monthly individual price reports collected by the Federal Public Service "Economy, SMEs, Self-Employed and Energy" for the computation of the Belgian National and Harmonized Index of Consumer Prices. In its complete version, it covers the 1989:01 - 2005:12 period. Considering the whole sample, would have involved analyzing more than 20,000,000 price records. For this project, we restricted the analysis to the product categories included in the Belgian CPI basket for the base year 1996, and restricted our period of observation to the 1994:07 - 2003:02 period. Our data set covers only the product categories for which the prices are recorded throughout the entire year in a decentralized way, i.e. 65.5%. of the Belgian CPI basket for the base year 1996. The remaining 34.5% relate to product categories that are monitored centrally by the Federal Public Services, such as housing rents, electricity, gas, telecommunications, health care, newspapers and insurance services and to product categories that are not available for sale during the entire year (some fruits and vegetables, winter and summer fees in tennis club). Price reports take into account all types of rebates and promotions, except those relating to the winter and summer sales period, which typically take place in January and July. In addition to the price records, the Belgian CPI data sets provides information on the location of the seller, a seller identifier, the packaging of the product (in order to identify promotions in quantity) and the brand of the product. For all products, the price concept used in this paper correspond to the log of price per unit.

The French CPI data set :

The French CPI data set contains more than 13,000,000 monthly individual price records collected by the INSEE for the computation of the French National and Harmonized Index of Consumer Prices. It covers the period July 1994:07 - February 2003. This data set covers 65.5%. of the French CPI basket. Indeed, the prices of some categories of goods and services are not available in our sample: centrally collected prices - of which major items are car prices and administered or public utility prices (e.g. electricity)- as well as other types of products such as fresh food and rents. At the COICOP 5-digit level, we have access to 128 product categories out of 160 in the CPI. As a result, the coverage rate is above 70% for food and non-energy industrial goods, but closer to 50% in the services, since a large part of services prices are centrally collected, e.g. for transport or administrative or financial services.

Each individual price quote consists of the exact price level of a precisely defined product. What is meant by "product" is 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, and to recover information on the type of outlet (hypermarket, supermarket, department store, specialized store, corner shop, service shop, etc.), the category of product and the regional area where the outlet is located (for confidentiality reasons, a more precise location of outlets was not made available to us). The sequences of records corresponding to such defined individual products are referred to as price trajectories. Importantly, if in a given outlet a given product is definitively 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. On top of the above mentioned information, the following additional information is recorded : the year and month of the record, a qualitative "type of record" code and (when relevant) the quantity sold. When relevant, division by the indicator of the quantity is used in order to recover a consistent price per unit.

Confidentiality data restrictions

Due to strong confidentiality restrictions, we are not allowed to provide anyone with the micro price reports underlying this work. However, a data set containing simulated data and the MatLab code of the estimation procedures are available on request. A SAS code is also available.

Appendix D - Detailed Estimates by Product Categories

The results for Belgium are given in Table D.1, and for France in Table D.2. The estimated values of the different parameters are presented in columns (2) to (9). Column (10) provides the correlation between the estimated component $\widehat{f}_t$ and the product category price index. Columns (11) to (13) provide descriptive statistics of the data set (the average number of observations per month, $\overline{N}$, the frequency of price changes, $Freq$, and the average size of price changes in absolute term, $|\Delta p|$. Columns (14) to (15) provide averages of the frequency of price changes, $\widehat{Freq}$, and the average size of price changes in absolute term, $\widehat{|\Delta p|}$, obtained on the basis of simulated data generated using the estimated structural parameters and the estimated f_t of each product categories. The simulation exercise is replicated 1000 times. The name of product categories for which the model fits the data poorly is right-aligned.

Table D.1 - Estimation Results - Belgium

Product category	ML Estimates									Observed data			Simulated data	
	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Energy														
Butane	0.007	0.006	0.040	0.215	0.028	0.880	0.000	0.049	0.998	128	0.742	0.029	0.909	0.055
Gasoline 1000-2000 liters	0.025	0.011	0.036	0.040	0.063	0.930	0.003	0.073	0.990	144	0.730	0.073	0.747	0.080
Eurosuper (RON 95)	0.009	0.002	0.014	0.019	0.022	0.790	0.001	0.026	0.999	247	0.720	0.027	0.771	0.030
Perishable food														
Paprika pepper	0.046	0.032	0.202	0.117	0.145	0.774	0.003	0.249	0.983	443	0.842	0.282	0.891	0.305
Skate (wing)	0.038	0.034	0.141	0.145	0.029	0.657	0.004	0.144	0.987	183	0.688	0.136	0.845	0.186
Oranges	0.079	0.063	0.159	0.109	0.040	0.734	0.016	0.164	0.993	447	0.619	0.183	0.731	0.232
Carrots	0.114	0.088	0.173	0.125	0.085	0.751	0.028	0.193	0.992	443	0.574	0.224	0.669	0.275
Apples, Granny Smith	0.088	0.068	0.126	0.075	0.053	0.744	0.023	0.137	0.996	443	0.564	0.170	0.649	0.200
Kiwis	0.141	0.112	0.203	0.135	0.046	0.863	0.039	0.208	0.988	443	0.542	0.244	0.639	0.310
Margarine (super)	0.135	0.087	0.046	0.132	0.010	0.913	0.158	0.047	0.884	438	0.189	0.053	0.196	0.080
Turkey filet	0.282	0.159	0.098	0.114	0.018	0.396	0.326	0.100	0.958	448	0.154	0.141	0.172	0.182
Sirloin	0.166	0.094	0.058	0.096	0.011	0.369	0.190	0.059	0.906	509	0.149	0.082	0.173	0.107
Cheese (Gouda type)	0.343	0.190	0.115	0.168	0.019	0.833	0.412	0.117	0.906	491	0.143	0.168	0.160	0.214
Full-fat fruit yoghurt	0.276	0.162	0.080	0.195	0.011	0.423	0.385	0.081	0.914	414	0.141	0.090	0.145	0.140
Butter	0.171	0.097	0.050	0.105	0.012	0.725	0.232	0.051	0.947	474	0.132	0.067	0.146	0.092
Emmentaler	0.285	0.155	0.087	0.138	0.021	0.801	0.371	0.089	0.901	353	0.126	0.124	0.142	0.165
Sausage	0.390	0.212	0.117	0.099	0.013	0.902	0.527	0.118	0.984	496	0.113	0.149	0.137	0.217
Cheese (Edam type)	0.322	0.173	0.086	0.135	0.017	0.805	0.483	0.088	0.966	334	0.109	0.112	0.119	0.160

Table D.1 - Estimation Results - Belgium (continued)

	ML Estimates									Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Belgian waffle	0.400	0.212	0.088	0.230	0.019	0.407	0.726	0.090	0.787	441	0.094	0.112	0.094	0.159
Country paté	0.396	0.203	0.098	0.133	0.018	0.631	0.643	0.100	0.959	484	0.090	0.130	0.100	0.184
Rice pudding	0.457	0.216	0.075	0.218	0.024	0.789	1.084	0.079	0.927	283	0.053	0.096	0.054	0.143
Pastry(carré glacé)	0.391	0.172	0.059	0.103	0.019	0.929	1.004	0.062	0.966	263	0.041	0.095	0.042	0.123
Pastry (éclair)	0.444	0.194	0.070	0.101	0.031	0.505	1.050	0.077	0.903	263	0.040	0.105	0.042	0.148
Swiss cake	0.506	0.223	0.065	0.267	0.021	−0.093	1.531	0.068	0.932	278	0.036	0.091	0.034	0.125
Whole wheat bread	0.129	0.055	0.020	0.140	0.013	0.777	0.283	0.024	0.935	269	0.033	0.037	0.044	0.049
Special bread	0.398	0.181	0.031	0.468	0.027	0.662	1.576	0.041	0.773	298	0.028	0.047	0.029	0.067
Bread roll	0.583	0.242	0.072	0.157	0.017	0.887	1.875	0.074	0.966	269	0.026	0.128	0.027	0.152
Non perishable food														
Frankfurters	0.237	0.154	0.071	0.142	0.017	0.775	0.315	0.073	0.861	369	0.175	0.076	0.176	0.122
Biscuits	0.225	0.146	0.067	0.188	0.019	0.863	0.297	0.070	0.984	444	0.175	0.076	0.175	0.116
Fruit juice	0.255	0.153	0.080	0.235	0.018	0.769	0.324	0.082	0952	475	0.162	0.106	0.167	0.144
Fishcakes	0.282	0.161	0.081	0.175	0.027	0.717	0.380	0.085	0.914	377	0.143	0.123	0.145	0.151
Val de Loire wine	0.310	0.182	0.086	0.216	0.007	0.923	0.455	0.086	0.963	349	0.136	0.101	0.140	0.149
Ice cream	0.321	0.176	0.090	0.208	0.025	0.805	0.450	0.094	0.962	318	0.126	0.136	0.133	0.170
Tinned apricot halves	0.284	0.156	0.076	0.161	0.019	0.827	0.420	0.078	0.940	398	0.118	0.099	0.125	0.140
Tinned tomatoes, peeled	0.450	0.252	0.107	0.320	0.025	0.662	0.753	0.110	0.963	457	0.113	0.128	0.113	0.192
Tinned peas	0.363	0.196	0.094	0.228	0.020	0.860	0.560	0.096	0.961	465	0.112	0.128	0.117	0.173
Tobacco	0.106	0.056	0.012	0.185	0.006	0.719	0.346	0.013	0.998	243	0.098	0.035	0.088	0.040

Table D.1 - Estimation Results - Belgium (continued)

	ML Estimates									Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\|\Delta p\|$	$Freq$	$\|\Delta p\|$
Sausage	0.444	0.233	0.112	0.180	0.007	0.962	0.717	0.112	0.998	479	0.093	0.134	0.105	0.205
Lemonade	0.431	0.212	0.089	0.183	0.024	0.737	0.824	0.092	0.536	295	0.068	0.106	0.070	0.157
Non durable goods														
Roses	0.078	0.034	0.180	0.210	0.044	1.190	0.013	0.185	0.979	160	0.678	0.218	0.781	0.270
Chrysanthemums	0.082	0.041	0.152	0.150	0.041	0.711	0.017	0.157	0.987	150	0.622	0.192	0.725	0.235
Compact Disc	0.150	0.097	0.064	0.070	0.013	0.912	0.141	0.065	0.949	173	0.217	0.083	0.240	0.113
Hair spray	0.102	0.157	0.140	0.165	0.005	0.722	0.030	0.140	0.942	363	0.154	0.063	0.599	0.200
Cat food	0.212	0.121	0.066	0.162	0.019	0.913	0.268	0.069	0.867	371	0.148	0.097	0.155	0.122
Nail polish	0.317	0.171	0.064	0.172	0.015	0.873	0.624	0.066	0.990	255	0.094	0.072	0.093	0.118
Water-based paint	0.349	0.182	0.053	0.169	0.007	0.951	0.929	0.054	0.998	217	0.069	0.058	0.068	0.097
Oil-based paint	0.400	0.206	0.061	0.192	0.005	0.825	1.067	0.061	0.997	185	0.066	0.061	0.062	0.104
Water charge	0.488	0.242	0.067	0.643	0.026	0.598	1.353	0.072	0.846	69	0.059	0.057	0.056	0.130
Engine oil	0.575	0.272	0.082	0.246	0.004	0.956	1.644	0.082	0.997	210	0.047	0.079	0.047	0.151
Dracaena	0.613	0.282	0.087	0.441	0.004	0.770	1.762	0.087	0.926	131	0.044	0.071	0.039	0.150
Dry battery	0.933	0.416	0.129	0.354	0.007	0.955	2.751	0.129	0.985	251	0.040	0.126	0.038	0.247
Wool suit	0.405	0.188	0.052	0.224	0.002	0.660	1.286	0.052	0.757	186	0.040	0.039	0.037	0.086
Infants' anorak (9 month)	0.148	0.102	0.055	0.187	0.004	0.819	0.162	0.055	−0.627	185	0.030	0.073	0.221	0.092
Men's socks	0.500	0.203	0.068	0.254	0.003	0.942	1.499	0.068	0.993	239	0.030	0.073	0.025	0.137
Dress fabric	0.115	0.044	0.058	0.143	0.003	0.819	0.093	0.058	0.990	139	0.029	0.035	0.213	0.124
Men's T shirt	0.170	0.131	0.087	0.225	0.004	0.887	0.135	0.087	0.942	232	0.028	0.103	0.312	0.144

Table D.1 - Estimation Results - Belgium (continued)

Product category	ML Estimates									Observed data			Simulated data	
	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Color film, 135-24	0.315	0.131	0.045	0.148	0.002	0.864	0.899	0.045	0.539	174	0.027	0.056	0.027	0.082
Zip fastener	0.210	0.085	0.022	0.063	0.008	0.666	0.766	0.023	0.977	204	0.024	0.048	0.023	0.054
Durable goods														
LaserJet printer	0.489	0.307	0.113	0.221	0.042	0.774	0.810	0.120	0.575	68	0.141	0.084	0.138	0.197
VCR, four-head	0.596	0.311	0.096	0.208	0.029	0.748	1.445	0.100	0.987	192	0.078	0.097	0.074	0.186
Compact hi-fi system	0.587	0.293	0.089	0.250	0.006	0.994	1.577	0.089	0.994	185	0.062	0.077	0.059	0.162
Natural gas heater	0.320	0.160	0.046	0.150	0.018	0.653	0.847	0.049	0.979	165	0.062	0.052	0.061	0.092
Calculator	0.727	0.352	0.134	0.305	0.007	1.005	1.608	0.134	0.959	152	0.057	0.124	0.062	0.240
Toaster	0.395	0.193	0.059	0.174	0.005	0.941	1.076	0.059	0.871	215	0.056	0.064	0.051	0.100
Suitcase	0.554	0.283	0.063	0.186	0.008	0.845	1.972	0.064	0.983	115	0.056	0.061	0.049	0.102
Electric coffee machine	0.443	0.219	0.070	0.203	0.005	0.900	1.142	0.070	0.770	225	0.056	0.061	0.055	0.118
Children's bicycle	0.458	0.221	0.066	0.159	0.020	0.419	1.240	0.069	0.958	154	0.054	0.066	0.052	0.124
Electric fryer	0.553	0.264	0.080	0.221	0.003	0.968	1.559	0.080	0.564	221	0.049	0.066	0.046	0.135
Dictionary	0.583	0.259	0.100	0.324	0.033	0.659	1.317	0.105	0.871	162	0.046	0.157	0.049	0.208
Bed, slatted base	0.538	0.248	0.065	0.269	0.018	0.577	1.752	0.067	0.847	163	0.040	0.056	0.036	0.115
Stainless steel pan	0.609	0.277	0.082	0.365	0.004	0.905	1.844	0.082	0.993	215	0.037	0.067	0.037	0.143
Hammer	0.888	0.406	0.093	0.263	0.016	0.687	3.409	0.094	0.963	185	0.036	0.065	0.032	0.161
Glass, 4 mm	0.422	0.185	0.055	0.152	0.009	0.933	1.305	0.056	0.990	100	0.035	0.078	0.036	0.117
Dining room oak furniture	0.105	0.162	0.125	0.161	0.010	0.894	0.036	0.125	0.855	168	0.032	0.040	0.566	0.180
Spherical glasses	0.641	0.293	0.074	0.219	0.007	0.549	2.257	0.074	0.924	157	0.032	0.056	0.032	0.123

Table D.1 - Estimation Results - Belgium (continued)

	ML Estimates									Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$Freq$	$\lvert\Delta p\rvert$
Wallet	0.140	0.085	0.047	0.177	0.005	0.891	0.169	0.047	0.976	162	0.032	0.050	0.182	0.084
Torus glasses	0.502	0.223	0.055	0.212	0.015	−0.003	1.802	0.057	0.864	159	0.031	0.055	0.028	0.097
Cup and saucer	0.109	0.167	0.086	0.163	0.005	0.880	0.056	0.086	0.971	210	0.030	0.071	0.469	0.122
Services														
Hourly rate, painter	0.261	0.127	0.033	0.167	0.010	0.544	0.804	0.035	0.983	129	0.055	0.040	0.051	0.069
Hourly rate, garage mech.	0.357	0.171	0.049	0.140	0.004	0.965	1.059	0.049	0.996	183	0.053	0.059	0.052	0.101
Annual cable subscription	0.133	0.062	0.019	0.068	0.013	0.711	0.313	0.023	0.882	66	0.051	0.029	0.055	0.047
Repair of central heating	0.371	0.175	0.068	0.153	0.004	0.855	0.825	0.068	0.995	123	0.051	0.053	0.059	0.128
Hourly rate, plumber	0.308	0.148	0.043	0.146	0.006	0.735	0.893	0.043	0.997	132	0.051	0.050	0.050	0.083
Sole meunière	0.429	0.194	0.053	0.205	0.019	0.530	1.338	0.056	0.950	153	0.040	0.066	0.038	0.106
Dry cleaning, shirt	0.520	0.232	0.069	0.180	0.005	0.995	1.596	0.069	0.997	147	0.036	0.068	0.035	0.127
Pepper steak	0.359	0.156	0.041	0.134	0.004	0.978	1.278	0.041	0.994	160	0.034	0.053	0.033	0.082
Permanent wave	0.594	0.266	0.064	0.274	0.003	0.919	2.245	0.064	0.986	198	0.034	0.066	0.031	0.121
Domestic service	0.404	0.179	0.045	0.127	0.006	0.824	1.467	0.045	0.976	143	0.033	0.050	0.032	0.092
Self-service meal	0.285	0.124	0.030	0.139	0.019	0.331	0.928	0.036	0.573	94	0.033	0.045	0.028	0.062
Parking spot in a garage	0.126	0.146	0.037	0.185	0.006	0.944	0.173	0.038	0.952	147	0.032	0.059	0.290	0.053
Wheel balancing	0.756	0.332	0.109	0.278	0.003	0.950	2.140	0.109	0.986	179	0.032	0.075	0.034	0.193
Special beer	0.545	0.239	0.054	0.146	0.009	0.939	2.212	0.055	0.992	221	0.030	0.084	0.028	0.110
Aperitif	0.486	0.210	0.051	0.191	0.006	0.942	1.878	0.051	0.998	227	0.029	0.084	0.029	0.111
Videotape rental	0.639	0.248	0.060	0.240	0.005	0.889	2.768	0.060	0.867	116	0.018	0.085	0.012	0.103

Table D.2 - Estimation Results - France

Product category	ML Estimates									Observed data			Simulated data	
	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Energy														
Eurosuper	0.004	0.003	0.018	0.026	0.016	0.792	0.000	0.024	0.993	1267	0.799	0.020	0.898	0.027
Gasoil	0.007	0.005	0.034	0.284	0.019	0.796	0.000	0.039	0.987	505	0.798	0.026	0.887	0.043
Perishable food														
Roast beef	0.225	0.147	0.096	0.196	0.009	0.742	0.214	0.096	0.985	1540	0.210	0.100	0.211	0.157
Beff burger	0.235	0.146	0.095	0.257	0.015	0.716	0.235	0.096	0.942	368	0.195	0.113	0.194	0.159
Lamb	0.257	0.173	0.117	0.300	0.017	0.933	0.227	0.119	0.994	659	0.233	0.131	0.237	0.196
Fresh pork meat	0.278	0.196	0.151	0.203	0.029	0.9090	0.206	0.153	0.694	915	0.270	0.182	0.285	0.248
Ham	0.228	0.163	0.130	0.281	0.017	0.921	0.162	0.131	0.976	976	0.287	0.152	0.297	0.210
Sausages	0.297	0.196	0.128	0.411	0.015	0.946	0.281	0.128	0.889	440	0.215	0.136	0.214	0.209
Chicken	0.163	0.119	0.093	0.317	0.022	0.955	0.114	0.095	0.961	971	0.257	0.122	0.319	0.160
Rabbit, game	0.123	0.100	0.115	0.105	0.023	0.870	0.053	0.117	0.920	204	0.436	0.148	0.477	0.182
Crème fraiche	0.160	0.113	0.071	0.312	0.006	0.971	0.147	0.071	0.756	231	0.211	0.163	0.242	0.118
Milky desserts	0.140	0.096	0.054	0.237	0.010	0.900	0.146	0.055	0.964	226	0.218	0.049	0.211	0.091
Cottage cheese	0.153	0.107	0.068	0.327	0.008	0.950	0.138	0.069	0.993	423	0.239	0.062	0.233	0.109
Processed cheese	0.132	0.097	0.066	0.385	0.015	0.955	0.105	0.067	0.978	84	0.275	0.061	0.269	0.106
Butter	0.151	0.111	0.084	0.138	0.007	0.941	0.110	0.085	0.995	508	0.257	0.074	0.278	0.130
Non perishable food														
Rusks and grilled breads	0.217	0.140	0.083	0.222	0.014	0.880	0.229	0.084	0.883	129	0.186	0.080	0.187	0.137
Flour	0.164	0.109	0.067	0.285	0.010	0.912	0.163	0.068	0.969	219	0.213	0.067	0.208	0.110

Table D.2 - Estimation Results - France (continued)

	ML Estimates									Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Pasta	0.123	0.236	0.126	0.321	0.016	0.960	0.048	0.127	0.793	323	0.178	0.071	0.529	0.206
Canned vegetables	0.279	0.174	0.094	0.320	0.008	0.946	0.339	0.094	0.946	1007	0.169	0.089	0.164	0.158
Sugar	0.126	0.075	0.031	0.096	0.005	0.894	0.206	0.031	0.965	193	0.170	0.029	0.125	0.065
Chocolate	0.188	0.130	0.076	0.233	0.010	0.837	0.190	0.076	0.984	381	0.212	0.063	0.212	0.126
Desserts	0.210	0.127	0.057	0.314	0.021	0.827	0.298	0.061	0.942	51	0.148	0.055	0.140	0.104
Coffee	0.202	0.142	0.087	0.233	0.011	0.907	0.190	0.088	0.933	544	0.232	0.077	0.238	0.150
Tea	0.181	0.116	0.051	0.248	0.013	0.639	0.255	0.052	0.991	92	0.174	0.041	0.162	0.094
Fruit juices	0.192	0.123	0.072	0.228	0.011	0.455	0.207	0.073	0.920	205	0.191	0.075	0.190	0.122
Whisky	0.070	0.056	0.037	0.103	0.007	0.553	0.053	0.038	0.437	153	0.303	0.029	0.294	0.058
Pet food	0.265	0.177	0.083	0.352	0.044	1.010	0.305	0.094	0.913	258	0.180	0.047	0.183	0.151
Non durable goods														
Fabrics	0.610	0.281	0.120	0.591	0.049	−0.597	1.173	0.129	0.516	124	0.066	0.194	0.054	0.230
Men coat	0.317	0.146	0.102	0.405	0.037	0.179	0.379	0.108	0.769	61	0.132	0.231	0.124	0.234
Men suits	0.333	0.168	0.113	0.355	0.036	0.709	0.379	0.119	0.726	45	0.167	0.235	0.159	0.251
Men trousers	0.411	0.207	0.121	0.331	0.031	−0.053	0.551	0.125	0.873	243	0.119	0.199	0.107	0.231
Skirt	0.457	0.220	0.139	0.508	0.049	0.445	0.579	0.147	0.903	60	0.139	0.308	0.129	0.319
Dress	0.561	0.268	0.164	0.753	0.094	0.663	0.679	0.189	0.544	23	0.145	0.391	0.130	0.403
Women trousers	0.456	0.239	0.128	0.378	0.040	0.187	0.633	0.134	0.856	164	0.119	0.195	0.109	0.240
Women jacket	0.451	0.220	0.136	0.491	0.054	0.739	0.569	0.146	0.816	51	0.143	0.302	0.130	0.311
Children trousers	0.467	0.247	0.138	0.356	0.037	0.652	0.620	0.143	0.502	122	0.129	0.212	0.118	0.256

Table D.2 - Estimation Results - France (continued)

	ML Estimates									Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Children suits	0.551	0.255	0.078	0.455	0.186	0.191	0.614	0.201	0.503	6	0.110	0.329	0.092	0.371
Men shirts	0.452	0.231	0.140	0.361	0.033	−0.429	0.580	0.144	0.824	182	0.138	0.258	0.128	0.284
Men socks	0.521	0.251	0.102	0.399	0.042	0.269	1.000	0.111	0.536	88	0.071	0.128	0.057	0.181
Men sweater	0.527	0.269	0.136	0.625	0.038	0.234	0.805	0.141	0.845	196	0.104	0.196	0.090	0.245
Women sweater	0.510	0.244	0.133	0.689	0.056	−0.530	0.735	0.145	0.686	113	0.101	0.256	0.090	0.274
Children sweater	0.535	0.261	0.136	0.528	0.065	0.774	0.774	0.151	0.354	75	0.102	0.243	0.089	0.272
Babies clothes	0.747	0.361	0.124	0.663	0.089	0.610	1.494	0.153	0.279	35	0.079	0.208	0.062	0.281
Men shoes	0.526	0.263	0.116	0.449	0.039	−0.213	0.921	0.122	0.803	195	0.088	0.161	0.076	0.215
Women shoes	0.534	0.266	0.134	0.408	0.038	0.846	0.838	0.139	0.518	223	0.105	0.234	0.094	0.274
Children shoes	0.585	0.282	0.140	0.346	0.049	−0.753	0.943	0.148	0.737	87	0.095	0.244	0.082	0.285
Blankets and coverlets	0.392	0.200	0.105	0.569	0.028	−0.094	0.580	0.108	0.562	163	0.112	0.157	0.094	0.187
Fabrics for furniture	0.463	0.235	0.091	0.489	0.033	0.093	0.901	0.097	0.515	145	0.085	0.109	0.070	0.167
Batteries	0.309	0.186	0.077	0.277	0.013	0.714	0.500	0.078	0.767	299	0.139	0.067	0.128	0.145
Car tyres	0.176	0.122	0.070	0.229	0.013	0.930	0.178	0.071	0.977	286	0.248	0.071	0.235	0.130
Musical disks	0.240	0.161	0.083	0.308	0.009	0.882	0.280	0.084	−0.857	277	0.12	0.106	0.197	0.160
Blank tapes and disks	0.364	0.199	0.086	0.379	0.016	0.237	0.618	0.087	0.560	277	0.105	0.073	0.089	0.145
Flowers	0.167	0.121	0.086	0.398	0.019	−0.674	0.129	0.088	0.880	64	0.273	0.083	0.285	0.143
Children books	0.363	0.186	0.060	0.408	0.020	0.588	0.854	0.063	0.949	150	0.076	0.049	0.063	0.113
Newspapers	0.100	0.043	0.012	0.036	0.013	0.813	0.229	0.018	0.961	86	0.050	0.036	0.048	0.042
Paper articles	0.511	0.285	0.126	0.498	0.035	0.925	0.813	0.131	0.836	217	0.116	0.132	0.107	0.228

TABLE D.2 - ESTIMATION RESULTS - FRANCE (CONTINUED)

	ML Estimates									Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$Freq$	$\lvert\Delta p\rvert$
Leather articles	0.365	0.188	0.077	0.404	0.031	0.424	0.654	0.083	0.759	165	0.094	0.095	0.078	0.146
Babies apparel	0.324	0.176	0.078	0.334	0.030	0.027	0.512	0.084	0.816	65	0.111	0.092	0.098	0.142
Durable goods														
Box-mattress	0.259	0.148	0.104	0.412	0.028	0.560	0.255	0.107	−0.282	72	0.209	0.166	0.191	0.190
Armchairs and canapes	0.267	0.166	0.097	0.481	0.022	0.916	0.294	0.099	−0.699	249	0.195	0.115	0.178	0.161
Washing machine	0.208	0.113	0.049	0.231	0.017	0.655	0.342	0.052	0.898	107	0.110	0.061	0.098	0.120
Vacuum-cleaner	0.362	0.190	0.083	0.431	0.026	0.687	0.613	0.087	0.416	125	0.106	0.092	0.086	0.146
Electrical tools	0.327	0.178	0.069	0.436	0.025	0.821	0.592	0.074	0.055	126	0.110	0.064	0.086	0.123
Bicycles	0.258	0.146	0.063	0.309	0.026	0.676	0.396	0.068	0.666	81	0.136	0.070	0.114	0.118
Trailor	0.506	0.319	0.113	0.634	0.063	0.803	0.811	0.129	−0.110	22	0.162	0.091	0.146	0.245
Phone set	0.220	0.123	0.060	0.290	0.020	0.841	0.310	0.064	0.987	143	0.148	0.082	0.135	0.115
TV set	0.243	0.146	0.052	0.281	0.056	0.911	0.314	0.077	0.912	12	0.167	0.096	0.153	0.132
Video camera	0.161	0.088	0.029	0.178	0.021	0.997	0.297	0.036	0.957	40	0.101	0.033	0.088	0.061
Music instrument	0.468	0.259	0.094	0.815	0.21	0.564	0.929	0.096	0.902	179	0.105	0.057	0.077	0.137
Electrical razor	0.436	0.251	0.093	0.636	0.046	0.800	0.751	0.103	0.777	38	0.127	0.077	0.103	0.167
Jewellery	0.373	0.205	0.086	0.325	0.019	0.977	0.645	0.088	0.870	342	0.109	0.079	0.095	0.154
Services														
Shoe repair	0.285	0.145	0.038	0.185	0.034	0.856	0.648	0.051	−0.073	93	0.069	0.044	0.060	0.100
Hourly rate in a garage	0.146	0.083	0.031	0.122	0.008	0.673	0.271	0.032	0.980	1205	0.116	0.031	0.110	0.064
Car rent	0.443	0.240	0.082	0.363	0.026	0.644	0.930	0.086	0.067	94	0.096	0.068	0.083	0.167

TABLE D.2 - ESTIMATION RESULTS - FRANCE (CONTINUED)

	ML Estimates									Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$\widehat{c}$	$\widehat{\sigma}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Moving services	0.280	0.162	0.070	0.407	0.035	0.796	0.407	0.078	0.832	58	0.147	0.088	0.131	0.140
Pet care	0.371	0.186	0.050	0.246	0.016	0.336	1.080	0.052	0.936	359	0.058	0.040	0.050	0.096
Cinemas	0.294	0.175	0.089	0.140	0.032	0.121	0.372	0.095	0.759	142	0.138	0.089	0.135	0.150
Classic lunch in rest.	0.203	0.146	0.102	0.228	0.007	0.895	0.16	0.102	0.670	3271	0.064	0.035	0.239	0.142
Coffee, hot drinks in bars	0.244	0.116	0.038	0.220	0.011	0.810	0.613	0.040	0.985	512	0.059	0.057	0.054	0.104
Beer in bars	0.255	0.125	0.038	0.189	0.010	0.859	0.676	0.039	0.983	349	0.063	0.047	0.057	0.083
Non alcool. bev. in bars	0.282	0.133	0.041	0.210	0.014	0.773	0.748	0.043	0.961	184	0.052	0.052	0.047	0.086
Full-board hotel room	0.189	0.115	0.086	0.311	0.007	0.955	0.169	0.086	0.985	183	0.159	0.086	0.208	0.144
Men hairdresser	0.267	0.128	0.041	0.159	0.009	0.889	0.689	0.042	0.982	549	0.056	0.038	0.049	0.082
Women hairdresser	0.298	0.150	0.052	0.239	0.010	0.842	0.689	0.053	0.978	409	0.070	0.041	0.059	0.095
Watch / clock repair	0.692	0.304	0.062	0.380	0.073	0.926	2.051	0.095	−0.639	88	0.036	0.081	0.027	0.161
Day-care center	0.437	0.190	0.030	0.145	0.033	0.015	1.754	0.044	−0.005	46	0.037	0.034	0.022	0.083
Home insurance	0.389	0.191	0.053	0.280	0.013	0.842	1.124	0.055	0.952	563	0.062	0.048	0.051	0.120
Car insurance	0.409	0.205	0.117	0.306	0.005	0.932	0.585	0.117	0.661	658	0.071	0.055	0.092	0.212

Appendix E - Simulation of Price Changes

In order to assess how well the model fits the data, we compare the realized frequency and average size of price changes with those obtained by simulating the model. More specifically, for each product category we simulate an unbalanced panel of price trajectories starting with p_{i0}, the observed initial value of each price trajectory i, using the estimate $\widehat{s}$, $\widehat{f_t}$ and randomly generated ε_{it}'s and s_i's with respective standard-errors $\widehat{\sigma}_\varepsilon$, $\widehat{\sigma}_s$ as well as estimated $\widehat{v}_i$. Indeed, as the true initial value p_{i0} is used as starting value of the i^{th} price trajectory, the true v_i should be used to simulate the subsequent price observations of that trajectory. Since v_i is unknown, the simulation exercise is based on an estimated $\widehat{v}_i$ which is computed by re-estimating our baseline model with trajectory specific fixed effects, keeping the other parameters of the model ($\widehat{s}$, $\widehat{\sigma}_\varepsilon$, $\widehat{\sigma}_s$, $\widehat{f_t}$) as given. The time dimension of the simulated trajectory for outlet i is set to coincide with the length of the associated realized price trajectory and the number of price trajectories in the simulated panels is given by the number of trajectories in the observed panels. The experiment is repeated 1000 times for each trajectory.