The Supplement to "Lumpy Price Adjustments: A Microeconometric Analysis"

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Abstract

This document provides supplemental materials for the paper Dhyne, Fuss, Pesaran, Sevestre (2010) "Lumpy Price Adjustments: A Microeconometric Analysis". It covers data sources, mathematical derivations and proofs, Monte Carlo simulations that shed light on the properties of the proposed estimation procedures, reports product specific estimates, and provides additional empirical results on the ability of state dependent pricing models to generate small price changes.

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1 Data Sources[1]

1.1 *The Belgian CPI data set*

The Belgian CPI data set contains monthly individual price records collected by the Belgian National Statistical Institute (NSI) for the computation of the Belgian National and Harmonized indices of Consumer Prices. In Dhyne *et al.* (2010), the analysis is restricted to the product categories included in the Belgian CPI basket for the base year 1996, and the sample period starts in July 1994 and ends in February 2003. The 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, such as housing rents, electricity, gas, telecommunications, health care, newspapers and insurance services and to seasonal product categories. Price records 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 retailer, a retailer identifier, the packaging of the product and the brand of the product. The price concept used in this article is the price per unit. This data set has been used in Aucremanne and Dhyne (2004, 2005) and in Dhyne and Konieczny (2007) and has been an input to Dhyne *et al.* (2006). Basic descriptive statistics for the product categories covered in Dhyne *et al.* (2010) are provided in Section 4 below.

As an example, Figure 1 displays 50 price trajectories[2] for oranges, taken from the Belgian sample. This figure illustrates how the different price trajectories co-move over the observation period but also the importance of idiosyncratic shocks in the pricing pattern. A closer look at three particular price trajectories (Figure 2) also illustrates the changes in the speed of price adjustment over time. In Figure 2, one may identify periods of frenetic small price changes (2nd semester of 1996) and periods of no price changes (in 2000) for the same store (dashed red trajectory), which indicates that a constant (S,s) model cannot fit this characteristic of the data and stressess the need for introducing a stochastic range of inaction in the state dependent model as it is done in Dhyne *et al.* (2010).

[1] *Confidentiality data restrictions :* We are not allowed to provide anyone with the micro price reports underlying this work.

[2] A price trajectory is the sequence of price records corresponding to a product of a given brand, quality and packaging sold in a particular outlet.

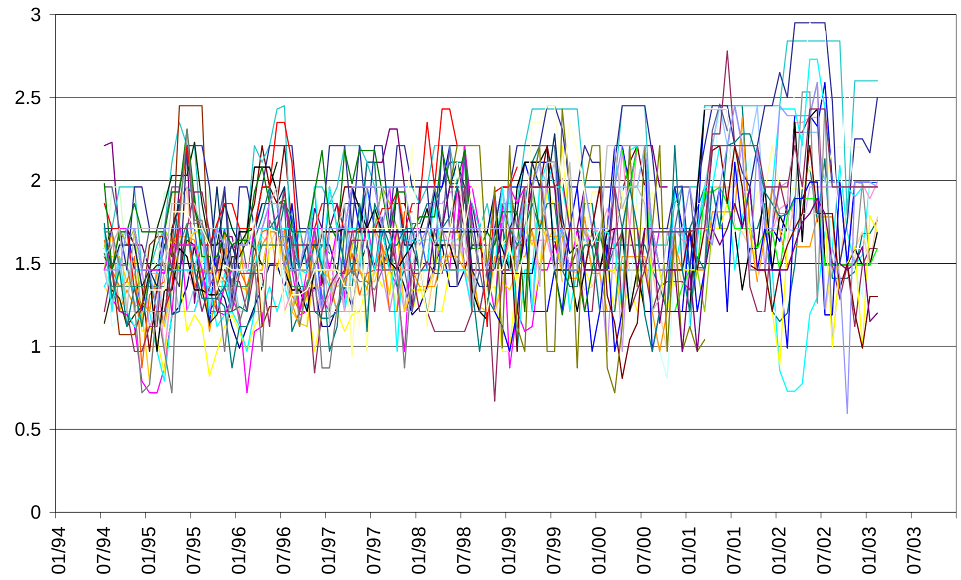

FIGURE 1. - 50 PRICE TRAJECTORIES - ORANGES (IN EUR/KG) - BELGIAN CPI

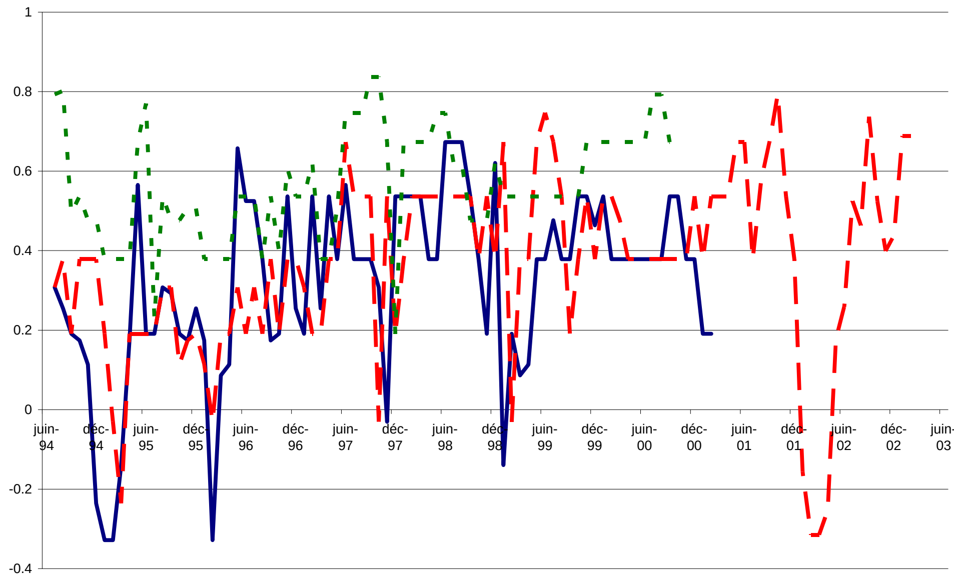

FIGURE 2. - THREE PRICE TRAJECTORIES FOR ORANGES IN BELGIUM

1.2 *The French CPI data set*

The French CPI data set contains monthly individual price records collected by the French national statistical institute (INSEE) for the computation of the French National and Harmonized Index of Consumer Prices. It covers the period July 1994 - 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: 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 seasonal fresh food products 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 and 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. 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. This data set has been used in Baudry *et al.* (2007), Fougère *et al.* (2007), Fougère *et al.* (2010) and has been an input to Dhyne *et al.* (2006). Basic descriptive statistics for the product categories covered in Dhyne *et al.* (2010) are provided in Section 4.

50 price trajectories for men' socks taken out from the French sample are presented in Figure 3. This figure also illustrates the heterogeneity in price setting practices and the surprizing fact of long periods of constant prices followed by small price changes. This graph also illustrates the occurrence of temporary price changes in our data sets.

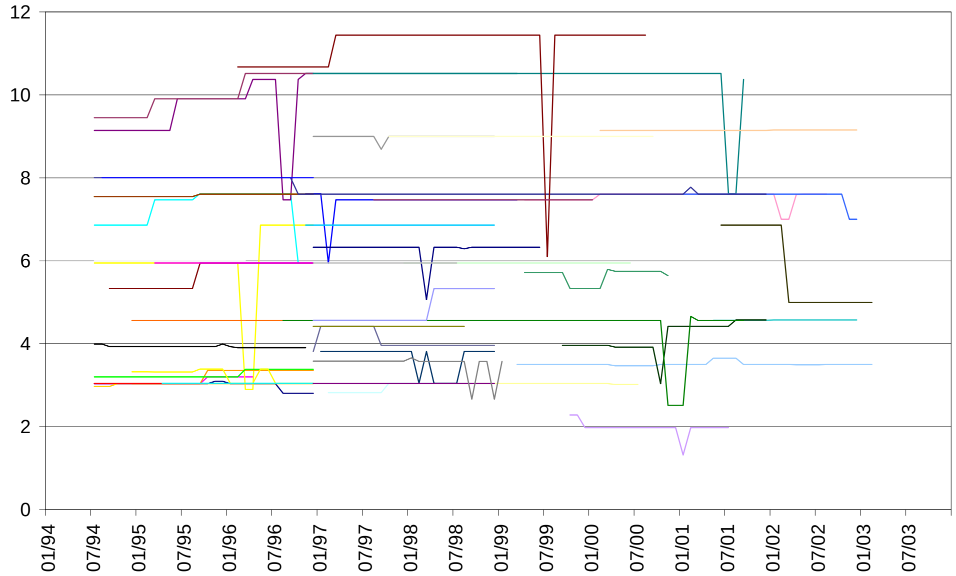

FIGURE 3 - 50 PRICE TRAJECTORIES - MEN'S SOCKS (IN EUR) - FRENCH CPI

1.3 *Advantages of CPI price records*

In the empirical literature on price adjustments, the two main sources of data are either CPI databases (f. i. Bils and Klenow, 2004, Klenow and Kryvstov, 2008, Nakamura and Steinsson, 2008 for the U.S, Dhyne *et al.*, 2006 and the different individual contributions to the ESCB Inflation Persistence Network referenced in that paper for the Euro area, Lach and Tsiddon, 1992, for Israël, or Gagnon, 2009, for Mexico) or scanner data (Levy *et al.*, 2010, Midrigan, 2010, Campbell and Eden, 2005 and Nakamura, 2008, Dossche *et al.*, 2006).

Compared to scanner data, the CPI data sets have a broader coverage. Indeed, CPI data sets not only cover products sold in supermarkets, as it is the case for scanner data, but also the prices of services. Prices in CPI data sets also concern different types of retailers, while scanner data only concern the pricing strategy of a particular supermarket chain. For instance, the Dominick's data set used in many recent papers for the US[3] (Levy *et al.*, 2010, Midrigan, 2010) only contains prices collected at Dominick's Finer Foods). Some scanner data sets contain information for more than one supermarket chain (f. i., Nakamura, 2008, uses a data set managed by AC Nielsen which covers 33 major distribution chains) but, still, they do not include other types of outlets.

Another advantage of the monthly CPI price data compared to scanner price data is that scanner price data, which are typically available at higher frequencies (daily or weekly), contain a lot of very short lived price changes, motivated mostly by strategic behaviour. When addressing the issue of the relative impact of idiosyncratic and common shocks on outlets' price-setting behaviour, using scanner data naturally increases the weight attached to the idiosyncratic components. Monthly CPI price records reflect part of this strategic pricing,[4] but because prices are collected once a month, in both large and small outlets, the relative importance of these strategic price changes is largely reduced.[5]

Finally, compared to some scanner data sets (Nakamura, 2008), CPI data sets are often available for much longer time periods.

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[3] This data set is available at http://research.chicagobooth.edu/marketing/databases/dominicks.

[4] When the statistical officer collects the price, it has to report the posted price that is applied when he visits the outlet, even if the posted price is a temporary promotion.

[5] Nakamura and Steinsson (2008) argue that the observed difference in the frequency of price changes obtained between the U.S. (Bils and Klenow, 2004, Klenow and Kryvstov, 2008) and the euro area (Dhyne et al., 2006) is explained by difference in the relative importance of temporary promotions, which seems to be more common in the US economy.

2 Some properties of the cross-sectional estimate of f_t

In Dhyne *et al.* (2010), the pricing behaviour of outlet i at time t is given by

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

where $I(a)$ is an indicator function that takes value 1 if $a > 0$, and 0 otherwise, p_{it} is the price of the product sold by outlet i at time t, f_t is the common component of the optimal price of outlet i at time t, $\mathbf{x}_{it}$ is a set of explanatory variables of the optimal price, v_i is the outlet specific random effect component of the optimal price, ε_{it} is the idiosyncratic component of the optimal price and s_{it} is the stochastic range of inaction of outlet i at time t, with

$$\begin{pmatrix} s_{it} \\ v_i \\ \varepsilon_{it} \end{pmatrix} |(f_t, \mathbf{x}_{it}', p_{i,t-1})' \backsim i.i.d.N \left(\begin{pmatrix} s \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_v^2 & 0 \\ 0 & 0 & \sigma_\varepsilon^2 \end{pmatrix} \right).$$

The estimation of the common factor f_t and of the other parameters of this model (namely s, 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 outlet specific random effect, v_i, and $\boldsymbol{\beta}$, the parameters associated with the observed explanatory variables, $\mathbf{x}_{it}$) are obtained using either an iterative procedure or maximum likelihood estimation (referred to as Full ML in Dhyne *et al.*, 2010). To obtain $\tilde{f}_t$, referred to as the cross-sectional estimates of f_t, using the iterative procedure, one needs to solve the following non-linear equation

$$\bar{p}_t = \tilde{f}_t + \bar{\mathbf{x}}_t'\boldsymbol{\beta} + \bar{g}_t(\tilde{f}_t), \quad (2)$$

where

$$\begin{aligned} \bar{p}_t &= \sum_{i=1}^N w_{it} p_{it}, \quad \bar{\mathbf{x}}_t = \sum_{i=1}^N w_{it}\mathbf{x}_{it}, \quad \bar{g}_t(f_t) = \sum_{i=1}^N w_{it} \left(g_{1,it} + g_{2,it} \right), \\ g_{1,it} &= d_{it} \left[\Phi\left(\frac{d_{it} - s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}} \right) - \Phi\left(\frac{d_{it} + s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}} \right) \right], \\ g_{2,it} &= \frac{\sigma_\xi^2}{\sqrt{\sigma_s^2 + \sigma_\xi^2}} \left[\phi\left(\frac{d_{it} - s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}} \right) - \phi\left(\frac{d_{it} + s}{\sqrt{\sigma_s^2 + \sigma_\xi^2}} \right) \right], \\ d_{it} &= f_t + \mathbf{x}_{it}'\boldsymbol{\beta} - p_{i,t-1}, \sigma_\xi^2 = \sigma_v^2 + \sigma_\varepsilon^2. \end{aligned}$$

and $\{w_{it}, i = 1, 2, .., N\}$ represent a predetermined set of weights such that $w_{it} = O(N^{-1})$, and $\sum_{i=1}^N w_{it}^2 = O(N^{-1})$.

For given values of $\boldsymbol{\theta}$, where $\boldsymbol{\theta} = (s, \boldsymbol{\beta}', \sigma_s^2, \sigma_v^2, \sigma_\varepsilon^2)'$, and for each t, Equation (2) provides a non-linear function in $\tilde{f}_t$. This equation has a unique solution as long as $s > 0$. 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 $N \to \infty$.

2.1 Uniqueness of the solution of Equation (2)

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

$$\begin{aligned}
\widetilde{\Delta p}_{it} &= z_{it}(f_t) + z_{it}(f_t)\left[\Phi\left(z_{it}(f_t) - \widetilde{s}\right) - \Phi\left(z_{it}(f_t) + \widetilde{s}\right)\right] \quad (3)\\
&+\delta^2\left[\phi\left(z_{it}(f_t) - \widetilde{s}\right) - \phi\left(z_{it}(f_t) + \widetilde{s}\right)\right] + \tilde{\eta}_{it}. \quad (4)
\end{aligned}$$

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

$$\begin{aligned}
\Psi(\tilde{f}_t) &= \sum_{i=1}^{N} w_{it}\{z_{it}(\tilde{f}_t) + z_{it}(\tilde{f}_t)\left[\Phi\left(z_{it}(\tilde{f}_t) - \widetilde{s}\right) - \Phi\left(z_{it}(\tilde{f}_t) + \widetilde{s}\right)\right] \quad (5)\\
&\quad + \delta^2\left[\phi\left(z_{it}(\tilde{f}_t) - \widetilde{s}\right) - \phi\left(z_{it}(\tilde{f}_t) + \widetilde{s}\right)\right]\} - a_{Nt} \quad (6)\\
&= 0, \quad (7)
\end{aligned}$$

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

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

Also the first derivative of $\Psi(f_t)$ is given by[6]

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

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

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 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.

2.2 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

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

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

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

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

3 Proof Lemma 3.1 in Dhyne *et al.* (2010)

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

$$\begin{aligned}
E\left[yI(y+a)\right] &= \sigma\phi\left(\frac{a+\mu}{\sigma}\right) + \mu\Phi\left(\frac{a+\mu}{\sigma}\right), \\
E\left[\phi\left(\frac{y+a}{b}\right)\right] &= \frac{b}{\sqrt{b^2+\sigma^2}}\phi\left(\frac{a+\mu}{\sqrt{b^2+\sigma^2}}\right), \\
E_y\left[\Phi\left(\frac{y+a}{b}\right)\right] &= \Phi\left(\frac{a+\mu}{\sqrt{b^2+\sigma^2}}\right),
\end{aligned}$$

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.

Proof of Lemma 3.1.

(1) To prove $E\left[yI(y+a)\right] = \sigma\phi\left(\frac{a+\mu}{\sigma}\right) + \mu\Phi\left(\frac{a+\mu}{\sigma}\right)$ we note that

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

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

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

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

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

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

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

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

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

(3) Finally, to prove $E\left(\Phi\left(\frac{y+a}{b}\right)\right)=\Phi\left(\frac{a+\mu}{\sqrt{b^2+\sigma^2}}\right)$ note that

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

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

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

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

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

■

4 Monte Carlo Simulations

This Section presents results from three sets of Monte Carlo simulations. The first set compares the estimates of f_t obtained from the non-linear cross-section average, given in equation (7) of Dhyne *et al.* (2010), with that obtained from a simple cross-section average of the observed prices. The second aims at assessing the accuracy of the estimates proposed in Dhyne *et al.* (2010) under alternative data generating processes and sample sizes. The last two evaluate the robustness of the estimation procedures to deviations from the underlying assumptions. In particular, we consider the implications of serial correlation and cross-sectional dependence in the idiosyncratic shock for the full ML estimates.

We generate the log price series according to the baseline model, (1), simulating the common factors as a first order autoregressive process. In our reference case, the sample sizes are set at $N = 50$, $T = 50$. In Table 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.

Table 1 reports the RMSE of estimating f_t by $\overline{p}_t$ and by the non-linear cross-section average $\widetilde{f}_t$, under different frequencies of price changes. The results indicate that the non-linear cross-section average, $\widetilde{f}_t$, outperforms the linear average, $\overline{p}_t$. and that the difference between the RMSE of $\widetilde{f}_t$ and that of $\overline{p}_t$ increases as the frequency of price changes become smaller.

Results reported in Table 2 allow a comparison of the following cases: (i) with and without random effects, (ii) panels of different cross-section dimensions, N small, $N = 25$ versus $N = 50$, (iii) cases with different average frequencies of price changes (0.27 versus 0.12), (iv) the case with a small idiosyncratic component and a large common factor versus one with a large idiosyncratic component and a relatively small common component. The last case corresponds to parameter values close to the estimates based on observed data. Our simulations show that estimated parameters are close to their true values, and that the band of inaction is estimated with high precision. Not surprisingly, the estimation of the common factor gets better as the cross-section dimension increases. The results in Table 2 also suggest that the estimation of f_t improves as the frequency of price changes and the size of the common shock increase.

Our third set of Monte Carlo simulations considers the issue of serial correlation of the idiosyncratic component while the model is estimated assuming serial independence. We model ε_{it} as an AR(1) process where the variance of ε_{it} is identical to that of the base case. The results, summarized in Table 3, indicate that serial correlation in the idiosyncratic component introduces an upward bias in the estimates of s and σ_s and a small downward bias in the estimates of σ_ε. The bias is negligible for low values of the serial correlation coefficient. It remains limited for small values of ρ. The bias becomes important only as serial correlation approaches the unit root case.

The fourth 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 decisions are centralized. In order to investigate this, two alternative specifications are chosen. The first is a Spatial Moving Average Model. The second is a 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 4.

As is well known in the literature on linear factor models (Stock and Watson, 1998, Pesaran, 2006), "weak" cross sectional dependence (in the sense defined in Chudik, Pesaran and Tosetti, 2010) does not affect the consistency of the estimates of the common factors using cross section averages or principle component approaches. 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 requires further investigation.

Table 1 - Monte Carlo Simulations

s	$freq(p_{it})$	$RMSE(\widetilde{f}_t)$	$RMSE(\overline{p}_t)$
0.05	0.69	0.0082	0.0085
0.10	0.44	0.0100	0.0169
0.15	0.28	0.0133	0.0329
0.20	0.18	0.0177	0.0498
0.25	0.12	0.0244	0.0661
0.30	0.08	0.0331	0.0818
0.35	0.06	0.0445	0.0969

Notes: 1000 replications, estimation by full ML. f_t is simulated as $f_t = 0.05 + 0.90 f_{t-1} + \omega_t$, ω_t~iid $N(0, \sigma_\omega^2)$, with $\sigma_\omega = 0.1$. σ_ε is set to 0.05 and σ_v to 0.025 and σ_s to 0.01, N=50 and T=50, $\widetilde{f}_t$ is estimated using the non-linear cross section average in equation (7) of Dhyne *et al.* (2010), s is the size of the price inaction band, and $freq(p_{it})$ is the frequency of price changes.

Table 2 - Monte Carlo Simulations

Average frequency of price changes $\sim$ 0.27 with random effects						
	s	σ_ε	σ_s	σ_v		
	0.15	0.05	0.01	0.025		
	$\widehat{s}$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_s$	$\widehat{\sigma}_v$	$RMSE(\widehat{f}_t)$	$\frac{std((\widehat{f}_t)}{std(f_t)}$
$N = 50, T = 50$	0.151 (0.0014)	0.049 (0.0011)	0.011 (0.0013)	0.027 (0.0030)	0.0137	1.0018
Average frequency of price changes $\sim$ 0.27 without random effect						
	s	σ_ε	σ_s	σ_v		
	0.15	0.05	0.01	0		
	$\widehat{s}$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_s$	$\widehat{\sigma}_v$	$RMSE(\widehat{f}_t)$	$\frac{std((\widehat{f}_t)}{std(f_t)}$
$N = 50, T = 50$	0.150 (0.0013)	0.049 (0.0011)	0.007 (0.0013)		0.0118	1.0018
$N = 25, T = 50$	0.150 (0.0019)	0.048 (0.0015)	0.006 (0.0018)		0.0169	1.0052
Average frequency of price changes $\sim$ 0.12 with random effect - large common component						
	s	σ_ε	σ_s	σ_v		
	0.300	0.050	0.100	0.025		
	$\widehat{s}$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_s$	$\widehat{\sigma}_v$	$RMSE(\widehat{f}_t)$	$\frac{std((\widehat{f}_t)}{std(f_t)}$
$N = 50, T = 50$	0.302 (0.0071)	0.047 (0.0017)	0.103 (0.0055)	0.029 (0.0036)	0.0221	1.0052
Average frequency of price changes $\sim$ 0.12 with random effect - large idiosyncratic component						
	s	σ_ε	σ_s	σ_v		
	0.300	0.100	0.125	0.250		
	$\widehat{s}$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_s$	$\widehat{\sigma}_v$	$RMSE(\widehat{f}_t)$	$\frac{std((\widehat{f}_t)}{std(f_t)}$
$N = 100, T = 100$	0.307 (0.0108)	0.099 (0.0027)	0.131 (0.0080)	0.247 (0.0246)	0.0676	1.1841

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^2_ε is the variance of the idiosyncratic component, σ^2_s is the variance of s_{it} the threshold parameter for price changes, $\frac{std(\widehat{f}_t)}{std(f_t)}$ is the ratio of the standard deviation of $\widehat{f}_t$ over the standard deviation of the true f_t.

Table 3 - Monte Carlo Simulations with serially correlated idiosyncratic component

	s	σ^2_ε	σ^2_s		
	0.35	0.005625	0.010		
	$\widehat{s}$	$\widehat{\sigma^2_\varepsilon}$	$\widehat{\sigma^2_s}$	$RMSE(\widehat{f}_t)$	$\frac{std((\widehat{f}_t)}{std(f_t)}$
ρ=0	0.357 (0.020)	0.0038 (0.0005)	0.0011 (0.002)	0.0453	1.343
ρ=0.10	0.359 (0.021)	0.0037 (0.0004)	0.011 (0.002)	0.0458	1.356
ρ=0.50	0.379 (0.024)	0.0033 (0.0004)	0.013 (0.003)	0.0484	1.400
ρ=0.90	0.464 (0.042)	0.0022 (0.0004)	0.023 (0.006)	0.0545	1.425
ρ=0.95	0.510 (0.054)	0.0017 (0.0003)	0.029 (0.009)	0.0552	1.376
ρ=0.99	0.574 (0.087)	0.0012 (0.0003)	0.038 (0.015)	0.0530	1.162

Notes: 1000 replications, $N = 50$, $T = 50$, 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 0.75. 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 2.

Table 4 - Monte Carlo Simulations with cross sectionally dependent idiosyncratic component

	s	σ^2_ε	σ^2_s		
	0.35	0.005625	0.010		
	$\widehat{s}$	$\widehat{\sigma^2_\varepsilon}$	$\widehat{\sigma^2_s}$	$RMSE(\widehat{f}_t)$	$\frac{std((\widehat{f}_t)}{std(f_t)}$
no cross-sectional dependence	0.357 (0.020)	0.0038 (0.0005)	0.011 (0.011)	0.0453	1.343
SMA$^{(1)}$	0.357 (0.020)	0.0035 (0.0004)	0.011 (0.002)	0.0479	1.369
10 factors$^{(2)}$	0.357 (0.020)	0.0036 (0.0004)	0.011 (0.002)	0.0480	1.375

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

$^{(1)}$ stands for the Spatial Moving Average model $\varepsilon_{it} = x_{it} + x_{i-1,t} + x_{i+1,t}$ with x_{it}˜iid $N(0, \sigma^2_x)$.. The value of σ_x is set so that $\sigma_\varepsilon = 0.075$.

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

5 Detailed results of Dhyne *et al.* (2010)

In this section, we reproduce the estimation results obtained for the different product categories considered in Dhyne *et al.* (2010). We also present some basic statistics regarding observed price changes.

The results for Belgium are given in Table 5, and for France in Table 6.

The estimated values of the different parameters are presented in columns (2) to (7).

Column (8) provides the correlation between the estimated common component $\widehat{f_t}$ and the product category price index.

Columns (9) to (12) provide descriptive statistics of the data set (the average number of observations per month, $\overline{N}$, the frequency of price changes, $Freq$, the average size of price changes in absolute term, $|\Delta p|$, and the share of price changes which are, in absolute terms, smaller than half of the average price change, $\Delta p < \frac{\overline{\Delta p}}{2}$.

Columns (13) to (14) provide averages of the frequency of price changes, $\widehat{Freq}$, and the average size of price changes in absolute terms, $\widehat{|\Delta p|}$, obtained on the basis of simulated data generated using the estimated structural parameters and the estimated f_t of each product category. 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_{it}'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, given the other parameters of the model ($\widehat{s}$, $\widehat{\sigma}_\varepsilon$, $\widehat{\sigma}_s$, $\widehat{f_t}$). 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.

The name of product categories for which the model fits the data poorly is right-aligned.

Table 5 - Estimation Results - Belgium

	ML Estimates							Observed data				Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\Delta p < \frac{\overline{\Delta p}}{2}$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Energy													
Butane	0.007	0.006	0.040	0.215	0.028	0.880	0.998	128	0.742	0.029	0.363	0.909	0.055
Gasoline 1000-2000 liters	0.025	0.011	0.036	0.040	0.063	0.930	0.990	144	0.730	0.073	0.165	0.747	0.080
Eurosuper (RON 95)	0.009	0.002	0.014	0.019	0.022	0.790	0.999	247	0.720	0.027	0.361	0.771	0.030
Perishable food													
Paprika pepper	0.046	0.032	0.202	0.117	0.145	0.774	0.983	443	0.842	0.282	0.310	0.891	0.305
Skate (wing)	0.038	0.034	0.141	0.145	0.029	0.657	0.987	183	0.688	0.136	0.386	0.845	0.186
Oranges	0.079	0.063	0.159	0.109	0.040	0.734	0.993	447	0.619	0.183	0.289	0.731	0.232
Carrots	0.114	0.088	0.173	0.125	0.085	0.751	0.992	443	0.574	0.224	0.269	0.669	0.275
Apples, Granny Smith	0.088	0.068	0.126	0.075	0.053	0.744	0.996	443	0.564	0.170	0.283	0.649	0.200
Kiwis	0.141	0.112	0.203	0.135	0.046	0.863	0.988	443	0.542	0.244	0.281	0.639	0.310
Margarine (super)	0.135	0.087	0.046	0.132	0.010	0.913	0.884	438	0.189	0.053	0.360	0.196	0.080
Turkey filet	0.282	0.159	0.098	0.114	0.018	0.396	0.958	448	0.154	0.141	0.399	0.172	0.182
Sirloin	0.166	0.094	0.058	0.096	0.011	0.369	0.906	509	0.149	0.082	0.474	0.173	0.107
Cheese (Gouda type)	0.343	0.190	0.115	0.168	0.019	0.833	0.906	491	0.143	0.168	0.428	0.160	0.214
Full-fat fruit yoghurt	0.276	0.162	0.080	0.195	0.011	0.423	0.914	414	0.141	0.090	0.448	0.145	0.140
Butter	0.171	0.097	0.050	0.105	0.012	0.725	0.947	474	0.132	0.067	0.354	0.146	0.092
Emmentaler	0.285	0.155	0.087	0.138	0.021	0.801	0.901	353	0.126	0.124	0.381	0.142	0.165
Sausage	0.390	0.212	0.117	0.099	0.013	0.902	0.984	496	0.113	0.149	0.473	0.137	0.217
Cheese (Edam type)	0.322	0.173	0.086	0.135	0.017	0.805	0.966	334	0.109	0.112	0.462	0.119	0.160
Belgian waffle	0.400	0.212	0.088	0.230	0.019	0.407	0.787	441	0.094	0.112	0.330	0.094	0.159
Country paté	0.396	0.203	0.098	0.133	0.018	0.631	0.959	484	0.090	0.130	0.395	0.100	0.184
Rice pudding	0.457	0.216	0.075	0.218	0.024	0.789	0.927	283	0.053	0.096	0.367	0.054	0.143
Pastry(carré glacé)	0.391	0.172	0.059	0.103	0.019	0.929	0.966	263	0.041	0.095	0.280	0.042	0.123
Pastry (éclair)	0.444	0.194	0.070	0.101	0.031	0.505	0.903	263	0.040	0.105	0.274	0.042	0.148

Table 5 - Estimation Results - Belgium (continued)

	ML Estimates								Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\Delta p < \frac{\overline{\Delta p}}{2}$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Swiss cake	0.506	0.223	0.065	0.267	0.021	−0.093	0.932	278	0.036	0.091	0.287	0.034	0.125
Whole wheat bread	0.129	0.055	0.020	0.140	0.013	0.777	0.935	269	0.033	0.037	0.240	0.044	0.049
Special bread	0.398	0.181	0.031	0.468	0.027	0.662	0.773	298	0.028	0.047	0.079	0.029	0.067
Bread roll	0.583	0.242	0.072	0.157	0.017	0.887	0.966	269	0.026	0.128	0.199	0.027	0.152
Non perishable food													
Frankfurters	0.237	0.154	0.071	0.142	0.017	0.775	0.861	369	0.175	0.076	0.383	0.176	0.122
Biscuits	0.225	0.146	0.067	0.188	0.019	0.863	0.984	444	0.175	0.076	0.333	0.175	0.116
Fruit juice	0.255	0.153	0.080	0.235	0.018	0.769	0.952	475	0.162	0.106	0.328	0.167	0.144
Fishcakes	0.282	0.161	0.081	0.175	0.027	0.717	0.914	377	0.143	0.123	0.346	0.145	0.151
Val de Loire wine	0.310	0.182	0.086	0.216	0.007	0.923	0.963	349	0.136	0.101	0.369	0.140	0.149
Ice cream	0.321	0.176	0.090	0.208	0.025	0.805	0.962	318	0.126	0.136	0.325	0.133	0.170
Tinned apricot halves	0.284	0.156	0.076	0.161	0.019	0.827	0.940	398	0.118	0.099	0.317	0.125	0.140
Tinned tomatoes, peeled	0.450	0.252	0.107	0.320	0.025	0.662	0.963	457	0.113	0.128	0.323	0.113	0.192
Tinned peas	0.363	0.196	0.094	0.228	0.020	0.860	0.961	465	0.112	0.128	0.343	0.117	0.173
Tobacco	0.106	0.056	0.012	0.185	0.006	0.719	0.998	243	0.098	0.035	0.006	0.088	0.040
Sausage	0.444	0.233	0.112	0.180	0.007	0.962	0.998	479	0.093	0.134	0.411	0.105	0.205
Lemonade	0.431	0.212	0.089	0.183	0.024	0.737	0.536	295	0.068	0.106	0.347	0.070	0.157
Non durable goods													
Roses	0.078	0.034	0.180	0.210	0.044	1.190	0.979	160	0.678	0.218	0.224	0.781	0.270
Chrysanthemums	0.082	0.041	0.152	0.150	0.041	0.711	0.987	150	0.622	0.192	0.159	0.725	0.235
Compact Disc	0.150	0.097	0.064	0.070	0.013	0.912	0.949	173	0.217	0.083	0.364	0.240	0.113
Hair spray	0.102	0.157	0.140	0.165	0.005	0.722	0.942	363	0.154	0.063	0.292	0.599	0.200
Cat food	0.212	0.121	0.066	0.162	0.019	0.913	0.867	371	0.148	0.097	0.290	0.155	0.122
Nail polish	0.317	0.171	0.064	0.172	0.015	0.873	0.990	255	0.094	0.072	0.241	0.093	0.118
Water-based paint	0.349	0.182	0.053	0.169	0.007	0.951	0.998	217	0.069	0.058	0.270	0.068	0.097

Table 5 - Estimation Results - Belgium (continued)

	ML Estimates							Observed data				Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\Delta p < \frac{\overline{\Delta p}}{2}$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Oil-based paint	0.400	0.206	0.061	0.192	0.005	0.825	0.997	185	0.066	0.061	0.291	0.062	0.104
Water charge	0.488	0.242	0.067	0.643	0.026	0.598	0.846	69	0.059	0.057	0.442	0.056	0.130
Engine oil	0.575	0.272	0.082	0.246	0.004	0.956	0.997	210	0.047	0.079	0.416	0.047	0.151
Dracaena	0.613	0.282	0.087	0.441	0.004	0.770	0.926	131	0.044	0.071	0.489	0.039	0.150
Dry battery	0.933	0.416	0.129	0.354	0.007	0.955	0.985	251	0.040	0.126	0.371	0.038	0.247
Wool suit	0.405	0.188	0.052	0.224	0.002	0.660	0.757	186	0.040	0.039	0.451	0.037	0.086
Infants' anorak (9 month)	0.148	0.102	0.055	0.187	0.004	0.819	−0.627	185	0.030	0.073	0.308	0.221	0.092
Men's socks	0.500	0.203	0.068	0.254	0.003	0.942	0.993	239	0.030	0.073	0.272	0.025	0.137
Dress fabric	0.115	0.044	0.058	0.143	0.003	0.819	0.990	139	0.029	0.035	0.421	0.213	0.124
Men's T shirt	0.170	0.131	0.087	0.225	0.004	0.887	0.942	232	0.028	0.103	0.355	0.312	0.144
Color film, 135-24	0.315	0.131	0.045	0.148	0.002	0.864	0.539	174	0.027	0.056	0.373	0.027	0.082
Zip fastener	0.210	0.085	0.022	0.063	0.008	0.666	0.977	204	0.024	0.048	0.162	0.023	0.054
Durable goods													
LaserJet printer	0.489	0.307	0.113	0.221	0.042	0.774	0.575	68	0.141	0.084	0.390	0.138	0.197
VCR, four-head	0.596	0.311	0.096	0.208	0.029	0.748	0.987	192	0.078	0.097	0.296	0.074	0.186
Compact hi-fi system	0.587	0.293	0.089	0.250	0.006	0.994	0.994	185	0.062	0.077	0.358	0.059	0.162
Natural gas heater	0.320	0.160	0.046	0.150	0.018	0.653	0.979	165	0.062	0.052	0.298	0.061	0.092
Calculator	0.727	0.352	0.134	0.305	0.007	1.005	0.959	152	0.057	0.124	0.428	0.062	0.240
Toaster	0.395	0.193	0.059	0.174	0.005	0.941	0.871	215	0.056	0.064	0.410	0.051	0.100
Suitcase	0.554	0.283	0.063	0.186	0.008	0.845	0.983	115	0.056	0.061	0.191	0.049	0.102
Electric coffee machine	0.443	0.219	0.070	0.203	0.005	0.900	0.770	225	0.056	0.061	0.437	0.055	0.118
Children's bicycle	0.458	0.221	0.066	0.159	0.020	0.419	0.958	154	0.054	0.066	0.407	0.052	0.124
Electric fryer	0.553	0.264	0.080	0.221	0.003	0.968	0.564	221	0.049	0.066	0.454	0.046	0.135
Dictionary	0.583	0.259	0.100	0.324	0.033	0.659	0.871	162	0.046	0.157	0.408	0.049	0.208
Bed, slatted base	0.538	0.248	0.065	0.269	0.018	0.577	0.847	163	0.040	0.056	0.341	0.036	0.115

Table 5 - Estimation Results - Belgium (continued)

	ML Estimates							Observed data				Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\|\Delta p\|$	$\Delta p < \frac{\overline{\Delta p}}{2}$	$\widetilde{Freq}$	$\widetilde{\|\Delta p\|}$
Stainless steel pan	0.609	0.277	0.082	0.365	0.004	0.905	0.993	215	0.037	0.067	0.336	0.037	0.143
Hammer	0.888	0.406	0.093	0.263	0.016	0.687	0.963	185	0.036	0.065	0.397	0.032	0.161
Glass, 4 mm	0.422	0.185	0.055	0.152	0.009	0.933	0.990	100	0.035	0.078	0.343	0.036	0.117
Dining room oak furniture	0.105	0.162	0.125	0.161	0.010	0.894	0.855	168	0.032	0.040	0.423	0.566	0.180
Spherical glasses	0.641	0.293	0.074	0.219	0.007	0.549	0.924	157	0.032	0.056	0.540	0.032	0.123
Wallet	0.140	0.085	0.047	0.177	0.005	0.891	0.976	162	0.032	0.050	0.301	0.182	0.084
Torus glasses	0.502	0.223	0.055	0.212	0.015	−0.003	0.864	159	0.031	0.055	0.532	0.028	0.097
Cup and saucer	0.109	0.167	0.086	0.163	0.005	0.880	0.971	210	0.030	0.071	0.323	0.469	0.122
Services													
Hourly rate, painter	0.261	0.127	0.033	0.167	0.010	0.544	0.983	129	0.055	0.040	0.450	0.051	0.069
Hourly rate, garage mech.	0.357	0.171	0.049	0.140	0.004	0.965	0.996	183	0.053	0.059	0.340	0.052	0.101
Annual cable subscription	0.133	0.062	0.019	0.068	0.013	0.711	0.882	66	0.051	0.029	0.438	0.055	0.047
Repair of central heating	0.371	0.175	0.068	0.153	0.004	0.855	0.995	123	0.051	0.053	0.436	0.059	0.128
Hourly rate, plumber	0.308	0.148	0.043	0.146	0.006	0.735	0.997	132	0.051	0.050	0.350	0.050	0.083
Sole meunière	0.429	0.194	0.053	0.205	0.019	0.530	0.950	153	0.040	0.066	0.333	0.038	0.106
Dry cleaning, shirt	0.520	0.232	0.069	0.180	0.005	0.995	0.997	147	0.036	0.068	0.309	0.035	0.127
Pepper steak	0.359	0.156	0.041	0.134	0.004	0.978	0.994	160	0.034	0.053	0.300	0.033	0.082
Permanent wave	0.594	0.266	0.064	0.274	0.003	0.919	0.986	198	0.034	0.066	0.350	0.031	0.121
Domestic service	0.404	0.179	0.045	0.127	0.006	0.824	0.976	143	0.033	0.050	0.366	0.032	0.092
Self-service meal	0.285	0.124	0.030	0.139	0.019	0.331	0.573	94	0.033	0.045	0.392	0.028	0.062
Parking spot in a garage	0.126	0.146	0.037	0.185	0.006	0.944	0.952	147	0.032	0.059	0.375	0.290	0.053
Wheel balancing	0.756	0.332	0.109	0.278	0.003	0.950	0.986	179	0.032	0.075	0.472	0.034	0.193
Special beer	0.545	0.239	0.054	0.146	0.009	0.939	0.992	221	0.030	0.084	0.237	0.028	0.110
Aperitif	0.486	0.210	0.051	0.191	0.006	0.942	0.998	227	0.029	0.084	0.246	0.029	0.111
Videotape rental	0.639	0.248	0.060	0.240	0.005	0.889	0.867	116	0.018	0.085	0.505	0.012	0.103

Table 6 - Estimation Results - France

	ML Estimates							Observed data				Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\Delta p < \frac{\overline{\Delta p}}{2}$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Energy													
Eurosuper	0.004	0.003	0.018	0.026	0.016	0.792	0.993	1267	0.799	0.020	0.374	0.898	0.027
Gasoil	0.007	0.005	0.034	0.284	0.019	0.796	0.987	505	0.798	0.026	0.319	0.887	0.043
Perishable food													
Roast beef	0.225	0.147	0.096	0.196	0.009	0.742	0.985	1540	0.210	0.100	0.543	0.211	0.157
Beff burger	0.235	0.146	0.095	0.257	0.015	0.716	0.942	368	0.195	0.113	0.453	0.194	0.159
Lamb	0.257	0.173	0.117	0.300	0.017	0.933	0.994	659	0.233	0.131	0.469	0.237	0.196
Fresh pork meat	0.278	0.196	0.151	0.203	0.029	0.9090	0.694	915	0.270	0.182	0.494	0.285	0.248
Ham	0.228	0.163	0.130	0.281	0.017	0.921	0.976	976	0.287	0.152	0.501	0.297	0.210
Sausages	0.297	0.196	0.128	0.411	0.015	0.946	0.889	440	0.215	0.136	0.500	0.214	0.209
Chicken	0.163	0.119	0.093	0.317	0.022	0.955	0.961	971	0.257	0.122	0.448	0.319	0.160
Rabbit, game	0.123	0.100	0.115	0.105	0.023	0.870	0.920	204	0.436	0.148	0.425	0.477	0.182
Crème fraiche	0.160	0.113	0.071	0.312	0.006	0.971	0.756	231	0.211	0.163	0.478	0.242	0.118
Milky desserts	0.140	0.096	0.054	0.237	0.010	0.900	0.964	226	0.218	0.049	0.469	0.211	0.091
Cottage cheese	0.153	0.107	0.068	0.327	0.008	0.950	0.993	423	0.239	0.062	0.485	0.233	0.109
Processed cheese	0.132	0.097	0.066	0.385	0.015	0.955	0.978	84	0.275	0.061	0.479	0.269	0.106
Butter	0.151	0.111	0.084	0.138	0.007	0.941	0.995	508	0.257	0.074	0.570	0.278	0.130
Non perishable food													
Rusks and grilled breads	0.217	0.140	0.083	0.222	0.014	0.880	0.883	129	0.186	0.080	0.522	0.187	0.137
Flour	0.164	0.109	0.067	0.285	0.010	0.912	0.969	219	0.213	0.067	0.471	0.208	0.110
Pasta	0.123	0.236	0.126	0.321	0.016	0.960	0.793	323	0.178	0.071	0.507	0.529	0.206
Canned vegetables	0.279	0.174	0.094	0.320	0.008	0.946	0.946	1007	0.169	0.089	0.505	0.164	0.158
Sugar	0.126	0.075	0.031	0.096	0.005	0.894	0.965	193	0.170	0.029	0.405	0.125	0.065
Chocolate	0.188	0.130	0.076	0.233	0.010	0.837	0.984	381	0.212	0.063	0.547	0.212	0.126
Desserts	0.210	0.127	0.057	0.314	0.021	0.827	0.942	51	0.148	0.055	0.440	0.140	0.104

Table 6 - Estimation Results - France (continued)

	ML Estimates								Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\Delta p < \frac{\overline{\Delta p}}{2}$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Coffee	0.202	0.142	0.087	0.233	0.011	0.907	0.933	544	0.232	0.077	0.459	0.238	0.150
Tea	0.181	0.116	0.051	0.248	0.013	0.639	0.991	92	0.174	0.041	0.400	0.162	0.094
Fruit juices	0.192	0.123	0.072	0.228	0.011	0.455	0.920	205	0.191	0.075	0.470	0.190	0.122
Whisky	0.070	0.056	0.037	0.103	0.007	0.553	0.437	153	0.303	0.029	0.480	0.294	0.058
Pet food	0.265	0.177	0.083	0.352	0.044	1.010	0.913	258	0.180	0.047	0.425	0.183	0.151
Non durable goods													
Fabrics	0.610	0.281	0.120	0.591	0.049	−0.597	0.516	124	0.066	0.194	0.257	0.054	0.230
Men coat	0.317	0.146	0.102	0.405	0.037	0.179	0.769	61	0.132	0.231	0.299	0.124	0.234
Men suits	0.333	0.168	0.113	0.355	0.036	0.709	0.726	45	0.167	0.235	0.380	0.159	0.251
Men trousers	0.411	0.207	0.121	0.331	0.031	−0.053	0.873	243	0.119	0.199	0.253	0.107	0.231
Skirt	0.457	0.220	0.139	0.508	0.049	0.445	0.903	60	0.139	0.308	0.188	0.129	0.319
Dress	0.561	0.268	0.164	0.753	0.094	0.663	0.544	23	0.145	0.391	0.426	0.130	0.403
Women trousers	0.456	0.239	0.128	0.378	0.040	0.187	0.856	164	0.119	0.195	0.271	0.109	0.240
Women jacket	0.451	0.220	0.136	0.491	0.054	0.739	0.816	51	0.143	0.302	0.434	0.130	0.311
Children trousers	0.467	0.247	0.138	0.356	0.037	0.652	0.502	122	0.129	0.212	0.250	0.118	0.256
Children suits	0.551	0.255	0.078	0.455	0.186	0.191	0.503	6	0.110	0.329	0.334	0.092	0.371
Men shirts	0.452	0.231	0.140	0.361	0.033	−0.429	0.824	182	0.138	0.258	0.556	0.128	0.284
Men socks	0.521	0.251	0.102	0.399	0.042	0.269	0.536	88	0.071	0.128	0.451	0.057	0.181
Men sweater	0.527	0.269	0.136	0.625	0.038	0.234	0.845	196	0.104	0.196	0.326	0.090	0.245
Women sweater	0.510	0.244	0.133	0.689	0.056	−0.530	0.686	113	0.101	0.256	0.354	0.090	0.274
Children sweater	0.535	0.261	0.136	0.528	0.065	0.774	0.354	75	0.102	0.243	0.540	0.089	0.272
Babies clothes	0.747	0.361	0.124	0.663	0.089	0.610	0.279	35	0.079	0.208	0.474	0.062	0.281
Men shoes	0.526	0.263	0.116	0.449	0.039	−0.213	0.803	195	0.088	0.161	0.383	0.076	0.215
Women shoes	0.534	0.266	0.134	0.408	0.038	0.846	0.518	223	0.105	0.234	0.428	0.094	0.274
Children shoes	0.585	0.282	0.140	0.346	0.049	−0.753	0.737	87	0.095	0.244	0.439	0.082	0.285

Table 6 - Estimation Results - France (continued)

	ML Estimates							Observed data				Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\Delta p < \frac{\overline{\Delta p}}{2}$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Blankets and coverlets	0.392	0.200	0.105	0.569	0.028	−0.094	0.562	163	0.112	0.157	0.505	0.094	0.187
Fabrics for furniture	0.463	0.235	0.091	0.489	0.033	0.093	0.515	145	0.085	0.109	0.462	0.070	0.167
Batteries	0.309	0.186	0.077	0.277	0.013	0.714	0.767	299	0.139	0.067	0.439	0.128	0.145
Car tyres	0.176	0.122	0.070	0.229	0.013	0.930	0.977	286	0.248	0.071	0.580	0.235	0.130
Musical disks	0.240	0.161	0.083	0.308	0.009	0.882	−0.857	277	0.12	0.106	0.477	0.197	0.160
Blank tapes and disks	0.364	0.199	0.086	0.379	0.016	0.237	0.560	277	0.105	0.073	0.372	0.089	0.145
Flowers	0.167	0.121	0.086	0.398	0.019	−0.674	0.880	64	0.273	0.083	0.490	0.285	0.143
Children books	0.363	0.186	0.060	0.408	0.020	0.588	0.949	150	0.076	0.049	0.434	0.063	0.113
Newspapers	0.100	0.043	0.012	0.036	0.013	0.813	0.961	86	0.050	0.036	0.214	0.048	0.042
Paper articles	0.511	0.285	0.126	0.498	0.035	0.925	0.836	217	0.116	0.132	0.511	0.107	0.228
Leather articles	0.365	0.188	0.077	0.404	0.031	0.424	0.759	165	0.094	0.095	0.490	0.078	0.146
Babies apparel	0.324	0.176	0.078	0.334	0.030	0.027	0.816	65	0.111	0.092	0.512	0.098	0.142
Durable goods													
Box-mattress	0.259	0.148	0.104	0.412	0.028	0.560	−0.282	72	0.209	0.166	0.385	0.191	0.190
Armchairs and canapes	0.267	0.166	0.097	0.481	0.022	0.916	−0.699	249	0.195	0.115	0.393	0.178	0.161
Washing machine	0.208	0.113	0.049	0.231	0.017	0.655	0.898	107	0.110	0.061	0.414	0.098	0.120
Vacuum-cleaner	0.362	0.190	0.083	0.431	0.026	0.687	0.416	125	0.106	0.092	0.451	0.086	0.146
Electrical tools	0.327	0.178	0.069	0.436	0.025	0.821	0.055	126	0.110	0.064	0.500	0.086	0.123
Bicycles	0.258	0.146	0.063	0.309	0.026	0.676	0.666	81	0.136	0.070	0.454	0.114	0.118
Phone set	0.506	0.319	0.113	0.634	0.063	0.803	−0.110	22	0.162	0.091	0.400	0.146	0.245
TV set	0.220	0.123	0.060	0.290	0.020	0.841	0.987	143	0.148	0.082	0.295	0.135	0.115
Video camera	0.243	0.146	0.052	0.281	0.056	0.911	0.912	12	0.167	0.096	0.281	0.153	0.132
Trailor	0.161	0.088	0.029	0.178	0.021	0.997	0.957	40	0.101	0.033	0.382	0.088	0.061
Music instrument	0.468	0.259	0.094	0.815	0.21	0.564	0.902	179	0.105	0.057	0.437	0.077	0.137
Electrical razor	0.436	0.251	0.093	0.636	0.046	0.800	0.777	38	0.127	0.077	0.436	0.103	0.167

Table 6 - Estimation Results - France (continued)

	ML Estimates								Observed data			Simulated data	
Product category	$\widehat{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_\varepsilon$	$\widehat{\sigma}_v$	$\widehat{\sigma}_\omega$	$\widehat{\rho}$	$r_{f,IP}$	$\overline{N}$	$Freq$	$\lvert\Delta p\rvert$	$\Delta p < \frac{\overline{\Delta p}}{2}$	$\widetilde{Freq}$	$\widetilde{\lvert\Delta p\rvert}$
Jewellery	0.373	0.205	0.086	0.325	0.019	0.977	0.870	342	0.109	0.079	0.541	0.095	0.154
Services													
Distribution of water	0.285	0.145	0.038	0.185	0.034	0.856	−0.073	93	0.069	0.044	0.431	0.060	0.100
Hourly rate in a garage	0.146	0.083	0.031	0.122	0.008	0.673	0.980	1205	0.116	0.031	0.321	0.110	0.064
Car rent	0.443	0.240	0.082	0.363	0.026	0.644	0.067	94	0.096	0.068	0.530	0.083	0.167
Moving services	0.280	0.162	0.070	0.407	0.035	0.796	0.832	58	0.147	0.088	0.346	0.131	0.140
Pet care	0.371	0.186	0.050	0.246	0.016	0.336	0.936	359	0.058	0.040	0.379	0.050	0.096
Cinemas	0.294	0.175	0.089	0.140	0.032	0.121	0.759	142	0.138	0.089	0.676	0.135	0.150
Classic lunch in rest.	0.203	0.146	0.102	0.228	0.007	0.895	0.670	3271	0.064	0.035	0.500	0.239	0.142
Coffee, hot drinks in bars	0.244	0.116	0.038	0.220	0.011	0.810	0.985	512	0.059	0.057	0.329	0.054	0.104
Beer in bars	0.255	0.125	0.038	0.189	0.010	0.859	0.983	349	0.063	0.047	0.368	0.057	0.083
Non alcool. bev. in bars	0.282	0.133	0.041	0.210	0.014	0.773	0.961	184	0.052	0.052	0.351	0.047	0.086
Full-board hotel room	0.189	0.115	0.086	0.311	0.007	0.955	0.985	183	0.159	0.086	0.427	0.208	0.144
Men hairdresser	0.267	0.128	0.041	0.159	0.009	0.889	0.982	549	0.056	0.038	0.405	0.049	0.082
Women hairdresser	0.298	0.150	0.052	0.239	0.010	0.842	0.978	409	0.070	0.041	0.452	0.059	0.095
Watch / clock repair	0.692	0.304	0.062	0.380	0.073	0.926	−0.639	88	0.036	0.081	0.500	0.027	0.161
Day-care center	0.437	0.190	0.030	0.145	0.033	0.015	−0.005	46	0.037	0.034	0.500	0.022	0.083
Home insurance	0.389	0.191	0.053	0.280	0.013	0.842	0.952	563	0.062	0.048	0.508	0.051	0.120
Car insurance	0.409	0.205	0.117	0.306	0.005	0.932	0.661	658	0.071	0.055	0.516	0.092	0.212

The above product specific estimates have been used to assess the relative contribution of each parameter characterizing both the outlets' environment and their price-setting behavior: common (σ_ω) and idiosyncratic (σ_ε) shocks, outlets' specific effects (σ_v), band of inaction characteristics (its mean, s, and volatility σ_s). More precisely, the following quadratic surface response regressions have been estimated for explaining the log odd ratio of the frequency of price changes, their magnitude and the log odd ratio of the proportion of small price changes, using the estimated parameters for the 172 products out of the 182 considered in Dhyne *et al.* (2010) for which the model performs reasonably well. The regression equation including all the estimated parameters, their squares, and their interaction terms is given by

$$\begin{aligned} y_i &= \beta_0 + \beta_1.\widehat{s}_i + \beta_2.\widehat{s}_i^2 + \beta_3.\widehat{\sigma}_{s,i} + \beta_4.\widehat{\sigma}_{s,i}^2 + \beta_5.\widehat{\sigma}_{\varepsilon,i} + \beta_6.\widehat{\sigma}_{\varepsilon,i}^2 \\ &\quad + \beta_7.\widehat{\sigma}_{\omega,i} + \beta_8.\widehat{\sigma}_{\omega,i}^2 + \beta_9.\widehat{\sigma}_{\nu,i} + \beta_{10}.\widehat{\sigma}_{\nu,i}^2 \\ &\quad + \beta_{11}.\left(\widehat{s}\widehat{\sigma}_s\right)_i + \beta_{12}.\left(\widehat{s}\widehat{\sigma}_\varepsilon\right)_i + \beta_{13}.\left(\widehat{s}\widehat{\sigma}_\omega\right)_i + \beta_{14}.\left(\widehat{s}\widehat{\sigma}_\nu\right)_i \\ &\quad + \beta_{15}.\left(\widehat{\sigma}_s\widehat{\sigma}_\varepsilon\right)_i + \beta_{16}.\left(\widehat{\sigma}_s\widehat{\sigma}_\omega\right)_i + \beta_{17}.\left(\widehat{\sigma}_s\widehat{\sigma}_\nu\right)_i \\ &\quad + \beta_{18}.\left(\widehat{\sigma}_\varepsilon\widehat{\sigma}_\omega\right)_i + \beta_{19}.\left(\widehat{\sigma}_\varepsilon\widehat{\sigma}_\nu\right)_i + \beta_{20}.\left(\widehat{\sigma}_\omega\widehat{\sigma}_\nu\right)_i + \beta_{21}.FR_i + \eta_i \end{aligned}$$

with $y_i = \ln \frac{Freq_i}{(1-Freq_i)}$, or $y_i = \left|\Delta p\right|_i$, or $y_i = \ln \frac{\left(\Delta p<\overline{\Delta p}/2\right)_i}{\left(1-\left(\Delta p<\overline{\Delta p}/2\right)_i\right)}$, where $(\Delta p < \overline{\Delta p}/2)$ is the share of price changes that are, in absolute terms, smaller than one half of the average price changes. FR_i is a dummy for the French CPI data set.

In Dhyne *et al.* (2010), the contribution of each of the parameter estimates ($\widehat{s}, \widehat{\sigma}_s, \widehat{\sigma}_\varepsilon, \widehat{\sigma}_\omega, \widehat{\sigma}_\nu$) to the explanation of y is assessed through the comparison of the goodness of fit of the model above with those of restricted equations in which we successively offset a specific factor or group of factors. The detailed estimation results of the full model are provided in Table 7 below.

Table 7 - Explaining the frequency, the size and the occurence of small price changes.

	$\ln \frac{Freq_i}{(1-Freq_i)}$	$\lvert\Delta p\rvert_i$	$\ln \frac{\left(\Delta p<\overline{\Delta p}/2\right)_i}{\left(1-\left(\Delta p<\overline{\Delta p}/2\right)_i\right)}$
$\widehat{s}$	-3.560 (-1.1)	-0.057 (-0.34)	-0.741 (-0.19)
$\widehat{s}^2$	2.674 (0.19)	0.258 (0.35)	2.046 (0.12)
$\widehat{\sigma}_s$	-20.597 (-2.61)	0.303 (0.75)	2.915 (0.31)
$\widehat{\sigma}_s^2$	106.743 (1.47)	-1.847 (-0.49)	-21.006 (-0.24)
$\widehat{\sigma}_\varepsilon$	36.548 (6.37)	0.471 (1.6)	27.276 (3.94)
$\widehat{\sigma}_\varepsilon^2$	-130.270 (-3.89)	-0.702 (-0.41)	-138.805 (-3.44)
$\widehat{\sigma}_\varpi$	28.844 (4.05)	0.496 (1.36)	-8.371 (-0.97)
$\widehat{\sigma}_\varpi^2$	-40.977 (-1.19)	0.061 (0.03)	20.683 (0.5)
$\widehat{\sigma}_\nu$	0.334 (0.29)	0.004 (0.07)	-3.693 (-2.63)
$\widehat{\sigma}_\nu^2$	-0.899 (-0.36)	0.034 (0.26)	1.457 (0.49)
$\widehat{s\sigma}_s$	-32.898 (-0.51)	-0.358 (-0.11)	6.547 (0.08)
$\widehat{s\sigma}_\varepsilon$	-56.882 (-1.6)	0.810 (0.45)	-51.000 (-1.19)
$\widehat{s\sigma}_\omega$	136.457 (2.43)	6.567 (2.28)	42.977 (0.64)
$\widehat{s\sigma}_\nu$	11.270 (1.52)	0.191 (0.5)	0.555 (0.06)
$\widehat{\sigma}_s\widehat{\sigma}_\varepsilon$	117.031 (1.56)	1.965 (0.51)	89.373 (0.99)
$\widehat{\sigma}_s\widehat{\sigma}_\omega$	-396.692 (-2.76)	-8.059 (-1.09)	-127.407 (-0.74)
$\widehat{\sigma}_s\widehat{\sigma}_\nu$	-17.672 (-1.04)	-1.367 (-1.57)	6.845 (0.33)
$\widehat{\sigma}_\varepsilon\widehat{\sigma}_\omega$	-30.218 (-0.67)	3.049 (1.32)	61.814 (1.14)
$\widehat{\sigma}_\varepsilon\widehat{\sigma}_\nu$	-9.985 (-0.75)	2.597 (3.78)	-0.679 (-0.04)
$\widehat{\sigma}_\omega\widehat{\sigma}_\nu$	28.366 (1.47)	-2.137 (-2.16)	10.957 (0.47)
Adjusted R^2	0.79	0.81	0.34

Note : t-stat in brackets. The constant term and the coefficient associated to the dummy for France are not reported.

6 Ability of state dependent pricing models to generate small price changes

Several recent papers point out that microeconomic price data exhibit a substantial proportion of small price changes. In our data sets, for instance, the percentage of price changes that are below half of the average price change equals 34% in the Belgian data set and and 50% in the French one. Klenow and Kryvstov (2008) highlight the failure of Golosov and Lucas (2007) type of models, with a fixed band of price inaction, to replicate small price changes. Some other models developped in the literature could in principle generate small price changes. Models with asymmetric bounds of inaction could account for small price changes provided these are concentrated either among price increases or among price decreases. Duration dependent models and time dependent models may generate small price changes because the decision to change prices is independent of the size of the desired price change. More recently, alternative state dependent models have been proposed to account for small price changes. On the one hand, Caballero and Engel (1999), Dotsey *et al.* (1999) and more recently Costain and Nakov (2008) develop models with stochastic ranges of inaction. On the other hand, Midrigan (2010) suggests that the synchronisation of price changes within the range of products of the same retailer helps explaining the occurrence of small price changes but this argument may not be really relevant when modelling the evolution of micro CPI price quotes[7].

The aim of this section is to evaluate the ability of alternative state dependent price setting models to reproduce a set of descriptive statistics, including the frequency of small price changes, as observed in our data sets. For each competing model, we compare the frequency and size of price changes, price increases and price decreases, and the frequency of small price changes, as observed in the data, with the ones simulated on the basis of estimated parameters. We perform this exercise for four products, belonging to the categories of processed food (roast beef), durable goods (woman's coat, and scrabble) and services (hourly rate in a garage). We also briefly discuss alternative econometric approaches. In short, our results clearly indicate that a model with stochastic range of inaction, where inaction bounds vary across both outlets and time, is the best suited to match the statistical specificities of the micro CPI data.

We consider the following five alternative specifications :

(i) a symmetric state dependent model with a fixed range of inaction

$$p_{it} = \begin{cases} p_{it-1} & \text{if } |f_t + u_i + \varepsilon_{it} - p_{it-1}| < s \\ f_t + u_i + \varepsilon_{it} & \text{otherwise} \end{cases}$$

[7]Even if the product coverage of CPI dataset is large, we clearly only observe a (small) fraction of the goods sold by any particular retailer. Moreover, the CPI data are collected at a monthly frequency by statistical officers, in contrast with the scanner data recorded automatically and weekly. In CPI data, what might be observed is synchronization of the collection of different prices in one outlet and not necessarily synchronization of price changes. This makes CPI data unappropriate to test Midrigan's assumption.

(ii) an asymmetric state dependent model with fixed ranges of inaction

$$p_{it} = \begin{cases} p_{it-1} & \text{if } -bs < f_t + u_i + \varepsilon_{it} - p_{it-1} < s \\ f_t + u_i + \varepsilon_{it} & \text{otherwise} \end{cases}$$

(iii) a symmetric state dependent model with seasonal ranges of inaction

$$p_{it} = \begin{cases} p_{it-1} & \text{if } |f_t + u_i + \varepsilon_{it} - p_{it-1}| < s + \sum_{j=1}^{11} s_j I\left(Month\left(t\right) = j\right) \\ f_t + u_i + \varepsilon_{it} & \text{otherwise} \end{cases}$$

where $Month\left(t\right)$ represents the month of period t and $I(.)$ is the indicator function;

(iv) a symmetric state dependent model with duration dependent ranges of inaction[8].

$$p_{it} = \begin{cases} p_{it-1} & \text{if } |f_t + u_i + \varepsilon_{it} - p_{it-1}| < s + \sum_{j=1}^{12} s_j I\left(DUR_{it} = j\right) + s_{13} I\left(13 \leq DUR_{it} \leq 24\right) \\ f_t + u_i + \varepsilon_{it} & \text{otherwise} \end{cases}$$

where DUR_{it} represents the duration since the last price change;

(v) a symmetric state dependent model with a stochastic range of inaction, i.e. the model we propose in the paper

$$p_{it} = \begin{cases} p_{it-1} & \text{if } |f_t + u_i + \varepsilon_{it} - p_{it-1}| < s_{it} \\ f_t + u_i + \varepsilon_{it} & \text{otherwise} \end{cases}$$

In the literature, models (i) to (iv) have been estimated using binary models with observable proxies for f_t. In line with this, we estimate these models with an iterative procedure, combining a binary response model to estimate the structural parameter and the cross-sectional average described in Section 3 of the paper to estimate the unobserved common component. Precisely, we use the following contributions to the likelihood for specifications (i) to (iv) :

[8] Given that most prices change within a year, we group durations that lie within 13 and 24 months together.

$$
\begin{aligned}
P\left[\Delta p_{it}=0\right] &= \pi_{1it}=\Phi\left(\frac{p_{it-1}+b_1-f_t-u_i}{\sigma_\varepsilon}\right)-\Phi\left(\frac{p_{it-1}-b_2-f_t-u_i}{\sigma_\varepsilon}\right) \\
P\left[\Delta p_{it}>0\right] &= \pi_{2it}=\Phi\left(\frac{f_t+u_i-p_{it-1}-b_1}{\sigma_\varepsilon}\right) \\
P\left[\Delta p_{it}<0\right] &= \pi_{3it}=\Phi\left(\frac{p_{it-1}-b_2-f_t-u_i}{\sigma_\varepsilon}\right)
\end{aligned}
$$

where in

$$
\begin{aligned}
(i) &: b_1=b_2=s \\
(ii) &: b_1=s; b_2=bs \\
(iii) &: b_1=b_2=s+\sum_{j=1}^{11} s_j I\left(Month\left(t\right)=j\right) \\
(iv) &: b_1=b_2=s+\sum_{j=1}^{12} s_j I\left(DUR_{it}=j\right)+s_{13} I\left(13\leq DUR_{it}\leq 24\right)
\end{aligned}
$$

Such econometric models do not take advantage of the information about the size of price changes; they rely solely on the frequency of price changes. An alternative would be to use a Tobit model. The contribution to the likelihood would be :

$$
\begin{aligned}
P\left[\Delta p_{it}=0\right] &= \pi_{1it}=\Phi\left(\frac{p_{it-1}+b_1-f_t-u_i}{\sigma_\varepsilon}\right)-\Phi\left(\frac{p_{it-1}-b_2-f_t-u_i}{\sigma_\varepsilon}\right) \\
P\left[\Delta p_{it}=\Delta p_{it}^*\right] &= \pi_{2it}=\frac{1}{\sigma_\varepsilon}\phi\left(\frac{p_{it}-f_t-u_i}{\sigma_\varepsilon}\right)
\end{aligned}
$$

However, because the range of inaction only contributes to the probability of no price changes, this parameter cannot be correctly estimated with a Tobit model.

A sample selection model in which the shocks in the selection equation and that in the price change equation are of equal variance, might be better suited. In a sample selection model, the different contributions to the likelihood are given by:

$$
\begin{aligned}
P\left[\Delta p_{it}=0\right] &= \pi_{1it}=\Phi\left(\frac{p_{it-1}+b_1-f_t-u_i}{\sigma_\varepsilon}\right)-\Phi\left(\frac{p_{it-1}-b_2-f_t-u_i}{\sigma_\varepsilon}\right)\\
P\left[\Delta p_{it}=\Delta p_{it}^{*}\left|\Delta p_{it}^{*}>b_1\right.\right] &= \pi_{2it}\\
&= \frac{1}{\sigma_\varepsilon}\phi\left(\frac{p_{it}-f_t-u_i}{\sigma_\varepsilon}\right)\times\\
&\quad \left[1-\Phi\left(\frac{p_{it-1}+b_1-f_t-u_i-\rho\left(p_{it}-f_t-u_i\right)}{\sigma_\varepsilon\sqrt{1-\rho^2}}\right)\right]\\
P\left[\Delta p_{it}=\Delta p_{it}^{*}\left|\Delta p_{it}^{*}<-b_2\right.\right] &= \pi_{3it}\\
&= \frac{1}{\sigma_\varepsilon}\phi\left(\frac{p_{it}-f_t-u_i}{\sigma_\varepsilon}\right)\times\\
&\quad \Phi\left(\frac{p_{it-1}-b_2-f_t-u_i-\rho\left(p_{it}-f_t-u_i\right)}{\sigma_\varepsilon\sqrt{1-\rho^2}}\right)
\end{aligned}
$$

where ρ is the correlation coefficient between the shock in the selection equation and the shock in the price change equation. However, in such a framework, if ρ is away from 1, the "price change" decision and the magnitude of price changes are disconnected, which contradicts the state-dependent pricing behaviour assumed in specifications (i) to (iv). However, the sample selection framework may be used to circumvent the identification problem of the Tobit model by estimating a so-called "Almost Tobit" model, which is a sample selection model for which the shocks in the selection equation and the price change equations are almost the same, i.e. they have equal variance and correlation arbitrarily set to 0.99.

For specification (v), we consider the iterative procedure described in Section 3 of the paper. We also estimated specification (v) by full ML. As shown in Table 12, both estimation procedures deliver similar results.

In Tables 8 to 11, we present the estimation results obtained for specifications (i) to (v) and compare their ability to replicate the frequency of price changes, the average size of price changes and the percentage of small price changes, observed in the data. We simulate price trajectories as follows. We generate 750 price trajectories using the estimated coefficient of the different specifications and we compute the frequency, size and share of small price changes using those simulated trajectories. We replicate this exercise 1000 times in order to compute the average simulated statistics presented in the Tables. To measure the goodness of fit of each estimated model, we also report the sum of squares of the relative difference between the simulated and true statistics (i.e., the frequency of price changes, the frequency of price increases, the frequency of price decreases, the average size of price changes, the average size of price increases, the average size of price decreases, the percentage of price changes below one half of the average price, and the frequency of price changes below one fourth of the average size).

Our results indicate that binary response methods are not well suited to estimate state dependent pricing models with a deterministic range of inaction (specifications (i) to (iv)). Surprisingly, these models provide bad estimates of the frequency of price changes when the estimated parameters are used to simulate price trajectories, although their estimation focus on the frequency of price changes. Because binary response models do not use the size of the observed price changes to estimate the structural parameters, this leads to an overestimation of the volatility of the idiosyncratic shocks. In turn, this overestimation explains the extremely poor performance of the binary response estimates in replicating the average size of price adjustments, and the frequency of small price changes. It also generates excessive price changes through the (too many) occurences of price reversals. As they seem to overestimate both the range of inaction and the magnitude of the idiosyncratic shocks, binary response models should therefore not be used to evaluate price adjustment costs, that depend on both the range of inaction and the size of the shocks in such models (see, Dixit, 1991).

Almost Tobit models provide more reasonable estimates of the range of inaction and of its volatility. Nevertheless, they also perform poorly in replicating both the frequency and the average size of price changes, except in the case of roast beef. For this product, Almost Tobit models perform well in capturing the average size of price changes but, as for the other products, the simulated frequency of price changes is much larger than the one observed in the data. The high frequency of price changes generated by these models may be due to the fact that the estimated range of inaction is very small. Because the estimated range of inaction s is smaller than the volatility of the idiosyncratic shock, the estimates are able to generate a small fraction of small price changes. Still, in all cases, the Almost Tobit estimates of specifications (i) to (iv) generate a fraction of small price changes that is far below the one observed in the data.

In order to circumvent the failure of Golosov and Lucas (2007) types of models to replicate small price changes, one possibility is to introduce variability in the inaction bounds. As shown in Tables 8 to 11, asymmetric inaction bounds (specificiation (ii)) does not increase the occurrence of small price changes. Introducing time variability in the inaction bounds, either in the form of seasonal range of inaction (specification (iii)), or through duration dependence (specification (iv)), does not improve the models performance either.

However, allowing for stochastic ranges of inaction, that vary both across outlets and over time (specification (v)), substantially outperforms all other models in terms of goodness of fit of the frequency of price changes and of the average size of price changes, as well as regarding the ability to generate a significant fraction of small price changes. For three of the four products considered, the stochastic range of inaction model explains around half of small price changes observed in the data. For "scrabble", it even captures up to 90 percent of price changes below one half of the average size and two third of price changes below one fourth of the average size. Nevertheless, with such models, the simulated frequency of small price change is still smaller than the observed one. This suggests that additional mechanisms may be at play, such as synchronisation of price changes within stores or strategic price decisions across outlets, for example. Testing the relevance of these phenomena is beyond the scope of this paper, and would require a different data set.[9]

[9] A higher frequency of observed price changes, a comprehensive dataset covering all products sold within a store, and all outlets in a given geographical area would be necessary.

Table 8 - Deterministic range of inaction versus stochastic range of inaction and Calvo pricing - Roast beef

Parameter	CPI Data	Deterministic r.o.i								Stoch. r.o.i
		Binary response				Almost Tobit				
		(i)	*(ii)*	*(iii)*	*(iv)*	*(i)*	*(ii)*	*(iii)*	*(iv)*	*(v)*
s	–	0.275	0.245	0.289	0.407	0.045	0.039	0.047	0.064	0.216
s_1	–	–	–	−0.026	−0.204	–	–	−0.008	−0.031	–
s_2	–	–	–	−0.021	−0.154	–	–	−0.005	−0.030	–
s_3	–	–	–	−0.026	−0.136	–	–	−0.004	−0.026	–
s_4	–	–	–	−0.016	−0.122	–	–	−0.002	−0.025	–
s_5	–	–	–	−0.007*	−0.099	–	–	0.001*	−0.022	–
s_6	–	–	–	−0.004*	−0.091	–	–	−0.001*	−0.019	–
s_7	–	–	–	0.000*	−0.101	–	–	0.000*	−0.020	–
s_8	–	–	–	−0.003*	−0.086	–	–	0.000*	−0.019	–
s_9	–	–	–	−0.018	−0.092	–	–	−0.003	−0.020	–
s_{10}	–	–	–	−0.032	−0.072	–	–	−0.005	−0.017	–
s_{11}	–	–	–	0.005*	−0.067	–	–	0.004	−0.015	–
s_{12}	–	–	–	–	−0.081	–	–	–	−0.016	–
s_{13}	–	–	–	–	−0.057	–	–	–	−0.012	–
b	–	–	1.242	–	–	–	1.336	–	–	–
σ_ε	–	0.165	0.165	0.166	0.188	0.068	0.068	0.068	0.071	0.064
σ_v	–	0.087	0.087	0.088	0.104	0.089	0.085	0.089	0.094	0.089
σ_s	–	–	–	–	–	–	–	–	–	0.118
$freq$	0.116	0.239	0.235	0.238	0.283	0.643	0.638	0.641	0.737	0.134
$freq^+$	0.066	0.120	0.126	0.120	0.143	0.323	0.336	0.322	0.371	0.068
$freq^-$	0.050	0.119	0.110	0.119	0.140	0.320	0.303	0.319	0.365	0.066
$\overline{\Delta p}$	0.081	0.389	0.389	0.391	0.393	0.108	0.108	0.108	0.103	0.116
$\overline{\Delta p^+}$	0.075	0.389	0.367	0.391	0.394	0.108	0.103	0.108	0.103	0.117
$\overline{\Delta p^-}$	0.089	0.389	0.414	0.391	0.392	0.107	0.113	0.108	0.102	0.116
$\Delta p < \overline{\Delta p}/2$	0.476	0.000	0.000	0.000	0.000	0.102	0.097	0.100	0.174	0.205
$\Delta p < \overline{\Delta p}/4$	0.237	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.083
Goodness of fit[1]		49.2	48.2	49.7	53.4	67.6	65.2	67.1	92.5	1.5

s is the average size of the price inaction band, σ_ε is the standard error of the idiosyncratic component, σ_s the standard error of the stochastic range of inaction s_{it}, σ_v the standard error of the random effect; $freq$ is the frequency of price changes, $freq^+$ the frequency of price increases, $freq^-$ the frequency of price decreases, $\overline{\Delta p}$ the average size of price chnages, $\overline{\Delta p^+}$ the average size of price increases, $\overline{\Delta p^-}$ the average size of price decreases, $\Delta p < \overline{\Delta p}/2$ the frequency of price changes below one half of $\overline{\Delta p}$, $\Delta p < \overline{\Delta p}/4$ the frequency of price changes below one fourth of $\overline{\Delta p}$.

(i) = fixed range of inaction ; (ii) = asymmetric range of inaction ; (iii) = seasonal range of inaction ; (iv) = duration dependent range of inaction ; (v) = stochastic range of inaction

[1] = sum of squares of the relative difference between the simulated and true statistics, $freq$, $freq^+$, $freq^-$, $\overline{\Delta p}$, $\Delta p < \overline{\Delta p}/2$ and $\Delta p < \overline{\Delta p}/4$.

* = not statistically significant at the 5% level.

Table 9 - Deterministic range of inaction versus stochastic range of inaction and Calvo pricing - Coat (woman)

Parameter	CPI Data	Deterministic r.o.i Binary response (i)	(ii)	(iii)	(iv)	Almost Tobit (i)	(ii)	(iii)	(iv)	Stoch. r.o.i (v)
s	–	13.918	12.685	–	–	0.088	0.071	–	–	0.448
s_1	–	–	–	–	–	–	–	–	–	–
s_2	–	–	–	–	–	–	–	–	–	–
s_3	–	–	–	–	–	–	–	–	–	–
s_4	–	–	–	–	–	–	–	–	–	–
s_5	–	–	–	–	–	–	–	–	–	–
s_6	–	–	–	–	–	–	–	–	–	–
s_7	–	–	–	–	–	–	–	–	–	–
s_8	–	–	–	–	–	–	–	–	–	–
s_9	–	–	–	–	–	–	–	–	–	–
s_{10}	–	–	–	–	–	–	–	–	–	–
s_{11}	–	–	–	–	–	–	–	–	–	–
s_{12}	–	–	–	–	–	–	–	–	–	–
s_{13}	–	–	–	–	–	–	–	–	–	–
b	–	–	1.812	–	–	–	1.533	–	–	–
σ_ε	–	6.525	8.361	–	–	0.105	0.104	–	–	0.062
σ_v	–	1.745	2.025	–	–	0.225	0.238	–	–	0.252
σ_s	–	–	–	–	–	–	–	–	–	0.205
$freq$	0.039	0.131	0.112	–	–	0.552	0.542	–	–	0.038
$freq^+$	0.024	0.066	0.067	–	–	0.276	0.293	–	–	0.018
$freq^-$	0.015	0.066	0.045	–	–	0.276	0.249	–	–	0.020
$\overline{\Delta p}$	0.050	17.95	22.360	–	–	0.180	0.179	–	–	0.107
$\overline{\Delta p^+}$	0.046	17.95	18.977	–	–	0.180	0.166	–	–	0.106
$\overline{\Delta p^-}$	0.056	17.95	27.434	–	–	0.180	0.196	–	–	0.108
$\Delta p < \overline{\Delta p}/2$	0.425	0.000	0.000	–	–	0.013	0.076	–	–	0.238
$\Delta p < \overline{\Delta p}/4$	0.242	0.000	0.000	–	–	0.000	0.000	–	–	0.105
Goodness of fit[1]		381196	604931	–	–	620.6	566.2	–	–	4.6

s is the average size of the price inaction band, σ_ε is the standard error of the idiosyncratic component, σ_s the standard error of the stochastic range of inaction s_{it}, σ_v the standard error of the random effect; $freq$ is the frequency of price changes, $freq^+$ the frequency of price increases, $freq^-$ the frequency of price decreases, $\overline{\Delta p}$ the average size of price chnages, $\overline{\Delta p^+}$ the average size of price increases, $\overline{\Delta p^-}$ the average size of price decreases, $\Delta p < \overline{\Delta p}/2$ the frequency of price changes below one half of $\overline{\Delta p}$, $\Delta p < \overline{\Delta p}/4$ the frequency of price changes below one fourth of $\overline{\Delta p}$.

(i) = fixed range of inaction ; (ii) = asymmetric range of inaction ; (iii) = seasonal range of inaction ; (iv) = duration dependent range of inaction ; (v) = stochastic range of inaction

[1] = sum of squares of the relative difference between the simulated and true statistics, $freq$, $freq^+$, $freq^-$, $\overline{\Delta p}$, $\Delta p < \overline{\Delta p}/2$ and $\Delta p < \overline{\Delta p}/4$..

* = not statistically significant at the 5% level.

Table 10 - Deterministic range of inaction versus stochastic range of inaction and Calvo pricing - Hourly rate in a garage

Parameter	CPI Data	Deterministic r.o.i								Stoch. r.o.i
		Binary response				Almost Tobit				
		(i)	(ii)	(iii)	(iv)	(i)	(ii)	(iii)	(iv)	(v)
s	–	0.898	–	–	0.790	0.080	0.033	–	0.083	0.347
s_1	–	–	–	–	0.139	–	–	–	0.008	–
s_2	–	–	–	–	0.201	–	–	–	0.010	–
s_3	–	–	–	–	0.221	–	–	–	0.000	–
s_4	–	–	–	–	0.142	–	–	–	−0.001	–
s_5	–	–	–	–	0.117	–	–	–	−0.005	–
s_6	–	–	–	–	0.046	–	–	–	−0.016	–
s_7	–	–	–	–	0.165	–	–	–	−0.002	–
s_8	–	–	–	–	0.209	–	–	–	0.013	–
s_9	–	–	–	–	0.080	–	–	–	−0.016	–
s_{10}	–	–	–	–	0.090	–	–	–	−0.002	–
s_{11}	–	–	–	–	−0.067	–	–	–	−0.003	–
s_{12}	–	–	–	–	−0.213	–	–	–	−0.040	–
s_{13}	–	–	–	–	−0.025	–	–	–	−0.012	–
b	–	–	–	–	–	–	11.424	–	–	–
σ_ε	–	0.391	–	–	0.356	0.097	0.151	–	0.085	0.049
σ_v	–	0.285	–	–	0.269	0.126	0.151	–	0.124	0.133
σ_s	–	–	–	–	–	–	–	–	–	0.166
$freq$	0.052	0.105	–	–	0.104	0.562	0.327	–	0.466	0.052
$freq^+$	0.051	0.054	–	–	0.053	0.290	0.241	–	0.240	0.038
$freq^-$	0.001	0.051	–	–	0.051	0.273	0.086	–	0.226	0.014
$\overline{\Delta p}$	0.060	1.130	–	–	1.068	0.165	0.256	–	0.158	0.100
$\overline{\Delta p^+}$	0.061	1.129	–	–	1.071	0.166	0.183	–	0.158	0.110
$\overline{\Delta p^-}$	0.024	1.131	–	–	1.064	0.164	0.463	–	0.157	0.075
$\Delta p < \overline{\Delta p}/2$	0.335	0.000	–	–	0.000	0.024	0.320	–	0.006	0.230
$\Delta p < \overline{\Delta p}/4$	0.201	0.000	–	–	0.000	0.000	0.120	–	0.000	0.100
Goodness of fit[1]		3905	–	–	3582	34955	3758	–	23952	82.1

s is the average size of the price inaction band, σ_ε is the standard error of the idiosyncratic component, σ_s the standard error of the stochastic range of inaction s_{it}, σ_v the standard error of the random effect; $freq$ is the frequency of price changes, $freq^+$ the frequency of price increases, $freq^-$ the frequency of price decreases, $\overline{\Delta p}$ the average size of price chnages, $\overline{\Delta p^+}$ the average size of price increases, $\overline{\Delta p^-}$ the average size of price decreases, $\Delta p < \overline{\Delta p}/2$ the frequency of price changes below one half of $\overline{\Delta p}$, $\Delta p < \overline{\Delta p}/4$ the frequency of price changes below one fourth of $\overline{\Delta p}$.

(i) = fixed range of inaction ; (ii) = asymmetric range of inaction ; (iii) = seasonal range of inaction ; (iv) = duration dependent range of inaction ; (v) = stochastic range of inaction

[1] = sum of squares of the relative difference between the simulated and true statistics, $freq$, $freq^+$, $freq^-$, $\overline{\Delta p}$, $\Delta p < \overline{\Delta p}/2$ and $\Delta p < \overline{\Delta p}/4$..

* = not statistically significant at the 5% level.

Table 11 - Deterministic range of inaction versus stochastic range of inaction and Calvo pricing - Scrabble

Parameter	CPI Data	Deterministic r.o.i Binary response (i)	(ii)	(iii)	(iv)	Almost Tobit (i)	(ii)	(iii)	(iv)	Stoch. r.o.i (v)
s	–	0.556	0.438	0.487	0.609	0.120	0.097	0.121	0.137	0.436
s_1	–	–	–	−0.026	−0.204	–	–	−0.008	−0.031	–
s_2	–	–	–	−0.021	−0.154	–	–	−0.005	−0.030	–
s_3	–	–	–	−0.026	−0.136	–	–	−0.004	−0.026	–
s_4	–	–	–	−0.016	−0.122	–	–	−0.002	−0.025	–
s_5	–	–	–	−0.007*	−0.099	–	–	0.001*	−0.022	–
s_6	–	–	–	−0.004*	−0.091	–	–	−0.001*	−0.019	–
s_7	–	–	–	0.000*	−0.101	–	–	0.000*	−0.020	–
s_8	–	–	–	−0.003*	−0.086	–	–	0.000*	−0.019	–
s_9	–	–	–	−0.018	−0.092	–	–	−0.003	−0.020	–
s_{10}	–	–	–	−0.032	−0.072	–	–	−0.005	−0.017	–
s_{11}	–	–	–	0.005*	−0.067	–	–	0.004	−0.015	–
s_{12}	–	–	–	–	−0.081	–	–	–	−0.016	–
s_{13}	–	–	–	–	−0.057	–	–	–	−0.012	–
b	–	–	1.242	–	–	–	1.336	–	–	–
σ_ε	–	0.285	0.288	0.299	0.284	0.131	0.127	0.130	0.134	0.089
σ_v	–	0.120	0.120	0.118	0.112	0.128	0.122	0.128	0.109	0.114
σ_s	–	–	–	–	–	–	–	–	–	0.208
$freq$	0.072	0.170	0.156	0.160	0.188	0.517	0.501	0.501	0.563	0.071
$freq^+$	0.043	0.086	0.090	0.079	0.095	0.260	0.273	0.252	0.284	0.038
$freq^-$	0.029	0.084	0.066	0.081	0.094	0.257	0.227	0.249	0.279	0.033
$\overline{\Delta p}$	0.149	0.741	0.737	0.770	0.705	0.232	0.227	0.233	0.228	0.176
$\overline{\Delta p^+}$	0.139	0.741	0.652	0.781	0.705	0.233	0.210	0.233	0.228	0.179
$\overline{\Delta p^-}$	0.165	0.741	0.852	0.759	0.705	0.232	0.248	0.232	0.227	0.173
$\Delta p < \overline{\Delta p}/2$	0.230	0.000	0.000	0.000	0.000	0.000	0.057	0.038	0.032	0.208
$\Delta p < \overline{\Delta p}/4$	0.128	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.085
Goodness of fit[1]		55.4	52.7	59.2	52.5	130.0	114.5	121.2	156.7	0.3

s is the average size of the price inaction band, σ_ε is the standard error of the idiosyncratic component, σ_s the standard error of the stochastic range of inaction s_{it}, σ_v the standard error of the random effect; $freq$ is the frequency of price changes, $freq^+$ the frequency of price increases, $freq^-$ the frequency of price decreases, $\overline{\Delta p}$ the average size of price chnages, $\overline{\Delta p^+}$ the average size of price increases, $\overline{\Delta p^-}$ the average size of price decreases, $\Delta p < \overline{\Delta p}/2$ the frequency of price changes below one half of $\overline{\Delta p}$, $\Delta p < \overline{\Delta p}/4$ the frequency of price changes below one fourth of $\overline{\Delta p}$.

(i) = fixed range of inaction ; (ii) = asymmetric range of inaction ; (iii) = seasonal range of inaction ; (iv) = duration dependent range of inaction ; (v) = stochastic range of inaction

[1] = sum of squares of the relative difference between the simulated and true statistics, $freq$, $freq^+$, $freq^-$, $\overline{\Delta p}$, $\Delta p < \overline{\Delta p}/2$ and $\Delta p < \overline{\Delta p}/4$..

* = not statistically significant at the 5% level..

Table 12 - Stochastic range of inaction : iterative procedure versus Full ML

	Roast beef			Coat (woman)			Garage			Scrabble		
	CPI	*Iter.*	*ML*	*CPI*	*Iter.*	*ML*	*CPI*	*Iter.*	*ML*	*CPI*	*Iter.*	*ML*
s	–	0.216	0.217	–	0.448	0.436	–	0.347	0.351	–	0.436	0.442
σ_ε	–	0.064	0.063	–	0.062	0.059	–	0.049	0.046	–	0.089	0.085
σ_v	–	0.090	0.086	–	0.252	0.274	–	0.133	0.132	–	0.114	0.115
σ_s	–	0.118	0.118	–	0.205	0.199	–	0.166	0.168	–	0.208	0.211
$freq$	0.116	0.134	0.134	0.039	0.038	0.038	0.052	0.052	0.052	0.072	0.071	0.070
$freq^+$	0.066	0.068	0.069	0.024	0.018	0.020	0.051	0.038	0.038	0.043	0.038	0.038
$freq^-$	0.050	0.066	0.065	0.015	0.020	0.018	0.001	0.014	0.014	0.029	0.033	0.032
$\overline{\Delta p}$	0.081	0.116	0.117	0.050	0.107	0.104	0.060	0.100	0.100	0.149	0.176	0.176
$\overline{\Delta p^+}$	0.075	0.117	0.117	0.046	0.106	0.106	0.061	0.110	0.110	0.139	0.179	0.180
$\overline{\Delta p^-}$	0.089	0.116	0.116	0.056	0.108	0.102	0.024	0.075	0.074	0.165	0.173	0.172
$\Delta p < \frac{\overline{\Delta p}}{2}$	0.476	0.205	0.205	0.425	0.238	0.239	0.335	0.230	0.232	0.230	0.208	0.210
$\Delta p < \frac{\overline{\Delta p}}{4}$	0.237	0.083	0.083	0.242	0.105	0.107	0.201	0.100	0.101	0.128	0.085	0.087
Goodness of fit[1]	–	1.5	1.5	–	4.6	4.1	–	82.1	79.5	–	0.3	0.3

s is the average size of the price inaction band, σ_ε is the standard error of the idiosyncratic component, σ_s the standard error of the stochastic range of inaction s_{it}, σ_v the standard error of the random effect; $freq$ is the frequency of price changes, $freq^+$ the frequency of price increases, $freq^-$ the frequency of price decreases, $\overline{\Delta p}$ the average size of price chnages, $\overline{\Delta p^+}$ the average size of price increases, $\overline{\Delta p^-}$ the average size of price decreases, $\Delta p < \frac{\overline{\Delta p}}{2}$ the frequency of price changes below one half of the average price change, $\Delta p < \frac{\overline{\Delta p}}{4}$ the frequency of price changes below one fourth of the average price change.

[1] = sum of squares of the relative difference between the simulated and true statistics, $freq$, $freq^+$, $freq^-$, $\overline{\Delta p}$, $\Delta p < \frac{\overline{\Delta p}}{2}$ and $\Delta p < \frac{\overline{\Delta p}}{4}$.

* = not statistically significant at the 5% level.

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