Price Changes - Stickiness and Internal Coordination in Multiproduct Firms♣

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Abstract

We assess empirically the micro-foundations of producers' sticky pricing behaviour by accounting for various functional forms of menu costs. Our analysis concerns multiproduct plants that are subject to product- and plant-specific shocks. The structural model developed is tested using monthly product- and plant-specific producer prices for Norwegian plants. We find two main explanations operating simultaneously for observing infrequent price change, many small price changes and (incomplete) synchronization of price changes. First, our estimates confirm the presence of fixed menu costs featuring economies of scope. Second, we add evidence for linear menu costs together with the presence of plant-specific shocks.

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1. Introduction

In economics the phenomenon of price rigidity has featured prominently on the research agenda for a long time. Price rigidity is often explained by costs of price changes due to producing new price lists, monthly supplemental price sheets, and informing and convincing interested parties. These are the classical menu costs as considered theoretically by Sheshinski and Weiss (1977, 1983). Typically such physical costs are independent of the size of the price changes (Levy *et al*., 1997). Recently, we have witnessed a number of both theoretical and empirical contributions that have greatly advanced our understanding of pricing decisions at the micro level. In particular, models including menu costs featuring economies of scope have received substantial attention (Midrigan, 2011; Alvarez and Lippi, 2014; and Alvarez *et al*., 2016). In such a setting there is a total fixed menu cost that is always incurred when firms adjust at least one price. In addition, the total fixed menu cost does not depend on the number of prices the firm adjusts. The popularity of a model featuring scope economies is due to its ability to explain three important properties of price data: infrequent price change, many small price changes and synchronization of price changes in multiproduct firms.

The only evidence based on structural estimates of economies of scope has been provided by Stella (2013). Midrigan (2011), Bhattarai and Schoenle (2014), Alvarez *et al.* (2016) calibrate a model showing that it is capable of explaining major moments of the data. Here we develop a structural model that also allows for statistically testing the importance of economies of scope. We consider additional types of menu cost specifications as well. This step is important to see whether identifying economies of scope is not due to misspecification of the model. In fact, we argue a model incorporating linear menu costs with plant-specific shocks may also generate infrequent price adjustment, many small price changes and synchronization.

We set up an optimization model of a firms' dynamic profit function. The model includes scope economies in the menu cost function. We specify a total fixed menu cost that is always incurred when the firm adjusts at least one price. However, the effective menu cost per good depends on how goods change prices. We also consider a general menu cost specification that depends on the size of the price change (cf. Rotemberg, 1982). We incorporate both linear and quadratic components. Both of these menu cost specifications can generate small price changes. The linear component also generates price stickiness and permits zeroes in the price change data. Altogether, we consider simultaneously three specifications for the shape of menu costs: fixed, linear and quadratic (convex) costs. Our model thus allows for two competing explanations for infrequent price adjustment, many small price changes and synchronization; first, economies of scope in the menu cost function, and second, a model featuring both linear costs and plant-specific shocks. Obviously, such plant level shocks induce synchronization of price adjustment.

The method employed can be described as structural estimation as the estimates enable us to trace back parameters in the optimization problem of firms' price decisions. In fact, a maximum likelihood model allows us to acquire parameter estimates that are related to the menu cost function.[1] We use a unique and relatively unexplored micro level dataset provided by Statistics Norway (SSB). The data are representative for the Norwegian economy and important moments resemble those of the Euro area as described by Vermeulen *et al*. (2012). The data is a panel with monthly observations for the period 2004-2009. Our estimates confirm the presence of scope economies in adjusting prices. However, they reveal also two other types of menu costs are statistically significant, i.e. linear and convex menu costs. However, convex menu costs are of minor economic importance. As we also find evidence of

[1]An advantage of our approach compared to calibration based methods is that our assumptions can be tested statistically.

plant-specific shocks, we conclude that the data support the view that key empirical moments are driven by two alternative model specifications that are both relevant statistically and economically at the same time: economies of scope and linear menu costs in combination with plant-specific shocks.

This manuscript continues as follows. In Section 2 we present the data. The model is developed in Section 3. The estimation method is depicted in Section 4. We present the estimation results in Section 5, and finally we conclude in Section 6.

2. The Data

The dataset used has been constructed by combining two different data sources, both obtained from Statistics Norway (SSB). The price data stem from a survey to determine the commodity price index for the Norwegian manufacturing sector. The survey provides monthly price observations. Such a dataset allows us to analyse price rigidity on the individual producer level. For data collection purposes firms may be targeted for certain, but not all of the products they manufacture. If Statistics Norway regards a subset of the products to be important to obtain an accurate estimate of the price index, data will be requested for these ones only. At the aggregate level, the price index is measuring the actual inflation on the producer level and is a key part of the short-term statistics that monitor the Norwegian economy. Though the firms targeted are relatively large compared to the original population, the data have to be, and are representative for Norway.

We investigate price quotes that are consequently obtained from firms operating in manufacturing industries.[2] A selection of producers report their prices on a monthly basis, and

[2]In the remainder of the paper we use the terms plant, firm, company and establishment interchangeably. To be precise the information provided by Statistics Norway is plant-specific.

large, dominating establishments are targeted in order to secure a high level of accuracy and relevance. The selection of respondents is furthermore updated on a regular basis, in order to make sure that the indices continuously are being kept relevant compared to the development of the Norwegian economy (SSB 2013a). The required information is collected through electronic reporting. Compulsory participation ensures a high response from the questioned producers. The gathered data is subject to several controls aiming at identifying extreme values and mistyping. Thus, the data are of very high quality.[3]

The price data are merged with data from the so called industry statistics. For all plants the structural business statistics are reported on a yearly basis, and is a part of SSB's industry statistics that provides detailed information about firms' activity (SSB 2013b). For each establishment represented in the dataset there is thus information listed on a number of variables related to their economic activity, including employment numbers, wages and the like. The structural statistics are only given for companies within certain industries, and this lays down constraints on the final dataset. As these structural statistics are linked to price data, the final sample of price observations comprises all products and manufacturing industries.

The manufacturing industry is faced with strong, international competition. For a small open economy like the Norwegian one, one might think international markets have an impact on prices. A firm may operate on both domestic and export markets. Hence, we record only domestic prices to avoid that our results are driven by exchange rate changes and competitive forces on international markets. In addition, without initiating a discussion about market definition and market power, our model will allow for the included firms to have some potential market power.

[3]This means that the number of a firm's product prices we observe provides a lower bound on the actual number. In addition, the number of prices changed by the firm provides a lower bound on the actual number.

We focus on multiproduct plants. Hence, in the final dataset we employ for the analysis, single product establishments are disregarded. Our final dataset covers the period 2004 until 2009. The number of observations in our dataset is 39,082. The number of establishments, products and (two digit NACE) sectors are 222, 855 and 16, respectively. On average a plant provides information on about 5 products in the actual data.[4] A comparison of the data to the European reference literature (summarized by Vermeulen *et al*., 2012) shows that Norwegian producers' pricing pattern is more or less in line with what is observed for the rest of Europe. Table 1 shows the distribution of the monthly prices changes. We see approximately 77% of zero price changes. This means that there must be some non-convex menu costs, as it is unlikely shocks are absent. This contradicts, or comes in addition to the convex costs suggested by Rotemberg (1982), which would induce very few zeroes. The large amount of zeroes could be caused by both linear and fixed adjustment costs. Note however, that we also see a mass point of small price changes around the zero consistent with Klenow and Malin (2010), Bhattarai and Schoenle (2014), Alvarez and Lippi (2014) and Alvarez *et al*. (2016). These can be explained by scope economies in menu costs. Convex adjustment costs may

[4]For some descriptive statistics see also Table A1 in the appendix. When estimating the model using the full data set, our maximum likelihood routine encountered convergence problems. For that reason we had to reduce the heterogeneity observed in the data. We excluded sectors producing capital goods. We also focus on single plant firms only. With this choice we are sure that the price decisions are not made beyond the plant level. In addition, we trimmed the data. In the initial sample prices range between (0.09, 4 835 000) NOK or (0.01, 500 000) EURO. After removing tails we lost 6% of the observations. In the sample used for estimation prices range between (20, 200 000) NOK or (2.50, 25 000) EURO. Price data are collected since 2002. We only used data from 2004-2009 as in 2003 a major change was implemented at Statistics Norway in the sampling procedure.

explain the large frequency of small price adjustments as well, because they put a penalty on large adjustments.

** Table 1: "Distribution of (monthly) price changes ($\Delta p / p$)" about here **

In Table 2 we depict some facts that tell that firms coordinate price changes internally. Most often, plants do not change a single price at all. In fact, at the plant level the frequency of full price change inaction is 69 percent. In about 18 percent of the observations establishments adjust all product prices. These numbers reveal that firms tend to synchronize price adjustment of the products they manufacture. However, firms do not necessarily adjust all their prices in a month. We find that about 13 percent of the sample represents instances where within one establishment price change and price inaction occur simultaneously. Hence, synchronization does happen often, but in a sizeable number of cases it is incomplete.

** Table 2: "Internal Coordination of Product Price Changes" about here **

3. The Model

In this section we develop a model that is capable of explaining three important aspects of micro level pricing data that have been observed frequently: infrequent price adjustment, many small price changes, and synchronization. The model nests two alternative explanations for these facts. First, the model is based on menu costs featuring economies of scope. Second, we consider a linear menu cost component complemented with plant-specific shocks.

The cost of price changes consists of producing new price lists, monthly supplemental price sheets, and informing and convincing interested parties (Sheshinski and Weiss, 1977, 1983). Traditionally such physical costs are independent of the size of the price changes

(Levy *et al*., 1997). In our model such a fixed cost of adjustment is given by a parameter a. A number of studies suggests that firms obtain cost advantages when synchronizing price changes (Midrigan, 2011; Alvarez and Lippi, 2014, Bhattarai and Schoenle, 2014). In line with these, we assume the total firm level fixed menu cost does not depend on the number of price adjustments. Hence, in our model firms have an incentive to synchronize price changes.

Simultaneous price changes are observed often in our data. However, firms do not always adjust all prices at the same time. Multiproduct firms may find it profitable to maintain prices of certain products while simultaneously changing others. This partial synchronization phenomenon is unaccounted for by Midrigan, and Alvarez and Lippi. To be able to replicate this pricing behaviour, we assume menu costs allow a firm to obtain economies of scope and that the cost is deducted from the profit of the products subject to a price change. Hence, the fixed cost a is divided by m_{it}, denoting the number of price changes by plant i in period t. This implies that the total fixed menu costs, a, do not depend on the number of price changes. One way of thinking about this is that each product manager that wants to change the product price he or she is responsible for, may participate in gathering information. The efforts required for each product manager depend on how much these costs can be shared amongst all of the product managers that want to adjust a price. Hence the more product prices are involved, the less effort each product manager needs to put in, which is reflected by dividing the fixed cost a by m_{it}. In addition, one may interpret such costs as stemming from communication costs of changing prices. Customers need to be informed of price changes, and also the sales force needs to be knowledgeable. To some extent such costs may be shared across various product accounts by a joint communication strategy. Whether such costs are relevant ultimately is an empirical question, and we allow the data to disclose the importance of these.

Some costs of changing prices depend on the size of the price adjustment. The larger the change the more managerial time is spent on the price change decision. Decision costs and internal firm communication increase for larger price changes. In addition, the firm is also likely to incur higher cost of negotiation and communication with customers (Zbaracki *et al.*, 2004). Firms could also be reluctant to change prices due to competitive forces. Product markets characterized by tough (international) competition potentially limit an establishment's ability to set prices at will. If customer demand is elastic, a price increase implies a reduction of demand, and price reductions increase the risk of price wars, for instance. As a consequence, menu costs may reflect competitive concerns faced by the establishment especially when large price changes are involved.

We consider two menu cost types that depend on the price change size. In the model below linear costs are represented by $b \cdot |\Delta P_{ijt}|$ where $\Delta P_{ijt} = P_{ijt} - P_{ijt-1}$ and P_{ijt} denotes the price of product *j* in month *t*. Furthermore, a convex cost component is given by the expression multiplied by the parameter c. The quadratic menu cost term $\left(\frac{\Delta P_{ijt}}{P_{ijt-1}}\right)^2 P_{ijt-1}$ implies that larger price changes are very costly. This penalty provides the establishment an incentive for the smaller price changes that we observe in the data descriptives.

We assume each plant produces N_{it} goods. Presuming monopolistic competition, the optimisation problem of a producer is to make a decision concerning product price changes maximising the present value of discounted cash flow:

$$(1) \qquad V_{it}\left(P_{ijt-1}, A_{ijt}, B_{ijt}\right) = \max_{\Delta P_{ijt},\, j\in\{1,N_{it}\}} E_t\left(\sum_{s=0}^{\infty}\left(\frac{1}{1+r}\right)^s \left(\sum_{j\in\{1,N_{it}\}}\left(\pi\left(A_{ijt+s}, B_{ijt+s} P_{ijt+s}\right) - C\left(\Delta P_{ijt+s}\right)\right)\right)\right).$$

The index *i* refers to a firm, the index *j* refers to a product, and the index *t* refers to a month. The expression $\pi\left(A_{ijt+s}, B_{ijt+s}, P_{ijt+s}\right)$ denotes the firm's revenue function net of wage costs for a product j at time $t+s$. The monthly discount rate is given by $\frac{1}{1+r}$. The expectations operator $E_t(\ )$ is included due to the stochastic variables A_{ijt} and B_{ijt} representing shocks to supply and demand of a product, respectively.[5] In the model $\Delta P_{ijt} = P_{ijt} - P_{ijt-1}$ is the decision variable. The realization of the shocks A_{ijt} and B_{ijt} in period t comes after ΔP_{ijt} is determined. The menu cost function for prices is given by

$$(2)\qquad C\left(\Delta P_{ijt}\right) = I\left(\Delta P_{ijt} \neq 0\right)\cdot\left(\frac{a}{m_{it}} + b\cdot\left|\Delta P_{ijt}\right| + \frac{c}{2}\cdot\left(\frac{\Delta P_{ijt}}{P_{ijt-1}}\right)^2 P_{ijt-1}\right)$$

where $I(.)$ is an indicator function equal to 1 if the condition in brackets is satisfied and zero otherwise.[6,7]

From a conceptual point of view, price change models and factor demand models are very similar.[8] Our dynamic price setting model is inspired by research on input demand where

[5]We will later on show that developments in prices set by competitors are captured by demand conditions reflected by B_{ijt}.

[6]As mentioned in footnote 3, we do not observe the actual numbers m_{it} and N_{it}. This means that the fixed menu cost a should in fact be divided by a higher number. As a consequence, a downward bias is expected for our estimate of the parameter a. For that reason our findings with respect to fixed menu costs should be interpreted as conservative.

[7]We abstract from asymmetry in the menu cost function. In the data firms have price increases and decreases simultaneously. With asymmetric costs a firm then incurs fixed menu cost for both. As we focus on synchronization, where the total fixed cost of price changes are shared across price changes, we disregard this issue.

[8]Various types of adjustment costs and their consequences have been reviewed by Hamermesh and Pfann (1996).

the size and timing of adjustment is determined by q - the expected marginal value of a unitary change in the decision variable (see for instance Abel and Eberly, 1994).[9] We define q_{ijt} as a measure of how the expected value of the plant changes when the price of product j is increased by one unit. In fact,

$$(3) \qquad q_{ijt} \equiv \frac{\partial V_{it}}{\partial P_{ijt}} = E_t\left(\sum_{s=0}^{\infty}\left(\frac{1}{1+r}\right)^s\left(\frac{\partial \pi\left(A_{ijt+s}, B_{ijt+s}, P_{ijt+s}\right)}{\partial P_{ijt+s}} - \frac{1}{1+r}\frac{\partial C\left(\Delta P_{ijt+s}\right)}{\partial P_{ijt+s}}\right)\right)$$

It represents the expected discounted value of marginal change in future profits minus the saved future menu costs.[10] More details around this expression for q will be discussed later on. The first order condition for price change equals

$$(4) \qquad q_{ijt} - b\cdot I\left(\Delta P_{ijt} > 0\right) + b\cdot I\left(\Delta P_{ijt} < 0\right) - c\left(\frac{\Delta P_{ijt}}{P_{ijt-1}}\right) = 0$$

A price will be changed in case the benefits are larger than the costs associated with the adjustment:

$$(5) \qquad q_{ijt}\Delta P_{ijt} > C\left(\Delta P_{ijt}\right)$$

Equations (4) and (5) inform us that prices behave according to the following rules[11]

$$(6) \qquad \frac{\Delta P_{ijt}}{P_{ijt-1}} = \frac{1}{c}\left(q_{ijt} - b\right) \text{ if } q_{ijt} \geq \sqrt{\frac{2\cdot a\cdot c}{m_{it}\cdot P_{ijt-1}}} + b.$$

[9]We do not specify a full DSGE model. This is done in order to focus on firms' pricing decisions and not let the analysis be affected by possible misspecifications or problems in other parts of the macro economy.

[10]Note that in equation (3) one could in principle multiply the two first order derivatives in brackets with $\frac{\partial P_{ijt+s}}{\partial P_{ijt}}$. However, because of the law of motion $\Delta P_{ijt} = P_{ijt} - P_{ijt-1}$, $\frac{\partial P_{ijt+s}}{\partial P_{ijt}} = 1$.

[11]Note that the first order conditions hold exactly in continuous time. We write the model in discrete time to facilitate bringing it to the monthly data.

This expression tells that a price increase occurs if q_{ijt} is larger than the associated price change costs. Similarly, for a price reduction, we have

$$(7) \qquad \frac{\Delta P_{ijt}}{P_{ijt-1}} = \frac{1}{c}\left(q_{ijt} + b\right) \text{ if } q_{ijt} \leq -\sqrt{\frac{2 \cdot a \cdot c}{m_{it} \cdot P_{ijt-1}}} - b\,.$$

From equations (6) and (7) we observe that small price changes are more likely with scope economies. If the number of prices to be adjusted - m_{it} - is large, the threshold will be low. In that case small shocks to q_{ijt} may induce small price changes.

For prices that are not adjusted we have the following condition:

$$(8) \qquad \frac{\Delta P_{ijt}}{P_{ijt-1}} = 0 \text{ if } -\sqrt{\frac{2 \cdot a \cdot c}{\left(m_{it}+1\right) \cdot P_{ijt-1}}} - b \leq q_{ijt} \leq \sqrt{\frac{2 \cdot a \cdot c}{\left(m_{it}+1\right) \cdot P_{ijt-1}}} + b\,.$$

Regarding equation (8) it is worth noting a division by $\left(m_{it}+1\right)$ is present in the expression for the thresholds, compared to a division by m_{it} in equations (6) and (7). We provide a derivation of equation (8) in Appendix A.[12]

Equations (6) and (7) show that if fixed menu costs are absent, i.e. $a = 0$, then the model is still capable of explaining the presence of zeroes in the price change data. The linear cost term b generates price rigidity. If $a = 0$ and $-b \leq q_{ijt} \leq b$, the firm will not adjust its price. Hence, linear costs induce infrequent price change. Strikingly, if $a = 0$ we will see many small price changes in the data. Minor deviations from the thresholds $q_{ijt} \geq b$ and $q_{ijt} \leq -b$ will induce small price changes. Finally, if the model also includes a plant-specific shock captured by q_{ijt}, we see immediately the model generates synchronization of price changes even if $a = 0$, and economies of scope are absent. This implies a model, where menu costs are

[12]The potential endogeneity problems related to the number of price changes, m_{it}, will be addressed when discussing the robustness of our findings.

linear and where shocks are plant-specific, is capable of explaining three key features of micro level data: infrequent price changes, small adjustments and synchronization.

If fixed costs are present, i.e. $a > 0$, small price changes are infrequent, and the tails of the price change distribution will become thicker. Fixed costs cause lumpy price changes because the thresholds in equations (6) and (7) increase in absolute value. Then firms will not adjust prices for quite some time, and once adjustment takes place the price change will be large. The convex costs parameter *c* affects pricing decisions as follows. From equations (6) and (7) it can be seen a higher value of the parameter *c* will decrease the response of the price change to the fundamental variables. Instead of making large price changes immediately firms will only make relatively small price modifications, and make a full response to a shock in several smaller steps.

Let us now consider in some more detail how economies of scope affect pricing decisions by considering a firm producing two goods. The analysis of price decisions is summarized in Figure 1. On the horizontal and vertical axes the marginal values of a price change for products 1 and 2 are provided, q_1 and q_2 respectively. For $j \in \{1, 2\}$ the thresholds determining when q_1 and q_2 are small or large enough to induce price change are given by: $S_j = \sqrt{\frac{2 \cdot a \cdot c}{2 \cdot P_{jt-1}}} + b$ and $T_j = \sqrt{\frac{2 \cdot a \cdot c}{P_{jt-1}}} + b$.

** Figure 1: Pricing decisions by a two product firm **

With $N_{it} = 2$, m_{it} can take the values $m_{it} \in (0, 1, 2)$. The inaction area I in the middle of the figure is caused by the presence of the fixed menu cost parameter, *a*, and the linear menu cost component, *b*. To see this, our equations (6) and (7) state that complete inaction, i.e. $m_{it} = 0$, requires $j \in \{1,2\}$, $-T_j < q_j < T_j$. The same equations (6) and (7) state that the firm will adjust both prices, i.e. $m_{it} = 2$, if $q_j \geq S_j$, or $q_j \leq -S_j$ for $j \in \{1,2\}$. This happens in the area denoted by II and III, bounded by what is referred to as S_j. It is scope advantages that create the difference between the thresholds S_j and T_j. More explicitly, for each product the threshold that prevents price adjustment decreases when m_{it} goes from 1 to 2. Let us now look at the potential case where $q_2 > T_2$, while $S_1 < q_1 < T_1$. In this case it is clear that the price of product 2 will be changed independent of whether the price of product 1 is changed or not. We see that if the price of product 1 will be changed too, $m_{it} = 2$, the relevant threshold will be S_1. Thus, we will end up with $m_{it} = 2$ instead of $m_{it} = 1$. Such a logic can also be applied in the case where $S_j < q_j < T_j$ for both products *j*. If the price adjustments can be coordinated, the relevant thresholds are S_j, not T_j, which results in $m_{it} = 2$. Therefore, in areas III, we see that in this case scope advantages cause joint price adjustments ($m_{it} = 2$) instead of no price change at all ($m_{it} = 0$). Finally, we have the case where only one product will be changed, for instance. $q_1 > T_1$ and $-S_2 < q_2 < S_2$. These are the areas denoted IV in the figure.

We observe that fixed menu costs featuring economies of scope induce price stickiness and hence infrequent adjustment. In addition, they make small price changes more likely as economies of scope tend to lower the thresholds determining when price change occurs. This reduces the size of price adjustment as well, as can be seen easily from equations (6) and (7).

Finally, the discussion above reveals economies of scope prompt synchronization of price change, which is seen most clearly by the presence of the areas with number III in Figure 1.[13]

Resuming, the model we developed provides and nests two alternative explanations for important stylized facts seen in many recent empirical contributions. In the next section, we will describe how we test empirically which features of the model hold when confronted with the data.

4. Estimation

Due to the presence of menu costs the firm's pricing decision is dynamic rather than static. In fact, optimizing the firm's value requires considering how setting current prices affects expected future profits and menu costs. This can be seen from our model by the role played by q_{ijt} denoting how a unitary change in the price of product *j* affects the expected value of the firm *i*. In equation (3) the expression for q_{ijt} is composed of discounted expected values of two elements; the marginal profit and the marginal menu cost function, respectively. The expression for q_{ijt} is essential in allowing us to estimate the parameters of the model. First, we show which elements of q_{ijt} play a major role in driving the firm's price change decision. Secondly, we derive the probability of price change which is a function of q_{ijt}.

To see which parts of q_{ijt} are important, we turn to the first element of q_{ijt}, i.e. $\frac{\partial \pi(.)}{\partial P_{ijt+s}}$. It reveals that a price change influences marginal profits in future periods. Let us for notational convenience temporarily abstract from sub-indices for the plant, product and time. We furthermore assume that the products of the multi-product firms are sufficiently

[13] The same principles apply with $N \geq 3$. The illustration of this in a two-dimensional setting is obviously harder.

differentiated in order to abstract from substitution and complementarity within the firm's portfolio of products. That means we are treating all products independent from each other. Essentially we follow Alvarez and Lippi (2014) assuming a monopolist sells *N* products with additively separable demands.[14] A product is assumed to be produced according to a Cobb-Douglas production technology with a flexible and homogeneous labour input component, *L*, and where w denotes the exogenous wage for a worker. The production is determined by $Q^S(L) = A \cdot L^{\alpha}$ where $0 < \alpha < 1$. The plants have some market power which might be modelled with an iso-elastic demand function given by $Q^D(P) = B \cdot \left(P / P_c \right)^{-\varepsilon}$ where $\varepsilon > 1$. The price of a plant's product is given by *P*, and P_c denotes the general price level in the industry. The price level P_c is exogenous to the firm reflecting that we employ a partial equilibrium model. Abstracting from inventory, profit for one of the firm's products is given

[14]See also their discussion on pages 95 and 96. This assumption is made for ease of computation. Note however, a firm is likely to conduct coordinated price adjustments. In case of substitution possibilities between the products a product-specific shock induces internal price coordination to avoid cannibalization of the firm's own products. On the other hand, product-specific shocks affect demand for a complementary product as well. Thus, internal product market dependency provides a benefit of price coordination. However, coordination of price change may be caused by menu costs providing scope advantages too. So disregarding a benefit of price coordination in the firm's profit function will make that the estimates of the fixed menu cost will be smaller to capture the benefits of coordination due to market dependency. Thus our estimates for the fixed menu costs, *a*, which cause coordination in our model, are likely to be biased downwards.

by $\pi(.) = P \cdot Q^D(P) - w \cdot L$. Note that A captures supply shocks and input factors that are predetermined. B captures demand shocks. With these assumptions profit is determined by $\pi(.) = P \cdot B \cdot (P/P^C)^{-\varepsilon} - w \cdot (B/A)^{1/\alpha} \cdot (P/P^C)^{-\varepsilon/\alpha}$. It can be shown that the first order derivative of profit $\pi(.)$ with respect to price P, $\frac{\partial \pi(.)}{\partial P_{ijt+s}}$, is a non-linear function of A, B, the wage rate w and the general price level P_c in the industry. It is worth noting that with our assumptions concerning the profit structure of the firm, sales volume does not feature explicitly in the marginal profit of the firm. Instead, demand conditions are represented by B and P_c.

The second term of equation (3), $\frac{1}{1+r}\frac{\partial C(\Delta P_{ijt+s})}{\partial P_{ijt+s}}$, depicts that a change in price saves menu costs in future periods. The convex component, which is inspired by Rotemberg (1982), one may abstract from in the *q* expression given that the price changes are rather small.[15] If the adjustment is small, the derivative of the quadratic adjustment cost expression, i.e. $\left(\frac{\Delta P_{ijt}}{P_{ijt-1}}\right)^2$, will be negligible in our proxy for *q* as given by equation (3). This assumption is supported by the descriptives already shown in Table 1.

We deal with the existence of the non-convex parts in the price adjustment costs in the spirit of Cooper *et al*. (2010, footnote 4). They observe that *q* does not include effects of the decision variable on the probability of adjustment even in case of non-linear adjustment. They argue as follows. To derive *q*, one takes the first order derivative of the firm's value function with respect to the decision variable (in our case prices) to obtain the marginal value of a

[15]In empirical factor demand models with quadratic adjustment cost components it has been a standard assumption to abstract from these future adjustment costs savings in the *q* expression (see Abel and Blanchard, 1986).

unitary change. The value function *V* compares over time the value of adjusting, *Va*, versus not adjusting, *Vn*: *V*=max(*Va*,*Vn*). The boundaries for the shocks to determine these two values *Va* and *Vn* are set such that the firm is indifferent between *Va* and *Vn* at the boundaries. A change in the decision variable might affect the boundaries and hence the future probability of adjustment. However, the effect of a change in the decision variable on the boundaries of the sets of action and inaction disappears, because at the boundary the firm is indifferent between adjustment and inaction: *Va* =*Vn*. Hence, the effects on the future probability of adjustment are irrelevant in *q*.[16]

We now turn to deriving the probability of price change. With the simplifications discussed above, we assume *q* is given by

(9) $$q_{ijt} = \gamma_0 + \gamma_1 ' X_{ijt} + \kappa_{it} - \eta_{ijt}$$

where the vector X_{ijt} contains variables observed by the econometrician and is multiplied by γ_1. The vector X_{ijt} contains information reflecting both supply and demand shifters *A* and *B*, approximated by year and monthly dummies. Furthermore, the vector includes two commodity group-specific dummies and a monthly commodity group-specific price index P_c for the relevant product. This index may pick up changes in demand conditions due to

[16]We have performed an *ad hoc* test to see whether disregarding marginal menu costs in proxying for *q* is not so harmful. We have included a dummy which takes the value one if there has been a price change for the product in one of the two previous months. The included dummy might pick up the effects of the discounted marginal value of a price change today, and therefore the future menu cost savings associated with the non-convex menu costs. The results indicate statistical insignificance of the dummy, which hints at that recent price changes hardly reduce expected marginal adjustment costs in the future, as pointed out by Cooper *et al*.

competition, but might also say something about the relevant cost-level in the industry not accounted for in the simple model to derive marginal profit. To proxy the marginal profit of the firm we incorporate the natural logarithm of the wage rate, *w* and its square to capture the non-linearity of marginal profit discussed above.[17] This latter variable is measured at the firm level, not the product level. The wage information is only available at a yearly frequency. Hence, the vector contains wage information of the previous year. This is consistent with an assumption that the plants use an AR(1) process to predict the wage rate. Using information of the previous year also reduces potential endogeneity problems. The monthly dummies may also pick up systematic deviation between the annual and monthly variables. In addition, they will control for general inflationary developments in the macro economy.

Importantly, there is also an additional parameter κ_{it} in equation (9). One explanation of price synchronization observed in the data could be that a plant is subject to a demand or supply shock that is common to all of its products driving all prices in the same direction simultaneously. To control for this, we implement a latent class model allowing for a shock that is plant- and time-specific.[18] The latent class approach is implemented by adding a shock κ_{it} to equation (9), where the process generating κ_{it} is characterized by two parameters to be estimated: ψ and κ. With probability ψ the shock $\kappa_{it} = \kappa$ and with probability $1-\psi$, $\kappa_{it} = 0$. All products within the plant are subject to this shock, which will be picked up by the latent class parameters. That means that if the observed coordination is only due to these

[17]The distribution of w_{it-1} is highly skewed due to which we had difficulty interpreting coefficients on the level of wages. Nevertheless, our menu cost estimates are hardly affected by the choice to take the log or level of the wage rate.

[18]Latent class models are also referred to as semiparametric heterogeneity models and finite mixture models (Cameron and Trivedi, 2005).

common shocks – and we have controlled for these - we would expect the fixed menu cost generating coordination as well to be insignificant. An advantage of this approach is that it potentially reduces biasedness of parameters due to endogeneity of the number of prices to be changed at the plant, m_{it}, by reducing misspecification of the model. The reason is that m_{it} is also largely driven by a plant level shock process. By including the latent class model generating plant level shocks this endogeneity issue is largely circumvented. We come back to this issue when we discuss robustness in the Results Section. Finally, the zero mean stochastic terms η_{ijt} are assumed to be normally distributed with variance σ_η^2.

Given the approximation of q_{ijt} it is possible to estimate the parameters of the model depicted in equations (6) and (7). Our approach is based on a two-step Heckman type selection estimator. First, an ordered response model is developed to estimate the probability of price increases, maintaining the current price, and price reductions. This model is based on the extensive margins of price changes. The main objective of the first step is to get an estimator for the determinants of q_{ijt}. Secondly, we estimate the equations determining the level of the price adjustment, using selection correction terms based on the estimates obtained from the ordered response model.[19]

Extensive Margin

Using equations (3), (4), (5) and (9) we show in Appendix B the log likelihood function is given by

[19]The use of two stage estimation methods is recommended in more complicated models in which maximum likelihood is computationally burdensome (Maddala, 1983, chapter 8). See also Nilsen *et al*. (2007) for a similar estimation procedure to analyse firm behaviour.

$$\ln L = \sum_{t=1}^{T} \sum_{\Delta P_{ijt}>0} \ln E\left(\Phi\left[\tilde{\gamma}_1' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 - \tilde{b}\right) - \sqrt{\frac{2\cdot\tilde{a}\cdot\tilde{c}}{m_{it}\cdot P_{ijt-1}}} \right] \right)$$

$$(10) \qquad + \sum_{t=1}^{T} \sum_{\Delta P_{ijt}<0} \ln E\left(\left\{ 1 - \Phi\left[\tilde{\gamma}_1' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 + \tilde{b}\right) + \sqrt{\frac{2\cdot\tilde{a}\cdot\tilde{c}}{m_{it}\cdot P_{ijt-1}}} \right] \right\} \right)$$

$$+ \sum_{t=1}^{T} \sum_{\Delta P_{ijt}=0} \ln E\left(\left\{ \begin{array}{l} \Phi\left[\tilde{\gamma}_1' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 + \tilde{b}\right) + \sqrt{\dfrac{2\cdot\tilde{a}\cdot\tilde{c}}{\left(m_{it}+1\right)\cdot P_{ijt-1}}} \right] \\ -\Phi\left[\tilde{\gamma}_1' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 - \tilde{b}\right) - \sqrt{\dfrac{2\cdot\tilde{a}\cdot\tilde{c}}{\left(m_{it}+1\right)\cdot P_{ijt-1}}} \right] \end{array} \right\} \right)$$

where the operator $E(\cdot)$ takes expectations with respect to the shock κ_{it} and $\Phi(\cdot)$ denotes a standard normal cumulative distribution function. A large number of the structural parameters in the model can be estimated. Nevertheless, the variance of the error term remains unknown, as is common in probit type models. As a consequence, the variance σ_η^2 of the error term in equation (9), has to be set equal to one. Hence, all structural parameter estimates have to be understood as relative to the standard deviation σ_η. This is not very harmful in terms of interpretation. For instance, if our estimate for the convex cost of price changes is $\tilde{c} = \frac{c}{\sigma_\eta}$, then according to equations (6) and (7) its inverse measures how much of a one standard deviation shock is transmitted into a price change. Likewise, the scaled parameters $\tilde{a} = \frac{a}{\sigma_\eta}$ and $\tilde{b} = \frac{b}{\sigma_\eta}$ measure how important the original parameters are in determining the decision whether or not to change price relative to a one standard deviation shock. From now on a ~ on top of a parameter indicates that the original parameter is divided by the standard deviation σ_η. Maximising the log likelihood in equation (10) allows us to acquire estimates of the following expressions: $\tilde{\gamma}_0, \tilde{\gamma}_1$, $\tilde{b}$, $\tilde{a} \cdot \tilde{c}$, $\tilde{\kappa}$ and ψ. To construct a proxy for *q* the estimates for $\tilde{\gamma}_0$ and $\tilde{\gamma}_1$ can be used.

Intensive margin

Once the estimates are obtained by maximising the log likelihood function, equations (6) and (7) can be used to determine a model for the size of the price change, driven by $\hat{q}_{itj}$. The hats above some parameters denote that estimated values based on the first-stage extensive margin have been used. This model needs to account for selection. We estimate the following two equations

$$(11) \qquad \frac{\Delta P_{ijt}}{P_{ijt-1}} = \frac{\left(\tilde{\gamma}_0 - \tilde{b}\right)}{\tilde{c}} + \frac{\left(\hat{\tilde{\gamma}}_1 X_{ijt} + \hat{\psi} \cdot \hat{\tilde{\kappa}} + \lambda_{ijt}^{+}\right)}{\tilde{c}} + \vartheta_{ijt}^{+}$$

for price increases, and

$$(12) \qquad \frac{\Delta P_{ijt}}{P_{ijt-1}} = \frac{\left(\tilde{\gamma}_0 + \tilde{b}\right)}{\tilde{c}} + \frac{\left(\hat{\tilde{\gamma}}_1 X_{ijt} + \hat{\psi} \cdot \hat{\tilde{\kappa}} - \lambda_{ijt}^{-}\right)}{\tilde{c}} + \vartheta_{ijt}^{-}$$

for price reductions. Equations (11) and (12) allow us to identify the parameter $\tilde{c}$ representing the quadratic adjustment cost component. With this estimate, and those obtained in the first step, it is then also possible to obtain the parameters of the fixed cost term, $\tilde{a}$. The terms ϑ_{ijt}^{+} and ϑ_{ijt}^{-} denote zero mean error terms while the expressions λ_{ijt}^{+} and λ_{ijt}^{-} are inverse Mills ratios. For some more detail we refer to Appendix C devoted to the estimation strategy.

5. Results

The main question addressed in this paper is which features of the model explain the data best. Two alternatives are offered for explaining infrequent price changes, small adjustment of prices, and synchronization. The first explanation, menu costs featuring economies of scope, holds if the parameter a is found to be significantly different from zero. The second explanation, linear menu costs combined with plant-specific shocks holds if the parameter b is significantly different from zero and when we find evidence for the latent class approach generating κ_{it}, characterized by two parameters: the probability ψ measuring the likelihood that the shock $\kappa_{it} = \kappa$. With probability $1-\psi$, $\kappa_{it} = 0$. All products within the plant are subject to this shock. Next to determining whether the parameters are statistically significant, we also assess to what extent the parameters are meaningful in an economic sense.

The estimation results are reported in Table 3. In column (1) we allow all the three adjustment costs components to take values different from zero, in column (2) we abstract from the latent class approach. Next we reintroduce the latent class approach but in column (3) we set $\tilde{a} = 0$ and in column (4) $\tilde{b} = 0$. The first observation we make, before one gets into details, is that there is a concave relationship between q and the wage rate. A second result worth noticing, is that the bootstrapped 95% confidence intervals for all the estimated adjustment costs parameters - $\tilde{a}$, $\tilde{b}$ and $\tilde{c}$ - show that these parameter estimates all are significantly different from zero. We also find evidence supporting the use of the latent class model. A second class exists with a probability of about 4.5 percent. The size of the shock $\tilde{\kappa}$ is positive and obtains a value of about 2.6. Given that it is scaled by the standard deviation of a normal distribution, i.e. $\tilde{\kappa} = \frac{\kappa}{\sigma_\eta}$, its size is quite large. It implies that once such a shock hits a plant, which is the case about once every 2 years, i.e. $1/\psi = 1/0.047 = 21$ months, price changes tend to be synchronized within the plant. Due to the large size of the shock, at least partly, synchronization is explained by plant-specific shocks. However, it is not the sole explanation of a price change to occur probably. In fact, Table 2 shows full synchronization happens relatively often with a frequency of about 18 percent. Hence, the shock process we identify does not explain the synchronization observed in the data entirely. We conclude from this that idiosyncratic shocks likely play an important role and may lead to synchronized price change as well. We have made an attempt to estimate a model including an additional latent class. However, in that case the estimation routine indicated a flat likelihood surface. In the context of a latent class model this is associated with over parametrization of the model, i.e. too many latent classes (Cameron and Trivedi, 2005). We interpret this as two classes already capturing the existing shock process quite well.

** Table 3: “Estimation Results” about here **

Starting with column (1), we observe the existence of significant linear menu costs, $\tilde{b}$. Estimating equations (11) and (12) by OLS reveals that the convex cost parameter $\tilde{c}$ is significantly different from zero. Bootstrapping yields that $\tilde{a}$ is different from zero as well according to common statistical conventions. These findings are in line with our descriptive statistics. They revealed a large amount of zeroes. Inactivity can be explained by both linear and fixed menu costs. As we control for common shocks to products within the firm coordination of prices is also explained by economies of scope in menu costs.

In column (2) we present results based on setting the parameters related to the latent class approach $\tilde{\kappa}$ and ψ equal to zero. We see that the performance of the model measured by the log likelihood is reduced from -25217.9 to -26373.1 by disregarding a common shock to the products. Note that the menu cost estimates are affected, but not dramatically. It appears that controlling for common shocks does not affect the main conclusions obtained from the model. Estimates of the menu cost parameters are quite robust. Based on these findings, we therefore conclude that coordination does not only stem from a common shock to the firm. Rather, coordination results also from the shape of the menu cost function.

When we turn to column (3), we reintroduce the latent class approach but set $\tilde{a}=0$.[20] Now the $\tilde{b}$ parameter is approximately 30 percent larger relative to the one in column (1). The reason is that there is no help from the square root in the threshold $\left|\sqrt{\frac{2\cdot\tilde{a}\cdot\tilde{c}}{m\cdot P}}+\tilde{b}\right|$ given that $\tilde{a}=0$. Thus, to ensure enough inaction, the $\tilde{b}$ parameter has to increase.

Let us now turn to the estimation results reported in column (4), setting $\tilde{b}=0$. Looking at the threshold for (in/)action, which is $\left|\sqrt{\frac{2\cdot\tilde{a}\cdot\tilde{c}}{m\cdot P}}+\tilde{b}\right|$, it is clear that when $\tilde{b}=0$, the product $\tilde{a}\cdot\tilde{c}$ has to be larger to induce inaction. Both parameters $\tilde{a}$ and $\tilde{c}$ increase in column (4). An indicator hinting at misspecification is the log-likelihood of the first-stage estimations. We find these to be -25217.9, -26373.1, -26042.1 and -32388.6 (columns 1, 2, 3, and 4 respectively). Thus the full model reported in column (1) outperforms all other models statistically when using conventional Likelihood Ratio tests. Thus this is our preferred specification. However, we see that disregarding the linear cost component as in column (4) seems most harmful.

We have also made an attempt to estimate a model without the assumption of economies of scope in price adjustment, such that firms do not benefit from internal price coordination. This can be implemented by assuming the fixed menu cost is given by $\tilde{a}$ rather than by $\frac{\tilde{a}}{m_{it}}$. For a model where coordination is absent (and therefore no benefits can be reaped from adjusting several product prices simultaneously) the maximum likelihood routine

[20]Note that if $\tilde{a}=0$, we have no exclusion restriction in the Heckman error correction term employed in the second step of the estimation procedure. So it is only identified by the functional form.

was driving the $\tilde{a}\cdot\tilde{c}$ term in $\sqrt{\frac{\tilde{a}\cdot\tilde{c}}{P_{ijt-1}}}$ towards zero, implying that the value of the square root becomes negligible. Then the model without coordination becomes observationally equivalent to the one presented in Table 3, column (3) where $\tilde{a}=0$. We observe that this specification is outperformed in terms of the value of the log likelihood function by the full model in column (1), with price coordination. This is clear evidence for the importance of internal price coordination.

Economic importance

To obtain some insight into the economic importance of the various menu cost components we conduct some exercises based on the results presented in column (1). Abstracting from fixed costs, i.e. $\tilde{a}$, we see that convex costs are more important than linear costs when $\Delta p/p$ is larger than 0.100 (=2*1.003/20.016).[21] This happens in about 2 percent of the observations. Thus, convex price adjustment costs are of minor importance. Focusing on non-convex costs, we find that the linear costs are largest when $\Delta p/p \geq \tilde{a}/\left(\tilde{b}\cdot m\cdot p\right)$.[22] Setting m = 1.06, the average number of simultaneous product price changes, and p = 1531, the average price, and using the parameter estimates for $\tilde{a}$ and $\tilde{b}$ reported in column (1), i.e. $\tilde{a}$ = 0.856 and $\tilde{b}$ = 1.003, we find that linear costs are largest when $\Delta p/p \geq 0.856/(1.003\cdot1.06\cdot1531) \approx 0$. This means that linear costs are relatively large.

Non-convex menu costs components induce inaction. To fully understand the importance of the linear and fixed costs, we conduct a counterfactual analysis. We calculate

[21]This calculation is based on the linear and convex elements of the menu costs; $\tilde{b}\Delta p \leq (\tilde{c}/2)\Delta p^2/p$ which gives $\Delta p/p \geq 2\tilde{b}/\tilde{c}$.

[22]This holds when $\tilde{b}\cdot\Delta p \geq \tilde{a}/m$.

the value of the threshold using estimates from the full model provided in column (1) of Table 3. By setting either the parameter $\tilde{a}$ or $\tilde{b}$ equal to zero in the thresholds $\left|\sqrt{\frac{2\cdot\tilde{a}\cdot\tilde{c}}{m\cdot P}}+\tilde{b}\right|$, while using the predicted q values - again from the full model - we calculate the alternative price adjustment probabilities based on the counterfactual thresholds.

** Table 4: “Data Frequency and Estimated Probability Price Change Regimes” about here **

In Table 4 we present the alternative probabilities and compare them with the actual price change frequencies observed in the data.[23] In column (1) the actual frequencies are presented. Comparing the actual frequencies and the probabilities calculated based on the extensive margin of the full menu costs model, reported in column (2), we conclude that the full model generates probabilities that come very close to the observed frequencies in the data. If we now set the fixed cost parameter $\tilde{a}=0$, see column (3), we observe a reduction of inaction according to the average probabilities. This finding suggests that even relatively small fixed menu costs generate substantial impact on the estimated results. The probability of inaction decreases with more than 10 percentage points, and the action probabilities increase correspondingly. When we continue to column (4), setting $\tilde{b}=0$, we see that abstracting from linear menu costs deteriorates the match between the probabilities calculated and the figures presented in the first column. This finding is also consistent with the bad performance of the specification where $\tilde{b}=0$ in Table 3. Thus, the findings indicate indeed that linear menu costs

[23]For each product price regime we have calculated the probability at a given point in time based on parameter estimates of the Ordered Probit model. The probability is the unweighted average of these probabilities across product price, for each month.

are important to understand staggered price setting in our data, though fixed costs cannot be neglected.

Our results relate to previous findings in the literature in the following way. The phenomenon of price rigidity is important to understand business cycle variation caused by nominal shocks as was recently confirmed by Nakamura and Steinsson (2010) who extend a simple menu cost model. For supermarkets costs of changing prices range between 1.7 and 1.8 percent of revenue (Slade, 1998; Aguirregabiria, 1999; Midrigan, 2011). For a manufacturing firm Zbaracki *et al*. (2004) find total menu cost of 1.2 percent of total revenue. Schoenle (2017) estimates annual menu costs of similar size. These studies have observed a substantial impact of menu costs on firm level pricing decisions. Our discussion of Table 4 confirms that fixed menu cost components have a notable impact on price rigidity. Though we have no estimate of the total size of menu costs - we do not have an estimate of the absolute size concerning menu cost parameters due to our estimation routine - our findings also support the view menu costs influence micro level price setting behaviour. Additionally, the results reported here give support to our theoretical model, and that the menu costs include convex, linear and fixed costs. Furthermore we find evidence for price coordination, in line with the models by Midrigan (2011), Alvarez and Lippi (2014), Bhattarai and Schoenle (2014), which suggests that pricing decisions are indeed subject to scope advantages. Due to these scope economies firms can reduce the impact of menu costs by coordinating price changes internally. However, we also find that a model incorporating linear menu costs combined with plant-specific shocks is capable of replicating the dynamics observed in recent micro level data sets on pricing decisions.

Robustness

The estimation results are robust to initiating the estimation algorithm from different sets of starting values. Thus the parameter estimates reported in Table 3 seem to correspond to a global maximum.

The number of product prices to be changed in the plant, m_{it}, potentially raises endogeneity concerns; m_{it} might be driven by plant level shocks correlated with the error component η_{ijt} in equation (9). Employing the latent class approach we have accounted for the endogeneity issue to some extent already. To further reduce the potential endogeneity problem, we employ a two-step control function approach inspired by Rivers and Vuong (1988) and discussed further by for instance Wooldridge (2014, 2015). We first estimate a model for the fraction of prices changed at the plant, i.e. m_{it}/N_{it}. Here we have used an interval regression model which is a generalization of censored regression, since the degree of coordination is such that $0 \le m_{it}/N_{it} \le 1$. An exclusion restriction in our control function approach is not essential due to the highly nonlinear nature of the first step model (Altonji *et al*., 2005; Card and Giuliano, 2013). The first stage delivers an estimation error measuring the difference between the realization of m_{it}/N_{it} and its predicted value: $\hat{v}_{it} = m_{it}/N_{it} - \hat{m}_{it}/N_{it}$. Like the latent term κ_{it}, this estimation error denotes a plant level shock. The residual $\hat{v}_{it}$ is to be included in equation (10). Note that in equation (11) we replace $\pm\left(\sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it}P_{ijt-1}}}\right)$ by $\pm\left(\sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it}P_{ijt-1}}}\right)+\alpha\cdot\hat{v}_{it}$ and $\pm\left(\sqrt{\frac{2\tilde{a}\tilde{c}}{(m_{it}+1)\cdot P_{ijt-1}}}\right)$ by $\pm\left(\sqrt{\frac{2\tilde{a}\tilde{c}}{(m_{it}+1)\cdot P_{ijt-1}}}\right)+\alpha\cdot\hat{v}_{it}$. When we estimate the model which includes both the latent variable κ_{it} and the residual $\hat{v}_{it}$, the results point into the direction of minor deviations from the structural parameter estimates presented in Column 1, Table 3. Such a finding is to be expected if the latent class approach has already reduced the potential endogeneity problem. As an additional exercise to address the endogeneity problem, we estimate a model corresponding to the model reported in Column 2 of Table 3, i.e. without the latent variable κ_{it}, but where we now include the residual $\hat{v}_{it}$ only. Again estimation results are in the order of magnitude of the already reported estimates in Column 1, Table 3. Based on these two additional exercises, we conjecture that endogeneity issues are not driving our main conclusions.

We have performed two additional analyses to see whether our results are driven by unobserved heterogeneity. First, we have also employed a version of the latent class model where we replaced the shock κ_{it} by a term κ_i, which is hence only plant-specific but time invariant. Hence, equation (9) becomes $q_{ijt} = \gamma_0 + \gamma_1 ' X_{ijt} + \kappa_i - \eta_{ijt}$. Second, we have also estimated the model for two different groups of firms in terms of the number of products they make, i.e. $N_{it} \leq 4$ and $N_{it} \geq 5$. The estimates for these two approaches to control for unobserved heterogeneity do not alter our conclusions. The results are not reported, but are available from the authors on request.

6. Conclusion

In this paper we develop a model that nests two alternative explanations for observing three well known empirical moments of price change data: infrequent price changes, many small price changes and synchronization. As has been shown previously these stylized facts can be explained by menu costs allowing for scope economies. We show that a model including linear menu costs and plant-specific shocks offers the same possibility.

We employ a structural estimation technique as it allows to trace parameters in the firm's optimization problem. The model is tested on a sample concerning Norwegian producer plants. Main features of these data resemble those of price behaviour of firms in

Euro zone countries. The estimates suggest all types of menu costs are important to explain micro level pricing dynamics. We find evidence of linear and fixed menu costs that account for inaction of price adjustment. Our estimates also suggest economies of scope in adjusting prices resulting in (incomplete) synchronization of price changes. Convex menu costs are statistically significant but of moderate economic importance. Finally, we observe the presence of plant-specific shocks driving the pricing behaviour of plants. Altogether these results imply that key stylized facts are explained by two alternative model specifications operating at the same time.

The results provided in this paper reveal the potential benefits of deviating from traditional menu cost models in which only fixed or convex costs are included. Our findings allow sharpening our judgement of menu cost types, and provide fruitful possibilities to be explored in future research. One of these concerns our finding of linear menu costs. In general equilibrium models these may entail first order welfare costs of inflation. So far in such models menu costs that are fixed or quadratic yield only second order costs and hence are negligible (Nistico, 2007; Burstein and Hellwig, 2008; Lombardo and Vestin, 2008). Hence, the question whether inflation in such a framework with linear menu costs is harmful is worth investigating.

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Table 1: Frequency of (monthly) price changes ($\Delta p \,/\, p$)

0.40 ≤	0.1		
0.30 ≤ < 0.40	0.1	0.075 ≤ < 0.100	0.8
0.20 ≤ < 0.30	0.2	0.050 ≤ < 0.075	1.8
0.10 ≤ < 0.20	1.1	0.025 ≤ < 0.050	3.4
0.00 < < 0.10	13.5	0.000 < < 0.025	7.5
0.00	76.5		
-0.10 ≤ < 0.00	7.9	-0.025 ≤ < 0.000	5.1
-0.20 ≤ < -0.10	0.6	-0.050 ≤ < -0.025	1.6
-0.30 ≤ < -0.20	0.1	-0.075 ≤ < -0.050	0.8
< -0.30	0.1	-0.100 ≤ < -0.075	0.4

Note: Frequency estimates are given in percent. The right part of the table denotes how the observations in the range 0.00 < < 0.10 and -0.10 < < 0.00 are distributed, respectively.

Table 2: Internal Coordination of Product Price Changes

	Frequency
No price change at all	69.1
Partial synchronization	12.5
All prices change	18.4

Note: Frequency estimates are given in percent.

Table 3: Estimation Results

	Column (1)		Column (2)		Column (3)		Column (4)	
	coeff	se	coeff	se	coeff	se	coeff	se
Maximum likelihood results								
$\ln w_{t-1}$	1.662	0.326	1.080	0.300	2.0045	0.311	1.033	0.327
$(\ln w_{t-1})^2$	-0.547	0.113	-0.389	0.104	-0.678	0.108	-0.291	0.113
$\tilde{a}\tilde{c}$	17.134	0.944	14.632	0.769	-	-	316.031	3.369
$\tilde{b}$	1.003	0.010	0.924	0.009	1.303	0.006	-	-
$\tilde{\kappa}$	2.568	0.057	-	-	2.578	0.054	3.094	0.057
ψ	0.047	0.003	-	-	0.044	0.002	0.051	0.003
LogL	-25217.9		-26373.1		-26042.1		-32388.6	
Nbr of observ.	39082		39082		39082		39082	
OLS with selection correction								
$1/\tilde{c}$	0.050	0.001	0.052	0.001	0.051	0.001	0.020	0.003
Bootstrap confidence intervals								
$\tilde{a}$	0.856	[0.455; 1.771]	0.754	[0.336;1.398]	-	-	6.326	[4.730; 9.463]
$\tilde{b}$	1.003	[0.836; 1.239]	0.924	[0.723;1.086]	1.303	[1.237; 1.503]	-	-
$\tilde{c}$	20.016	[16.429; 25.837]	19.393	[15.533;23.875]	19.449	[15.099; 20.646]	49.956	[45.110; 60.312]

Notes: Commodity specific price indices, commodity type dummies, year dummies and monthly dummies are included in the first stage equations. All the parameters except for ψ should be thought of as normalized by the standard deviation σ_η. In square brackets 95% confidence intervals are provided obtained by bootstrapping. For a description of the bootstrap procedure see also Appendix C.

Table 4: Data Frequency and Estimated Frequency Price Change Regimes

	Column (1) Data Frequency	Column (2) Full Model	Column (3) Full Model & $\tilde{a} = 0$	Column (4) Full Model & $\tilde{b} = 0$
Price Increase	14.8	14.7	22.6	45.1
Inaction	76.5	75.5	63.7	23.7
Price Decrease	8.7	9.4	13.7	30.3

Note: Frequency estimates are given as a percent.

Table A1: Descriptive Statistics, final sample

	Mean	SD
p	1,535.26	2,922.40
$\Delta p/p$	0.003	0.03
w	4.05	0.98
ln w	1.37	0.23
$(\ln w)^2$	1.93	0.65
m	1.06	2.01
N	4.56	2.56
P_c	118.09	10.86
L	105.18	126.79

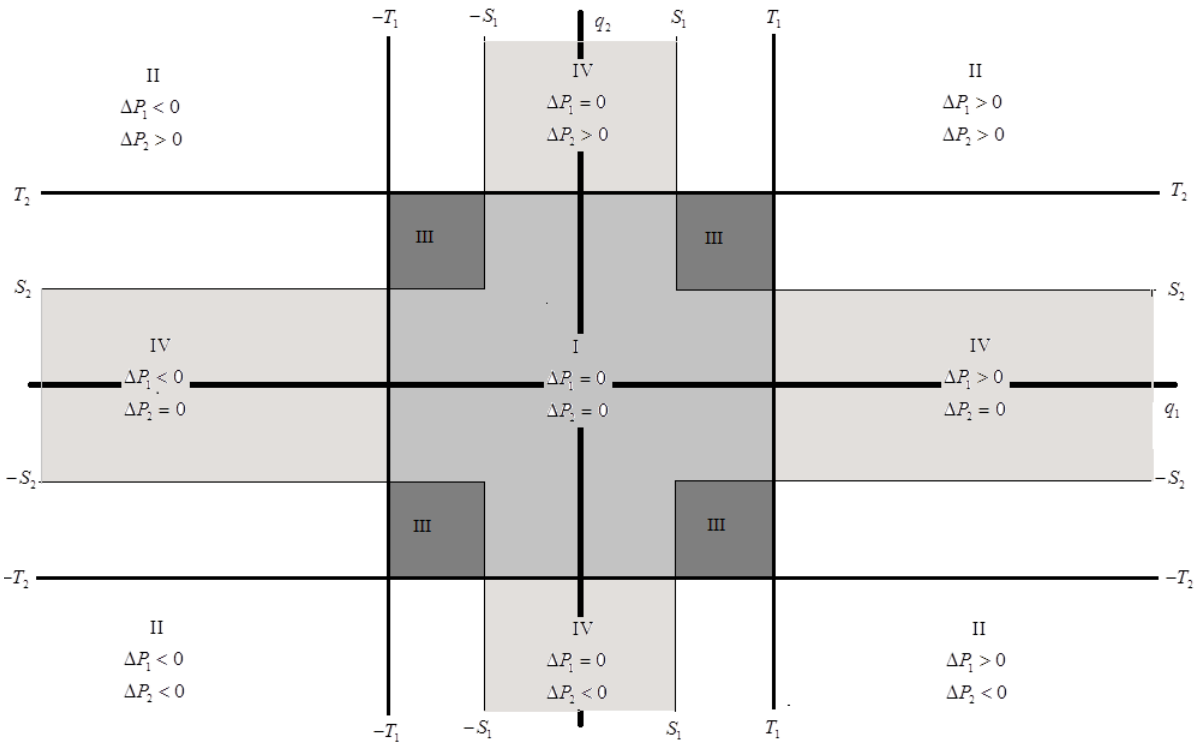
Notes: These statistics are based on the sample used for estimating the model. The number of observations for monthly data is 39,082. For yearly data the number of observations equals 10,238. p, w, m, N, P_c and L denote the monthly price level [in NOK], the yearly individual average wage level [in 100,000 NOK], the observed number of product price changes in a month, the number of products observed in a month, the monthly commodity group-specific price index for the relevant product and the number of employees, respectively.

Table A2: Distribution of data across sectors

SIC	Percentage
15 Manufacture of food products and beverages	16.18
17 Manufacture of textiles	5.32
18 Manufacture of wearing apparel; dressing and dyeing of fur	3.75
19 Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	0.55
20 Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	9.79
21 Manufacture of pulp, paper and paper products	4.27
24 Manufacture of chemicals and chemical products	6.20
25 Manufacture of rubber and plastic products	8.59
26 Manufacture of other non-metalic mineral products	14.65
27 Manufacture of basic metals	1.14
28 Manufacture of fabricated metal products, except machinery and equipment	12.17
29 Manufacture of machinery and equipment n.e.c.	4.39
31 Manufacture of electrical machinery and apparatus n.e.c.	1.10
32 Manufacture of radio, television and communication equipment and apparatus	1.78
33 Manufacture of medical, precision and optical instruments, watches and clocks	1.35
36 Manufacture of furniture; manufacturing n.e.c.	8.79
Total	100

Notes: Industry codes and classification have been collected from SSB and are based on NACE Rev. 1.1. To limit heterogeneity in our dataset we excluded sectors producing capital goods. More precisely, the capital goods sectors excluded have 3 digit NACE codes 281, 284, 291, 295, 311, 322, 331, 332, 342, 343, 351. In addition we trimmed the data removing tails. See also footnote 4.

Figure 1: Pricing decisions by a two product firm



Appendix A: Explanation equation (8)

We consider how at the firm level the optimization works to determine which prices have to be adjusted. Coordination provides individual product managers the possibility to share the fixed menu costs. Then, the fixed menu cost for a single price is divided by the number of products to be changed. This fixed menu cost is smallest if all prices of the firm are adjusted, i.e. when $m_{it} = N_{it}$. Whether all prices are changed or not is determined by applying equation (6) and (7) where $m_{it} = N_{it}$. If these equations are satisfied all prices will be adjusted. If some prices are not meeting the requirement stated in equation (6) or (7) with $m_{it} = N_{it}$, these prices not satisfying the condition will not be changed. They will remain unadjusted in this specific period, as the fixed menu cost per product price will only increase from now on, as it is divided by a smaller actual number of product prices being changed, i.e. $m_{it} < N_{it}$.

The next step in the optimization is to set m_{it} equal to the number of prices satisfying equations (6) and (7) in the previous optimization round. Now consider whether it is optimal to change the remaining product prices by checking whether the conditions in equations (6) and (7) are satisfied applying the new number m_{it} in the thresholds. If some prices do not meet the requirements, they are now also skipped from the set of price change candidates and the optimization process will be repeated with a smaller number of candidate prices $m_{it} < N_{it}$. This process will continue until all prices in the set of candidates are meeting equation (6) or (7) and then they will be changed. Alternatively, it may be optimal to change no prices at all. Let us assume now $0 < m_{it} < N_{it}$ and that m_{it} is the actual number of prices to be changed. We know from this that in the previous round of the optimization process all prices that remain unchanged satisfy $-\sqrt{\frac{2 \cdot a \cdot c}{(m_{it}+1) \cdot P_{ijt-1}}} - b \le q_{ijt} \le \sqrt{\frac{2 \cdot a \cdot c}{(m_{it}+1) \cdot P_{ijt-1}}} + b$, as in equation (8). Note that the boundaries set on q_{ijt} in this expression are stricter when dividing by $(m_{it}+1)$ rather than by m_{it}. The set of product prices to be changed is given by

$$\left\{ k \in \{1,..,N_i\} \wedge \left(q_{ikt} \le -\sqrt{\frac{2\cdot a\cdot c}{m_{it}\cdot P_{ikt-1}}} - b \vee q_{ikt} \ge \sqrt{\frac{2\cdot a\cdot c}{m_{it}\cdot P_{ikt-1}}} + b \right) \right\}.$$

Appendix B: Derivation of the likelihood function

To obtain the log likelihood function we first consider the probability that in a month *t* a set of product prices is unchanged at plant *i*. Suppose first that the number of prices that remains unchanged equals 2 as represented by area I in Figure 1. To obtain the probability of that event, we need to subtract from the probability $\Pr(\text{Area I}) = \prod_{\Delta P_{ijt}=0}\left(\Pr\left(-\sqrt{\frac{2\tilde{a}\tilde{c}}{P_{ijt-1}}}-b \le q_{ijt} \le \sqrt{\frac{2\tilde{a}\tilde{c}}{P_{ijt-1}}}+b\right)\right)$, the probability mass associated with the squares marked by the roman number I. For the two product firm this probability mass equals

$$\Pr(\text{Area III}) = \prod_{j\in\{1,2\}}\left(\Pr\left(\sqrt{\frac{\tilde{a}\tilde{c}}{P_{jt-1}}}+b \le q_{ijt} \le \sqrt{\frac{2\tilde{a}\tilde{c}}{P_{jt-1}}}+b\right)+\Pr\left(-\sqrt{\frac{2\tilde{a}\tilde{c}}{P_{jt-1}}}-b \le q_{ijt} \le -\sqrt{\frac{\tilde{a}\tilde{c}}{P_{jt-1}}}-b\right)\right)$$

Subtracting this probability is required only in case the number of prices that are unchanged satisfies $N_{it} - m_{it} \ge 2$. More generally, using equation (9) and assuming the number of product prices that is adjusted is equal to m_{it}, the contribution of the likelihood function of this part of the data set for firm *i* at month *t* equals

$$\Pr\left(\Delta P_{ijt} \mid \forall j : \Delta P_{ijt} = 0\right) =$$

$$\prod_{\Delta P_{ijt}=0}\left(\Pr\left(-\sqrt{\frac{2\tilde{a}\tilde{c}}{(m_{it}+1)P_{ijt-1}}}-b \le q_{ijt} \le \sqrt{\frac{2\tilde{a}\tilde{c}}{(m_{it}+1)P_{ijt-1}}}+b\right)\right)$$

$$-\prod_{\Delta P_{ijt}=0;N_{it}-m_{it}\ge 2}\left(\Pr\left(\sqrt{\frac{2\tilde{a}\tilde{c}}{(m_{it}+2)P_{ijt-1}}}+b \le q_{ijt} \le \sqrt{\frac{2\tilde{a}\tilde{c}}{(m_{it}+1)P_{ijt-1}}}+b\right)\right.$$

$$\left.+\Pr\left(-\sqrt{\frac{2\tilde{a}\tilde{c}}{(m_{it}+1)P_{ijt-1}}}-b \le q_{ijt} \le -\sqrt{\frac{2\tilde{a}\tilde{c}}{(m_{it}+2)P_{ijt-1}}}-b\right)\right)$$

This equation can be rewritten as follows

$$\Pr\left(\Delta P_{ijt} \mid \forall j : \Delta P_{ijt} = 0\right) =$$

$$\prod_{\Delta P_{ijt}=0}\left(\Pr\left(-\sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+1\right)P_{ijt-1}}}-b \le q_{ijt} \le \sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+1\right)P_{ijt-1}}}+b\right)\right)\cdot\left(1-\prod_{\Delta P_{ijt}=0;N_{it}-m_{it}\ge 2}\left(1-\theta_{ijt}\right)\right)$$

where

$$\theta_{ijt} = \frac{\left(\Pr\left(-\sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+2\right)P_{ijt-1}}}-b \le q_{ijt} \le \sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+2\right)P_{ijt-1}}}+b\right)\right)}{\left(\Pr\left(-\sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+1\right)P_{ijt-1}}}-b \le q_{ijt} \le \sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+1\right)P_{ijt-1}}}+b\right)\right)}$$

Note that $0 < \theta_{ijt} < 1$. For optimization purposes we take the log likelihood. Hence, we obtain

$$\ln\left(\Pr\left(\Delta P_{ijt} \mid \forall j : \Delta P_{ijt} = 0\right)\right) =$$

$$\sum_{\Delta P_{ijt}=0}\left(\ln\left(\Pr\left(-\sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+1\right)P_{ijt-1}}}-b \le q_{ijt} \le \sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+1\right)P_{ijt-1}}}+b\right)\right)\right.$$

$$\left.+\ln\left(1-\prod_{\Delta P_{ijt}=0;N_{it}-m_{it}\ge 2}\left(1-\theta_{ijt}\right)\right)\right)$$

To reduce the complexity of the optimization problem, we use that $\ln\left(1-\prod_{\Delta P_{ijt}=0;N_{it}-m_{it}\ge 2}\left(1-\theta_{ijt}\right)\right) \approx -\prod_{\Delta P_{ijt}=0;N_{it}-m_{it}\ge 2}\left(1-\theta_{ijt}\right) \approx 0$. The time to compute bootstrap confidence intervals for the parameter estimates takes about a week for a single specification of the model. Hence, we make this simplification. However, the contribution of the expression to the log likelihood is very small in most cases as in 69.1 percent of the data points we observe no price change at all. Partial price synchronization occurs in 12.5 percent of the data points. For the estimates we have obtained and which are presented in Table 3 we find that $\theta_{ijt} \approx 1$. Since it is at least two prices that are unchanged, the expression $\prod_{\Delta P_{ijt}=0; N_{it}-m_{it}\geq 2} \left(1-\theta_{ijt}\right) \approx 0$, as it involves at least one multiplication of two probabilities. Hence, using equations (6), (7) and (9) the log likelihood function we employ is given by equation (10).

We see in equation (10) that the denominators of the thresholds are not always the same. This is due to our derivations resulting in equations (6), (7) and (8). The likelihood for price changes may also be developed as follows. It is based on the notion that in the previous round of the optimisation problem a certain product price has remained being a candidate to change. However, it now needs to satisfy a stricter threshold. Hence, for a price increase the likelihood contribution equals the conditional probability of satisfying the stricter threshold given that the price did satisfy a less strict threshold in the previous round, multiplied with the unconditional probability the price did satisfy the threshold of the previous round in the optimisation process. This means that the contribution to the likelihood is: $\Pr\left(q_{ijt} \geq \sqrt{\frac{2ac}{m_{it}P_{ijt-1}}} + b \,\middle|\, q_{ijt} \geq \sqrt{\frac{2ac}{(m_{it}+1)P_{ijt-1}}} + b \right) \cdot \Pr\left(q_{ijt} \geq \sqrt{\frac{2ac}{(m_{it}+1)P_{ijt-1}}} + b \right)$. This expression is equal to $\Pr\left(q_{ijt} \geq \sqrt{\frac{2ac}{m_{it}P_{ijt-1}}} + b \right) = E\left(\Phi\left[\tilde{\gamma}_1{}' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 - \tilde{b}\right) - \sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it}P_{ijt-1}}} \right] \right)$ which we see in equation (10). For the case of a price decrease an analogous argument can be put forward. Due to the difference between the thresholds in equation (8) we find in Table 4 that we present later the probabilities of the various cases do not add up to 1 precisely in case the parameter $a \neq 0$, but they are very close to 1.

Appendix C: Estimation strategy

The two inverse Mills ratios we employ equal the expected value of the error term in equation (9), conditional upon being in either the price increase or price reduction regime. These correction terms are given by

$$\lambda_{ijt}^{+} = E\left(\frac{\phi\left[\tilde{\gamma}_1{}' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 - \tilde{b}\right) - \sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it} P_{ijt-1}}} \right]}{\Phi\left[\tilde{\gamma}_1{}' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 - \tilde{b}\right) - \sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it} P_{ijt-1}}} \right]} \right)$$

and

$$\lambda_{ijt}^{-} = E\left(\frac{\phi\left[\tilde{\gamma}_1{}' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 + \tilde{b}\right) + \sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it} P_{ijt-1}}} \right]}{1 - \Phi\left[\tilde{\gamma}_1{}' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 + \tilde{b}\right) + \sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it} P_{ijt-1}}} \right]} \right)$$

where $\phi(\cdot)$ denotes a standard normal distribution function. Note that expectations have to be taken with respect to κ_{it}. Equations (11) and (12) can be estimated simultaneously by OLS after replacing $\tilde{\gamma}_1$, λ_{ijt}^{+} and λ_{ijt}^{-} by the values calculated from the estimates acquired from the maximum likelihood routine. Note that the size of the price, P_{ijt-1}, does not enter equations (11) and (12) determining the size of the price change. It does feature in the threshold equation. As a result we have a meaningful exclusion restriction that facilitates estimating price change equations using the selection correction terms.

Maximum likelihood estimation of equation (10), and the OLS estimation of equations (11) and (12) representing the level of price changes yields consistent parameter estimates if the explanatory variables are uncorrelated with the error terms. However, the estimates of standard errors of the latter two equations are not consistent due to the generated regressor problem. Since there is just one generated regressor in each equation, *t*-statistics can still be used to test the hypotheses their coefficient is equal to zero (Pagan, 1984). Furthermore, we can also trace back estimates of the other structural parameters.

In the estimation routine the parameters $\tilde{a}$, $\tilde{b}$ and $\tilde{c}$ can take any value, though we restrict the product $\tilde{a} \cdot \tilde{c}$ to be positive to make sure we do not get a negative number in the argument of the square root in the threshold. To ensure symmetry of the *c* parameter we estimate equations (11) and (12) simultaneously by

$$\frac{\Delta P_{ijt}}{P_{ijt-1}} = \xi_0 + I\left(\Delta P_{ijt} > 0\right) \cdot \frac{\left((\hat{\tilde{\gamma}}_0 - \hat{\tilde{b}}) + \hat{\tilde{\gamma}}_1 X_{ijt} + \hat{\psi} \cdot \hat{\tilde{\kappa}} + \overset{+}{\lambda}_{ijt}\right)}{\tilde{c}} + I\left(\Delta P_{ijt} < 0\right) \cdot \frac{\left((\hat{\tilde{\gamma}}_0 + \hat{\tilde{b}}) + \hat{\tilde{\gamma}}_1 X_{ijt} + \hat{\psi} \cdot \hat{\tilde{\kappa}} - \overset{-}{\lambda}_{ijt}\right)}{\tilde{c}} + \vartheta_{ijt}$$

Using a bootstrap routine we obtain confidence intervals of the parameter estimates of $\tilde{a}$, $\tilde{b}$ and $\tilde{c}$. The confidence intervals are based on 200 replications for the Ordered Probit model and the price level equations. This works as follows. From the dataset we use to estimate the model, we draw *N* observations with replacement, where *N* is the number of plants analysed for the initial estimations. This means we cluster around the producers. The ordered probit model is estimated first to obtain estimates $\tilde{\gamma}_0, \tilde{\gamma}_1$, $\tilde{b}$, $\tilde{a} \cdot \tilde{c}$, $\tilde{\kappa}$ and ψ, for each new bootstrap sample. Next, we estimate the price change equations. This step is replicated 200 times. After 200 replications, we have obtained a distribution for each parameter of interest. The 95% confidence interval for these parameters is based on the limits of the 2.5% and 97.5% quantiles.

Alternative estimation strategies

We have also investigated the possibility to obtain the parameters in a one-step estimation yielding no convergence however and we were unable to estimate the menu cost parameters with any precision. One reason might be that in the one step likelihood model, where - abstracting from the latent shock κ_{it} - the log likelihood is given by

$$\ln L = \begin{array}{l} \sum_{t=1}^{T} \sum_{\Delta P_{ijt} \neq 0} \ln \phi \left(\tilde{\gamma}_0 + \tilde{\gamma}_1^{'} X_{ijt} - \tilde{b} \cdot I\left(\Delta P_{ijt} > 0\right) + \tilde{b} \cdot I\left(\Delta P_{ijt} < 0\right) - \tilde{c}\, \frac{\Delta P_{ijt}}{P_{ijt-1}} \right) \\ + \sum_{t=1}^{T} \sum_{\Delta P_{ijt} = 0} \ln \left\{ \begin{array}{l} \Phi\left[\tilde{\gamma}_1^{'} X_{ijt} + \left(\tilde{\gamma}_0 + \tilde{b}\right) + \sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+1\right) P_{ijt-1}}} \right] \\ - \Phi\left[\tilde{\gamma}_1^{'} X_{ijt} + \left(\tilde{\gamma}_0 - \tilde{b}\right) - \sqrt{\frac{2\tilde{a}\tilde{c}}{\left(m_{it}+1\right) P_{ijt-1}}} \right] \end{array} \right\} \end{array}$$

and $\phi(.)$ denotes the probability density function of a normal distribution, the threshold parameter $\tilde{a}\tilde{c}$ is identified only by the observations where price change equals zero. Instead, in equation (10) the positive and negative price change observations advance estimating the thresholds as well.

As shown, the interdependency between the price changes – economics of scope – is easily incorporated in the *q* framework. One may also employ simulated method of moments (SMM) to estimate the structural model outlined above. However, as prices cannot be regarded as independent, in an SMM routine this expands the state space considerably. Firms in our sample on average report about 5 product prices (and some firms even report as many as 20 different prices). Assuming for each of these 5 product prices 100 points are used in a grid, one would already have a state space with at least $100^5 = 10^{10}$ points, as in this calculation stochastic processes expanding the dimensionality of the state space have not been accounted for yet. In spite of necessary simplifying assumptions used when approximating the marginal value of a unitary price change, i.e. *q*, we prefer the ML routine to the SMM due to computational feasibility.