CESifo Working Papers

www.cesifo.org/wp

Price Changes – Stickiness and Internal Coordination in Multiproduct Firms

Wilko Letterie
Øivind A. Nilsen

CESifo Working Paper No. 5701
Category 6: Fiscal Policy, Macroeconomics and Growth
January 2016

ISSN 2364-1428

CESifo
Center for Economic Studies & Ifo Institute

CESifo *Working Paper No. 5701*

Price Changes – Stickiness and Internal Coordination in Multiproduct Firms

Abstract

We assess empirically the micro-foundations of producers' sticky pricing behaviour. The intertemporal profit function considered accounts for various functional forms of menu costs. The focus is on the analysis of multiproduct plants, and the menu costs therefore also allow for economies of scope. The structural model developed is tested on a merged panel of monthly product- and plant-specific producer prices and yearly plant-specific producer statistics for Norwegian plants. We find evidence of linear and fixed menu costs that account for inaction of price adjustment. Convex menu costs are statistically significant but of moderate importance. Finally, our estimates suggest economies of scope in adjusting prices resulting in (incomplete) synchronization of price changes.

JEL-codes: E300, E310.

Keywords: price setting, micro data, multiproduct firms.

*Wilko Letterie**
Maastricht University
School of Business and Economics
Department of Organization and Strategy
P.O. Box 616
The Netherlands – 6200 MD Maastricht
w.letterie@maastrichtuniversity.nl

Øivind A. Nilsen
Norwegian School of Economics
Department of Economics
Norway – 5045 Bergen
oivind.nilsen@nhh.no

*corresponding author

December 22, 2015
The paper was partly written while Nilsen was visiting the Center for Macroeconomic Research – University of Cologne (CMR), whose hospitalities are gratefully acknowledged. We also like to thank for valuable comments during presentations at Mannheim University; the 5th Cologne Workshop on Macroeconomics (CMR 2014); the Norwegian School of Economics in Bergen; Maastricht University; the Annual Norwegian Business Economics and Finance Conference (FIBE) in Bergen; the 37th Meeting of the Norwegian Association for Economists in Bergen; the Royal Economic Society Conference 2015 in Manchester, Statistics Norway in Oslo, the 8th Nordic Econometric Meeting in Helsinki, and by Saskia ter Ellen. The usual disclaimer applies.

1. Introduction

Classical models in economic theory predict that if prices are fully flexible a "monetary change results only in proportional changes in prices with no impact on real prices or quantities" (Romer, 2012). However, we observe in practice that nominal shocks have real effects in the short run, and the reason for this lies in the fact that prices are sticky. Thus, in macro-economic research it is important to understand how sticky prices are.

Price rigidity may be caused by menu costs (cf. Sheshinki and Weiss, 1977, 1983). Menu costs are motivated by the fact that changing prices induces direct costs (repricing, new promotional materials, new promotions) or indirect costs (annoyance among consumers, etc.). Such menu costs are related to price changes, such that patterns of price adjustment can be described as "zeroes and lumps". Indeed, descriptive evidence from micro data suggests that there are several consecutive periods where no price changes occur, and then one observes significant changes for a short period (Álvarez *et al*., 2006; Dhyne *et al*., 2006; Vermeulen *et al*., 2012). Such patterns may be explained by non-convex or fixed menu costs. At the same time, rather small price changes occur frequently as well. Such small adjustments might stem from convex adjustment costs. For instance, in the model by Rotemberg (1982) deviations from current prices induce quadratic costs.

For the most commonly used macroeconomic models accounting for price rigidity it is often assumed that producers in the economy only change prices at a given time randomly, so-called Calvo pricing (Calvo, 1983).[1] In this model a lag in price adjustment at the micro level is introduced that is technically attractive, however it does not tell us much about the structural causes of persistency in prices. Mankiw and Reis (2002) use an alternative model formulation

[1]Prices also play an important role in macroeconomic models with intermediate goods. The producer level price adjustment, which is responding to shocks to production costs and demand for intermediate goods, is transmitted to the consumer level prices. Cornille and Dossche (2008) show that the degree of producer price rigidity will be decisive in an inflation-targeting central bank. In addition, 60 percent of the value of a consumer good is generated on the producer level in industrialized economies (Burstein *et al*. 2000).

where prices are free to change, but where new information can only be obtained randomly at a given time. In a recent work by Mackowiak and Wiederholt (2009), it is instead assumed that firms are free to choose when information is to be obtained, but that the capacity to process new information is limited.

With detailed data on product prices, production costs and quantities it should be possible to learn more about what the main reasons for the price changes of firms' products are. A problem in all the empirical research related to pricing, is access to good microeconomic data (Klenow and Malin, 2010). Some of the earliest work with microeconomic data is Cecchetti (1986) who analysed price adjustments related to various news and weekly magazines. Using individual transaction prices Carlton (1986) studied how the prices of goods were adjusted in concentrated industries and he analysed how rigidity depends on the relationship between buyers and sellers, while Blinder (1991) based his study on interviews with business leaders. In a rather recent paper from Sweden by Carlsson and Skans (2012), the authors use price data at the product unit level of industrial manufacturers along with labour costs to investigate the micro foundations of different assumptions about sources of price rigidities. Using a reduced form model, these authors find that the Swedish data indicate limited support for the conclusions found by Mankiw and Reis (2002), and Mackowiak and Wiederholt (2009), while the results seem to be reasonable in light of the time-dependent Calvo model.

The presence of menu costs can be investigated by estimation of a reduced form threshold pricing model of the (S,s) type (*cf.* Sheshinksi and Weiss, 1977, 1983). For instance, Lein (2010) recently found that models of price adjustment gain significant explanatory power when state-dependent variables are added. This result hints at the relevance of menu cost models. Likewise, menu costs are found to affect firm decisions in an analysis of Dhyne *et al*. (2011) and Honoré *et al*. (2012).

Other studies have made an effort to estimate structural parameters of the menu cost function underlying firm pricing decisions. Levy *et al*. (1997) find that the labour cost of workers spending time on changing prices, referred to as direct physical pricing costs, are about 0.7% of annual revenues. Including indirect costs as well Slade (1998) finds that changing prices costs approximately 1.7% of revenues for saltine crackers. Using Spanish supermarket data Aguirregabiria (1999) estimates similar costs of changing prices. Midrigan (2011), using supermarket data as well, concludes his model calibrations suggest price adjustment costs of about 2%. For changing magazine prices costs are about 2-4% according to Willis (2000) using the data employed by Cecchetti (1986).

Zbaracki *et al.* (2004) find evidence that costs of changing prices may vary with the size of the price adjustment. The larger the change the more managerial time is spent on the pricing decision, and, in addition, internal firm communication increases. Furthermore, the firm is also likely to incur higher cost of negotiation and communication with customers to explain the decision. Though several studies exist, to the best of our knowledge only a few have made an effort to obtain structural estimates for fixed, linear and quadratic cost components in the menu cost function. Note that Zbaracki *et al.* argue that fixed costs are small.[2] They also observe that various scholars have found that fixed menu costs are not high enough to cause price rigidity. For that reason, we consider linear menu costs as well, which is an alternative functional form potentially capturing price stickiness. Linear menu costs allow for zeroes in price change data as do fixed menu costs.

In this paper we focus on multiproduct plants. We follow Midrigan (2011) and Alvarez and Lippi (2014) in assuming that the total fixed menu costs do not depend on the number of prices the firm changes. Thus, our model also allows for scope economies when a firm adjusts prices. Typically such economies of scope contribute to explaining synchronization of price

[2]See the references in their footnote 2.

adjustment and a large frequency of small price changes. We deviate a bit from those two studies. Our data indicates synchronization occurs often. However, the number of partial synchronization events, where at the same time within a plant some prices are changed and some are not adjusted, is not negligible. This incomplete synchronization phenomenon is not accounted for by Midrigan, and Alvarez and Lippi. To capture partial price change synchronization the fixed menu cost is deducted from the profit of products undergoing price changes.

We focus on firms' pricing behaviour using a unique and relatively unexplored Norwegian micro dataset. The data are based on micro level data from Statistics Norway (SSB). The primary source is surveys sent to firms, where monthly prices (and price changes) are observed for several products. Firms are repeatedly surveyed. Statistics Norway also checks the data thoroughly, for instance to detect huge differences from the previously reported prices for a given firm and product, since the data are used to build the national monthly producer price index. Thus, the data is a panel with monthly observations for the period 2004-2009. This high frequency of price data, together with the high data quality, make the data very appropriate for our purpose.[3] These firm/product level data are matched with annual firm-level production income- and costs, and labour stock data.

The method we use can be described as structural estimation as the estimated parameters enable us to trace back parameters in the optimization models of firms' price decisions. An advantage of our approach compared to calibration based methods is that our assumptions can be tested statistically.[4] Our goal is to first set up an optimization model of a firms' dynamic profit function. This model includes a function for the menu costs explicitly. In fact, we consider simultaneously three specifications for the shape of menu costs: fixed, linear and quadratic

[3]A clear benefit of disaggregated data is that it is less likely to shield adjustment patterns.
[4]See Midrigan (2011) as an example for a calibration based method.

(convex) costs. A maximum likelihood (ML) model allows us to acquire parameter estimates that are related to the decision to adjust prices (i.e. the extensive margin). Next, we obtain a deeper insight into the structural parameters by also estimating a model for the size of price adjustment (the intensive margin). We correct for selection bias at the second estimation stage.

To explain a large frequency of zero price adjustments, many small price changes and (partial) synchronization of price changes our estimates reveal all types of menu are statistically significant. The findings show the presence of linear and fixed menu costs generating sticky prices. Convex menu costs are of minor importance. Furthermore, our estimates suggest economies of scope in adjusting prices resulting in internal price coordination reflected by (incomplete) synchronization of price changes.

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. 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. As a consequence, the data have to be, and are representative for Norway.

We investigate price quotes that are consequently obtained from firms operating in manufacturing industries. A selection of producers report their prices on a monthly basis, and 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.[5]

The price data are merged with data from industry statistics. 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. Note however, without initiating a discussion about market definition and market power, our model will allow for the included firms to have some potential market power.

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

[5]We like to note that 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. 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.

the actual data.[6] 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, and at the same time no fat tails, as we would expect to see if there are significant fixed adjustment costs. Convex adjustment costs may explain the large frequency of small price adjustments, because they put a penalty on large adjustments.

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

We focus on multiproduct plants. Hence, in the final dataset we employ for the analysis, single product establishments are disregarded. 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

[6]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. 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, 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.

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

The cost of price changes consists of producing new price lists, monthly supplemental price sheets, and informing and convincing interested parties. These are the classical menu costs as considered theoretically by Sheshinki and Weiss (1977, 1983). Typically such physical costs are independent of the size of the price changes (Levy *et al.*, 1997; Zbaracki *et al.*, 2004). 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). 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.[7] This specification implies that the total fixed menu costs, a, do not depend on the number of price changes.

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 cost 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. In such an environment, 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 $b \cdot \left|\Delta P_{ijt}\right|$. Furthermore, a convex cost component is given by the expression multiplied by the parameter c. The quadratic menu cost term implies that larger price changes are very costly. This penalty provides the establishment an incentive for smaller price changes as we see in the data descriptives.

From a conceptual point of view, price change models and factor demand models are very similar.[8] Inspired by research on input demand where the size and timing of adjustment is determined by q - the shadow value of a unitary change in the decision variable (see for instance Abel and Eberly, 1994) - we extend a static price-setting model by incorporating menu costs

[7]In the remainder of the paper we use the terms plant, firm and establishment interchangeably.
[8]Various types of adjustment costs and their consequences have been reviewed by Hamermesh and Pfann (1996).

for prices.[9] The idea is to employ a menu cost function that is capable of replicating the main empirical features of the data as described in the preceding section. These facts are: i) a large frequency of zero price adjustments; ii) many small price changes and iii) (partial) synchronization of price changes.

We assume each plant produces N_{it} goods. Presuming monopolistic competition, by setting product prices plants maximise the present value of discounted cash flow, given by

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

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*. The monthly discount rate is given by $\frac{1}{1+r}$. The variables A_{ijt} and B_{ijt} denote the state of supply and demand of a product, respectively.[10] The menu cost function for prices is given by

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

[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]Developments in prices set by competitors are captured by demand conditions reflected by B_{ijt}.

where $I(.)$ is an indicator function equal to 1 if the condition in brackets is satisfied and zero otherwise.[11] The motivation for the various menu cost components is already given above.[12]

The first order conditions inform us that prices behave according to the following rules[13]

$$(3) \qquad \frac{\Delta P_{ijt}}{P_{ijt-1}} = \frac{1}{c}\left(q_{ijt} - b\right) \text{ if } q_{ijt} \geq \sqrt{\frac{2 \cdot a \cdot c}{m_{it} \cdot P_{ijt-1}}} + b \ .$$

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

$$(4) \qquad \frac{\Delta P_{ijt}}{P_{ijt-1}} = \frac{1}{c}\left(q_{ijt} + b\right) \text{ if } q_{ijt} \leq -\sqrt{\frac{2 \cdot a \cdot c}{m_{it} \cdot P_{ijt-1}}} - b$$

From equations (3) and (4) 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:

$$(5) \qquad \frac{\Delta P_{ijt}}{P_{ijt-1}} = 0 \text{ if } -\sqrt{\frac{2 \cdot a \cdot c}{\left(m_{it}+1\right) \cdot P_{ijt-1}}} - b \leq q_{ijt} \leq \sqrt{\frac{2 \cdot a \cdot c}{\left(m_{it}+1\right) \cdot P_{ijt-1}}} + b$$

[11]As mentioned in footnote 5, 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.

[12]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.

[13]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.

Regarding equation (5) it is worth noting a division by $(m_{it}+1)$ is present in the expression for the thresholds, compared to a division by m_{it} in equations (3) and (4). To explain this, consider how to determine which prices to adjust. It is assumed that coordination gives that the fixed price menu costs is divided by the number of products to be changed. The fixed menu cost for each single price is smallest if all prices of the firm are adjusted, i.e. when $m_{it}=N_{it}$. Whether to change all prices is determined by applying equation (3) and (4) 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 (3) or (4) 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 (3) and (4) in the previous optimization round. Now consider whether it is optimal to change the remaining product prices by checking whether the conditions in equations (3) and (4) are satisfied applying the new number m_{it} in the thresholds. If some prices do not meet the requirements, they will be skipped again 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 (3) or (4) 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 $-\sqrt{\dfrac{2\cdot a\cdot c}{(m_{it}+1)\cdot P_{ijt-1}}}-b\le q_{ijt}\le\sqrt{\dfrac{2\cdot a\cdot c}{(m_{it}+1)\cdot P_{ijt-1}}}+b$. Note that the boundaries set on q_{ijt} in

this expression are stricter when dividing by $(m_{it}+1)$ rather than by m_{it}. So the thresholds in equation (5) have to be calculated in this manner. The set of product prices to be changed is given by $\left\{ k \in \{1,..,N_i\} \wedge \left(q_{ikt} \leq -\sqrt{\dfrac{2 \cdot a \cdot c}{m_{it} \cdot P_{ikt-1}}} - b \;\vee\; q_{ikt} \geq \sqrt{\dfrac{2 \cdot a \cdot c}{m_{it} \cdot P_{ikt-1}}} + b \right) \right\}$.

Equations (3) and (4) 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. Strikingly, if a = 0 we will see not so many large price changes in the data. Minor deviations from the thresholds $q_{ijt} \geq b$ and $q_{ijt} \leq -b$ will induce small price changes. Hence, linear costs also make a firm abstain from changing prices. Typically, such costs will induce many zeroes in price change data, but actual changes can still be small. However, 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 (3) and (4) 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.

Now consider the convex costs parameter *c*. Such costs provide an incentive to smooth price changes. In fact, convex costs make larger adjustments costly. 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. This can be seen from equations (3) and (4), as a higher value of the parameter *c* will decrease the response of the price change to the fundamental variables.

4. Estimation

In all of the cases discussed in the previous section, the shadow value of a price is given by

$$(6) \qquad q_{ijt} = E_t\left(\sum_{s=0}^{\infty}\left(\frac{1}{1+r}\right)^s\left(\frac{\partial\pi\left(A_{ijt+s},B_{ijt+s},P_{ijt+s}\right)}{\partial P_{ijt+s}}-\frac{1}{1+r}\frac{\partial C\left(\Delta P_{ijt+s}\right)}{\partial P_{ijt+s}}\right)\right).$$

The expression denotes how a unitary change in the price of product *j* affects the value of the firm and is composed of discounted expected values. The two main elements are in the inner brackets of equation (6) and relate to the marginal profit and the marginal menu cost function, respectively. The first element, $\frac{\partial\pi(.)}{\partial P_{ijt+s}}$, reveals that a price change influences marginal profits in future periods. In addition, a change in price saves menu costs in the future as depicted by the second term, $\frac{\partial C(.)}{\partial P_{ijt+s}}$.

To be able to estimate the model depicted in the previous section, we have to approximate the shadow value of a price change. According to equation (6) we have to derive the product specific profit expressed by $\pi\left(A_{ijt+s},B_{ijt+s},P_{ijt+s}\right)$. To that end, assume a Cobb-Douglas production technology with a flexible labour input component, *L*, and an iso-elastic demand equation. Thus, the plants have some market power. We abstract from sub-indices for the plant, product and time for notational convenience. Then production is determined by $Q^S(L) = A\cdot L^{\alpha}$ where $0<\alpha<1$ and the iso-elastic demand function is 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. Profit for a single product is given by $\pi(A,B,P) = P\cdot Q^D(P) - w\cdot L$, if w denotes the wage for a worker.[14] The wage is exogenous to the establishment. Note that *A* captures supply shocks and input factors that are predetermined like capital. *B* captures demand shocks.

[14]We consider only one margin of adjustment in input factors, i.e. labour. Developments in prices of other input factors are picked up by the industry price, P_c, by assumption.

We abstract from inventory. With these assumptions the first order derivative of profit with respect to price can be obtained. It can be shown that this expression is a non-linear function of the state of supply A, the state of demand B, the wage rate w and the general price P_c in the industry. We assume q can be approximated by

$$q_{ijt} = \gamma_0 + \gamma_1 ' X_{ijt} - \eta_{ijt} \tag{7}$$

where the vector X_{ijt} contains variables observed by the econometrician and is multiplied by γ_1 . 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 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.[15,16] 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.[17] The monthly dummies may also pick up systematic deviation between the annual and monthly variable.

---

[15]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.

[16]With our assumptions it is straightforward to show that marginal profit is based on a product specific real wage bill and a product specific real revenue. However, our data do not provide the level of detail to employ such product specific variables (except for product prices). In addition, product specific demand and supply elasticities would be necessary. Such information is unavailable as we lack data on product specific values of production.

[17]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 and this timing is

The expression for q, eq. (6), also includes future menu cost savings associated with a price change today, $\frac{\partial C(.)}{\partial P}$. In empirical factor demand models with quadratic adjustment costs components it has been a standard assumption to abstract from these future adjustment costs savings in the q expression (see Abel and Blanchard, 1986). This simplification has been motivated by the fact that if the adjustment is small, the derivative of the quadratic adjustment cost expression can be disregarded. In our context, it means that assuming that the price change rate is small, this quadratic term $\left(\frac{\Delta P_{ijt}}{P_{ijt-1}}\right)^2$ will be negligible in our proxy for q as given by equation (6).[18]

One explanation of price synchronization observed in the data could be that a plant is subject to a 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.[19] 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

---

also consistent with a story where there might be some delays before cost changes are passed through to prices.

[18]Cooper *et al*. (2010, footnote 4) 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 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. We have performed an *ad hoc* test to see whether disregarding marginal menu costs in q is not so harmful based on this finding. In the same spirit as for wages, assuming that lagged values may predict future values, we also 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*.

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

due to these common shocks – and we have controlled for these - we would expect the fixed menu cost generating coordination to be insignificant. The latent class approach is implemented by adding a shock κ_{it} to equation (7) yielding $q_{ijt} = \gamma_0 + \gamma_1 ' X_{ijt} + \kappa_{it} - \eta_{ijt}$, where κ_{it} can assume two values: the value 0 and the value κ, with probability $1-\psi$ and ψ, respectively. The probability ψ and the coefficient κ are parameters to be estimated. Finally, the parameter γ_0 in eq. (7) represents a constant term, while the zero mean stochastic terms η_{ijt} are assumed to be normally distributed with variance σ_η^2.

Given the approximation of the shadow value it is possible to estimate the parameters of the model depicted in equations (3) and (4). 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 the shadow value of prices. 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.[20]

[20]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.

Extensive Margin

Using equations (3), (4) and (5) the log likelihood function is given by

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

$$(8) \qquad + \sum_{t=1}^{T} \sum_{\Delta P_{ijt}<0} \ln E\left(\left\{1 - \Phi\left[\tilde{\gamma}_1{}' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 + \tilde{b}\right) + \sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it} P_{ijt-1}}}\right]\right\}\right)$$

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

where the operator $E(\cdot)$ takes expectations with respect to the shock κ_{it} and $\Phi(\cdot)$ denotes a standard normal cumulative distribution function.[21] 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 (7), has to be set equal to one. Hence, all structural parameter estimates have to be

[21] We see in equation (8) that the denominators of the thresholds are not always the same. This is due to our derivations resulting in equations (3), (4) and (5). 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: $\Pr\left(q_{ijt} \geq \sqrt{\frac{2 \cdot a \cdot c}{m_{it} \cdot P_{ijt-1}}} + b \,\middle|\, q_{ijt} \geq \sqrt{\frac{2 \cdot a \cdot c}{\left(m_{it}+1\right) \cdot P_{ijt-1}}} + b\right) \cdot \Pr\left(q_{ijt} \geq \sqrt{\frac{2 \cdot a \cdot c}{\left(m_{it}+1\right) \cdot P_{ijt-1}}} + b\right)$. This expression is equal to $\Pr\left(q_{ijt} \geq \sqrt{\frac{2 \cdot a \cdot c}{m_{it} \cdot P_{ijt-1}}} + b\right) = E\left(\Phi\left[\tilde{\gamma}_1{}' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 - \tilde{b}\right) - \sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it} P_{ijt-1}}}\right]\right)$ which we see in equation (8). 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.

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 (3) and (4) 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 (8) 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.[22] 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 (3) and (4) 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

[22]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.

$$(9) \quad \frac{\Delta P_{ijt}}{P_{ijt-1}} = \frac{\left(\tilde{\gamma}_0 - \tilde{b}\right)}{\tilde{c}} + \frac{\left(\hat{\tilde{\gamma}}_1 X_{ijt} + \hat{\psi} \cdot \hat{\tilde{\kappa}} + \hat{\lambda}^{+}_{ijt}\right)}{\tilde{c}} + \vartheta^{+}_{ijt}$$

for price increases, and

$$(10) \quad \frac{\Delta P_{ijt}}{P_{ijt-1}} = \frac{\left(\tilde{\gamma}_0 + \tilde{b}\right)}{\tilde{c}} + \frac{\left(\hat{\tilde{\gamma}}_1 X_{ijt} + \hat{\psi} \cdot \hat{\tilde{\kappa}} - \hat{\lambda}^{-}_{ijt}\right)}{\tilde{c}} + \vartheta^{-}_{ijt}$$

for price reductions.[23] Equations (9) and (10) 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. These latter two ratios equal the expected value of the error term in equation (6), conditional upon being in either the price increase or price reduction regime. These correction terms are given by

$$(11) \quad \lambda^{+}_{ijt} = E\left(\frac{\phi\left[\tilde{\gamma}_1' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 - \tilde{b}\right) - \sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it} P_{ijt-1}}}\right]}{\Phi\left[\tilde{\gamma}_1' X_{ijt} + \kappa_{it} + \left(\tilde{\gamma}_0 - \tilde{b}\right) - \sqrt{\frac{2\tilde{a}\tilde{c}}{m_{it} P_{ijt-1}}}\right]}\right)$$

and

[23] To ensure symmetry of the c parameter we estimate equations (9) and (10) simultaneously by $\frac{\Delta P_{ijt}}{P_{ijt-1}} = \xi_0 + I\left(\Delta P_{ijt} > 0\right) \cdot \frac{\left((\hat{\tilde{\gamma}}_0 - \hat{\tilde{b}}) + \hat{\tilde{\gamma}}_1 X_{ijt} + \hat{\psi} \cdot \hat{\tilde{\kappa}} + \hat{\lambda}^{+}_{ijt}\right)}{\tilde{c}} + I\left(\Delta P_{ijt} < 0\right) \cdot \frac{\left((\hat{\tilde{\gamma}}_0 + \hat{\tilde{b}}) + \hat{\tilde{\gamma}}_1 X_{ijt} + \hat{\psi} \cdot \hat{\tilde{\kappa}} - \hat{\lambda}^{-}_{ijt}\right)}{\tilde{c}} + \vartheta_{ijt}$.

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

where $\phi(\cdot)$ denotes a standard normal distribution function. Note that expectations have to be taken with respect to κ_{it}. Equations (9) and (10) 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 (9) and (10) 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 (8), and the OLS estimation of equations (9) and (10) 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. Using a bootstrap routine we obtain confidence intervals of the parameter estimates of $\tilde{a}$, $\tilde{b}$ and $\tilde{c}$.[24]

[24]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 estimation rounds, we have obtained a distribution for each

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

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

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 (8) 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

parameter of interest. The 95% confidence interval for these parameters is based on the limits of the 2.5% and 97.5% quantiles.

process 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.

5. Results

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.[25] We also find evidence supporting the use of the latent class model. A second class exists with a probability of about 4.5 percent.

** Table 3: "Estimation Results" about here **

Starting with column (1), we observe the existence of significant linear menu costs, $\tilde{b}$. Estimating equations (9) and (10) 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

[25]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.

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 $\tilde{a}=0$.[26] 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 $\left|\sqrt{\frac{2\tilde{a}\tilde{c}}{mP}}+\tilde{b}\right|$ 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 $\left|\sqrt{\frac{2\tilde{a}\tilde{c}}{mP}}+\tilde{b}\right|$, 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

[26]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.

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.

To obtain some insight into the 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).[27] 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 $\Delta p / p \geq \tilde{a} / \left(\tilde{b} \cdot m \cdot p\right)$.[28] 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 $\Delta p/p \geq 0.856/(1.003 \cdot 1.06 \cdot 1531) \approx 0$. This means that linear costs are relatively large.

Counterfactual analysis and robustness checks

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 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 $\left|\sqrt{\frac{2\tilde{a}\tilde{c}}{mP}} + \tilde{b}\right|$, while using the predicted q values - again from the full model - we calculate the alternative price adjustment probabilities based on the counterfactual thresholds.

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

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

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

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 $\dfrac{\tilde{a}}{m_{it}}$. For a model where coordination is absent (and therefore no benefits can be reaped from adjusting several product prices simultaneously) the maximum likelihood routine was driving

[29]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.

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.

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 firm specific but time invariant. Hence, equation (7) 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.

We conclude this section with a brief review of how our results relate to previous findings in the literature. 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. Studies that have measured menu costs typically report their small size. 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. Furthermore, Nakamura and Zeron (2010) find that small menu costs can have a notable effect on the short run response of prices to costs. Even though menu costs are small these studies have observed a substantial impact 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) and Alvarez and Lippi (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.

6. Conclusion

In this paper we investigate empirically various functional forms of menu costs. The model is tested on a sample based on repeated survey data merged with census data concerning Norwegian producer plants. We observe three main features in the data. First, plants adjust prices infrequently as only 23 percent of the price observations change from one month to another. Secondly, multiproduct firms do coordinate price changes very often. Conditional on observing at least one product price change, the plant adjusts all product prices, i.e. full coordination, in 56 percent of the cases, but incomplete coordination is observed alternatively. Third, one does observe a large frequency of small price changes within the data.

The theoretical model generates price stickiness due to the inclusion of linear and fixed menu costs. This feature hence captures the first empirical fact. Our model also incorporates economies of scope in price adjustment. This implies that firms benefit from simultaneous price changes, which explains the second empirical fact described above. Our specification allows incomplete price synchronization to be optimal as well. In the model we control for unobserved heterogeneity by including plant specific time varying shocks. This mitigates that internal price coordination is driven by common plant-specific shocks only. The model also includes traditional convex costs providing plants the incentive to conduct small price changes. The economies of scope in our model also contribute to explaining small price changes. If the fixed costs are shared among several products a small shock in the driving force of prices will lead to a small price change; the third empirical feature we highlighted.

We employ a structural estimation technique as it presents the possibility to trace parameters in the firm's optimization problem. We argued estimation of the model by maximum likelihood currently is the preferred technique due to its computational feasibility especially when modelling and testing economies of scope. 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. This finding is also supported by a counterfactual analysis where we analyse to what extent abstracting from the non-convex menu costs changed the probability of price adjustment. Convex menu costs are statistically significant but of moderate importance. Finally, our estimates suggest economies of scope in adjusting prices resulting in (incomplete) synchronization of price changes.

Sticky prices are explained by linear and fixed menu costs in our study. Such price stickiness is important to understand the monetary non-neutrality generated by existing macro-economic models. In addition, we find firms have an incentive to coordinate internal prices evidenced by economies of scope. 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.

References:

Abel, A.B. and O. Blanchard (1986), “The present value of profits and cyclical movements in investment” *Econometrica* 54, 249–273.

Abel, A.B. and J.C. Eberly (1994), “A unified model of investment under uncertainty” *American Economic Review* 84, 1369–1384.

Álvarez, L.J., E. Dhyne, M. Hoeberichts, C. Kwapil, H. Le Bihan, P. Lünnemann, F. Martins, R. Sabbatini, H. Stahl, P. Vermeulen and J. Vilmunen (2006), “Sticky prices in the Euro area: A summary of new micro evidence” *Journal of the European Economic Association*, 4(2-3), 575-584.

Alvarez, F., and F. Lippi (2014), “Price setting with menu cost for multiproduct firms” *Econometrica*, 82(1), 89-135.

Aguirregabiria, V. (1999), “The dynamics of markups and inventories in retailing firms” *Review of Economic Studies,* 66(2), 275-308.

Blinder, A.S. (1991), “Why are Prices Sticky? Preliminary results from an interview study” *American Economic Review*, 81, 89-96.

Burstein, A., J. Neves, and S. Rebelo (2000), “Distribution costs and real exchange rate dynamics during exchange-rate-based-stabilizations” *National Bureau of Economic Research* Working Paper No. 7862.

Calvo, G. A., (1983), “Staggered prices in a utility-maximizing framework”, *Journal of Monetary Economics*, 12, 383-398.

Cameron, A.C. and P.K. Trivedi (2005), “Microeconometrics, methods and applications.” Cambridge University Press.

Carlton, D. (1986), “The rigidity of prices” *American Economic Review*, 76, 255-74.

Carlsson, M. and O. N. Skans (2012), “Evaluating microfoundations for aggregate price rigidities: Evidence from matched firm-level data on product prices and unit labor cost” *American Economic Review*, 102(4), 1571-95.

Cecchetti, S.O. (1986), “The frequency of price adjustment: A study of the newsstand prices of magazines” *Journal of Econometrics*, 31, 255-74.

Cornille, D. and M. Dossche (2008), “Some evidence on the adjustment of producer prices” *Scandinavian Journal of Economics*, 110, 489-518.

Cooper, R., J.C. Haltiwanger and J.L. Willis (2010) “Euler equation estimation for discrete choice models: A capital accumulation application.” *National Bureau of Economic Research* Working Paper No. 15675.

Dhyne, E., L.J. Álvarez, H. Le Bihan, G. Veronese, D. Dias, J. Hoffmann, N. Jonker, P. Lünnemann, F. Rumler and J. Vilmunen (2006), “Price changes in the Euro area and the United States: Some facts from individual consumer price data” *Journal of Economic Perspectives*, 20(2), 171-192.

Dhyne, E., C. Fuss, H. Pesaran, and P. Sevestre (2011), “Lumpy price adjustments: A microeconometric analysis” *Journal of Business and Economic Statistics*, 29(4), 529-540.

Hamermesh, D.S. and G.A. Pfann (1996), “Adjustment costs in factor demand” *Journal of Economic Literature*, 34, 1264-1292.

Honoré, B.E., D. Kaufman and S. Lein (2012), “Asymmetries in price setting behaviour: New microeconometric evidence from Switzerland” *Journal of Money Credit and Banking*, 44, 211-236.

Klenow, P.J., and B.A. Malin (2010), “Microeconomic evidence on price-setting” in *Handbook of Monetary Economics*, vol. 3, ed. by B.M. Friedman and M. Woodford, Chapter 6, Amsterdam: Elsevier, 231-284.

Levy, D., M. Bergen, S. Dutta and R. Venable (1997), “The magnitude of menu costs: Direct evidence from large U.S. supermarket chains” *Quarterly Journal of Economics*, 112(3), 791-825.

Lein, S.M. (2010), “When do firms adjust prices? Evidence from micro panel data” *Journal of Monetary Economics,* 57, 696-715.

Mackowiak, B. and M. Wiederholt (2009), “Optimal sticky prices under rational inattention" *American Economic Review*, 99(3), 769-803.

Maddala, G.S. (1983), “Limited dependent and qualitative variables in econometrics.” Cambridge University Press.

Mankiw, N. G., and R. Reis (2002), “Sticky information versus sticky prices: a proposal to replace the New-Keynesian Phillips curve”, *Quarterly Journal of Economics,* 117 (4), 1295-1328.

Midrigan, V. (2011), “Menu costs, multiproduct firms, and aggregate fluctuations” *Econometrica*, 79(4), 1139-1180.

Nakamura, E., and J. Steinsson (2010) “Monetary non-neutrality in a multisector menu cost model” *Quarterly Journal of Economics,* 125, 961-1013.

Nakamura, E., and D. Zerom (2010) “Accounting for incomplete pass-through” *Review of Economic Studies*, 77, 1192-1230.

Nilsen, Ø. A., K. G. Salvanes and F. Schiantarelli (2007), “Employment adjustment, the structure of adjustment Costs, and plant size”, *European Economic Review* 51(3), 577-598.

Pagan, A., (1984), “Econometric issues in the analysis of regressions with generated regressors” *International Economic Review,* 25, 221–247.

Romer, D. (2012), “Advanced Macroeconomics*”* 4/e, McGraw-Hill Higher.

Rotemberg, J. (1982), “Sticky prices in the United States”, *Journal of Political Economy,* 90 (6), 1187-1211.

Sheshinksi, E. and Y. Weiss (1977), “Inflation and the costs of price adjustment” *Review of Economic Studies*, 44, 287-303.

Sheshinksi, E. and Y. Weiss (1983), “Optimum pricing policy under stochastic inflation” *Review of Economic Studies*, 50, 513-529.

Slade, M.E. (1998). “Optimal pricing with costly adjustment: Evidence from retail-grocery prices” *Review of Economic Studies*, 65(1), 87-107.

SSB (2013a), “Commodity price index for the industrial sector” http://www.ssb.no/en/priser-og-prisindekser/statistikker/vppi?fane=om.

SSB (2013b), “Structural business statistics for manufacturing, mining and quarrying” http://ssb.no/en/energi-og-industri/statistikker/sti/aar-endelige/2013-05-28?fane=om#content.

Vermeulen, P., D. Dias, M. Dossche, E. Gautier, I. Hernando, R. Sabbatini, and H. Stahl, (2012), "Price-setting in the euro area: some stylised facts from individual producer price data", *Journal of Money, Credit and Banking,* 44(8), 1631–1650.

Willis, J.L. (2000), "Estimation of adjustment costs in a model of state-dependent pricing" Research Working paper RWP 00-07, Federal Reserve Bank of Kansa City.

Zbaracki, M.J., M. Ritson, D. Levy, S. Dutta and M. Bergen, (2004), "Managerial and customer costs of price adjustment: Direct evidence from industrial markets" *Review of Economics and Statistics*, 86(2), 514-533.

Table 1: Distribution 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

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: 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	-	-
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 footnote 24.

Table 4: Data Frequency and Estimated Probability 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	0.148	0.147	0.226	0.451
Inaction	0.765	0.755	0.637	0.237
Price Decrease	0.087	0.094	0.137	0.303

Table A1: Descriptive Statistics, final sample

	Mean	SD
p	1,531.18	2,915.19
$\Delta p/p$	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	117.96	10.77
L	114.66	144.04

Notes: These statistics are based on the sample used for estimating the model. The number of observations is 39,082. 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 6.