Discussion paper

Intermittent Price Changes in Production Plants: Empirical Evidence using Monthly Data

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Intermittent Price Changes in Production Plants: Empirical Evidence using Monthly Data[*]

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Abstract

The price-setting behaviour of manufacturing plants is examined using a large panel of monthly surveyed plant- and product-specific prices. The sample shows a high frequency of zero changes, relatively small price changes, and a strong seasonal price change pattern. The intermittent feature of price changes is modelled with thresholds which are lower in January, and a quadratic loss–function associated with the distance from target price. The findings show statistically significant pricing thresholds, which are only two thirds in January, and partial adjustment parameters implying that 60% of the deviation between the target price and current price is closed each month.

Keywords: Price Setting, Micro Data, Simulated Method of Moments

JEL classification: E30, E31, E37.

Number of words: 10296

1 Introduction

Most modern macroeconomic models assume price stickiness, i.e. that price setters are faced with frictions, without sufficient knowledge about the underlying microeconomic implications. This calls for a further empirical assessment of the theoretical premises in the macroeconomic models we use today.

A common method for analysing price stickiness is to investigate the role of thresholds in the pricing patterns of individual firms. In this literature, the (S, s) rule proposed by Sheshinski and Weiss (1977) plays an important role. Sheshinski and Weiss (1977) argued that firms kept the price fixed within the certain bounds, denoted (S, s). As a result, prices exhibit a pattern of inaction followed by large price changes, so called "zeros and lumps". The authors argue that this pattern is caused by the fact that changing the price induces a fixed cost for the firm, which is referred to as the menu cost. The (S, s) methodology has later been adopted and further extended by many, and thereby represents a large share of the current price stickiness literature (see e.g. Caballero and Engel, 1993; Ratfai, 2006; Alvarez et al., 2011; Dhyne et al., 2011; Honoré et al., 2012). An essential assumption in these models is that adjustment costs are independent of the size of the price change (Zbaracki et al., 2004).

One aspect to consider when searching for thresholds in pricing patterns is whether the thresholds are symmetric, i.e. if the magnitude of the thresholds are the same upwards and downwards. A study on microeconometric evidence from Switzerland by Honoré et al. (2012), finds a smaller upper than lower threshold. According to this study, price changes are more likely to be positive than negative, ceteris paribus. The study ignores, however, the magnitude of price changes, as only the frequency and the duration of inaction are accounted for. Loupias and Sevestre (2012), on the other hand, include the magnitude of price changes, and find that when firms face cost variations, they appear to adjust their prices more often and more rapid upwards

than downwards.

The counterpart of the (S,s) methodolgy in the price stickiness literature assume that the adjustment cost is a convex function of the size of the price change, i.e. that larger changes lead to higher costs (Rotemberg, 1982). While the assumption of fixed costs implies that one should observe large and infrequent price changes, the convex cost assumption implies the opposite: frequent changes of small size. As emphasized by Zbaracki et al. (2004), most of the literature finds evidence supporting the former. However, if there are only fixed and not convex price adjustments costs, we fail to see why the pricing data shows a relatively high proportion of small price changes.[1]Earlier research with (S, s) pricing rules has in part failed to include small price changes.

As highlighted by Klenow and Malin (2011), access to good microeconomic data is crucial, and is a common problem in all empirical research related to pricing. The basis of our analysis is monthly collected micro price data for Norwegian manufacturers. Although consumer prices are relevant for the monitoring of inflation by central banks, it is the prices on producer level that are most often modelled into the macroeconomic policy models (Vermeulen et al., 2012). Accordingly, knowledge about producer price adjustments is essential to improve macroeconomic modelling and central bank policies.

In this paper we propose a model where the adjustment towards the new price is conditional on both thresholds and partial adjustments. Our model therefore allows for both inaction and inertia in pricing. The hypothesis is that the firm is faced with a fixed cost when setting a new target price and that there are costs associated with deviating from the frictionless price in addition to convex costs associated with adjusting to this price. For example, as in Zbaracki et al. (2004), the convexity of

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[1]The study of Eichenbaum et al. (2014) on CPI data suggests that the observance of small price changes is largely due to measurement errors and quality adjustments, and should therefore be neglected. However, the study is opposed by a vast majority of empirical research suggesting that small price changes are relatively common (Klenow and Kryvtsov, 2008; Barros et al., 2009; Bhattarai and Schoenle, 2014; Midrigan, 2011; Wulfsberg, 2016).

managerial-, customer- and negotiation costs makes the firm favour slow adjustments and small price changes. Thus, our model sets out to explain both the occurrence price adjustments of different sizes and inaction. The model is tested on a dataset based on survey data behind the commodity price index for the Norwegian industrial sector (PPI). These data include monthly prices quotations for a representative sample of Norwegian plants. The data show a high frequency price change inaction, by relatively small price changes when changed, and by a much higher occurrence of price changes in the beginning compared to the end of a year. To analyse the intermittent nature of the model, a simulated method of moments is used. The estimations reveal thresholds such that prices are changed only if the deviations from the underlying frictionless prices are approximately 15 percent. When changed, the prices are changed rather quickly with only 10 percent of the initial gap existent after three months. The asymmetry between upward- and downward rigidities are minor but statistically significant. Finally, the thresholds in January are approximately two thirds compared to the other months.

The remainder of the paper is organized as follows. Section 2 describes the data, while the model, method and moments are presented in Section 3. Section 4 reports and discusses the results and Section 5 gives some concluding remarks.

2 Data

The basis for our empirical analysis is the survey data behind the commodity price index for the Norwegian manufacturing industry (PPI) obtained from Statistics Norway (SSB).[2] The data are collected on a monthly basis for a selection of Norwegian plants.[3] Plants with more than 100 employees are included in the sample at all times, and the selection of producers is updated continuously, securing a high level of rel-

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[2]See SSB (2015) for more information about the PPI.

[3]In the remainder of the paper we use the terms plant, firm, producer and establishment interchangeably.

evance (SSB, 2015). Plants are repeatedly surveyed, participation is compulsory and Statistics Norway revise the data regularly to detect measurement errors and non-conformity.[4] Considering this, and that the PPI is an important tool for governing bodies, it is fair to assume that the data is representative for Norwegian producers and of high quality.

The initial dataset contains monthly price observations for Norwegian producers ranging from year 2002 until 2009. In the construction of the final dataset for this study, plants with observations for less than 24 months have been omitted, as well as plants with less than 10 employees. Furthermore, only years with observations for all months in a given year are included. Due to the implementation of a new sampling procedure at Statistics Norway, there was a clear shift in the reported price change frequency in 2004. We therefore choose to discard the data prior to January 2004. Furthermore, plants related to the energy sector (oil, gas, electricity, etc.), and mining and quarrying have been left out of the sample as they are known to have an abnormally high adjustment frequency. The original dataset also contains prices for both domestic and export markets, but to prevent interference by exchange rate movements and international competition, export market prices are omitted. Additionally, as very large price changes are likely to reflect changes to design or quality of the product rather than common pricing decisions, price growth observations outside the [0.01, 0.99] interval we consider to be new products. Finally, we focus on single plant firms only.[5] This leaves us with a final sample of 76 804 observations for 1676 products over the years 2004-2009 covering 21 2-digit SIC2002 industry codes.

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[4]One plant might be recorded with one or multiple products. It should be noted 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.

[5]With this choice, we are sure that the price decisions are not made beyond the plant level.

2.1 Descriptives

[Figure 1 "Distribution of Price Change Rates" about here]

Figure 1 shows the proportion of observations in different price change intervals, both for the actual data and for the later preferred simulated model (black, and grey columns, respectively). As seen, observations with price changes with absolute value less than 0.005 represent the majority of the dataset. We will later on refer to this as the "zero price-change" interval. In other words, most observations are characterized with inaction. This indicates the existence of fixed price adjustment costs. At the same time, we observe that a substantial proportion of the observations are small price changes in the intervals between 0.5% and 5.0% (in absolute value). If there is only a fixed cost, which is independent of the magnitude of the price change, one would not expect to see these small price changes. This observation could, however, be an indication of convex adjustment costs, which put a penalty on large adjustments and thereby force the producers to adjust gradually. The observation of several periods of inaction combined with series of small price changes may tell a story of firms being faced with both fixed and convex price adjustment costs.

In order to identify lumpy adjustment behaviour, we rank for each plant, for each year, the 12 monthly price changes from lowest to highest.[6] Rank 1 thereby represents the average largest monthly price change, Rank 2 the average second largest price change, and so on. The intuition is that if there is a large gap between the largest (smallest) and the second largest (second smallest) price change compared to the other ranks, this indicates that producers are faced with fixed costs of adjustment and therefore change the price quite substantially when first changing it. Opposite, with normally distributed shocks to the fundamentals, and no adjustment costs, one would expect the mean investment rate of adjacent observations to be rather similar,

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[6]Such a measure has been used in the investment- and labour demand literature (see for instance Doms and Dunne (1998), Nilsen and Schiantarelli (2003) and Varejão and Portugal (2007)).

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and therefore that there is a downward sloping linear relationship between the ranks (for more details, see Doms and Dunne 1998).

[Figure 2 "Ranked Price Change Rates" about here]

Figure 2 shows the ranking of the monthly price changes of each plant by month for every year, and then taking the average of each rank across plants and years. As seen from Figure 2, there is a gap of approximately 3 percentage points between both the first and second rank and the eleventh and twelfth rank. In contrast, the differences between the intermediate ranks are modest. The importance of episodes characterized by relatively large prices changes is consistent with nonconvexities in adjustment costs. Note however, even though the difference between the gaps on the edges and the gaps between the middle ranks is existent, the potential co-existence of both fixed and convex adjustment costs can not be excluded. That means, even if fixed adjustment costs are preventing the firms to adjust continuously, when they actually do change their price, convex costs are forcing them to do so gradually.[7]

[Figure 3 "The Occurrence of Price Changes by Months" about here]

Figure 3 shows the average share of price change quotations within each month. The shares are given as the number of price changes larger than |0.005| within each month divided by the total number of price quotations within the same month. As seen, there is a relatively high price change frequency in the beginning of the year compared to the remaining months. This seasonality could of course be explained by producers' economic environment, for instance seasonal demand effects. Furthermore, it may be explained by staggered contracts with for instance price contracts starting in January with a duration of one year (see for instance Taylor (1980, 1999)). It should be noted that the higher incidence of price changes in January, is also consistent

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[7]In addition, we observe that all the ranks are shifted to the left, as only rank five is below zero. This observation is expected as inflation will cause the producers to have more positive price changes than negative.

with theories focusing on the costs of information acquisition and processing (see Maćkowiak and Wiederholt (2009) and Mankiw and Reis (2002)).

3   Model, Method and Moments

As already discussed, there are several theories that could explain the intermittent price adjustment patterns observed in many datasets at both consumer level and at producer level. Here we suggest a simple reduced form model that describes production plants' price adjustment behaviour with the following three features; plants adjust prices infrequently as only 20 percent of the price observations change from one month to another, there is a lot of small price changes, and there is a seasonal pattern in the incidence of price changes with most price changes taking place in January.

3.1   Model Specification and Predefined Parameters

As firms require a degree of monopoly power to be able to set prices, we assume that producers operate in monopolistic competitive markets. Furthermore, it is assumed that each firm is able to continuously observe and monitor its frictionless price without any costs.

We start from the observations of high frequencies of zero price adjustments. This would be observed if there would be some menu costs, and that it would be costly to continuously adjust the product prices. The firm operates with a target price (in logs) for product i at time t denoted $p_{it}^{\#}$, and leave this unchanged unless the distance to the frictionless price p_{it}^{*} (also in logs) is becoming too large. The latter mentioned p_{it}^{*} represents the frictionless equilibrium price decided by the market conditions. The costs associated with setting a new target price is $F \cdot I\left(p_{it}^{\#} \neq p_{it-1}^{\#}\right)$, where F is the actual costs and $I\left(p_{it}^{\#} \neq p_{it-1}^{\#}\right)$ is an indicator function. The formation of the target

price is determined by:

$$p_{it}^{\#} = \begin{cases} p_{it}^{*} & if \ \mid p_{it}^{*} - p_{it-1}^{\#} \mid > \tau \\ p_{it-1}^{\#} & otherwise \end{cases} \qquad (1)$$

where τ denotes a threshold. Thus, if the shock to the frictionless price is large enough, in absolute value, relative to its target value, the firm finds it profitable to set a new target price and to start to adjust its price in response to the shock. The formulation in eq. (1) states that the threshold is symmetric, i.e. that the "band of inaction" is the same whether the price shock is positive or negative. We relax this restriction and allow the thresholds for price increase and price decreases to be different. With this modification, the formation of the target price is determined by:

$$p_{it}^{\#} = \begin{cases} p_{it}^{*} & if \ p_{it}^{*} - p_{it-1}^{\#} > U \ or \ p_{it}^{*} - p_{it-1}^{\#} < L, \\ p_{it-1}^{\#} & otherwise \end{cases} \qquad (2)$$

where U denotes the upper threshold and L denotes the lower threshold, i.e. $L \leq 0 \leq U$. It means that the target price is changed only if the frictionless price moves outside the interval determined by L and U. Opposite, if the frictionless price is larger than L and lower than U, the producer leaves its target price $p_{it}^{\#}$ unchanged.

Following Alvarez et al. (2011), Dias et al. (2015), and others, we let the logarithm of the frictionless nominal price for product i at time t, denoted by p_{it}^{*}, follow a random walk with drift:

$$p_{it}^{*} = \alpha + p_{it-1}^{*} + \varepsilon_{it}, \qquad where \ \varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^{2}) \qquad (3)$$

Here α denotes the deterministic drift, and ε_{it} denotes idiosyncratic shocks with variance σ_{ε}^{2}. If α were not included, trend inflation would be embedded into the threshold parameters and therefore bias the results. If α is set too low (too high) compared to the actual trend inflation, the estimated threshold parameters L and U

would be biased downwards (upwards). The deterministic trend parameter, α, is set as close to the actual inflation as possible to limit the effect of inflation bias.[8] The idiosyncratic shock parameter, ε_{it}, is meant to reflect any shocks to either demand, cost or technology excess of the underlying trend captured by the trend parameter α.[9] In principle, it is possible to allow for serial correlation in ε_{it}, but for computational ease and in order to simplify the exposition, we assume that the shocks are serially uncorrelated.

Even though the firm has decided to change its target price, and therefore also to change the price of the given product, it does not move directly to the new target price. As discussed by for instance Zbaracki et al. (2004), price change costs also include convex components such it is costlier to make one larger price change compared to several smaller ones. Furthermore, the descriptive evidence given in Figure 1 indicates that smaller prices changes are not that uncommon, while larger price changes are. Nevertheless, there might also be losses of being too far away from the new target price $p_{it}^{\#}$. A formulation that encompasses both these elements, given that the deviation between the new frictionless price, p_{it}^{*}, and the target price $p_{it}^{\#}$ is large enough to initiate price changes, the "out-of-equilibrium costs" could be modelled as follows

$$AC(p_{it}) = C \cdot \left\{ (1 - \theta) \left(p_{it} - p_{it}^{\#} \right)^2 + \theta \left(p_{it} - p_{it-1} \right)^2 \right\} \tag{4}$$

Thus, the formulation consists of a weighted sum (where $0 \leq \theta \leq 1$) of two

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[8]We could also include α as a parameter to be estimated. A simpler approach, as adopted here, is to perform a series of simulations with different values for α. We comment on this further when testing the robustness of our model.

[9]An argument against letting demand-, technology-, and or cost- shocks to be treated identically is that firms react quicker to positive than to negative cost shocks, but slower to positive than to negative demand shocks (see for instance found in Dias et al. (2015) and Loupias and Sevestre (2012)). Differencing between the types of shocks would implicate a more sophisticated derivation of both the frictionless price and the inertia parameters than presented above. Furthermore, with the available data it might also be difficult to identify different types of shocks. Considering this, and that the focus of our paper is the combination of thresholds and inertia, we choose to include the shocks as an aggregate effect (see Appendix for an analysis how the price is affected by demand-, technology, and cost- shocks).

quadratic terms, which denotes the difference between the new price and the target price, and the difference between the new price and the previous price, respectively. A plant seeks to minimise these "out-of-equilibrium costs" $AC(.)$. The first order condition of equation (4) with respect to new current price p_{it} rearranged is therefore;

$$(p_{it} - p_{it-1}) = (1 - \theta)\left(p_{it}^{\#} - p_{it-1}\right) \tag{5}$$

Thus, we have the traditional partial adjustment model where the "out-of-equilibrium costs" $AC(.)$ prevent the producer to adjust immediately to its target price, only that the "usual" frictionless seen in partial adjustment models is exchanged with the target price $p_{it}^{\#}$. An implication is that the producer will close $(1 - \theta)$ of the deviation between the target price and the old actual price. For example, $\theta = 0.10$ will implicate that the producer closes 90 percent of its desired price change in the first period. If the target price remains unchanged in the subsequent period, the producer will close 90 percent of the remaining price gap. This will keep on until the producer decides to set a new target price or when the target price is reached.

To avoid the restriction that the weights in equation (4), $(1 - \theta)$ and θ, are common to price increases and price decreases, we allow the model specification for asymmetric inertia in addition to the already discussed asymmetric thresholds. This reflects asymmetric adjustment costs discussed and analysed in the microeconomic literature (e.g. Peltzman, 2000; Yang and Ye, 2008; Xia and Li, 2010; Lewis, 2011; Loy et al., 2016). Thus, we allow p_{it} to have three outcomes, depending on whether the price is either equal to the target price, heading upwards or heading downwards. If the price is heading upwards, θ_{up} is supposed to capture upward inertia. Conversely, if the price is heading downwards, θ_{down} is supposed to capture downward inertia.

Thus, we let the logarithm of the nominal price of product i at time t be given by:

$$(p_{it} - p_{it-1}) = \begin{cases} (1 - \theta_{up})(p_{it}^{\#} - p_{it-1}) & if \ p_{it}^{\#} - p_{it-1} > 0.005, \\ 0 & if \ |p_{it}^{\#} - p_{it-1}| \le 0.005, \\ (1 - \theta_{down})(p_{it}^{\#} - p_{it-1}) & if \ p_{it}^{\#} - p_{it-1} < -0.005, \end{cases} \quad (6)$$

As seen from (6), we consider price differences within the following bounds $[-0.005, 0.005]$ as zeros. Such small variations are likely to have little economic meaning. In addition, the numerical simulations described in subsequent section, makes it necessary to allow for small deviations from a mathematical true zero. Thus, our definition of zero corresponds to the definition used in later applied moments. The formulation in (6) also implies that the price does not adjust further when the deviation from the target price gets small enough.

It should be mentioned that if $\theta_{up} \neq 0$, $\theta_{down} \neq 0$, $U = L = 0$, the model specification reduces to a partial adjustment model (since then $p_{it}^{*} = p_{it}^{\#}$ and eq.s (1) and (2) would be irrelevant). Conversely, if $\theta_{up} = \theta_{down} = 0$, $U \neq 0$, $L \neq 0$, the model reduces to a (S, s) pricing model.[10] Note also, if the target price $p_{it}^{\#}$ would not have been introduced explicitly, the (symmetric) threshold specification would be as follows;

$$p_{it} = \begin{cases} p_{it}^{*} & if \ | p_{it}^{*} - p_{it-1} | > \tau \\ p_{it-1} & otherwise \end{cases} \quad (7)$$

Furthermore, the (symmetric) partial adjustment expression would then be:

$$(p_{it} - p_{it-1}) = \begin{cases} (1 - \theta)(p_{it}^{*} - p_{it-1}), & if \ |p_{it}^{*} - p_{it-1}| > 0.005, \\ 0 & if \ |p_{it}^{*} - p_{it-1}| \le 0.005, \end{cases} \quad (8)$$

Note however, then the price-adjustment process would stop when $p_{it}^{*} - p_{it-1}$ would

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[10]Eq. (5) states that conditional on changing, one immediately goes to the new target price.

reach the threshold τ. Thus, without the target price $p_{it}^{\#}$ in the model we would not observe that many small price changes and p_{it}^{*} would never will be fully reached.[11]

It is assumed that the friction parameters U, L, θ_{up} and θ_{down} are all independent of product characteristics. There is a broad agreement in the literature that price setting is heterogeneous across sectors, firms and products (Álvarez et al., 2006; Nakamura and Steinsson, 2008; Dhyne et al., 2011; Fougère et al., 2007; Dias et al., 2015)). Instead of controlling for such heterogeneity by introducing product- or firm specific friction parameters, we will estimate the model for different product groups and therefore allowing *all* parameters to take different values when checking the robustness of our model.

[Figure 4: Illustration of Price Change Process - about here]

In Figure 4 we illustrate how our model is working. Starting with the evolvement of the frictionless price, p^{*}, we see clearly the upward trend, but an interim period with sudden price decreases. The thresholds have a constant distance relative to the actual price (bold line). We see in period $t = t^A$, the frictionless price has evolved such that is larger than the upper threshold U, and consequently is the target price and the actual price both changed. We see however, that the actual price is moving slowly towards the new target price. This is caused by the inertia parameter(s) θ. In period $t = t^B$ a sudden negative shock comes, pushing the target price below the lower threshold L. Subsequently the price is reaching this new target price. Thus, we see that price changes can be caused by accumulated small shocks, or one large shock to the underlying frictionless price. We also see intermittence, and small price changes consistent with the descriptive statistics. Finally, the figure shows that the thresholds change across time.

Finally, the numbers from the descriptive statistics shows that the incidence of

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[11]Dhyne et al. (2011) have such a model, but with asymmetries. To be able to incorporate the existence of small price changes, they let the threshold be stochastic.

price changes is 31% in January, while the average over the other eleven months is 19%. To control for this seasonal effect, we include a January specific parameter, defined as $0 \leq y \leq 1$, which is multiplied with the threshold parameters U and L if the current month is January. This enables the model to lower the thresholds in the beginning of each year and thereby increase the probability of a price change. Furthermore, this might also reflect the potential existence of staggered contracts starting in January and with 12 months duration.[12]

This leaves us with the following parameters to be estimated:

$$\text{Standard deviation of idiosyncratic shocks: } \sigma_\varepsilon$$

$$\text{Upper threshold: } U$$

$$\text{Lower threshold: } L$$

$$\text{Inertia upwards: } \theta_{up}$$

$$\text{Inertia downwards: } \theta_{down}$$

$$\text{January specific scalar: } y$$

In our main estimates, we set $\alpha = 0.0025$, which gives an annual inflation equal to 0.03, close to the average annual inflation rate of the producer price index (PPI) between the years 2004 and 2009.

3.2 Estimation Method

Given that the empirical model does include the thresholds, the model does not have an analytical closed form solution. This again prevent us from using "standard" regression techniques. Therefore, we estimate our specification using a Simulated Method of Moments (SMM). This estimation technique allows some of the parameters to be estimated, in our case σ_ε^2, U, L, θ_{up}, θ_{down}, and y. Other parameters are

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[12]Nilsen et al. (2016) show, using the same rawdata as used in this paper, a flat price change hazard with a peak after 12 months.

predefined to reduce the computational burden. In short, SMM seeks to minimize the distance between two sets of moments, the moment vector generated conditional on a vector of parameters to be estimated β, and the corresponding moment vector in the actual data, i.e. to find the vector of unknown parameters β that minimizes the following quadratic form $J(\beta)$:

$$J(\beta) = [\Phi^A - \frac{1}{\kappa} \sum_{j=1}^{\kappa} \Phi^S(\beta)]' W [\Phi^A - \frac{1}{\kappa} \sum_{j=1}^{\kappa} \Phi^S(\beta)] \qquad (9)$$

where Φ^A and $\Phi^S(\beta)$ denote the vector of m actual moments and the vector of m simulated counterparts respectively. W denotes an optimal weighting matrix, while κ denotes the number of panels with the same size as the actual data. The measure of the distance between two sets of moments, $J(\beta)$, has a χ^2 distribution with $m - l$ degrees of freedom, where l is the number of unknown parameters.[13]

When searching for values of β that minimize the criterion function, an annealing cooling algorithm is used. On the basis of starting values for the estimated parameters, this routine takes random jumps in a predefined parameter space. The routine accepts worse solutions with a decreasing probability, which ensures that the global optimum is found. As the final solution is somewhat sensitive to the initial values, we do several computations with different starting values.

3.3 Selection of moments

The model should explain both inaction and small price changes (defined as less than 5 percent in absolute value and strictly positive) at the same time, the proportion of

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[13]See the appendix for more details about the Simulated Method of Moments approach.

observations within the following intervals are included[14]:

$$-0.050 \leq p_{it} - p_{it-1} < -0.025$$

$$-0.025 \leq p_{it} - p_{it-1} < -0.005$$

$$-0.005 \leq p_{it} - p_{it-1} \leq 0.005 \qquad (10)$$

$$0.005 < p_{it} - p_{it-1} \leq 0.025$$

$$0.025 < p_{it} - p_{it-1} \leq 0.050$$

These moments should contribute in identifying all the parameters, especially the threshold parameters and inertia parameters: Non-zero U and L will cause zero-inflated price changes, and positive θ_{up} and θ_{down} will cause small price changes.

Larger inertia parameters, θ_{up} and θ_{down}, will make plants smooth their adjustments over time, which implicates that there will be several consecutive periods of small price changes. A consequence of this gradual adjustment is increased serial correlation in price changes. To identify θ_{up} and θ_{down}, we therefore choose to include the following correlation coefficient moments:

$$Corr[p_{it} - p_{it-1}, p_{it-1} - p_{it-2}] \; if \; p_{it} - p_{it-1} > 0.005 \qquad (11)$$

$$Corr[p_{it} - p_{it-1}, p_{it-1} - p_{it-2}] \; if \; p_{it} - p_{it-1} < -0.005 \qquad (12)$$

On the other hand, the threshold parameters U and L will also be affected by these moments, as larger $|U|$ and larger $|L|$ will lead to more inaction and lower serial correlation. The asymmetry is such that the moment in (11) should identify θ_{up}, while the moment in (12) should identify θ_{down}.

The standard deviation of the shocks to frictionless price, σ_ε, is likely to be directly related to the standard deviation of price changes, $sd(p_{it} - p_{it-1})$. We therefore choose to include the standard deviation of price changes as a moment. The standard

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[14]Our definition of small price changes (less than five percent) is consistent with the assumptions of Klenow and Kryvtsov (2008) and Eichenbaum et al. (2014).

deviation or variance of price changes is also likely to be affected by the friction parameters: As already pointed out, larger $|U|$ and $|L|$ leads to more inaction and thereby lower variance of the observed price changes. The aforementioned equation (5) shows that larger values of θ leads to price changes of more similar size which again will reduce the variance of price changes. Thus, the standard deviation of price changes will not only identify σ_ε, but it will also contribute to the identification of U, L, θ_{up} and θ_{down}.

The January specific scalar, y, is supposed to capture the abnormally high adjustment frequency in the beginning of the year. As a primary identifier, the following moment is therefore included:

$$\frac{\text{Number of price quotations with } |p_{it} - p_{it-1}| > 0.005 \text{ in January}}{\text{Total number of price quotations in January}}$$

In order to replicate the initial high share of price changes observed in the data, the model will therefore select a value of y such that the thresholds in January are lower than in the rest of the year.

As previously mentioned, ranked price changes can be a good indicator of lumpy adjustment behaviour. Four of the ranks presented are therefore used as moments. More specifically, we include the two first and the two last ranks. These are meant to be the primary identifiers of the threshold parameters U and L. The ranks are likely to be affected by σ_ε and the inertia parameters as well: More variation in the frictionless price will cause more variation in the ranks and higher inertia parameters will bring the ranks closer to each other. Hence, the rank moments will also affect θ_{up}, θ_{down} and σ_ε.

One might think that the use of ranks is just another way of describing the seasonal effects, and thus that there is not much gain in adding ranks for identification. When holding for each month the share of the highest ranked price changes (rank 1 observations), the evolvement of these shares mimic very much the pattern of price

changes by months. Formal testing shows a corr. coeff. of 0.99 (and z-value = 21.7). That means that within each plant (and year), the pattern of largest price changes follows to a large extent the same pattern as the frequencies of price changes seen in Figure 1. On the other hand, the correlation of the share of the lowest ranked price changes, and the frequency of price changes by month, is small (0.11) and statistically insignificant. Thus, there are likely benefits with regard to identification from including both the Jan-effect, and information about the highest and lowest ranks.

4 Results

Table 1 shows the parameter estimates for the various model specifications by columns. Standard errors are presented in parentheses. The parameter estimates and standard errors are presented in the upper part of the table. The corresponding moments of the various model specifications are presented in the lower part of the table. We estimate all specifications against the 13 moments already described, i.e. distribution of $\triangle p/p$, Jan-effect, serial correlations, st.error of $\triangle p/p$, and rank-moments.[15]

[Table 1 "Parameter Estimates and Moments" about here]

Starting with a broad look at this table, we see that all the estimated parameters are statistically significant (with the exception of the ones in Column (5)). In Column (1), we report the results of the full model which include both thresholds and partial adjustment parameters, and that their magnitude depends on whether prices are increasing/decreasing relative to previous month.

The $U = 0.1398$ states that the distance between the frictionless price and the existing target price, $p_{it}^* - p_{it-1}^{\#}$, has to be almost 14 percent before a price-adjustment process is initiated. Then the actual price changes are decided by the partial adjustment model. The value of $\theta_{up} = 0.3698$ is to be interpreted as the producer will close

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[15] All the estimation results are robust to initiating the estimation algorithm from different sets of starting values. Thus, the parameter estimates reported seem to correspond to global maxima.

63 percent ($= 1 - 0.3698$) of its desired price change, $p_{it}^{\#} - p_{it-1} (= p_{it}^{*} - p_{it-1})$, in the same period as it decides to reset the target price and start a price increase process. The parameter estimates of $U = 0.1398$ and $\theta_{up} = 0.3698$ together state that the initial price increase will be at least 0.0881 of the current price.[16] Thus, the new prices are reached quite quickly. The lower threshold, $L = -0.1669$ states that the (absolute) distance between the frictionless price and the existing target price, $\left| p_{it}^{*} - p_{it-1}^{\#} \right|$, has to be almost 17 percent before a price decrease process takes place. And the producer will again quite quickly adjust to the new lower price, seen from the θ_{down} $= 0.4094$.[17] The values of $\theta_{up} = 0.3694$ and $\theta_{down} = 0.3964$ state that the producers put more weight on $\left(p_{it} - p_{it}^{\#} \right)$ than the $(p_{it} - p_{it-1})$ in the out-of-equilibrium costs function (eq. (4)). Said differently, it seems to be more important to close the gap relative to the new target price than reducing the implied convex adjustment costs associated with the period to period adjustment. Furthermore, the findings suggest that adjustments are faced with two different forms of frictions. Firstly, the effect of the threshold is that it must be desired to change the price by at least the size of the threshold before the firm decides to adjust. Secondly, the effect of the inertia is that the initial price change will be equal to $(1 - \theta)$ of the target price gap $p_{it}^{*} - p_{it-1}$, while subsequent adjustments will be smaller. The January effect, meant to capture the fact that the incidence of price changes is higher in January compared to the other months, states that the thresholds U and L are two thirds in January compared to the other months. This is consistent with theories focusing on the costs of information acquisition and processing but might also be consistent with the existence of staggered contracts with duration of one year.

The model performs relatively well, as seen from the J-statistic in the last row.

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[16] The initial price increase is found by multiplying U with $(1 - \theta_{up})$: $0.1398 \times (1 - 0.3698) \approx 0.0881$.

[17] The initial price decrease will be at least 0.0986 of the current price, and there will subsequently be several smaller adjustments downwards until the firm reaches the target price or decides to set a new one. Thus one may think that price changes of 8.5% and 10.0% (initial price changes for positive and negative price adjustments, respectively) are definitely not ignorable.

This reflects that the empirical moments, reported in the lower part of the table, are matched quite well with the empirical ones reported in last column of the table, Column (8).[18]

In Column (1) are the magnitude of the parameter estimates for the pairs U and L, and θ_{up} and θ_{down}, very similar, even though their significance clearly states that they are statistically different ($|L| \neq U$, and $\theta_{up} \neq \theta_{down}$). Still, when forcing the parameters within each pair to be the same (in absolute values), reported in Column (2), the J-statistic states a worse model fit.[19]

We have also tested a frictionless model, reported in Column (3). What we see is a very bad model fit, both measured by the J-statistic, and by comparing the individual moments of the simulated model with the empirical ones. Thus, a model without any price adjustment frictions is inferior compared to the two former models. The frictionless model in Column (3) states that the estimated standard error $\hat{\sigma}_{\varepsilon}^{frictionless} = 0.0012$ and that the frequency of zero price changes is 0.9814. In our model we have $\triangle p_{it}^* = p_{it}^* - p_{it-1}^* = 0.0025 + \varepsilon_{it}$ where $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^2)$. Note also, in a frictionless model will $p_{it} = p_{it}^*$, i.e. the new price is equal to the frictionless price. Simple calculation shows that $\sigma_{\varepsilon} = 0.0029$ is necessary in a frictionless model to get 80% of the observations of $\triangle p_{it}^*$ (and therefore also $\triangle p_{it}$) within the interval [-0.005, 0.005], the "zero price changes"-interval moment. When our frictionless model gives the best fit with a frequency of zero price changes of 0.9814, it is due to the other moments which force the standard error $\hat{\sigma}_{\varepsilon}^{frictionless} = 0.0012$ for best possible weighted match with all of the empirical moments.[20] We have also tested specifications where only

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[18]The J-statistic has a χ^2distribution where the degrees of freedom are determined by the number of moments being matched minus the number of parameters estimated. Though compared to similar studies, the J-statistics reported in Table 1 are low and thus satisfactory, the numbers imply that all specifications are rejected.

[19]Clearly, the difference in J-statistic $= 59.7$ ($=235.5$-175.8), $df = 2$, indicates that this restriction largely distorts the performance of the model.

[20]The J-statistic is 2546.3 for the estimated frictionless model, while it is $J = 16805.0$ when we set $\sigma_{\varepsilon} = 0.0029$. It turns out that when we force the magnitude of σ_{ε} going from the $\hat{\sigma}_{\varepsilon}^{frictionless} = 0.0012$ up to $\sigma_{\varepsilon} = 0.0029$, we get too many small positive price adjustments $\langle 0.5\%, 2.5\%]$ very quickly. This indicates that the moments describing the distribution is good for identification of the

parts of the friction parameters are present. In Column (4) we include only the threshold parameters U and L, while in Column (5) we have estimated a pure partial adjustment model. The results of the latter one is identical to the ones reported in Column (3).[21] The overall finding based on the results reported in Columns (1)-(5), is that a full model with both asymmetric price thresholds and asymmetric partial adjustment process, is the preferred specification.

As an additional way to show the model fit, in addition to the J statistics and the individual moments compared to their empirical counterpart, we report the whole distribution of price changes, the share of price changes in given month, and the mean price-change for all ranks. Going back to Figures 1-3, we have there reported the simulated moments for the full model (grey bars) reported in Table 1, Column (1). Starting with the predictions of monthly changes (Figure 1), show that the seasonal pattern is reasonably good. Especially for the share of price changes, and the ranks (Figure 2, and Figure 3, respectively) the fit is also very good for the moments not used when estimating the model. We interpret this as supporting evidence for our model formulation.

4.1 Robustness checks and discussion

In our underlying frictionless price, modelled as a random walk with a deterministic trend, the predetermined trend parameter $\alpha = 0.0025$ which corresponds to an annual price increase of 3 percent. Two alternative simulations are done where α is set equal to 0.0016 and 0.0035. These denoted α^{low} and α^{high}, corresponds to an underlying annual price increase of 2% and 4%. The results of these two alternative trends, and using the full specification, are reported in Table 1, Columns (6)-(7). The model fit,

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variance of the underlying process of the frictionless nominal prices.

[21]The similarity of the two sets of results is as expected. The two serial correlation moments meant to capture inertia are based on the autocovariance of $\triangle p_{it}^* = p_{it}^* - p_{it-1}^*$. When the process of p_{it}^* is a random walk with a drift, the two autocovariances - upwards and downwards - should both be zero. Thus, when $U = L = 0$, there is neither anything in the model nor moments that help identifying the frictionless model and the partial adjustment model from each other. The results should therefore be the same for the two model specifications, as we do get.

measured by the J-statistic, is worse when using the alpha low. Still comparing the individual coefficients, U and L are both somewhat lower compared to the full model when $\alpha = 0.0025$. The largest difference, moderate though, is for the θ_{up} (0.3698 and 0.2979, Column (6) and Column (1) respectively). Turning to the α^{high} results, we see to overall picture is that the J statistic is very close to the initial one reported in Column (1). Again the overall picture is that the coefficients are more or less the same. The conclusion we draw from this robustness check, is that the initial guess of $\alpha = 0.0025$ is not too wrong, and if any changes should be made, the α should be set somewhat higher rather than lower compared to 0.0025.[22] Admittedly, we have considered to estimate α, instead of pre-determining it as now. Nevertheless, the small deviation between the estimates based on different values of α tells us that the gain from doing this is limited.

[Table 2: Estimation Results by Product Groups - about here]

As already mentioned, earlier research has shown that there is significant heterogeneity in pricing patterns, both between firms and between products. To address this in our study, we estimate the model for five different product groups. These results are reported in Table 2. What we see is a very good model fit, seen from the low J statistics, much better than the J statistics found when estimating the model with the sample of all product types (Table 1, Column 1). This shows that also in our data there is difference in the pricing patterns between products, and that these differences should be taken into account. Starting with "Capital goods", we see much larger thresholds compared to our previous results. Furthermore, the difference in thresholds in January and the other months is substantial. The product "Durables", "Intermediate goods", and "Non-durables, food", seem to have a quite similar pricing pattern with an upper threshold U in the interval 0.12-0.15, and with the lower

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[22]A regression model where the dependent variable is log-transformed product prices, and where a time trend together with product-specific dummies, month-specific dummies and year-specific dummies are included, gives a time-trend $\alpha = 0.0029$, which corresponds to a 3.5% annual increase.

threshold L significantly larger (in absolute terms). The reduction of the threshold in January is smaller for these three product groups than for the other two. For the last group, "Non-durables, non-food", we also find the two thresholds U and L to be very similar as for "Durables", "Intermediate goods", and "Non-durables, food". We notice, however that the two θs for "Non-durables, non-food" are close to zero, indicating that the gap between the old and new price is closed momentarily. It should be mentioned, though, that this latter group of goods, "Non-durables, non-food", is quite heterogeneous with production of textiles and footwear, pharmaceuticals, and sports goods. Nevertheless, the results shown in Table 2 state clearly that there is huge difference in price change patterns across product groups.

[Table 3: Counterfactual Analyses Results - about here]

An interesting question is the importance of the respective price adjustment parameters in explaining the main characteristics of observed price changes. To shed some more light over this, we simulate the preferred asymmetric model under exactly the same circumstances as the estimated model, but setting different price adjustment cost parameters to zero, and measure the impact on the set of moments used for identification. Table 3 shows the result of this exercise. The first thing to notice for all of three sets of results, is the huge increase in the J-statistic, meaning that overall model fit is much worse when some of the friction parameters are ignored. A more detailed look, starting with Column (1) where the two θs are set equal to zero, we see an increased share of zero price changes, no small price changes and therefore also an increase in the observations outside the [-5%, 5%] interval. The two inertia parameters, θs, are therefore very important for creating small price changes. Omitting them from a model would lead to a conclusion that the dynamics of price changes described as zeros and lumps driven by a fixed costs model. Turning to Column (2) where the thresholds are ignored, the model with is extremely bad, especially in producing a

large enough share of inaction. Thus, both sets of friction parameters, inertia and thresholds, are important for understanding the dynamics of price changes.[23], [24]

As already mentioned, each plant may produce one or several products.[25] In our model we have treated each product independent from each other. That means we have ignored the strategic complementarity in the adjustments of multiple products and assume that the various products are sufficiently differentiated in order to abstract from substitution within the plant's portfolio of products.[26] We have analysed the various components of the prices in the dataset by using a multi-level mixed effects linear regression model (see Baltagi et al., 2001). (Log-) prices are regressed on time effects (a linear time trend, month- and year dummies) with random intercepts at both the plant and the product-within-plant level such that products are nested within plants. The analysis shows that the price variation is mainly driven by variance in plant specific effects, and to a smaller degree variance in product specific effects. Admittedly, this interrelation between the products within each plant is ignored in our analysis. One modification to control for this effect would be to introduce two variance components in our idiosyncratic shocks σ_ε^2, such that $\sigma_\varepsilon^2 = \sigma_p^2 + \sigma_u^2$ where σ_p^2 denotes variance of product-specific shocks, and σ_u^2 denotes idiosyncratic product shocks. One could also consider to model frictions at the level of the plant, not at the level of products. Our simplification of the shock process is likely to overestimate the importance of the threshold parameters, since they will pick up the effect of both

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[23]A more complicated shock process of the frictionless prices has been considered. Indeed, ignored persistency in the shock process is likely to bias the θ parameters. However, our random walk is of course highly persistent. Furthermore, our estimation results show that the distance between existing prices and target prices is closed quit quickly. Thus it is not clear, though, what one would gain from a modification of the shock process of the frictionless prices.

[24]We have also estimated a model where we look at annual data, i.e. the price changes from June one year to June the subsequent year, and of course estimated with a different moment vector. Unsurprisingly, these results indicate much smaller thresholds, asymmetric but still statistically significant. The downward inertia parameter θ_{down} is significant, while $\theta_{up} = 0$. Thus, time aggregation blurs the price changing picture compared to using a model that are able to take advantage of the monthly frequency. These results are not reported, but available from the authors on request.

[25]The mean number of products per producer is 5, while the maximum is 20.

[26]See also Woodford (2003) and Gertler and Leahy (2008) for discussions about strategic complementarity and "real rigidity" but then in relation to firms' competitors.

price change costs, and to some degree shocks that are common to all products of a producer. The sketched changes would be interesting extensions of our model. Again it is a matter of identification and tractability of the model. Note however, there are no other variables than prices in the data with monthly frequency. Neither is there anything about product specific quantities and costs, only plant level (annual) information. Thus, we leave these potential extensions for a later paper.

Our estimates show that price adjustment frictions are important for understanding the intermittent price adjustment pattern seen in the data, and that ignoring frictions bias our results. Furthermore, our findings of both thresholds and inertia together, indicate that different forms of rigidities exist in the data, which is only partly consistent with the assumptions of macroeconomic pricing models. Some menu cost models include thresholds with (S, s) pricing rules, while others incorporate inertia by assuming partial adjustments. However, none of the models incorporates both thresholds and inertia in price setting. In general, macro models therefore fail to include all the evidence provided in this paper. Moreover, our findings imply the occurrence of both large and small price changes. While the threshold parameters enable inaction, the inertia parameters implicate a large initial price change followed by smaller adjustments. Accordingly, the results imply that our model is able to account for periods of inaction, as well as both large and small price changes. In contrast, models such as in Golosov and Lucas (2007) and Gertler and Leahy (2008), explain patterns of inaction followed by large price changes by assuming thresholds, but these models seem to neglect small price adjustments. Our findings indicate that prices are similarly flexible upwards and downwards.[27] The seasonal effect, picked up by our January parameter, y, may come from uneven staggering of nominal contracts and could have implications for the effectiveness of monetary policy interventions taking

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[27]The literature is not conclusive when it comes to whether nominal price rigidities are symmetric or not. For studies finding asymmetry, see for instance Dias et al. (2015); Laxton et al. (1995, 1999); Dolado et al. (2005); Dobrynskaya (2008).

place in different months of the year (for related findings, see Olivei and Tenreyro (2007)).

5 Concluding Remarks

In this paper we specify and estimate a model that describes production plants' price adjustment behaviour. The model includes thresholds which are lower in January than in the other months, together with a quadratic loss–function associated with the distance from a target price. The simplistic reduced form model is tested on a sample based on repeated monthly plant- and product-specific survey data from the Norwegian manufacturing industry. The model is meant to reproduce the following features of the data. First, plants adjust prices infrequently as only 20 percent of the price observations change from one month to another. Secondly, the is a seasonal pattern in the incidence of price changes, with most price changes taking place in January. Thirdly, there is also a lot small price changes.

The simulated method-of-moment estimates reveal thresholds that are such that prices are only changed if the deviation from the target price to the underlying frictionless price is larger than approximately 15 percent. However, if the shocks are such that the prices should be changed, the gap between the current price and the new target price is reduced quite quickly and only 10 percent of the initial gap exists after three months. There are statistically significant cost differences whether the prices should move upwards or downwards. However, the magnitude of these differences are very moderate. Furthermore, the January-effect, indicating that the thresholds are only two third this month, is consistent with theories focusing on the costs of information acquisition and processing, and/or on staggered contracts.

Several checks are applied to test the robustness of the model and findings. First, the preferred specification outperforms a frictionless model, or models with only some parts of the price adjustment friction parameters present. A counterfactual analysis

where some of the friction parameters are set equal to zero, shows that the moment fit becomes much worse compared to the preferred model specification. Furthermore, the model seems to be fairly robust to changes in the underlying deterministic trend, as our approximation of the trend gives better fit than alternative approximations.

While our evidence implies both large and small price changes, many model contributions in the literature are only able to account for one of these two characteristics. Having said this, there are a few of the models assuming thresholds in the price setting are able to explain small price changes. These models assume either stochastic thresholds or economies of scope in price setting, and represent an increasingly sophisticated group of pricing models in which more micro evidence is incorporated. However, our model is rather simple and transparent, and computationally easy.

There are a set of issues we have not addressed and that need to be explored in future work. The model is admittedly a reduced form model. A more structural model would be more informative. This would call for a full dynamic- specification and optimisation. However, with the current dataset there is no information about quantities, even though annual revenues and costs are available at plant level. Furthermore, the only information available at product level with monthly frequency is prices themselves. Thus, a structural model would partly require non-verifiable assumptions about inputs and outputs. Still, our findings strongly indicate that such a model needs to include both convex and non-convex price adjustment costs. Our goods-specific estimates also point in the direction for taking into account and control for product (and plant) specific heterogeneity. Note however, the mixed frequency of price information, and other plant-or firm-specific information (monthly versus annually), give some econometric challenges. Still, the evidence provided in this paper, based on a simple and transparent simulation model, shows the importance and potential fruitfulness of using model formulations and estimation techniques that able to take into account the non-convexities in price adjustment costs function.

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Figures
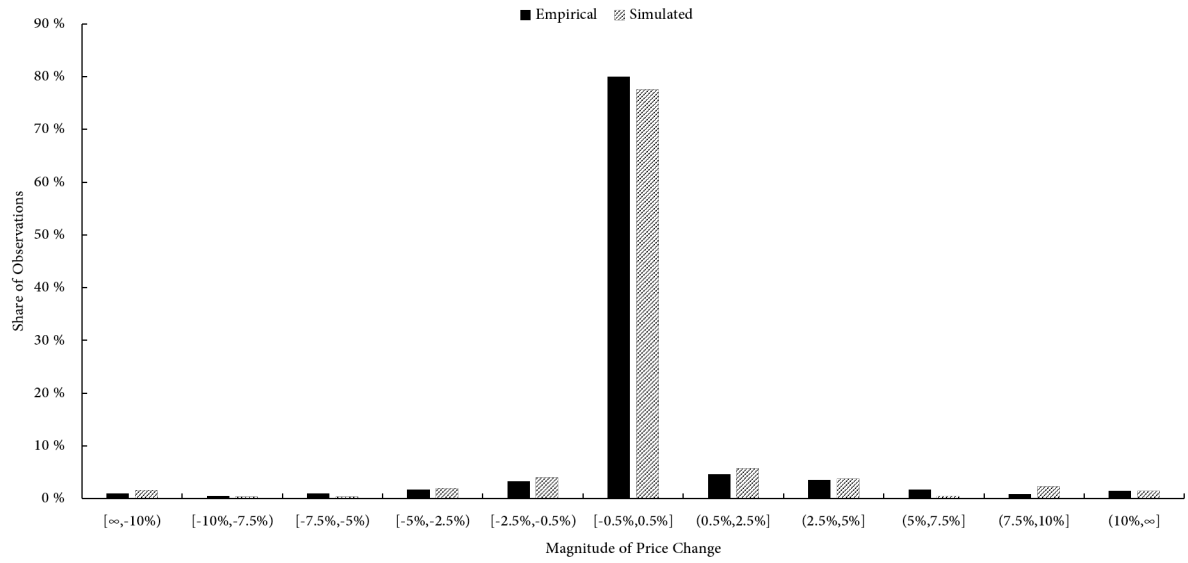
Note: *The figure shows the proportion of observations in different price change intervals. The price changes in this figure are calculated using the following logarithmic approximation:* $\ln(p_{it}) - \ln(p_{it-1}) \approx \frac{p_{it} - p_{it-1}}{p_{it-1}}$ *, where p_{it} denotes price. Because this is a differenced variable, we loose one observation for every product.*

Figure 1: Empirical and Simulated Distribution of Monthly Price Changes
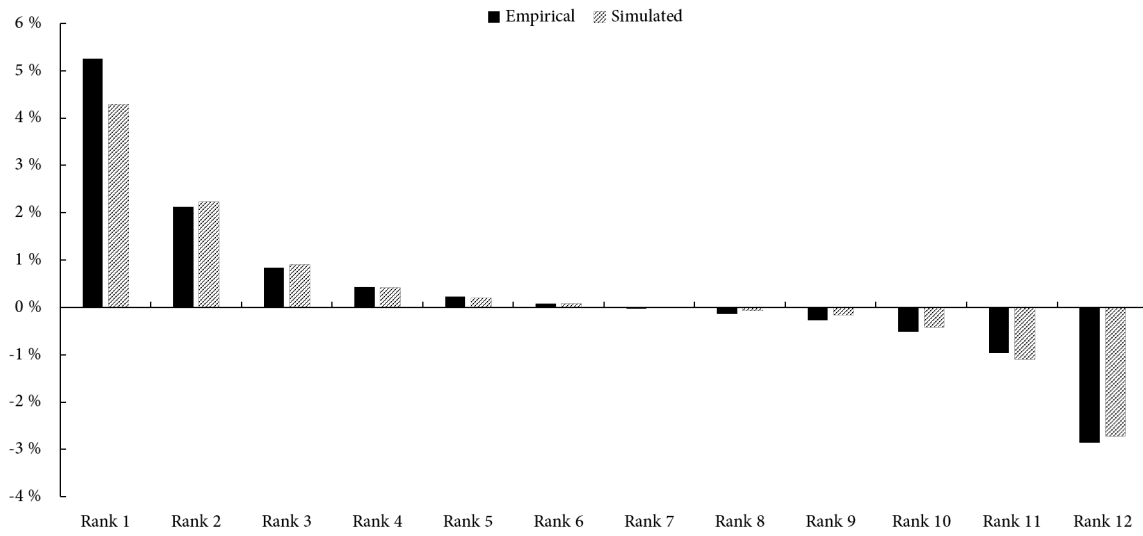
Note: *Ranks are first calculated on a yearly basis for every product before they are averaged across products and years. Rank 1 represents the average highest monthly price change and rank 12 represents the average lowest monthly price change.*

Figure 2: Empirical and Simulated Ranks
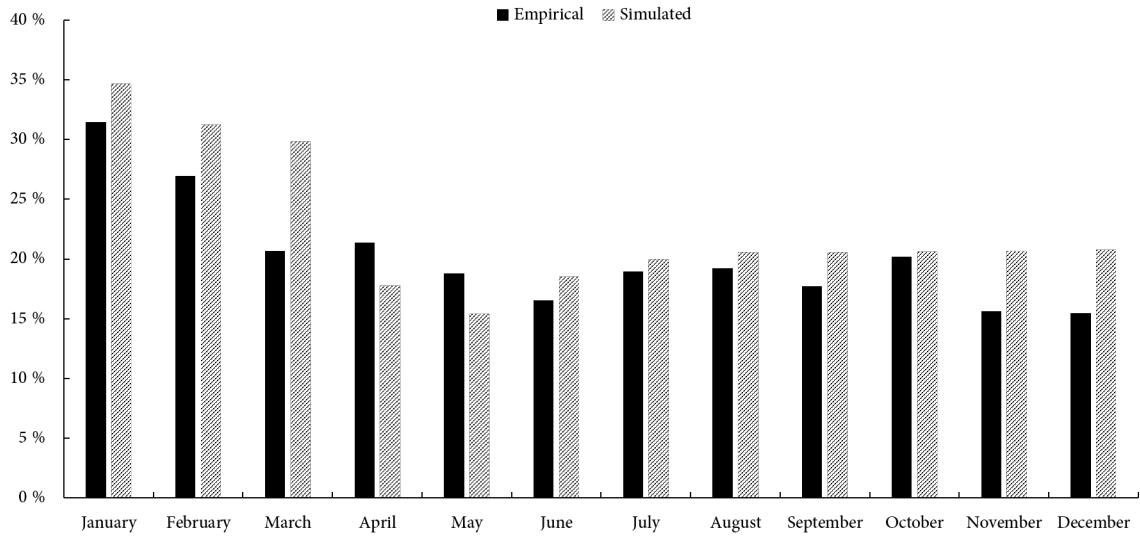
Note: *The figure shows the average frequency of producer price changes in the years 2004 to 2009 by calendar month. Shares are given as the number of price changes larger than 0.5% within each month divided by the total number of price quotations in the month.*

Figure 3: Average Share of Price Changes, by month - empirical and simulated
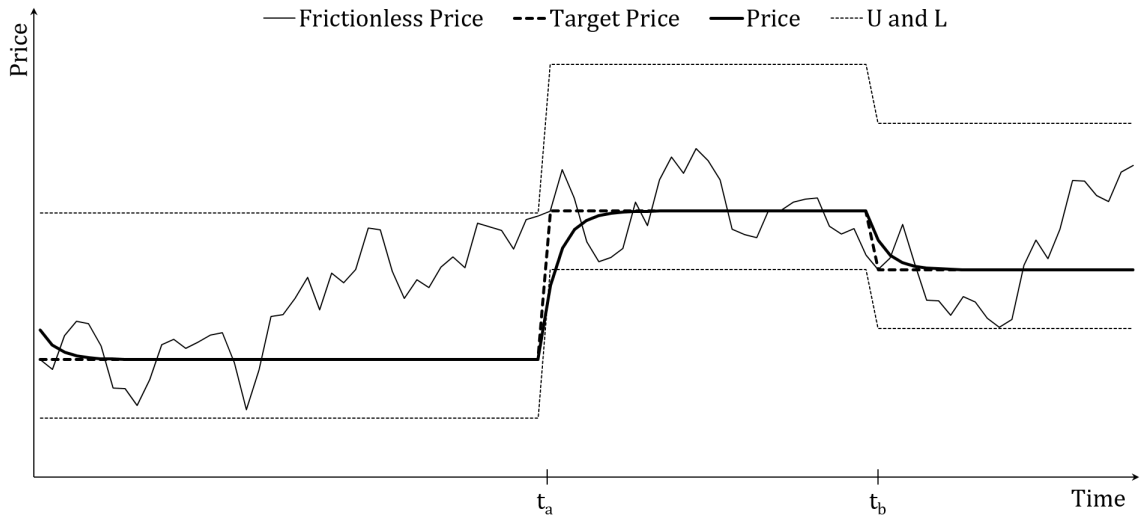
Note: The figure illustrates the dynamics of the full model with thresholds and inertia. In order to simplify the exposition, a manipulated price series is used.

Figure 4: Illustration of the Price Changing Process

Tables

Specifications:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ_ε	0.0417	0.0397	0.0012	0.0161	0.0012	0.0410	0.0412	-
	(0.0007)	(0.0007)	(1.98E-05)	(0.0010)	(1.98E-05)	(0.0006)	(0.0007)	-
U	0.1398	0.1439	-	0.0440	-	0.1182	0.1281	-
	(0.0034)	(0.0026)	-	(0.0004)	-	(0.0019)	(0.0029)	-
L	-0.1669	-0.1439	-	-0.1289	-	-0.1799	-0.1624	-
	(0.0035)	(0.0026)	-	(0.0252)	-	(0.0033)	(0.0044)	-
θ_{up}	0.3698	0.3787	-	-	0.0000	0.2979	0.3580	-
	(0.0030)	(0.0027)	-	-	(0.0000)	(0.0066)	(0.0050)	-
θ_{down}	0.4094	0.3787	-	-	0.0000	0.3720	0.3861	-
	(0.0099)	(0.0027)	-	-	(0.0000)	(0.0072)	(0.0097)	-
y	0.7120	0.7319	-	0.6346	-	0.6809	0.6928	-
	(0.0166)	(0.0161)	-	(0.0221)	-	(0.0148)	(0.0167)	-
Moments								
$[-5.0\%, -2.5\%\rangle$	0.0188	0.0226	0.0000	0.0000	0.0000	0.0186	0.0193	0.0171
$[-2.5\%, -0.5\%\rangle$	0.0410	0.0387	0.0000	0.0000	0.0000	0.0384	0.0370	0.0331
$[-0.5\%, 0.5\%]$	0.7786	0.7745	0.9814	0.9387	0.9814	0.7900	0.7739	0.8000
$\langle 0.5\%, 2.5\%]$	0.0592	0.0648	0.0186	0.0000	0.0186	0.0504	0.0578	0.0470
$\langle 2.5\%, 5.0\%]$	0.0379	0.0371	0.0000	0.0278	0.0000	0.0349	0.0430	0.0362
Chgs in Jan	0.3325	0.3315	0.0185	0.2001	0.0185	0.3348	0.3478	0.3146
Serial corr (up)	-0.3642	-0.3086	0.0106	-0.0590	0.0106	-0.4879	-0.4454	-0.1358
Serial corr(down)	-0.2636	-0.3211	0.0000	0.0000	0.0000	-0.2916	-0.2909	-0.3851
$sd(p_{it} - p_{it-1})$	0.0275	0.0267	0.0012	0.0142	0.0012	0.0283	0.0276	0.0413
Rank 12	-0.0263	-0.0260	0.0005	-0.0053	0.0005	-0.0302	-0.0257	-0.0286
Rank 11	-0.0108	-0.0102	0.0012	0.0000	0.0012	-0.0113	-0.0100	-0.0097
Rank 2	0.0218	0.0211	0.0039	0.0103	0.0039	0.0202	0.0237	0.0213
Rank 1	0.0429	0.0422	0.0045	0.0271	0.0045	0.0423	0.0460	0.0526
J:	175.8	235.5	2546.3	819.2	2546.3	347.7	188.8	-

The column numbers represents the following specifications: (1): Full model, (2): Full model with symmetric friction parameters, (3): Frictionless, (4): No inertia parameters, (5): No threshold parameters, (6): Full model with $\alpha = 0.0017$, (7): Full model with $\alpha = 0.0033$, (8): Empirical moments.

Table 1: Estimation Results and Empirical Counterparts

Specifications:	(1) Capital goods	(2) Durables	(3) Intermediate goods	(4) Non-durables, food	(5) Non-durables, non-food
σ_e	0.0297 (0.0018)	0.0413 (0.0035)	0.0512 (0.0015)	0.0484 (0.0020)	0.0188 (0.0044)
U	0.2820 (0.0608)	0.1193 (0.0058)	0.1561 (0.0038)	0.1527 (0.0042)	0.1700 (0.0149)
L	-0.2647 (0.0699)	-0.2397 (0.0314)	-0.2119 (0.0081)	-0.1621 (0.0056)	-0.2061 (0.1609)
θ_{up}	0.3050 (0.0226)	0.2994 (0.0254)	0.3555 (0.0039)	0.4068 (0.0177)	0.0262 (0.0024)
θ_{down}	0.2520 (0.0337)	0.4433 (0.0201)	0.4778 (0.0138)	0.3755 (0.0171)	0.0026 (0.1714)
y	0.4184 (0.0861)	0.8198 (0.0870)	0.7116 (0.0258)	0.8834 (0.0389)	0.6161 (0.0645)
Moments					
$[-5.0\%, -2.5\%\rangle$	0.0053	0.0107	0.0218	0.0236	0.0000
$[-2.5\%, -0.5\%\rangle$	0.0108	0.0232	0.0432	0.0516	0.0000
$[-0.5\%, 0.5\%]$	0.9133	0.8257	0.7498	0.7305	0.9814
$\langle 0.5\%, 2.5\%]$	0.0240	0.0414	0.0621	0.0791	0.0005
$\langle 2.5\%, 5.0\%]$	0.0172	0.0361	0.0375	0.0361	0.0000
Chgs in Jan	0.3399	0.2300	0.3539	0.3071	0.1776
Serial corr(up)	-0.3581	-0.5031	-0.3398	-0.2587	0.0000
Serial corr(down)	-0.4010	-0.1192	-0.1057	-0.2772	0.0000
$sd(p_{it} - p_{it-1})$	0.0222	0.0270	0.0325	0.0319	0.0200
Rank 12	-0.0108	-0.0214	-0.0314	-0.0360	-0.0030
Rank 11	-0.0027	-0.0089	-0.0147	-0.0143	0.0000
Rank 2	0.0103	0.0192	0.0257	0.0258	0.0029
Rank1	0.0329	0.0395	0.0504	0.0481	0.0317
N	243	134	807	359	133
J	93.7	75.9	85.7	40.5	75.7

Note: standard errors in parentheses, N denotes number of products, J denotes the criterion value.

Table 2: Estimation Results by Product Groups

	(1)	(2)	(3)
Specifications:	No inertia	No thresholds	No friction parameters
σ_ε	0.0417 (0.0005)	0.0417 (0.0009)	0.0417 (0.0001)
U	0.1398 (0.0033)	- -	- -
L	-0.1669 (0.0064)	- -	- -
θ_{up}	- -	0.3698 (0.0199)	- -
θ_{down}	- -	0.4094 (0.0185)	- -
y	0.7120 (0.0143)	- -	- -
$[-5\%, -2.5\%)$	0.0000	0.1327	0.1508
$[-2.5\%, -0.5\%)$	0.0000	0.2406	0.1733
$[-0.5\%, 0.5\%]$	0.9396	0.1434	0.0958
$(0.5\%, 2.5\%]$	0.0000	0.2484	0.1811
$(2.5\%, 5.0\%]$	0.0000	0.1625	0.1678
Chgs in Jan	0.1891	0.8571	0.9046
Serial corr (up)	-0.0193	0.2326	0.0006
Serial corr (down)	0.0000	0.2344	0.0008
$sd(p_{it} - p_{it-1})$	0.0413	0.0277	0.0417
Rank 12	-0.0421	-0.0388	-0.0653
Rank 11	-0.0025	-0.0264	-0.0437
Rank 2	0.0175	0.0342	0.0523
Rank 1	0.0659	0.0455	0.0705
J	3 213.8	28 850.6	27 037.6

Table 3: Counterfactual Analysis

A   Appendices

	Coef.	Std. Error	Z-value	95% Conf. Interval	
$[-5\%, -2.5\%)$	0.0171	0.0009	19.0000	0.0154	0.0189
$[-2.5\%, -0.5\%)$	0.0331	0.0017	19.0400	0.0297	0.0365
$[-0.5\%, 0.5\%]$	0.8000	0.0062	128.6700	0.7878	0.8122
$(0.5\%, 2.5\%]$	0.0470	0.0022	21.8100	0.0428	0.0512
$(2.5\%, 5.0\%]$	0.0362	0.0010	36.0400	0.0343	0.0382
Chgs in Jan	0.3146	0.0094	33.3700	0.2961	0.3330
Serial corr (up)	-0.1358	0.0284	-4.7700	-0.1915	-0.0800
Serial corr (down)	-0.3851	0.1341	-2.8700	-0.6479	-0.1222
$sd(p_{it} - p_{it-1})$	0.0413	0.0027	15.0200	0.0359	0.0466
Rank 12	-0.0286	0.0012	-22.9100	-0.0310	-0.0261
Rank 11	-0.0097	0.0006	-16.7200	-0.0108	-0.0085
Rank 2	0.0213	0.0007	28.6900	0.0199	0.0228
Rank 1	0.0526	0.0014	38.0200	0.0499	0.0553

Note: The first five rows represents the total shares of observations within the given intervals and the following row represents the share of price changes in January.

Table A1: Bootstrapped Moments with Std. Errors

A.1 A Simple Model for Frictionless Price

Assume a Cobb-Douglas production technology with a flexible input factor, K. The costs of this factor is exogenous to the plant and denoted r. Assume also that the plants have some market power and demand is given by an iso-elastic function. Also assume that goods are sufficiently differentiated in order to abstract from substitution within a multi-product-firm's portfolio of products. We abstract from sub-indices for the plant, product and time for notational convenience. Then production is determined by $Q^S(K) = A \cdot K^a$ where $0 < a < 1$ and the iso-elastic demand function is given by $Q^D(P) = B \cdot \left(P/P^C\right)^{-\epsilon}$ where $\epsilon > 1$. 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 plant which implies that we employ a partial equilibrium model. Abstracting from inventory, profit for a single product is then given by

$$\pi(A, B, P^C, r) = P \cdot B \cdot \left(P/P^C\right)^{-\epsilon} - r \cdot \left(\frac{B}{A}\right)^{1/a} \cdot \left(P/P^C\right)^{-\epsilon/a},$$

where A captures supply shocks, and B captures demand shocks. With these assumptions the first order derivative of profit $\pi(.)$ with respect to price P can be expressed as follows;

$$P^* = \underbrace{\left[\frac{\epsilon}{a(\epsilon-1)} B^{\frac{1-a}{a}} A^{-\frac{1}{a}}\right]^{\frac{a}{\epsilon(1-\gamma)}}}_{(1)} \times \underbrace{r^{\frac{a}{\epsilon(1-\gamma)}}}_{(2)} \times \underbrace{(P^C)^{\frac{1-a}{\epsilon(1-\gamma)}}}_{(3)}, \quad where \ \gamma = a(1 - \frac{1}{\epsilon})$$

This expression is a non-linear function of the state of supply A, the state of demand B, the input costs r, and the general price in the industry P^C. Given that $a < 1$, we see that a positive supply shock, $A \uparrow$, will implicate a lower price, as expression (1) will get a lower value. This could, for example, be that the producer obtains better technology that increases productivity. We also see that a positive demand shock, $B \uparrow$, will implicate a higher price, as the net effect on expression (1) will be positive. Furthermore, if producers are faced with a positive cost shock, $r \uparrow$, the frictionless equilibrium price will increase, as expression (2) will be more positive. Note however that the degree of pass-through, the share of the cost increase that will be borne by costumers, depends on the parameter values. Higher competitor's prices, $P^C \uparrow$, induce also a price increase. In our model setup presented in the main text, part of this latter effect - that the general price level increases - is picked up by the trend parameter α. The remaining supply-, demand-, and cost- shocks, together with the non-deterministic part of the competitor's prices, will all be picked up by the idiosyncratic shocks, ε_{it}, in the model presented in the main text. Finally, we see that the marginal effects of the various shocks affect the price differently.

A.2 Simulated Method of Moments

In the Simulated Method of Moments (SMM) approach, κ simulated datasets are generated for N panels and $96 + T$ time periods. N and T are set equal to the number of panels and time periods in the empirical data.[28] In order to limit the impact of initial conditions, the first 96 time periods (8 years) are discarded when calculating the simulated moments, leaving only T time periods.[29]

If we let the vector of l unknown parameters be denoted by the vector β, the optimal vector of unknown parameters, $\hat{\beta}$, is given by:

$$\hat{\beta} = \underset{\beta}{argmin} \, [\Phi^A - \frac{1}{\kappa} \sum_{j=1}^{\kappa} \Phi^S(\beta)]' W [\Phi^A - \frac{1}{\kappa} \sum_{j=1}^{\kappa} \Phi^S(\beta)] \tag{13}$$

where W denotes the optimal weighting matrix, and Φ^A and $\Phi^S(\beta)$ denote the vector of m actual moments and the vector of m simulated counterparts respectively. The weighting matrix W is given by the inverse of the variance-covariance matrix of $[\Phi^A - \frac{1}{\kappa} \sum_{j=1}^{\kappa} \Phi^S(\beta)]$, which is best estimated using the following matrix (see Lee and Ingram (1991)):

$$W = [(1 + \frac{1}{\kappa})\Omega]^{-1} \tag{14}$$

Here, Ω denotes the variance-covariance matrix of the empirical moments, Φ^A. Ω is obtained by a block bootstrap with replacement on empirical data. An implication of using this weighting matrix is that moments with a large variation are given less weight than moments with a small variation.

The standard errors of the parameters are given by the square roots of the diagonals of the variance-covariance matrix for $\hat{\beta}$, which is given by:

$$Q_s(W) = (1 + \frac{1}{\kappa})[\frac{\partial \Phi^S(\hat{\beta})}{\partial \beta}' W \frac{\partial \Phi^S(\hat{\beta})}{\partial \beta}]^{-1} \tag{15}$$

Here, $\frac{\partial \Phi^S(\hat{\beta})}{\partial \beta}$ is the Jacobian $m \times l$ matrix of the moment vector with respect to the parameter vector β evaluated at $\hat{\beta}$. In lack of an analytical solution of the components of this matrix, numerical derivatives are used. More specifically, we use the symmetric difference quotient which is given by:

$$f'(x) \approx \frac{f(x+h) - f(x-h)}{2h} \tag{16}$$

In expression (16), x denotes the components of $\hat{\beta}$, $f(x)$ denotes the components of $\Phi^S(\hat{\beta})$ and h is a small positive number. A problem with this approach is that the approximate depends on the size of h. We therefore follow Bloom (2009) and calculate four values of the numerical derivative with steps of 0.1%, 1%, 2.5% and 5% from $\hat{\beta}$, and use the median value of these numerical derivatives.

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[28]See for instance McFadden (1989); Pakes and Pollard (1989) for more details regarding the approach.

[29]In our estimation we use $\kappa = 10$, and have $N = 1676$ and $T = 60$.

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