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Price Change Frictions in Production Plants

LEARNING FROM A SIMULATION STUDY

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Abstract

Price stickiness is often taken for granted in modern macroeconomic models, without adequate knowledge of the underlying microeconomic foundations. We want to assess whether the assumptions of price stickiness are consistent with actual pricing patterns. There is a broad consensus in the literature that prices exhibit a pattern of inaction followed by large price changes, so called “zeros and lumps”. A key topic, however, is how to explain the observance of small price changes. This thesis proposes a model specification which sets out to explain small price adjustments, as well as inaction and large price changes.

We search for evidence of thresholds and inertia in producer price data. Parameters are estimated using a Simulated Method of Moments (SMM) approach, based on yearly product specific price observations from the Norwegian manufacturing industry. In the simulation model, the adjustment towards the frictionless price is conditional on thresholds and partial adjustments. Price frictions seem to play a major role in explaining how producers change prices, as modeling with friction parameters gives a much better fit than frictionless modeling.

Overall, the evidence in this thesis supports assumptions of nominal stickiness. We find evidence of both thresholds and inertia in the price setting, which indicates that prices are affected by different forms of rigidities. Even when we control for inflation, our findings suggest that there are more frictions downwards than upwards. Thus, we can cannot exclude the possibility that it is easier to increase than to decrease prices.

An assessment of the literature shows that, in general, macroeconomic models fail to include all the evidence presented in this thesis. While some models assume that firms have pricing thresholds, others assume inertia in the price setting. However, none of the models considered incorporates the combination of both features. Our findings therefore suggest new ways in which macroeconomic models can be improved.

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1 Introduction

1.1 Motivation and Purpose

How monetary policy affects economic activity is a classic issue in macroeconomics. Measures taken by the central banks are assumed neutral in the long run, as nominal prices will adjust and offset the effect on real prices. In the short run, however, the notion of nominal price stickiness may cause an effect on real values in the economy. If nominal prices are sticky, measures used by central banks, such as the interest rate, may have short run effects on the economic activity. These policy effects may be large, even though the frictions are small at the micro level (Romer, 2012).[1] If, on the other hand, prices are fully flexible, monetary action does not affect real prices. Thus, the existence of nominal rigidities is a prerequisite for the functioning of monetary policy measures. The assumption of price stickiness is often taken for granted in macroeconomic models, without adequate knowledge about the underlying microeconomic foundations. Overall, there seems to be a need for an empirical assessment of the theoretical premises in the macroeconomic models we use today.

One way to look for price frictions in empirical data is to search for thresholds in the pricing patterns of individual firms. A method commonly used to search for pricing thresholds is the (s, S) rule proposed by Sheshinski and Weiss (1977). In this method, firms follow a pricing rule where (s, S) denotes the bounds in which the nominal price is kept fixed. As a result, prices exhibit a pattern of inaction followed by large price changes, so called “zeros and lumps”. The authors argued that this pattern is caused by the fact that changing the price induces a cost for the firm, which is referred to as the menu cost. The (s, S) methodology has later been adopted

[1] See appendix A.7 for an illustration of a representative firm’s incentive to change its price in response to a fall in aggregate output.

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 is that firms set prices according to market conditions, and the methodology thereby implies state dependency. Furthermore, these models usually assume that the adjustment cost is independent of the size of the price change (Zbaracki et al., 2004).

An important issue when searching for thresholds in prices is whether there seems to be symmetry in the findings, i.e. if the frictions have the same size upwards and downwards. If the thresholds are asymmetric, this suggest that there are more frictions one way than the other. For example, one might find only upper thresholds and no lower thresholds, which indicate that there are more frictions upwards than downwards. However, most research in the field of asymmetric price frictions points to the opposite result, that firms are more willing to increase than to decrease prices. A study on microeconometric evidence from Switzerland, which allows for asymmetric thresholds and heterogeneity (the thresholds can vary over time and differ across products) finds a smaller upper than lower threshold. According to this study, price changes are more likely to be positive than negative. The study ignores, however, the magnitude of price changes, as only the frequency and the duration of inaction are accounted for (Honoré et al., 2012). 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. This study allows for heterogeneity in the thresholds across years, industries, firms and products.

A challenge in studies of thresholds in firm pricing is how to include small price changes. Earlier research with (s, S) pricing rules has in part failed to include small price changes. One example is Dhyne et al. (2011), which in a model with time- and outlet varying symmetric thresholds, find it difficult to explain small adjustments. Similarly, using a model that allows for heterogeneity across firms, Asphjell (2014) finds no evidence of quadratic adjustment costs and fails to explain small price changes.

Another approach in the literature is to 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.[2]

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, which is obtained from Statistics Norway (SSB). Although consumer prices are relevant for the monitoring of inflation by central banks, it is the prices on producer level that are modeled into the macroeconomic policy models (Vermeulen et al., 2012). Accordingly, knowledge about producer price adjustments is essential to improve macroeconomic modeling and central bank policies.

In this thesis, we propose a model where the adjustment towards the frictionless price is conditional on thresholds and partial adjustments. Our model therefore allows for both inaction and inertia in pricing. The hypothesis is that the firm has a fixed cost when setting a new target price and that there exist convex costs associated with adjusting to this price. For example, as in Zbaracki et al. (2004), the convexity of managerial-, customer- and negotiation costs makes the firm favor slow adjustments

[2] 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; Wulfsberg, 2009; Barros et al., 2009; Bhattarai and Schoenle, 2014; Midrigan, 2011, etc.).

and small price changes. The intuition is that the periods of inaction in the data <are explained by fixed costs, while the observance of small price changes are explained by convex adjustment costs. Thus, our model sets out to explain both the occurrence of large and small price adjustments in the data. A quote from Zbaracki et al. (2004), who study a large U.S. industrial manufacturer and its customers, sums up the justifications of our model:

> *"The firm often reacted to major changes in supply and demand conditions slowly and/or partially because of the convexity of the costs they faced in justifying and communicating these changes to other members of the organization and to their customers."*

1.2 Research Question

Below is the formulation of the research question of our thesis.

> *How do price frictions affect producer price changes? Are there evidence of certain thresholds and/or inertia in producer pricing, and how do these findings relate to assumptions in modern macroeconomic models?*

1.3 Outline

The thesis is structured in the following way. Chapter 2 presents an overview of relevant macroeconomic literature on price stickiness, and serves as a basis for the discussion in the analysis. Chapter 3 presents detailed descriptions of the data used in our thesis and give considerations related to inclusions and exclusions of certain parts of the dataset. Chapter 4 presents our model and chapter 5 analyzes our findings. Finally, chapter 6 summarizes our thesis and draws out some important conclusions.

2 Macroeconomic Pricing Models

The literature on price stickiness can be divided in two categories: Time dependent models and state dependent models. In models assuming time dependency, price changes occur with fixed intervals and are independent of the economic environment. In state dependent models, firms change prices at random points in time and as a response to changes in market conditions.

The extensive literature on the topic requires that this review focuses on what is most relevant for our thesis. In particular, the relevance of models assuming time dependency is restricted in our research.

Two arguments advocate our decision to concentrate on state dependent pricing. Firstly, we use yearly data in our research.[3] It can be argued that researchers using monthly observations should account for seasonality, as descriptive price data shows spikes in certain months, especially in January. The notion of seasonality is closely related to assumptions in time dependent models, particularly that firms change prices in fixed time intervals. Thus, time dependency would be relevant using monthly data. Secondly, our model specification assumes that price changes are driven by shocks in the economy.[4] Considering that we use yearly data, and that our model does not include any time dependent components, this chapter will focus entirely on models assuming state dependency.

The following sections will review the underlying micro assumptions of commonly used state dependent pricing models. The models are divided into three groups, depending on what is assumed to cause the price rigidity. These are menu cost models, convex adjustment cost models and consumer anger models. We propose a model that allows for inaction, as well as both small and large price changes. Accordingly, we want to

[3]Our decision to use yearly data is discussed in chapter 3 and section 4.4.
[4]See section 4.1 for a presentation of our model solution.

know whether the underlying micro assumptions in macro models are consistent with these characteristics.

In addition to serve as an introduction to macroeconomic price stickiness models, this chapter will be used as a basis when comparing the existing literature with our empirical findings in chapter 5. A summary of the discussion in this chapter is presented in Table 1.

2.1 Menu Costs

Descriptive research shows evidence of prices remaining unchanged for several months (Álvarez, 2008). One possible reason for this observation is that the action of changing the price of a product induces a cost for the firm. An example of such a cost is the direct cost for a restaurant of printing new menus, which is where the term "menu costs" originates from. Menu cost models assume that firms have to pay a lump sum, or a menu cost, to adjust the price of a product. Thus, the price changes are not assumed continuous. Instead, the firms adjust prices if the expected profit of changing the price is higher than the menu cost, which is likely to imply infrequent adjustments.

Traditionally, classic menu cost models set out to explain price patterns characterized by series of inaction followed by large price changes, so called "zeros and lumps". Sheshinski and Weiss (1977) laid the foundation for the current literature on menu costs. The idea is that prices exhibit a pattern of finite intervals where nominal price is held constant, followed by discrete price adjustments. This lumpy pricing pattern is justified by the direct costs which incur in both the decision process itself and in the distribution of information to customers and other stakeholders. Examples of direct costs are the costs of producing new price lists, retagging, making new promotions and informing and convincing interested parties.

Several studies from the last decade build on the literature assuming pricing thresholds. Golosov and Lucas (2007) develop a model of a monetary economy where price rigidities are due to fixed adjustment costs which are calibrated using micro data. Gertler and Leahy (2008) use a similar approach, and add certain technical assumptions that permit an approximate analytical solution. In general, classic menu cost models, such as the above, assume that price changes are infrequent and large.

Other menu cost models allow for small adjustments. One example is Dotsey et al. (1999), who assume that the adjustment cost is stochastic, which may imply that firms make small price changes when the cost is low. Further examples include the several contributions in recent years assuming economies of scope in price setting (Lach and Tsiddon, 2007; Midrigan, 2011; Alvarez and Lippi, 2014). This assumption implies that in multi-product firms, the total menu costs are independent of the number of prices the firm changes. Hence, small price adjustments arise naturally because once a firm pays the menu cost, it can adjust the prices of more than one good. The models assuming stochastic menu costs and the models assuming economies of scope in price setting allow for price changes of all sizes, and therefore stand out from traditional menu cost models.

2.2 Convex Adjustment Costs

While menu cost models assume that the costs of adjustment make firms change prices infrequently, the opposite is the case in convex adjustment cost models. These models assume that adjustment costs increase convexly with the size of the price change. Here, firms increase the price of a product as often as possible, i.e. each period.

Because convex adjustment costs put a penalty on large adjustments, many small price changes occur. In Rotemberg (1982), the price is set by minimizing deviations from the frictionless price subject to quadratic frictions, which implies that large adjustments are very costly.[5] In another model, Kozicki and Tinsley (2002) capture price frictions through a polynomial characterization. Both these approaches to modeling frictions result in gradual price adjustments. Accordingly, pricing models assuming convex adjustment costs imply small and frequent price changes.

2.3 Consumer Anger

Another theory of price stickiness is the reluctance to increase prices in fear of negative reactions from consumers. Models building on such theories assume that consumers have imperfect information about the pricing process. The information the consumers have is varying over time, and their reactions to price increases will also be changing over time. Thus, the firms adjust their prices infrequently and with certain intervals, depending on the views of consumers (Álvarez, 2008).

In Rotemberg (2005), consumers react negatively only when they are convinced that prices are unfair. The assumption is that price changes trigger the consumers to reflect on whether the price level is fair or not. A price increase is considered fair, if consumers perceive that this increase reflects a change in the costs of the firm. Conversely, if the price change is not justified, both price decreases and price increases are unwanted. The intuition is that a price decrease followed by a price increase of the same size would cause consumers to react negatively, while keeping the price constant would not trigger any reactions from consumers.[6] In consistence with the findings of Zbaracki et al. (2004), this model assumes that firms are more worried about negative reactions

[5] Adjustment costs may also be modeled by linear frictions, such as in Letterie and Nilsen (2016). In models assuming linear adjustment costs, the punishment on large price changes are softer than in the models assuming quadratic costs, but still the adjustment costs are increasing with the size of the price change and may therefore contribute in explaining small price changes.

[6] Note that the common assumption is that consumers' reactions to price changes are embedded into the demand curve. Therefore, one could argue that consumer anger does not cause rigidities. However, the model discussed here assumes that price stickiness is caused by frictions due to irrational consumer behavior, as consumers are assumed to maximize something beyond their material payoffs.

to large price increases than they are about smaller ones. Accordingly, large price changes may occur, but small price adjustments are preferred. Overall, consumer anger models imply infrequent price changes of all sizes.

	Infrequent adjustments	Small adjustments
Menu Costs		
Dotsey et al. (1999)	Yes	Yes
Gertler and Leahy (2008)	Yes	No
Golosov and Lucas (2007)	Yes	No
Sheshinski and Weiss (1977)	Yes	No
Economies of Scope		
Alvarez and Lippi (2014)	Yes	Yes
Lach and Tsiddon (2007)	Yes	Yes
Midrigan (2011)	Yes	Yes
Convex Costs of Adjustment		
Kozicki and Tinsley (2002)	No	Yes
Rotemberg (1982)	No	Yes
Consumer Anger		
Rotemberg (2005)	Yes	Yes

Table 1: Underlying Assumptions of Different Macro Models

3 Data and Descriptive Statistics

The basis for our empirical analysis is the raw data behind the commodity price index for the Norwegian industrial sector (VPPI) obtained from Statistics Norway (SSB).[7] The data is collected on a monthly basis for a selection of Norwegian producers. Firms 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 relevance (SSB, 2015; Asphjell, 2014). Firms are repeatedly surveyed, participation is compulsory and Statistics Norway revise the data regularly to detect measurement errors and nonconformity. Considering this, and that the VPPI 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 exact dataset we have gained access to is prepared by Asphjell (2014) and contains monthly price observations for Norwegian producers ranging from year 2001 until 2009. In this dataset, firms with observations for less than 24 months have been omitted, as well as firms with less than 10 employees and firms consisting of several plants. Furthermore, producers related to the energy sector (oil, gas, electricity, etc.) 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 (Letterie and Nilsen, 2016). Additionally, since 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 are considered new products.

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. Following Letterie and Nilsen (2016), we therefore choose to discard the data prior to January 2004.

[7] See SSB (2015) for more information about the VPPI.

In order to focus our analysis on the manufacturing sector, we also choose to omit products related to mining and quarrying. Lastly, to avoid controlling for seasonal differences in firms pricing decisions, we use yearly observations (June every year) instead of monthly. Even though abstaining from using monthly data disregards valuable information, we found it necessary due to computational considerations.[8] This leaves us with a final sample of 4864 observations for 1584 products over the years 2004-2009 covering 21 2-digit SIC2002 industry codes.[9]

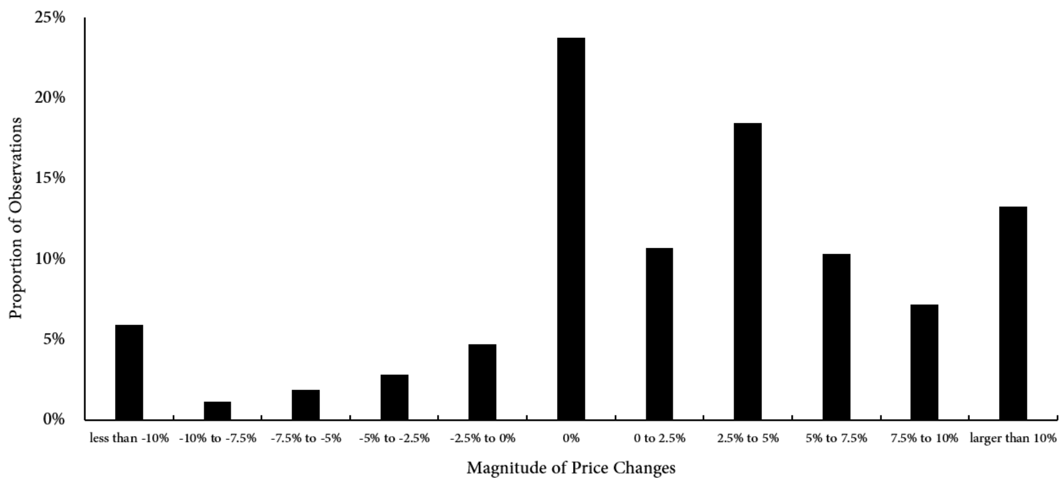


Figure 1: Distribution of Yearly Price Changes (June to June)

Figure 1 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 year for every product.

If adjustment costs are fixed, and not dependent on size, one would expect to observe several periods of inaction as well large price changes. As we can see from Figure 1, observations with price changes equal to zero represent the largest proportion. This means that most observations are characterized with inaction, which is a clear

[8]Our decision to use yearly data is discussed in chapter 3 and section 4.4.
[9]See appendix A.1 for distribution of industries represented.

indication of fixed adjustment costs. There is also a high proportion of price changes above ten percent, which further asserts the existence of fixed adjustment costs.

At the same time, we observe that a substantial proportion of the observations are small positive price changes below five percent. 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.

By looking at the negative price changes, we see that most of them are below minus ten percent, but also that there is a substantial share above minus five percent. The observation of several periods of inaction combined with series of both small and large price changes may tell a story of firms being faced with both fixed and convex adjustment costs. Nevertheless, Figure 1 shows only the aggregate share of price changes in different intervals, and thereby does not tell anything about the individual pricing decisions of each producer. We will therefore look at a more product specific approach in the following.

In order to identify lumpy adjustment behavior, Doms and Dunne (1998), Nilsen and Schiantarelli (2003) and Varejão and Portugal (2007) suggest ranking the price changes from lowest to highest for each panel and comparing the first and last rank to the rest, which is what we have done below.

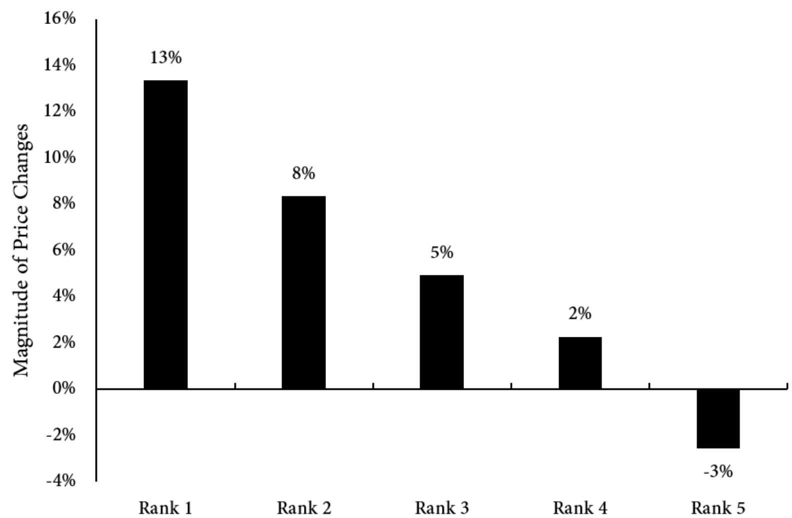


Figure 2: Price Changes by Rank (means)

Figure 2 is constructed by ranking the price changes of each firm by year and taking the average of each rank across firms. We see that there are five ranks, one for each year. Rank 1 thereby represents the average highest price change, Rank 2 the average second highest price change, and so on. The intuition is that if there is a large gap between the average largest (smallest) and average second largest (second smallest) price change, this should indicate that producers are faced with fixed costs of adjustment. On the contrary, Varejão and Portugal (2007) argue that if the ranks have no signs of gaps and are of similar magnitude, this may indicate that adjustment costs are convex, rather than fixed. If there are no costs preventing the producer from adjusting continuously, one should expect to see a more linear distribution of the ranks.

As we can see from Figure 2, there is a gap of approximately five percentage points between both the first and second rank and the fourth and fifth rank. In contrast, the difference between the three ranks in between is approximately three percentage points. Since the differences on the extreme points are higher than the rest, one could argue that producers are faced with fixed adjustment costs.

However, since the difference between the gaps on the edges and the gaps between the middle ranks is relatively small, the potential existence of both fixed and convex adjustment costs can not be excluded. The intuition behind this argument is that fixed adjustment costs are preventing the firms to adjust continuously and when they do change their price, convex costs are forcing them to do so gradually. Ceteris paribus, fixed costs would therefore make the gaps larger, while convex costs would make the gaps smaller. The larger convex costs compared to fixed costs, the more linear is the relationship between the ranks.

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, but whether inflation is the only factor causing this skewness is ambiguous.[10]

What we have learned from the descriptive statistics presented in this chapter is that producer pricing is characterized with a high degree of inaction, as well many periods with both small and large price changes. While it is impossible to make any conclusions regarding pricing behavior on the basis of these characteristics, they play an important role when designing the model solution presented in the following chapter.

[10]See e.g. Honoré et al. (2012) for a discussion on the prevalence of positive price changes when inflation is equal to zero.

4 Econometric Approach

The price pattern of inaction and series of both small and large price changes is consistent with findings in other countries (see e.g. Klenow and Kryvtsov, 2008; Barros et al., 2009; Midrigan, 2011; Bhattarai and Schoenle, 2014). The purpose of this chapter is to propose a model specification that can explain these characteristics.

In chapter 2, we found that assumptions in several macroeconomic pricing models implicate that price changes are either large and infrequent or small and frequent. However, neither of these implications seems to fit the characteristics described above. Standard (s, S) models suggest a pricing pattern with several periods of inaction followed by large price changes, while standard partial adjustment models suggests that prices change continuously in small steps. Many have proposed alternative model specifications to explain price rigidity, but most find it difficult to explain both inaction and small price changes (Dhyne et al., 2011).

In this chapter, we present a model solution where we let an (s, S) rule decide when producers change prices, but instead of being forced to adjust immediately, we allow them to adjust gradually to the new price. The intuition is that the (s, S) rule should explain periods of inaction and large price changes, and that the gradual adjustment should explain small price changes.

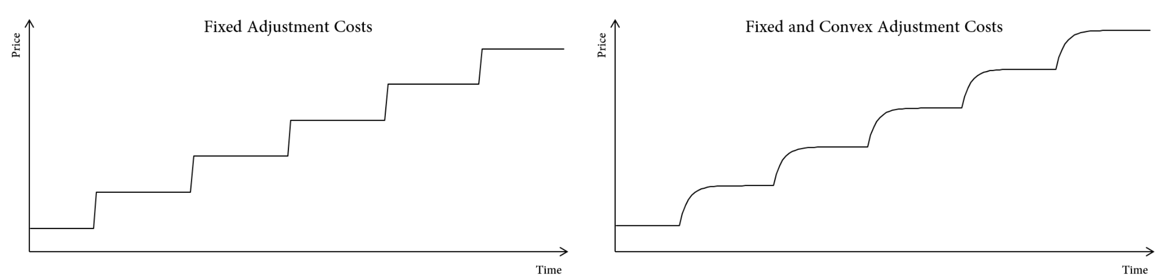


Figure 3: Potential Evolution of Prices

Figure 3 illustrates the difference between a traditional (s, S) pricing model and our specification. The figure assumes that producers are faced with only positive shocks, which implicates that prices are either constant or increasing. This simplification is done for illustration purposes.

The graph to the left shows a potential evolution of prices if producers are faced with only fixed costs of adjustment, as in a traditional (s, S) pricing model. Firms will then adjust immediately to the new price whenever the expected profit of changing the price exceeds the fixed cost of adjustment. The result is a lumpy pricing pattern characterized by inaction and large price changes.

The graph to the right illustrates a potential evolution of prices in our model specification, where producers are faced with both fixed and convex costs of adjustment. Instead of getting a lumpy pricing pattern similar to the graph to the left, we allow producers to be able to adjust to their target price in a smooth fashion. This target price is defined as the desired price if there is no inertia. In particular, our model suggests the following price change process: Firstly, the producer decides to set a new target price if the expected profit of changing the price exceeds the fixed cost of setting a new target price. Secondly, convex costs put a penalty on large price changes, preventing producers to adjust to their new target price immediately. The result is that producers have gradual adjustments, with inaction as well as both large and small price changes.

One reason why we may observe the behavior described above is that the costs of justifying and communicating price changes, both internally and externally, tend to increase with the size of the price change. Examples include factors such as increased internal discussion regarding larger price changes, restricted authority to alter prices among middle management, anticipation by customers, etc.. To minimize such costs, firms might prefer to change prices gradually, instead of immediately (Zbaracki et al., 2004).

4.1 Model Solution

As firms require a degree of monopoly power to be able to set prices, we assume that the producers operate in monopolistic competitive markets.[11] Following Alvarez et al. (2011), Dias et al. (2015), and others, we let the logarithm of the frictionless nominal price, denoted by p^*_{it}, for product i at time t follow a random walk with drift:

$$p^*_{it} = \alpha + p^*_{it-1} + \varepsilon_{it}, \qquad where\ \varepsilon_{it} \sim N(0, \sigma^2_\varepsilon) \tag{4.1}$$

which by repeated substitution gives:

$$p^*_{it} = p^*_{i0} + t \times \alpha + \sum_{j=1}^{t} \varepsilon_{ij} \tag{4.2}$$

Here, ε_{it} denotes idiosyncratic shocks with variance σ^2_ε, and α denotes the deterministic drift. ε_{it} is thought to reflect any shocks to either demand, cost or technology. 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. The resulting p^*_{it} represents the frictionless equilibrium price decided by the market conditions applicable for each individual product.

Furthermore, we let the logarithm of the nominal target price for product i at time t, which we define as the desired price if there is no inertia, be determined by:

$$p^{\#}_{it} \begin{cases} = p^*_{it} & if\ p^*_{it} - p_{it-1} > U\ or\ p^*_{it} - p_{it-1} < L, \\ = p^{\#}_{it-1} & otherwise \end{cases} \tag{4.3}$$

$$where\ L \leq 0 \leq U$$

[11] These markets have the following characteristics: differentiated products; many firms; no entry and exit cost; independent decision making; market power; and imperfect information (Romer, 2012).

which implicates that producers set their target price ($p^{\#}_{it}$) equal to the frictionless price (p^{*}_{it}) if the gap between the frictionless and current price is larger than U or lower than L. The upper and lower thresholds are thereby represented by U and L respectively, and are supposed to capture the fixed costs of setting a new target price. There are two implicit assumptions behind this formulation. First, since we use yearly data, the target price stays fixed at least one year. Second, each firm is able to continuously observe and monitor its frictionless price without any extra costs, i.e. we assume that producer pricing is state dependent.[12]

Finally, we let the logarithm of the nominal price of product i at time t be given by:[13]

$$p_{it}\begin{cases} = (1-\theta_u)p^{\#}_{it} + \theta_u p_{it-1}, & if\ p^{\#}_{it} - p_{it-1} > 0, \\ = (1-\theta_l)p^{\#}_{it} + \theta_l p_{it-1}, & if\ p^{\#}_{it} - p_{it-1} < 0, \\ = p_{it-1}, & if\ p^{\#}_{it} - p_{it-1} = 0, \end{cases} \tag{4.4}$$
$$where\ \theta_u \wedge \theta_l \in [0,1]$$

Expression (4.4) allows for the possibility that convex adjustment costs prevent the producer to adjust immediately to its target price. This is done by letting the evolution of price changes be decided by a partial adjustment model. An implication is that the producer will close $(1-\theta)$ of its desired price change in the same period as it decides to change its 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 following period, it will close 90 percent of the remaining price change. This will keep on until the producer decides to set a new target price or when the target price is reached.

If $\theta = 0$, product i will reach its target price immediately, but if $\theta > 0$, the producer

[12] For a discussion on state dependency, see chapter 2.

[13] The first two expressions are derived from a traditional partial adjustment model: $(p_{it}-p_{it-1}) = (1-\theta)(p^{\#}_{it} - p_{it-1})$.

will adjust to the new target price over several time periods. Ceteris paribus, a larger θ means a smaller initial adjustment and more price inertia as it will take longer time for product i to reach its target price. A smaller θ will have the opposite effect: A larger initial adjustment and less price inertia as it will take shorter time for the product to reach its target price. Since we observe both large and small price changes, we expect θ to be closer to zero than to one.

In order to control for asymmetry in the inertia parameters, we have allowed p_{it} to have three outcomes, depending on whether the price is either equal to the target price, heading upwards or heading downwards. We see that $p_{it} = p_{it-1}$ if the product has reached its target price, which implicates that the price stays fixed until the firm decides to set a new target price. If the price instead is heading upwards, θ_u is supposed to capture inertia caused by convex costs of adjustment upwards. Conversely, if the price is heading downwards, θ_l is supposed to capture inertia caused by convex costs of adjustment downwards.

We see that if $\theta_u \neq 0$, $\theta_l \neq 0$, $U = L = 0$, the specification reduces to a partial adjustment model, and conversely, if $\theta_u = \theta_l = 0$, $U \neq 0$, $L \neq 0$, the model reduces to an asymmetric (s, S) pricing model.

This leaves us with the following parameters to be estimated:

$$\begin{aligned}
\text{Variance of idiosyncratic shocks: } & \sigma_\varepsilon^2 \\
\text{Upper threshold: } & U \\
\text{Lower threshold: } & L \\
\text{Inertia upwards: } & \theta_u \\
\text{Inertia downwards: } & \theta_l
\end{aligned}$$

Estimating a symmetric partial adjustment model is rather straight forward, and can be done using simple estimation techniques. However, as emphasized by Di Iorio and

Fachin (2006), estimating lumpy adjustment behavior, which is one of the properties of our specification, is challenging. Because our specification does not have an analytical closed form solution, it cannot be estimated using standard regression techniques. In addition, since we want to include the magnitude of price changes, the commonly used binary response models are ruled out (Dhyne et al., 2011). Others have used various Maximum Likelihood approaches, but these often result in imprecise estimates with large standard errors and unclear confidence intervals (Asano, 2002; Rota, 2004; Di Iorio and Fachin, 2006). Therefore, we choose to follow Ejarque and Nilsen (2007); Bloom (2009); Asphjell (2014); Asphjell et al. (2014), as we estimate our specification using a Simulated Method of Moments approach, which is presented in the following section.

4.2 Simulated Method of Moments

In its simplest form, the Simulated Method of Moments (SMM) approach sets out to match empirical moments using simulated data which is a function of both predetermined and unknown parameters.[14] The moments are characteristics from the data that are eligible to identify the unknown parameters. Examples of such moments include the standard deviation of a variable, the correlation between two variables, etc.. In the SMM approach, κ simulated datasets are generated for N panels and $100 + T$ time periods, where N and T denote the number of panels and time periods in the empirical data respectively. In order to limit the impact of initial conditions, the first 100 time periods are discarded when calculating the simulated moments, leaving only T time periods.[15]

If we let the vector of l unknown parameters be denoted by β, the SMM approach

[14]Our explanation of the Simulated Method of Moments approach is based on Mcfadden (1989); Pakes and Pollard (1989); Adda and Cooper (2003). See these papers for more details regarding the approach.

[15]In our estimation we use $\kappa = 10$, and have $N = 1584$ and $T = 5$.

selects the set of β that minimizes the following criterion function:

$$\Gamma(\beta) = [\Phi^A - \frac{1}{\kappa}\sum_{j=1}^{\kappa}\Phi^S(\beta)]'W[\Phi^A - \frac{1}{\kappa}\sum_{j=1}^{\kappa}\Phi^S(\beta)] \tag{4.5}$$

That is, the optimal vector of unknown parameters, $\hat{\beta}$, is given by:

$$\hat{\beta} = \underset{\beta}{argmin}\,[\Phi^A - \frac{1}{\kappa}\sum_{j=1}^{\kappa}\Phi^S(\beta)]'W[\Phi^A - \frac{1}{\kappa}\sum_{j=1}^{\kappa}\Phi^S(\beta)] \tag{4.6}$$

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. Now, we see that $\Gamma(\beta)$ is the weighted difference between the actual and simulated moments. $\Gamma(\beta)$ have a χ^2 distribution with $m-l$ degrees of freedom, which implies that $m \geq l$ is a necessary condition.[16] The weighting matrix is given by the inverse of the variance-covariance matrix of $[\Phi^A - \frac{1}{\kappa}\sum_{j=1}^{\kappa}\Phi^S(\beta)]$, which according to Lee and Ingram (1991) is best estimated using the following matrix:

$$W = [(1+\frac{1}{\kappa})\Omega]^{-1} \tag{4.7}$$

Here, Ω denotes the variance-covariance matrix of the empirical moments, Φ^A, and $(1+\frac{1}{\kappa})$ is a precision penalty due to the random nature of empirical data. Ω is obtained by a block bootstrap with replacement on empirical data. In this procedure, 1000 draws from the initial distribution are used to calculate the empirical moments 1000 unique times, which is then utilized to calculate Ω. An implication of using this weighting matrix is that moments with a large variation are given less weight than moments with a small variation.

In order to say something about the significance of our parameter estimates, we need to obtain their standard errors. These are calculated by taking the square roots of

[16] If $m = l$, the model is said to be just identified, and if $m > l$, the model is said to be overidentified.

the diagonals of the variance-covariance matrix for $\hat{\beta}$, which is given by:

$$Q_s(W) = (1 + \frac{1}{\kappa})[\frac{\partial \Phi^S(\hat{\beta})}{\partial \beta}' W \frac{\partial \Phi^S(\hat{\beta})}{\partial \beta}]^{-1} \tag{4.8}$$

Here, $\frac{\partial \Phi^S(\hat{\beta})}{\partial \beta}$ is the Jacobian matrix of the moment vector with respect to the parameter vector β evaluated at $\hat{\beta}$.[17] In lack of an analytical solution of the components of this matrix, numerical derivatives are used as approximations. More specifically, we use the symmetric difference quotient which is given by:

$$f'(x) \approx \frac{f(x+h) - f(x-h)}{2h} \tag{4.9}$$

In expression (4.9), x denotes the components of $\hat{\beta}$, $f(x)$ denotes the components of $\Phi^S(\hat{\beta})$ and h is a small positive number. Figure 4 illustrates that the approximation is given by the slope of the straight line between $x + h$ and $x - h$.

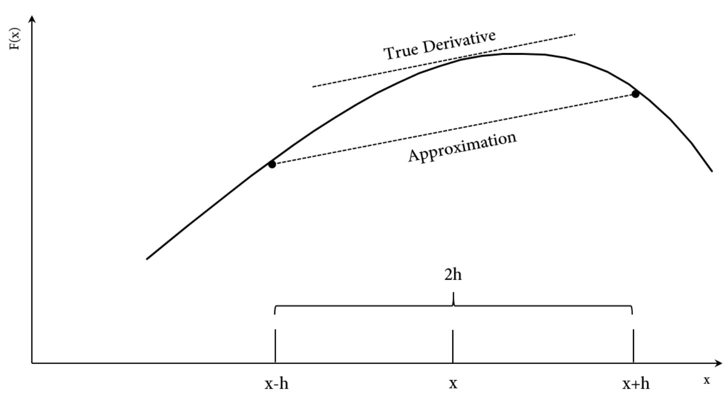


Figure 4: Symmetric Difference Quotient

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. This should make the numerical derivatives more robust to

[17] This implies that $\frac{\partial \Phi^S(\hat{\beta})}{\partial \beta}$ is a $m \times l$ matrix.

outliers caused by discontinuities in $\Gamma(\beta)$. The W is the same weighting matrix as used in the criterion function.

When searching for values of β that minimize the criterion function, we have used a brute-force approach. That is, we search for values for every parameter within a certain grid. The grid is defined as an interval between a starting value and an ending value with a certain precision for every parameter. For example, if the starting value is 0.00, the ending value is 0.20 and the precision is 0.05, we would run simulations with parameter values equal to 0.00, 0.05, 0.10, 0.15 and 0.20. In order to capture parameter estimates of all sizes, we start out by doing simulations with a large grid, and a relatively low precision. The program then selects the values within this grid that minimize $\Gamma(\beta)$. Following this, we do repeated simulations in which we gradually decrease the grid interval, while we increase the precision until we get a $\hat{\beta}$ vector with a satisfactory number of decimals.

Since the criterion function may contain multiple local optima, we would recommend future research to use an annealing cooling algorithm as well. This routine can be better suited to find a global optimum because it searches for values that lie far off from the current best guess. However, an annealing cooling algorithm is not entirely foolproof in locating global optima either. This is because it requires both a predefined first and second guess at the parameter estimates, which will have an effect on the final results. Considering the limited time we had available, and that an annealing cooling algorithm is extremely slow, we choose to leave the implementation of this routine for future research.

We have now established the dynamics of our proposed model and the estimation technique we want to use. In the next section, we bring these two together in a discussion on the set of moments we want to include.

4.3 Moment Selection

In this section, we present moments that are supposed to identify each applicable parameter. It should be noted, however, that there will be some effects across moments and parameters, i.e. some moments will effect several parameters, and vice versa.

The variance of the shocks to frictionless price, σ_ε^2, is likely to be directly related to the variance of price changes. We therefore choose to include the standard deviation of price changes as a moment. The intuition is that σ_ε^2 should be identified through the matching process of this moment, i.e. if $sd(\frac{p_t - p_{t-1}}{p_{t-1}})$ is the same in the empirical and simulated data we would argue that $\hat{\sigma_\varepsilon^2} \approx \sigma_\varepsilon^2$. However, the variance of price changes is also likely to be affected by the friction parameters in opposite ways: While higher U and L will increase the variance, higher θ_u and θ_l will reduce the variance. Thus, the standard deviation of price changes will not only identify σ_ε^2, it will also contribute to the identification of U, L, θ_u and θ_l.

As discussed in chapter 3, ranked price changes can be a good indicator of lumpy adjustment behavior. We would therefore like to include the same ranks as presented in the data section as moments. These are meant to be the primary identifiers of the threshold parameters U and L. As in the discussion above, the ranks are likely to be affected by σ_ε^2 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, ceteris paribus. Hence, even though the primary objective of the rank moments is to identify U and L, they will also affect θ_u, θ_l and σ_ε^2.

Higher inertia parameters will make firms 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 small price changes, ceteris paribus. To identify θ_u and θ_l, we therefore choose to include the following moments:

$$Corr[I(smallchange^u)_t, I(smallchange^u)_{t-1}] \tag{4.10}$$

$$Corr[I(smallchange^l)_t, I(smallchange^l)_{t-1}] \tag{4.11}$$

Here, $I(smallchange^i)_t$ is an indicator variable that has the value 1 if the price change is within the (0%, 5%] interval (zero to five percent), and the value 0 otherwise. i denotes whether the change is positive (u) or negative (l). The intuition is that the moment in (4.10) should identify θ_u, while the moment in (4.11) should identify θ_l. The threshold parameters will also be affected by these moments, as larger $|U|$ and larger $|L|$ will lead to more inaction and lower serial correlation, and vice versa.

Finally, as we want our model to explain both inaction and small price changes at the same time, we include the proportion of observations within the following intervals:

$$\begin{aligned} 5\% \geq \frac{p_{it} - p_{it-1}}{p_{it-1}} &> 2.5\% \\ 2.5\% \geq \frac{p_{it} - p_{it-1}}{p_{it-1}} &> 0\% \\ \frac{p_{it} - p_{it-1}}{p_{it-1}} &= 0\% \\ -2.5\% \leq \frac{p_{it} - p_{it-1}}{p_{it-1}} &< 0\% \\ -5\% \leq \frac{p_{it} - p_{it-1}}{p_{it-1}} &< -2.5\% \end{aligned} \tag{4.12}$$

These moments are what we define as the distribution of "small" price changes, and should contribute in identifying all the parameters, especially the threshold parameters and inertia parameters: Non-zero U and L will cause inaction, and positive θ_u and θ_l will cause small price changes, ceteris paribus. 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).

Up until now, the contents of this chapter have been presented in its most general form and can be applied to similar empirical data in any country. In the following sections, some of the details are specific to our data, but the discussion and insights given are relevant for every application of the proposed model solution.

4.4 Assumptions

As with all estimation techniques, our approach depends on a set of assumptions, some easier justified than others. This section provides an overview of these assumptions and a discussion of their implications.

When we estimate our model specification, we assume that the friction parameters are constant across products and time. This means that U, L, θ_u and θ_l are independent of product characteristics and do not vary across time.

Assuming time-constant friction parameters are not considered restrictive, especially when working with a small T like we do (Di Iorio and Fachin, 2006). Though, it should be noted that according to the findings of Gautier and Le Bihan (2011), allowing for time-varying thresholds can provide better explanatory power regarding small changes.

However, assuming constant friction parameters across firms and products may be regarded as restrictive. This is because there seems to be 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). One way of controlling for such heterogeneity, is to allow for product- or firm specific friction parameters. This would enable the researcher to explain producer pricing on a more specific level, but would also complicate the inference of the friction parameters. Considering that the aim of this thesis is to explain producer pricing on an aggregate level, and not the exact price development of each producer, we choose to make this simplification. If it is desired to allow for more heterogeneity in producer pricing, our model could easily be estimated on a more specific level. For future research, it could also be interesting to incorporate economies of scope in the price setting rule.

In our model, demand shocks, technology shocks and cost shocks are considered as one aggregate effect. More specifically, the idiosyncratic shocks to frictionless price, ε_{it}, are meant to capture shocks to costs, technology and/or demand of product i at time t. An argument against this is found in Dias et al. (2015) and Loupias and Sevestre (2012), as both studies find opposite asymmetries: Firms react quicker to positive than to negative cost shocks, but slower to positive than to negative demand shocks. Nevertheless, differencing between the types of shocks would implicate a more sophisticated derivation of both the frictionless price and the inertia parameters than we have presented above. Considering this, and that the focus of our thesis is the combination of thresholds and inertia, we choose to include the shocks as an aggregate effect.

Furthermore, we do not allow common shocks to have an effect on the course of the frictionless price. This is a simplification that is done for computational ease. However, both Dhyne et al. (2011) and Golosov and Lucas (2007) find that idiosyncratic (and not common) shocks are what drives the majority of price changes, which asserts our approach.

As stated in section 4.1, we assume that ε_{it} is normally distributed with mean of zero, variance equal to σ_{ε}^2 and is without any serial correlation. If other distributions are thought to better depict the true path of the frictionless price, this can be altered without much hassle. In theory, the mean and persistence could also be included as parameters to be estimated. However, this would have required more computational resources.

By not including persistence in the frictionless price, we risk getting a biased estimate of the inertia parameters. If there indeed exists persistence in the shocks, and we do not control for it, the persistence is likely to be captured by the θ parameters. However, including a persistence parameter would also make it harder to isolate the effect of the θ parameters. Considering this, and that it is unlikely that there is considerable persistence in the shocks on a yearly basis, we assume that the shocks are serially uncorrelated.

In addition, our model specification allows for both asymmetric thresholds and asymmetric inertia, i.e. it is not a necessary condition that $|U| = |L|$ or that $\theta_u = \theta_l$. This contradicts with the traditional assumption that the adjustment cost is a fixed cost associated with printing new pricing lists, retagging, making new promotions, etc., as one would expect these to be independent of the sign of the price change. However, several recent contributions in the microeconomic literature have found evidence of asymmetries in price setting, and some explain this with asymmetric adjustment costs (e.g. Peltzman, 2000; Yang and Ye, 2008; Xia and Li, 2010; Lewis, 2011; Loy et al., 2016). One example of such adjustment costs are asymmetric "mistake costs", where the intuition is that the costs of making errors in pricing are asymmetric: Pricing mistakes downwards are more costly than upwards. A second and related example is asymmetry in costs of stock-outs, which refers to the fact that there is lower risk of stock-outs if the price is set too high than if it is set too low (Loy et al., 2016). A third example is "consumption inertia" which suggests that consumption habits cause demand to respond gradually (and not instantly) to price changes. The argument is that this inertia makes it more attractive to increase prices than to lower them (Xia and Li, 2010). Other explanations to asymmetric pricing includes asymmetric search behavior and differences due to the shape of the demand curve (Yang and Ye, 2008; Lewis, 2011; Loy et al., 2016).

It should also be noted that we use yearly data (June to June) when estimating our model specification. One could, however, argue that monthly observations should be preferred, as data observed on a monthly basis captures more information. For instance, in order to get inertia parameters larger than zero in our estimations, producers must set a target price with at least a two year horizon. If not, one would not observe the gradual adjustment we hypothesize. If we instead used monthly data, the inertia would capture any gradual adjustment over executive months, which could be argued to be more likely to occur. We are also missing temporary changes during each year: If a producer decides to change its price between June in one year and June in a second year, our estimation would not capture it as long as the producer return to its original price before June in the second year.

These potential problems could be solved by future research using monthly data. To control for seasonality, we would suggest to estimate two sets of threshold parameters, one set for January and another set for the rest of the year. The intuition behind this specification is that the thresholds in January together with the inertia parameters should capture the abnormally high price change frequency in the beginning of the year, while the other set of thresholds should capture the rest of the price changes.

Using monthly data would imply a significantly larger simulated dataset and require more parameters to be estimated, which in turn would increase the computational time considerably. Due to constraints on time and resources, we therefore let this be an exercise for future research, and we focus entirely on yearly observations in this thesis. Considering studies such as Álvarez et al. (2006), which find that firms in the Euro area have an average price duration close to one year, this may be a fair assumption.

4.5 Predefined Parameters

An implication of using the SMM approach is that some parameters need to be predefined. This is not only necessary to confine the required computational resources, some parameters also need to be predefined due to the nature of the approach. This section presents the predefined parameters in our model specification, and provides a discussion around them.

Our decision to include a trend parameter in the frictionless price is based on Ball and Mankiw (1994). They emphasize that trend inflation can cause positive cost shocks to trigger greater adjustment than negative costs shocks of the same size.[18] The intuition is that if the nominal price of a product is constant, the real price (i.e. price relative to other products) is falling because of inflation. Hence, a positive cost shock means that the nominal price is rising while the real price is falling, creating a large gap between the nominal and real prices of the firm. In contrast, if the firm wants to lower the real price, it does not need to pay the adjustment cost, as inflation does much of the work. As a result, positive cost shocks are more likely to induce price adjustments than are negative cost shocks, and the positive adjustments that occur are larger than the negative adjustments.

In order to control for the asymmetric price adjustment effect of trend inflation, we have incorporated the deterministic growth (α) in the frictionless price. The logic is that if α were not included, trend inflation would be embedded into the threshold parameters.

By not including α, we would effectively get a simulated frictionless price below its empirical counterpart. In order to get simulated prices closer to the observed series, the simulation model is then likely to set U closer to zero and L more negative, such that the probability of positive price changes would increase, while the probability of negative price would decrease. Thus, if α is set too low (or equal to zero), the estimated threshold parameters would be biased downwards. Conversely, if α is set too high compared to the actual trend inflation, the threshold parameters U and L would be biased upwards. The simulated frictionless price would then be above

[18]See appendix A.6 for an illustration of the effect on the frictionless price of a cost shock.

its actual counterpart, and the model would select threshold parameters that limit positive price changes and allow more negative price changes.

On the one hand, we would like an α that is as close to the actual inflation as possible, because this would limit the effect of the inflation bias. On the other hand, we want to minimize the number of estimated parameters, since we have limited resources available. As a compromise, we include α as a predetermined parameter equal to 0.03, which is the average annual inflation rate of the producer price index (PPI) between year 2004 and 2009. In order to test the robustness of this approximation, we have performed series of simulations with different values for α in chapter 5.

An implication of using the SMM approach is that we need to set the initial values of the simulated dataset. As the parameters estimated in our model solution depend on changes, and not absolute values, in the price series, the initial values should not affect the estimates. Nevertheless, for the sake of good order, we set the initial values of frictionless prices to match the price series in the empirical data. That is, we let the initial frictionless price, p^*_{i0}, be given by a random draw from a normal distribution with both mean and variance equal to 2.5. The simulated price series for the last five years then get a mean and standard deviation similar to the observed price series.[19]

[19]Yearly box-plots for both the simulated and observed price series are given in appendix A.8.

5 Results and Analysis

In the following chapter, we present our main findings and discuss the robustness of our results. Furthermore, we assess to what extent our results are consistent with macroeconomic models and discuss the implications of our findings for monetary policy.

5.1 Results

Column (1) in Table 2 presents the estimation results of our least restricted model. This specification allows for both asymmetric thresholds and asymmetric inertia, as we differentiate between upper and lower pricing thresholds, as well as between inertia in price increases and price decreases. In this simulation, we find that $U = 0.010$, $L = -0.043$, $\theta_u = 0.000$ and $\theta_l = 0.116$. We see that all parameters, except the one representing inertia upwards, are statistically significant at the 1 percent level, or less. Accordingly, there is at least a 99 percent probability that the estimated friction parameters capture the actual characteristics and are not due to chance.

The interpretation of $U = 0.010$ and $\theta_u = 0.000$ is that the firm adjusts immediately to the frictionless price, as long as the gap between the frictionless and current price is larger than 0.010. $L = -0.043$ and $\theta_l = 0.116$ have the following interpretation. The initial price decrease will be at least 0.038 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.[20]

While our findings suggest that adjustments upwards are subject to threshold effects exclusively, two different forms of frictions may affect adjustments downwards. Firstly, the effect of the lower threshold is that it must be desired to decrease the price by

[20]The initial price decrease is found by multiplying L with $(1-\theta_l)$: -0.043 $\times (1-0.116) \approx -0.038$.

at least 0.043 before the firm decides to adjust downwards.[21] Secondly, the effect of inertia downwards is that the initial price decrease will be equal to 0.884 of the target price gap, while subsequent adjustments will be smaller.[22]

As the initial adjustment of 0.038 is a minimum, larger price drops are allowed. For example, if the firm would be faced with a negative shock making $p^*_{it} - p_{it-1} = -0.100$, this would cause an initial adjustment of -0.088 of its current price. This initial adjustment would occur because -0.100 is below the lower threshold of -0.043, and since we have an inertia downwards of 0.116 it would not adjust fully in the first period.

	(1)	(2)	(3)
	All frictions	No inertia	Symmetric thresholds
σ^2_ε	0.051 (.00137)	0.037 (.00062)	0.037 (.00060)
U	0.010 (.00092)	0.015 (.00055)	0.015 (.00055)
L	-0.043 (.00257)	-0.014 (.00075)	-0.015 (.00067)
θ_u	0.000 (.)		
θ_l	0.116 (.04364)		
N	1584	1584	1584
$\Gamma(\hat{\beta})$	507.645	541.705	586.082

Note: All parameter values are statistically significant at the one percent level (p<0.01), standard errors in parentheses, N denotes number of products and $\Gamma(\hat{\beta})$ denotes the information criterion.

Table 2: Estimation Results

[21] Setting a new target price requires that the price gap, $p^*_{it} - p_{it-1}$, is lower than -0.043.

[22] The target price gap refers to the difference between the target price and the current price: $p^{\#}_{it} - p_{it-1}$.

To assess the relative importance of the various parameters in our model specification, we have estimated more restrictive models as well. These models are presented in Column (2) and (3) in Table 2 and are discussed in the following.

Column (2) shows the estimation results without inertia parameters. An implication of this specification is that the producer adjusts immediately to its target level, whenever it finds it optimal to adjust. In other words, this specification is similar to an (s, S) model with asymmetric thresholds. Table 2 shows that we get a statistically significant upper threshold of 0.015, and a statistically significant lower threshold of -0.014. These results suggest that the producer adjusts upwards only when it is optimal to increase the price by at least 0.015, and only adjusts downwards when it is optimal to decrease the price by at least 0.014. It follows that the estimated thresholds from this specification differ from the least restrictive model in Column (1).

However, when it comes to the model fit, the least restrictive model presented in Column (1) outperforms the more restrictive model in Column (2). The critical value is 15.507 for the χ^2 distribution with eight degrees of freedom for 95 percent significance. Since the difference between the criterion value, $\Gamma(\hat{\beta})$, from the least restrictive model and the model without inertia is approximately 34, we can easily reject the hypothesis that $\theta_l = 0$.[23] Therefore, the specification with inertia parameters provides a better fit than the specification without these parameters.

Column (3) shows a simulation with symmetric thresholds and no inertia, which could explain rigidities caused by fixed menu costs that are independent of the sign of the price change. As we can see, this simulation gives statistically significant symmetric thresholds equal to $|0.015|$. Although, the specification with asymmetric thresholds and inertia reduces the criterion function by more than the critical value. Thus, the least restrictive version of our model provides the best fit.

[23] The difference in criterion value in the models in Column (1) and Column (2) is given by: $541.705 - 507.645 \approx 34$

By looking at the estimated values for σ_ε^2 in the three model specifications, we see that this parameter decreases from 0.051 to 0.037 when θ_u and θ_l is set equal to zero. This means that less variance is preferred in the shocks of the frictionless price when the simulation is subject to more restrictions. One explanation can be the relatively frequent occurrence of small price changes in the data. While the model in Column (1) is able to recreate small price changes by using the inertia parameters, the specifications in Column (2) and (3) do not have this ability. These two specifications therefore choose to decrease the variance of shocks, so that the probability of small price changes becomes larger, ceteris paribus. This argument is also valid when explaining the lower absolute values of L compared to Column (1). Since the simulation is unable to recreate small price reductions with the inertia parameter, it chooses a lower $|L|$ to increase the probability of small price changes.

A consequence of manipulating parameters to increase the probability of small price changes is that the simulation is unable to replicate large price changes. This effect is also reflected in the model fit. The reason why the simulation chooses to prioritize the moments connected to the small price changes is the weighting matrix W, which will be explained in greater detail below.

Table 3 compares the moments from the empirical data with the moments obtained from simulations with and without friction parameters. Column (2) in Table 3 presents the moments from the actual data, Column (3) presents the moments obtained from our least restrictive model, and Column (4) shows the moments from a simulation where all parameters are set equal to zero. Additionally, Column (1) in reports the z-values obtained from the block bootstrap procedure used to calculate the weighting matrix. A higher |z|-value implies that the moment has a smaller variance and that it gets relatively more weight, and a smaller |z|-value has the opposite effect. The closer the simulated moments are to their empirical counterparts, the better the model fits the data.

	(1)	(2)	(3)	(4)
	Bootstrap z-values	Actual	Full Model	Frictionless
-5% to -2.5%	11.74	0.028	0.037	0.087
-2.5% to 0%	14.24	0.047	0.041	0.134
0%	30.84	0.237	0.246	0.000
0% to 2.5%	21.46	0.107	0.112	0.167
2.5% to 5%	29.49	0.185	0.185	0.174
Serial corr (u)	9.60	0.183	0.014	0.006
Serial corr (d)	2.44	0.055	0.249	0.006
Std($\frac{p_t - p_{t-1}}{p_{t-1}}$)	16.05	0.112	0.048	0.056
Rank 1	27.12	0.132	0.085	0.095
Rank 2	27.26	0.082	0.051	0.058
Rank 3	17.64	0.049	0.027	0.030
Rank 4	10.82	0.022	0.007	0.002
Rank 5	-8.11	-0.027	-0.022	-0.036
$\Gamma(\hat{\beta})$	-	-	507.645	2133.996

The top five rows is the distribution of prices within the respective intervals, $\Gamma(\hat{\beta})$ *denotes the criterion function.*

Table 3: Empirical and Simulated Moments

By looking at the z-values for ranks and distribution of price changes, we see that these moments have a small variation of similar size. As such, one should expect that these moments were given approximately equal weights in the simulations. However, the frictionless simulation seems to fit the rank moments much better than it fits the moments for distribution of price changes. The simulated ranks are fairly close to the actual ranks, while the distribution of price changes are far from its empirical counterparts. One explanation is that the frictionless simulation is allowed to manipulate only the standard deviation of the shocks, and not the other parameters, which prevents the simulation to hold prices constant. Since the simulation is unable to recreate the high proportion of zero price changes found in the actual data, it chooses to replicate the rank moments instead of the distribution of price changes.

Furthermore, we see that the serial correlation moments have large variations, and should therefore be given less weight. This is reflected in the bad fit for these moments given by both the frictionless simulation and the simulation with frictions. Excluding the serial correlation moments is therefore not likely to have an effect on the estimated parameters.

Similarly, we see that both simulations fit the standard deviation of price changes moderately, which reflects the medium sized variation of this moment. Overall, the weighting matrix seems to work as intended, as the estimates for moments with a low variance are more precise than the estimates for moments with a high variance.

Even though the frictionless simulation provides a good fit to the rank moments, the full model is superior. The main reason is that the simulation with frictions has a much better fit on the moments for distribution of price changes. The outperformance is reflected in the criterion function, where we see that $\Gamma(\hat{\beta})$ for the frictionless simulation is four times larger than $\Gamma(\hat{\beta})$ for the simulation with frictions.[24]

5.2 Robustness

In the following, we will assess the robustness of our results by doing several computational exercises.

Earlier research suggest that there is heterogeneity in pricing patterns, both between firms and between products (Midrigan, 2011; Dhyne et al., 2011; Honoré et al., 2012;

[24]The χ^2 value for 8 and 12 degrees of freedom at a five percent significance level is 15.51 and 21.03 respectively. Thus, both simulations can easily be rejected as the true representation of the data. This is common, however, in literature employing the SMM approach (Bloom, 2009; Asphjell et al., 2014; Asphjell, 2014).

Loupias and Sevestre, 2012; Asphjell, 2014). To look for evidence of heterogeneity between products, we have done individual simulations for five different product groups. Appendix A.4 presents the estimation results of these simulations.

For the product group "non-durables, food" we find a statistically significant upper threshold equal to 0.100 and a statistically significant inertia upwards of 0.450. At the same time, we find no evidence of frictions downwards in this product group.[25] In all the other product groups we find no signs of frictions upwards, while we get statistically significant parameter values for frictions downwards in three out of four simulations. These are the results of simulations in the three product groups "capital goods", "durables" and "intermediate goods", which together make up 73 percent of the dataset. Our results therefore seem fairly robust to heterogeneity across product groups.

In our estimation of the frictionless price, we include the deterministic trend, α, as a predetermined parameter equal to 0.03. As discussed in chapter 4, the distance between this approximation and the actual trend inflation is likely to affect the estimated parameters. We have therefore done two alternative simulations where α is set equal to 0.02 and 0.04 respectively. Appendix A.5 presents the estimation results of these simulations.

While we expected that the threshold parameters would be sensitive to changes in the trend parameters, we find no evidence of this effect. The parameters σ_ε^2 and θ_l are the only ones which are considerably affected by our manipulations of the α parameter. When we increase the α parameter, the simulation prefers higher values of σ_ε^2 and θ_l. A higher value of the σ_ε^2 parameter will imply larger and more frequent price

[25] The product group "non-durables, food" consists of meat and fish products, fruit and vegetables, animal oils and fats, dairy products, etc. (see appendix A.3). Ward (1982) argues that firms that produce perishable products might hesitate to increase prices in fear of reduced sales leading to spoilage. Ward's argument is challenged by Heien (1980), who argues that the costs of stock outs are higher for products that are more expensive for the consumer to store in the household (perishable products). Our evidence of frictions upwards in this product group seem to favor the former explanation.

changes, while a higher θ_l will give smaller price reductions with higher frequency. The net effect of increasing the α parameter will therefore be more frequent price changes, with price increases larger than price decreases. When we instead decrease the α parameter, we find that the simulation prefers lower values of both σ_ε^2 and θ_l. A lower σ_ε^2 and a lower θ_l will imply less frequent price changes, with price increases slightly larger than price decreases. As the empirical data shows high shares of both small and large price changes, the implications of reducing the α parameter are likely to provide a bad fit. Conversely, increasing the alpha is in favor of these empirical observations, and it is therefore more likely that our approximate of 0.03 is too low rather than too high. Nevertheless, when we set the trend equal to 0.02 and 0.04, the criterion values are significantly higher than in our main specification. Thus, the approximation of $\alpha = 0.03$ provides the best fit, and our results seem fairly robust to changes in the deterministic trend.

5.3 Implications

As can be seen by the friction parameters analyzed above, we find clear signs of both thresholds and inertia in the price setting. The question is whether these frictions are large enough to cause significant nominal rigidities and therefore affect output. Romer (2012) shows that the firm level gain of changing the price is small, even if the shift in the demand curve is large.[26] As the firm has a small incentive to change the price in response to an aggregate shock in demand, the firm may keep the price constant. An implication is that small frictions at the micro level can cause significant nominal rigidities and have a large effect on output. We can therefore conclude that our estimated frictions are sufficiently large to affect economic activity.

Our findings of both thresholds and inertia indicate that different forms of rigidities exist in the data, which is only partly consistent with the assumptions

[26] See appendix A.7 for a static model illustrating the incentive of the firm to change its price.

of macroeconomic pricing models. As discussed in chapter 2, some menu cost models include thresholds with (s, S) pricing rules, while others, such as the consumer anger model of Rotemberg (2005), 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 thesis.

Moreover, our findings imply the occurrence of both large and small price changes. These implications arise because of our findings of statistically significant friction parameters. 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.

Only half of the models considered in the literature review of chapter 2 allow for both large and small price changes. Models accounting for both features include the menu cost model of Dotsey et al. (1999), the consumer anger model of Rotemberg (2005), as well as the models assuming economies of scope by Alvarez and Lippi (2014); Lach and Tsiddon (2007); Midrigan (2011). The remaining price stickiness models considered fail to explain either large or small price changes. In Rotemberg (1982) and Kozicki and Tinsley (2002), the assumption is that convex adjustment costs punish large adjustments, and these models therefore have trouble explaining large 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.

We find no evidence of symmetric frictions, as we get different parameter values upwards versus downwards. It follows that firms are more sensitive to positive than to negative idiosyncratic shocks.[27] Our findings imply that we cannot exclude the

[27] See appendix A.6 for an illustration of the effects on the frictionless price of shocks in demand, costs and technology.

possibility that prices are more flexible upwards than downwards.

The potential existence of asymmetric pricing has important implications for monetary policy making. Firstly, if prices are more flexible upwards than downwards, this will cause the relationship between inflation and aggregate demand (the Philips Curve) to become non-linear, calling for asymmetric monetary policy rules (Laxton et al., 1995). More specifically, interest rate increases must be larger when inflation is above target than interest rate cuts when inflation is below target (see e.g. Dias et al., 2015; Laxton et al., 1995, 1999; Dolado et al., 2005; Dobrynskaya, 2008). Secondly, as we find no evidence of inertia upwards, this indicates that large positive monetary shocks become neutral because firms find it optimal to adjust immediately when the price gap is larger than the upper threshold. Hence, our findings suggest that positive monetary policy shocks have real effects if they are sufficiently small, i.e. as long as the price gap is within the bounds of inaction.[28]

[28]Generally, in static (deterministic) settings, an implication of standard menu cost models is that only small monetary shocks will have real effects (Ravn and Sola, 2004).

6 Conclusion

The existence of sticky prices is crucial for the functioning of monetary policy. While measures taken by the central banks are assumed neutral in the long run, the notion of nominal stickiness may enable monetary policy to have short term effects on the economy. If, on the other hand, prices are fully flexible, nominal prices will adjust and offset the effect on real prices. The aim of this thesis has therefore been to gain greater insight into the nature of sticky prices.

Overall, the evidence provided in this thesis support macro assumptions of nominal stickiness. Price frictions seem to play an important role in explaining producer pricing, as we find evidence of both thresholds and inertia in price setting. These findings indicate that prices are affected by different forms of rigidities, which likely will cause different price patterns. While pricing thresholds may cause a pattern of inaction followed by large price changes (zeros and lumps), inertia in the reaction to shocks may cause gradual adjustments. The existence of both types of rigidities may explain the observation of both small and large price changes in the actual data.

However, we find no evidence of symmetric price frictions, as we get different parameter values upwards versus downwards when using our least restrictive model. While this model indicates negligible frictions upwards, it suggests that it must be optimal to decrease the price by at least 4.3 percent before the producer decides to adjust downwards. Furthermore, it suggests that the initial price decrease will be at least 3.8 percent of the current price, while the rest of the desired price decrease will be distributed in the following periods. According to these findings, we cannot exclude the possibility that price increases are more flexible than price decreases.

Our results are obtained through repeated simulations, and are backed up by several robustness exercises. We compare our findings with results from a frictionless model, as well as with models that are more restrictive. The comparisons show that the model with asymmetric frictions outperforms the other selected model specifications, as it fits better to the actual data. In addition, the model seems to be fairly robust to changes in the deterministic trend, as our approximation of the trend gives better fit than alternative approximations.

The sample of macroeconomic models reviewed in chapter 2, have varying consistency with our findings of different types of price frictions. In general, macroeconomic models fail to include all the evidence presented in this thesis. Some models assume that firms have pricing thresholds and others assume inertia in the price setting. However, none of the models incorporates the combination of these two features.

While our evidence implies both large and small price changes, many contributions in the literature only account for one characteristic to the exclusion of the other: The models describing a pattern of inaction followed by large adjustments have difficulties explaining the observation of small price changes, and vice versa. Amongst the models inconsistent with our findings is the renowned menu cost model of Golosov and Lucas (2007). Only 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.

Every study that relies on modeling exercises have to simplify and focus exclusively on certain factors, which is also the case in this thesis. There are undoubtedly elements that are not accounted for in the analysis, and future researchers are encouraged to explore new possibilities within the topic of price stickiness. Inflation dynamics is a complex field of study, and a clear consensus regarding the most appropriate pricing model is yet to be reached. In order to optimize policies and their implications for the economy, we should therefore strive to discover and implement empirical evidence into macro models.

A Appendices

A.1 Distribution of Industries in the Dataset

2-digit code	Standard Industrial Classification (SIC2002)	Frequency	Percent
15	Manufacture of food products and beverages	935	19.22
16	Manufacture of tobacco products	8	0.16
17	Manufacture of textiles	185	3.80
18	Manufacture of wearing apparel; dressing and dyeing of fur	110	2.26
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	16	0.33
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	510	10.49
21	Manufacture of pulp, paper and paper products	178	3.66
22	Publishing, printing and reproduction of recorded media	3	0.06
24	Publishing, printing and reproduction of recorded media	324	6.66
25	Manufacture of rubber and plastic products	328	6.74
26	Manufacture of other non-metallic mineral products	493	10.14
27	Manufacture of basic metals	60	1.23
28	Manufacture of fabricated metal products, except machinery and equipment	496	10.20
29	Manufacture of machinery and equipment n.e.c.	521	10.71
31	Manufacture of electrical machinery and apparatus n.e.c.	76	1.56
32	Manufacture of radio, television and communication equipment and apparatus	81	1.67
33	Manufacture of medical, precision and optical instruments, watches and clocks	136	2.80
34	Manufacture of motor vehicles, trailers and semi-trailers	108	2.22
35	Manufacture of other transport equipment	1	0.02
36	Manufacture of furniture; manufacturing n.e.c.	280	5.76
37	Recycling	15	0.31

Industry codes and classification have been obtained from SSB (2016).

Table A1: Distribution of Industries in the Dataset

A.2 Product Groups

3-digit code	Standard Industrial Classification (SIC2002)	Number of products	Share of dataset
Capital goods		238	15.03 %
281	Manufacture of structural metal products		
282	Manufacture of tanks, reservoirs and containers of metal; manufacture of central heating radiators and boilers		
291	Manufacture of machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines		
292	Manufacture of other general purpose machinery		
293	Manufacture of agricultural and forestry machinery		
294	Manufacture of machine tools		
295	Manufacture of other special purpose machinery		
311	Manufacture of electric motors, generators and transformers		
322	Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy		
331	Manufacture of medical and surgical equipment and orthopedic appliances		
332	Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except		
342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semitrailers		
343	Manufacture of parts and accessories for motor vehicles and their engines		
351	Building and repairing of ships		
Intermediate goods		771	48.67 %
156	Manufacture of grain mill products, starches and starch products		
157	Manufacture of prepared animal feeds		
171	Preparation and spinning of textile fibers		
172	Textile weaving		
173	Finishing of textiles		
176	Manufacture of knitted and crocheted fabrics		
201	Saw milling and planning of wood; impregnation of wood		

3-digit code	Standard Industrial Classification (SIC2002)	Number of products	Share of dataset
202	Manufacture of veneer sheets; manufacture of plywood, laminboard, particle board, fiber board and other panels and boards		
203	Manufacture of builders' carpentry and joinery		
204	Manufacture of wooden containers		
211	Manufacture of pulp, paper and paperboard		
212	Manufacture of articles of paper and paperboard		
241	Manufacture of basic chemicals		
243	Manufacture of paints, varnishes and similar coatings, printing ink and mastics		
246	Manufacture of other chemical products		
251	Manufacture of rubber products		
252	Manufacture of plastic products		
261	Manufacture of glass and glass products		
262	Manufacture of non-refractory ceramic goods other than for construction purposes; manufacture of refractory ceramic products		
265	Manufacture of cement, lime and plaster		
266	Manufacture of articles of concrete, plaster and cement		
267	Cutting, shaping and finishing of ornamental and building stone		
268	Manufacture of other non-metallic mineral products		
271	Manufacture of basic iron and steel and of ferro-alloys		
274	Manufacture of basic precious and non-ferrous metals		
275	Casting of metals		
285	Treatment and coating of metals; general mechanical engineering		
286	Manufacture of cutlery, tools and general hardware		
287	Manufacture of other fabricated metal products		
312	Manufacture of electricity distribution and control apparatus		
313	Manufacture of insulated wire and cable		
315	Manufacture of lighting equipment and electric lamps		
321	Manufacture of electronic valves and tubes and other electronic components		
333	Manufacture of industrial process control equipment		
371	Recycling of metal waste and scrap		

3-digit code	Standard Industrial Classification (SIC2002)	Number of products	Share of dataset
Non-durables, food		324	20.45 %
151	Production, processing and preserving of meat and meat products		
152	Processing and preserving of fish and fish products		
153	Processing and preserving of fruit and vegetables		
154	Manufacture of vegetable and animal oils and fats		
155	Manufacture of dairy products		
158	Manufacture of other food products		
159	Manufacture of beverages		
160	Manufacture of tobacco products		
Non-durables, non-food		123	7.77 %
174	Manufacture of made-up textile articles, except apparel		
175	Manufacture of other textiles		
177	Manufacture of knitted and crocheted articles		
182	Manufacture of other wearing apparel and accessories		
191	Tanning and dressing of leather		
193	Manufacture of footwear		
222	Printing and service activities related to printing		
244	Manufacture of pharmaceuticals, medicinal chemicals and botanical products		
245	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations		
364	Manufacture of sports goods		
Durables		128	8.08 %
297	Manufacture of domestic appliances n.e.c.		
323	Manufacture of television and radio receivers, sound or video recording		
334	Manufacture of optical instruments and photographic equipment		
361	Manufacture of furniture		
362	Manufacture of jewelery and related articles		
Total		1584	100 %

Table A2: Product Groups

A.3 Distribution of Yearly Price Changes by Product Groups

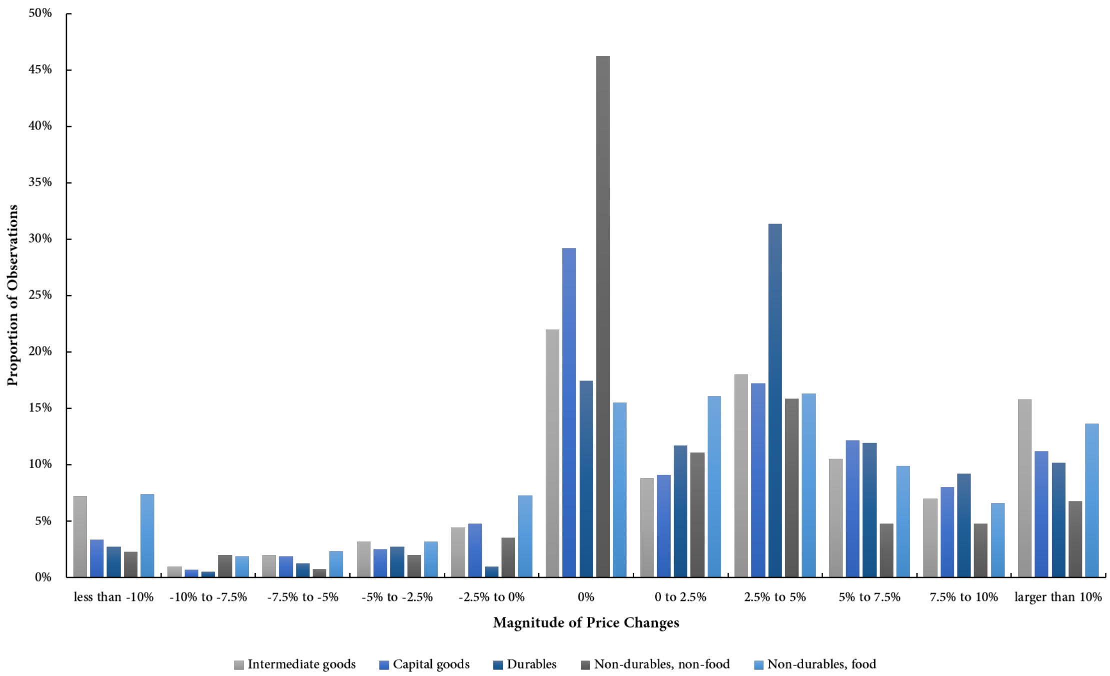


Figure A1: Distribution of Yearly Price Changes by Product Groups

A.4 Estimation Results in Different Product Groups

	Capital goods	Durables	Intermediate goods	Non-durables, food	Non-durables, non-food
σ_e^2	0.075	0.050	0.100	0.050	0.100
	(24.215)	(18.280)	(28.461)	(28.630)	(5.786)
U	0.000	0.000	0.000	0.100	0.000
	(.)	(.)	(.)	(21.103)	(.)
L	-0.100	-0.100	-0.125	0.000	-0.600
	(-12.078)	(-10.013)	(-21.912)	(.)	(-0.583)
θ_u	0.000	0.000	0.000	0.450	0.000
	(.)	(.)	(.)	(13.411)	(.)
θ_l	0.250	0.250	0.225	0.000	0.025
	(8.103)	(4.427)	(16.432)	(.)	(0.022)
N	238	128	771	324	123
$\Gamma(\hat{\beta})$	188.144	2869.017	423.687	99.55	27.61

Note: z-statistics in parentheses, N denotes number of products, $\Gamma(\hat{\beta})$ denotes the information criterion. The results presented in this table are from searches within a large interval with a small precision, which is done to save time. The exact parameter estimates are therefore not representative, but the exercise provides a guideline for the sign and magnitude of the potential coefficients in more precise simulations.

Table A3: Estimation Results by Product Groups

A.5 Estimation Results with Different Trend Parameters

	(1)	(2)	(3)
	$\alpha = 0.02$	$\alpha = 0.03$	$\alpha = 0.04$
σ_e^2	0.045	0.051	0.060
	(.00088)	(.00137)	(.00206)
U	0.010	0.010	0.010
	(.00070)	(.00092)	(.00110)
L	-0.045	-0.043	-0.045
	(.00150)	(.00257)	(.00351)
θ_u	0.000	0.000	0.000
	(.)	(.)	(.)
θ_l	0.050	0.116	0.200
	(.02602)	(.04364)	(.04787)
N	1584	1584	1584
$\Gamma(\hat{\beta})$	692.827	507.645	525.474

Note: All parameter values are statistically significant at the one percent level (p<0.01), N denotes number of products, standard errors are in parentheses, $\Gamma(\hat{\beta})$ denotes the information criterion.

Table A4: Estimation Results with Different Trend Parameters

A.6 A Simple Model for Frictionless Price

If we assume that producer profit is given by:

$$\pi = p \times D(p) - wL,$$

where p denote the prices, w denotes the costs, $D(p)$ denotes the demanded quantity and L denotes labor. Supplied and demanded quantity are given by:

$$\begin{aligned} Q^S &= AL^a \\ Q^D &= Bp^{-\epsilon} \end{aligned}$$

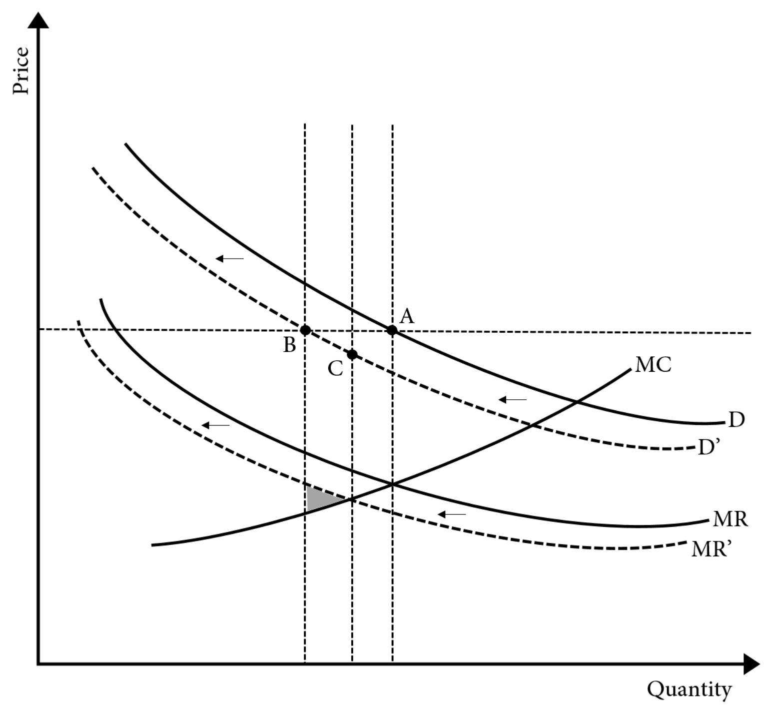
and the frictionless equilibrium price can be derived as:

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

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. Given that $a < 1$, 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. Thus, if the customers demand more goods, they have to pay a higher price per good, ceteris paribus. Finally, if producers are faced with a positive cost shock, $w\uparrow$, the frictionless equilibrium price will increase, as expression (2) will be more positive. Therefore, any increase in costs will be borne by costumers.

A.7 The Incentive of a Firm to Change the Price

The following illustration is based on Romer (2012). Consider an economy consisting of many price setting firms. Assume that the economy is initially at flexible price equilibrium, i.e. the price of each firm is such that if aggregate demand is at its expected level, marginal revenue equals marginal costs. If a firm pays a menu cost, it sets its price to the new profit maximizing level. As the economy is large, each firm takes other firms' actions as given. When all other firms hold their prices fixed, constant nominal prices are an equilibrium if the maximum gain for the firm of changing its price is less than the menu cost. The general issue involved is illustrated in Figure A2.



Note: This figure is taken from Romer (2012)

Figure A2: A Representative Firm's Incentive to Change its Price

In Figure A2, the representative firm starts in equilibrium with marginal cost equal to marginal revenue, Point A. Consider a contractionary monetary policy measure from the Central Bank, e.g. an increase in the interest rate. This will cause a fall in aggregate demand, which, with other prices unchanged, reduces aggregate output, and shifts the demand curve to the left. An implication is lower demand for the firm's products, and the marginal revenue curve shifts in. If the firm does not change its price, it ends up in Point B. Here, the firm has some incentive to reduce the price, as the marginal revenue exceeds marginal costs. The firm's alternative is to adjust the price downwards to the new equilibrium in Point C. The area of the shaded triangle shows the additional profits to be gained from adjusting the price downwards, and thereby increasing quantity. As long as the shaded triangle is small, the firm has a small incentive to change its price, even if the shift in its demand curve is large. Thus, small frictions on firm level may have large effects on output.

A.8 Yearly Boxplots

Yearly boxplots for the empirical and simulated nominal price series are given below. Here, the bottom and top of each box represents the 75th and 25th percentiles respectively, the line inside the boxes show the median, and the top and bottom of the whiskers show the upper and lower adjacent value. The dots represent outside values in each year.

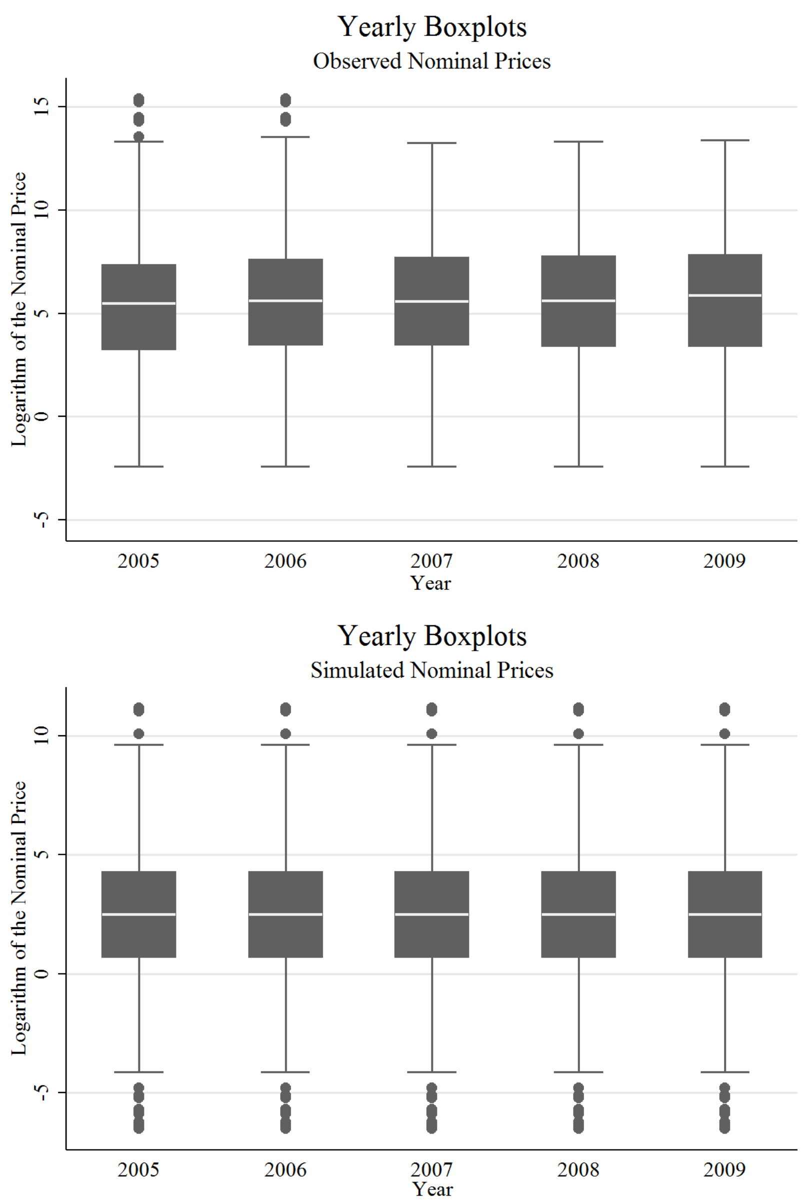


Figure A3: Yearly Boxplots for Empirical and Simulated Data

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