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Pricing Behavior of Multiproduct Firms

Evidence from Norwegian PPI Data

Ingrid Kristine Leinum and August Riise

Supervisor: Øivind Anti Nilsen

M.Sc. in Economics and Business Administration
Economics and Finance

NORWEGIAN SCHOOL OF ECONOMICS

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Abstract

According to New Keynesian theory, monetary policy works in the short run because of micro level wage and price rigidities. There is broad consensus that nominal price rigidities exist. Enhanced knowledge of the microeconomic mechanisms that generate such rigidities is important as it might improve the design of macroeconomic models, and ultimately the implementation of monetary policy. Although most macroeconomic models assume price setting by single-product firms, most price adjustment decisions are in fact made by multiproduct firms. Therefore, accounting for the multiproduct dimension is of great importance as new insight might have implications for macroeconomic model design. Recently, more researchers have focused on the multiproduct dimension both theoretically and empirically. However, the field still remains largely unexplored.

The aim of this thesis is to examine the pricing behavior of multiproduct firms empirically. Using a relatively unexplored dataset on Norwegian PPI data from 2004-2009 we present descriptive statistics on the frequency, size and dispersion of price changes and analyze how these statistics relate to the number of goods produced in a given plant. Furthermore, we apply a discrete choice model for the price adjustment decision at the extensive margin and look for evidence of within-firm synchronization in the timing of price changes. We also look for evidence of scope economies in price adjustment leading to within-firm synchronization.

These are our key findings: Firstly, the frequency, size and dispersion in the size of price adjustments appear not to be systematically related to the number of goods produced. Secondly, there is a large degree of within-firm synchronization in the timing of price adjustments. Thirdly, we find in our data only partial support for the hypothesis of a common cost for price adjustments that yields scope economies.

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1. Introduction

1.1 Statement of Purpose and Motivation

Monetary policy is an important tool for central banks in their efforts to stabilize prices and set countercyclical policies. However, this tool is restricted in the sense that it cannot affect output in the long run. Long-run real output is determined by factors like resources, labor, technology and innovation. This implies that nominal prices eventually offset the initial effect of monetary shocks on real prices. In the short run, the characteristics of nominal prices, the degree of stickiness, determines the responsiveness of economies to monetary shocks (Fabiani *et al.*, 2010). If prices are sticky, we expect monetary policy to have real effects on economic activity in the short run. If prices are flexible, we expect a stronger degree of monetary neutrality. Thus, the behavior of price setters, the microeconomic foundation of monetary policy, becomes important when determining the degree of monetary non-neutrality. In this context, it is fruitful to investigate different aspects of such micro-rigidities: How often do producers adjust prices? By how much? Does it matter if firms produce more than one good? Are there economies of scope in price setting? These are questions a large body of literature has tried to answer and to which this paper is closely related.

While the majority of the literature has focused on consumer prices, a growing number of researchers have recognized the significance of producer prices as well. Vermeulen *et al.*, (2012) present several reasons to investigate producer prices more closely. Perhaps most important is the notion that society may suffer welfare losses if producer prices are ignored by monetary policy makers. Huang and Liu (2005) emphasize the importance of central banks stabilizing PPI, in addition to the CPI and the output gap, to achieve optimal allocations in monetary policy. According to Cornille and Dossche (2008), the adjustment of producer prices is decisive for how shocks to production costs and demand for intermediate goods are transmitted to consumer prices. Therefore, the degree of producer price stickiness affects an inflation targeting central bank's relative weighting of producer and consumer prices. Burstein *et al.* (2003) document that 60% of a consumption goods value is generated at the production stage. If producer level and consumer level prices differ in how they respond to shocks, empirical evidence on both levels is important for the design of monetary policy (Cornille and

Dossche, 2008).[1] In this thesis, we use a relatively unexplored dataset on Norwegian PPI data from 2004-2009 to shed light on the pricing behavior of multiproduct firms.

To explain micro-level rigidities and predict output effects of monetary shocks a number of hypotheses and models have been brought forward in the price stickiness literature.[2] The assumptions calibrated into the various models yield results that differ substantially. Consequently, the literature holds several explanations as to how, and to what extent, micro level prices respond to monetary shocks. Midrigan (2006) argues that, in order to study the aggregate effects of macroeconomic models, the models must be rendered consistent with the micro-level adjustment practices observed in the data. The micro-level empirical evidence presented in this thesis is an important contribution in this context.

Since most producers in the micro data are in fact multiproduct producers, it is important to examine empirically whether the number of goods produced leads to variations in pricing behavior, as evidence of systematic variations can have implications for the design of macro models. The theoretical extension from single to multiproduct firms allows for scope economies in the sense that an adjustment cost, a “menu cost”, can be shared between several products, providing an incentive for producers to coordinate the timing price adjustments within the firm. In the literature, the assumption of scope economies has increased the degree of monetary non-neutrality in menu cost models. Thus, finding evidence of scope economies leading to within-firm synchronization in price adjustment is important as it supports the idea of menu costs as a mechanism for price rigidity.

The multiproduct dimension has received increased attention in recent years, but the field remains largely unexplored. The aim of this thesis is to provide empirical evidence on the pricing behavior of multiproduct firms.[3] Using a relatively unexplored dataset underlying the Norwegian producer price index we provide key descriptive statistics and apply a discrete

[1] The importance of producer prices has also been brought forward by the Inflation Persistence Network (IPN), a network of researchers who aim to study patterns of inflation persistence across European countries. This network has produced multiple empirical studies of key price adjustment statistics (see, for example Vermeulen *et al.*, 2007; Cornille and Dossche, 2008; Gautier, 2008).
[2] See, e.g. Taylor (1980), Calvo (1983), Mankiw and Reis, (2001), and Álvarez and Lippi (2014) for contributions within the “state-dependent” strain of the literature, and Sheshinski and Weiss (1992), Golosov and Lucas (2007) and Midrigan (2011) contributions within the “menu cost” strain.
[3] Throughout this thesis we use the terms firm/producer interchangeably.

choice model to investigate synchronization in the timing of price changes. We also look for evidence of menu cost induced scope economies.

1.2 Research Question

The following describes the research question this paper sets out to answer:

How does the frequency, size and dispersion of price changes relate to the number of goods produced by firms? Do multiproduct firms coordinate the timing of their price changes, and is there evidence of scope economies in the price setting behavior of multiproduct firms?

1.3 Outline

The rest of this thesis is organized as follows. Chapter two serves as a point of departure where we provide a broad overview of the existing body of literature on price adjustments and recent developments therein. We familiarize the reader with the earlier empirical findings in the literature, and we present and explain the intuition behind time-dependent, state-dependent and multiproduct pricing models. This chapter serves as an important backdrop for the discussion following our empirical analysis.

In chapter three we provide a detailed description of the dataset used in our empirical analysis. We present important features of the dataset and explain some adjustments that have been made. In chapter four we present and discuss the methodological approaches we will apply in the analysis.

In chapter five we present our empirical findings. We first present summary and descriptive statistics of the pricing behavior of multiproduct producers. In particular, we present figures of how the frequency, size and dispersion of price changes relate to the number of goods produced. We then estimate a discrete choice model to examine within-firm synchronization in the timing of price adjustments. We discuss the limitations and test the robustness of our results. We also elaborate on our findings and how these relate to previous findings in the price adjustment literature. We summarize our findings and provide some closing remarks in chapter six.

2. Price Adjustment Literature

It is a common assumption in macroeconomic models that "*for monetary disturbances to have real effects, there must be some type of rigidity or imperfection*" (Romer, 2012, p.238). Micro level empirical evidence show that price rigidities indeed exist, and much research has been devoted to understanding how rigid prices are and the causes of such rigidities. The New Keynesian Phillips curve framework is the dominant approach to price modeling (Alvarez, 2008).[4] While sophisticated dynamic stochastic general equilibrium (DSGE) models are widely used in academia and by central banks, there is no consensus about the ideal model design (Romer, 2012, p.313). New insight in micro-level price adjustments can have implications for the design of such models and is of great importance to economists and policymakers.

Some important early contributions to the price adjustment literature were made by Cecchetti (1986), who found evidence of rigid prices using data on newsstand prices of US magazines. Lach and Tsiddon (1992) found evidence of staggered pricing in a study of disaggregated data on Israeli foodstuff prices. The early price adjustment literature almost exclusively focused on consumer prices rather than producer prices.[5] An exception can be found in Carlton (1986), who looked at producer prices in an analysis of individual transaction prices. He found a significant degree of price rigidity and a high degree of heterogeneity in price adjustment behavior across different sectors. While the findings of these seminal works are theoretically interesting, the generalizability is limited due to the narrow set of data used.

Among the first to provide more broad-based evidence of price rigidities were Bils and Klenow (2004) who used price data on 350 categories of consumer goods and services. As Malin and Klenow (2010) highlight, data availability has greatly improved in recent years and the increased access to microeconomic data underlying CPIs and PPIs has led to a burst in the number of micro-price studies. Consequently, researchers have been able to produce broad-based evidence on important price behavior statistics like the frequency and size of price changes, and the degree of heterogeneity in pricing behavior across products. Nakamura and Steinsson (2008) analyze a broad set of US consumer goods data. Vermeulen *et al.* (2012)

[4] The New Keynesian Phillips Curve is derived by aggregating the behavior of price-setters facing barriers to price decisions (Romer, 2012, p.331).
[5] The importance of producer prices is discussed in section 1.1.

analyze producer price data from the Euro area and find that 21% of prices are adjusted each month. In a tedious review of micro price studies Malin and Klenow (2010) find that prices change at least once a year, the frequency of price changes varies across different goods, and more cyclical goods adjust their price more frequently. According to Romer (2012, p.337-338), a key finding from this literature is that price adjustments lack a clear pattern.

There is much heterogeneity in pricing patterns across different product groups. Vermeulen *et al.* (2007) document that price changes are most frequent in the energy sector, less frequent in food and intermediate goods and least frequent in non-durable non- food and durable goods. Regarding the size of price changes, several studies have found that while the average size is large, small price changes are also prevalent in the data (see, for example Midrigan (2006) and Klenow and Kryvstov (2008)).

The price adjustment literature classifies models according to the assumed underlying source of rigidity and distinguishes between time-dependent and state-dependent models. In time-dependent pricing models, the decision to change prices is triggered by the passage of time. In state-dependent models, price changes are triggered by developments in the economic environment and independent of the passage of time (Romer, 2012, p.313). There is an ongoing debate about the relevance of state relative to time-dependent models, and many model modifications have been proposed to match the empirical findings: *"Indeed, current frontier models are consistent with several cross-sectional facts about the size-distribution as well as the timing of price changes uncovered by the micro-data. An open issue in this research agenda concerns the nature of, or the appropriate underlying friction used to model, sticky prices."* (Alvarez *et al*., 2016b).

2.1 Time-dependent Models

In time-dependent pricing models the, decision to change prices is determined by time elapsed and independent of the state of the economy (Alvarez *et al.,* 2016b). The work of Taylor (1980) and Calvo (1983) are recognized as seminal in this strain of the literature. In these models, prices are set by multi-period contracts or commitments that must be renewed due expiration. In between the time of adjustment, prices are predetermined and fixed. The contract expiration is determined by time and not economic developments (Romer, 2012, p.314).

In Taylor models, the opportunity to change prices arrives *deterministically*. Throughout the contract period the probability of a price change, the hazard rate, is zero and at the end of the contract period the probability of changing the price is 1 (Taylor, 1980). The most widely used pricing rule in the derivation of New Keynesian Phillips Curves and DSGE models is Calvo pricing (Alvarez, Burriel and Hernando, 2005). Calvo models assume that the opportunity to adjust prices arrives *stochastically*. The firms change their prices with a probability of θ and leave their prices unchanged with a probability $(1-\theta)$. Aggregated there is a fraction of firms in the economy that will adjust their prices each period, while the remaining will not. Since the timing of price adjustment in these models is exogenous and unresponsive to the state of the world, prices adjust slowly to nominal disturbances. Accordingly, demand disturbances have real effects (Midrigan, 2006).

Throughout the years, researchers have presented various extensions to time-dependent models. Alvarez *et al.* (2005) present a model with Calvo pricing allowing for heterogeneity by introducing different groups with different pricing strategies. Another model related to time-dependent pricing is the sticky-information model by Mankiw and Reis (2001). In this model the rigidity is caused by the flow of information: Obtaining and processing new information bears a cost. Thus, firms may decide to ''purchase'' this information at certain moments in time and let the price follow a predetermined path between the price changes. The rigidity then occurs because, while a fraction of firms in the economy receives new information, the remaining firms continue to set prices based on old information. Time-dependent pricing rules are widely used in macroeconomic modeling because they are technically attractive, but have been subject to criticism. Midrigan (2006) argues that the exogenous nature and lack of micro foundation make time-dependent models unfit for researchers who wish to study policy questions of interest. In later years, researchers have displayed a growing interest for state-dependent models.

2.2 State-dependent Models

While the pricing behavior in time-dependent models is exogenous, the opposite holds true for state-dependent models. In these models, firms adjust prices as a response to changes in the economic environment. A physical cost of price adjustment causes nominal rigidities and endogenous pricing behavior (Midrigan, 2006).

The idea of a price adjustment cost, a 'menu cost,' originates from Sheshinski and Weiss (1977). The intuition is that adjusting nominal prices induces a cost. Therefore, decisions of whether to adjust prices when a price gap occurs hinge on a cost-benefit analysis.[6] Only when the benefit of adjustment is larger than the cost of adjustment will the firm change the price. The name 'menu cost' stems from the cost of printing new restaurant menus. One could think of such costs as the direct cost of relabeling and repricing, but also as indirect costs such as managers spending time on decision making and consumer anger. Zbaracki *et al*. (2004) document that, in addition to physical costs, the process of changing prices often includes information gathering costs, decision making and communication cost and that managers are reluctant to change prices due to fear of negative customer reactions.

While the standard menu cost model assumes a fixed cost of changing prices, Rotemberg (1982) assumes convex adjustment costs. When adjustment costs are convex, large price changes are penalized and thus the firms will adjust prices more frequently and by smaller amounts. This can create small price changes similar to that observed in the data.[7] Letterie and Nilsen (2016) also include linear adjustment costs, which penalize large adjustments, but with a smaller penalty than in the convex case.[8]

Some researchers have questioned state-dependent models' ability to generate a monetary transmission mechanism. State-dependent models have been found to adjust more rapidly to monetary shocks than time-dependent models, because the composition of firms that choose to change their prices varies with the type of shock. The effect of a monetary shock depends not only on how *frequent* prices change, but also on *which* prices change. This is known as the selection effect (Romer, 2012, p.332). A strong selection effect implies a high degree of monetary neutrality. In the classic menu cost setting where firms produce a single good, Golosov and Lucas (2007) found that the effects of monetary shocks were close to neutral. Others have introduced multi-product settings that allow for economies of scope and obtain predictions similar to that of time-dependent models.[9]

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[6] Alvarez *et al.* (2016b) define a price gap as the log difference between the current nominal price, and the profit maximizing price for a good *i*.
[7] Dotsey *et al*. (1999) assume stochastic adjustment cost as a way of generating small price changes. If the cost is low, small price changes may occur.
[8] Letterie and Nilsen (2016) find that the presence of linear and fixed adjustment costs generate sticky prices.
[9] See for example, Lach and Tsiddon (1996) and Midrigan (2011)

There is empirical evidence of firms using both time and state dependent pricing rules. Fabiani *et al.* (2005) survey around 11 000 companies in the Euro area and find that ⅓ follow time-dependent pricing rules, while the remaining use pricing rules with some element of state-dependency. Regarding the predictive power of state and time-dependent models, Klenow and Kryvstov (2008) find that second-generation state-dependent models produce the most successful predictions. In a recent paper, Alvarez *et al.* (2016b) compare several of the time and state-dependent models in the literature and find that the models only differ if the monetary shock is sufficiently large. Recent literature has made efforts to unite the time and state-dependent models. Here, the price change decision depends on both the duration since last price change and the state of the world. One such model is presented by Alvarez *et al*. (2016a), who extend the work by Alvarez and Lippi (2014) and introduce a random menu cost component.[10] This component is exogenously determined and thereby draws on an important feature of time-dependent models.

2.3 Multiproduct Firms

Our work is related to the multiproduct literature on price dynamics. There are several reasons why the study of multiproduct firms represents a fruitful avenue of research. Firstly, the fact that producers more often than not set prices for multiple products has been largely overlooked by the early literature on price dynamics (Lach and Tsiddon, 1996). Indeed, our dataset on producer prices shows that 95% of prices are set by firms with more than one good. Secondly, the multiproduct extension from the prevailing assumption of single-product firms has enabled researchers to explain the large fraction of small price changes observed in the data (Midrigan, 2006). In a seminal paper, Lach and Tsiddon (1996) presented the hypothesis of a common cost of price adjustments as a way to generate small price changes. Intuitively, a large fraction of small price changes contradicts the standard menu cost model with a fixed adjustment cost and $n=1$, in which the decision to change a price hinges on a cost-benefit analysis.[11] In this setup, price changes are expected to be fairly large. However, in a *multiproduct* setting the fixed cost of adjustment will be shared by all products and yield positive returns to scale in price adjustment and promote synchronization (Lach and Tsiddon, 1996; 2007). Providing evidence of scope economies in price adjustment is thus an important contribution in the state

[10] Another example can be found in Bonomo, Carvalho and Garcia (2012).
[11] n denotes the number of goods produced.

dependent strain of the price adjustment literature as it supports the idea of a menu cost as a mechanism to generate rigidities.

Several factors may explain synchronization. Firstly, firms may choose to synchronize due to scope economies. Secondly, as found by Fisher and Konieczny (2000), part of the synchronization is likely explained by common shocks in the economy. Thirdly, synchronization may arise from products being strategic complements. Goods are strategic complements if a firm benefits from increasing (decreasing) the price of one good whenever a price of another good increases (decreases) (Carvallo, 2010).

Sheshinski and Weiss (1992) were among the early contributors allowing for a multiproduct environment and were the first to propose the idea that a fixed adjustment cost independent of the number of goods produced could lead to scope economies and synchronization. Lach and Tsiddon (1996) and Fisher and Konieczny's (2000) studies of consumer prices both present evidence of synchronization within firms, but staggering across firms, supporting the the menu cost hypothesis proposed by Sheshinski and Weiss (1992).

Golosov and Lucas (2007) calibrated a menu cost model in which a strong selection effect caused the real effects of monetary shocks to be far less than those predicted by time-dependent models.[12] This result contradicts the literature consensus on menu costs, namely that such costs provide a mechanism through which monetary shocks work (Midrigan, 2011). As a response, Midrigan (2011) presented a model for retail price data in which he allowed for economies of scope in the price adjustment technology to match the fraction of small price changes. He also matched the excess kurtosis of the size of price changes observed in the data.[13] This reduced the responsiveness of price setters and thereby dramatically increased the degree of monetary non-neutrality.

One of the fundamental reasons the model presented by Golosov and Lucas (2007) generated small effects of monetary shocks is that it had very little heterogeneity in the size of price changes.[14] That is, they assumed that those who adjust prices following an idiosyncratic shock

[12] For a more detailed discussion of the selection effect, see, e.g. Midrigan (2006) and Golosov and Lucas (2007).
[13] After Midrigan (2011), the kurtosis of the size-distribution of price changes has been recognized as an important price behavior statistic. Kurtosis plays a central role in the transmission of monetary shocks. E.g., Alvarez et al. (2016a) develop a model featuring both small and large price changes that lead to excess kurtosis.
[14] In the Golosov and Lucas model, the kurtosis of the size of price changes was set to 1, which is the lowest possible.

are those whose prices lie near the adjustment threshold. Thus, since the real effect of monetary shocks depends on the size of the price level response, little heterogeneity yields a weaker degree of monetary non-neutrality (Midrigan, 2011). A large degree of heterogeneity in the size of price changes, on the other hand, will yield a stronger degree of monetary non-neutrality since the firms responding to monetary shocks are randomly chosen and the average size of the response is therefore likely to be much more dispersed.[15]

Several other researchers have studied the multiproduct dimension both empirically and theoretically. In the theoretical literature, different values of *n,* the number of goods, are modeled. Midrigan (2011) explores the case where n=2 and Bhattarai and Schoenle (2014) explore the case where n=3. Alvarez and Lippi (2014) present a theoretical model with a fixed menu costs and producers with an arbitrary number of goods. This way, they extend the contributions by Midrigan (2011) and Bhattarai and Schoenle (2014). For a given level of a monetary shock, their model produces larger effects as the number of goods produced approaches infinity.[16] They also provide empirical evidence of imperfect within-firm synchronization.[17] Similar results can be found in Letterie and Nilsen (2016), who study price change dynamics under different assumptions about the form of the menu cost. They observe perfect synchronization in 56% of the cases while partial synchronization accounts for the rest, implying some product-specific cost component in the price adjustment behavior. Finally, Bhattarai and Schoenle (2014) continue along the lines of Midrigan (2011) and Alvarez (2014). In their study of US producer prices, they uncover systematic patterns in price setting behavior as firms produce more goods.

From a broad perspective, we see our paper as a contribution to the existing body of literature on pricing behavior and multiproduct firms. In particular, this paper shares the empirical objective of Bhattarai and Schoenle (2014) of exploring synchronization and the extent to which pricing behavior differs as the number of goods produced differs.

[15] Since we average across all small and all large price changes, the kurtosis will be higher (Midrigan, 2011).
[16] This is merely a technical solution to their model, practically, this implies that n>10.
[17] At more disaggregated levels, their findings also support the hypothesis that synchronization is more likely within narrow product categories (See for example Carvallo, 2010).

3. Presentation of the Data

In this chapter, we present the dataset used in this thesis. Our empirical analysis is conducted using two datasets that are both related to the Norwegian manufacturing sector. The datasets are made available by Statistics Norway (SSB).[18] From the data underlying the commodity price index for the industrial sector (PPI) we have monthly price quotations reported by Norwegian producers. Information about these producers is merged with annual structural producer statistics.

3.1 The Commodity Price Index for the Industrial Sector

The commodity price index for Norwegian producers (PPI) is an important short term statistic for the surveillance of the economic activity in Norway. The index is based on a monthly survey sent out by SSB to Norwegian producers, in which they are asked to provide price quotes for their products. On the micro level, this survey allows for the study of producer price rigidities.[19] On the aggregated level, the PPI measures the actual producer-level inflation. Price observations for the PPI index are gathered from companies within oil and gas extraction, mining, mining and support service facilities, energy and manufacturing. Companies that employ 100 or more people are included in the sample on a permanent basis (SSB, 2015).

Since the PPI is an important statistic in the monitoring of the Norwegian economy, a number of measures are taken to ensure high data quality. Firstly, survey attendance is compulsory and producers that fail to answer are followed up by SSB. To keep the index as representative of the economy as possible, survey participants are continuously asked to update their sample of product prices. Secondly, the survey targets large plants within their respective industries to ensure accuracy at a low cost. Furthermore, SSB conduct quality controls where they check for extreme values in the answering scheme, this includes examining whether the price quote

[18] SSB is the Norwegian abbreviation for "Statistisk Sentralbyrå", which translates into Statistics Norway.

[19] The survey measures three statistics: The price index for domestic first hand production (PIF), the PPI and the VPPI. In turn, these statistics are used to cover the price development in the import, export and domestic market. In our analysis, only price observation from the domestic market will be used.

deviates too much from the previous month and controlling for punching mistakes (SSB, 2015).[20]

3.2 Structural Producer Statistics

The monthly price observations are supplemented with annual structural statistics in the manufacturing, mining and quarrying industry. These statistics provide a detailed overview of the activity in the respective sectors and include statistics on wages, sales and employment for each establishment (SSB, 2016). The final dataset used in our analysis is constrained by the fact that these structural statistics are only provided for companies in certain industries.

3.2.1 The Standard Industrial Classification Codes

In order to compare and analyze economic activities, a uniform system, the standard industrial classification (SIC), has been developed. This SIC is one of the most important standards of economic statistics as it enables comparisons across time and countries (SSB, 2016). The observations in this paper are classified according to SIC2002, which acts as a standard to hierarchically code products according to their principal activity. The SIC-classification allows for analysis at a fairly detailed level. SSB classify industry sub-groups from two to five-digit level, which is the most detailed level (SSB, 2016).

3.3 Adjustment to the Dataset

The datasets used have been merged and prepared by Asphjell (2014).[21] Firstly, the final sample only contains information on privately owned single-plant producers with more than 10 employees. Price observations series for less than 24 months have been removed along with price growth observations outside the [0.01, 0.99] interval. The latter manipulation stems from the assumption that large price changes likely reflect changes in quality and not a common

[20] As Letterie and Nilsen (2016) point out, Statistics Norway's sampling procedure entails the possibility that the sampled number of goods per firm is different from the actual number of goods produced per firm. This is because SSB request information on a subset of products they deem to be important for the PPI index. This means that the reported number of goods produced represents a lower bound for the actual number of goods produced.

[21] Magne Asphjell, then a PhD Candidate at The Department of Economics at The Norwegian School of Economics, prepared this dataset. More information about the dataset can be found in Asphjell (2014).

price change decision. After these adjustments, the data contains 94 308 observations tracking 389 producers and 1807 products throughout the period 2002 to 2009.

Additionally, some final adjustments have been made by the authors of this thesis. Firstly, we exclude observations prior to 2004. The motivation for this adjustment is that a shift in SSBs sampling procedure was implemented in 2003 (Letterie and Nilsen, 2016). This adjustment reduces our dataset with 14 004 observations, or about 15%. Next, we exclude from the dataset two-digit SIC industries we consider less relevant for our analysis.[22] This reduces the dataset with 2040 observations. The final data used in this thesis consists of 78 264 observations of 1 673 unique products divided between 374 producers during the period 2004-2009. The producers are categorized according to 20 two-digit level SIC categories. We refer to Table A.1 in the appendix for a detailed overview of industries and their respective codes.

[22] We remove sector 13 “Mining of metal ores”, sector 14 “mining and quarrying”, and sector 37 “Recycling” as we judge them to be less relevant as mining and recycling differs from manufacturing in the traditional sense.

4. Methodological Approach

Before we proceed to our analysis, we must make a number of methodological choices regarding how to approach the data to best answer our research questions. First, we must aggregate our data in a way that offers insight into the multiproduct dimension. Secondly, we must make methodological choices related to the computation of the frequency of price adjustments. Finally, we must decide on a proper estimation method to study the price adjustment decision for multiproduct producers at the extensive margin.

4.1 Grouping Firms to Capture the Multiproduct Dimension

We want to uncover differences in price setting behavior as the number of goods produced increases. For this purpose, we follow a method similar to that of Bhattarai and Schoenle (2014) and classify producers according to their mean number of goods produced. In the following, we explain our classification method and discuss its limitations and strengths.

We group producers according to the mean number of goods produced throughout their time in the data in the following way. First, we count the number of unique products *j*, for each producer *i,* in each year.[23] We then calculate the mean of this number across years. This gives us one number for each producer - the average number of goods produced. Finally, we classify producers into good bins based on their average number of goods produced.

<u>The bins are defined in the following way:</u>
Bin 1-3: firms producing 1 to 3 goods.
Bin 3-5: firms producing more than 3 to 5 goods.
Bin 5-7: firms producing more than 5 to 7 goods.
Bin >7: firms producing more than 7 goods.

We verify that our choice of cutoff-points that define the bins is not decisive for our results. We test several classification alternatives, for example, three or five bins rather than four, without any significant changes to our results. Our decision to classify producers into four bins

[23] Our dataset consists of *monthly* observations. We verify that whenever a producer changes the *number of goods produced*, such a change is exclusively made in the beginning of a calendar year, i.e. the number of goods produced by producer *i* every *month* in a given calendar year is constant throughout the year.

is based on a trade-off between information granularity and having a sufficient number of observations in each bin.

Another concern might be classifying producers that vary the number of goods produced by large amounts from one year to the next. Such a producer may be classified into a bin unrepresentative of its true pricing behavior and bias the price patterns in the bin.[24] We argue that this is not an issue, as most firms in the data do not vary their number of goods produced substantially. When firms vary the number of goods produced, they usually increase or decrease production by 1 good. Furthermore, as long as classification errors occur randomly, they will be averaged out as we calculate our statistics. With this classification scheme, producers in higher bins produce a larger number of unique goods than those in lower bins. This allows us to analyze differences in price setting behavior across bins and examine whether producers with many goods differ from producers with few goods.

4.2 Frequency of Price Changes

The frequency of price changes is one of the most important statistics with regards to the rigidity of prices (Vermeulen *et al.*, 2007). Calculating the frequency of price changes can be done in several ways. In this section, we discuss alternative methods and explain the methodological approach used in our analysis.

4.2.1 Terminology

A *price quotation* is the price level of a product sold by a producer at a given time. Our dataset consists of monthly price quotations, and P_{ijt} denotes the price for a product j, sold by firm *i*, at time *t*. A *price spell* denotes the sequence of time between two price changes for product *j* in firm *i*. Since we have monthly price data, a price spell denotes the number of months between two price changes. A price spell is *censored* if it lacks a specified start or end date. Left-censored price spells end with a price change, but the start date is unspecified. Right-

[24] A hypothetical example to illustrate this issue: A producer might produce eight goods and exhibit a certain price setting behavior in year one. In year two this producer reduces the number of goods produced from eight to one, and correspondingly changes its price setting behavior. Classifying this producer into an appropriate bin is not straightforward.

censored price spells start with a price change, but the end date is unspecified (Aucremanne and Dhyne, 2004)

4.2.2 Calculating Price Change Frequency

There are two alternative methods for calculating the frequency of price changes: We can either compute the frequency of price changes directly, using *the frequency approach*. Alternatively, we can use *the duration approach*, where we first compute the average duration of price spells and calculate the implied frequency in the next step.[25] According to Aucremanne and Dhyne (2004), the direct computation of the duration of price spells can only be done if price spells are uncensored.[26] Our dataset has several censored price spells. This makes it hard to justify a duration approach for the purpose of calculating the frequency.[27] Therefore, we chose to use the frequency approach in our analysis. The frequency approach estimates the frequency of price changes as the share of price quotations changing in a given period. We calculate the frequency in three steps.

1. We define a binary variable indicating when a price change occurs. This variable gains value whenever the price quote of a product (*j,i*), in a given month, differs from the price quote in the previous month.[28]

$$Y_{ijt} = \begin{cases} 1 \; if \; P_{ij,t} \neq \; P_{ij,t-1} \\ 0 \; otherwise \end{cases} \qquad (1)$$

The sum of this variable, $\sum Y_{ijt}$, gives the number of price changes over time for product (*i, j*).

2. We define a binary variable that gains value if a price quotation for a product (*i, j*) is observable for two consecutive months.

[25] The frequency approach is based on how frequent price changes occur in the dataset (F). The duration approach is based on the duration of price spells for each product (D). The methods are related in the following way: D = 1 / F, so that one statistic implies the other.

[26] Using the duration approach if you have uncensored price spells may lead to a selection bias because long price spells are more likely to be censored and eliminated from the data (Aucremanne and Dhyne, 2004).

[27] In our dataset we typically have censored price spells when it is a producer's first or last month present in the data, as the prior/next price quotation is unobserved.

[28] In this exercise we do not count a missing price as a price change.

$$X_{ijt} = \begin{cases} 1 \; if \; P_{ij,t} \; and \; \; P_{ij,t-1} \; are \; both \; observed \\ 0 \; if \; P_{ij,t} \; is \; observed, but \; not \; P_{ij,t-1} \end{cases} \tag{2}$$

The sum of this variable, $\sum X_{ijt}$, gives us the price spell for each product j. That is, the number of months the product is observed in the data.

3. Using these binary variables we calculate the product level price change frequency.

$$F_{ij} = \frac{\sum_{t=2}^{T} Y_{ijt}}{\sum_{t=2}^{T} X_{ijt}} \tag{3}$$

The product level price change frequency is given by the number of price changes as a share of the number of price quotations, summarized over time.[29] Note that the summation goes from period *t = 2* because we do not know if the first price observed is new or old.

4.3 Computing Bin-level Statistics

In order to make comparisons of price setting behavior across bins, we must aggregate the frequency and size of price changes from product level statistics to bin level statistics. We compute bin level statistics following a three-step procedure.[30]

As a first step, we compute product level statistics. The product level frequency of price changes is defined as the number of price changes over the total number of price spells for product (*i, j*). The product level size of price changes is defined as the percentage level change from the last observed price. In step two, we calculate the median frequency (size) across all products within a firm.[31] This gives each producer a number representing its median frequency (size) of price changes. Finally, we calculate the mean across all producers in each bin.[32] We now have a number for the mean frequency (size) of price changes in each bin.

[29] Eq. (1) can easily be modified to indicate a positive price change, $PosY_{ijt} = \begin{cases} 1 \; if \; P_{ij,t} > \; P_{ij,t-1} \\ 0 \; otherwise \end{cases}$ or a negative price change, $NegY_{ijt} = \begin{cases} 1 \; if \; P_{ij,t} < \; P_{ij,t-1} \\ 0 \; otherwise \end{cases}$.

[30] A similar procedure can be found in Bhattarai and Schoenle (2014).

[31] We verify that taking the mean at the firm level yields similar results, but use the median to minimize the effect of outliers.

[32] We verify that calculating the the median gives similar results as the mean, but has a larger standard error.

4.4 Synchronization of Price Changes

We want to analyze multiproduct producers' decision to adjust prices. At the extensive margin, the producer can choose to either adjust the price of good *i* upward, leave the price unchanged, or adjust the price downward. We are particularly interested in the *within-firm synchronization* in the timing of price adjustments. That is, how the fraction of *other* price changes within firm *i* affects the probability of adjusting the price of good *j* in firm *i.* For this purpose, we estimate a discrete choice ordered probit model. In the following, we explain the main features of the model and argue why it is the preferred choice for our purpose. We also explain how we compute a measure of within-firm synchronization.

4.4.1 The Ordered Probit Model

The choice of estimation method depends on whether the dependent variable should be considered ordinal or nominal. Long (1997) argues that an ordered probit model is appropriate if the discrete outcomes are naturally rankable.[33] We argue that the price adjustment decision outcomes are rankable in the sense that "no adjustment" ranks below "upward adjustment" and above "downward adjustment". We therefore proceed with the ordered probit model.[34] The ordered probit model is based on a measurement model where an *unobserved* variable, Y^*, ranges from $-\infty$ to ∞ and is mapped over an *observed* variable, Y. The unobserved variable is divided into the observed variable when certain thresholds, T_i, are passed. The ordered probit model is derived in the appendix and a more detailed description of the model can be found in Long (1997).

We are interested in the *observed* outcomes of the adjustment decision, Y: *"upward adjustment"*, *"no adjustment"* and *"downward adjustment"*. The latent variable Y^* may be thought of as deviation from the optimal price of a product. A producer will adjust the price of a good upward (downward) whenever the actual price is sufficiently below (above) the

[33] An alternative method is estimating a multinomial logit model that does not assume rankable outcomes. If the dependent variable is ordinal, using a multinomial logit model induces a loss of efficiency since it does not utilize all available information. Moreover, a multinomial model would entail a risk of violating the independence of irrelevant alternatives assumption (IIA).

[34] An alternative model is the ordered logit. The key difference between the ordered logit and the ordered probit is that the logit model assumes a logistic distribution, while the probit model assumes a standard normal distribution (Greene, 2009). The discrete choice literature has yet to reach a consensus regarding which model is preferable and the models yield similar results.

optimal price. That is, whenever the benefit of adjustment exceeds the cost. Otherwise, no adjustment will be preferred. Thus, the observed outcome of Y is a function of the deviation from optimal price and the thresholds, T_i

$$\mathrm{Y} = \begin{cases} 2 \Rightarrow \text{upward price adjustment if} & -\infty \leq \mathrm{Y}_i^* < \mathrm{T}_1 \\ 1 \Rightarrow \text{no price adjustment if} & \mathrm{T}_1 \leq \mathrm{Y}_i^* < \mathrm{T}_2 \\ 0 \Rightarrow \text{no price adjustment if} & \mathrm{T}_2 \leq \mathrm{Y}_i^* < \infty \end{cases} \qquad (4)$$

4.4.2 Interpretation

Due to their complex nature there is no simple solution to the interpretation of nonlinear models. Long (1997, 2007) argues that determining important findings and presenting these in an elegant way requires detailed post-estimation analysis. Appropriate interpretation methods for nonlinear models include tables and plots of predicted probabilities and marginal effects and discrete changes in the probabilities.

The predicted probability of the outcome Y = m given the independent variables X_i is calculated as $\Pr(Y_i = m \mid X_i) = \theta(T_m - X_{i\beta}) - \theta(T_{m-1} - X_{i\beta})$. From this the effect of an independent variable on the outcome variable can be analyzed by plotting the probability curve, holding all other variables constant at their mean. Another interpretation method is examining the marginal effect, which captures the instantaneous rate of change of the curve relating the independent variable X_i to the outcome probability $Pr(Y = m|X_i)$. In our analysis we calculate marginal effects holding all other variables at their mean. Long (1997) argues that, if the probability curve changes rapidly, measures of discrete changes are more informative.[35] The discrete changes in our analysis are centered changes, calculated by adding the mean $\pm\frac{1}{2}$ standard deviation. In our analysis we will be using the aforementioned interpretation approaches to shed light on the price adjustment decision.

[35] The discrete change measures the change in the predicted probability for a change in the independent variable from a start value to an end value.

4.4.3 Measuring Within-firm Synchronization

To measure the degree of within firm synchronization in the timing of price changes we use a method similar to that used by Midrigan (2006) and Bhattarai and Schoenle (2014). We compute the fraction of prices by producer i that changes in a given period. To avoid simultaneity bias we exclude the price change of the good we are trying to explain. This gives us a measure that enables us to estimate how the fraction of price adjustments of the *remaining* goods within firm i affect the probability of adjusting the price of good j.

5. Empirical Analysis

How often do prices change? By how much? Are price changes dispersed? These are questions we ask in the first part of this analysis to examine the pricing behavior of multiproduct firms. We then ask whether multiproduct firms coordinate their timing of price changes and look for evidence of scope economies in the pricing behavior of multiproduct firms. First, we present some summary statistics.

5.1 Aggregated Summary Statistics

The mean (median) number of goods produced per firm in the data is 5.4 (5) with a standard deviation of 3.25. Out of 374 producers, 73 produce only one good on average during their time in the data. This means 80% of firms produce more than one good, on average. Furthermore, more than 95% of all prices in the data are set by producers with more than one good. This contrasts with the macroeconomic assumption that prices are set by single-product firms.

The average monthly price change frequency is about 24%.[36] This is somewhat higher than the mean frequency found for European producer prices, which Vermeulen *et al*. (2012) document is 21%. As we would expect in an inflationary environment, positive price changes are more frequent than negative price changes The frequency of positive changes is 15% and the frequency of negative changes is 9%. We find little evidence of downward rigidities as price reductions are common. Out of all price adjustments, 62% are upward and 38% are downward adjustments. The mean (median) size of price adjustments in the data is 4.7% (3.75%). This is slightly lower than that found in the European data.

It appears as if the frequency and size of price adjustments differ across the number of goods produced. Firms that produce 1 (5) good(s) on average have a price change frequency of 44% (26%). Similarly, firms with 1 (5) good(s) change their prices by 4.9% (4.5%), on average. Motivated by these statistics and inspired by the methods used by Bhattarai and Schoenle (2014), we continue to pursue this research avenue. In the following, we classify producers in

[36] We first calculate the the frequency of price changes in each month by dividing the number of price changes by the total number of price quotations in a given month. Then we calculate the mean across months.

four bins according to their number of goods produced and present key descriptive statistics across these bins.

5.2 Summary Statistics Across Bins

Table 1 - Summary Statistics, by Bins

		Number of goods			
		1-3	3-5	5-7	> 7
Number of Firms		202	93	54	25
Number of goods		467	468	393	345
Fraction of Goods		27,9	27,9	23,5	20,6
Mean workers per firm		105	98	96	188
Mean Workers per Good		67	23	16	20
Median Workers per Good		36	16	10	10
Mean Number of Goods		1,9	4,3	6,1	9,8
Std.Dev		(0.82)	(0.58)	(0.57)	(2.63)
Median Number of Goods		2	4	6	9
Min Number of Goods		1	3,2	5,2	7,2
Max Number of Goods		3	5	7	19
*N**	*78 264*	*20 700*	*21 684*	*21 024*	*14 856*

*Number of total observations in the dataset.

Table 1. Summary statistics, by bins. We group firms in four classification bins according to their mean number of goods produced during their time in the dataset. We first calculate the number of goods produced by each firm in every year. Next, we calculate a weighted mean across years for each firm. This gives each firm one number representing its mean number of goods produced. Finally, we calculate the mean across all producers in each bin. The mean (median) workers per good is calculated as the mean (median) workers per firm divided by the mean number of goods produced by firms throughout their time in the dataset.

Table 1 displays summary statistics across the four good bins. The mean (median) number of goods produced is 1.9 (2), 4.3 (4), 6.1 (6) and 9.8 (9), in each respective bin. The vast majority of firms, nearly 80%, are located in bin 1-3 and bin 3-5. However, firms in bin 5-7 and >7 account for a large fraction of price quotations in the PPI data. Indeed, firms in bin 5-7 and >7 set nearly 45% of all prices due to their large number of goods produced. This is also evident from the number of observations in each bin: 46% of all observations are in bins 5-7 and >7.[37]

[37] We note that bin >7 has few firms compared to the other bins. A reason to keep this bin is that it allows us to separate out producers that might exhibit extreme and unrepresentative values. This way we exclude these effects from bin 5-7.

Although the mean number of workers per firm, used as a proxy for firm size, is high in bin >7 compared to the remaining bins, there is no clear trend in the mean and median number of workers per good across bins. Thus, we can verify, at least to some extent, that the distribution of the number of goods produced is not systematically driven by firm size. We provide more detailed tests of this in section 5.6. As discussed in the methodology chapter, our method of binning leaves room for potential sampling errors into the wrong bin. Again, we note that, as long as these errors occur randomly, they will be averaged out as we calculate our statistics.

5.3 Frequency of Price Changes

We analyze price adjustment behavior at the extensive margin by examining the frequency of price changes and ask whether the number of goods produced by a firm influence how often the firm decides to adjust prices.

The frequency of price changes tends to be an important and much-targeted calibration variable in menu cost models.[38] Frequent price changes indicate that prices are flexible and infrequent price changes indicate that prices are sticky, which again implies a stronger effect of monetary shocks. In the presence of scope economies, we would expect the frequency of price changes to increase in the number of goods produced as the cost of adjustment is shared between the products. Calculating the mean price change frequency across bins allows us to map out how this statistic varies as the number of goods produced increases. Figure 1 shows this graphically.

[38] See, for example Midrigan (2011) and Alvarez and Lippi (2014).

Figure 1 - Mean Frequency of Price Changes

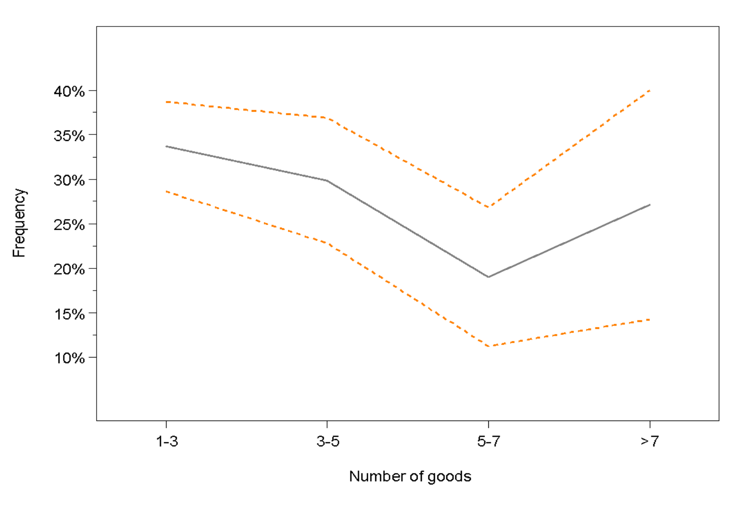

Figure 1. Mean frequency of Price Changes with 95% CI bands. We first calculate the frequency at the product level. Next, we calculate the median frequency across all products within a firm. This gives each producer a number representing its median frequency of price changes. Finally, we calculate the mean across all producers in each bin. We compute the CI bands as mean frequency +-1.96*std. Error across firms.

From Fig. 1 we observe a decrease in the price change frequency as we move from bin 1-3 to bin 5-7, and an increase from bin 5-7 to bin >7. The error bands do not allow us to say that the difference in frequency between bin 1-3, 3-5 and >7 is statistically significant. Thus, Fig. 1 suggest that there is no difference in how often the firms in these bins adjust their prices. The frequency of price changes in bin 5-7 is lower than the frequency in bin 1-3, indicating that firms that produce between 5 and 7 goods adjust prices less frequently than firms producing between 1 and 3 goods. This result is quite different from that of Bhattarai and Schoenle (2014) as they find a positive relationship between price change frequency and goods produced - a finding that is consistent with scope economies in price adjustment. Nonetheless, the number of goods produced does not seem to be decisive for how often firms adjust prices.

5.4 Size of Price Changes

In this section, we explore price adjustment behavior at the intensive margin by examining how the size of price changes, conditional on adjustment, relates to the number of goods produced.

The size of price changes is an important statistic in the price stickiness literature. Larger adjustments in response to monetary shocks decrease the degree of monetary non-neutrality.

In a multiproduct setting, the size of price changes is an interesting statistic since many researchers assume positive returns to scope in price changes.[39] In the presence of scope economies we would expect the average size of price changes to decrease in the number of goods produced. When the adjustment cost is shared between the products, more prices are adjusted even if the deviation from the optimal price is small. Calculating the mean size of price changes across bins allows us to map out how this statistic varies as the number of goods produced increases. Figure 2 shows this graphically.

Figure 2 - Mean Size of Price Changes

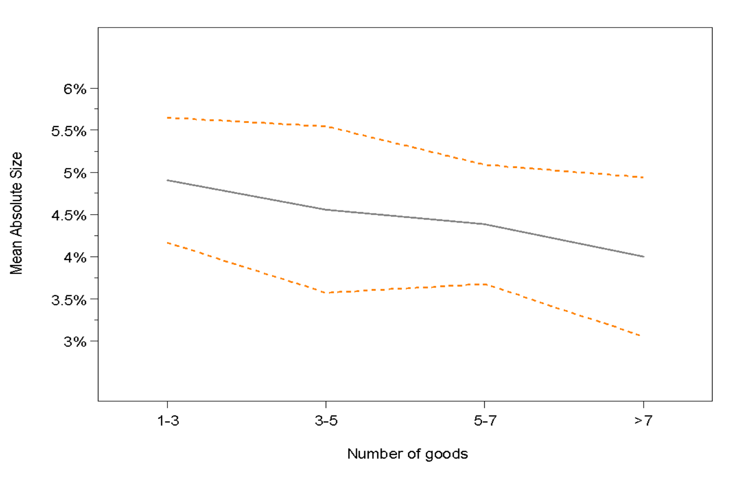

Figure 2. Mean size of price changes with 95% CI bands. We first calculate the size of price changes at the product level. Next, we calculate the median size across all producers within a firm. This gives each producer a number representing its median size of price changes. Finally, we calculate the mean across all producers in each bin. We use the reported standard error to compute the CI bands as mean size +/-1.96*std. Error across firms.

Although the data suggests a weak negative trend in the size of price adjustments as firms produce more goods, consistent with scope economies, the error bands do not allow us to say that this trend is statistically significant. This indicates that the number of goods produced is not decisive for how much firms adjust prices. When we decompose the absolute size into upward and downward adjustments, the result remains largely unchanged. Figure A.1 and A.2 in the appendix illustrate this graphically. Thus, price adjustment at the intensive margin does not seem to relate to the number of goods produced.

Related to the size of price changes, we provide another statistic that has received increased attention in tandem with the multiproduct extension - the fraction of small price changes. We ask whether the fraction of small price changes varies across good bins. In the presence of

[39] See, for example, Midrigan (2011) and Alvarez and Lippi (2014).

economies of scope, we expect the fraction of small price changes to increase in the number of goods produced. We define a small price change as a price change with an absolute size smaller than a specified fraction (*0.5*) of the mean size of price changes for a given producer.[40] That is:

$$\text{Small price change} = \left|\Delta P_{ijt}\right| \leq 0.5\left|\overline{\Delta P_{it}}\right| \qquad (5)$$

where ΔP_{ijt} denotes the price change of a product *j* in firm *i* at time *t*. We calculate the fraction of small price changes using Eq. (5) at the product level. Then we calculate the mean across goods for each producer. Finally, we calculate the mean across producers in each bin. Our results show that small price changes are prevalent in the data. Figure 3 shows graphically that there is a positive trend in the fraction of small price changes. This is in line with what we would expect in the presence of scope economies since firms with more goods will adjust prices even if the deviation from the optimal price is minor. Firms producing between 1 to 3 goods have a mean fraction of about 28%, and about 40% of price changes are small for producers with more than 7 goods. According to the error bands, however, the differences across bins are not statistically significant. Therefore, we cannot say with certainty that the fraction of small price changes increases as firms produce more goods.

Figure 3 - Fraction of Small Price Changes

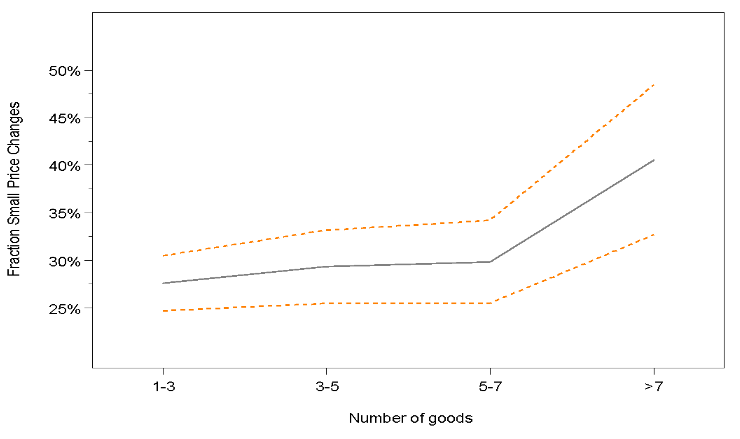

Figure 3: The fraction of small price changes. A price change is considered small if the absolute size of the change is smaller than a specified fraction (0.5) of the mean size of price changes for a given producer. The number of small price changes are then divided by the total number of changes in the firm. Then we calculate the mean fraction of small price changes across all producers in each bin. We use the reported standard error to compute the CI bands as the mean +/-1.96*std. Error across firms.

[40] This is the same definition as used in Midrigan (2011).

5.5 Dispersion of the Size of Price Changes

As Midrigan (2011) points out, the effects of monetary shocks in menu cost models depend on the treatment of the dispersion of the size of price changes. Recall from Section 1.4 that a large degree of dispersion of the size of price changes implies a weaker selection effect and in turn a stronger degree of monetary non-neutrality. As a measure of dispersion, we study the kurtosis of the size of price changes. In the presence of scope economies, we would expect larger dispersion in the size of price changes when firms produce more goods. When a firm-specific adjustment cost is shared between several products, we are more likely to observe both small and large price changes. We define the kurtosis, *K,* as the ratio of the fourth moment about the mean, μ, and variance, σ, squared. That is

$$K = \frac{\mu_4}{\sigma^4}$$

We first calculate the kurtosis for each producer before we calculate the mean across producers in each bin.

Figure 4 - Mean Kurtosis

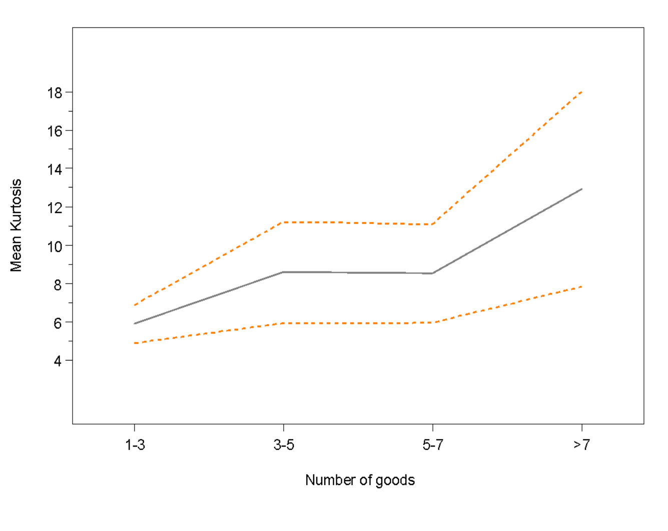

Figure 4: Mean kurtosis. We define the kurtosis (K) as the ratio of the fourth moment about the mean and variance squared $K = \frac{\mu_4}{\sigma^4}$. That is, we first calculate the kurtosis for each producer. Then we calculate the mean across all producers in each bin. We use the reported standard error to compute the CI bands as mean kurtosis +/-1.96*std. Error across firms.

We observe in the data that all bins exhibit excess kurtosis in the distribution of the size of price changes.[41] Figure 4 shows this graphically. The kurtosis increases from 6 in bin 1-3 to 13 in bin >7. This supports the empirical findings and theoretical assumptions made by

[41] The normal distribution has a kurtosis equal to 3. Excess kurtosis implies a kurtosis higher than 3.

Alvarez and Lippi (2014) and Midrigan (2011) and implies a weaker selection effect than predicted by Golosov and Lucas (2007). Although we observe a positive trend across bins, we cannot say with statistical certainty that the kurtosis of the size of price changes increases when firms produce more goods.

5.6 Discussion

We emphasize that the study of price change characteristics across bins should be exercised with caution as our results may be driven by heterogeneity across product groups and sectors. As pointed out by Vermeulen *et al*. (2007), there is much heterogeneity in the pricing behavior across product groups and industries. If a certain product group dominates a particular good bin, the variations we observe might portray heterogeneity in price behavior of different product groups, rather than the effect of the number of goods produced. Table A.3 in the appendix shows how the frequency of price changes evolves across bins at the two-digit SIC sectoral level. For instance, in sector 28 "*manufacture of fabricated metal products, except machinery and equipment*" the frequency of price changes decreases from 32% in bin 1-3 to 21% in bin >7. In sector 15 "*manufacture of food products and beverages*" the frequency increases from 39% in bin 1-3 to 45% in bin >7. Clearly, there is much variation in the pricing behavior across sectors.

To test whether our results still hold when we recognize this heterogeneity we estimate *two* linear regressions. We regress the frequency (size) of price changes on the mean number of workers per firm, 19 industry dummies to control for sectoral heterogeneity and our four bin dummies.[42] The result from these two regressions are reported in Table A.2 in the appendix. The T-statistics on all bin-dummies *except for bin 5-7* in the frequency-regression imply that our coefficients are *not* statistically significant at any reasonable level. This is consistent with the finding that the number of goods produced is not decisive for price adjustments at the intensive margin, while at the extensive margin, only firms in bin 5-7 differ from firms in bin 1-3 in how often they adjust prices.

[42] In these two regressions, we use the mean workers per firm as a proxy for firm size and industry dummies are at the two-digit Standard Industrial Classification (SIC) level. Bin 1-3 is omitted from the regression to serve as a reference bin.

The empirical evidence presented in this chapter confirms several key assumptions that are modeled into frontier menu cost models. We document that both small price changes and excess kurtosis are prevalent in the data. These statistics hint at the strength of the selection effect in such models. As previously mentioned, in the presence of scope economies we expect all of the calculated statistics, except the size of price changes, to be increasing in the number of goods produced. All of our calculated statistics, except the frequency of price changes, have the expected direction but differences across bins are not statistically significant. Hence we are not able to reproduce the findings of Bhattarai and Schoenle (2014), who find systematic patterns in the pricing behavior as firms produce more goods.

5.7 Within-firm Synchronization

To further analyze the pricing behavior of multiproduct firms we go beyond descriptive statistics and estimate an ordered probit model for the price adjustment decision at the extensive margin. We look for evidence of within-firm synchronization and ask whether the decision to change the price of a particular good is affected by the price adjustment decisions of the remaining goods within the same firm. Furthermore, we look for evidence of scope economies leading to within-firm price synchronization.

In recent research, several studies have presented models that allow for economies of scope in price adjustment. In a multiproduct setting a firm-specific menu cost that is shared among the produced goods gives firms an incentive to adjust several prices simultaneously. This motivates us to search for evidence of within-firm synchronization in the data. Even so, observing synchronization is consistent with, but not *sufficient* evidence of scope economies. Economy-wide shocks, industry shocks and firm-specific shocks are also likely to encourage a producer to coordinate internal price adjustments. Furthermore, goods may be strategic complements. That is, they are related in the sense that whenever the price of a particular good is adjusted, it is strategically beneficial to also adjust the price of the complementary good in the same direction. For the purpose of investigating within-firm synchronization, we apply a discrete choice model.

5.8 The Ordered Probit Model

Recall from section 4.4.2 that we are interested in the observed outcomes *upward adjustment, no adjustment* and *downward adjustment* and how the explanatory variables of interest affect the probability of observing the respective outcomes. We present plots of the predicted probabilities and tables of marginal effects and discrete changes in the predicted probabilities to illustrate this.

We first estimate a baseline model for the price adjustment decision. As control variables, we include two measures of within-firm synchronization. Firstly, the fraction of *upward* price changes within firm *i*. Secondly, the fraction of *downward* price changes within firm *i*. Both measures are computed based on the adjustment decision of all goods other than the good in question.[43] Additionally, we include as a measure of synchronization at the sectoral level, the fraction of *upward* (*downward*) price changes within the same two-digit SIC sector level. Again, these measures are computed based on the adjustment decision of all goods, excluding the good in question. We also include as control variables the monthly inflation for the manufacturing sector (PPI) to control for economy-wide disturbances that might lead to synchronized price adjustments.[44] Further, we control for evolvement over the period 2004-2009 by including a time trend, and we include the mean number of workers in the firm as a proxy for firm size.

The coefficients of the within-firm synchronization measures, the fraction of other upward (downward) price changes within the firm, have the expected signs and are statistically significant. The coefficient of the PPI inflation is also statistically significant, while the within-industry synchronization measures are not. We present the regression output in appendix A.5 and turn our attention to a more in-depth post-estimation interpretation of the significant effects of our variables of interest.

The mean predicted probability of observing an upward price adjustment is 14.4%. This is slightly lower than the observed upward price adjustments of 14.8% in the data. The mean predicted probability of no price adjustment is 76.7%, a slight overestimation compared to the

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[43] As pointed out by Midrigan (2006) we exclude the good for which the decision is estimated to avoid simultaneity bias.

[44] Increased inflation is likely to increase the difference between current and optimal price.

75.8% cases observed in the data. For a downward adjustment, the mean predicted probability is 9.5% as opposed to the observed 9.4%. We present in Figs. 5 and 6 two predicted probability plots illustrating how the price adjustment decision is affected by the fraction of price changes of other goods within the firm. The plots imply a strong degree of within-firm synchronization in the timing of price adjustments. Plots of the associated marginal effects are presented in Figures A.3 and A.4 in the appendix.

Figure 5 - Predicted Probabilities

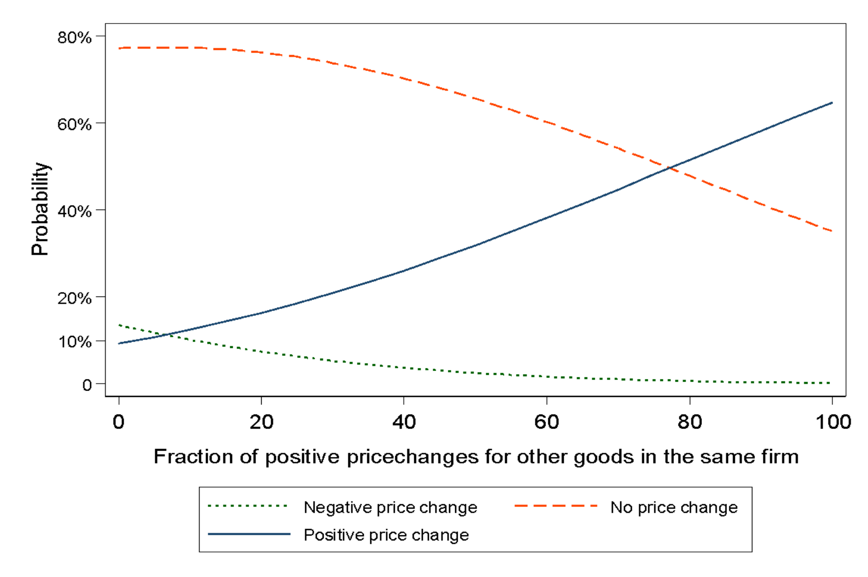

Figure 5: Predicted outcome probabilities over the fraction of positive price changes of other goods in the same firm. We compute predicted probabilities when all other explanatory variables are held at their mean.

Figure 5 illustrates that, when the fraction of upward price adjustments within firm *i,* excluding good *j*, increases, the probability of observing an upward price adjustment for good *j* increases. Both the probability of no adjustment and a downward adjustment decreases. The probability of a downward price adjustment falls relatively rapidly and converges toward zero. When the fraction of other price adjustment is low, "no adjustment" is the most likely observed outcome. When the fraction of other upward price adjustments reaches 80%, the probability of an upward adjustment surpasses no adjustment as the most likely outcome. At this point, the probability of an upward adjustment is about 50%. Clearly, a positive price adjustment is more likely when the fraction of other goods within the same firm adjusting upward increases.

Figure 6 - Predicted Probabilities

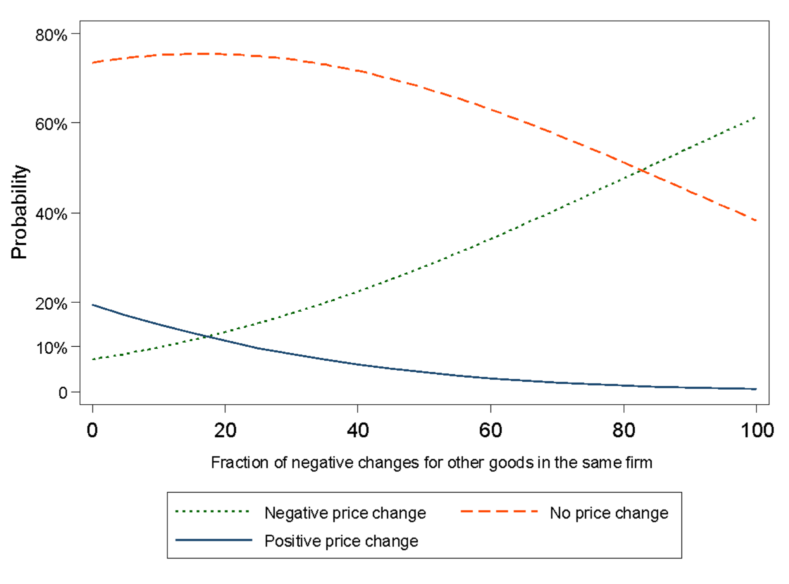

Figure 6: Predicted outcome probabilities over the fraction of negative price changes of other goods in the same firm. We compute predicted probabilities when all other explanatory variables are held at their mean.

Figure 6 shows that as the fraction of downward price adjustments within firm *i,* excluding good *j*, increases, the probability of observing a downward price adjustment for good *j* increases. The probability of no price adjustment increases slightly at first but starts to decrease when the fraction of other downward price adjustments reaches about 25%. The probability of an upward price adjustment decreases and converges toward zero as the fraction of negative price adjustments increases. Again, this confirms a strong degree of within-firm synchronization.

In the continued analysis we present tables of the marginal effects on the outcome probabilities of a change in the independent variable, holding other variables at their mean. We also present discrete change measures of how the outcome probabilities are affected when the independent variables change with one standard deviation around its mean.

Table 2 - Marginal Effects and Discrete Change, Ordered Probit

	Marginal effects			+/ - 1/2 SD		
Model 1	Negative change	No change	Positive change	Negative change	No change	Positive change
△ Fraction positive firm	-0,14 %	-0,43 %	0.57%	-4,50 %	-1,90 %	6,40 %
△ Fraction negative firm	0,55 %	-0,36 %	-0,18 %	4,30 %	1,80 %	-6,00 %

Table 2. Baseline model. Marginal and discrete change effects on outcome probabilities when the fraction of positive (negative) price changes of the other goods in a firm increase by 1%. Effects are calculated when all other variables are held at their mean. Explanatory variables are the fraction of positive (negative) price changes of other goods in the same firm, the fraction of positive (negative) price changes of other goods in the same 2-digit SIC industry, mean workers per firm, monthly PPI, and a time trend.

Again, it is evident that firms synchronize prices. Column 1 in Table 2 shows marginal effects when the fraction of positive (negative) price adjustments within a firm increase with 1%. When the fraction of positive price adjustments within the firm increases by 1%, the probability of observing an upward price adjustment increases with 0.57%. The probability of no price adjustment and a downward price adjustment decreases with 0.43% and 0.14%, respectively. A 1% increase in the fraction of negative price adjustments within the firm leads to a 0.55% increase in the probability of a downward adjustment and a decrease in the probability of no adjustment and upward adjustment with 0.36% and 0.18%, respectively.

From Figs. 5 and 6 we observe that the probability curve is approximately linear when the fraction of same-sign price adjustments is high, but nonlinear when the fraction is low. To improve our understanding of the economic significance and the extent of within-firm synchronization, we examine how the outcome probabilities are affected when the fraction of price adjustments within the firm changes by 1 standard deviation around its mean. Reported effects are presented in column 2 in Table 2. For a 1 standard deviation change around the mean in the fraction of other upward adjustments, the likelihood of an upward price adjustment increases by 6.4%, while the probability of not adjusting the price or adjusting downward decreases with 1.9% and 4.5%, respectively. An equivalent change in the fraction of negative price adjustments within the firm increases the likelihood of a downward price adjustment by 4.3%. The probability of not adjusting also increases by 1.8%. As expected, the probability of adjusting upward decreases by 6%. To summarize: when the fraction of other price adjustments within a firm increase, the likelihood of adjusting the price of a given good in the same direction increases. This effect is both statistically and economically significant. The degree of synchronization is stronger for positive price adjustments than negative price adjustments. Evidently, multiproduct producers in our data do in fact synchronize price adjustment decisions.

We have established that multiproduct producers synchronize the timing of price adjustment decisions. This finding is consistent with findings from previous literature and what we would expect in the presence of scope economies. Recall that synchronization might be explained by other factors than economies of scope. We suspect that some of the observed synchronization stems from certain industries, producers or product groups facing common changes in the economic environment, which encourage producers to adjust the price of several goods in the same direction simultaneously. In the continued analysis we want to contest our findings. If we observe within-firm synchronization after controlling for such common shocks, we can argue that economies of scope is a likely explanation of the remaining synchronization.

For the purpose of controlling for various types of changes in the economic environment we estimate *three* models where we, in addition to the explanatory variables in the baseline model, include fixed effects by dummy variables.[45,46] We first estimate a model where we include 19 dummies at the two-digit SIC industry level. These are meant to capture industry-level common shocks that might lead to within-firm synchronization in the timing of price changes. We also include 11 month-dummies to control for seasonal variations. After including these control variables, we do not observe any difference in the effect of the explanatory variables on the response probabilities compared to our baseline model. Thus, the within-firm synchronization does not appear to be affected by industry wide shocks at the two-digit SIC level and seasonal variations. The regression output, marginal effects and discrete changes for the model are reported in Table A.4 and A.5 in the appendix.

As a more rigorous test of our findings of within-firm synchronization, we estimate a model where we include more detailed dummies to accommodate fixed effects at the *five-digit* SIC

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[45] The inclusion fixed effects by dummy variables in nonlinear models is disputed. In short, the concern is with an issue often referred to as *the incidental parameters problem*. This problem states that the inclusion of dummy variables as an attempt to estimate fixed effects may result in biased coefficients. However, this bias is most present for small values of T - the length of the panel (see, for example Greene (2002). The "small T problem" is less likely to affect our results significantly. We therefore proceed with the fixed effects dummy approach.

[46] Alternatively, if we assume that the fixed effects are uncorrelated with the explanatory variables, we could estimate a random effects model (Greene, 2002)). However, as Midrigan (2007) point out, this assumption is inappropriate in our case because of an endogeneity problem: If a particular good adjust prices frequently, and this good belongs to a product group that adjusts prices frequently, then it is more likely that this good adjusts prices frequently merely because it belongs to this product group. This endogeneity problem rules out the random effects model.

industry level along with month dummies. Even after including these control variables it is highly evident that firms synchronize the timing of price adjustments within the firm. Compared to the baseline model, we observe a decrease in the effect of the explanatory variables on the choice probabilities. The results are presented in Table 3 below.

Table 3 - Marginal Effects and Discrete Change, Ordered Probit

	Marginal effects			+/ - 1/2 SD		
Model 3	Negative change	No change	Positive change	Negative change	No change	Positive change
△ Fraction positive firm	-0,16 %	-0,25 %	0,41 %	-3,70 %	-1,60 %	5,30 %
△ Fraction negative firm	0,48 %	-0,33 %	-0,15 %	3,60 %	1,50 %	-5,10 %

Table 3. Model with 5-digit SIC dummies and month dummies to control for fixed effects. Marginal and discrete change effects on outcome probabilities when the fraction of positive (negative) price changes of the other goods in a firm increase by 1%. Effects are calculated when all other variables are held at their mean. Explanatory variables, in addition to the aforementioned dummies, are fraction of positive (negative) price changes of other goods in the same firm, the fraction of positive (negative) price changes of other goods in the same 2-digit SIC industry, mean workers per firm, monthly PPI and a time trend.

As Column 1 in Table 3 shows, the effect of the fraction of other price adjustments on the outcome probabilities is weaker compared to the baseline model. This indicates that part of the observed synchronization in our baseline model was caused by shocks at a fairly disaggregated industry level. When the fraction of other positive price changes within the firm increases with 1%, the probability of an upward adjustment now increases by 0.41%, compared to the previous 0.57%. The probability of a downward price adjustment now decreases with 0.16%. The decrease in the probability of no adjustment is now 0.25%, compared to the previous 0.43%. The effects on the respective outcome probabilities of an increase in the fraction of downward adjustments within the firm are also weakened. Discrete changes are reported in Column 2 in Table 3. When the fraction of upward price adjustments within the firm changes by 1 standard deviation around its mean, the probability of a positive price change increases by 5.3%, a decrease from the previous 6.4% in the baseline model. The probability of no adjustment and a negative adjustment decreases with 1.6% and 3.7%, respectively. An equivalent change in the fraction of negative changes within the firm decreases the probability of an upward price adjustment by 5.1%. The probability of no adjustment and a downward adjustment increases with 1.5% and 3.6%, respectively. Again, the results are both statistically and economically significant.

As a final test of our finding of within-firm synchronization in the timing of price changes, we utilize that each producer in the data is identified by a unique number. It might be the case that firms synchronize the timing of price adjustments as a response to idiosyncratic changes at the *firm* level.[47] We include in our estimation *producer fixed* effects to control for shocks at the firm level. We also include industry fixed effects at the two-digit SIC industry level and, again, month dummies to control for seasonal variations. When we include such detailed effects, our model no longer provides evidence of within-firm synchronization in the timing of price adjustments.

5.9 Discussion of Findings

We find strong evidence of within-firm synchronization. That is, the likelihood of adjusting the price of a given good upward (downward) increases when the fraction of other upward (downward) price changes in the firm increases. This is still true even after controlling for industry shocks at the two-digit and five-digit SIC level. This result is consistent with findings from the previous literature and what we would expect in the presence of scope economies. However, in our most rigorous attempt to control for other potential explanations for the observed synchronization, that is, when we control for shocks at the *firm* level, our findings no longer hold. This last finding indicates that we cannot rule out the possibility that the observed within-firm synchronization in our baseline model was caused by firm-specific and industry common shocks, and not scope economies. The idea of a menu cost leading multiproduct producers to coordinate the timing of price adjustments finds only partial support in our data.

In the following section we review and compare our findings to previous findings in the literature and discuss limitations we suspect might affect our results. In state-dependent models, price adjustments are triggered by changes in the economic environment. Our data show that, indeed, firms synchronize the timing of price adjustments as a response to common shocks. We document within-firm synchronization even after controlling for industry shocks at fairly detailed levels, a finding that is consistent with scope economies in price adjustment.

Failure to document within-firm synchronization in our final estimation, where firm-specific shocks are controlled for, is inconsistent with a central assumption in the menu cost strain of the price adjustment literature. In particular, the assumption that, in a multiproduct setting,

[47] For example, a producer might unexpectedly win a contract, experience a breach of contract, or unforeseen manufacturing defects.

positive returns to scale in price adjustment incentivize a producer to adjust several of its prices simultaneously. This is a crucial assumption because it has dramatically increased the degree of monetary non-neutrality in menu cost models (see, for example Midrigan (2006) and Alvarez and Lippi (2014)). Furthermore, this finding differs from previous *empirical* findings in the literature that support the hypothesis of scope economies leading to synchronization. Both Fisher and Konieczny (2000) and Midrigan (2011) find that *part* of the synchronization is likely due to the presence of scope economies after controlling for shocks. As pointed out by Midrigan (2011), models that seek to study aggregate effects of monetary shocks must be rendered consistent with the microeconomic foundations. If synchronization is solely caused by shocks and not by scope economies, the validity of frontier menu cost models that assume economies of scope in price adjustment is challenged.

We emphasize that our results should be interpreted cautiously. In particular, our last finding does not coincide with our expectations nor with findings from previous literature. We suspect that we might have biased estimates and therefore run a high risk of making a type II error if we dismiss that within-firm synchronization is partially explained by scope economies. In our attempt to control for shocks at the two-digit SIC industry and at the firm level we include a large number of dummy variables, one per firm, which induces a loss of useful variation. Furthermore, the fixed effect dummy variable approach means that we cannot rule out the incidental parameters problem, under which the maximum likelihood estimator is inconsistent. We also suspect that our model might suffer from an omitted variable problem. In particular, it could be the case that certain goods within a firm are linked together by some underlying relationship that causes firms to adjust the prices of these goods simultaneously. That is, for *other* reasons than common shocks or scope economies. If this is the case, failure to account for this might bias our results in either direction. Ideally, we would dig further into the finding of no within-firm synchronization by controlling for such unobserved relationships. [48] As this would require estimation techniques beyond the scope of this thesis, we encourage future research to take this into account when examining within-firm synchronization.

[48] To accommodate such unobserved heterogeneity, we could estimate a latent class model allowing for latent groups, where the probability of being in a given group is also a parameter to be estimated (Cameron and Trivedi (2005)).

6. Conclusions

Price stickiness is crucial for monetary policy to have real effects. New evidence from micro-level data is of paramount importance for the improvement current macroeconomic models and a large body of price adjustment literature has been devoted to understanding the mechanisms that generate price stickiness. Most firms produce more than one good, a fact relatively few studies within the price adjustment literature have incorporated both empirically and theoretically. The purpose of this paper has been to contribute with micro-level evidence of the pricing behavior of multiproduct firms.

We start out by providing empirical evidence on how the frequency, size and dispersion of price changes relate to the number of goods produced. For this purpose, we group producers in four classification bins according to their mean number of goods produced. This is a fruitful contribution as evidence of systematic patterns across the number of goods produced might have implications for the design of macro models. Next, we estimate a discrete choice model to investigate within-firm synchronization in the timing of price adjustments. Sticky prices might be caused by a cost associated with the decision to adjust a price. If firms produce more than one good, a *firm-specific* adjustment cost will be shared between the goods, and it will be beneficial to coordinate price adjustments. Finding evidence of scope economies leading to within-firm synchronization hints at the presence of such a cost. Hence, it is fruitful to examine the *source* of within-firm synchronization.

In our analysis, we use a relatively unexplored dataset on Norwegian producers to shed light on the pricing behavior of multiproduct firms. In the first part of our analysis, we find that the frequency, size and dispersion in the size of price adjustments appear not to be systematically related to the number of goods produces. In the second part of our analysis, we find that there is a large degree of within-firm synchronization in the timing of price adjustments. We find in our data only partial support for the hypothesis of a common cost for price adjustments that yield scope economies.

We use an approach similar to that of Bhattarai and Schoenle (2014). Using producer price data from the US, they find significant and systematic relationships as firms produce more goods. Compared to their findings, we find much weaker evidence that pricing behavior varies as firms produce more goods. Consistent with the literature, and as we would expect in the presence of scope economies, there is a large degree of within-firm synchronization. This is true even after controlling for shocks at fairly disaggregated levels. However, after controlling for shocks at the producer level, we no longer observe within-firm synchronization.

Midrigan (2006) assumed scope economies as a mean to generate small prices changes. If this assumption is not empirically founded, the origins of small price changes must be found elsewhere. We encourage future research to pick up this line of thought and explore the generalizability of our findings. An important limitation to our findings is that we do not control for the possibility that part of the observed within-firm synchronization stems from unobserved relationships between goods in the same firm that causes the decision maker to adjust prices simultaneously. If this is indeed the case, our results might be biased in either direction. Also, we cannot rule out the possibility that our estimates are affected by the incidental parameters problem. On these grounds, it would be fruitful for future research to employ more sophisticated estimation techniques in the study of synchronization. Future research is still needed to more fully understand the multiproduct dimension as this field of study remains largely unexplored.

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8. Appendix

Table A.1 – Distribution of SIC 2 Digit Codes

Two-digit SIC Code	Principal Activity	Number of Price Quotes	Share of Dataset
15	Manufacture of food products and beverages	15684	20,04 %
16	Manufacture of tobacco products	156	0,20 %
17	Manufacture of textiles	2856	3,65 %
18	Manufacture of wearing apparel; dressing and dyeing of fur	1788	2,28 %
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	276	0,35 %
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	8172	10,44 %
21	Manufacture of pulp, paper and paper products	2952	3,77 %
22	Publishing, printing and reproduction of recorded media	60	0,08 %
24	Manufacture of chemicals and chemical products	5304	6,78 %
25	Manufacture of rubber and plastic products	5112	6,53 %
26	Manufacture of other non-metallic mineral products	7788	9,95 %
27	Manufacture of basic metals	984	1,26 %
28	Manufacture of fabricated metal products, except machinery and equipment	7776	9,94 %
29	Manufacture of machinery and equipment n.e.c	8124	10,38 %
31	Manufacture of electrical machinery and apparatus n.e.c	1344	1,72 %
32	Manufacture of radio, television and communication equipment and apparatus	1284	1,64 %
33	Manufacture of medical, precision and optical instruments, watches and clocks	2280	2,91 %
34	Manufacture of motor vehicles, trailers and semi-trailers	1728	2,21 %
35	Manufacture of other transport equipment	24	0,03 %
36	Manufacture of furniture; manufacturing n.e.c	4572	5,84 %
Total		*78 264*	*100 %*

Note: 2 Digit Standard Industrial Codes (SIC) are obtained from SSB according to the SIC2002 standard. See SSB (2013)

Table A. 2 - Robustness Regressions

	Size of Price Changes	Frequency of price changes
	Controlling for	Controlling for
Explanatory Variables	Firm size and sector fixed effects	Firm size and sector fixed effects
Workers	0.0015	0.0325
	(0.76)	(2.27)
Bin 3-5	-0.14	-2.6
	(-0.22)	(-0.6)
Bin 5-7	-0.16	-12.4^{*}
	(-0.22)	(-2.35)
Bin >7	-0.48	-10.18
	(-0.46)	-1.38
_cons	4.86	16.85*
	(4.96)	(2.48)
N	*374*	*374*

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Sector fixed effects are omitted.

Dummy for Bin 1 is omitted.

Table A.1: Robustness regressions: We regress the mean frequency and size of price changes on the different bin dummies to check whether our results hold when we control for heterogeneity and firm size. We include mean workers per firm as a proxy for firm size and include two-digit industry SIC dummies to control for industry-fixed effects. The reported t-statistics (parentheses) on the bin-dummies indicate that the coefficient on the bin-dummies are not significant.

Table A. 3 - Frequency Distribution Two Digit SIC Industry

2 digit sector	Bin 1-3	Bin 3-5	Bin 5-7	Bin >7	Total
15	39,21	40,89	25,35	44,64	38,47
16		5,71			5,71
17	28,48	3,35	4,69		16,20
18	4,80	4,26	3,10		4,24
19	3,56				3,56
20	46,62	39,79	28,99	38,47	41,29
21	49,61	33,95	4,97		40,25
22	15,03				15,03
24	35,77	47,77	32,38	7,04	36,25
25	32,60	20,98	7,43		27,09
26	27,68	53,32	16,33	7,04	26,75
27	77,00	38,95			70,08
28	32,94	24,85	7,84	21,98	27,36
29	19,48	14,35	37,48	9,38	18,05
31	4,35	33,58			28,71
32	23,23	17,66			20,14
33	22,70	49,94	3,94	5,08	22,63
34	5,92		13,78		10,51
35	0,00				0,00
36	15,09	4,93	25,67	31,43	16,19
Total	33,66	29,83	19,00	27,10	30,16
Number of observations	202	93	54	25	374

Figure A.1 - Size of Positive Price Changes

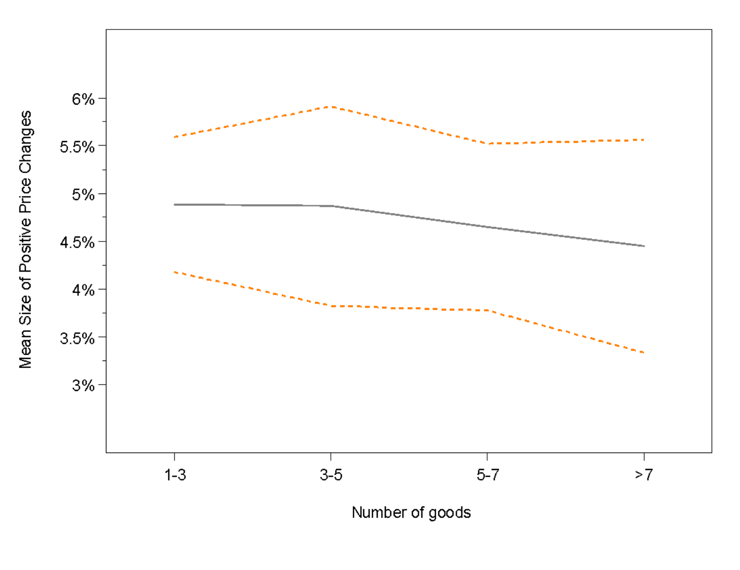

Figure A.1: Mean size of positive price changes. We first calculate the size of positive price changes at the product level. Next, we calculate the median positive size across all producers within a firm. This gives each producer a number representing its median positive size of price changes. Finally, we calculate the mean across all producers in each bin. We use the reported standard error to compute the error bands as mean size +-1.96*std. Error across firms.

Figure A.2 - Size of Negative Price Changes

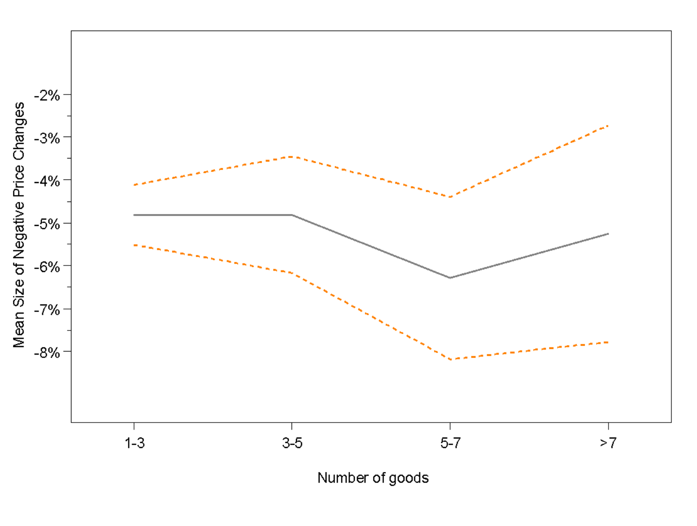

Figure A.2: Mean size of negative price changes. We first calculate the size of negative price changes at the product level. Next, we calculate the median negative size across all producers within a firm. This gives each producer a number representing its median negative size of price changes. Finally, we calculate the mean across all producers in each bin. We use the reported standard error to compute the error bands as mean size +-1.96*std. error across firms.

Figure A.3 - Marginal Effects

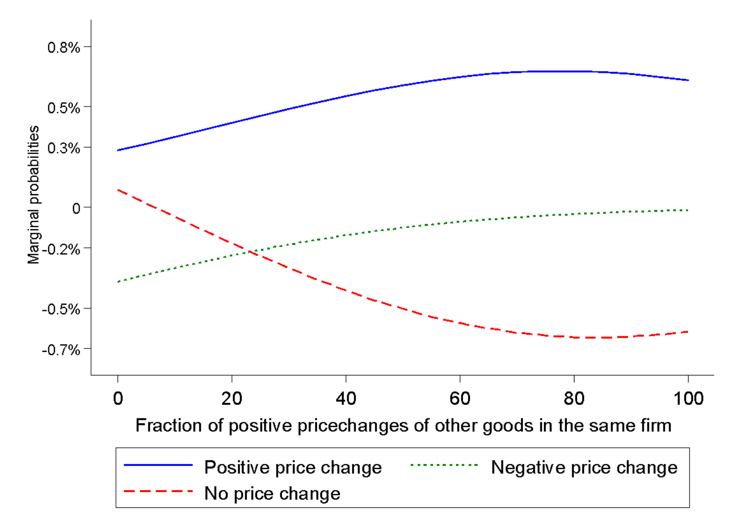

Figure A.3: Marginal effects of the choice probabilities over the fraction of positive price changes of other goods in the same firm. We compute marginal effects when all other explanatory variables are held at their mean.

Figure A.4 - Marginal Effects

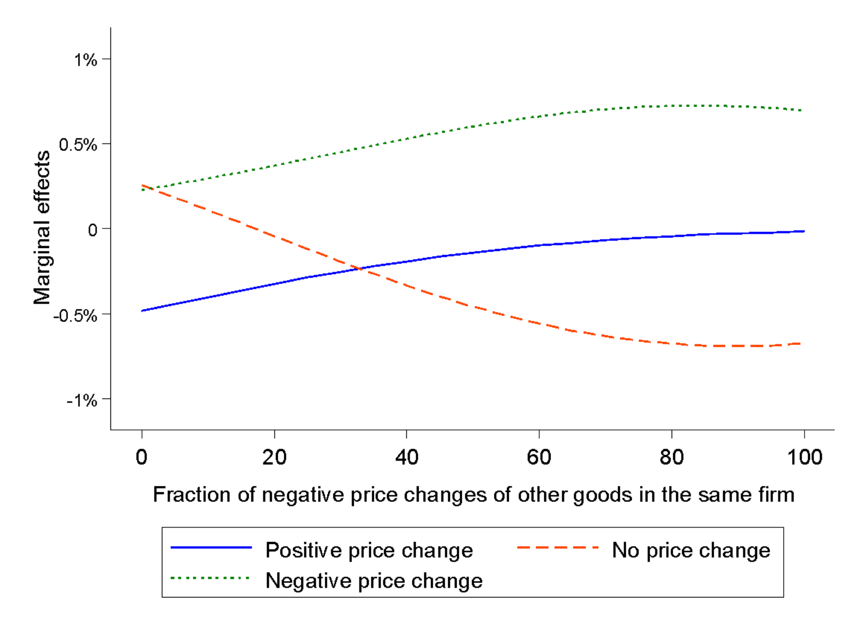

Figure A.4: Marginal effects of the choice probabilities over the fraction of negative price changes of other goods in the same firm. We compute marginal effects when all other explanatory variables are held at their mean.

Table A.4 - Marginal Effects and Discrete Change, Ordered Probit

	Marginal effects			+/ - 1/2 SD		
Model 2	Negative change	No change	Positive change	Negative change	No change	Positive change
△ Fraction positive firm	-0,14 %	-0,43 %	0.57%	-4,50 %	-1,90 %	6,40 %
△ Fraction negative firm	0,55 %	-0,36 %	-0,18 %	4,30 %	1,80 %	-6,00 %

Table A.4: Model with 2-digit SIC dummies and month dummies to control for fixed effects. Marginal and discrete change effects on outcome probabilities when the fraction of positive (negative) price changes of the other goods in a firm increase by 1%. Effects are calculated when all other variables are held at their mean. Explanatory variables, in addition to the aforementioned dummies, are fraction of positive (negative) price changes of other goods in the same firm (2-digit industry), mean workers per firm, monthly PPI and a time trend.

Table A.5 - Regression Output, Ordered Probit Model

Explanatory Variables	Model 1	Model 2	Model 3	Model 4
Fraction positive changes firm	0.0176***	0.0177***	0.0146***	-0.0569***
	(0.00108)	(0.00108)	(0.00113)	(0.00612)
Fraction negative changes firm	-0.0183***	-0.0183***	-0.0155***	0.0560***
	(0.00115)	(0.00114)	(0.00118)	(0.00626)
Fraction positive changes sector	0.00161	0.000739	-0.0865***	0.0136
	(0.00154)	(0.00163)	(0.00747)	(0.0117)
Fraction negative changes sector	-0.00109	3.93e-05	0.0827***	-0.0165
	(0.00166)	(0.00175)	(0.00732)	(0.0124)
Mean workers per producer	-1.39e-06	-1.30e-05	-8.26e-06	0.00587***
	(0.000167)	(0.000169)	(0.000211)	(0.00170)
Monthly PPI	0.0573***	0.0321**	0.0324**	0.0327**
	(0.0101)	(0.0146)	(0.0146)	(0.0146)
Constant cut 1	-1.228***	-1.183***	-1.629***	-1.474***
	(0.0134)	(0.0241)	(0.254)	(0.0743)
Constant cut 2	1.204***	1.252***	0.815***	0.981***
	(0.0140)	(0.0246)	(0.254)	(0.0743)
Log Pseudolikelihood	-51921	-51844	-51637	-51385
Pseudo R2	0.0102	0.0117	0.0156	0.0204
Observations	*75,288*	*75,288*	*75,288*	*75,288*
2 digit SIC* fixed effects		YES		YES
Month fixed effects		YES	YES	YES
Producer fixed effects				YES
5 digit SIC* fixed effects			YES	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Standard Industrial Classification. See chapter 3 for more information.
Dummies and time trend omitted.

Table A.5: The table reports regression output for four estimated ordered probit models. Among the variables, fraction positive (negative) changes firm (sector) represents the fraction of positive (negative) price changes of other goods within the same firm (sector). Mean workers per producer represents the mean workers per producer and monthly PPI refers to the monthly change in the PPI inflation.

Derivation of the Ordered Probit Model

The ordered probit model is derived by assuming a relationship between an unobserved latent variable, Y*, and the observed outcome variable, Y, according to the measurement model

$$Y_i = m \;\; if \;\; \mathrm{T}_{m-1} \leq Y^* < \mathrm{T}_m \;\; for\; m = 1\; to\; j \tag{1}$$

Where T_i are cut-off points that map the latent variable Y* to the observed categories. Y* is a linear combination of the explanatory variables, **X**, and the error term ε_i. The error term is normally distributed with mean 0 and a variance of 1. The structural model is

$$Y^* = X_i\beta + \varepsilon_i \tag{2}$$

The pdf is $\phi(\boldsymbol{\varepsilon}) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\varepsilon^2}{2}\right)$ (3)

The cdf is $\boldsymbol{\theta}(\boldsymbol{\varepsilon}) = \int_{-\infty}^{\varepsilon} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt$ (4)

From this we can compute the probability of observing values of Y = m given **X**

$$\Pr(Y_i = m\; given\; X_i) = (\mathrm{T}_m - X_i\beta) - (\mathrm{T}_{m-1} - X_i\beta) \tag{5}$$

The regression is estimated by maximum likelihood estimation. To identify the model either $\beta 0$ or T1 is constrained to 0. The log likelihood equation is

$$L(\beta, \{\mathrm{T}|y, X\} = \sum_{j=1}^{J} \sum_{y_i = j} \ln\left[F\left(\mathrm{T}_j - X_i\beta\right) - F(\mathrm{T}_{j-1} - x_i\beta)\right] \tag{6}$$