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Synchronization of Price Changes within Firms and Industries

A micro-level analysis using PPI data

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Abstract

Macroeconomic and monetary policy rely heavily on the assumption of price rigidity in the short run. In the literature there is broad consensus on the existence of such rigidities, but their origins remain to be fully understood. Our thesis contributes to this field of research, examining the pricing behavior of multiproduct firms in Norwegian product markets.

Using a relatively unexplored dataset on Norwegian PPI data, we provide evidence on price rigidity at the producer level. We document that firm behavior to a certain extent depend on the number of products produced by a firm, a finding that is not accounted for in traditional macroeconomic models. Furthermore, we employ a multinomial logit model to examine synchronization of price changes, both within-firm and within-industry. We find strong evidence of within-firm synchronization. This synchronization is independent of the direction of the price changes, supporting the theory of economies of scope in menu costs. Moreover, we find some evidence of within-industry synchronization of price changes, indicating the presence of strategic complementarity in pricing decisions at the industry level. However, the industry synchronization effects are found to be small, suggesting that producers have a degree of pricing power, as they appear to be able to disregard competitor behavior to a certain extent. These findings shed light on the competitive environment in Norwegian product markets. Combined with earlier literature they have potentially important implications for the micro-foundations of macroeconomic models and monetary policy.

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1 Introduction

1.1 Motivation and purpose

Macroeconomic and monetary policy rely heavily on the assumption of price rigidity in the short run. If the money supply increases, production and employment is stimulated through increasing real money balances, which yields short-run monetary non-neutrality (Taylor, 1999). The assumption of price rigidity can be traced to David Hume more than 200 years back, and the aggregate empirical evidence on the existence of price rigidity is solid. However, research also show that the pricing behavior of firms is highly heterogeneous (Nakamura and Steinsson, 2008), and the mechanisms behind this heterogeneity, as well as its implications for price rigidity, remain to be fully understood.

With data accessibility and quality continuously evolving, substantial research have been conducted into the pricing behavior of firms the last decades. Among the questions typically asked in the literature is by how much are prices typically changed; how often they are changed; and whether firms exhibit synchronization trends, both within the firm and within industries. The main theoretical framework for explaining within-firm synchronization is economies of scope in price changes, while cross-firm synchronization can be theoretically explained by strategic complementarities and strategic interaction (Bhattarai and Schoenle, 2014). Our paper contributes to this field of research with a focus on within-firm and within-industry synchronization of price changes.

As argued by Vermeulen et al. (2012), the producer prices are the prices that are ultimately modelled in macroeconomic models. When practicing inflation targeting it is crucial to know how shocks to production costs are transmitted to consumer prices (Cornille and Dossche, 2008), as stabilizing consumer prices is the ultimate goal of such stabilization policies. Detailed knowledge of the microeconomic transmission mechanisms, from monetary and aggregate shocks to consumer and producer prices, is thus a highly relevant and active field of research. Such research is relevant for central banks modeling the macroeconomic responses as well as regulators seeking to understand competitive dynamics.

Traditional macroeconomic models generally assume producers to be single-product firms and could therefore be less suited to analyze price dynamics of an economy in which multi-product firms are largely prevalent (Bonomo et al., 2020). With data becoming richer and more available, empirical research on multi-product firms has flourished since the early 2000s; the prevalence of menu costs, scope economies in price changes, and a high degree of within-firm synchronization has been documented in a number of countries (Alvarez and Lippi, 2014; Bhattarai and Schoenle, 2014; Letterie and Nilsen, 2020). Letterie and Nilsen (2020) argue that within-firm synchronization of price changes increases the rigidity of individual product prices compared to the single-product models, as pricing decisions also depend on the benefits of changing the price of other products.

While Bhattarai and Schoenle (2014) find evidence of a high degree of within-firm synchronization, increasing with the number of products, they also consider synchronization at the industry level. They find industry synchronization of price changes to be prevalent, but less so than at the firm level. Furthermore, they find that price change synchronization at the industry level seems to be declining as the number of products in a given firm increases. This extension is motivated by Bhaskar (2002), arguing that industry-level synchronization is more likely within product groups with high elasticity of substitution. Bhaskar argues that this substitutability leads to rich patterns of strategic interaction, and that it can generate stable staggering of prices. The basic, intuitive argument of this result is the point that strategic complementarities should be stronger within industries than across industries.

Using a rich and relatively unexplored dataset on Norwegian PPI data, exploring the extent of this strategic interaction will be the aim of this paper. To what degree do we observe firm behavior changing with the number of products produced by the firm, and do we find evidence of within-firm synchronization of price changes? Can the dataset be disaggregated to competitive product markets where the products are relevant substitutes? Do we observe synchronization in these disaggregated markets? The rich dataset allows us to investigate strategic interactions and industry synchronization at a high level of detail. Answers to these questions could help in creating a broad fundament for producer price modeling when paired with previous research on the field.

1.2 Research question

More specifically, the research question we seek to answer is the following:

"Do actors in related and competing product markets appear to synchronize their price changes? What are the magnitudes of within-firm and within-industry synchronization of price changes? How do these measures relate to the number of products produced by the manufacturer?"

Within-firm synchronization has been extensively researched (see e.g. Lach and Tsiddon, 1996; Midrigan, 2011; Alvarez and Lippi, 2014; Letterie and Nilsen, 2020), while synchronization of price changes across competing products has been less so. Here, we can compare our results to those of Bhattarai and Schoenle (2014) using US PPI data, and Dedola et al. (2019) using Danish PPI data. Overall, it is highly interesting to compare our results to international research into pricing behavior, with the aim to thereafter discuss the implications of our findings regarding price stickiness and monetary policy. Considering the relative magnitudes of the effects we find, we also reflect on which theoretical frameworks seem the most relevant in explaining the observed pricing behavior.

1.3 Outline

This thesis is organized in the following way. In chapter 2 we review the research literature on pricing behavior and price stickiness. The aim of the chapter is to familiarize the reader with the relevant concepts and theories applied throughout the analysis. The chapter initially provides a broad overview of research into pricing behavior, and how the research is categorized. The following subsections, section 2.1-2.3, outline the relevant theoretical baseline for the analysis.

In chapter 3 we present the data used in the analysis. We first explain the structure and characteristics of the dataset. The chapter also provides an overview of the adjustments made to the dataset, and how the data are merged across years. In chapter 4 we present the methodology applied in our analysis, emphasizing the formulas, assumptions, and reasoning for the choice of methods.

Throughout chapter 5, we present our main findings. The chapter starts off by presenting summary statistics and an overview of price change frequencies, the size and the dispersion of price changes. We then present our industry categorization, and a number of measures across these industries. The final part of the analysis concerns multiproduct behavior and price change synchronization, where we quantify and discuss within-firm and within-industry synchronization of price changes, as well as how this behavior changes with the number of products manufactured by the firm.

In chapter 6 we summarize our main findings, and discuss their implications and relevance.

2 Literature Review

Understanding pricing behavior is important for a range of issues in macroeconomics, such as the welfare consequences of business cycles and optimal monetary policy (Nakamura and Steinsson, 2008). The rationale for empirical research into pricing behavior is pointed out by Alvarez et al. (2006): *"A better empirical understanding of individual price-setting is crucial for building macroeconomic models of inflation with adequate microeconomic foundations that may help in the design of monetary policy".*

Among the pioneers of empirical research on pricing behavior was Cecchetti (1986), who found substantial price stickiness in US magazine prices, and strong empirical support for sticky price models based on monopolistic competition. Carlton (1986) found significant rigidities, but also a great deal of heterogeneity with regards to price durations as well as the size of changes on products used in manufacturing. These early contributions were important in laying the foundations of research on pricing behavior. Data have become richer and more accessible in recent years (Klenow and Malin, 2010), and the earlier literature has thus been revived using new and broader evidence, starting with Bils and Klenow (2004).

The literature on price change behavior is typically divided into two main categories; state dependent and time dependent models (Alvarez et al., 2017). Sheshinski and Weiss (1977) develop a model based on the assumption that there are real costs associated with the price-change process, in which firms fix the nominal price over constant intervals. Thus, the real price fluctuates over the fixed period. Their paper, describing how pricing decisions are related to inflation rates and other relevant states of the economy, has been developed into several state dependent model classes: Menu cost models (Golosov and Lucas, 2007; Alvarez and Lippi, 2014), convex cost models (Rotemberg, 1982), and consumer anger models (Zbaracki et al., 2004; Rotemberg, 2005).

Regarding time dependency, Calvo (1983) presents a model in which firms change price upon receiving a random signal (shock). The signal is stochastic and independent across firms and geometrically distributed over the time span. The Calvo model assumes a constant hazard rate, in which the hazard rate is defined as the probability of a price change. This assumption has been extensively crosschecked, with Nakamura and Steinsson

(2008) finding that the hazard rate seems to be downward sloping for the first few months following a price change, and then flat.

Bhattarai and Schoenle (2014) research the pricing behavior of multiproduct firms, by first examining how the aggregate behavior changes with the number of products, and then focusing on synchronization behavior both within-firm and -industry. They find multiproduct firms to conduct significantly more frequent and small price changes. Further, they provide evidence of synchronization of price changes both within-firm and within-industry. Their results indicate that industry synchronization is decreasing with the number of goods produced by the firm, while within-firm price change synchronization seems to increase with the number of goods produced internally.

In a similar study to Bhattarai and Schoenle's, Dedola et al. (2019) find the frequency and size of price changes in Denmark to be broadly unrelated to the number of products within-firm. Regarding synchronization, they find within-firm synchronization to increase and within-industry synchronization to decrease with the number of manufactured products. Considering multiproduct firms, Letterie and Nilsen (2020) find many infrequent and small price changes as well as a high degree of within-firm synchronization. Their model provides evidence of scope economies in price changes, linear and convex adjustment costs, as well as evidence on the presence of firm-specific shocks.

To the best of our knowledge, relatively few empirical research papers have been published considering within-industry price change synchronization. However, as most published research points out, pricing behavior is highly heterogenous across firms and industries. According to Fabiani et al. (2005), stemming from a survey of firms, coordination failure (competitor behavior) is among the most important factors in explaining firm's pricing behavior, ranking behind implicit contracts, explicit contracts, and cost-based pricing.

2.1 Price rigidity: Background and empirical evidence

In the long run, the amount of money in circulation does not affect anything real, such as how much people work or their consumption (Lucas, 1996). This concept, called neutrality of money, implies that central banks should not seek to impact long-run production and activity levels in the economy as this will create economic imbalances. However, economists have for long assumed wages and prices to be rather rigid in the short run, implying a tradeoff between employment (output) and inflation and thus making room for stabilization policy (Romer, 2012). This relationship was shown by Phillips (1958) to be strong and stable, and the relationship became known as the Phillips curve. The Phillips curve implies that you can hold the economy at a growth beyond the "equilibrium level" simply by accepting higher inflation.

The belief in this stable long-run tradeoff shattered through the 1960s, with Friedman (1968) arguing that the Phillips curve fails to distinguish between nominal and real variables. If output, or employment, was kept above its long-run equilibrium at a "cost" of higher inflation, price setters and employees would eventually adjust their demands and expectations upward, weakening or even abolishing the tradeoff. Since then the Phillips curve has been revised to be consistent with such rational expectations, to what is called the New Keynesian Phillips Curve (NKPC). The NKPC is now a dominant approach to macroeconomic modeling (Alvarez, 2008).

Besides the magnitude of work seeking to model and explain pricing behavior, several papers of a more descriptive nature on pricing behavior have been published the last decades. Vermeulen et al. (2012) sum up the findings from European markets, based on individual papers from Belgium, France, Germany, Italy, Portugal and Spain. On average, they find that 21% of producer prices tend to change each month, with substantial heterogeneity. They also find the price changes to oftentimes be large relative to the inflation rate, indicating the presence of a selection effect.[1]

Nakamura and Steinsson (2008) do similar work on US data. They find a median price change frequency for finished-goods of 10.8%, with the 55th percentile being a frequency of 18.7%. The reasoning for this result lies in the substantial heterogeneity; most product categories with price change frequency above the median have a frequency substantially above 10.8%. Having presented these results, they conclude that finished-goods exhibit substantial price rigidity in the US.

The abovementioned statistics all indicate some degree of price rigidity in European and US producer prices. Though several models and explanations have been proposed toward explaining where the rigidity stems from, no collective agreement on the microeconomic

[1]Selection effect: As suggested by Caplin and Spulber (1987), firms choose to change the prices that are the furthest from the optimal price level when hit by a monetary shock

foundations has been reached. While Nilsen et al. (2018) find evidence of time dependency, menu costs and shocks related to state dependency does also seem to play a role in explaining price rigidity (Midrigan, 2011; Alvarez and Lippi, 2014).

2.2 State dependent models

State-dependent models assume rigidity in pricing behavior to originate from economic conditions. In these models firms have the ability to change their prices at any point in time, but face some sort of adjustment costs to do so. This causes price rigidity, as profit-maximizing firms consider this cost when setting prices (Romer, 2012). These adjustment costs are typically modelled either as convex costs or as "menu costs" (Blinder et al., 1998). In the models of convex costs adjustment costs are assumed to follow a convex function of the size of the price change. Thus, large price changes induce higher marginal adjustment costs. Rotemberg (1982) argue that such costs cause gradual price adjustment increasing the price rigidity. In the presence of convex adjustment costs we would expect to see a pattern of small and frequent price changes as large price changes would be penalized. To explain the presence of large price changes in the data, Nilsen and Vange (2019) propose a model combining the concept of convex adjustment costs with menu costs. This is consistent with the findings of Zbaracki et al. (2004) who find components of managerial and consumer costs to be convex, while physical costs are not. Moreover, they find the physical costs to be small compared to other components.

The concept of menu costs was first considered theoretically by Sheshinski and Weiss (1977). They propose that firms face a fixed cost of changing prices, independent of the size of the price change. Opposed with such costs the optimal pricing strategy would be to follow an (S,s) rule keeping the nominal price constant until the real price reaches a threshold s. As a result of this pricing strategy we would expect to see a price pattern with periods of inaction followed by relatively large price changes. The costs inducing this pattern has later been referred to as "menu costs" referring to the physical cost restaurants face when printing new menus. The term does not only cover the physical cost of changing prices, but also managerial and customer related costs associated with price changes (Zbaracki et al., 2004).

A shortcoming of the classical menu cost model is that it fails to explain small price changes (Klenow and Kryvtsov, 2008). To explain this Dotsey et al. (1999) introduce a stochastic menu cost model where the size of the adjustment costs are distributed independently across time and firms. This allows for small price changes as some firms face low adjustment costs reducing the adjustment threshold s. A similar approach is taken by Burstein (2006) studying the adjustment cost of pricing plans. Golosov and Lucas (2007) argue that these models do not allow for sufficient heterogeneity in terminal prices and propose an alternative model calibrated with micro price data. Inspired by Caplin and Spulber (1987) they suggest that firms choose to change the prices that are the furthest from the optimal price level when hit by a monetary shock. This selection effect reduces the price rigidity implying a high degree of monetary neutrality.

Newer literature on menu costs has focused on the multiproduct aspect of pricing behavior (Midrigan, 2011; Alvarez and Lippi, 2014; Bhattarai and Schoenle, 2014; Yang, 2019; Bonomo et al., 2020; Stella, 2020; Letterie and Nilsen, 2020). Lach and Tsiddon (1996) argue that multiproduct firms face economics of scope in menu costs as the marginal adjustment cost will fall if the firm decide to change more than one price. Midrigan (2011) illustrates this using the traditional restaurant example; if a single item on the menu needs repricing the restaurant will have to pay the cost of printing new menus. Conditional on paying this cost repricing other items on the menu will be costless. This can explain why we often observe small price changes in data, an observation that as mentioned contradicts the predictions of classical menu cost models (Lach and Tsiddon, 2007).

An implication of economies of scope in menu costs is that we would expect to see within-firm synchronization of price changes. Bhattarai and Schoenle (2014) find that when the price of one good in a firm changes there is a large increase in the probability that the price of other goods within the same firm change in the same direction. This synchronization is found to be stronger than the within-industry synchronization supporting the theory of economics of scope in menu costs. Dedola et al. (2019) support the findings of within-firm synchronization. They also find the probability of a negative price change to increase if other prices in the firm are changed upward. In other words, they find the probability of holding the price constant to be decreasing, while the probability of both upward and downward changes increase, supporting the theory of economics of scope in menu costs.

2.3 Strategic complementarity and synchronization

The concept of strategic complements and substitutes was first introduced by Bulow et al. (1985) to describe observed strategic interactions in oligopoly theory. Broadly they define two actions to be strategic complements (substitutes) if an increase in the action of one agent increases (decreases) the optimal action of the other agent. In terms of pricing decisions this means that if two goods are strategic complements it will be optimal to increase (decrease) the price of a good if the prices of other competing goods rise (fall).

The early literature on strategic complementarity in pricing was linked to the concept of coordination failure (Ball and Romer, 1991). Cooper and John (1988) derived an abstract game to prove how strategic complementarity can lead to multiple equilibria and a serve as multiplier of the effect of changes in exogenous variables. The different equilibria have corresponding welfare levels, and Cooper and John argue that strategic complementarity can explain how an economy might end up in a suboptimal low-activity equilibrium, as the actors in the economy fail to coordinate their actions.

The model derived by Cooper and John only contains real variables and thus their paper does not consider monetary non-neutralities. Ball and Romer (1990) argue that nominal rigidities causing monetary non-neutrality can be explained by a combination of real rigidities and frictions in nominal adjustment. In Ball and Romer (1991) they further develop this theory and show that strategic complementarity as a source of real rigidity, combined with menu costs causing nominal frictions, lead to multiple equilibria in the degree of rigidity. They propose that if firm i exhibit menu costs the price rigidity of firm j will increase as their optimal pricing strategy depend on the strategy of firm i. Thus, the presence of strategic complementarity amplifies the real effects of nominal frictions.

Synchronization of pricing decisions as a result of strategic complementarity may arise at different levels in the economy. Carvalho (2006) show how heterogeneity in price stickiness and strategic complementarities impact the rigidity of the aggregate price level as sectors with frequent price changes are influenced by slower adjusting sectors and vice versa. This relationship is found to be asymmetric as the slow adjusting sectors seem to have a disproportionate effect on the aggregate price level in the economy.

Bhaskar (2002) finds that strategic complementarities are stronger within an industry than at the aggregate level. He argues that the elasticity of substitution is greater for products within an industry than across industries, implying a higher degree of synchronization within industries. This is in line with the findings of Blinder et al. (1998) who find that competitive pressure and the desire to maintain or increase market shares are some of the main reasons why firms hesitate to raise prices when demand rises.

Despite the findings of synchronization researchers have questioned the magnitude of the amplification of nominal rigidities. Klenow and Willis (2016) find that a model with demand side strategic complementarity requires implausibly large idiosyncratic shocks to match micro level price changes. Burstein and Hellwig (2007) introduce a menu cost model with pricing complementarities calibrated with product level price data and market shares. They find that the complementarities are too weak to generate real effects. Nakamura and Steinsson (2010) suggest that the effect of strategic complementarity depends on if it stems from nonisoelastic demand and fixed factors of production, or real wage rigidity and sticky intermediate inputs. They find that strategic complementarity caused by the later mechanisms do not require unrealistically large menu costs or idiosyncratic shocks to match the data. However, the degree of complementarity is found to be quantitatively insignificant.

3 Data

The empirical analysis in this thesis is conducted combining two data sources, both supplied by Statistics Norway (henceforth SSB). The price data, with monthly records, is used to develop statistics such as the Norwegian producer price index (PPI) and the price index for first-time domestic sales (PIF) (SSB, 2020). These data are merged with structural data on the firms, with yearly records. The structural data allow us to investigate and control for attributes such as firm size (number of employees) and cost (wage) shocks in our analyses.

3.1 The pricing dataset

The overall pricing dataset consists of about 630 disctinct product groups, for which monthly prices are collected and divided into the subcategories domestic, import and export prices.[2] The pricing dataset applied in our analysis covers the years 2005-2016. The producer price index (PPI), developed on the grounds of this pricing data, is published monthly (SSB, 2020). Products registered in the dataset are subject to continuous revisions, implying that the price history will be of varying length across products.

As the main purpose of this paper is to consider pricing behavior within firms and industries, we do not consider the prices of import and export products. These prices are likely to be set considering different criterion than the domestic products, and analyzing them gives exposure to noise such as exchange rate movement (Letterie and Nilsen, 2020). Furthermore, export prices are irrelevant as they do not represent prices on products sold on the Norwegian market. Import prices could be relevant, but the exposure to exchange rate movement makes analyzing the data less desirable.

SSB applies several control mechanisms in the collection procedure: Large price changes relative to the last reported price are flagged; the collection schemes are manually controlled for administrative characteristics; product groups are randomly controlled to avoid reporting errors. In the case of non-reported prices in the monthly collection, follow-up is prioritized toward products that have a large influence on the aggregate levels

[2]Product groups defined by SSB, based on CPA (statistical classification of products by activity) classifications.

(SSB, 2020). The overall implication is that the data quality should be high and thus relevant to our micro-level research on producer pricing behavior.

3.2 Data categorization and aggregation levels

The dataset contains several identificators that are used to distinguish the observations. Each record in the base dataset contains an enterprise and a firm identificator. These identificators are relevant to separate different producers' price observations on comparable products. Furthermore, to distinguish the products, the dataset provides two product identificators; the statistical classification of products by activity (CPA) and the harmonized system (HS). In our analysis these product identificators are used to classify different industries.

3.2.1 Defining firms and enterprises

The distinction between an enterprise and a firm is rather formal. An enterprise is the legal, "top-level" entity that is required to report accounting on a regular basis. The enterprise, or group, oftentimes owns many firms. Rather simplistically, we refer to a firm as the entity producing related products and making day-to-day decisions on their product sortiment. The enterprise will typically have the power to overrule their firm's decisions. However, in the daily operations, it seems appropriate to assume that most decisions are conducted at the firm level. This reasoning also implies that the firm is the entity you will usually deal with in person. Furthermore, earlier work on Norwegian PPI data have mainly considered firm behavior. Thus, we conduct our analyses at the firm level.

3.2.2 Choice of product classification system

The statistical classification of products by activity (CPA) system is EU's standard for products grouped after industry, while the harmonized system (HS) is an international customs and statistical nomenclature (SSB, 2020). Both systems are specified to six digits internationally, while the harmonized system has additional national codes at the seven and eight digit level. The logic of the two classification systems is similar, with the first two digits defining the broad category, and the next four more closely specifying the given product (Eurostat, 2008; Norwegian Toll Customs, 2020).

In choosing between the two classification systems, a few observations are relevant. Firstly, as apparent from the name, the CPA is centered around activity type more so than a single end product. Being a customs nomenclature, the HS codes are more product centered. This is desirable for our analysis. Furthermore, the CPA code for what otherwise seems to be the same product, with constant or similar price, is at times changing from year to year. If a price change analysis is based on a code that changes from year to year, the product will be registered as a new product after the change, which is undesirable. This phenomenon is more prevalent in the CPA code system, although there are classification changes in the HS codes as well. Overall, the HS codes are the preferred classification system for our analysis. We refer to table 3.1 below for an overview of the system's structure.

Table 3.1: Illustrating example of the structure of the HS codes

HS-code	Name
Section I	Live animals; animal products
04	Dairy produce; birds' eggs; honey; edible products of animal origin
04.06	Cheese and curd
04.06.10	Fresh (unripened or uncured) cheese
04.06.10.01	Whey cheese
04.06.10.09	Other
04.06.20	Grated or powdered cheese, of all kinds
04.06.30	Processed cheese, not grated or powdered
04.06.40	Blue-veined cheese and other cheese containing veins produced by Penicillium roqueforti
04.06.40.01	Roquefort
04.06.40.05	Gorgonzola
04.06.40.07	Other
04.06.90	Other cheese
04.06.90.30	Feta and similar cheese
04.06.90.82	Camembert
04.06.90.84	Brie
04.06.90.97	Other, unpasteurized
04.06.90.98	Other

3.3 The firm structure dataset

Related to the pricing dataset, data on firm structure is also provided by SSB. These data cover all Norwegian firms, not only those represented in the price data. The data are provided with yearly records. The structure dataset contains enterprise and firm identificators equal to those in the pricing dataset, allowing us to match each firm in the pricing data with detailed firm structure data. Among other things, the structure data provide records on the number of employees, net revenues, hours worked, and wage bills. Furthermore, the dataset contains complete records of the relationship between the top-level enterprises and their subordinate firms. This information is used to 1) control for cost (wage) growth with regards to the pricing behavior, and 2) assess the generalizability of our data, comparing the firms represented in the pricing data to the average Norwegian firm.

From table A1.2 in the appendix we can see that the firms represented in the price data tend to have more employees than the average Norwegian firm. In addition, the firms are part of enterprises that are rather large. These findings are consistent across most industries in the dataset.

3.4 Merging and adjustments to the final dataset

3.4.1 Merging the pricing dataset

The datasets provided by SSB consist of separate data files for the respective years 2005-2016. Although significant portions of the products are observed across many years, we need to identify the products uniquely in order to analyze the pricing behavior over time. Although the HS codes are designed to identify and distinguish product categories, they do not identify products that are similar but still unequal within a given firm. Thus, the pricing data is matched across years using a short number, unique to each product within a firm. The final matching of price observations over time is thus conducted matching the products on the firm identificators, the HS code, and the short number.

As elaborated earlier, the HS codes are changing less than the CPA codes. Matching the price observations using HS codes is therefore the most precise method, and the CPA codes are excluded from our merged dataset. However, we still experience some breaks in product time series stemming from a change in HS code. These observations are still kept in the dataset, as they can be analyzed as new products. We do, however, lose duration on the pricing time series of these observations as a break in HS code leads to the product being defined as a new product.

3.4.2 Adjustments and final dataset

Some records in the data are incomplete. For instance, we have 334 observations without enterprise and firm identificators. These observations are dropped. Furthermore, 6241 observations have the HS-code "99999999", which represents the category "undefined". Also these observations are dropped, as the pricing behavior on these products cannot be interpreted meaningfully. About 7% of the prices are imputed by SSB as they are non-reported. This may lead to misinterpretation as the prices set by the firm are not necessarily observable to SSB. Thus, such instances are corrected by setting the imputed prices equal to the reported price at time $t-1$ following earlier work on the same data.

Next, the dataset has some observations with large price changes. We define large changes as price changes outside the interval [-0.49, 0,99].[3] If prices are reduced by more than 49%, or increased by more than 99%, they are likely related to a change of quality or even representing a new product. As such changes are unlikely to be normal price changes, 296 observations with large positive changes and 327 observations with large negative changes are dropped.

Finally, we exclude the SIC sectors representing mining and quarrying, water supply and sewage, and wholesale and retail.[4] These sectors are of little relevance when analyzing producer pricing behavior. In addition, mining and quarrying industries are known to have an abnormally high adjustment frequencies (Nilsen and Vange, 2019).

The final pricing dataset contains 208 391 price observations on 2880 products, distributed across 516 firms. For more details on the distribution of these observations across product categories, see table A3.1 in the appendix.

[3]The size of a price change is calculated using the formula $\frac{P_t - P_{t-1}}{P_{t-1}}$

[4]SIC: Standard Industrial Classification. An activity based industry classification system, found in the structure data.

4 Methodology

4.1 The frequency of price changes

Price adjustment behavior may be assessed on the intensive margin, focusing on the size of price changes, or on the extensive margin, assessing the discrete choice of changing prices or not. When calculating the price change frequency and synchronization behavior we consider price changes on the *extensive margin*. A consequence of this is that all price changes, independent of size, will be weighted equally when calculating the frequency.

Following the definitions of Baudry et al. (2004) our dataset consist of several sequences of price quotes, $P_{ijk,t}$, indicating the price of product i produced by firm j in industry k at time t. A sequence of unchanged price quotes is called a *price spell*, and a sequence of successive price spells is called a *trajectory*. Price spells and trajectories can be either *censored* or *uncensored* depending on the available data. A censored price spell is one without an observed start or ending point while uncensored ones have a defined start- and end-periods.

4.1.1 The frequency approach

The frequency of price changes can be found using two different methodological approaches: the frequency approach and the duration approach. As indicated by their names the frequency approach is based on the frequency of price changes as a share of price quotations in a given period while the duration approach computes the frequency as the inverse of the duration of the spells. The two methods give the same results as long as the data contain only uncensored price spells. This is because censored price spells must be excluded from the frequency calculation using the duration approach as they have unknown durations (Veronese et al., 2005). Aucremanne and Dhyne (2004) argue that excluding censored price spells might cause a selection bias as long price spells are more likely to be censored. As our data contain a relatively large proportion of censored price spells we use the frequency approach in our analysis. Using the frequency approach, the price change frequency can be calculated in the following steps:

First we define an indicator variable, $I_{ijk,t}$, indicating whether there has been a change in the price of product i produced by firm j in industry k from period $t-1$ to period t.

$$I_{ijk,t} = \begin{cases} 1 & \text{if } P_{ijk,t} \neq P_{ijk,t-1}, \text{ and } P_{ijk,t} \text{ and } P_{ijk,t-1} \text{ are both observed} \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

The sum of this variable, $\sum_{t=1}^{T} I_{ijk,t}$, gives the total number of price changes for product ijk.

Then we define a second indicator variable $J_{ijk,t}$

$$J_{ijk,t} = \begin{cases} 1 & \text{if } P_{ijk,t} \text{ and } P_{ijk,t-1} \text{ are both observed} \\ 0 & \text{if } P_{ijk,t} \text{ is observed, but not } P_{ijk,t-1} \end{cases} \tag{4.2}$$

$J_{ijk,t}$ indicates if the price of product ijk has been observed for two successive months. The sum of this variable, $\sum_{t=1}^{T} J_{ijk,t}$, will give the number of price quotes used in calculating the price change frequency of product ijk. As it is not possible to determine whether the first price in a trajectory is a result of a price change or not it will not be used in the calculation of the price change frequency, thus $J_{ijk,t}$ will be zero if a given price quote is the first one in a trajectory.

The price change frequency of a given product can be found using the defined indicator variables as the frequency, F_{ijk}, is given by the number of price changes as a share of the number of price quotes.

$$F_{ijk} = \frac{\sum_{t=1}^{T} I_{ijk,t}}{\sum_{t=1}^{T} J_{ijk,t}} \tag{4.3}$$

4.2 Where are pricing decisions made?

One important consideration for our analyses is where pricing decisions are made. Our dataset contains identificators of enterprises as well as firms, and pricing decisions should be attributed to one of the entities. We argue that, in the case of an enterprise owning multiple firms, day-to-day operating decisions like a price change is likely to be made by the firm. Typically, the enterprise is a governing body with auditory requirements, and the corporate management team and boards is situated in the enterprise part of larger organizations (Jones, 2013). We argue that the pricing decisions are likely to be delegated to the firm level in most cases, although it should be clear that "where pricing decisions are made" has no single answer.

Our final dataset contains a yearly average of 339 enterprises and 361 firms. Thus, the reality of the pricing dataset in isolation is that there is a 1-to-1 relationship between most firms and their associated enterprises in the price data. Thus, our results would at most change marginally depending on which entity is used in our analyses. However, the pricing dataset does not cover the full range of Norwegian ownership structures. Crosschecking the structure dataset, we find that many enterprises covered in the pricing dataset in reality have several underlying firms, although they on average only are represented by one or a few firms as shown in table A1.2.

4.3 Multiproduct aspect

To assess whether the pricing behavior changes with the number of products within a firm, we follow a procedure similar to Bhattarai and Schoenle (2014), Dedola et al. (2019), Letterie and Nilsen (2020) and a master thesis on multiproduct behavior by Leinum and Riise (2016). The idea is to group the firms into bins in which the behavior is likely to be similar. The bins are used in several parts of the empirical analysis; initially, we investigate how price change frequency and other descriptive measures on pricing behavior change over bins. Then, the bins are used to assess whether price change synchronization, both within-firm and within-industry, changes with the number of products the firm produces.

4.3.1 Computing multiproduct bins

The first stage of making the bins is to compute the average number of products firm j has across the time periods the firm is represented in the dataset ($\overline{Z}_j$). As the average is computed over periods in which a firm is represented in the data, the average will never be below 1. The result is in most cases a decimal number. This calculation is then used to group the firms into the following bins;

$$Bin = \begin{cases} 1-3 & \text{if } 1 \leq \overline{Z}_j < 3 \\ 3-5 & \text{if } 3 \leq \overline{Z}_j < 5 \\ 5-7 & \text{if } 5 \leq \overline{Z}_j < 7 \\ >7 & \text{if } \overline{Z}_j \geq 7 \end{cases} \tag{4.4}$$

To maximize comparability to the aforementioned studies using similar PPI datasets, we have chosen bin sizes similar to these papers. We have investigated whether the results change when defining the bins differently, either through making larger or smaller bins. The results do not differ much qualitatively, although the exact point estimates differ. Prioritizing comparability, we use the bin definitions of previous papers.

4.3.2 Computing bin-level statistics

Using bins, we present estimates of how the price change frequency and the size of price changes relates to the number of products within firms. Calculating such measures is done in three steps, following the procedure of Bhattarai and Schoenle (2014). First, we calculate the measures at the product level. Thus, we first calculate a product specific price change frequency, or the absolute percentage value of each price-change on a product. Next, we find the median of these measures across the products within a firm. The final step is to calculate the average of these numbers within the bins the firms are grouped in.

4.3.3 A note on product sortiments

A potential problem with the binning procedure may arise if the number of products within a firm varied widely across periods. The consequence would be that some firms could be grouped into the wrong bins for large periods of the analysis. For instance, a firm could have an average of 3.1 products, and thus being grouped into the bin "3-5". In reality this firm could have 2 products for most of the timespan, and then 7 products for a short period of time. However, we argue that this problem is minimal:

Firstly, we refer to the sampling procedure of SSB. The procedure revolves around selecting relevant and representative products for a given category, and then following the specific products over extended periods. The product sample is only revised yearly by SSB, implying that random noise and large changes in product sortiment are rare happenings.

We have also investigated the development in products per period within-firm more formally. Having generated a variable counting the observed number of products within firm j and industry k in period t ($Z_{jk,t}$), we can investigate the typical change in the size of the product sortiment by defining a variable:

$$\Delta Z_{j,t} = \sum_{k=1}^{K} \left(Z_{jk,t} - Z_{jk,t-1} \right) \tag{4.5}$$

The mean change in product sortiment is -0.0004, with a standard deviation of .32. Only 0.7% of the observations include a change in product sortiment outside the [-1, 1] interval, while close to 2% of the observations have a change in product sortiment of exactly +/- 1 product. Thus, our conclusion is that the binning procedure yields the correct bin in most periods for all firms. Furthermore, mistakes can be assumed to be averaged out, as changes in product sortiment in the dataset occurs randomly across firms.

4.4 Price change synchronization

4.4.1 Measuring price change synchronization

To measure the degree of synchronization within-industry and within-firm, we employ a method similar to Bhattarai and Schoenle (2014), Dedola et al. (2019) and Letterie and Nilsen (2020). The aim is to quantify to which degree price changes on other products within the firm, or within the industry, have an effect on the probability of a price change. To estimate the degree of within-firm synchronization, we calculate the fraction of products within the firm that change price upwards (downwards), excluding the product we are trying to explain. To do this we first define two binary variables, $U_{ijk,t}$ and $D_{ijk,t}$, indicating whether a price change is positive or negative, where $I_{ijk,t}$ is the previously defined variable indicating a price change.

$$U_{ijk,t} = \begin{cases} 1 & \text{if } P_{ijk,t} > P_{ijk,t-1} \text{ and } I_{ijk,t} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4.6}$$

$$D_{ijk,t} = \begin{cases} 1 & \text{if } P_{ijk,t} < P_{ijk,t-1} \text{ and } I_{ijk,t} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4.7}$$

The fraction of within-firm positive and negative price changes ($UF_{ijk,t}$ and $DF_{ijk,t}$) is then given by the sum of these variables over the sum of price observations for firm j at time t, excluding the good we are trying to explain.

$$UF_{ijk,t} = \frac{\left(\sum_{i=1}^{I}\sum_{k=1}^{K} U_{ijk,t}\right) - U_{ijk,t}}{\sum_{k=1}^{K} Z_{jk,t} - 1} \tag{4.8}$$

$$DF_{ijk,t} = \frac{\left(\sum_{i=1}^{I}\sum_{k=1}^{K} D_{ijk,t}\right) - D_{ijk,t}}{\sum_{k=1}^{K} Z_{jk,t} - 1} \tag{4.9}$$

The intuition behind using such fractions is the following: "*If a firm changes 20% of its other product prices in a given period, does this impact the probability of changing the price on this product, and if so - by how much?*". By excluding the product we are trying to explain from the fraction calculations, we avoid issues of simultaneity bias between the independent and dependent variables.[5]

4.4.2 Measuring industry synchronization

We calculate similar fraction measures to those within-firm to capture industry synchronization. In many cases, a single firm has multiple products in the same industry, whether we define the industry at the 4 digit or 6 digit HS level. For more depth on this issue, we refer to table A2.1 in the appendix. For instance, several industries on the HS4 level have 3 products, of which 2 are produced by the same firm.

When calculating the fraction of price changes within the industry, we must first decide what to do with competing products within a firm. Bhattarai and Schoenle (2014) do not specify how they handle such internal but seemingly competing products. If we

[5]See Wooldridge (2016), p. 538. for a detailed explanation of the concept simultaneity bias

assume that price changes within an industry are largely driven by industry specific shocks and competitive forces, we argue that including products that are sold by the same firm would be correct. Furthermore, by excluding all within-firm price changes from the industry fractions, we implicitly make the stance that within-firm synchronization is more important, and that two price changes from the same firm cannot stem from forces in the industry. This is a clear drawback.

Keeping all changes within-firm in the industry fractions, the aim is to capture price change synchronization between related and/or competing *products*. However, including within-firm price changes in the industry price-change fractions does have drawbacks as well. There is a correlation between the within-industry and within-firm fractions as several industries only contain a single firm, as shown in figure A2.1. This could potentially cause a problem of multicollinearity, leading to lower precision and larger standard errors of the estimated coefficients. However, it does not lead to biased estimates (Wooldridge, 2016).

Our preferred measure of industry synchronization is the fraction of changes within the industry not correcting for whether competing products are produced by the same firm. This has the advantage of not attributing all price changes within the firm to within-firm price change synchronization. These fractions are also in line with the work of Dedola et al. (2019). The within-industry fractions are calculated summing the number of upward and downward changes over all products (i) and firms (j) for each industry in a given time period, excluding the good we are trying to explain:

$$UI_{ijk,t} = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J} U_{ijk,t} - U_{ijk,t}}{\sum_{j=1}^{J} Z_{jk,t} - 1} \tag{4.10}$$

$$DI_{ijk,t} = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J} D_{ijk,t} - D_{ijk,t}}{\sum_{j=1}^{J} Z_{jk,t} - 1} \tag{4.11}$$

4.4.3 Level of industry aggregation

To measure industry synchronization we first have to define what we consider an industry. In the industrial organization literature there is no single definition of a market or an industry (Tirole, 1988). Robinson (1933) suggest that you can define a market by starting with one good and look at the substitutes of this good. Then, you find the substitutes of the substitutes and continue until you find a gap in the chain of substitutes. Another approach is to use prices to define industries. Goods in an industry are likely to be hit by the same supply and demand shocks. Thus, we expect the prices of goods within an industry to correlate (Tirole, 1988). Tirole also points out that an industry should not be defined too narrowly, as that would lead to few substitutes; nor should it be defined too broadly, as the markets defined should allow a single description of the main interactions among firms.

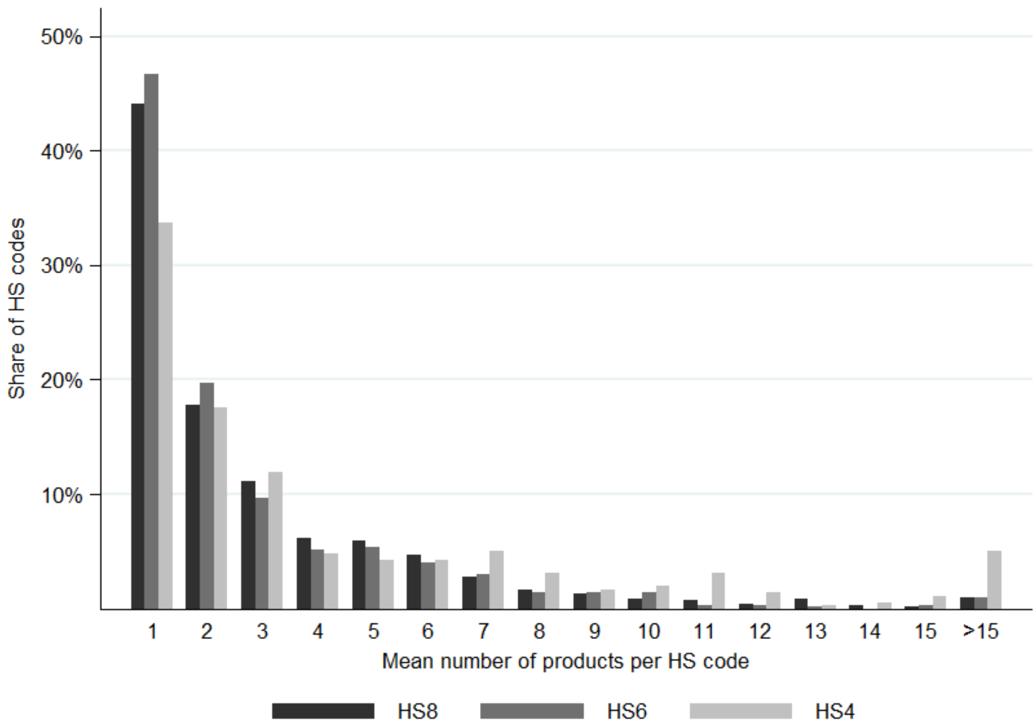
On the two digit level each HS code represent a broad variety of products, e.g. 04 "dairy products" and 70 "glass and glassware". Even though one could argue that there is some level of substitutability between products within these categories we find them too broad; dairy products include subcategories ranging from milk, to cheese, to natural honey. Thus, we prefer disaggregating further, as the strategic complementarities are likely to be stronger at a more disaggregated level.

In a paper aiming to estimate the effects of monetary policy on pricing behavior Balleer and Zorn (2019) control for industries at the 4-digit level using Elementary Price Indices (EPIs) for all major industrial products. The EPI classification system is specified to 9 digits, but the German statistical bureau (FSO) only provides statistics at the 4-digit level for data disclosure reasons. Balleer and Zorn provide an example of the 4-digit level categorization as "Processed and Preserved Potatoes". This is highly comparable to the aggregation in the HS codes, where 07.01 represents "Potatoes, fresh or chilled".

Furthermore, Bhattarai and Schoenle (2014) measure within-industry synchronization using NAICS (North American Industry Classification System) codes at the 6-digit level. The NAICS is activity based, with the 6-digit level representing for instance 111211 "Potato Farming" or 311421 "Fruit and Vegetable Canning" (NAICS, 2020). In light of the arguments made by Bhaskar (2002) that price synchronization is more probable between products of high substitutability, we argue that the HS codes are advantageous to the NAICS codes used by Bhattarai and Schoenle. This because we believe the HS codes represent more closely defined product groups than an activity based system such as NAICS.

To estimate industry synchronization we need at least two products within an industry. From figure 4.1 we can see that, on all aggregation levels, a substantial part of the unique HS-codes only have one product in our sample. This fraction is largest at the HS6 level where 47% of the HS codes on average have one single product. At the 4-digit HS level, 67% of the observed products have relevant competing products[6], which yields substantial amounts of data for the measurements. Additionally, we are aiming for comparability to Bhattarai and Schoenle's study. Bearing in mind that Balleer and Zorn (2019) employed 4-digit EPI product categorizations and that these codes are relatively comparable to the 4-digit HS codes, the 4-digit level is the aggregation level applied throughout our analysis.

Figure 4.1: Number of products per HS code



Note: The mean number of products per HS code is calculated by first finding the distinct number of products with a given HS code in a given year. The yearly numbers are used to find a mean number of products represented in each code. This mean is then rounded to the closest integer. Furthermore, we find the number of HS codes with on average one product represented in the sample etc. This number is divided by the total number of distinct HS codes in our dataset to find the share of HS codes with a given number of products.

[6]Although 67% of the products have competitors, parts of these are within-firm. Looking at appendix A2.1, we see that 39% of the HS codes involves multiple firms at the HS4 level

4.4.4 The multinomial logistic model

To measure the degree of synchronization of price changes we want to see how the probability of changing the price of a product varies with the fraction of price changes of other products within the same product category, or other products within the firm. In every period the firms can choose between three mutually exclusive actions; increase prices, decrease prices or keep them unchanged. These kind of categorical responses can be modeled using a set of multinomial models.

If the categories can be ranked one could use ordered logit or probit models. In our case the categories could be said to be ranked as keeping prices unchanged rank below increasing prices and above decreasing prices. A key assumption of these ordered models is the proportional odds assumption stating that the relationship between each pair of outcome groups is the same, giving one set of model coefficients. In our case this would mean that if a one unit increase in the fraction of industry price changes increase the odds of a positive price change by X relative to the other categories, it would also increase the odds of a positive price change or keeping the price constant relative to a negative price change by X. As emphasized by Ball and Mankiw (1994) firms tend to behave differently when increasing and decreasing prices. Thus the proportional odds assumption is not likely to hold in our case and we will proceed with an unordered model.

The most frequently used unordered model is the multinomial logit model (Long and Freese, 2006). The model uses the logistic distribution to model the probability of an outcome as a function of the independent variables. It can be explained using a latent variable model. A continuous latent variable $p_{itj}*$ can be expressed as:

$$p_{ijk,tc}* = \beta_c x_{ijk,t} = \gamma_{c1} UI_{ijk,t} + \gamma_{c2} DI_{ijk,t} + \rho_{c1} UF_{ijk,t} + \rho_{c2} DF_{ijk,t} + \phi_c z_{ijk,t} + \epsilon_{ijk,t} \quad (4.12)$$

UI and DI give the fractions of positive and negative price changes in the industry and are included to estimate the within-industry synchronization of price changes. UF and DF give the fractions of price changes of other products produced by the same firm to estimate the within-firm synchronization. We have also included a set of control variables to control for exogenous shocks, represented by vector z. These include yearly and monthly dummies to control for seasonal and yearly effects, and the sector specific PPI to control for aggregate shocks to the industries. We also include wage per worker, logarithmically transformed, to control for cost shocks. Conditional on these variables the observed price change can be expressed as:

$$p_{ijk,t} = \begin{cases} -1 & \text{if } -\infty < p_{ijk,tc}* < \tau_1 \\ 0 & \text{if } \tau_1 < p_{ijk,tc}* < \tau_2 \\ 1 & \text{if } \tau_2 < p_{ijk,tc}* < \infty \end{cases} \tag{4.13}$$

The parameters are estimated using the maximum likelihood estimation. As explained by Davidson and MacKinnon (2004) this is done by maximizing the loglikelihood given by:

$$\sum_{ijk}\sum_{t}\left(\sum_{c} I(p_{ijk,t} = c)\beta_c x_{ijk,t} - ln\Big[\sum_{c} exp(\beta_c x_{ijk,t})\Big]\right) \tag{4.14}$$

Where $I(p_{ijk,t} = c)$ is an indicator function taking the value of 1 if the observed pricing decision equals c and 0 otherwise. The probability of a given outcome $c = \{-1, 0, 1\}$ can then be expressed as:

$$Pr(p_{ijk,t} = c|x_{ijk,t}) = \frac{exp(\beta_c x_{ijk,t})}{\sum_c exp(\beta_c x_{ijk,t})}, \tag{4.15}$$

4.4.5 Interpreting the model coefficients

The output of a multinomial logit regression gives coefficients of the outcomes relative to a selected base outcome. The estimated parameters can be interpreted as the change in log odds of the outcome relative to the base outcome. This interpretation has limited practical applicability and the results of multinomial logistic regressions are therefore usually reported in terms of odds ratios, predicted probabilities or as the marginal effects of a change in an independent variable on the probability of a given outcome (Long, 1997). Thus, our model results are presented using marginal effects and visualized using predicted probabilities.

5 Empirical Analysis

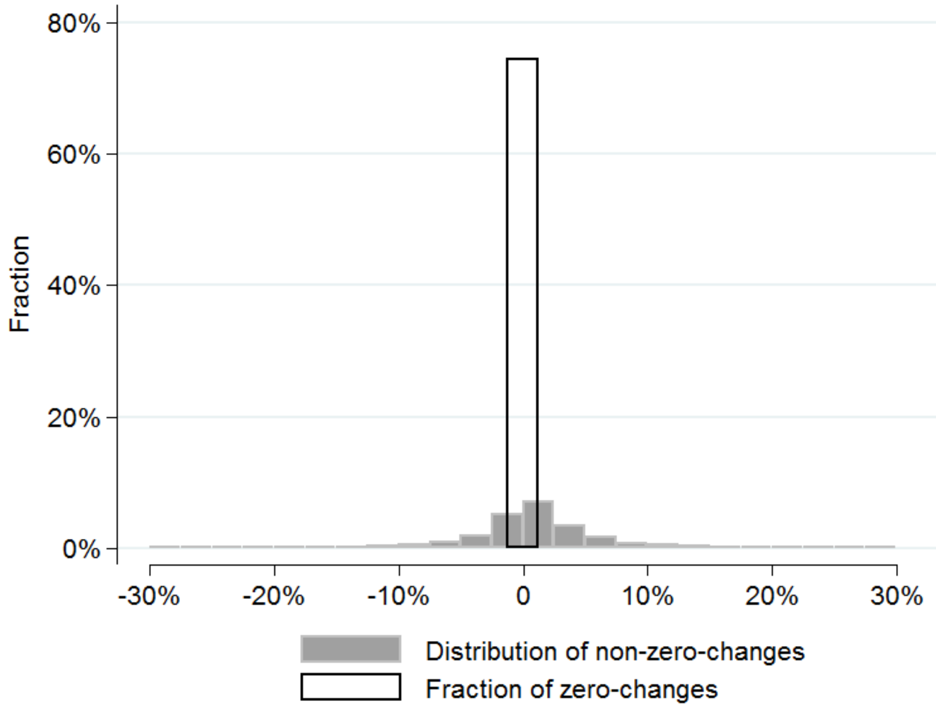
Research on pricing behavior is important to optimize monetary policy as well as to understand the welfare consequences of business cycles (Nakamura and Steinsson, 2008). As our dataset is rather large, covering 12 years of producer pricing, it is well-equipped to shed new light on behavioral tendencies and price change synchronization within firms and industries.

5.1 Aggregate summary statistics

In our data we find a mean price change frequency of 24.7%. The median price change frequency is found to be 9.4%. This points to the heterogeneity in the data; large shares of the dataset have infrequent price changes, while those who change price more often have a very high price change frequency. For instance, the 90th-percentile of products have a price change frequency of 85.7%.

Among other aggregate statistics, the absolute percentage size of price changes has a mean (median) size of 5.0% (2.5%). The median size of upward changes is 2.7%, while the median downward change is -2.3%. These numbers are in line those of Vermeulen et al. (2012), who present statistics for several European countries. They find a median price increase of 3% and a median decrease of 2%. The distribution of the size of price changes is visualized in figure 5.1 on the next page. The figure indicates that price changes outside the [-10%, 10%] interval are rather rare. We can also see that a large majority of the price changes are in the interval [-2.5%, 2.5%]. Contrasting this to the theory of menu costs, one could thus argue that the selection effect seems to be of low importance, as there is little evidence of large price adjustments being the norm.

Figure 5.1: Distribution of price changes



Note: The figure gives the distribution of the price changes observed in the dataset as the percentage change from one period to the next. The horizontal axis gives the percentage price change and the vertical axis gives the fraction of observations within a given interval of percentage price changes. The outlined bar gives the fraction of zero-changes, meaning the fraction of price quotes in the dataset where the price does not change from one period to the next.The gray bars give the distribution of the percentage change of the price changes excluding these zero-changes. Price changes outside the [-30%, 30%] interval (in total 0.4% of the observations) are excluded from the figure.

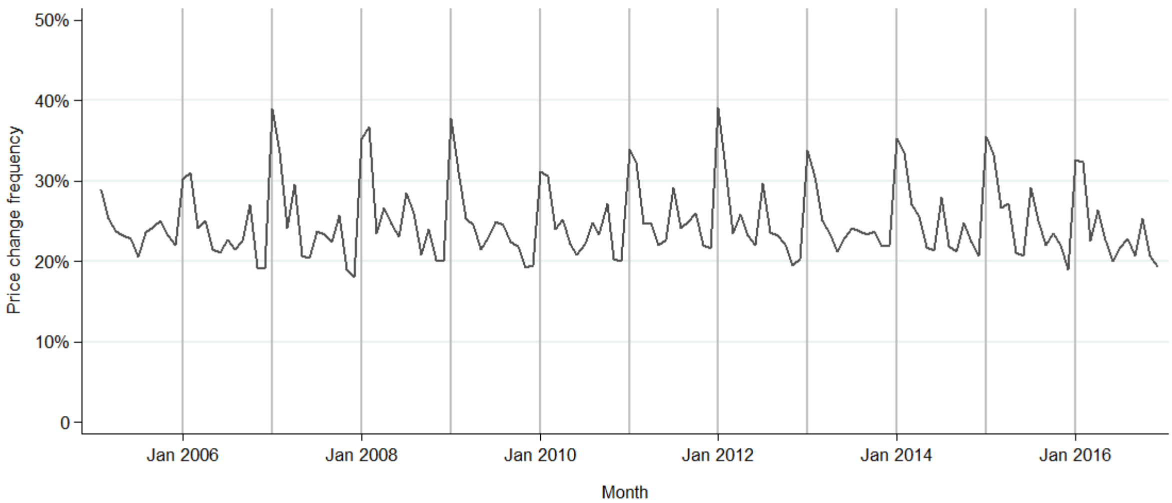
Further, as is to be expected in an inflationary environment, more price changes are positive than negative: 59.9% of the observed price changes in the sample are upward changes. This can be compared to the average for the Euro area, which exhibits an average price change frequency of 21% of which 12% are upward changes, implying that 57% of the price changes are upward (Vermeulen et al., 2012). The time span covered by Vermeulen et al. goes from mid-to-late 1990s until mid 2000s, and the average PPI inflation hovers around 2%.[7] This implies that the data is highly comparable to the Norwegian dataset as the average yearly PPI inflation in Norway from 2005 to 2016 was 2.1% (SSB, 2020).

The data also points to clear seasonality trends, with substantial excess price change frequency each January. The mean price change frequency in January is 34.9%, while the

[7]Both the mean PPI inflation for the Euro area, and the PPI inflation for each country represented in the data, is depicted graphically in Vermeulen et al. (2012) figure 3. In an earlier working paper they give the exact averages to be 1.0% in Germany, 0.7% in France, 1.5% in Italy, 2.1% in Spain, 1.5% in Belgium and 1.7% in Portugal (Vermeulen et al., 2007)

lowest mean frequency appears in December, with 20.1%. Only February appears to be even close to the excess frequency in January, having a mean frequency of 32.1%. This points to large shares of price changes appearing early in the year. The seasonality of price changes is visualized in figure 5.2 below. The figure clearly underlines the importance of controlling for seasonality in our multinomial logit models.

Figure 5.2: Price change frequency, 2005-2016



Note: Monthly frequency of price changes from January 2005 to December 2016. The frequency is calculated as the number of price changes within a given month divided by the number observations in that month. If the price quote is the first one in a spell it is not included in the denominator as there is not possible to tell whether there has been a change in the price or not.

5.2 Pricing behavior across product groups

As can be seen from Norwegian Toll Customs (2020), the HS codes are divided into 20 product sections. Table 5.1 presents the mean and median price change frequency across these product sections, and the share of price observations the section has in the dataset. The table indicates that there is substantial heterogeneity across product groups. This is in line with the findings of previous research on pricing behavior (e.g. Vermeulen et al., 2012; Nakamura and Steinsson, 2008; Nilsen et al., 2018).

Table 5.1: Mean and median frequency over HS sections

	Section	Price change frequency Mean	Price change frequency Median	Share of dataset
1	Meat	41.2	29.4	4.1
2	Vegetables	20.3	10.5	1.2
3	Fats and oils	33.0	11.9	0.5
4	Prepared foodstuffs	34.5	16.1	16.8
5	Minerals	26.9	10.2	1.6
6	Chemicals	25.3	7.6	9.2
7	Plastic articles	28.2	8.4	5.7
8	Skin and leather articles	6.4	3.5	0.8
9	Wood articles	34.6	15.8	8.7
10	Paper	29.2	12.9	3.1
11	Textiles	12.2	6.3	4.6
12	Other personal apparel	2.3	0.0	0.1
13	Stone and glass	22.0	8.4	6.2
14	Precious metals	15.5	8.4	0.9
15	Metallic products	22.6	7.4	10.8
16	Machines	12.2	7.0	15.2
17	Vehicles	11.5	10.9	2.0
18	Measuring instruments	17.2	6.3	2.4
20	Misc. articles	24.7	9.1	6.1

Note: All numbers are in percentages. Price change frequencies are first calculated on the product level as the number of price changes over the number of observations for a given product. Section mean and median gives the mean and median frequencies of the products within a section. Section names are abbreviated. Full names can be found in appendix A1.1. Further descriptive statistics on section level can be found in appendix A3.1.

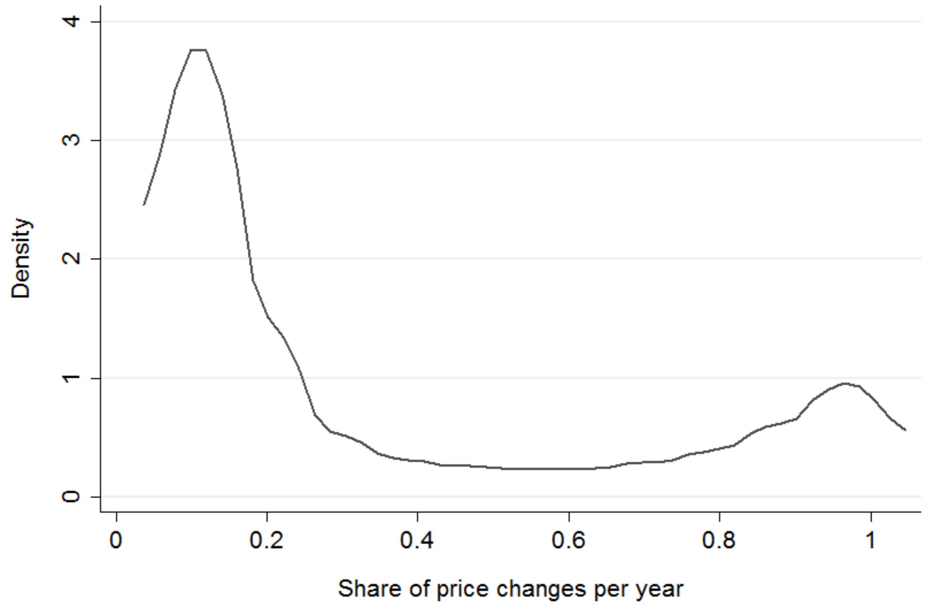
Perhaps somewhat surprisingly, the food-related sections 1-4 are exhibiting rather high price change frequency. However, all prepared food products belong to section 4 (prepared foodstuffs). Processed meat products such as sausages or beefs belong to section 4; section 1 (meat) typically represents intermediate goods not yet fully processed for consumption.

Vermeulen et al. (2012) report that processed food has an average price change frequency across Europe of 27%. In all countries reported except for Belgium, processed food exhibits significantly higher price change frequency than the average across the whole sample. Our findings are in line with these numbers, although the estimated frequency is somewhat higher.

Having an overview of the pricing behavior across product groups, we turn to considering the differences in behavior. Figure 5.3 plots the kernel density distribution of the share of price changes per year. Products with one price change a year have a share of $1/12 =$

0.083. Thus, the figure indicates that there is a large group of products with one to two price changes a year, and a second group of products with highly frequent price changes.

Figure 5.3: Kernel density distribution; share of price changes per year

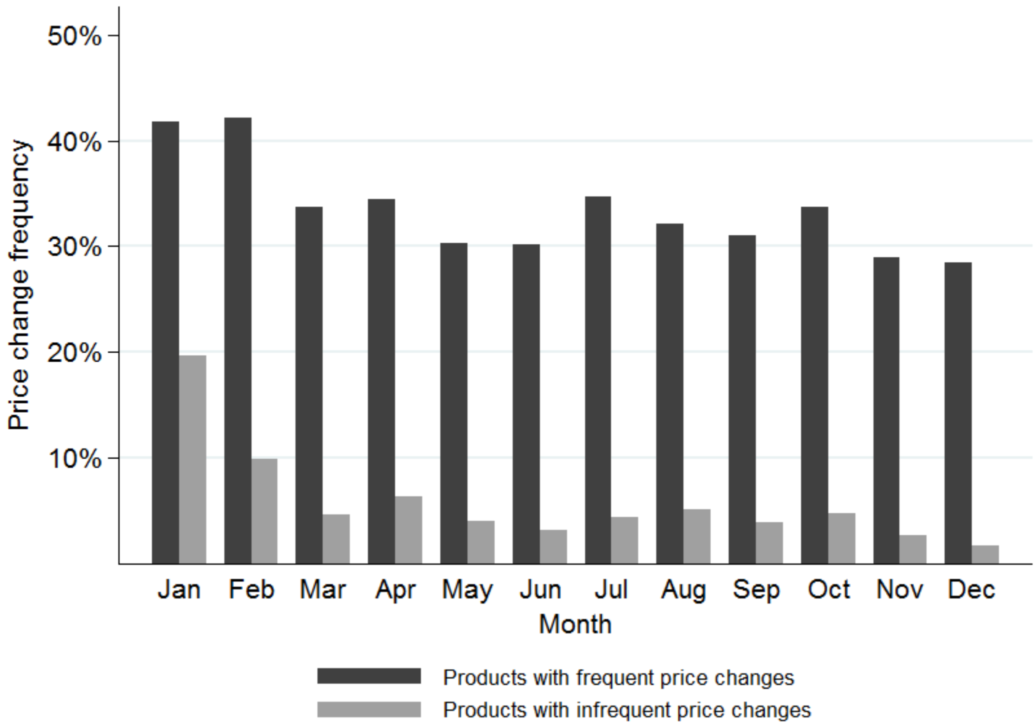


Note: For each product the number of price changes in a given year is divided by the number of price observations. The kernel density plot gives the distribution of this yearly share of price changes. We use the share of price changes rather than the number of price changes as some products are included for less than 12 months in a given year.

Motivated by the density plot, we have grouped the HS 4-digit product groups into the behavioral categories "frequent" and "infrequent" price changes. If a HS 4-digit product group has an average share of price changes below 0.09 per year, i.e. slightly above one change per year, it is defined to be a group with "infrequent" price changes. This categorizes 31% of the distinct products as infrequent price changers, and 69% as frequent changers. As the products are grouped according to the mean share of changes in their HS 4-digit code, some products will have behavior different to their peers. Details on the grouping is shown in the appendix, figure A3.1.

Figure 5.4 indicates that both the frequent and infrequent groups have excess price change frequency in January and February. The price change frequency in January relative to the frequency in the remaining months is clearly larger in the infrequent group, as could be expained by the presence of explicit contracts with a one-year duration (Alvarez et al., 2006). As discussed by Nakamura and Steinsson (2008), there also appear to be some degree of quarterly excess price change frequency, with April, July and October exhibiting somewhat higher price change frequency than their nearby months. Although the frequency of price changes seems somewhat more evenly distributed in the product groups categorized as frequent changers, also this group exhibits excess frequency early on in the year.

Figure 5.4: Monthly price change frequency



Note: Monthly price change frequencies are given as the number of price changes in a given month divided by the number of observations in that month.

5.3 Multiproduct behavior

Across the whole sample, the dataset includes 516 distinct firms and 2880 products. The average numbers per year are 361 firms and 1469 products. The mean (median) number of products per firm is 3.71 (3). Thus, it is clear that multiproduct firms are largely prevalent in the economy. We group all firms in the dataset into bins depending on the average number of products they are represented with per period. The bins are outlined in table 5.2.

Table 5.2: Summary statistics by multiproduct bins

	Number of products			
	1-3	3-5	5-7	>7
Number of firms	280	116	68	52
Number of products	636	721	629	894
Share of dataset	21.1%	25.2%	22.9%	30.8%
Mean number of products	1.8	4.2	6.2	10.3
Standard error of mean	0.1	0.1	0.1	0.5
Std. Dev. number of products	0.8	0.6	0.5	3.6
25% percentile	1.0	3.8	5.9	7.8
Median	1.9	4.0	6.0	9.4
75% percentile	2.7	4.8	6.7	10.9
Minimum number of products	1	3.0	5.1	7.2
Maximum number of products	3.0	5.0	7.0	25.4
Mean employment	99.9	85.0	88.6	156.5
Median employment	49.3	52.9	56.8	74.8
Mean empoyment per product	69.4	20.9	14.6	15.2

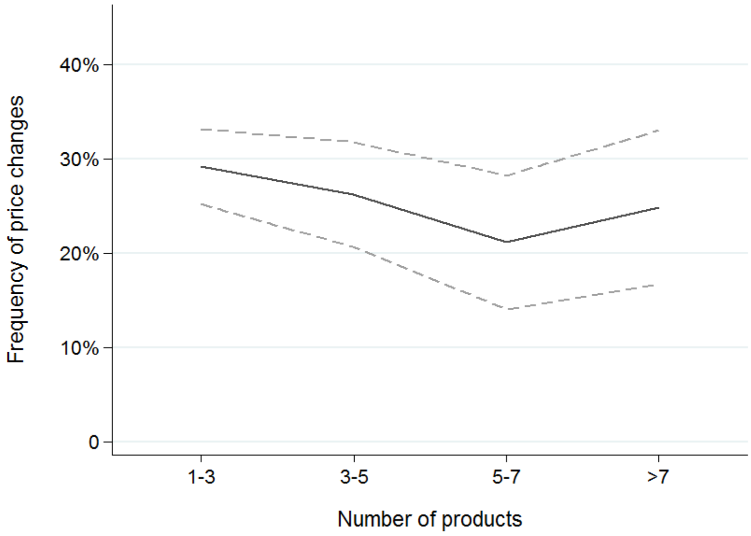
Note: All firms are classified based on the mean number of products over the periods the firm is represented in the dataset. The number of firms and products gives the total number of firms and products in a bin over the total sample period. Bin level descriptive statistics on the number of products are calculated based on the mean number of products of the firms in a given bin. To find the mean and median employment we first find the mean number of employees in each firm. The mean and median are calculated by taking the mean and median of this mean value across all firms in a bin. Mean employment per product is found by dividing the mean employment by the mean number of products in each firm.

We see that the largest fraction of price observations stem from firms grouped in the >7 bin. These firms are rather large relative to the average Norwegian firm, having a mean (median) of 156.5 (74.8) employees. There are rather few firms in the larger bins, but as they have more products, they account for large shares of our observations. In terms of number of firms, most firms belong to bin 1-3. It should also be noted that the firms in bin 1-3 are not necessarily small; they might just be represented with fewer products in the sample on average. Firms in bin 1-3 have a median employment quite close to those in bins 3-5 and 5-7, while their mean employment is actually above bins 3-5 and 5-7. This indicates that there are some relatively large firms grouped into bin 1-3.

5.3.1 The frequency of price changes

A natural point of departure is to investigate how the price change frequency changes with bins. Lach and Tsiddon (1996) argue that firms face economies of scope in menu costs, meaning that changing price on multiple products is costless once paying the cost of changing the price of one products. Thus, the intuition would be that the price change frequency should increase with the number of products.

Figure 5.5: Mean price change frequency over bins



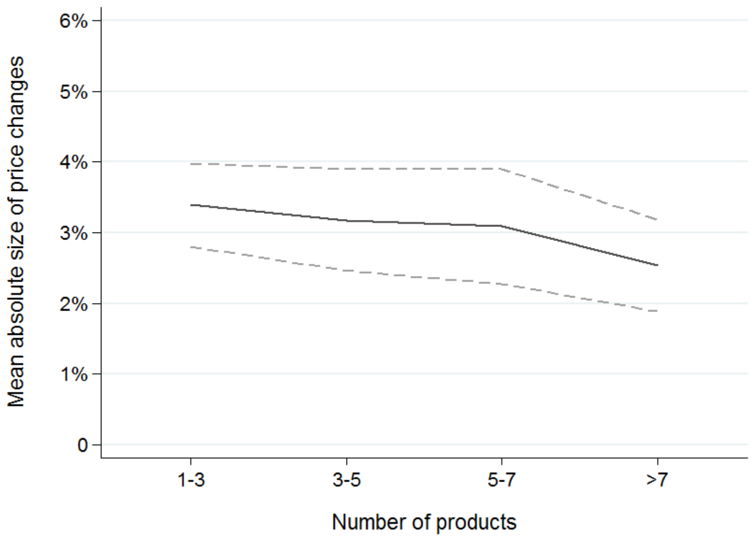
Note: To find the mean price change frequency in each bin we first calculate the product level frequencies. Next, we find the median frequency across all products in each firm. The bin level mean frequency is given by the average of these median frequencies. The dashed lines represent the 95% CI. They are given by +/- 1.96 times the standard error across firms.

The middle line represents the estimated price change frequency in the respective bins, and the dashed lines represent the confidence interval, calculated as +/- 1.96 times the standard error of the mean frequencies across firms. We see that the calculated frequency starts somewhat high, before falling as the number of products increase, then increasing going from bin 5-7 to >7. This result is close to that of Leinum and Riise (2016), who did a similar analysis for the years 2005-2009. However, as indicated from the figure, the trend is not significant. Thus, we do not find any evidence of the frequency increasing with the number of products. This is quite different to Bhattarai and Schoenle (2014), who find a significant increase in frequency as the number of products increase. On the contrary, our results are in line with Dedola et al. (2019), who write that *"the frequency of price changes is broadly independent of the number of goods per firm"* analyzing Danish PPI data.

5.3.2 The size of price changes

As elaborated earlier, the aggregate mean (median) absolute percentage size of price changes is 5.0% (2.5%). If economies of scope in menu costs are relevant in explaining pricing behavior, we would expect firms with multiple products to have smaller price changes, as even small price changes can be beneficial when the adjustment costs are shared between several products.

Figure 5.6: Mean absolute size of changes over bins



Note: To find the mean absolute size of price changes in each bin we first calculate the mean absolute size of price changes at the product level. Next, we find the median absolute size across all products in each firm. The bin level mean is given by the average of these median absolute sizes. The dashed lines represent the 95% CI. They are given by +/- 1.96 times the standard error across firms.

From figure 5.6, we see that the absolute size of price changes seem to be somewhat declining with the number of products within firms.[8] However, the differences does not appear to be significant, except for the difference between bins 1-3 and >7. The trend is similar to the one found by Leinum and Riise (2016), but their analysis found no significant differences. Although our results point in the same direction as Bhattarai and Schoenle (2014), their results differ as they find a significant difference between all bins. Furthermore, their mean absolute size of price change are significantly higher, with bin 1-3 having a mean absolute size of 8.50%, falling to a mean of 6.6% in bin >7. Thus, some of the differences in results are likely to stem from differences in the underlying data, with

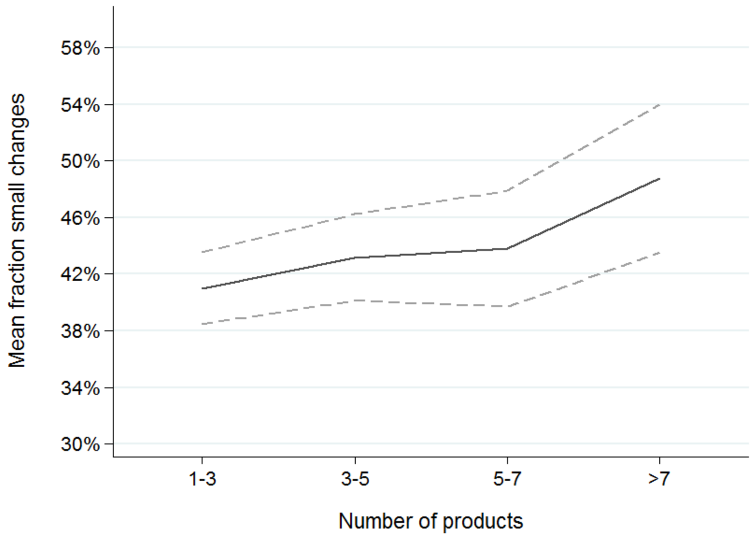
[8]Figure 5.6 plots the mean absolute size of changes. For details on the mean size of positive and negative changes separately we refer to figure A3.2 in the appendix

our dataset having a lot of changes in the interval [-2.5%, 2.5%]. The mean absolute size of changes is about half the size of Bhattarai and Schoenle's results for the US.

5.3.3 The fraction of small changes

In relation to the mean absolute size of changes, a relevant statistic is the fraction of small changes. A change is classified as small if it is smaller than 0.5 times the mean absolute percentage size of price changes within the firm, following Midrigan (2011).

Figure 5.7: Mean fraction of small price changes



Note: We define a small change as a change that is smaller than 0.5 times the firm level mean absolute percentage change. To find fraction of small price changes in each bin we first calculate the fraction of small price changes in each firm. The bin level mean is given by the average of the firm level fractions. The dashed lines represent the 95% CI. They are given by +/- 1.96 times the standard error across firms.

Figure 5.7 indicates that the fraction of small changes increases in the number of products, with bin >7 having the largest fraction of small changes, with 49%. Furthermore, the confidence intervals indicate that firms in bin >7 have significantly more small changes than all other bins. Although the exact values of our fractions differ somewhat from those calculated by Bhattarai and Schoenle (2014), this result points in the same direction as their estimates. Their estimates indicate that the fraction of small changes in bin 1-3 is 38%, while bin 7 has a fractiton of small changes at 55%; our results indicate a range from 41% in bin 1-3 to 49% in bin >7.

5.3.4 Discussion of results: Multiproduct behavior

In the presence of scope economies in menu costs, one would expect the price change frequency and the fraction of small changes to increase, and the mean size of changes to decrease with the number of products within-firm. Similarly to Leinum and Riise (2016) using a comparable dataset over the years 2005-2009, we find the expected results except for when considering the price change frequency. Firms producing >7 products appear to have a significantly larger fraction of small changes than all other bins, and a significantly smaller mean size of changes than firms producing 1-3 products. Also Letterie and Nilsen (2020) do not find the price change frequency to be increasing in the number of products within-firm.

Our results place themselves somewhere inbetween the papers of Bhattarai and Schoenle (2014) and Dedola et al. (2019). While the former find systematic differences across bins, the latter find no clear evidence of such differences. One possible explanation of the different results may be varying data collection procedures in the retrieval of PPI data. Perhaps one of the procedures more correctly indicate the actual number of products of a firm. However, this cannot be crosschecked without access to the data sources and collection procedures used in the mentioned papers.

One potential problem may arise if there are systematic differences in the firm structure and product offerings across bins. For instance, as shown in table 5.2, we see that firms in bin 1-3 have a relatively high mean employment; especially on a per-product basis. If this indicates that the typical products in bin 1-3 are different from products in the other bins, this might explain why the firms in bin 1-3 appear to have the highest price change frequency. Assessing this further, we have examined the distribution of observations to the HS sections within the bins compared to the overall shares of the aggregate dataset. The table can be found in appendix table A3.3. It indicates that firms in bin 1-3 are slightly overrepresented in meat, paper, and metallic products. The clearest difference between the bins is in prepared foodstuffs. Here, bin 7 has a substantial overrepresentation compared to all other bins. However, we verify that our results are robust to these differences, as indicated by appendix table A3.4. Regressing the calculated measures on indicator variables for the different bins, controlling for HS 2-digit product groups and the number of employees, we find no significant differences in the price change frequency across bins.

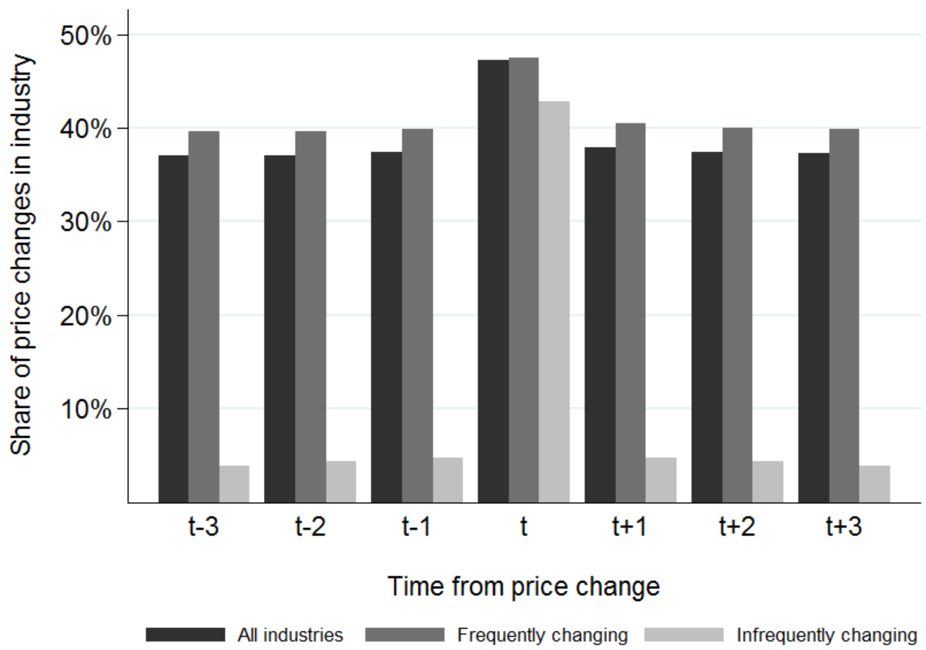
Producers in bin 7 have a significantly smaller mean size of changes than bin 1-3, and they have a significantly larger fraction of small changes than both bin 1-3 and 3-5.

5.4 Descriptive evidence of industry synchronization

One way to look into pricing behavior within product groups could be to examine whether the pricing behavior changes with the number of products in a group. However, SSB's data collection process is centered around collecting the most relevant prices on different products, which we argue is unlikely to average out to the true number of products in a product market. Furthermore, this bias is more likely to occur in the markets with many products with small market shares. Thus, we avoid examining the relationship between pricing behavior and the number of products in an industry, as this cannot be inferred from our data.

Instead, we consider the fraction of changes on other products within an industry when there has been a price change on product i. Figure 5.8 shows how this fraction varies in the months leading up to, and lagging, a price change on product i at time t.

Figure 5.8: Fraction of price-changes within-industry: Leads and lags



Note: The figure gives the mean fraction of within industry price changes leading up to and after a price change at time t. To find the mean fractions we first find the fractions of price changes in the industry of product i leading up to and lagging each observed price change of product i. Next, we find the mean of these fractions for all price changes in the dataset. The mean is also found conditional on whether the price change is in a frequently or infrequently changing industry.

The figure indicates that changes tend to coincide to a certain extent. The fraction of changes on other products increases by 9.8 percentage points in a month where product i has a price change considering the full dataset; for frequently changing products, the fraction increases by 7.6 percentage points; and for infrequently changing products the increase is 38.2 percentage points. Large parts of this tendency can likely be explained by seasonality and aggregate shocks, which is addressed in the multinomial logit model. Especially in the infrequently changing group there seem to be a clear tendency of coinciding price changes. The effects of this graph that cannot be explained by our remaining control variables are likely to be related to industry price synchronization behavior.

Furthermore, the descriptive evidence provides no basis to assume a leading or lagging relationship; there seem to be no tendency of excess share of changes on other products in the months prior or following a price change on product i.

5.5 The multinomial logit model

To investigate price change synchronization we apply a multinomial logit model with three discrete outcomes; negative change, no change, and positive change. The main results of interest are the marginal effects on the probability of these outcomes with regards to an increasing fraction of upward and downward changes within-firm and within-industry. As control variables, we include 2-digit SIC sectoral monthly PPI to control for exogenous shocks at the sector level. To control for cost shocks within the firms, we include the logarithmically transformed wage per employee, which is accounted for on a yearly basis. This is included as it is assumed that large shocks to costs (wages) are likely to induce a price change. Finally, we control for yearly and monthly effects. Standard errors are clustered at the firm level to mitigate potential problems related to products within a firm.

Marginal effects for all explanatory variables can be found in appendix table A3.5 and A3.6.

5.5.1 Marginal effects, frequent and infrequent product groups

Our categorization of HS 4-digit product groups defines a group as "infrequent" if prices change on average less than 1.1 times per 12 months. Product groups with a higher share of changes than this are defined as "frequent". Such a categorization defines 31% of our observations as "infrequent" changers, and 69% as "frequent" changers.

As we suspect the infrequently changing products to be under long term contracts with yearly durations, they might bias our estimates of within-industry synchronization. The high price change frequency in January is likely to stem from renegotiation of contracts rather than synchronization due to strategic complementarity. For this reason we have run our regression model on our total dataset as well as the subset of products with frequent price changes.

To make our results comparable to previous research we report the marginal effects in terms of a one percentage point as well as a half standard deviation increase in the explanatory variables. The marginal effects can be interpreted as following: A one percentage point (1/2 standard deviation) increase in the fraction of positive price changes in the industry increase the probability of a positive price change by 0.06 (0.66) percentage points when we consider all products in the dataset, all else equal.[9] Details on the marginal effects are presented in table 5.3 on the next page.

[9]The size of the standard deviations of the fractions can be found in appendix table A3.9

Table 5.3: Marginal effects overview and by behavior

	Marginal effects (dy/dx)		+/- 1/2 Std. Dev.	
	All observations	Products with frequent changes	All observations	Products with frequent changes
Positive price change				
Fraction up industry	0.06***	0.05*	0.66***	0.56*
	(0.02)	(0.02)	(0.19)	(0.25)
Fraction down industry	-0.02	-0.05*	-0.15	-0.48*
	(0.02)	(0.03)	(0.18)	(0.23)
Fraction up firm	0.48***	0.61***	6.69***	8.56***
	(0.04)	(0.05)	(0.59)	(0.64)
Fraction down firm	0.37***	0.46***	4.05***	5.06***
	(0.03)	(0.03)	(0.35)	(0.37)
Negative price change				
Fraction up industry	0.00	-0.03	0.01	-0.28
	(0.01)	(0.02)	(0.13)	(0.17)
Fraction down industry	0.03	0.01	0.24	0.09
	(0.02)	(0.02)	(0.17)	(0.22)
Fraction up firm	0.27***	0.34***	3.85***	4.76***
	(0.03)	(0.04)	(0.48)	(0.51)
Fraction down firm	0.36***	0.45***	3.95***	4.97***
	(0.05)	(0.05)	(0.50)	(0.55)

Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: "Positive price change" gives the marginal effect on the probability of a positive price change and vice versa. Marginal effects in percentage points are given by a one percentage point and half a standard deviation change in the explanatory fraction variables. Standard errors in parantheses. Other control variables include PPI, sector specific PPI, wage per employee, seasonal and yearly dummies as well as industry dummies at the HS2 level. Marginal effects are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Full regression outputs are found in the appendix A3.5. Standard deviations of explanatory variables are found in table A3.9 in the appendix.

We find a significant relationship between the fraction of both positive and negative price changes within the firm and the probability of positive and negative price changes. The marginal effects are significant in both sets of products. However, the marginal effects seem to be somewhat higher when we consider only the products with frequent price changes, suggesting a higher degree of within-firm synchronization of price changes for these products. Somewhat surprisingly, all within-firm marginal effects are positive, suggesting that an increasing share of positive price changes within the firm also increase the probability of a negative price change, and vice versa. If the observed synchronization was solely caused by firm specific shocks we would not expect to see this, as a shock likely would impact all products within a firm in the same direction. However, in the presence of economies of scope in menu costs the result seems fully reasonable; a firm can very well choose to reduce the price of one product while increasing the price of most other. These results are qualitatively in line with the findings of Dedola et al. (2019). Bhattarai and Schoenle (2014) also find that an increase in the within-firm fraction of positive price changes increase the probability of a positive price change, and vice versa. However, they do not report the effect of an increase in the fraction of negative changes on the probability of a positive change, or the effect of an increase in the fraction of positive changes on the probability of a negative change.

In terms of industry synchronization our results differ qualitatively depending on whether we use the full sample of products or only those with frequent price changes. If we include all observations we find a significant positive effect of the fraction of positive changes in the industry on the probability of a positive change. All other industry variables are found to be insignificant. For the frequently changing products we also find a negative marginal effect of the fraction of negative changes on the probability of a positive price change. This suggest that the probability of increasing prices decreases when the prices of competing products decrease. As mentioned this marginal effect is not significant when we use all observations in our model suggesting that there is a difference between the degree of synchronization in the two groups.

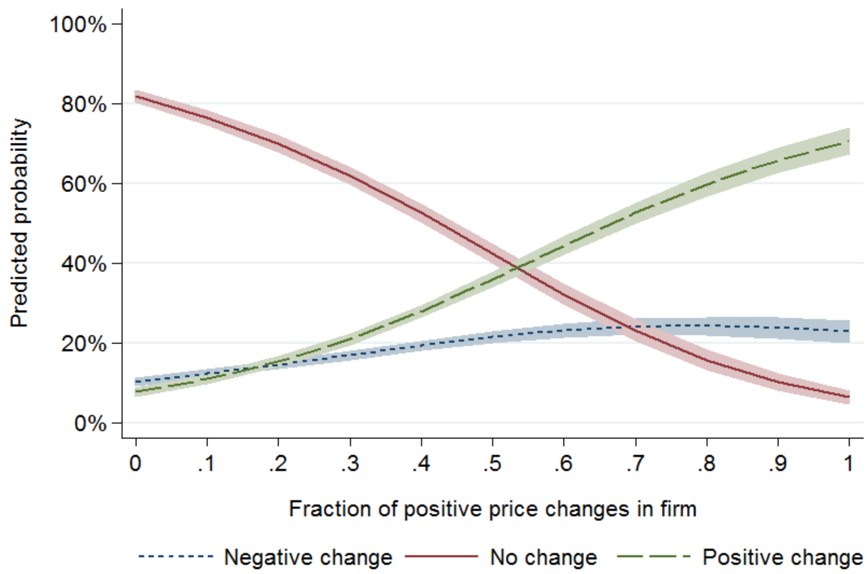
Considering the frequently changing product groups our results are qualitatively similar to those of Dedola et al. (2019). Our results are also in line with Bhattarai and Schoenle (2014), but they find significant effects for all reported industry fractions. The marginal effects of the industry variables are significantly smaller than those of the within-firm variables implying a quantitatively lower synchronization at the industry level relative to the firm level. This is in line with the findings of both Dedola et al. (2019) and Bhattarai and Schoenle (2014).

5.5.2 Predicted probabilities

Using the estimated marginal effects from the multinomial logit model we plot the predicted probabilities of the three discrete outcomes using the estimates for the frequently changing products. The two first plots illustrate the probabilities of the different outcomes conditional on the fraction of positive and negative price changes within the same firm.

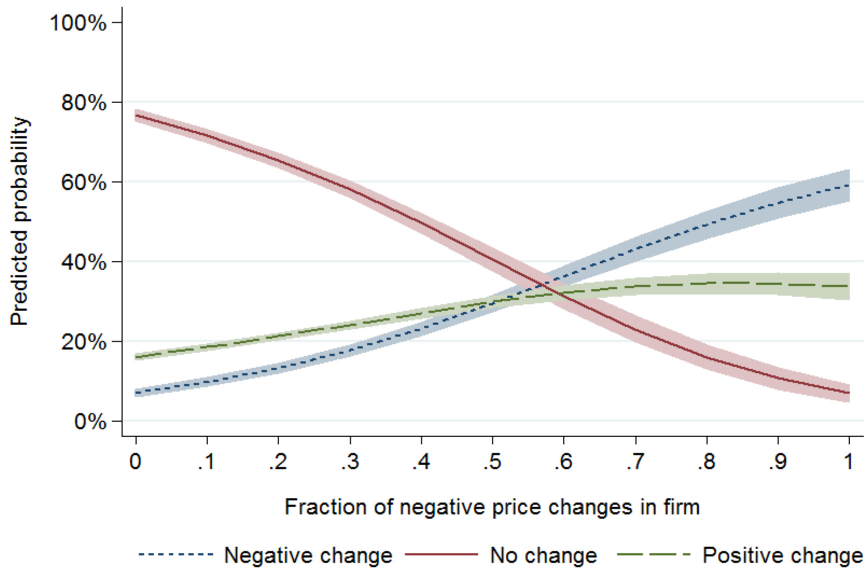
From figure 5.9 we can see that the probability of both a positive and a negative price change on a given product i increase as the fraction of positive price changes in the firm increases. The effect is strongest for the probability of a positive change. Conversely, the probability of not changing the price of product i decreases as the fraction of positive changes increases. We see the same trends in figure 5.10, the probability of a change increases with the fraction of negative changes in the firm. Both plots suggest a strong degree of within-firm synchronization of price changes.

Figure 5.9: Predicted probabilities conditional on the fraction of other positive changes in firm; within-firm synchronization



Note: Predicted probabilities of discrete pricing decision over the fraction of positive price changes on other products in the same firm. The shaded area represent the 95% confidence interval of the predicted probability. Predicted probabilities are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors are clustered at firm level. Only industries categorized as "Frequently changing" are included it the estimation.

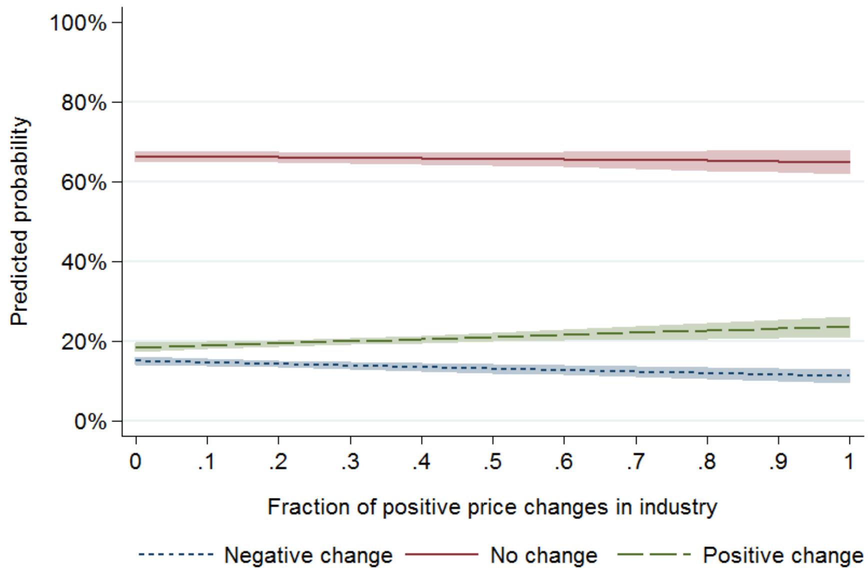
Figure 5.10: Predicted probabilities conditional on the fraction of other negative changes in firm; within-firm synchronization



Note: Predicted probabilities of discrete pricing decision over the fraction of negative price changes on other products in the same firm. The shaded area represent the 95% confidence interval of the predicted probability. Predicted probabilities are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors are clustered at firm level. Only industries categorized as "Frequently changing" are included it the estimation.

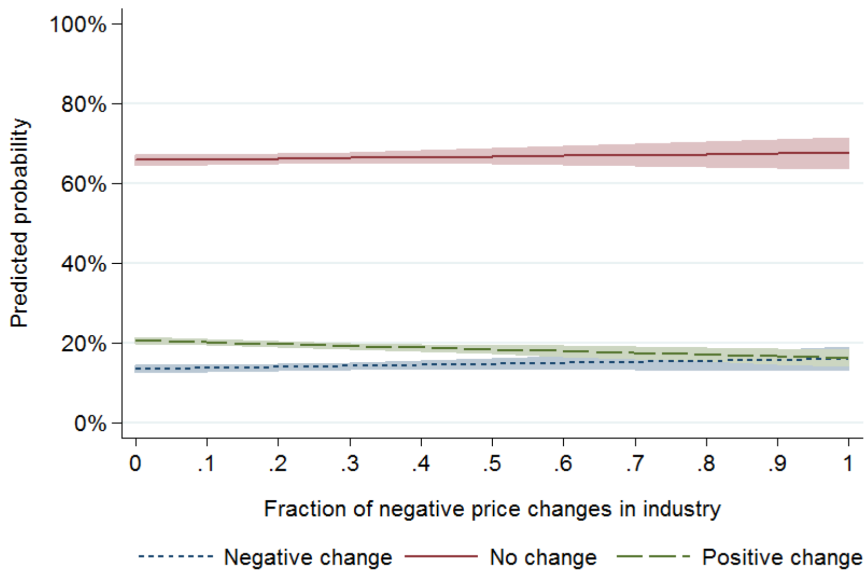
Turning to price change synchronization within industries, an increasing fraction of upward changes within the industry increases the probability of increasing the price of product i. Even though the marginal effect of the fraction of positive price changes in the industry is significantly different from zero, the effect is still weak in an economic sense as the effect is small. This can also be seen from figure 5.11 as the predicted probabilities stay relatively unchanged as the fraction of positive price changes in the industry increases. The same small effects are found for the fraction of negative changes illustrated in figure 5.12. The overall implications of the predicted probabilities is that there seem to be some within-industry synchronization of price changes, but this effect is rather small.

Figure 5.11: Predicted probabilities conditional on the fraction of other positive changes in industry; within-industry synchronization



Note: Predicted probabilities of discrete pricing decision over the fraction of positive price changes on other products in the same industry. The shaded area represent the 95% confidence interval of the predicted probability. Predicted probabilities are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors are clustered at firm level. Only "Frequently changing" industries are included it the estimation.

Figure 5.12: Predicted probabilities conditional on the fraction of other negative changes in industry; within-industry synchronization



Note: Predicted probabilities of discrete pricing decision over the fraction of negative price changes on other products in the same industry. The shaded area represent the 95% confidence interval of the predicted probability. Predicted probabilities are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors are clustered at firm level. Only "Frequently changing" industries are included it the estimation.

5.5.3 Marginal effects across bins

To consider whether the synchronization measures vary with the number of products within-firm, we estimate the multinomial logit model on the bins separately. Table 5.4 presents the marginal effects using +/- 1/2 the standard deviation of the presented explanatory variables.

Table 5.4: Marginal effects by number of products

	Number of products				All frequently
	1-3	3-5	5-7	>7	changing products
Positive price change					
Fraction up industry	0.49	0.26	0.43	0.48	0.56*
	(0.28)	(0.38)	(0.25)	(0.47)	(0.25)
Fraction down industry	-0.45	-0.04	0.12	-0.22	-0.48*
	(0.30)	(0.29)	(0.21)	(0.55)	(0.23)
Fraction up firm	5.29***	8.23***	3.66***	9.63***	8.56***
	(0.93)	(1.05)	(0.94)	(0.78)	(0.64)
Fraction down firm	3.21***	5.17***	2.22***	5.46***	5.06***
	(0.54)	(0.66)	(0.58)	(0.49)	(0.37)
Negative price change					
Fraction up industry	-0.09	-0.09	0.02	-0.05	-0.28
	(0.17)	(0.27)	(0.11)	(0.39)	(0.17)
Fraction down industry	0.01	0.18	0.20	0.01	0.09
	(0.18)	(0.38)	(0.15)	(0.64)	(0.22)
Fraction up firm	2.45***	5.27***	1.57***	5.65***	4.76***
	(0.56)	(0.91)	(0.45)	(0.58)	(0.51)
Fraction down firm	2.54***	5.12***	1.46***	6.69***	4.97***
	(0.61)	(0.88)	(0.42)	(0.67)	(0.55)

Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: "Positive price change" gives the marginal effect on the probability of a positive price change and vice versa. Marginal effects in percentage points across bins are given by half a standard deviation change in the explanatory fraction variables. Standard errors in parentheses. Other control variables include PPI, sector specific PPI, wage per employee, seasonal and yearly dummies as well as industry dummies at the HS2 level. Marginal effects are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. The marginal effects are calculated separately for each bin. Full regression outputs are found in the appendix A3.6.Standard deviations of explanatory variables are found in table A3.9 in the appendix.

From table 5.4, we can see that the generalized effects over the bins are the following:

For the different bins, none of the within-industry marginal effects are significantly different from zero. As the marginal effects appear similar to those of all frequently changing products, this might be in part due to fewer observations in the bins relative to the complete sample. The result indicate that within-industry price change synchronization is not all that important in explaining pricing behavior once controlling for shocks and seasonality. Bhattarai and Schoenle (2014) and Dedola et al. (2019) find the industry synchronization to decrease over the number of products produced by a firm. Conversely, we do not find any clear trends of synchronization increasing or decreasing with the number of products. However, the signs of the marginal effects are the same as those found in both of these papers.

Concerning within-firm price change synchronization, the effects are clear and meaningful across all bins. Contrary to the research on Danish and US producer pricing behavior (Dedola et al., 2019; Bhattarai and Schoenle, 2014), we do not find any clear trend of within-firm synchronization increasing with the number of products. However, the synchronization appears to be of largest magnitude within the bins 3-5 and >7.

5.5.4 Implications of model choice

A property of the multinomial logit model is that:

$$\frac{Pr(p_{ijk,t} = c|x_{ijk,t})}{Pr(p_{ijk,t} = k|x_{ijk,t})} = \frac{exp(\beta_c x_{ijk,t})}{exp(\beta_k x_{ijk,t})} \tag{5.1}$$

Thus, the odds ratio of two outcomes, c and k, is independent on other alternative outcomes as it only depends on the explanatory variables and parameters associated with outcomes c and k. This is called the independence of irrelevant alternatives (IIA). In our case the independence of irrelevant alternatives implicates that if we eliminate the option of decreasing prices the odds ratio of increasing prices and keeping them unchanged should stay unchanged. We argue that this is unlikely as the firms who initially would decrease their prices would prefer keeping them unchanged to increasing them, changing the odds ratio. Thus, the assumption is likely to be violated.

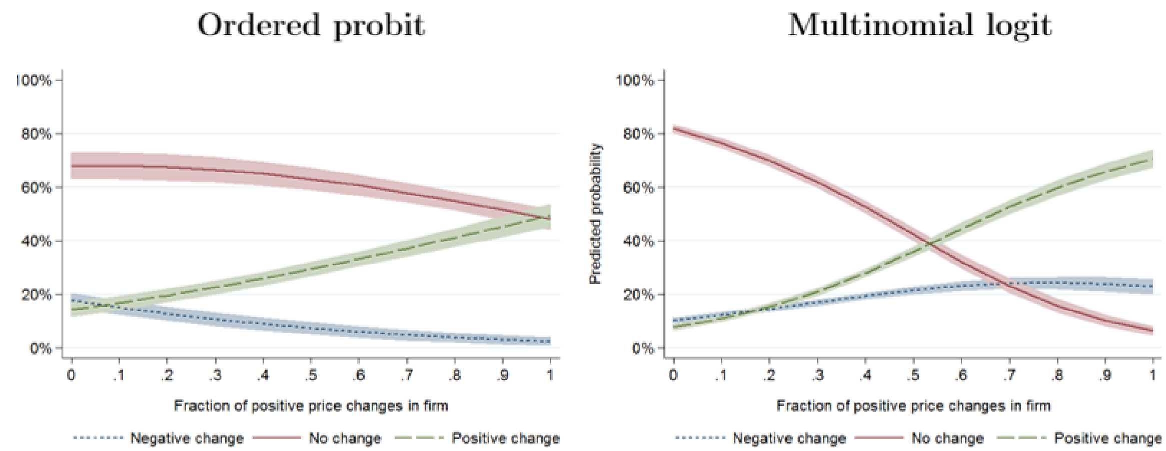
An alternative to the multinomial logit model is the ordered probit model used in the papers of Letterie and Nilsen (2020) and Leinum and Riise (2016). The ordered probit model does not rely on the assumption of independence of irrelevant alternatives, but it requires the relationship between each pair of outcome groups to be the same. This assumption is not likely to hold, as firms tend to behave differently when increasing and decreasing prices (Ball and Mankiw, 1994).

To assess the implications of model choice we run both models with the same explanatory variables. A comparison of the marginal effects of the two models can be found in table A3.7 in the appendix.

The marginal effects of within-industry synchronization are somewhat higher using the ordered probit model, and all marginal effects are statistically significant. Qualitatively the results of the ordered probit are similar to those of the multinomial logit, and the economic significance of the within-industry synchronization is low as the magnitudes of the marginal effects are low.

As for the within-firm synchronization the results of the ordered probit model differ substantially from those of the multinomial logit. Both models give positive marginal effects of an increase in the fraction of positive (negative) changes on the probability of a positive (negative) price change. The marginal effects of the fractions of the opposite sign are positive using the multinomial logit model, but negative using the ordered probit. Thus, the probit model suggest that an increase in the fraction of positive price changes decreases the probability of a negative price change, and vice versa. The difference between the results of the two models is illustrated by the predicted probabilities in figure 5.13, where the probability of a negative price change fall as the fraction of positive price changes increases using the ordered probit model. The predicted probability plots associated with changes in the other fractions can be found in figures A3.3-A3.6 in the appendix.

Figure 5.13: Predicted probabilities of other positive changes in firm



Note: Predicted probabilities of discrete pricing decision over the fraction of positive price changes on other products in the same firm. The shaded area represent the 95% confidence interval of the predicted probability. Predicted probabilities are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors are clustered at firm level. Only "Frequently changing" industries are included in the estimation.

From these results we can conclude that the choice of model is of high importance. As discussed the predictions of the multinomial logit model support the theory of economics of scope in menu costs, as an increase in the fractions of positive and negative price changes increase the probability of both increasing and decreasing prices. We argue that the probit model does not give the same clear indication of economics of scope in menu costs, as an increase in the fractions only increase the probability of a price change of the same sign. The estimated effects using the probit model might also stem from firm specific shocks, as a positive firm-specific shock would make it favorable to increase the prices of all goods in the firm, and vice versa, as predicted by the model. Thus, the results of the models may have different implications. However, which model is the most correct is hard to say, as the assumptions of both models seem to be violated in some way. To make our results comparable to those of Bhattarai and Schoenle (2014) and Dedola et al. (2019) we use a multinomial logit model in our analyses.

5.5.5 Discussion of results: Synchronization behavior

Within-firm synchronization

The results of the multinomial logit model indicate that within-firm price change synchronization is highly prevalent, and that firms to a large extent synchronize price changes as a whole rather than the direction of changes. That is, we find the probability of a negative price change to significantly increase if the fraction of positive changes within the firm is increasing, and vice versa.

Bhattarai and Schoenle (2014) do not report their results in this regard; that is, the impact of the fraction of positive changes on the probability of a negative price change and vice versa. We find qualitatively similar results to Dedola et al. (2019), but they find slightly smaller orders of magnitude regarding the marginal effects. We argue that the within-firm synchronization can be explained by the theories of menu costs and scope economies in price changes; changing the price of other products are costless or cheap once deciding to change price of one good (Midrigan, 2011). Thus, every product will have its price adjusted in the appropriate direction, as a result of the specific conditions applied to that product. If the synchronization was caused by solely firm-specific shocks we would not expect to see the same results, as the shock would impact all products in the same direction.

The results of the multinomial logit model differ from those of Letterie and Nilsen (2020) and Leinum and Riise (2016) using an ordered probit model. They also find strong evidence of within-firm synchronization of price changes, but find that the probability of a negative price change fall as the fraction of positive price changes increase, a result that we argue in part can be explained through firm-specific shocks rather than economics of scope in menu costs. However, when we employ an ordered probit model on our dataset we find results similar to those of Letterie and Nilsen (2020) and Leinum and Riise (2016). This indicates that the model choice is of high importance, but that none of the models are clearly superior as some assumptions of both seem to be violated.

Contrary to the papers of Bhattarai and Schoenle and Dedola et al., our estimates of within-firm synchronization do not appear to be related to the number of products within the firm. One reason could be that there might be systematic differences in the product offerings of firms in the different bins. If so, this is biasing our results.[10] Otherwise, one could perhaps argue that any multiproduct firm faces the same incentive to synchronize price changes, regardless of the absolute number of products.

Within-industry synchronization

As for industry synchronization, our results are qualitatively in line with both Bhattarai and Schoenle (2014) and Dedola et al. (2019). Positive price changes seem to be more likely when the fraction of positive changes within-industry increase, and less likely when the fraction of negative changes increase - and vice versa for negative price changes. Several of these estimates are not significantly different from zero, in contrast to the studies we compare our results to. Discussing the reasoning for the lack of significance, two explanations seem plausible: Firstly, the effects appear relatively small, so that the economic effect might actually be insignificant. However, the order of magnitude of our industry synchronization appear quite in line with both Bhattarai and Schoenle and Dedola et al. Secondly, the clearest, obvious difference between our analysis and these papers lies in the number of observations. Dedola et al.'s paper contains about six hundred thousand (600 000) observations in all, and well above hundred thousand (100 000) in every bin. Bhattarai and Schoenle do not specify their aggregate number of price

[10]See appendix table A3.3 for the distribution of observations within the bins.

observations, but their bins contain between 2160 firms (bin >7) to 13 577 firms (bin 3-5). Thus, their dataset is likely to be much larger than both Dedola et al.'s and the one employed in this analysis.

The low and partially insignificant marginal effects give limited evidence of within-industry synchronization of price changes, suggesting that competitor's decisions have no economically significant impact on pricing behavior. This is contrary to what we would expect in a competitive environment where we expect goods to be strategic complements. We find three plausible explanations for this:

Firstly, aiming to maximize relevance for the Norwegian economy at a low cost, SSB's collection process emphasizes covering large firms where they are dominant (SSB, 2020). Thus, the dataset does not cover all firms active in a given industry or product group. An implication of this sampling procedure is that we have have rather few products in each industry. As shown in figure 4.1 73% of the industries have three or less products on the HS4 level. A consequence of this is that the industry fractions are highly sensitive to the actions of one or a few firms, and that the input of the fractions might not be representative for the industry as a whole. Thus, our dataset might be less suited to estimate industry synchronization than within-firm synchronization. In addition, smaller firms with potentially less market power might be more likely to synchronize price changes. As the dataset contains mostly rather large firms the synchronization of such smaller firms is not possible to estimate with the data we have. Thus, the overrepresentation of large firms might bias our results reducing the estimates of within-industry synchronization.

Secondly, our industry classifications might not correctly identify products considered as strategic complements. The HS4 categorization allows for some difference between products within the same industry. However, we have examined the model results using 2-digit and 6-digit HS levels. Both levels give results that are qualitatively similar to the HS4 model, as shown in appendix table A3.8. All marginal effects have the same signs, and are not significantly different from those at the 4-digit level. In the HS2 model the industry fraction of positive price changes has a larger effect on the probability of a positive price change. This marginal effect is significant at the 0.1 percentage level. No other industry marginal effects in the HS 2-digit model are significant. However, when using 2-digit HS codes, relatively different products are considered to be competing: For instance the dataset contains a lot of machines (HS code 84). These include 4-digit codes such as 8414 "Air compressors" and 8433 "Mowers and harvesting machinery". Thus, we argue that the apparent synchronization in the HS 2-digit model is likely to stem, at least in part, from cost shocks and input prices correlating rather than strategic interaction in the pricing decisions as the end products are rather different. The model with HS 6-digit codes is very close to the one using 4-digit codes, but we see no further benefits using this model: Here, competing products are defined so narrowly that much larger parts of the products have no competitors compared to the HS 4-digit model.

Thirdly, if our results do not stem from the data being unrepresentative, they indicate relatively weak competition: If there are few competing substitute products available, firms may not be that sensitive to changes in the prices of competing products. Grimsby et al. (2019), examining the development of market concentration in Norway on behalf of the Norwegian Competition Authority, find a substantially larger market concentration in Norway compared to the EU and US.[11] Domestic market concentration may be less relevant considering the manufacturing industry as much of it is exposed to international competition. However, as we have excluded export and import prices as well as products without domestic prices, we argue that the findings of Grimsby et al. (2019) are of some relevance to the products covered in this analysis. Thus, the low degree of industry synchronization may indicate a low degree of access to substitutable products. However, the argument is relevant for the studies from Bhattarai and Schoenle (2014) and Dedola et al. (2019) as well, as the economic significance of the industry synchronization appears rather low in all studies. Thus, the low importance of industry synchronization may indicate that large shares of producers in Norway, as well as abroad, have a degree of pricing power and are able to disregard competitor behavior to a certain extent.

[11]Market concentration is measured using the Herfindal-Hirschman Index (HHI). The analysis covers all sectors in the Norwegian economy.

6 Conclusion

The purpose of this paper is to contribute with micro-evidence on producer pricing behavior, and evidence on price change synchronization within firms and industries. Such insights may have important implications for the real effects of monetary policy and can shed light on the competitive environment in Norwegian product markets. Thus, the findings presented in this thesis may be relevant for both central banks and competition authorities.

Pricing behavior is known to be highly heterogenous. To gain an overview of the aggregate producer pricing behavior, we decompose the aggregate behavior across HS (harmonized system) product sections. We find relatively low price change frequencies with considerable heterogeneity across seasons and product groups, suggesting that there is substantial rigidity in Norwegian producer prices.

Furthermore, we observe several products with rather infrequent price changes, and another set of products with more frequent changes. Assessing the seasonality tendencies of these groups, we find excess price change frequency in January and February in both groups - but this excess price change frequency is far larger in the infrequently changing product groups, pointing toward the prevalence of explicit contracts with a one-year duration (Alvarez et al., 2006).

Traditional macroeconomic models assume firms to be single product entities. A new wave of studies have challenged this assumption, showing that multiproduct firms are largely prevalent and, importantly, that multiproduct firms tend to behave differently from single product firms. We document that the mean size of changes tend to decrease with the number of products within a firm, and that the fraction of small changes tend to increase in the number of products. This suggest that the number of products produced by a firm has an impact on pricing behavior.

Several studies have documented the prevalence of within-firm synchronization of price changes (Midrigan, 2011; Bhattarai and Schoenle, 2014; Yang, 2019; Dedola et al., 2019; Letterie and Nilsen, 2020; Bonomo et al., 2020). Examining the pricing behavior on the extensive margin, using a multinomial logit model, we document a high degree of within-firm synchronization of price changes. Furthermore, we find the synchronization to be largely independent of the direction of changes. We argue that this finding mainly support the theory of scope economies in menu costs rather than firm- or sector-specific shocks, as such shocks are likely to impact all products in the same direction. As emphasized in literature, within-firm synchronization reduces the responsiveness of a single product price to shocks, as the pricing decision depend on the benefits of changing other prices as well. Thus, economics of scope in menu costs increase the price rigidity (Midrigan, 2011). We find the synchronization effects to be economically significant and they should therefore be accounted for in macroeconomic models - who traditionally model firms as single product entities.

Bhaskar (2002) argues that synchronization of price changes due to strategic complementarity is more prevalent between products with a high degree of substitutability, and thus it should be more prevalent within industries than across industries. Motivated by the findings of Bhattarai and Schoenle (2014) and Dedola et al. (2019), we examine the synchronization within 4-digit HS product groups, under the assumption that products within a group are relatively substitutable. We document industry synchronization to be prevalent, and the results point toward strategic complementarity in pricing decisions: If product prices in the industry are changing upward (downward), the probability of an upward (downward) change increases. These results are comparable to those of Bhattarai and Schoenle (2014) and Dedola et al. (2019). However, in economic terms, the synchronization appears to be of minor importance in explaining pricing behavior at the aggregate level as the synchronization effects are rather low.

To the extent that these results are not biased by the prevalence of large firms in our data, we argue that they serve as an indicator of relatively weak competition. If there are few competing substitute products available, firms may not be that sensitive to changes in the prices of competing products. Grimsby et al. (2019), on behalf on the Norwegian Competition Authority, found the aggregate market concentration in Norway to be substantially larger than in the EU and US. Assuming that this holds when considering only the manufacturing industry, it can explain and underpin this result: The low economic significance of industry synchronization may indicate that large fractions of Norwegian firms have pricing power and are able to disregard competitor behavior to a certain extent. This has important implications for the efficiency of the markets covered in our analysis.

Such pricing power allows producers to increase their margins, reducing the efficiency of the markets and redistributing wealth from consumers to producers.

Regarding implications for the price rigidity, Ball and Romer (1991) argue that even a small degree of strategic complementarity may increase the price rigidity as it amplifies the impact of nominal rigidities such as menu costs. Thus, our findings related to within-industry synchronization may have implications for price rigidity, even though the synchronization effects are small. However, the magnitude of impact on the price rigidity is unknown and estimating it is beyond the scope of our analysis.

While our results support previous research regarding within-firm synchronization of price changes, the paper is among the first to apply PPI data to examine synchronization of price changes on the industry level. Although our results indicate low within-industry synchronization at the aggregate level, the result may be different considering specific industries. A limitation of the PPI dataset is that the true number of actors within an industry is unknown. If the detailed pricing data is combined with data on market concentration and the degree of exposure to international competition, an interesting avenue of future research could be to examine whether industry price change synchronization changes with these characteristics.

Regarding the limitations of our study the main consideration is that we, in many industries, observe relatively few competitors. This may not reflect reality, as we are aware that the sampling procedure of PPI data induces a bias toward large firms. As such, further research and considerations are required to assess the generalizability of our findings.

Overall, we find evidence of substantial price rigidity, which in part can be explained by scope economics in menu costs. Strategic complementarity within industries might also play a role in amplifying these rigidities. Combined with earlier literature these findings have important implications for the micro foundations of macroeconomic models and policy. However, further research is still needed to fully understand the multiproduct and synchronization dimensions of pricing behavior. Our findings also indicate that producers have a degree of pricing power, a finding that is relevant for both competition authorities and central banks as it impacts the market efficiency and responsiveness to monetary policy.

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Appendix

A1 Data

Table A1.1: HS sections, full names

Section	Section name
1	Live animals; animal products
2	Vegetable products
3	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes
4	Prepared foodstuffs; beverages, spirits and vinegar; tobacco and manufactured tobacco substitutes
5	Mineral products
6	Products of the chemical or allied industries
7	Plastics and articles thereof; rubber and articles thereof
8	Raw hides and skins, leather, fur, skins and articles thereof; saddlery and harness; travel goods, handbags and similar containers; articles of animal gut (other than silk-worm gut)
9	Wood and articles of wood; wood charcoal; cork and articles of cork; manufactures of straw, of esparto or of other plaiting materials; basket ware and wickerwork
10	Pulp of wood or of other fibrous cellulosic material; recovered (waste and scrap) paper or paperboard; paper and paperboard and articles thereof
11	Textiles and textile articles
12	Footwear, headgear, umbrellas, sun umbrellas, walking-sticks, seat-sticks, whips, riding-crops and parts thereof; prepared feathers and articles made therewith; artificial flowers; articles of human hair
13	Articles of stone, plaster, cement, asbestos, mica or similar materials; ceramic products; glass and glassware
14	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin
15	Base metals and articles of base metal
16	Machinery and mechanical appliances; electrical equipment; parts thereof; sound recorders and reproducers; television image and sound recorders and reproducers, and parts and accessories of such articles
17	Vehicles, aircraft, vessels and associated transport equipment
18	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; clocks and watches; musical instruments; parts and accessories thereof
19	Arms and ammunition; parts and accessories thereof
20	Miscellaneous manufactured articles
21	Works of art, collectors' pieces and antiques

Table A1.2: Size of firms in price data relative to the average Norwegian firm

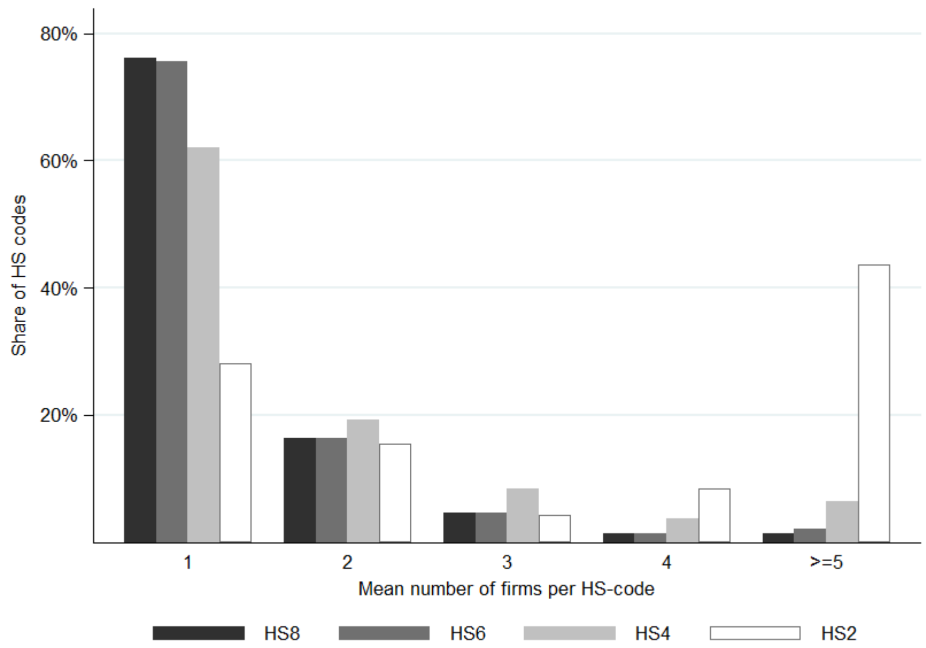
SIC07	Number of employees		Number of firms per enterprise		
	All firms	Firms in dataset	All enterprises	Enterprises represented in dataset	Firms per enterprise in dataset
10	20.64	119.78	1.14	4.25	1.15
11	31.93	161.38	1.15	3.81	1.02
13	5.57	46.73	1.04	2.01	1.00
14	2.28	44.08	1.00	1.00	1.00
15	4.37	23.93	1.00	1.00	1.00
16	8.37	85.10	1.04	1.97	1.05
17	52.15	165.57	1.11	1.59	1.05
18	5.66	26.88	1.02	1.00	1.00
20	36.51	118.20	1.20	2.11	1.00
21	68.88	209.84	1.14	2.02	1.00
22	12.54	60.37	1.06	1.53	1.00
23	12.12	63.82	1.24	4.39	1.14
24	68.54	259.41	1.13	1.76	1.13
25	10.63	61.75	1.03	1.93	1.00
26	27.02	126.19	1.07	1.36	1.00
27	18.62	145.24	1.08	2.57	1.08
28	15.76	114.29	1.06	1.54	1.01
29	26.63	44.25	1.13	1.64	1.00
30	43.96	35.67	1.11	4.95	1.08
31	7.93	74.14	1.01	1.18	1.00
32	4.28	63.65	1.02	1.14	1.00
33	9.66	194.65	1.06	9.43	1.00

Note: For the number of employees "All firms" give the mean number of employees for all firms included in the firm structure dataset. First we find the average number of employees per firm over the period 2005-2016. The yearly averages are used to calculate the SIC average. The "Firms in dataset" column gives the mean number of employees using only the firms represented in the PPI dataset.

The mean number of firms per enterprise is calculated in the same way as the mean number of employees. The "All firms" column gives the mean number of firms per enterprise for all firms included in the firm structure dataset. "Enterprises represented in dataset" gives the same statistic for firms represented in the PPI dataset. "Firms per enterprise in dataset" gives the mean number of firms per enterprise in the PPI dataset. This means that on average the enterprises with SIC 10 represented in the dataset have 4.25 firms. However, in the PPI data they are on average represented with only 1.15 firms. Only observations after 2010 are included in the enterprise calculations as we do not have data on the firm-enterprise structure prior to 2011.

A2 Methodology

Figure A2.1: Number of firms per HS code



The mean number of firms per HS code is calculated by first finding the distinct number of firms producing products with a given HS code in a given year. The yearly numbers are used to find a mean number of firms represented in each code. This mean is then rounded to the closest integer. Furthermore, we find the number of HS codes with on average one firm represented in the sample etc. This number is divided by the total number of distinct HS codes in our dataset to find the share of HS codes with a given number of firms.

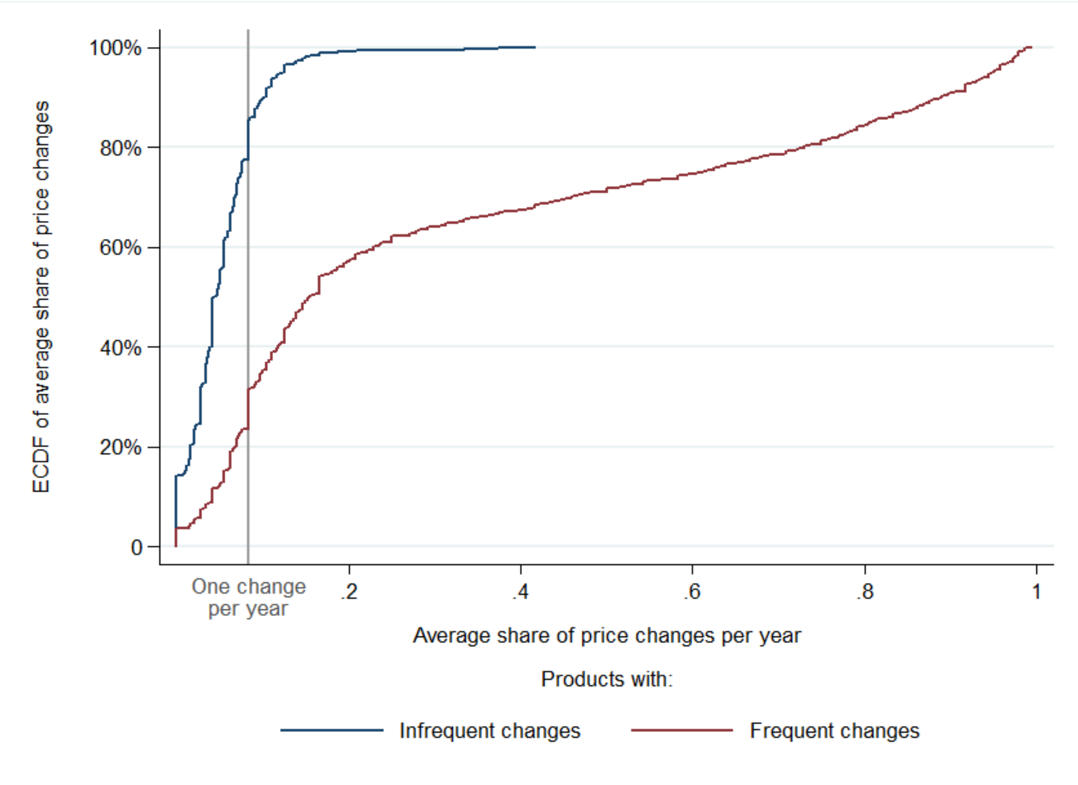
Table A2.1: Number of firms and products per HS code

Number of Products	Number of Firms	Average number of HS4 codes	Number of Products	Number of Firms	Average number of HS4 codes	Number of Products	Number of Firms	Average number of HS4 codes
1	1	85.8	12	5	.7	22	7	.6
2	1	28	12	8	.5	22	8	.1
2	2	13.6	13	1	.3	23	4	.3
3	1	21.1	13	2	1.8	23	8	.2
3	2	9.6	13	3	.3	23	9	.3
3	3	3.1	13	4	.8	23	10	.2
4	1	5.5	13	5	.3	24	5	.3
4	2	4.9	13	6	.2	24	9	.1
4	3	.2	13	7	.2	25	5	.3
4	4	.3	13	8	.3	25	6	.2
5	1	5.3	14	2	.1	25	7	.3
5	2	6.7	14	3	.3	25	10	.2
5	3	1.7	14	5	.3	26	4	.2
5	4	.5	14	6	.5	26	5	.3
5	5	.2	14	7	.6	26	6	.1
6	1	4.3	14	8	.3	26	7	.2
6	2	5.4	15	2	.1	26	11	.2
6	3	5.5	15	3	.1	27	4	.1
7	1	3.1	15	4	.8	27	6	.3
7	2	2.9	15	5	.7	27	8	.1
7	3	2.5	15	6	.8	28	5	.2
7	4	.9	15	7	.2	28	7	.6
7	5	.2	15	8	.3	28	8	.1
8	1	1.1	15	9	.2	29	7	.1
8	2	4.3	16	2	.1	29	8	.3
8	3	1.8	16	3	.3	29	11	.1
8	4	.8	16	4	1	30	7	.1
8	5	.8	16	5	.5	30	8	.1
8	6	.8	16	6	.3	30	9	.1
9	1	.7	17	2	.1	31	8	.1
9	2	1.2	17	4	.3	31	9	.1
9	3	2.4	17	5	.3	32	8	.3
9	4	.3	17	6	.7	32	9	.1
9	5	.4	17	10	.1	33	9	.2
9	6	.7	18	2	.1	33	10	.3
9	7	.1	18	3	.3	34	9	.5
10	1	1.2	18	4	.8	35	9	.3
10	2	.8	18	5	.8	35	10	.2
10	3	1.6	18	7	.4	35	11	.1
10	4	1.6	19	2	.3	36	10	.1
10	5	.4	19	3	.1	36	11	.1
10	7	.1	19	4	.2	37	10	.2
10	8	.1	19	5	.3	38	11	.1
11	2	4.6	19	7	.3	42	9	.1
11	3	2.9	19	12	.2	43	10	.1
11	4	.6	20	3	.3	49	16	.1
11	5	.6	20	4	.2	51	17	.3
11	6	.2	20	7	.2	55	17	.1
11	7	.4	20	13	.1	56	15	.1
11	8	.4	21	4	.2	56	16	.1
12	1	.2	21	5	.1	56	17	.2
12	2	1.8	21	8	.3	58	16	.1
12	3	1.7	21	9	.1	58	17	.1
12	4	.8	22	4	.2			

Note: The table gives the yearly average number of HS4 codes with a given number of firms and products. For example, there are on average 9.6 HS4 codes in the dataset that are represented with three product produced by two different firms. To calculate the averages we first find all combinations of number of firms and number of products in a given year as well as the frequency of this combination. The average number of HS4 codes is given by the mean of these yearly frequencies.

A3 Analysis

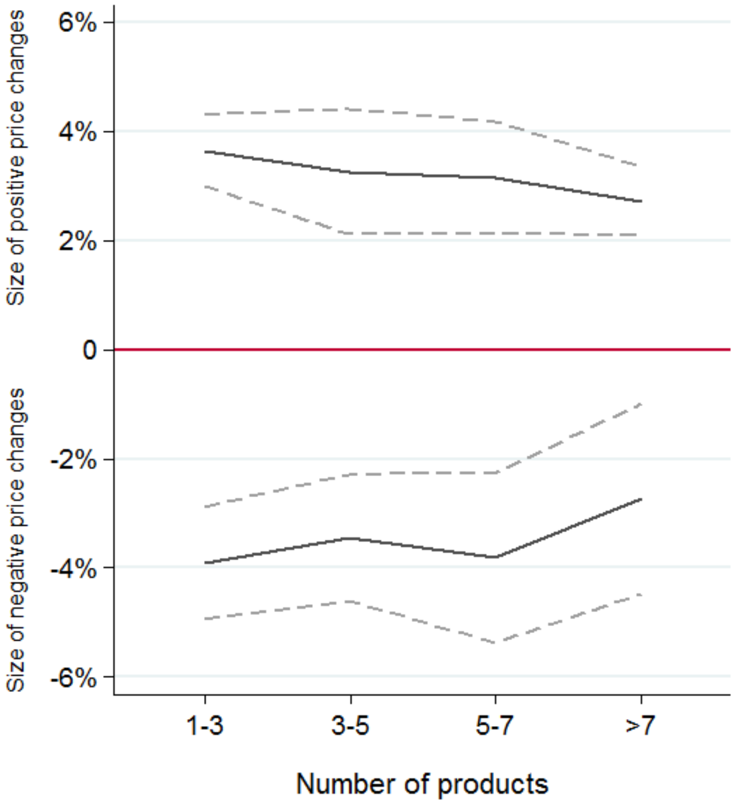
Figure A3.1: Cumulative distribution of share of price changes per year



Note: The graph shows the cumulative distribution of the mean share of price changes per product in the two behavioural categories. First we calculate the yearly share of price changes for each product. Based on these yearly shares we find the mean share of price changes per year for each product.

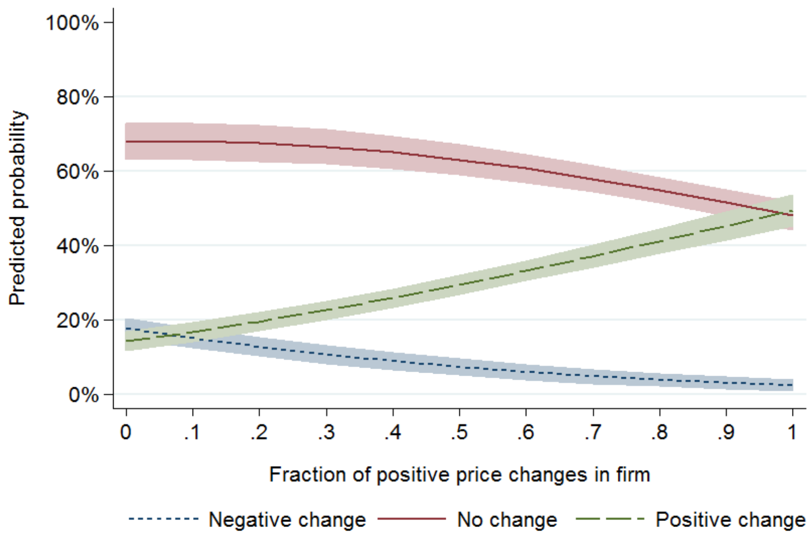
Figure A3.1 shows the cumulative distribution of the mean share of price changes per year for the industries categorized as infrequently and frequently changing. As the products are categorized based on the industry level share of price changes per year some products with few changes per year will be categorized as frequently changing an opposite. From the figure we can see that about 85% of the products categorized as infrequently changing change on average less than one time per year. The corresponding measure for the frequently changing products is about 30%.

Figure A3.2: Mean size of positive and negative price changes over bins



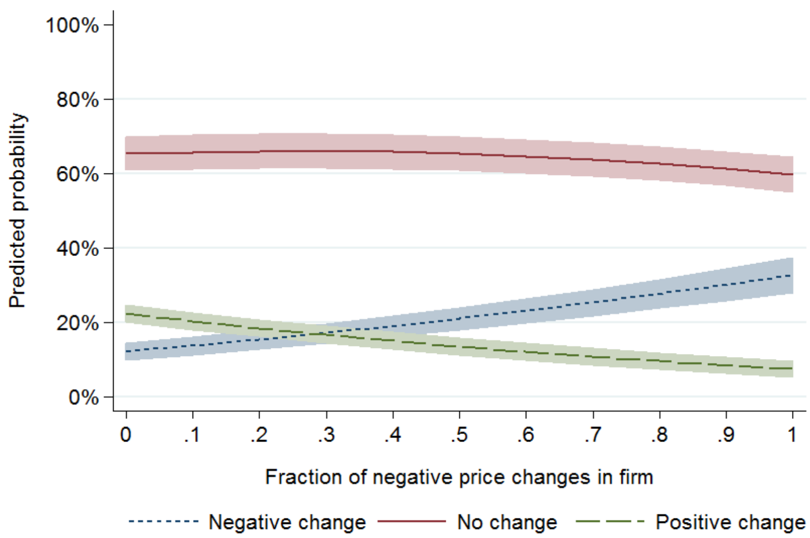
Note: To find the mean size of positive and negative price changes in each bin we first calculate the mean size of positive and negative price changes at the product level. Next, we find the median sizes across all products in each firm. The bin level means are given by the average of these median sizes. The dashed lines represent the 95% CI. They are given by +/- 1.96 times the standard error across firms.

Figure A3.3: Predicted probabilities conditional on the fraction of other positive changes in firm , ordered probit



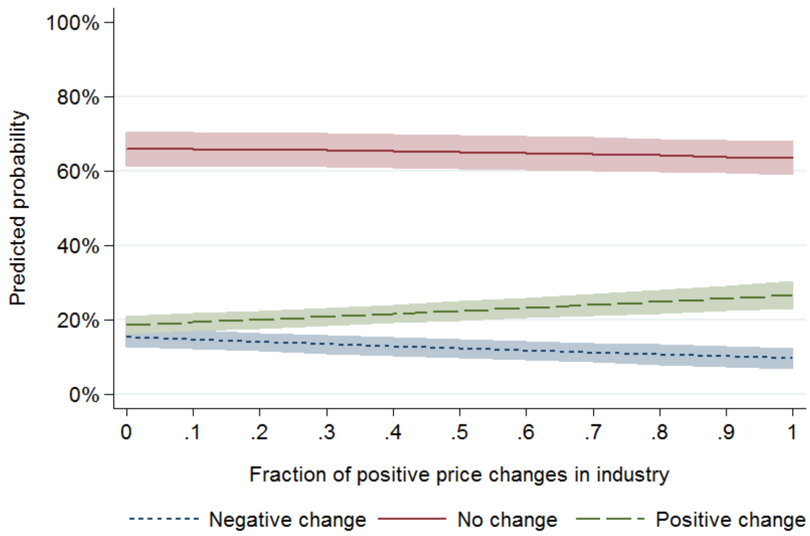
Note: Predicted probabilities of discrete pricing decision over the fraction of positive price changes on other products in the same firm. The shaded area represent the 95% confidence interval of the predicted probability. Predicted probabilities are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors are clustered at firm level. Only industries categorized as "Frequently changing" are included it the estimation.

Figure A3.4: Predicted probabilities conditional on the fraction of other negative changes in firm, ordered probit



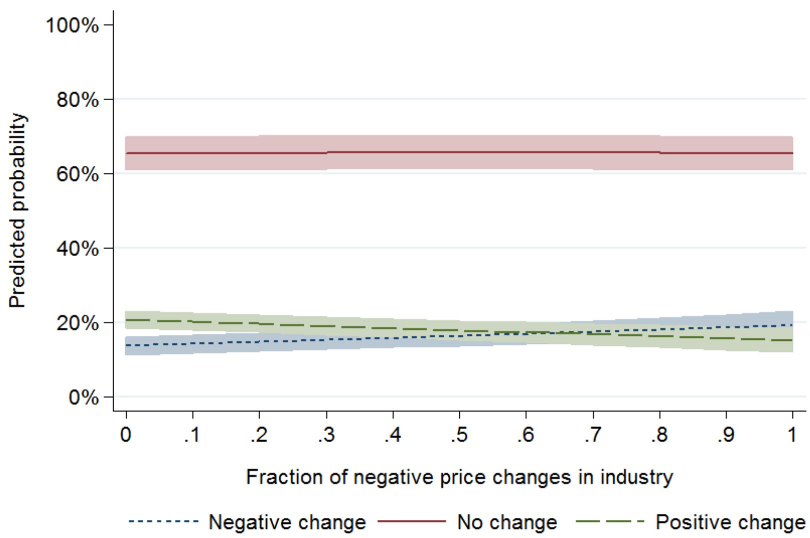
Note: Predicted probabilities of discrete pricing decision over the fraction of negative price changes on other products in the same firm. The shaded area represent the 95% confidence interval of the predicted probability. Predicted probabilities are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean.Standard errors are clustered at firm level. Only industries categorized as "Frequently changing" are included it the estimation.

Figure A3.5: Predicted probabilities conditional on the fraction of other positive changes in industry, ordered probit



Note: Predicted probabilities of discrete pricing decision over the fraction of positive price changes on other products in the same industry. The shaded area represent the 95% confidence interval of the predicted probability. Predicted probabilities are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean.Standard errors are clustered at firm level. Only industries categorized as "Frequently changing" are included it the estimation.

Figure A3.6: Predicted probabilities conditional on the fraction of other negative changes in industry, ordered probit



Note: Predicted probabilities of discrete pricing decision over the fraction of negative price changes on other products in the same industry. The shaded area represent the 95% confidence interval of the predicted probability. Predicted probabilities are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean.Standard errors are clustered at firm level. Only industries categorized as "Frequently changing" are included it the estimation.

Table A3.1: Descriptive statistics over HS sections

Section	Number of firms	Number of products	Share of dataset	Frequency	
				Mean	Median
1	14.70	58.98	4.08%	41.18	29.41
2	3.99	16.97	1.17%	20.30	10.53
3	2.37	7.53	0.52%	32.99	11.89
4	41.88	243.66	16.84%	34.50	16.08
5	9.24	23.26	1.61%	26.86	10.17
6	33.10	133.00	9.19%	25.34	7.63
7	23.36	83.14	5.74%	28.19	8.39
8	2.51	11.84	0.82%	6.38	3.50
9	35.18	126.52	8.74%	34.61	15.79
10	14.68	45.48	3.14%	29.20	12.90
11	17.06	67.11	4.64%	12.15	6.29
12	1.88	4.60	0.13%	2.30	0.00
13	22.15	89.24	6.17%	21.97	8.42
14	4.33	12.33	0.85%	15.50	8.39
15	41.42	155.58	10.75%	22.57	7.37
16	54.74	219.31	15.15%	12.21	6.99
17	5.63	29.15	2.01%	11.51	10.87
18	7.00	34.56	2.39%	17.23	6.29
20	22.63	87.58	6.05%	24.65	9.09

Note: Number of firms and products give the mean number of firms and products in the section. Share of dataset gives the share of the total price quotes. Price change frequencies are first calculated on the product level as the number of price changes over the number of observations for a given product. Section mean and median gives the mean and median frequencies of the products within a section. Frequencies are estimated as percentages.

Table A3.2: Descriptive statistics, end use

	Number of firms	Number of products	Share of dataset	Price change frequency
Consumer goods				
Non-durables, food	53.42	277.08	19.43%	34.16
Non-durables, non-food	12.50	34.00	2.37%	33.82
Durables	55.17	198.08	13.90%	15.77
Intermediate goods	229.58	742.00	52.13%	26.00
Capital goods	44.75	172.08	12.17%	10.47

Note: Number of firms and products are mean values calculated as the average number of products and firms per year. Price change frequency is given by the number of price changes over the number of observations in each category. Frequencies are given in percentages

Table A3.3: Section weights across bins

	Section	Weight of full dataset	Number of products							
			1-3		3-5		5-7		>7	
			Weight	Diff.	Weight	Diff.	Weight	Diff.	Weight	Diff.
1	Meat	4.08	6.28	2.20	4.71	0.63	0.81	-3.27	4.48	0.40
2	Vegetables	1.17	0.84	-0.34	1.32	0.15	0.56	-0.62	1.74	0.57
3	Fats and oils	0.52	0.82	0.30	1.12	0.60				
4	Prepared foodstuffs	16.84	7.18	-9.65	13.33	-3.50	13.55	-3.28	28.76	11.92
5	Minerals	1.61	3.61	2.00	0.54	-1.07	2.80	1.19	0.22	-1.38
6	Chemicals	9.19	9.31	0.12	8.01	-1.18	7.78	-1.41	11.12	1.93
7	Plastic articles	5.74	7.91	2.17	9.33	3.58	5.37	-0.37	1.61	-4.13
8	Skin and leather articles	0.82	0.45	-0.36	0.61	-0.21	2.48	1.66		
9	Wood articles	8.74	7.84	-0.91	9.92	1.18	10.20	1.45	7.32	-1.42
10	Paper	3.14	6.35	3.21	2.55	-0.59	3.60	0.46	1.09	-2.06
11	Textiles	4.64	5.42	0.78	4.92	0.28	4.54	-0.10	3.95	-0.69
12	Other personal apparel	0.13	0.14	0.00	0.33	0.19	0.07	-0.06		
13	Stone and glass	6.17	7.03	0.86	5.35	-0.82	10.37	4.21	3.12	-3.05
14	Precious metals	0.85	2.29	1.44	1.46	0.61				
15	Metallic products	10.75	13.56	2.81	5.98	-4.77	9.05	-1.70	13.98	3.23
16	Machines	15.15	13.23	-1.92	20.81	5.65	12.07	-3.09	14.15	-1.00
17	Vehicles	2.01	0.86	-1.16	1.21	-0.81	3.84	1.83	2.11	0.10
18	Measuring instruments	2.39	2.48	0.09	1.64	-0.75	3.15	0.76	2.37	-0.02
20	Misc. articles	6.05	4.41	-1.64	7.98	1.93	9.84	3.79	2.78	-3.27

The table gives the weights of the different sections in the bins as well as the total dataset. The weights are calculated as the number of price quotes in a given section in a bin over the number of price quotes in the bin. The *Diff.* columns give the difference between weight in the full dataset and the weight in the relevant bin. All numbers are in percentages

Table A3.4: Robustness regressions, multiproduct behavior

	Price change frequency	Size of price changes	Fraction of small price changes
Constant	0.494***	0.017	0.465***
	(0.101)	(0.013)	(0.062)
Bin 1-3	0.036	0.010*	-0.076**
	(0.039)	(0.005)	(0.024)
Bin 3-5	0.026	0.006	-0.052*
	(0.043)	(0.005)	(0.027)
Bin 5-7	0.011	0.005	-0.007
	(0.047)	(0.006)	(0.029)
Bin >7	*Omitted*	*Omitted*	*Omitted*

Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The multiproduct measures are regressed on the explanatory multiproduct bins, as well as HS 2-digit product groups to eliminate the variation potentially explained by different weights in product groups. The number of employees is included as a proxy to control for firm size.

Table A3.5: Multinomial logit, marginal effects

	All observations	Products with frequent changes
Positive price change		
Fraction up industry	0.06***	0.05*
	(0.02)	(0.02)
Fraction down industry	-0.02	-0.05*
	(0.02)	(0.03)
Fraction up firm	0.48***	0.61***
	(0.04)	(0.05)
Fraction down firm	0.37***	0.46***
	(0.03)	(0.03)
Sector specific PPI	0.00***	0.01***
	(0.00)	(0.00)
log(wage per employee)	0.03***	0.03**
	(0.01)	(0.01)
Negative price change		
Fraction up industry	0.00	-0.03
	(0.01)	(0.02)
Fraction down industry	0.03	0.01
	(0.02)	(0.02)
Fraction up firm	0.27***	0.34***
	(0.03)	(0.04)
Fraction down firm	0.36***	0.45***
	(0.05)	(0.05)
Sector specific PPI	0.00***	0.00***
	(0.00)	(0.00)
log(wage per employee)	0.03***	0.04**
	(0.01)	(0.01)

Significance levels: * $p < 0.05$, *** $p < 0.01$, *** $p < 0.001$

Note: "Positive price change" gives the marginal effect on the probability of a positive price change and vice versa. Marginal effects in percentage points are given by a one percentage point change in the explanatory variables. Other control variables include yearly, monthly and HS2 dummies. Marginal effects are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors in parentheses.

Table A3.6: Multinomial logit over bins, marginal effects

	Number of products			
	1-3	3-5	5-7	>7
Positive price change				
Fraction up industry	0.062*	0.020	0.035*	0.024
	(0.031)	(0.030)	(0.017)	(0.026)
Fraction down industry	-0.069	-0.003	0.012	-0.013
	(0.043)	(0.030)	(0.020)	(0.036)
Fraction up firm	0.501***	0.524***	0.232***	0.394***
	(0.047)	(0.039)	(0.029)	(0.031)
Fraction down firm	0.382***	0.433***	0.181***	0.302***
	(0.043)	(0.037)	(0.027)	(0.024)
Sector specific PPI	0.009***	0.005**	0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
log(wage per employee)	0.064*	0.044*	0.003	0.012
	(0.031)	(0.018)	(0.007)	(0.007)
Negative price change				
Fraction up industry	-0.013	-0.004	0.001	-0.001
	(0.020)	(0.014)	(0.008)	(0.014)
Fraction down industry	0.004	0.011	0.017	0.000
	(0.025)	(0.024)	(0.012)	(0.027)
Fraction up firm	0.206***	0.222***	0.089***	0.162***
	(0.032)	(0.026)	(0.014)	(0.018)
Fraction down firm	0.288***	0.274***	0.106***	0.234***
	(0.040)	(0.029)	(0.017)	(0.026)
Sector specific PPI	-0.005***	-0.003*	0.000	-0.001**
	(0.001)	(0.001)	(0.000)	(0.000)
log(wage per employee)	0.051*	0.035**	0.004	0.011
	(0.022)	(0.012)	(0.005)	(0.007)

Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: "Positive price change" gives the marginal effect on the probability of a positive price change and vice versa. Marginal effects in percentage points are given by a one percentage point change in the explanatory variables. Other control variables include yearly, monthly and HS2 dummies. Marginal effects are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors in parentheses.

Table A3.7: Multinomial logit model and ordered probit model, marginal effects

	Multinomial logit	Ordered probit
Positive price change		
Fraction up industry	0.05*	0.08***
	(0.02)	(0.02)
Fraction down industry	-0.05*	-0.06***
	(0.03)	(0.02)
Fraction up firm	0.61***	0.29***
	(0.05)	(0.02)
Fraction down firm	0.46***	-0.20***
	(0.03)	(0.02)
Sector specific PPI	0.01***	0.01***
	(0.00)	(0.00)
log(wage per employee)	0.03**	-0.01
	(0.01)	(0.00)
Negative price change		
Fraction up industry	-0.03	-0.06***
	(0.02)	(0.01)
Fraction down industry	0.01	0.05***
	(0.02)	(0.01)
Fraction up firm	0.34***	-0.22***
	(0.04)	(0.01)
Fraction down firm	0.45***	0.15***
	(0.05)	(0.02)
Sector specific PPI	0.00***	-0.01***
	(0.00)	(0.00)
log(wage per employee)	0.04**	0.00
	(0.01)	(0.00)

Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: "Positive price change" gives the marginal effect on the probability of a positive price change and vice versa. Marginal effects in percentage points are given by a one percentage point change in the explanatory variables. Other control variables include yearly, monthly and HS2 dummies. Marginal effects are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors in parentheses. Only "frequently changing" industries are used in the estimation.

Table A3.8: Multinomial logit with different levels of industry aggregation, marginal effects

	Level of industry aggregation		
	HS2	HS4	HS6
Positive price change			
Fraction up industry	0.12***	0.05*	0.05**
	(0.03)	(0.02)	(0.02)
Fraction down industry	-0.06	-0.05*	-0.02
	(0.03)	(0.03)	(0.02)
Fraction up firm	0.61***	0.61***	0.60***
	(0.05)	(0.05)	(0.05)
Fraction down firm	0.45***	0.46***	0.45***
	(0.03)	(0.03)	(0.03)
Sector specific PPI	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
log(wage per employee)	0.04**	0.03**	0.04**
	(0.01)	(0.01)	(0.01)
Negative price change			
Fraction up industry	-0.04	-0.03	-0.01
	(0.02)	(0.02)	(0.01)
Fraction down industry	0.01	0.01	0.02
	(0.03)	(0.02)	(0.02)
Fraction up firm	0.34***	0.34***	0.33***
	(0.04)	(0.04)	(0.04)
Fraction down firm	0.46***	0.45***	0.45***
	(0.05)	(0.05)	(0.05)
Sector specific PPI	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
log(wage per employee)	0.04**	0.04**	0.04**
	(0.01)	(0.01)	(0.01)

Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: "Positive price change" gives the marginal effect on the probability of a positive price change and vice versa. Marginal effects in percentage points are given by a one percentage point change in the explanatory variables. Other control variables include yearly, monthly and HS2 dummies. Marginal effects are calculated for HS2 category 36 "Plastics and articles thereof" in April 2010. All other variables are held at their mean. Standard errors in parentheses. Only "frequently changing" industries are used in the estimation.

Table A3.9: Standard deviations of explanatory variables

Variable	1/2 standard deviation
Fraction up industry	10.95
Fraction down industry	8.97
Fraction up firm	14.07
Fraction down firm	10.95

Note: All standard deviations are in percentage points