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Uniform Pricing in Norwegian Grocery Retail

An Empirical Study on Pricing Strategies at Norwegian Grocery Retail Chains

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Executive Summary

This work regards to pricing strategies in the Norwegian grocery retail. More specifically, it focuses on uniform pricing at *NorgesGruppen*, Norway's largest grocery retail group. Sales data from 2013 to 2018 of all of *NorgesGruppen's* stores are used to analyze its current strategy. This aims at being able to show whether *NorgesGruppen* uses a national, uniform pricing strategy on a group-/ or chain-level, a zone pricing strategy, or even a store-level pricing strategy. The analysis showed, that *NorgesGruppen's* chains follow different pricing strategies. Not all follow a pure national pricing strategy, as some chains use discounts in just some of their stores. This work could not show a specific strategy on such deviations, as they are not related to elasticity or income. Still, this work showed within-chain price deviations to be significantly lower than between-chain deviation. Uniform pricing seems, with smaller exceptions, to be the standard.

An introduced optimization model based on each store's elasticity highlighted the large potential of store-individual pricing. Due to some limitations, the model did not return specific values. Still, by optimizing prices for each product on a store-level, introducing a more price-discriminating pricing scheme, profits can clearly be increased.

Despite its huge potential to increase profits, more sophisticated pricing models are still not widely introduced, as uniform pricing is the predominant pricing strategy in grocery retail. Explanations include consumers' fairness expectation on being priced equally, menu costs, meaning the cost of changing prices, as well as a softening of price competition by committing to uniform prices. Consumers' fairness perception was analyzed by conducting a consumer survey of 294 consumers. The responses agreed on existing research, but also showed the potential of improved pricing schemes.

Keywords: *NorgesGruppen*, uniform pricing, elasticity, grocery retail, pricing strategy, zone pricing, profit maximization, optimization model, sales data, menu costs, consumer fairness perception, questionnaire, price competition, Norway

Contents

List of Figures

List of Tables

1 Introduction

Different pricing strategies have been subject to numerous studies. The influence on profits, market share, and customer satisfaction, especially their sense of justice, plays a big role when companies decide on their pricing strategies. In general, most of the research so far focuses on four different pricing strategies.

The first strategy is **national pricing**, in which prices are set constant over all stores within a country. This could include a **group-level pricing** strategy, introducing uniform pricing for all chains within one group. More often, national pricing is considered as a **chain-level pricing** strategy, meaning uniform pricing within chains. This was already subject of studies of DellaVigna and Gentzkow (2019) about different retail stores in the US, Lloyd et al. (2014) and Norman (1981) regarding grocery stores in the UK, Olczak (2015) about optician retail chains in the UK and many more regarding different markets and occasions (soft drinks, McMillan (2007); movie tickets, Orbach and Einav (2007); power exchange markets, Kahn et al. (2001); rental cars, Cho and Rust (2010); online music, Shiller and Waldfogel (2011)).
National pricing developed to become the expected strategy by consumers over the last decades (Foros et al., 2018). Furthermore, caused by its simplicity (Norman, 1981), it became more and more the "default" strategy for most businesses and especially for the retail business. Both effects, consumers' expectation as well as the simplicity for retailers led to national pricing being widely used today.

The second pricing strategy, **zone pricing**, shows a higher degree of price discrimination. This is done by setting different prices between zones, but equal prices within those certain areas. These areas may correlate with borders, geographic landmarks, or other lines. Within these areas, prices are fixed but may deviate from pricing in other areas. Such pricing strategies are for example discussed by Adams and Williams (2019), Montgomery (1997) and Peeters and Thisse (1996). They state that zone pricing may be a good middle course between national pricing and perfect price discrimination, nearly maximizing profits while reducing the negative aspects of more detailed pricing.

The third pricing strategy comes along with a higher degree of price discrimination and sets prices individually for each store. In theory, this **store-level pricing** strategy is considered as *perfect*, as revenues are maximized on a store-level. Such a pricing strategy may be, in comparison to the fourth pricing strategy, highly feasible with already available data. Still, scholars mention many disadvantages of such strategies as well, which will be outlined in chapter 5 in more detail. Noteworthy articles are the ones from Besanko et al. (2003), DellaVigna and Gentzkow (2019), Montgomery (1997), and Cooper (2003).

The fourth strategy is even going further, setting prices individually per customer, based on demographic values, customer preferences as well as their willingness to pay. Such an **individual pricing strategy** does require detailed customer information and is, therefore, not yet largely introduced. Many grocery retailers do have some kind of bonus system/ customer memberships, which they use to gain personal data. This data is already in use to generate personalized offers, the main focus of such programs as of today is in most cases nevertheless to increase sales by increasing customer loyalty and satisfaction (Bridson et al., 2008). Still, as *Big Data* may in the future be more generally available (i.e. for all or at least most customers), this may change the pricing strategies of many companies. E-commerce may offer a great chance to create more detailed consumer profiles in the future, as more and more online shopping enables retailers to connect different purchases with specific customers. Such pricing strategies are not yet largely discussed regarding retail but in their welfare implications. Noteworthy works are especially the ones by Bar-Gill (2019), Bergemann et al. (2015), and Bhaskar and To (2004).

In theory, the more price discrimination takes place, especially in a monopolistic market, the higher profits are. In oligopoly or even in competitive markets, this may not be applicable. An unsatisfied fairness perception of customers, menu costs, or the softening of price competition by uniform pricing are the most often discussed reasons. Furthermore, many more restrictions and requirements must be kept in mind, which will also be discussed in chapter 5 in greater detail. Scholars discussed will include Kahneman et al. (1986), Orbach and Einav (2007), McMillan (2007), Corts (1998), and others.

This paper uses sales data from supermarkets in Norway from Norway's biggest grocery retail group, *NorgesGruppen*, covering 43.2 percent of the revenue of grocery retail in Norway in 2018 (Delfi, 2019). The data set includes data from 2,327 stores of four main chains, namely *Joker*, *Kiwi*, *SPAR*, *MENY*, and *CC-Mat* with just three stores. This represents a considerable share of 60.4 percent of the total of 3,851 stores (Dagligvarehandelen, 2019) on average in the period of 2013 - 2018 in Norway.

This paper analyses *NorgesGruppen's* pricing strategy and concludes that a uniform, national pricing strategy is used on a chain-level. This paper shows pricing differences between chains, stating that there is no group-wide uniform pricing strategy in place. Also, this work shows that differences within chains are either not significant or significant but very small. This agrees on what Cooper (2003) found to be true for the UK retail market. National pricing (on a chain-level) is widely used. There does not seem to be any strategy to strategically price by elasticity or by income. Furthermore, an optimization model based on elasticity is introduced, highlighting the large potential non-uniform pricing may have. Besides some limitations, which will be discussed later, the model shows the attractiveness of price increase as a reaction to inelastic demand. Norman (1981) argues that uniform pricing strategies can never, or just under fierce competition, be optimal. The introduced optimization by elasticity can, therefore, help to increase profits.

A survey that was conducted as part of this work highlighted the importance of consumer communication. The risk of losing customers by violating their fairness perception is imminent and may endanger a retailers' long-term success. When considering how such a finer, more discriminatory pricing scheme could look like, the findings imply that pricing by elasticity may be hard to communicate. Pricing schemes based on household income seemed to gain a higher agreement, but may be harder to accomplish. Finally, zone-pricing can be considered to be widely accepted, while still offering the chance to optimize prices.

Chapter two offers an overview of the data used, the preparation process as well as a descriptive analysis of the demographic data. Chapter three presents the actual retail data used, analyzing pricing strategies as mentioned above, considering demographics as well as elasticity. The fourth chapter introduces a profit maximization model to analyze the impact of a more detailed pricing strategy with a higher level of price discrimination. This chapter aims at being able to show whether such a pricing strategy is attractive for *NorgesGruppen* and what gains possibly to expect. Chapter five includes the discussion of reasons, why national pricing is still the most predominant pricing strategy, implications, as well as the conclusion of this work.

2 Data

2.1 Demographics in Norway

Demographic data was obtained by Statistics Norway (*Statistisk sentralbyrå*), Norway's national statistical institute. The data set includes median household incomes and the number of households for all of Norway's municipalities for the years 2013-2018 (Statistisk Sentralbyrå, 2019).

Norway is organized in counties (*fylke*), municipalities (*kommune*) as well as postal-code-areas within these municipalities (*postnummer*). The original data set for statistical data for numbers between 2013 and 2018 included 430 municipalities in 19 counties.

Norway undertook a major reform of municipalities and counties which started in 2017, continuing to 2020. As there were changes already taking place in 2017, the first data set had already to be edited accordingly. Most early changes were only changes regarding postal codes and names of municipalities in the preparation of the main "wave" of the reform. As these changes were not yet including merges and the like, it was possible to re-merge the values before and after the changes to achieve complete data sets. According to the data, values followed the trend of slight growth in median income as well as in the number of households. These 430 municipalities plus their statistical data could have been used for all further analyses.

NorgesGruppen's store data, which was obtained separately, included 2,327 stores in 1.342 different postal-code-areas (see chapter 2.2). Contrary to the statistical data, *NorgesGruppen* uses the most recent postal codes for all its stores, even if the data was collected when the prior structure was still in place. Therefore, the original demographic data set had to be edited to fit the new postal codes and structures.

Especially in 2019, many municipalities were merged, new municipalities founded as well as new counties created. All in all, the number of municipalities was decreased. Since the 1st of January 2020, Norway is made up of 11 counties and 356 municipalities as well as numerous postal-code-areas. For all municipalities which were merged or changed in any form, weighted average values have been calculated. The original data set gave median household income. Since no better fitting data was available, the weighted average was calculated based on the number of households to arrive at historical values for the new structure. An example can be seen in Table 1.

In the original data, median household income varies widely from 533 (thousand NOK) at the 10th-percentile municipality in 2015 to up to 762 (thousand NOK) at the 90th-percentile municipality in 2018. In general, median household income grew by an average of 1.45 percent from 2013 to 2018. The total median income is 621 (thousand NOK).

The municipalities with the highest median income are mostly close to larger cities, representing economic centers in Norway, which may influences optimal pricing (see table 12 in the appendix). Even if marginal cost differences are often considered to be small (Stroebel and Vavra (2019) and DellaVigna and Gentzkow (2019)), other scholars mention differences based on a store's location and remoteness (Handbury and Weinstein (2015), Ambrose (1979), Atkin and Donaldson (2015), and many more). Larger cities themselves are almost not represented in the list of top total income municipalities (see table 13 in the appendix).

The number of households also varies widely between municipalities, ranging from 529 households at the 10th-percentile to 10,620 households at the 90th-percentile. On average, each municipality has 5,497 households.

To allow for further analysis, the average median income over the whole period was calculated. Even if this mixes up the concept of averages with the concept of medians, it may offer relevant insight into the average wealth of a municipality.

It is important to mention that the demographic data was still on a municipality-level and, therefore, not being used to be merged with other data. Therefore, a more detailed list of all postal-code-areas was used (Posten Norge AS, 2020). Each municipality can be made up of multiple postal-code-areas. The two separate data sets were merged using the postal-code-area's official names. As the demographic data is available on municipality-level, each postal-code-area was assigned the values

Municipality	Median Income 2013	Households 2013
Bø i Telemark	526,000	2,667
Sauherad	566,000	1,894
Midt-Telemark	542,610	4,561

Table 1: Merging of municipalities (example)

Notes: Example of two municipalities being merged into one new. The Median Income of the new municipality is the weighted average (by households) of the two prior municipalities.

of its municipality. Furthermore, county numbers were added for each municipality (Kartverket, 2020) to enable further analyses, especially regarding zone pricing.

The final demographic data set included all 356 municipalities (see figure 1) with 1,819 different village-names and a total of 5,085 different postal codes, each postal-code-area bearing the municipalities median income as well as its number of households for the whole period and following the new structure introduced as of 1st of January 2020. Special areas (e.g. Jan Mayen) were excluded from the data set due to insufficient data. All those areas nevertheless would have been excluded later on, as none of *NorgesGruppen's* stores are in any of these areas.

For further analyses, especially regarding elasticity and its influence on optimal pricing, the statistical data was merged with the store data, as described in the next chapter.

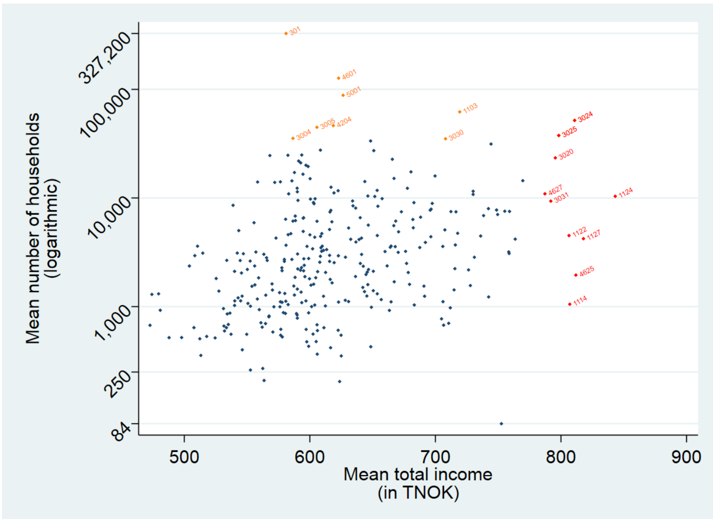


Figure 1: Municipalities by income and number of households

Notes: The graph displays all municipalities in the final data set after all merges. The x-axis describes each municipality's mean total income. The y-axis shows each municipality's mean number of households (logarithmic). Small numbers refer to municipalities' postal codes and are shown for selected municipalities.
The ten municipalities with the highest mean number of households are presented in orange and correlate with the municipalities found in table 13. The ten municipalities with the highest mean total income are presented in red, partly correlating with the ones in table 12. Due to the merges described in chapter 2.1, the values don not correlate completely.

2.2 Store Data

NorgesGruppen provided a more detailed store list, including the variables Store ID, each store's postal code as well as latitude and longitude of each store. For a map of all stores see figure 14 in the appendix.

Using each store's postal code, this data was merged with the more detailed statistical data described before (see chapter 2.1). As mentioned before, the demographic data was calculated on a municipality level. Stores in the same municipalities, therefore, have the same demographic values, even if they may have deviating postal codes or deviating target-customers.

After being merged, each store had the variables as described before: the median household income, the number of households for the period 2013 -2018 as well as average median income and average household numbers over all 6 years.

When comparing demographics statistics of the different chains, the values show large deviations (see table 14). Stores of *MENY* for example seem to be located in urban, high-income locations. Joker's stores on the other hand seem to be located in much more rural areas, also showing lower values regarding store income. This supports the hypothesis, that there is, without taking into account each chains' pricing strategy, price discrimination through store localization.

To allow for further analyses, the developed data set containing stores as well as the corresponding demographic data was merged with the full retail data set as described in chapter 2.3.

2.3 Retail Data

The retail data used in this paper was provided by *NorgesGruppen*. The data set includes all products sold between the years 2013 and 2018. Each row in the data set represents one specific product in a specific week sold by a specific store. This "row" will from now on be referred to as an observation. Products are defined by a product name as well as by its EAN (European Article Number). Each product can theoretically have multiple EANs, used in different stores, sizes, designs, or sale campaigns. The data set includes 883,105,714 observations, 38,325 different products with 38,341 different EANs (just some products do have multiple EANs assigned), 2,327 different stores, and 312 weeks with sales.
The stores covered five chains: *Joker* (873 stores) *Kiwi* (735 stores), *SPAR* (424

stores), *MENY* (292 stores), and *CC-Mat* (3 stores). As CC-Mat is just of minor importance, its' stores are included in the analysis but outcomes are often not described in further detail. Variables used in this paper are, besides the aforementioned, the weekly quantity, the weekly sales price as well as the product category each product belongs to as defined by *NorgesGruppen*.

Before being able to use the data set in a meaningful way, various steps had to be performed. The first step includes the cleaning, merging, and preparation of the data set and is described in chapter 2.3.1. The second step was to introduce a selection of product groups and products to reduce the number of data points and to increase the meaningfulness of the analyses. This process is described in chapter 2.3.2.

2.3.1 Data Cleaning, Merging, and Preparation

To prepare the data for further use, the data first had to be further processed. Some of the variables had to be transformed while others had to be renamed or formatted to fit the other data sets regarding stores and demographics.

Besides dropping variables that are not used, product categories were extracted for all products from another, smaller data set and merged to be included in the full data set. Those categories were of special interest when deciding on the products to be used.

In the original data set, weeks that run over two months were split up and presented as two different observations. While this enables calculating monthly values, it does bring in difficulties for weekly calculations. In retail, advertisements and special sales are done on a weekly basis, or on fixed week-days, not considering that a new month started. Therefore, sales numbers were summed up and reduced to one observation per store, week, and product.

Furthermore, the observations had to be merged with statistical data of the stores to include postal codes (ZIP) of each store, store names, other additional information like latitude and longitude as well as the whole demographic data as described in chapter 2.1 and 2.2. To merge, each store's unique store ID was used. Stores that were either not included in the store-data or stores that were only in the store-data but not in the original data set were excluded from the further analysis. Stores that haven't been included in the store data but were contained in the sales data may refer to stores which have seen changes (e.g. store ID), as the store list was up to date while the sales data was collected 2013 - 2018. Stores that were not in the sales data may refer to stores that were not operational in the years which are considered for this work. This may be due to closure, construction, or even an opening after the end of this data set.

2.3.2 Sample Selection

For most analyses, this paper focused on a selection of products. The products were selected by a high sales volume (quantity) and high sales (sales turnover). These criteria enable a higher accuracy of the further analysis.

The selected products include one product from different categories. The categories used are soda, bread, minced meat, dressing, sauces and oils, egg, ready-made food, juice, coffee, fresh and processed meat, milk products, cheese, paper products, two types of spread, chocolate, butter, sweets, and beer. The selection of the categories is based on the aforementioned criteria, also covering all major categories with significant sales ($>$5%). The selection is similar to the one used by DellaVigna and Gentzkow (2019) but representing the Norwegian market more accurately.

These product categories all together cover approximately 69 percent of total sales. Of all product categories, 9 are durable goods while 10 are considered perishable. The selected products are widely available and are sold multiple times per week per store in an average store, generating between 23 (lowest) and 297 (highest) thousand NOK of revenue in such an average store.

A list of the selected products in more detail, their respective product categories as well as simple descriptive statistics for each product can be found in the appendix (see table 15, table 16, and table 17).

3 Descriptive Analysis of Retail Data

In the first part of this chapter, *NorgesGruppen's* sales data will be used to see whether a national pricing strategy is actually in place, whether there are differences in the pricing strategies in its' different chains as well as whether there are changes over time. This will also include a possible impact of geographic differences on the pricing strategy, possibly showing a zone pricing strategy.

In the second part, the focus will switch to the impact of demographics on the pricing strategy, especially the impact of higher median income on prices. If there should be some degree of optimal pricing, prices are expected to grow with higher median incomes.

The third part continues where the second part ended but will analyze the data considering elasticity. Expanding the findings of the prior part, elasticity will include changes in prices and its corresponding reaction regarding the sales volume.

3.1 Uniform Pricing and Pricing Strategies

As described before, *NorgesGruppen* may follow one of the prior discussed pricing strategies. Therefore, different tests were performed.

To see the degree of overall differences in pricing, a weekly (w) average price per product (e) for each chain (c) $\breve{p}_{ecw}$ as well as an average price per product for all chains $\tilde{p}_{ew}$ was calculated for each week. In the next step, the absolute deviation $d_{abs_{esw}}$ and relative deviation $d_{rel_{esw}}$ from these average weekly prices have been calculated per observation by using the weekly price of a product per store (s) p_{esw}. The absolute price deviation corresponds to the difference of actual prices to the weekly average price (in NOK). The within-chain deviation was calculated as follows.

$$\begin{aligned}
\breve{p}_{ecw} &= \frac{\sum_{s_c}[p_{esw}]}{N_{e_c}} \\
d_{abs_{esw}} &= p_{esw} - \breve{p_{ecw}} \\
d_{rel_{esw}} &= \frac{p_{esw} - \breve{p}_{ecw}}{\breve{p}_{ecw}}
\end{aligned} \tag{1}$$

The price deviation from the overall average price of a product was calculated similarly, replacing $\breve{p}_{ecw}$ with $\tilde{p}_{ew}$ as well as the number of observations per product per chain N_{e_c} with the overall number of observation per product over all chains N_{ec}.

The relative deviation describes the percentage difference to the calculated weekly average price. Comparisons were made on a store level (compare figure 2), chain level (compare figure 3a) as well as on a geographical zone level (compare figure 4).

Uniform Pricing To see the overall degree of uniformity of pricing over all of *NorgesGruppen's* stores, the aforementioned variable is used. The price deviations lie between -.21 at the 5th-percentile to .17 at the 95th-percentile. As this variable represents a relative value, calculate around zero, it mainly serves in representing the standard deviation of .12. Still, it means that price fluctuations of -21 percent to 17 percent are not very special, even when taking into account all observations. As many products are not on sale on a regular basis, this shows the large deviations in pricing between stores and chains. This can also be seen graphically in figure 2, where the stores are already grouped by chains, suggesting differences between chains.

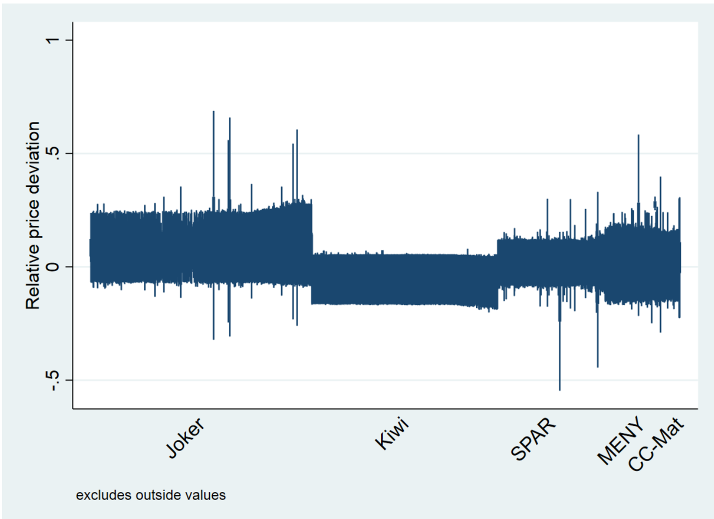


Figure 2: Relative price deviations by store and chains

Notes: The graph displays the relative price deviation from the average product price of all chains per week as a boxplot. Each boxplot represents one store, including all products over all weeks sold at each store. Outsiders are excluded. The x-axis represents all stores, grouped by chains. The y-axis represents the deviation, a value of .1 means for example a 10 percent difference of the weekly price at one store for one product in comparison to the average weekly price over all chains. Due to the large number of stores, the single boxplots can not be seen clearly. Nevertheless, the graph helps to point out differences between stores as well as similarities within chains. A more detailed representation of stores of just one chain can be seen in figure 20a.

It can be concluded, that *NorgesGruppen* does not charge the same prices at all stores at any time. As this analysis includes stores from multiple chains, it seems that *NorgesGruppen* has different pricing strategies at the chain-level. This finding is not surprising but serves as the basis for further analyses.

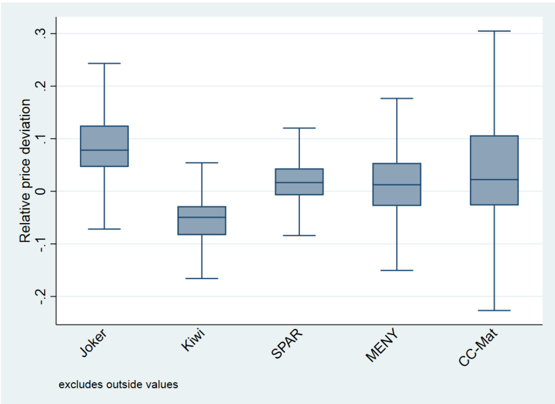
Regarding different products, price deviations were very different between products (see figure 15 in the appendix). Some products seem to be more intensely used for discounts, while others do not show large fluctuations in prices. Tomato ketchup (product (4)) shows a larger span, with the 5th-/ and 95th-percentile ranging around -.5 and .5 relative deviation from the average price. This again means that price deviations of up to -50 percent from the average price, but also price increases of up to 50 percent are not uncommon. Minced meat (product (3)) on the other hand, as sold by different chains, shows very little fluctuations with the 5th-/ and 95th-interval being less than .1 around its mean.

As this analysis is done on an aggregated level, larger differences in a products' base price across chains would be shown as large deviations (and, therefore, a larger span in the boxplot). Lloyd et al. (2014) state, that sales account for up to 43 percent of the variation in prices, with the rest stemming from differences in the base prices. To see whether this is the case, the same calculation and graphical representation were done on a chain-level. Figure 16 in the appendix illustrates this for four of the products. All four products did not show extreme ranges in figure 15. Differences across chains were similar to the already shown deviating pricing strategies between chains and will be discussed in the next chapter. Between products, differences can clearly be seen.

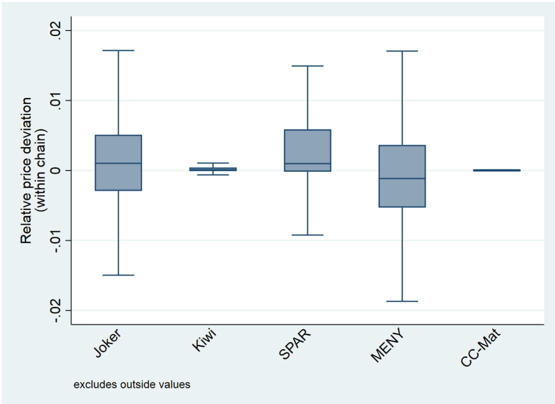
When looking at changes over time, it is again important to separate between within-chain and between-chain relative price deviations. Figure 17a shows a smoothed time series for between-chain price deviations. Even if changes over time are low, there is a clear trend to higher deviations. From 2013 to 2018, between-chain relative price deviations increased by around four percent. This highlights that uniform pricing on a group-level does not exist as of today and that the development does not show a trend to such a pricing-strategy.

Chain-Level Pricing On the chain-level, figures 2, 15, and 16 already showed larger differences between chains but low differences within these chains. Within chains, there seems to be much more uniform pricing. This means, that prices in different stores within one chain do not deviate much. Prices deviate -.02 at the

5th-percentile and .02 at the 95th-percentile. Comparing the standard deviation of .12 (overall price deviation) with the standard deviation of .04 within chains further confirmed that. This effect can again be seen graphically in figure 3a for between-chain deviations and in figure 3b for within-chain deviation. The graphs show the relative price deviation between-/ and within-chains as boxplots for all stores within the sample over the selected products, grouped by chains. Even graphically, large changes between chains can be seen, while the boxplots within chains seem to be quite similar. Here it is important to keep in mind the different ranges of the axes.



(a) Between-chain price deviations



(b) Within-chain price deviations

Figure 3: Relative price deviations within-/ and between-chains by chain as boxplots

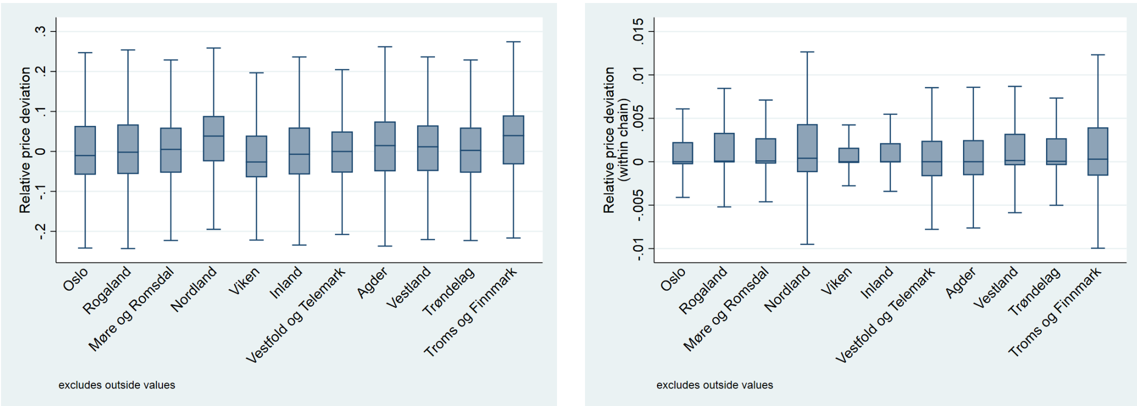
Notes: The graphs display the range of price deviations from the average product prices as a boxplot for each chain. Each box represents the 25th to 75th-percentile. The adjacent lines follow Tukey's definition of using 1.5 times the interquartile range (IQR). The graphs use data on an observation-level as described in chapter 2.3. Each observation, therefore, covers one price and quantity and the described relative price deviation from the overall (a) and the within-chain (b) average weekly price per store, product, and week.
(a) The graph displays the range of relative price deviations from the average product price per week over all chains. The graph shows large differences in average prices between chains. Furthermore, each chains' range deviates greatly from other chains. *Kiwi* seems to offer below-average prices most of the time, while *Joker* offers clear above-average prices. *CC-Mat* is included with very limited observations, explaining the large range and limiting the meaningfulness.
(b) Similar to (a), the graph displays the range of relative deviations from the average product price (per week) as a boxplot for each chain. The difference is, that the chain-average weekly price is used. The graph, therefore, shows the range of within-chain weekly deviation. Again, *Kiwi* and *CC-Mat* show the lowest deviations within-chain, while especially *MENY* shows considerably more deviation. Mind that the scale of the within-chain price deviations ranges from -.02 to .02 while the overall deviation chart ranges from -.2 to .3.

Generally, different pricing strategies can be seen, as strategies deviate within *Norges-Gruppen* within chains. Especially *Kiwi*, possibly also *CC-Mat* follow an *everyday* *low pricing strategy* (EDLP), making little use of sales and discounts, but, therefore, offering generally lower prices. The numbers show very little differences between their stores over the weeks. As was shown in figure 16, some products are used for discounts even at this chain, while others show no deviation of prices at all. It is also interesting, that Kiwi not just follows an EDLP strategy, but that prices between its stores do almost not deviate. For Kiwi, it is valid to state that it follows a national, uniform pricing strategy.

Other chains generally price higher but, therefore, make greater use of sales and discounts (e.g. stores of *Joker*, *SPAR*, or *MENY*). These chains show far larger price deviations from the overall average price. Hitsch et al. (2019) call such a strategy Hi-Lo (High-Low), showing, in comparison to the steady EDLP strategy, phases with high prices (base price) and with low prices (sales discounts). Also, prices at these chains deviate far more within the chains over the weeks (see figure 3b). As even those larger deviations are, when seen in comparison to the between-chain deviations, very low, one can state that all chains within *NorgesGruppen* follow a national pricing strategy, even if some chains allow for deviations.

When again looking at changes over time, this effect of separated pricing strategies of the different chains, but almost uniform pricing within those chains can be seen. Comparing figure 17a with figure 17b highlights this. While figure 17a showed an increase of between-chain deviations, 17b shows a decreasing trend for within-chain deviations. While the difference in pricing strategies of different chains increases, prices within chains are even becoming more and more uniform.

Zone Pricing The same calculations as above were done to see the influence of geographic deviation on prices. The most logical zones would be counties, possibly further grouped into other geographical zones like *North/ South* or *West-Coast/ South-Coast/ Inland/ etc.* Calculations for Norway's counties show that there are significant differences, all county means deviate significantly from the hypothesized mean of zero, but that these differences are very small (see table 19 in the appendix). This can again also be seen graphically. Figure 4a shows the different counties. Differences are existent but are very small. Figure 4b shows the relative within-chain deviation for all counties. Deviations are already by far lower, with counties average price deviations closely fluctuating around zero. Both findings do not yet imply any causality. Some counties may have a higher appearance of low-cost-stores, while others may have a higher occurrence of high-cost stores. Also for within-chain deviation, the composition of stores may influence average values, as pricing deviates largely between chains. Differences may, therefore, be dependent on each chains' occurrence. Such price discrimination through localization will be discussed in chapter 3.2. General differences can already be seen when looking at all stores' locations (figure 14).



(a) Between chains (b) Within chains

Figure 4: Relative price deviations by county as boxplots

Notes: Graph (a) displays price deviations from the average weekly product price (as introduced at the beginning of this chapter) as a boxplot by county over all chains. Each boxplot includes data of all stores in one county as described in chapter 2. The y-axis represents the relative (percentage) price deviations from each product's weekly average price over all weeks and products. Outside values are excluded. Graph (b) describes the same for within-chain deviations. Differences are, as seen before when comparing relative price deviation between chains and within chains, much smaller. The generally higher prices in Nordland can, even more when seeing the (comparably) large within-chain deviations, be explained by a higher occurrence of *Joker*-stores (see figure 14).

There could nevertheless be zone pricing at a chain level, while overall prices are very similar. Figure 18 in the appendix shows the relative price deviations by counties and by chains. While again clear deviations can be seen between chains, within chains deviation in different counties seem to be small. When looking at each chain separately, one can see how similar prices between counties are (see figure 19 in the appendix for a more detailed graph for just one chain). The observed (small but significant) variations (see figure 4), therefore, esteem most likely from a diverse composition of stores.

Other geographical zones as described before (*North*/ *South*, etc.) could not be observed. Within chains, prices seem to be set independent of any zones. In general, it can be concluded that there is not yet strategic zone pricing in place at any of *NorgesGruppen's* chains as of today. This matches the findings of Hitsch et al. (2019)

who find that prices within chains are much more similar than prices across stores of different chains, concluding that zone pricing is not (yet) an applied strategy.

3.2 Pricing and Demographics

As some differences exist, these could esteem from different pricing regarding household income in these regions. DellaVigna and Gentzkow (2019) found a small but significant correlation at US-stores as they analyzed small deviations from national, standardized pricing. As within chain differences are marginal, possibly chains with generally lower prices (like *Kiwi*) could be located in areas with lower income. A calculated linear regression, using the variables *relative price deviation* and *median household income* showed that there is a statistically relevant relation between these two variables. Still, this shown relation is very small. In fact, following a mean income increase by 100,000 NOK of a county would lead to an expected decrease in price deviation by .00547, thus correlating with lower prices. This means, for example, that prices in municipalities at the 10th-percentile of income are 1.25 percent lower than those at the 90th-percentile of income (compare chapter 2.1). The same applied for the *number of households*, where also a statistically significant, but relatively low difference can be observed. More rural areas are charged more. Per 100,000 inhabitants, price deviation is reduced by .00271, thus again correlating with lower prices. As differences in the number of households are much smaller, the influence of it is considerably lower even if the regression coefficients are somewhat similar. In the third regression, both factors have been taken into account. Surprisingly, both factors showed even bigger significant regression coefficients (see table 2). It can, therefore, be concluded that small, low-income municipalities are charged more when compared to bigger, higher-income municipalities. This agrees with the already mentioned findings of DellaVigna and Gentzkow (2019), Handbury and Weinstein (2015), Atkin and Donaldson (2015), and Ambrose (1979).

All three regressions have explanatory worth, as their R^2 deviates significantly from zero (F-test; 99th-confidence interval). Nevertheless, all three regressions show very low values for their R^2, thus signaling a bad fit of the linear model. Also, all findings are significant at the one percent level of significance (α) according to the t-test.

In the following figure (figure 5), one can see all observations in the data set. Vertical lines often represent observations within one store, but also different stores within the same municipality or in municipalities with similar household income. As the mean

	(1)	(2)	(3)
	Relative price deviation (dev_price_rel)		
Total income	$-5.47e-08^{***}$		$-6.54e-08^{***}$
	(-88.87)		(-103.89)
Number of households		$-2.71e-08^{***}$	$-3.69e-08^{***}$
		(-61.06)	(-81.38)
Constant	0.0346^{***}	0.0014^{***}	0.0433^{***}
	(88.34)	(28.87)	(196.59)
Observations	7,891,202	7,891,202	7,891,202

t statistics in parentheses

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

Table 2: Regression table: relative price deviation

Notes: The table states the linear regression model for both, the relation of the relative price deviation (percentage deviation of weekly price to the overall weekly product mean) to the mean total income as well as to the number of households. The table furthermore shows their significance as tested by a t-test (t statistics in parentheses, significance represented by stars).

median household income over all years was used, each store stays on each specific position on the horizontal axis. The red line represents the calculated regression line ((1) in table 2). As the slope of the calculated, significant linear regression line is very small, it cannot be seen graphically.

It can still be true that there is an effect on the chain-level, while on an overall level this effect is covered due to the number of stores. For this analysis, the store-mean of the relative price deviations was calculated per store. This means, that each store is assigned one average value, signaling its average relative price deviation (between-chains). The analysis on an overall level regarding the mean total household income as before shows a statistically significant negative correlation. This just agrees on what was presented on the observation level (compare table 2). The regression has an explanatory worth (significant F-statistic) while the linear regression fits the data relatively bad, reducing the relevance of this analysis.
The regressions on a chain-level show deviating, non-significant correlations. Except for one chain, all regressions are not significantly relevant. When considering these imperfect results, the outcomes are mixed, not showing a clear trend. This can again also be seen graphically in figure 22 in the appendix. More details can be found in table 20. It seems that on a chain-level, prices do increase with rising household income. This would agree with the findings of DellaVigna and Gentzkow (2019).

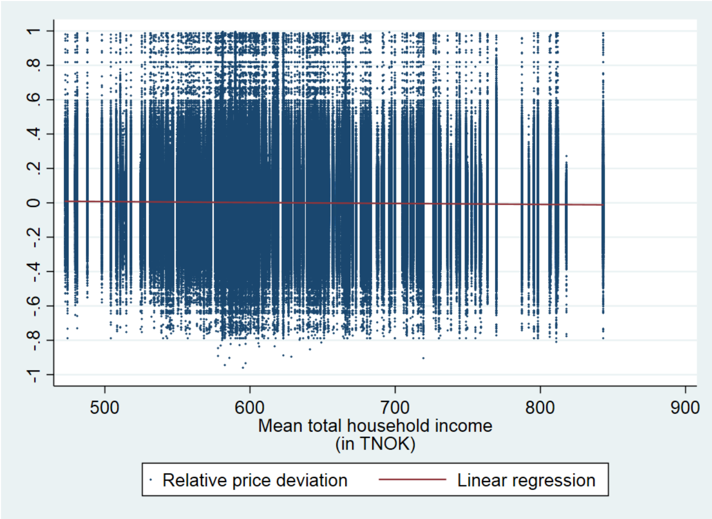


Figure 5: Relative price deviations relating to household income

Notes: Each dot represents one single observation. The y-axis shows the relative deviation of prices from the average per product. The x-axis shows household income. As the household income per store stays unchanged over the period, each store's observations range along one x-axis-position. The red line shows the regression line in regard to income as introduced in table 2. It is important to mention that the graph is somewhat misleading, as most of the observations are close to the zero-deviation-line and large deviations (+/- .6) are very seldom. Due to the number of observations, this cannot be clearly seen.
Figure 22 shows the same with the average relative price deviation per store.

Still, as the calculated correlations are not significant, it is not possible to draw conclusions.

The stores, nevertheless, deviate in their locations. Even if prices within-chains do not significantly correlate to household income, price discrimination could exist trough store localization. Chapter 3.1 showed significant deviations in prices between chains. Furthermore, the chains do deviate in their locations in regard to income and the number of households (see table 14). *Joker's* stores are for example located in much smaller municipalities than the ones of other chains. Also, the store income is generally lower. The analysis in chapter 3.1 showed, that prices are significantly higher than those of other chains. This also explains the findings presented in figures 2 and 22. It can be concluded, that price discrimination trough store localization exists and that this effect outweighs other effects like lower prices in lower-income stores within chains.

Generally, it can be concluded that there is a statistically significant influence on relative price deviation for both, mean household income as well as the mean number of households. Stores in high income and populated counties seem to offer the lowest prices. Again, it is important to keep in mind that both effects are very small and don't seem to be systematical. Furthermore, the data does not show any significant differences between chains regarding pricing based on income.

3.3 Pricing and Elasticity

Calculating elasticity is often equated with using available data on prices and quantities to linear regress some kind of elasticity. As some products were introduced or abolished in between 2013 and 2018, such an approach may lead to wrong elasticity estimations. Furthermore, simple linear regression models using the so far used variable *relative price deviation* on an observation-level do simply not lead to meaningful results, as demand elasticity may be greatly over-/ or underestimated, depending on natural fluctuations in demand in many stores.

Therefore, calculations were again based on the work of DellaVigna and Gentzkow (2019). Instead of using relative deviations per observation, logarithmic values per store (s) were used. The logarithmic price deviation per observation was calculated as the log of the price deviation from the overall mean price per product (e) and store (s) $\hat{p}_{es}$. Similarly, a logarithmic quantity deviation was calculated per store as the log of the deviation from the mean price per product and store $\hat{q}_{es}$.

$$\begin{aligned} \log\_p\_dev_{esw} &= log(\hat{p}_{es})p_{esw} \\ \log\_q\_dev_{esw} &= log(\hat{q}_{es})q_{esw} \end{aligned} \tag{2}$$

Finally, a linear regression per store was used to derive each store's elasticity. The regression used the independent variable *log price deviation* and the variable *log quantity deviation* as the dependent variable (see equation 2).

To arrive at meaningful elasticity estimates, some constraints were used. First, all weeks with negative quantity or prices were excluded. Such values can arise following product returns but are relatively seldom and do not occur at stores and products with usually high (sales) quantities. To not include introduction-/ or termination-phases, meaning weeks with less representative demand, weeks with less than 40 percent of the pre-cleansing-average of demand were excluded. Contrary to other calculation methods, the method used by DellaVigna and Gentzkow (2019) considers all products over the whole-time horizon to increase reliability. To exclude unusual stores, all stores with less than 500 observations in total were excluded. This "cap" represents around 10 percent of the 5,400 possible observations for a store carrying all products during their general availability as stated in table 17. Those constraints together excluded 689,181 observations (8.73 percent of all observations at this stage).

Logarithmic elasticity arrives at much more meaningful outcomes compared to simple linear regression. Expressing elasticity this way is represented by a linear logarithmic elasticity that is described with a constant β_s per store s as well as a variable (slope) η_s per store. The logarithmic quantity per store (s) and product (e) can, therefore, be described as:

$$\log(q_{se}) = \eta_s * log(p)_{se} + \beta_s \tag{3}$$

Elasticity (η_s) ranging from -2.4614 at the 10th-percentile to -.4904 at the 90th-percentile. Constants (β_s) ranging from 3.3699 (at the above-mentioned 10th-percentile for the regression coefficient of price deviation) to 1.4793 (at the 90th-percentile for the regression coefficient of price deviation). An increase in log prices by 1.0 log points leads to a decrease in log quantity of η_s log points.

This calculation of elasticity does not, in contrast to the one by DellaVigna and Gentzkow (2019), account for endogeneity. Many possible side-effects of the real world were not included in this model. Such side-effects could be product-year or even product-week-of-year effects as introduced for example by DellaVigna and Gentzkow (2019). This includes dependencies on the weather (e.g. barbecuing may be more usual on warm summer weekends), crises (e.g. COVID-19, leading to a temporal demand increase in toilet paper and other products, independent of product prices) and many more effects. As such effects were not considered and this calculation of elasticity considered all "normal" weeks between 2013 and 2018 per store, the elasticity as calculated may over-/ or underestimate consumer's reaction to price changes. Furthermore, the elasticity was calculated per store, not being dependent on a specific product. The elasticity between products can be considered to fluctuate widely. This effect was not considered to guarantee a sufficiently large data set for each store to increase its reliability. All in all, these limitations may lead to a biased calculation of elasticity. Nevertheless, the calculated values seem to fit quite well, and will, therefore, be used for further analyses. Developing a more abstract model for calculating elasticity may help to gain a better insight, but may also endanger the reliability of the calculation, as more and more external values are taken into account.

Price deviation/ elasticity To answer the question of whether *NorgesGruppen* charges its customers based on elasticity, a regression is used. As the independent variable, the calculated and described elasticity per store (variable component, ηs) is used. The dependent variable is the store-mean of the already used variable *relative price deviation*.

The calculated linear regression shows that there is a statistically relevant relation between these two variables. The F-statistic indicates statistically significant findings (99th-significance interval). The regression has an explanatory worth, even more as the R^2 indicates a relatively good linear fit of the data ($R^2 = .68$). The regression model returns a negative correlation, indicating lower prices for stores with less elastic customers. Again, this finding is significant following the t-statistic. Figure 6 shows the graphical representation of the data as well as the regression line (more specific data can be found in table 3 in the appendix).

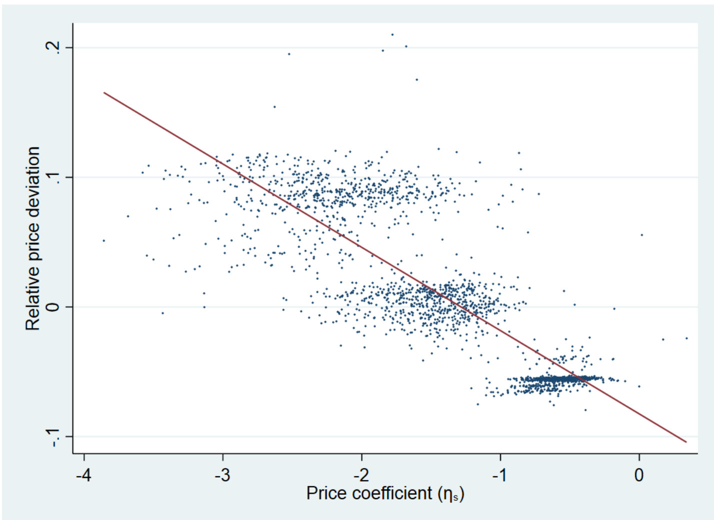


Figure 6: Regression of elasticity on relative price deviations

Notes: The figure shows the impact of elasticity (independent variable) on price deviations (dependent variable). Each observation represents one store, with it's store specific elasticity as well as its average relative price deviation over all weeks and products. The red line indicates the linear regression, as stated in table 3. A more detailed view by chains (nothing else changed) can be found in the appendix (figure 23), more detailed information on the regression in table 21 (1).

Besides the regression statistics (F-value, R^2 as well as t-statistics) stating an explanatory worth of the model, a relatively good linear fit as well as significant findings, two things catch the eye. First, the model shows a negative influence of the price coefficient (elasticity) on average prices. This is somewhat surprising, as comparable models would expect prices to rise with decreasing elasticity. Optimization models (like the one introduced in chapter 4) optimize profits by charging elastic consumers less while charging inelastic customers more. Secondly, although the R^2 shows a good fit, the graphical representation in figure 6 shows multiple data "clouds". Even with the linear regression being downwards sloped, within those groups, this effect seems to be much smaller, if not reversed. As pricing strategies between chains deviate (see chapter 3.1) and target customers do as well, it could be possible that these "clouds" may represent different chains.

To check on this, the regression was repeated by chains. For a graphical representation of this, see figure 23 in the appendix. The statistical results (see table 21 in the appendix) are much more mixed, showing just partially significant results. Those results indicate a positive relation, with prices being slightly higher (higher relative price deviation) with decreasing elasticity.

Nevertheless, it is possible to conclude that pricing in general does not correlate strategically with elasticity. Taking elasticity into account when deciding on prices may, therefore, helps to increase profits.

Elasticity/ store income Another interesting point raised by DellaVigna and Gentzkow (2019) is the relationship between elasticity and store income. Again, a linear regression was calculated. As the independent variable, store income is used (compare chapter 2.3). As the dependent variable, the elasticity per store (variable component, η_s) is used.

The calculated linear regression (see table 3) shows that there is a statistically significant relationship between these two variables. The regression has some explanatory worth (F= 10.30***, p<0.001). The linear regression does fit the data to a very small extent as indicated by its very low R^2 value (R^2 = .0051). The regression states a positive relationship between store income and elasticity (η_s). Higher income is correlated with less elastic demand. Per 100 TNOK store income (a store's consumers' average household income), the (negative) price coefficient is reduced by .0785 log points. This effect is statistically significant.

Figure 7 shows all observations (stores) as well as the linear regression. As the observations are widely spread, one can easily see the widespread of the data around the regression line as indicated by its low R^2-value.

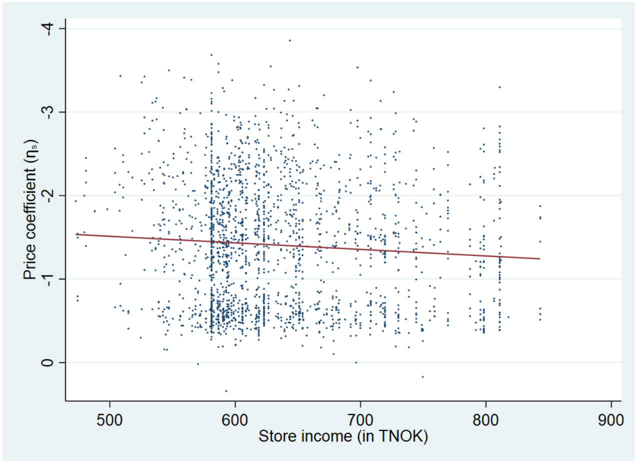


Figure 7: Regression of store income on elasticity

Notes: The figure shows the impact of store income (independent variable) on the elasticity (dependent variable). Each observation represents one store, with its store specific elasticity over all weeks and products as well as it's mean household income. The red line indicates the linear regression, as stated in table 3 (2). Mind that the scale of the y-axis is reversed.

	(1) Relative price deviation	(2) Elasticity (η_s)
Elasticity (η_s)	$-.0643^{***}$	
	(-66.59)	
Store income		$7.85e-7^{**}$
		(3.22)
Elasticity (β_s) Constant	$-.0825^{***}$	-1.9052^{***}
	(-53.31)	(-12.29)
Observations	2,048	2,048

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Regression table: elasticity

Notes: The table states regressions with regard to elasticity. (1) shows the same results for the linear relation of store elasticity (η_s) and relative price deviation as used in the prior chapter. The results are discussed in the first part of this chapter. See figure 6. (2) describes the linear regression store income and store elasticity (η_s). The result is further described in the second part of this chapter. See figure 7 for a graphical presentation.

4 Demand Estimation and Optimal Prices

To be able to make statements about individual store pricing in comparison to national pricing, a pricing model is introduced. The model maximizes profits per store and product by calculating an ideal price. The calculation is based on elasticity as done by DellaVigna and Gentzkow (2019). The (logarithmic) elasticity per store that is used in the model was introduced and described in chapter 3.3.

In the first part, the model and all its variables are described. In the second part, the outcomes are described and set in comparison to findings by other scholars.

4.1 Model

The model introduced in this paper is a standard profit maximization model. The model aims at returning "optimal" prices for each product and each store to maximize profits.

Variable	Variable description
s	store
e	product (per EAN)
p_{se}	price (per product and store)
$\hat{p}_{se}$	average price before optimization (per store and product)
q_{sep}	quantity (per store, product and price)
$\hat{q}_{se}$	average quantity before optimization (per store and product)
mc_e	marginal cost (per product)
C_s	fixed cost (per store)
η_s	elasticity (variable, per store)
β_s	elasticity (constant coefficient, per store)

Table 4: Variables used in the optimization model

The overall optimization problem reads as follows, maximizing the total profits of the whole group by maximizing the profits of each of its stores for each of its products.

$$\begin{aligned} \max_{p_{se}} \quad & \sum_s [\sum_e [q_{sep} * (p_{se} - mc_e)] - C_s] \\ \text{s.t.} & \sum_e [q_{sep} * (p_{se} - mc_e)] - C_s \geq 0 \\ & p_{se} \geq mc_e \end{aligned} \tag{4}$$

Two side conditions do apply, both finally did not influence the models' outcomes. First, each store's profit has to cover its fixed costs to enable sustainable profit. This is to make sure that all stores do make profits. Second, each store's new average price per product has to at least cover its marginal costs. This is especially important, as the calculated values represent medium-term perfect prices. A sustainable, economic strategy should, therefore, require each product at each store to cover at least its variable costs. If not, a store should possibly not sell this specific product. This condition is relatively vague, as some products could be sold below marginal costs to increase sales of other products.

The model uses the following variables, which are discussed very shortly. Table 4 gives an overview of all variables.

Prices The central variable used in this model is each product's price p_{se} per store. This value is to be used as the independent variable. Starting from the old average price of a product per store $\hat{p}_{se}$, the logarithmic change in prices is calculated (see equation 2). This logarithmic price change ($log\_p\_dev_{se}$) is then used regarding the quantity estimation.

Elasticity and quantities Concerning elasticity, the already discussed values are used. η_s describes the (variable) elasticity of demand and describes the logarithmic demand change as a reaction on a logarithmic price change. β_s describes the constant correlation coefficient as returned by the model. This value was not used in the analysis in chapter 3 but is of great importance in the optimization model. η_s and β_s together enable an estimation of the new demanded quantity as a reaction to changes in prices.

$$\log(q)_{se} = \eta_s * log(p)_{se} + \beta_s \tag{5}$$

To arrive at the new estimated demand, the average pre-optimization quantity of each product per store $\hat{q}_{se}$ is used. This value and the logarithmic quantity change enable estimating the after-optimization quantity q_{se}.

$$q_{se} = \hat{q}_{se}^{log(q)_{se}} \tag{6}$$

Marginal cost Regarding marginal cost, gross profit margins are used. In the period from 2013 to 2018, *NorgesGruppen's* gross profit margin fluctuates just slightly with an average gross profit margin $\bar{r}$ of 23.2 percent (compare table 18, Norges-

Gruppen (2019)). Using this value as well as the pre-optimization average prices per product over all stores and weeks enables to estimate the marginal cost mc_e of each product.

Fixed costs The model generally uses fixed costs per store C_s. Regarding the model, this value is not used in the optimization, as it is a constant independent variable and, therefore, not subject to any optimization related changes. Generally, a higher utilization can help to increase profits due to fixed costs degression. Fixed costs can be used to generally check on each store's profitability.

In the model, each product-store-pair can be seen as one single optimization problem than can be solved. To solve the optimization problem, *Excel Solver* was used for each product-store-pair. A *Microsoft Virtual Basic Macro* was used to solve problem-by-problem.

4.2 Outcomes and Limitations

The model states a steep increase in prices and, therefore, in profits. For almost 76 percent of product-store-pairs, it recommends an increase in prices bigger than 50 percent. For slightly more than two percent of all pairs does the model recommend lowering prices. As consumers act inelastic when not considering side-effects, price increases seem to be the most effective way to increase profits. In many cases, the model would recommend increasing prices to infinity, as logarithmic values imply a lower, but never ceasing demand. While logarithmic elasticity helps to estimate consumers' reactions very well at values close to the mean, extreme values are very unrealistic. To still come to a conclusion, this analysis of outcomes focuses on the case where price increases were limited to 50 percent. The model reduces the sales quantity by 44 percent on average, as prices are increased. Some products did not seem to generate profits according to the model. This may be due to the estimation of marginal cost, but might as well be true. Another explanation could be, that elasticity could very badly fit the real world. The model, therefore, recommended ceasing selling some products at some stores. Based on price elasticity and due to the increased prices, profits rose by 160 percent in average per product-store-pair, more than doubling profits. This again does not include fixed costs nor does it includes differences in marginal costs (see chapter 5.3 for a discussion).

As discussed in chapter 3.3, the calculation of elasticity was based solely on the available data regarding prices and quantities. Side-effects like product-year or even product-week-of-year effects as introduced for example by DellaVigna and Gentzkow (2019) were not included, to keep the calculation reliable and comprehensible. Still, it is important to keep in mind that the calculated elasticity may, therefore, be biased, not representing consumers' reactions perfectly. As elasticity is used as the main input for the optimization model, the models' findings have to be analyzed carefully.

The model does show the potential of optimizing prices on a product-store basis, based on each store's demand elasticity. It also shows that a much more sophisticated elasticity estimation would be needed to be able to make more specific comments on possible gains of non-uniform pricing. This would exceed the scope of this work.

The model does not return specific values, nor does it enable clear recommendations on what prices to increase at which stores and which ones to decrease to increase overall profits.

Two other papers already discussed similar models, gaining similar but more specific results. Both focused, at least mainly, on grocery retail. In both models, a much more detailed approach to derive elasticity is used.

DellaVigna and Gentzkow (2019) used data that is very similar to the one used by this work. They furthermore used the discussed optimization model this work is based on. Also, they used a gross profit margin of 25 percent and an operating profit margin of 3 percent. Both values are very similar to the actual values with *NorgesGruppen's* gross profit margin of 23.2 percent being just marginally lower and its operating profit margin with 3.9 percent being marginally higher (see table 18 in the appendix). On a store-level, they estimate the losses of uniform pricing against optimal pricing on 8.88 percent. They found that high elasticity (low income) stores were nearly optimal, with losses being 0.74 percent at the 25th-percentile. Contrary, losses were up to 22.94 percent at the 90th-percentile, outlining the profit opportunity given by lower elasticity at high-income stores. They also argue that stores do adjust prices with elasticity and income. The data used in this paper partly showed a similar significant relation but failed to show this effect regarding chains (see chapter 3.2). When considering such a (chain-level) effect, they found the potential of reduced losses of 6.48 percent at the store-level.

Montgomery (1997) also used supermarket scanner data and introduced a profit maximization model based on individualized pricing. Each store sets its separate everyday price in contrast to base pricing strategies by the chain to maximize its profits. As a base value, he also used a uniform "national" price. As he used only one specific product (orange juice), his findings are also giving an orientation on the impact while not claiming absolute completeness. He finds, that using an optimal micro-marketing strategy with constraints at the chain-level would possibly increase profits by 4.5 percent while not increasing average prices. This value could be further increased when using an optimal micro-marketing strategy with zones (allowing for average price increases in certain zones), increasing profits by up to 10 percent. He furthermore argues that this increase in gross profits would result in an increase in the operating profit by 33 percent to 83 percent.

The model introduced in this paper as well as the works by DellaVigna and Gentzkow (2019) and Montgomery (1997) show that optimizing prices on a store-level would enable a significant increase in profits. As of today, uniform pricing is still the standard, which is puzzling when considering these results.

5 Discussion

5.1 Explanations

As described before, uniform pricing can be seen on various occasions, industries, and products. Explanations, why companies like *NorgesGruppen* are still pricing uniformly, are already discussed by many scholars. Kahneman et al. (1986) and Orbach and Einav (2007) see the violated *Fairness Perception* of customers as the main reason why not to charge different prices. Some are seeing menu costs as the main reason (McMillan, 2007), others see a softening of price competition due to hidden collaboration (Corts, 1998) as the main reason. Other reasons do exist, this work will nevertheless focus on the mentioned, most often discusses explanations.

5.1.1 Fairness Perception

A violation of the fairness perception of customers is mentioned by many scholars. To mention just some, Orbach and Einav (2007), McMillan (2007), and Kahneman et al. (1986) are all discussing the fairness perception in some way. Fairness and the perception of customers are often described as crucial to long-term success. Okun (p. 170, 1981) states, that "price increases based on cost increases are generally accepted as fair, but price increases based on demand increases are ruled out as unfair".

Kahneman et al. (1986) state that these price changes are judged in relation to a *reference transaction*. Increasing prices that are not justified by cost increases or cost differences are perceived unfair. They state that models for price-optimization may lack constraints on customer satisfaction or perceived fairness, therefore, lacking usability for long-run optimization. They further outline, that customers who may suspect being unfairly treated to search for alternatives and, therefore, drop out of the customer base of a retailer, threatening long-term success. Transferred to grocery shopping, price differences between stores may be accepted following cost differences. Communicating higher costs in rural areas may be possible without harming the perception of fairness. Pricing areas that are similar in their cost structure but differ in consumers' elasticity, would mean to maximize profits by profiting on differences in demand.

As there is no recent proof of this theory, Kahneman et al. (1986) were the last to include consumer's answers, a short questionnaire was done. A total of 294 responses were recorded. Due to the recent situation, while this work was done (COVID-19), the questionnaire was done via the internet. The respondent's group, therefore, shifted away from Norway. Furthermore, the respondents were mainly students and part of low-income households. The full questionnaire as well as a far more detailed analysis of the findings can be found in the appendix (see appendix 1).

Besides these internal threats to validity, the findings of the questionnaire were clear. The respondents confirmed the findings of Kahneman et al. (1986) and Okun (1981), that price increases based on cost increases are much more accepted and considered fair than cost increases by a peak in demand. Respondents described price increases caused by cost increases as necessary (49 percent) and reasonable (39 percent), highlighting the high level of acceptance. Price increases as a reaction to higher demand were deemed opportunistic (51 percent), unfair (12 percent), or even greedy (23 percent). This can also be seen by comparing the following two direct answers: 82 percent agreed or strongly agreed on the statement that a price increase as a result of cost increases is to be considered fair, while just 19 percent agreed that a price increase after an increase in demand is to be considered fair. These differences are statistically significant (see table 8).

Another section of the questionnaire focused on whether flexible pricing should be based on elasticity or average income. DellaVigna and Gentzkow (2019) conclude without any further analysis, that the fairness perception cannot be a big influencing factor, as pricing by income would increase fairness instead of reducing it. This statement cannot be confirmed by these findings, as consumer's perception was strongly different. All in all, slightly more people disagree/ strongly disagreed (44 percent) than agreed/ strongly agreed (35 percent) on the statement that pricing by income is to be considered fair. Pricing by elasticity was deemed unfair by most respondents (57 percent). This may partly be due to the perception and description of elasticity as being similar to the flexibility of consumers but follows the findings of Eizenberg et al. (2016) who describe a case where such pricing policies further increase financial inequality.

Overall, most respondents agreed or fully agreed (64 percent) on the statement, that grocery retailing should adhere to fairness and other related social norms, even if that reduces their profit. This finding influences pricing strategies, but also shows consumers' expectation of today's firms. Corporate social responsibility (CSR) seems to be gaining more and more importance.

Regarding their expectation of the level of uniform pricing, 52 percent of the respondents agreed that prices should be equal on a zone-level. This answer gained the highest agreement out of the options that prices should be equal nation-wide (44 percent agreed), zone-wide or don't have to be equal at all (34 percent agreed). This finding, again, is statistically significant, with the agreement on zone-pricing being the highest out of the three options. While consumers seem to accept national differences, this does not solve the problem of how to best design such a pricing theme.

Following the theory and the findings presented, it is hard to measure the impact on *NorgesGruppen's* pricing dilemma exactly. Pricing each store differently without any, in the eyes of the consumers, "valid" reason may lead to reactions in demand and should be kept in mind. As these differences could be introduced gradually, the *reference transaction* may change over time, therefore, changing consumer's perception (Kahneman et al., 1986). Zone pricing could furthermore be a way to introduce more optimized pricing without, or at least with reduced, customer reaction.

5.1.2 Menu Costs

Another explanation, first discussed by Sheshinski and Weiss (1977), is menu costs, which regards to the costs that occur for changing prices. Mankiw (2007) states that this may lead to prices that are unchanged in the short-term, as firms may try to avoid these additional costs. He mainly focuses on a store's reaction on price increases by its competitors and not on more individualized pricing. McMillan (2007) discusses menu costs in more detail. He separates menu costs in two different, separable types of menu costs: *physical menu costs* and *managerial menu costs*. *Physical menu costs* describes the cost of physically changing prices. In food retail, this covers the process of printing and changing the price tags. McMillan states that these costs may have been an influencing factor in the past but do not explain uniform pricing as of today. Supermarkets use price tags for every product (SKU), prices are very seldom printed on the product itself. Price deviations between stores would, therefore, not lead to higher costs as each store could use another price when printing it's price tags. Furthermore, many grocery stores (including the ones from *NorgesGruppen*) do use electronic price tags that allow changes without any further costs occurring. McMillan concludes that physical menu costs are most likely not part of the explanation, which seems to be valid for *NorgesGruppen's* pricing strategy as well. The second type of menu costs are *managerial menu costs*. DellaVigna and Gentzkow (2019) also discuss these costs but call them *managerial decision-making costs*. They see them mainly as upfront managerial costs, more like an investment to enable more differentiated pricing. McMillan (2007) describes these costs as a constantly occurring cost, as personnel or outside consulting would be needed to determine these more optimal prices. He also does mention high up-front costs, making it a strategic long-term decision instead of a week-by-week or store-by-store-decision.

In case of *NorgesGruppen*, this paper as well as DellaVigna and Gentzkow (2019) propose a pricing strategy based on elasticity to increase overall profit. A more detailed model, more detailed (store-specific) information, as well as high commitment, would be necessary to implement an optimal pricing scheme, keeping in mind menu cost.

5.1.3 Softening of Price Competition

In existing research, the softening of price competition is said to be another possible reason why companies price uniformly. Corts (1998) states, that deviating from uniform pricing may lead to increased price competition. If one firm starts to price differently based on some internal criteria, other companies may do the same, but ending up with other results. One firm's model would imply lowering prices in cities, as elasticity is likely to be higher there. Another firm could get the results to lower prices in remote areas, as household income is likely to be lower there. This would lead to lower prices in many areas, increasing the pressure for all competing firms to lower their prices to prevent losing customers. The whole situation is described as a prisoner's dilemma: if just one company would implement a higher degree of price discrimination, it would lead to increased profits. But it would also force its competitors to do the same. The result would be, as described before, a possible drop in prices in all areas. While this raises the consumer surplus, it would lower the retail company's surplus. If all companies unilaterally commit to sticking to uniform pricing, all companies may profit. Corts (1998) also states, that price discrimination that is widely accepted or implicitly agreed on may not lead to the aforementioned effect, as all companies would implement this price discrimination the same way. Examples are discounts for seniors, students, or loyalty-programs (DellaVigna and Gentzkow, 2019).

Foros et al. (2018) mostly agree on those theories, but state that in many cases the described prisoner's dilemma does not even exist. They introduced a Hotelling model with two competing firms. Both firms choose, in different steps, between uniform or personalized pricing. In opposition to Thisse and Vives (1988), they find that personalized pricing does not reflect an unambiguous solution. In their model, it is in some cases optimal for both companies to commit to uniform pricing to prevent an aggressive response. This agrees with the findings of Corts (1998). What they do agree on is that "a firms' incentives to undertake price-softening behavior depend on the rival's choice between uniform and personalized pricing, and not the firms' own choice" (Foros et al. (2018)).

Norman (1981) states, that for uniform pricing to be optimal, competitive forces have to be strong. Just then could uniform pricing be optimal. As this is given in the retail market, which is considered to be one of the most competitive markets (SOURCE), uniform pricing could be optimal. He, therefore, agrees on the above-stated findings of Foros et al. (2018), DellaVigna and Gentzkow (2019), and Corts (1998).

It is not clear to what extent *NorgesGruppen's* competitors would follow any new pricing strategy that would be based on consumer's elasticity. McMillan (2007), as well as Foros et al. (2018), conclude that in some cases the assumption that, like proposed by the prisoner's dilemma, the unambiguous reaction of one firm observing another to price discriminate and, therefore, to shift to a higher degree of price discrimination may not hold.

5.2 Implications and Conclusion

As of today, *NorgesGruppen's* seems to follow a national pricing strategy on a chain-level. As presented before, there are differences between the pricing strategies of different chains. While some chains seem to follow an *everyday low pricing strategy* (EDLP), other stores follow a High-Low strategy, using special discounts and sales as a marketing instrument, but, therefore, having higher base prices. Those findings were significant and shown in different analyses. Besides that, there seem not to be larger differences within chains, neither based on geographical circumstances (zone pricing) nor the average household income or average household elasticity. *NorgesGruppen's* chains do not seem to have a more discriminating pricing scheme in place.

The optimization model introduced in this work showed the possibility of increasing profits in comparison to recent pricing strategies. *NorgesGruppen's* can raise profits by deviating from its pricing strategy of national pricing (see chapter 4) which is in place so far. The model used the demand elasticity to maximize profits. The model concluded that profit increases of 160 percent may be feasible. As this model is a simple optimization model without considering many of the constraints of the real world, this number merely serves as an indicator. The model most likely overestimated how inelastic consumer are, therefore, proposing very large price increases over almost all products. In how far the proposed price increases (or decreases) are feasible was not part of this model. The model aimed at offering a reference when thinking about increasing price discrimination. It can be concluded that there is the chance of additional profits by optimizing prices regarding elasticity, as already proposed by other scholars.

When introducing greater levels of price discrimination, other factors should be kept in mind, as being presented in chapter 5.1. Many scholars mention such explanations of disadvantages when deviating from simple (national) pricing strategies. As menu costs may burden *NorgesGruppen* with high administrative costs, it may reduce the actual gain of such a strategy. Furthermore, price competition may be excelled when *NorgesGruppen's* introduces a more detailed pricing strategy, resulting in possible price wars, making it impossible to follow the prices proposed by the model. And finally, the questionnaire in this work indicates, that consumers would barely accept price increases not being resulted by cost increases on the retail side as well as pricing behavior based on store-income or store-elasticity without a feeling of being treated *unfairly*. As discussed before, this may lead to a loss of consumers and may finally also exceed the profit surplus generated by a more discriminatory pricing strategy. The questionnaire was introduced to a global audience, therefore, the Norwegian customer's perception may deviate.

One important factor is, that consumers may forget these price increases over time. As they grow accustomed to the new prices, this reduces the negative impact. For that, it is important to implement newer pricing strategies "step-by-step". Finally, zone pricing may be an excepted, organizationally feasible and almost perfectly optimized strategy to introduce a more price discriminating pricing.

This work does not conclude with clear recommendations. Still, it concludes with the statement, that a deviation from national pricing may increase profits considerably. When doing so, it is important to keep the discussed influencing factors in mind.

The effects of menu costs and the described softening of price competition could also be analyzed in more depth. This work focused on existing research. Both topics are very interesting, possibly influencing pricing strategies heavily.

5.3 Discussion and Limitations

This work clearly helped to shed some light on NorgesGruppen's pricing strategy as well as possible improvements. Nevertheless, it also showed opportunities for further research. Such work could focus on the following, interesting topics.

When referring to elasticity, this work used the elasticity as calculated. Holmes (1989) argues, that there are two types of elasticity: industry-demand elasticity and cross-price elasticity. Where the first measures the consumer's likeliness to consume less, the second measures the likeliness of consumers to switch where they buy. In grocery retail, the composition in regard to specific products will deviate largely. Furthermore, cross-price elasticity could lead to some customers changing their preferred store or chain within *NorgesGruppen*, therefore, reducing the negative consequences of losing some consumers at one specific store.

Furthermore, the model, but especially the calculated elasticity did not take into account many of the real worlds' effects. Product-specific effects, the world economy, and other effects could be included in a more sophisticated model to not just give recommendations but to actually be able to implement specific, elasticity-based prices.

The marginal costs in the introduced model have been estimates, based on operating profit margins. Differences in the cost structure of different products, especially regarding private labels vs brands, have not been considered. Fixed costs per store, but also deviating transportation and rent costs have also not been considered, as such differences are considered to be small. Still, a more sophisticated model could include better data to arrive at superior outcomes.

Appendix

Appendix 1: Questionnaire consumers' fairness perception

Introduction and description Regarding consumer's fairness perception, as discussed in chapter 5.1, no more specific information was available. Many scholars, Orbach and Einav (2007), McMillan (2007), Kahneman et al. (1986) and Okun (1981) to mention just some already discussed before, mention and discuss consumers' fairness perception. In almost all instances this is based on theoretical implications. While most arguments may sound valid, no data-based proof is used.

Kahneman et al. (1986) are the only ones who use data. Their questions influenced the set-up and the questions of this questionnaire the most. Especially two questions (questions 1 and 3) were added to possibly cross-check the finding of this questionnaire with the finding made by Kahneman et al. (1986).

In the following, the structure, the questions as well as the given possible answers and scales are described. Thereafter, the way of gaining responses is described, being itself followed by a summary of the respondents' group as well as their answers. Finally, the results are displayed, and possible conclusions are drawn.

Structure and questions The questionnaire is split up into four sections: a short description, the main body of questions, concluding questions as well as demographic data questions. The structure follows suggestions by Vomberg (2018).

In the **first section**, a short description is given, without going into detail. The original text can be seen as part of the following questionnaire.

In the **second section**, the main body of questions is asked. The first question regards to *Price increase as result of cost increases.* It reads as following:

> **Price increase as a result of cost increases:** *Imagine the following situation: A store increases its prices by an significant amount (e.g. 10 percent), after its own cost (to buy the product) increased by the same amount. The retailers profit will, therefore, remain unchanged. Statement: This price increase is to be considered fair.*

The question was to be answered using a five scale point *Likert Scale*, following the typical scale from *Highly disagree* (1) to *Highly agree* (5).

> **Price increase as a result of cost increases:** *Imagine the same situation (see above). I would consider this behavior to be described as ...*

The question was to be answered using predefined adjectives (*Opportunistic, Unfair, Reasonable, Necessary, Greedy* or by adding an own adjective to describe this situation.

> **Price increase as a result of peak in demand:** *Imagine the following situation: A store increases its prices on toilet paper by an significant amount (e.g. 10 percent), following the recent peak in customer demand. The cost structure of the retailer is unchanged, the retailers profit will increase. Statement: This price increase is to be considered fair.*

The question was to be answered using a five scale point *Likert Scale*, following the typical scale from *Highly disagree* (1) to *Highly agree* (5).

> **Price increase as a result of peak in demand:** *Imagine the same situation (see above). I would consider this behavior to be described as ...*

The question was to be answered using predefined adjectives (*Opportunistic, Unfair, Reasonable, Necessary, Greedy* or by adding an own adjective to describe this situation.

> **In my opinion, prices should be equal in stores of one chain...** *Please complete the sentence according to your personal view.*

The question was to be answered for three different options: *Nation-wide*,*County-wide* and *Prices don't have to be equal.* For the answer, a five scale point *Likert Scale* was used, following the typical scale from *Highly disagree* (1) to *Highly agree* (5).

> **Price-setting based on average income** *Imagine prices are not set equally over all stores nationwide. Instead, prices are calculated based on the average income of customers of a specific store/ area. Higher average income from customers of a specific store leads to price increases at this store, while prices are reduced for stores with (in average) low-income customers. Statement: This increases fair-*

ness in pricing.

The question was to be answered using a five scale point *Likert Scale*, following the typical scale from *Highly disagree* (1) to *Highly agree* (5).

Price-setting based on consumer flexibility (elasticity) *Imagine prices are not set equally over all stores nationwide. Instead, prices are calculated based on the average flexibility of customers of a store (elasticity; consumers' reaction to price increases). More flexible consumers might be able to shop somewhere else. Stores with generally inflexible (inelastic) customers will charge higher prices, while stores with more flexible (elastic) customers will charge lower prices. Statement: This increases fairness in pricing.*

The question was to be answered using a five scale point *Likert Scale*, following the typical scale from *Highly disagree* (1) to *Highly agree* (5).

In the **third section**, two more general questions are raised. The idea is to give the respondents space for concluding thoughts after answering the more situation-based questions. Questions have been:

General perception *Statement: Grocery/ retail stores should adhere to fairness and other related social norms (unwritten rules of a society) even if that reduces their profit.*

The question was to be answered using a five scale point *Likert Scale*, following the typical scale from *Highly disagree* (1) to *Highly agree* (5).

Is there anything else you want to say?

This question was designed as an open question, allowing respondents to express any further views or thoughts.

The **fourth section** covered questions regarding demographic data. This data enabled further analyses and checks to possibly increase the correctness of any results. Questions have been the following:

Country *Please enter the country you identify with the most. If your country is not included in the list, please select "Others".*

This question was to be answered selecting one of the options from a drop-down list.

Age *Please enter your age (in years).*

This question was to be answered selecting one of the options from a drop-down list.

Gender *Please select your gender.*

This question was to be answered selecting one of the options from a drop-down list.

Profession *Please select your (main) profession at the time of the survey.*

This question was to be answered selecting one of the options from a drop-down list.

Household Income *Please select your average (gross) household income per year; Values given in NOK and EUR.*

This question was to be answered selecting one of the options from a drop-down list. Options ranged from zero up to larger than 700.000 NOK or 62.000 EUR.

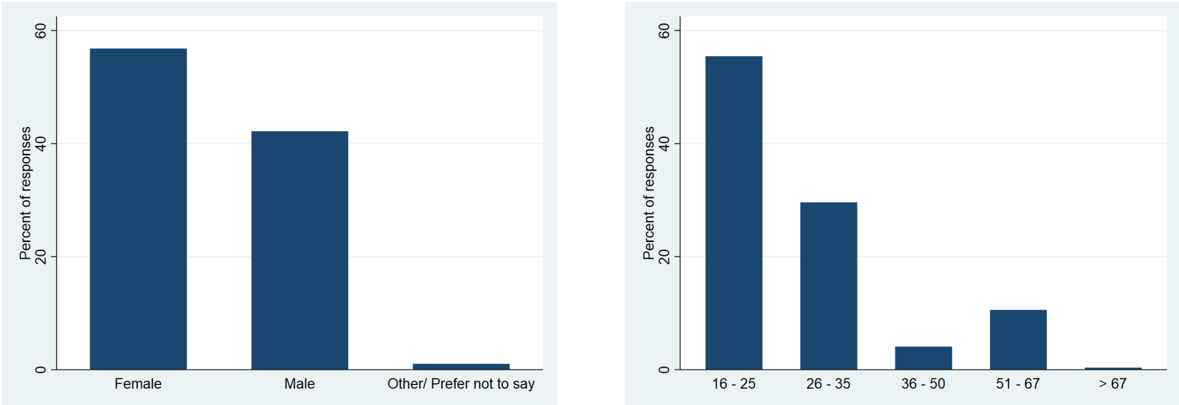
Household size *Please select the number of persons in your household [including you]. The household corresponds to the household you took into account for the household income.*

This question was to be answered selecting one of the options from a drop-down list.

Method This questionnaire was designed as an online questionnaire using *Google Forms*. It was distributed via various channels, including Facebook, mail, private messages, etc. To increase the respondents' motivation, a voucher lottery was added, which was possible to enter after submitting the questionnaire. To reach a wider audience, the questionnaire was also translated into German. The questions as well as possible answers have been carefully translated.

Respondent analysis A total of 294 responses were recorded (N=294). Of these, 167 (57 percent) were female while 124 (42 percent) were male; the rest decided not to enclose information (3; 1 percent). Regarding the respondents' age, the by far largest share was younger than 35 years old (250; 85 percent).

Most of the respondents were students (167; 57 percent), while also a considerable group was currently employed or self-employed (103; 35 percent). The same can be seen when looking at average (gross) household income per year. The most often selected answer was 0-100,000 NOK (104; 35 percent), which does not come as a surprise keeping in mind the number of students. The median household income of the respondents was 100,001-300,000 NOK, which is far less than the average Norwegian household income of 593,000 NOK in 2013 and 666,000 NOK in 2018.

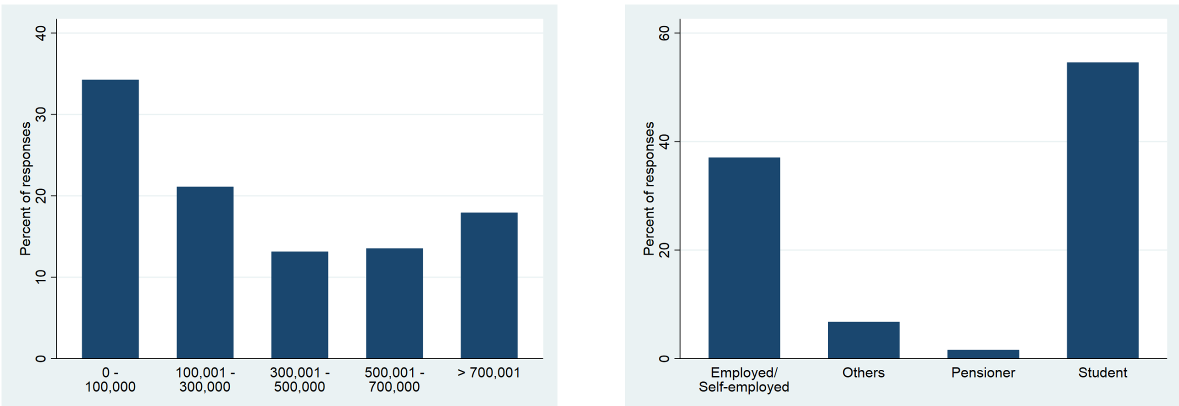


(a) Gender distribution

(b) Age distribution

Figure 8: Gender and age distribution of the respondents (N=294) in percent.

The respondents did belong, on average, to households being considered low-income households, which may influenced the answers given. As most of the respondents answered to be students, single households are the most recorded in this questionnaire (103; 35 percent).



(a) Household income (in NOK)

(b) Profession distribution

Figure 9: Household income and profession distribution of the respondents (N=294) in percent

Furthermore, most respondents came from Germany (231; 79 percent), Norway (34; 12 percent), or Austria (9; 3 percent).

As this group was very homogeneous and biased towards German, students, and low-income households, the results may have a lower degree of statistical significance. Still, the results may give a clear hint into consumers' perception. It especially can be used to complement the findings of Kahneman et al. (1986).

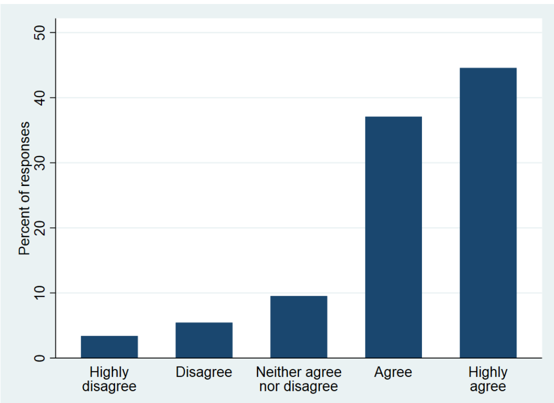
Country	Number of respondents	
	Absolute	Relative
Germany	231	78.57
Norway	34	11.56
Austria	9	3.06
Italy	4	1.36
Other	16	5.44
	294	100

Table 5: Country of origin (survey respondents)

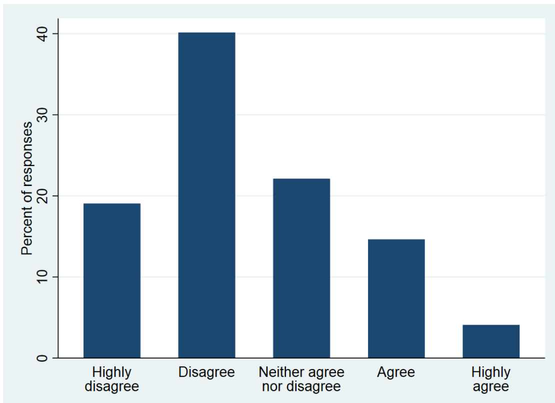
Notes: *Others* include the options China, France, India, Sweden, Switzerland, and Others.

Results

The results do in parts correlate to what was shown by Kahneman et al. (1986). The first two questions were, as discussed before, based on their questionnaire. While being confronted with the statement that a price increase as a reaction to the retailers' own cost increase is to be considered fair, most respondents agreed or highly agreed (240; 82 percent). Just a minor part disagreed or highly disagreed (26; 9 percent). The second question stated, that a price increase as a reaction to a demand increase without any changes in the retailers' cost increase is to be considered fair. In this case, fewer agreed or highly agreed (55; 19 percent), while more disagreed or highly disagreed (174; 59 percent).



(a) Scenario 1: Cost increase



(b) Scenario 2: Demand increase

Figure 10: Acceptance of price increases (two different scenarios)

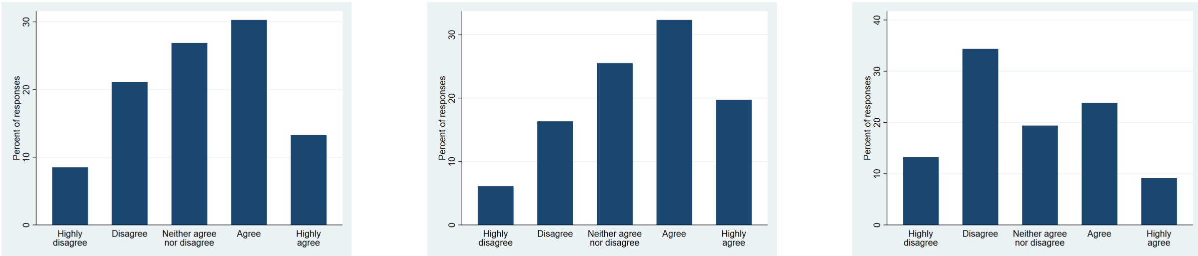
The differences in consumer perception are significant, as tested by a t-test for two sample means (see table 6).

Group	Obs	Mean	Standard deviation	95% confidence interval	
Germany	291	4.1375	1.0281	4.0188	4.2561
Norway	291	2.4502	1.0828	2.3252	2.5751
Total	582	3.2938	1.3512	3.1838	3.4038
					t = 19.2770
					df = 578.4450
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0	
Pr(T<t) = 1.0000		Pr(|T|>|t|) = .0000		Pr(T>t) = .0000	

Table 6: T-test on the fairness perception of price increases

Notes: The table shows a two-sample t-test with unequal variances. The t-test tests the hypotheses, that there is no significant difference in the means of both group's answers (H_0 hypothesis). The mean of both questions is used. Satterthwaite's degrees of freedom are used.
The test shows significant differences, with price increases caused by cost increases being more accepted compared to those as a reaction on demand increases.

Being asked about what level consumers expect uniform pricing, the respondents' answers give a clear hint on what may be possible. While many more agreed or strongly agreed that prices should be uniform on a national level (128; 44 percent), the range of answers was relatively wide. Being asked the same question in regard to county-wide uniform pricing (zone pricing), even more agreed or highly agreed that prices should be uniform (153; 52 percent). Following the same trend, being asked whether they agree that prices don't have to be equal at all, a large share of respondents disagreed or highly disagreed (140; 48 percent). While the answer may be seen as a clear statement against individual pricing per store, a surprisingly high number of respondents agreed or highly agreed (99; 34 percent). Furthermore it is important to mention that such questions seem to be hard to answer, which can be seen on the high degree of neutral answers (24 percent on average). Just taking into account these questions, uniform pricing on a national level seems not to be expected by consumers, while completely individual pricing seems to be "too much". Some solution in between (e.g. zone pricing) seems to get the highest agreement.



(a) ... Nation-wide (b) ... County-wide (c) ... don't have to be

Figure 11: Statement-Question: Prices should be equal...

To test this statement, two separate t-tests for two-variable means were conducted. Both t-tests show a significantly higher agreement on count-wide uniform pricing then nation-wide or individual pricing (see table 7).

Group	Obs	Mean	Standard deviation	95% confidence interval	
National pricing	294	3.1871	1.1636	3.0535	3.3206
Zone pricing	294	3.4320	1.1657	3.2992	3.5648
Total	588	3.3095	1.1657	3.2151	3.4039
					t = -2.5591
					df = 585.9800
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0	
Pr(T<t) = .0054		Pr(|T|>|t|) = .0107		Pr(T>t) = .9946	

(a) T-test: Nation-wide and county-wide

Group	Obs	Mean	Standard deviation	95% confidence interval	
Zone pricing	294	3.4320	1.1657	3.2992	3.5648
Individual pricing	294	2.8129	1.2040	2.6747	2.9511
Total	588	3.1224	1.2196	3.0237	3.2212
					t = 6.3571
					df = 585.0700
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0	
Pr(T<t) = 1.0000		Pr(|T|>|t|) = .0000		Pr(T>t) = .0000	

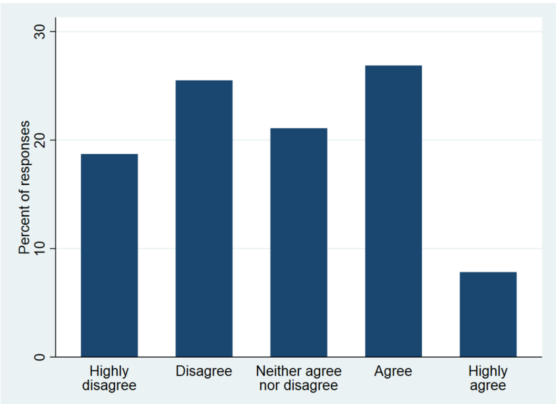
(b) T-test: County-wide and individual

Table 7: T-test for pricing uniformity

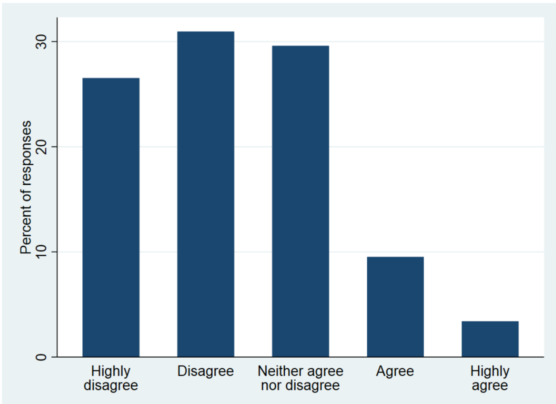
Notes: The table shows two-sample t-tests with unequal variances. The t-tests test the hypothe-

ses, that there is no significant difference in the means of each two group's answers (H_0 hypothesis). The mean of both questions is used. Satterthwaite's degrees of freedom are used.
The tests show significant differences in both cases, with zone pricing gaining a statistically significant higher agreement compared to national or store-level pricing.

Besides questions regarding when and where prices should be set equal, the question of how prices can be set was also raised. The two options discussed where price-setting by average household income and price-setting by elasticity. While there may be a relationship between those two options, they do not correlate completely. Poorer households may also are very inelastic due to reasons of lower mobility (Eizenberg et al., 2016). Pricing by income seems to be the option with the higher agreement. Still, just a small share considered pricing by average household income as fair (102; 35 percent). Pricing by elasticity was considered fair (agreed/ highly agreed) by just 38 respondents (13 percent). 169 disagreed or strongly disagreed (57 percent). One reason may be the above mentioned, taking inflexible, poorer consumers into account. Another reason may be that older people often are less mobile as well, most likely being the ones paying more.



(a) Based on average household income



(b) Based on average customer elasticity

Figure 12: Scenarios for a higher degree of price discrimination

Again, a t-test for two sample means was conducted (see table 8). The t-test shows a significantly higher agreement for pricing based on income compared to pricing based on elasticity.

Group	Obs	Mean	Standard deviation	95% confidence interval	
Germany	294	2.7959	1.2444	2.6531	2.9388
Norway	294	2.3231	1.0714	2.2002	2.4461
Total	588	2.5595	1.1840	2.4636	2.6554
					t = 4.9368
					df = 573.3290
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0	
Pr(T<t) = 1.0000		Pr(|T|>|t|) = .0000		Pr(T>t) = .0000	

Table 8: T-test on the fairness perception of different pricing strategies

Notes: The table shows a two-sample t-test with unequal variances. The t-test tests the hypothesis, that there is no significant difference in the means of both group's answers (H_0 hypothesis). The mean of both questions is used. Satterthwaite's degrees of freedom are used.
The test shows significant differences, with prices being based on average household income being more accepted compared to prices being set based on consumer elasticity.

Finally, the respondents were asked whether or not they expect retail/ grocery stores to adhere to fairness and other related social norms (unwritten rules of society) even if that reduces their profit. 188 respondents (64 percent) agreed or highly agreed on the fact that grocery/ retail stores should abide by such social norms.

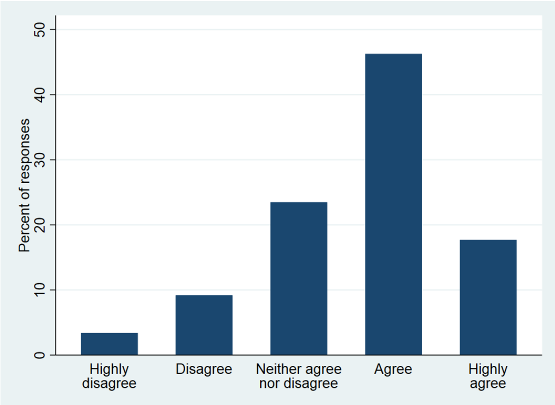


Figure 13: Consumers' expectation of obedience to social norms

In this case, it would be interesting to know whether there is any significant difference regarding this perception of nationality. This case is of increased importance, as most of the respondents where from Germany, while *NorgesGruppen* operates in Norway. Based on the collected data, there is a difference in the answers recorded, but the difference is not fully significant. Norwegians agreed less to the statement, that grocery retail should adhere to social norms, even if that reduces their income.

Group	Obs	Mean	Standard deviation	95% confidence interval	
Germany	231	3.6840	.9823	3.5566	3.8113
Norway	34	3.4412	1.0785	3.0649	3.8175
Total	265	3.6528	.9963	3.5323	3.7733
					t = 1.2393
					df = 41.4624
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0	
Pr(T<t) = .8889		Pr(|T|>|t|) = .2222		Pr(T>t) = .1111	

Table 9: T-test on the general perception of retailers corporate responsibility

Notes: The table shows a two-sample t-test with unequal variances. The t-test tests the hypothesis, that there is no significant difference in the means of both group's answers (H_0 hypothesis). The mean of both questions is used. Satterthwaite's degrees of freedom are used.
The test shows differences, with respondents originating from Norway showing lower agreement compared to those from Germany. Germany and Norway cover 90 percent of all answers. The findings are not significant.

Some more tests were conducted, to better understand the collected data. Such tests were in regard to the influence of the country of origin and the profession on the different price-setting strategies. More information can be found in appendix 2.

Conclusion This questionnaire proves, by and large, the findings Kahneman et al. (1986). It offers a view on consumers' expectations on pricing strategies in consumer retail. Taking into account this answer may help to understand the benefits of national pricing, but also shows that such a pricing strategy may not even be necessary to prevent consumers' satisfaction. Furthermore, it offers hints on how to set up a more price discriminating pricing scheme. Finally, it showed that consumers do expect grocery retailers to adhere to social norms.

Appendix 2: Questionnaire consumers' fairness perception - test statistics

Group	Obs	Mean	Standard deviation	95% confidence interval	
Germany	231	2.7965	1.2674	2.6322	2.9084
Norway	34	2.7059	1.1685	2.2982	3.1136
Total	265	2.7849	1.2534	2.6333	2.9365
					t = .4177
					df = 45.2225
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0	
Pr(T<t) = .6609		Pr(|T|>|t|) = .6782		Pr(T>t) = .3391	

(a) T-test: by country

Group	Obs	Mean	Standard deviation	95% confidence interval	
Employed	103	2.7282	1.3372	2.4668	2.9895
Student	167	2.8024	1.1885	2.6208	2.9840
Total	270	2.7741	1.2454	2.6249	2.9233
					t = -.4620
					df = 196.8870
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0	
Pr(T<t) = .3223		Pr(|T|>|t|) = .6446		Pr(T>t) = .6777	

(b) T-test: by profession

Table 10: T-test for price-setting based on income by country and profession

Notes: The table shows two-sample t-tests with unequal variances. The t-tests test the hypotheses, that there is no significant difference in the means of both group's answers (H_0 hypothesis) and for both tests. The mean of both questions is used. Satterthwaite's degrees of freedom are used.

Both t-tests show respondents agreement on price-setting by income. (a) shows this for two countries, Germany and Norway. These cover 90 percent of all responses. (b) shows the same by profession, namely for employees and students. These cover 92 percent of all responses. The tests show mixed results, with no clear answers to be given.

The tests do not show significant results. Whether or not nationality and profession influence the agreement on price-setting by income can not be answered by this questionnaire.

Group	Obs	Mean	Standard deviation	95% confidence interval	
Germany	231	2.2208	1.0668	2.0825	2.3591
Norway	34	2.7059	.9701	2.3674	3.0444
Total	265	2.2830	1.0656	2.1541	2.4119
					t = -.2.6864
					df = 45.5838
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0	
Pr(T<t) = .0050		Pr(|T|>|t|) = .0100		Pr(T>t) = .9950	

(a) T-test: by country

Group	Obs	Mean	Standard deviation	95% confidence interval	
Employed	103	2.1456	1.0610	1.9383	2.3530
Student	167	2.4671	1.0630	2.3047	2.6295
Total	270	2.3444	1.0717	2.2160	2.4729
					t = -2.4164
					df = 216.4240
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0	
Pr(T<t) = .0083		Pr(|T|>|t|) = .0165		Pr(T>t) = .9917	

(b) T-test: by profession

Table 11: T-test for price-setting based on elasticity by country and profession

Notes: The table shows two-sample t-tests with unequal variances. The t-tests test the hypotheses, that the two that there is no significant difference in the means of both group's answers (H_0 hypothesis) and for both tests. The mean of both questions is used. Satterthwaite's degrees of freedom are used.

Both t-tests show respondents agreement on price-setting by elasticity. (a) shows this for two countries, Germany and Norway. These cover 90 percent of all responses. (b) shows the same by profession, namely for employees and students. These cover 92 percent of all responses.

The tests show significant results. Norwegians showed a significantly higher agreement on such pricing strategy as did Germans. Furthermore, employees showed a significantly lower agreement than did students. Translation difficulties could have influenced the answers, as elasticity is often equated with flexibility. This has a negative reputation, as flexibility is less about the willingness to pay but more about not being able to switch.

Figure 14: Map of all of *NorgesGruppen's* stores

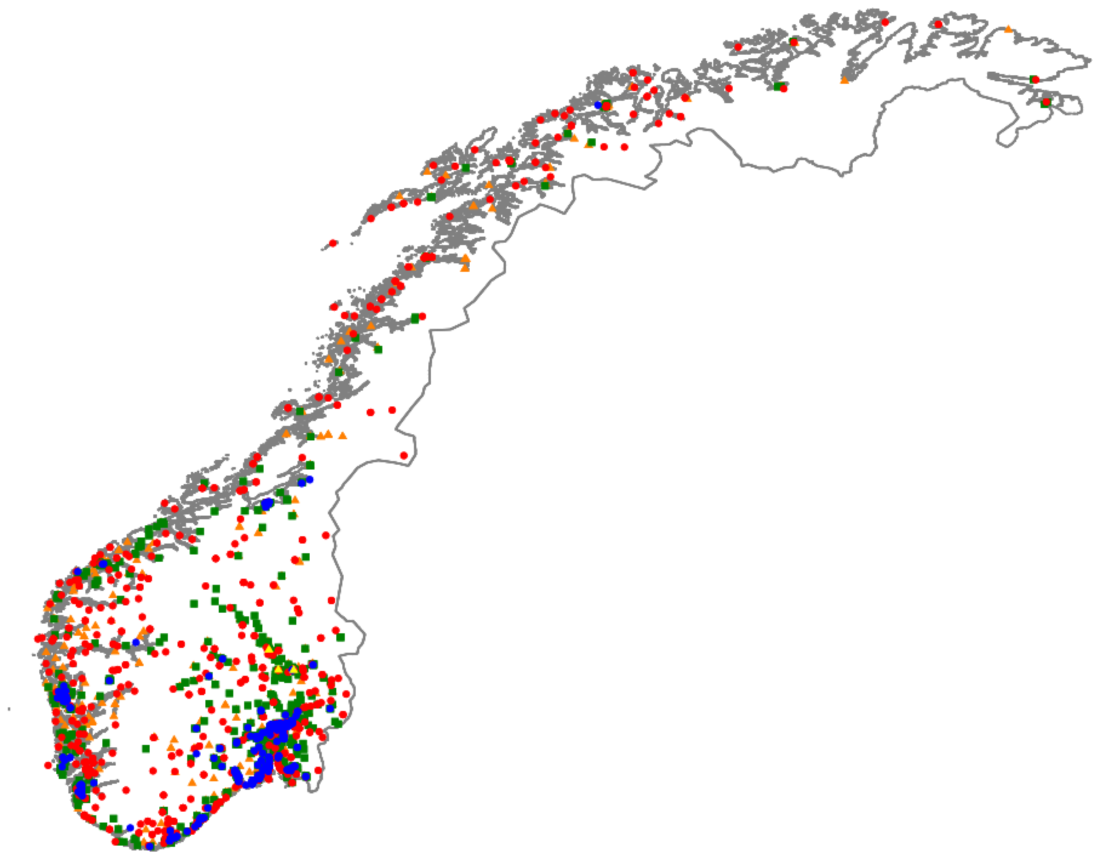


Figure 14: Map of all of *NorgesGruppen's* stores

Notes: The graph shows all stores of all chains belonging to *NorgesGruppen* with their location within Norway.
● refers to the stores of *Joker*, ● refers to those of *Kiwi*, ■ refers to the ones from *SPAR*, ▲ refers to the ones from *MENY*, and ▲ refers to the three stores of *CC-Mat*.
Mind that in metropolitan areas, especially Oslo, Stavanger, and Bergen, the graphical representation lacks accuracy as numerous stores are very close to each other.

Source: shape based on **GADM (2018)**

Figure 15: Deviation in prices by products

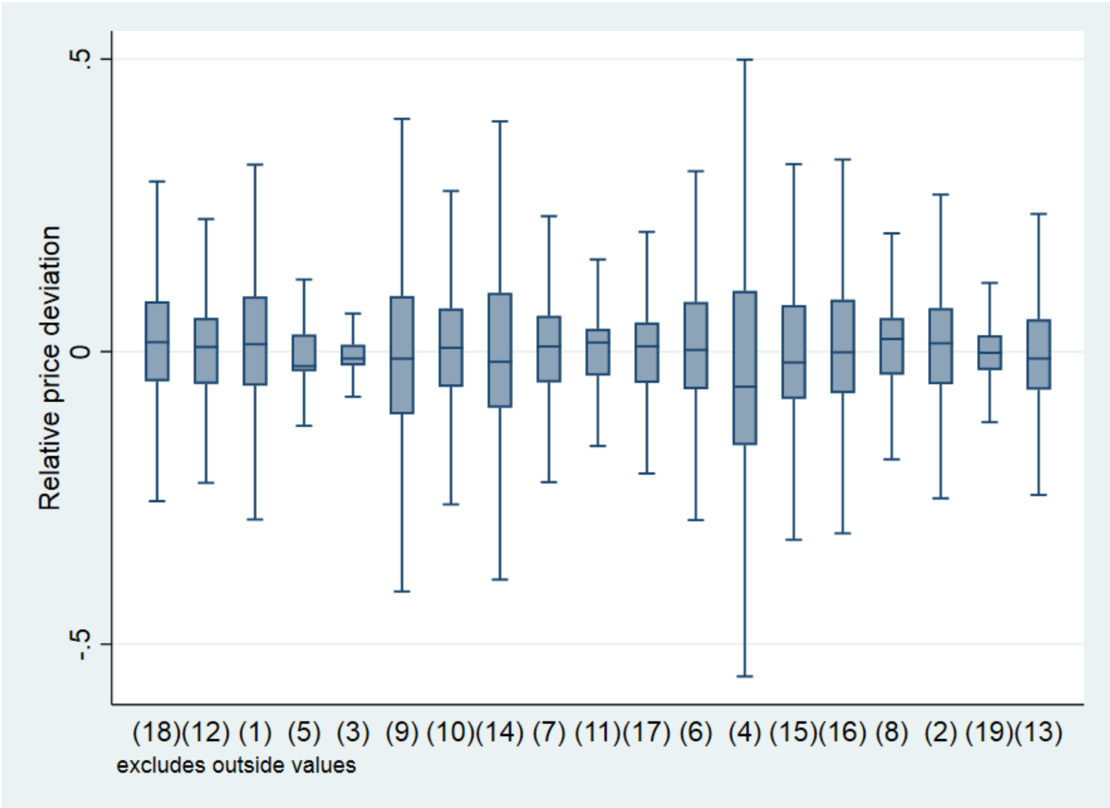
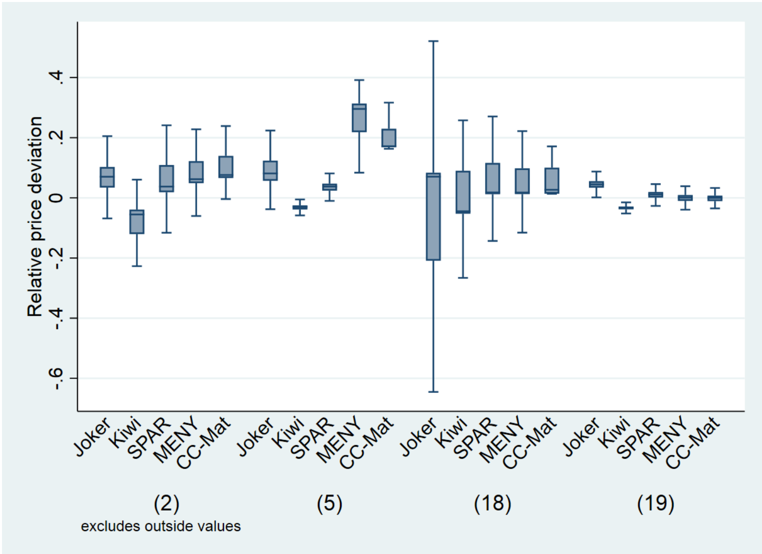


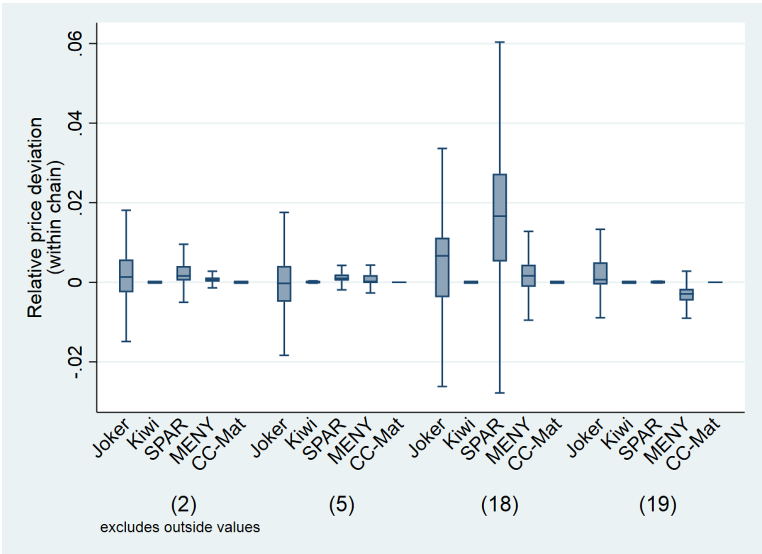
Figure 15: Relative price deviations by product as a boxplot

Notes: The graph shows a boxplot of the relative price deviations per product over all chains and weeks. The ranges vary widely, depending on the specific product. Product numbers refer to the product numbers as introduced in table 15. Also, see graph 16 for a more detailed view (by chains for selected products).

Figure 16: Deviation in prices by products and chains (selection)



(a) Between-chains price deviation

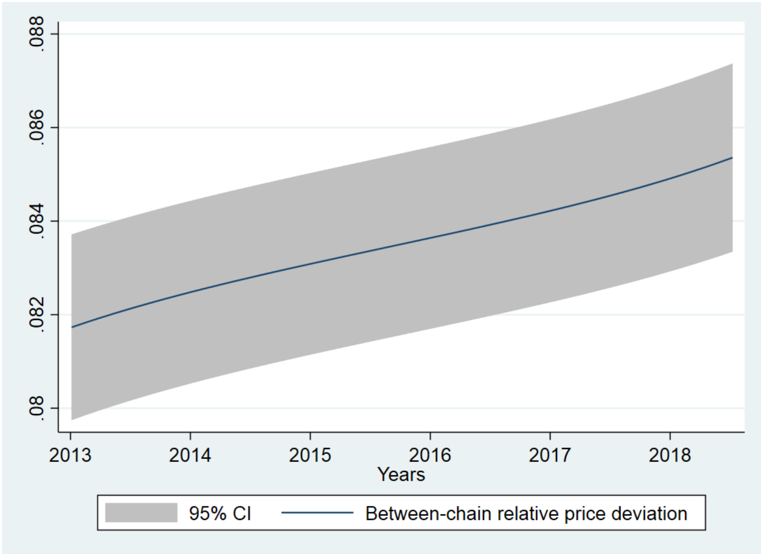


(b) Within-chain price deviation

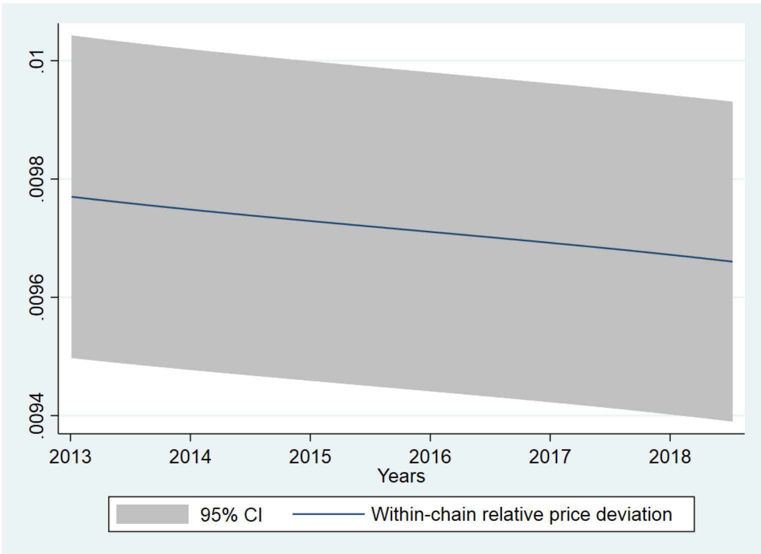
Figure 16: Relative price deviations by products and chains as a boxplot

Notes: The graph shows the boxplots of the relative price deviation for four selected products separately for each chain. One can clearly see differences in the chains' pricing strategies as outlined before. Furthermore, differences in products can be seen.
Eggs (product (5)) and beer (product (19)) are almost not used for discounts, while bread (product (2)) and sweets (product (18)) are used much more. Mind that advertising alcoholic products is not permitted in Norway.

Figure 17: Deviation in prices over time



(a) Between-chain price deviations



(b) Within-chain price deviations

Figure 17: Relative price deviations between-/ and within-chains over time

Notes: The graphs show smoothed time series with their 95%-confidence interval (in grey). Weekly average values over all products and stores were used. Data ranged from week 1 in 2013 to week 52 in 2018. (a) shows the time series for between-chain relative price deviations. A slight increase over the analyzed time horizon can be observed. Different chains/ stores within *NorgesGruppen* seem to deviate more and more in their pricing strategy. (b) shows the same for within-chain deviations. In this case, the average within-chain relative price deviation seems to decrease, possibly meaning that prices within chains are becoming more and more uniform. Mind that the graphs include all chains.

Figure 18: Deviation in prices per chain and region

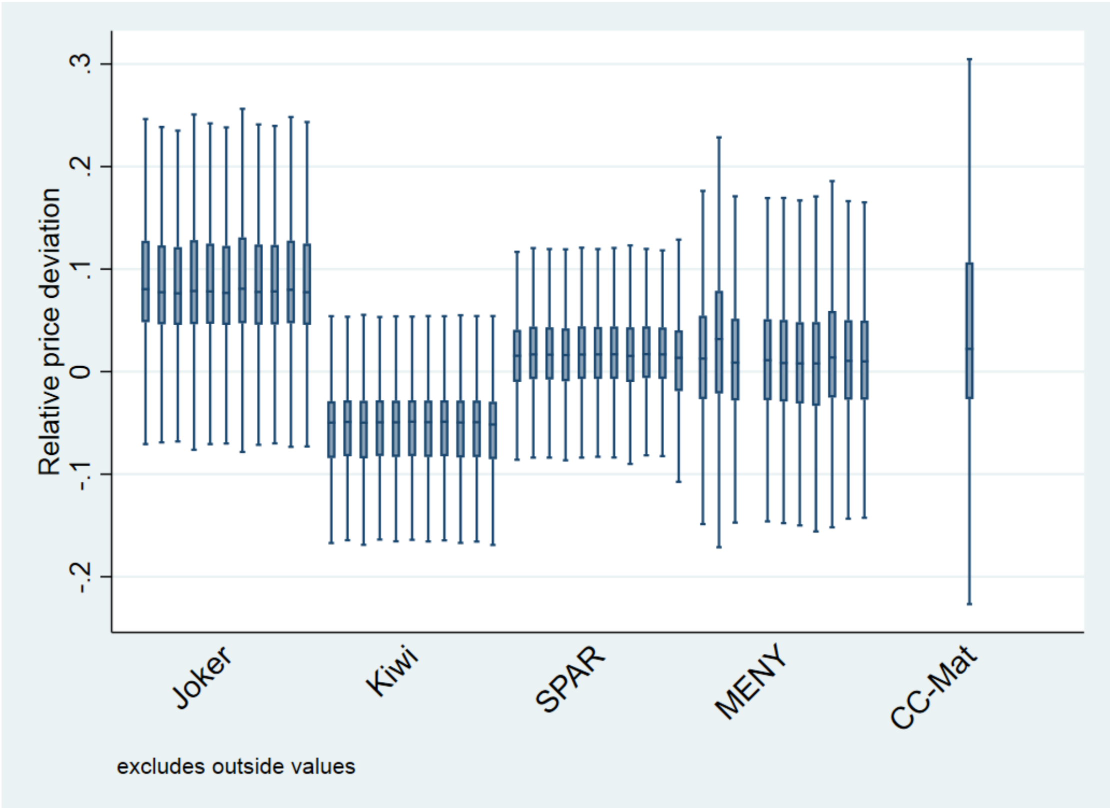


Figure 18: Relative price deviations by chains and counties as a boxplot

Notes: Each boxplot represents one county as described in chapter 2. The y-axis represents the relative (percentage) price deviations over all products.
Mind that not all chains are present in all counties. *CC-Mat* is just available in *Innlandet*, while *MENY* is available in all counties except *Nordland*.

Figure 19: Deviation in prices for one chain and all regions

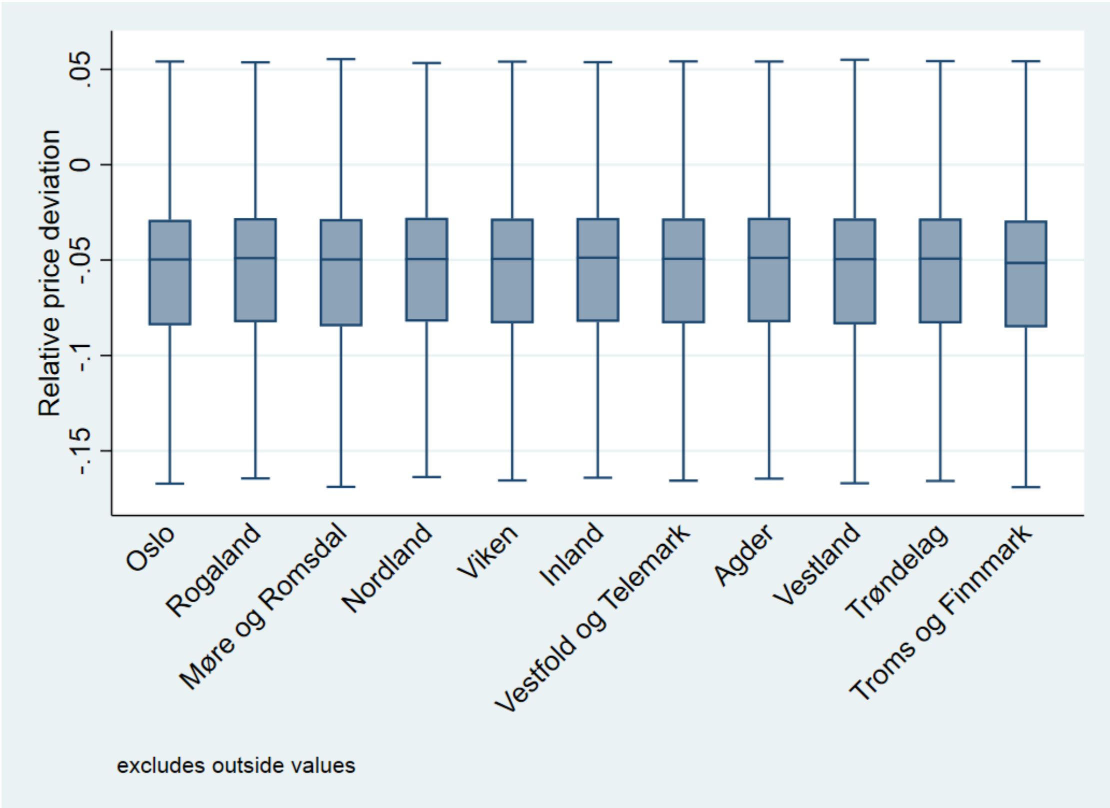
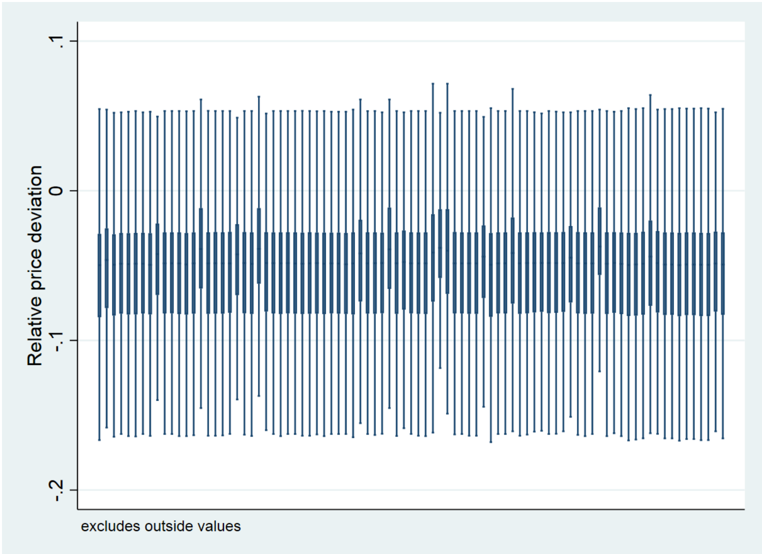


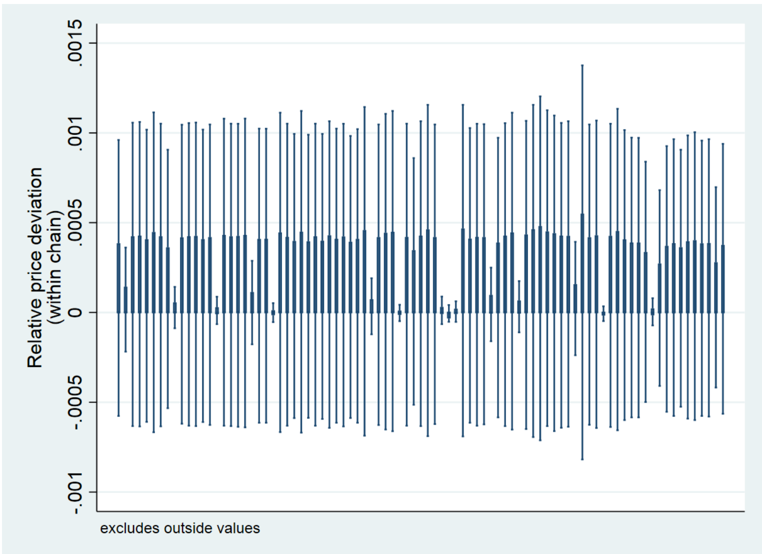
Figure 19: Relative price deviations for one chain by counties as a boxplot

Notes: Each boxplot represents one county as described in chapter 2. The y-axis represents the relative (percentage) price deviations over all products. The graph shows deviations for one chain (*Kiwi*). This graph is an extension to figure 18.

Figure 20: Deviation in prices for one chain



(a) Between-chains price deviation



(b) Within-chain price deviation

Figure 20: Relative price deviations for one chain by stores as a boxplot

Notes: The graph displays stores with their relative deviation from the average product price for one chain (*Kiwi*). Each boxplot displays one store. The x-axis represents different stores, due to visibility, this covers an excerpt of 87 stores. The y-axis in (a) represents the variable *relative price deviation*, while in (b) it represents the *within-chain relative price deviation*.
It is important to mention that the relative price deviations for stores of Kiwi are very small, even more so within the chain. For an accumulated graphical representation see figure 3.

Figure 21: Operating profit margin *NorgesGruppen*

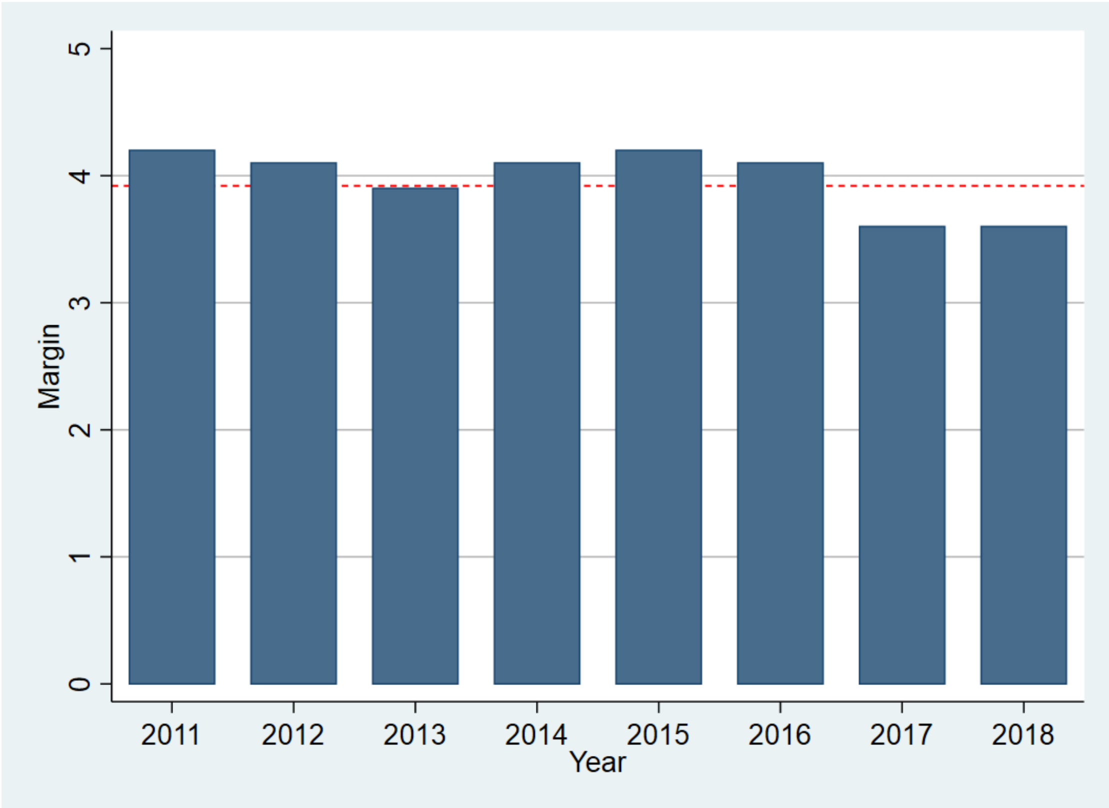


Figure 21: *NorgesGruppen's* operating profit margin 2011-2018

Notes: The graph displays the operating profit margin of *NorgesGruppen* as published in their annual reports. The red dot line refers to the average operating profit margin from 2013 to 2018 of 3,92%. More specific values can be found in table 18.

Source: NorgesGruppen (2019)

Figure 22: Regression of price deviations and income by chains *Norges-Gruppen*

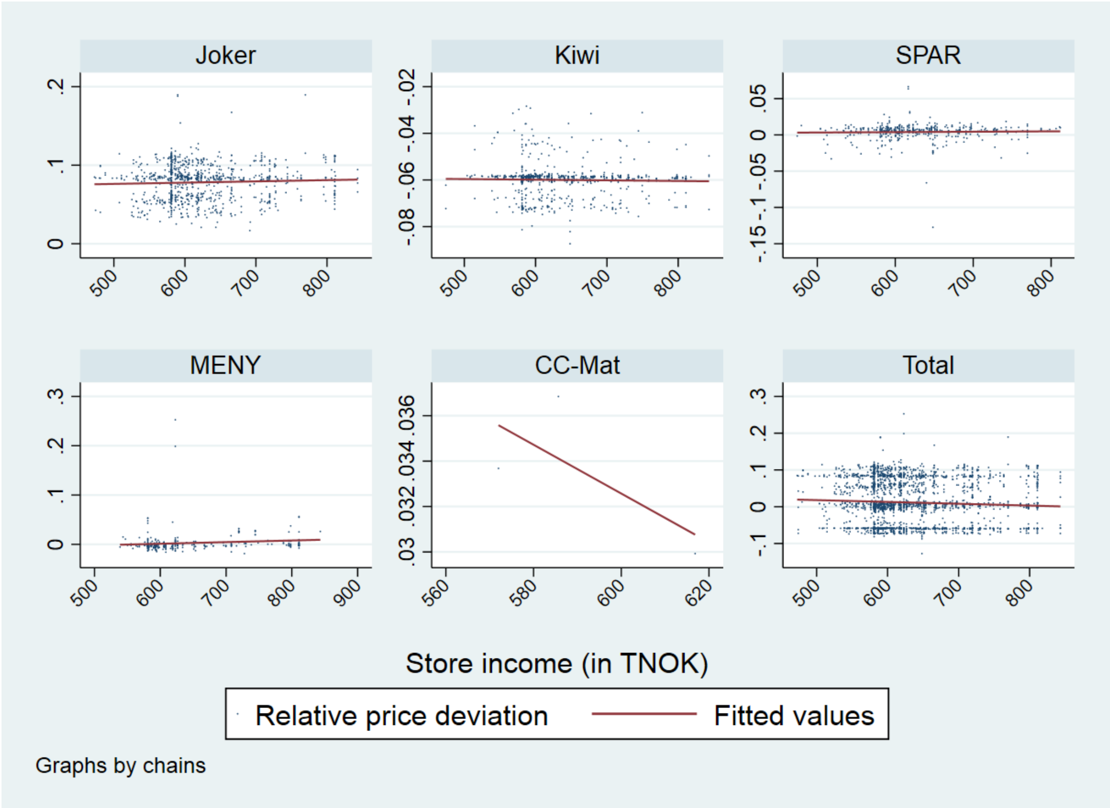


Figure 22: Regression of price deviations and income by chains

Notes: The graph displays the mean relative price deviation per store (each observation corresponds to one store) for each chain. The red line corresponds to the linear regression. Details can be found in table 20. Mind that the regression line being downwards sloped for the case of taking into account all observations. On a chain level, the regression line is upwards sloped for *Joker*, *SPAR*, and *MENY*.

A similar analysis with unaggregated data can be seen in figure 5.

Figure 23: Regression of price deviations and price coefficient by chains *NorgesGruppen*

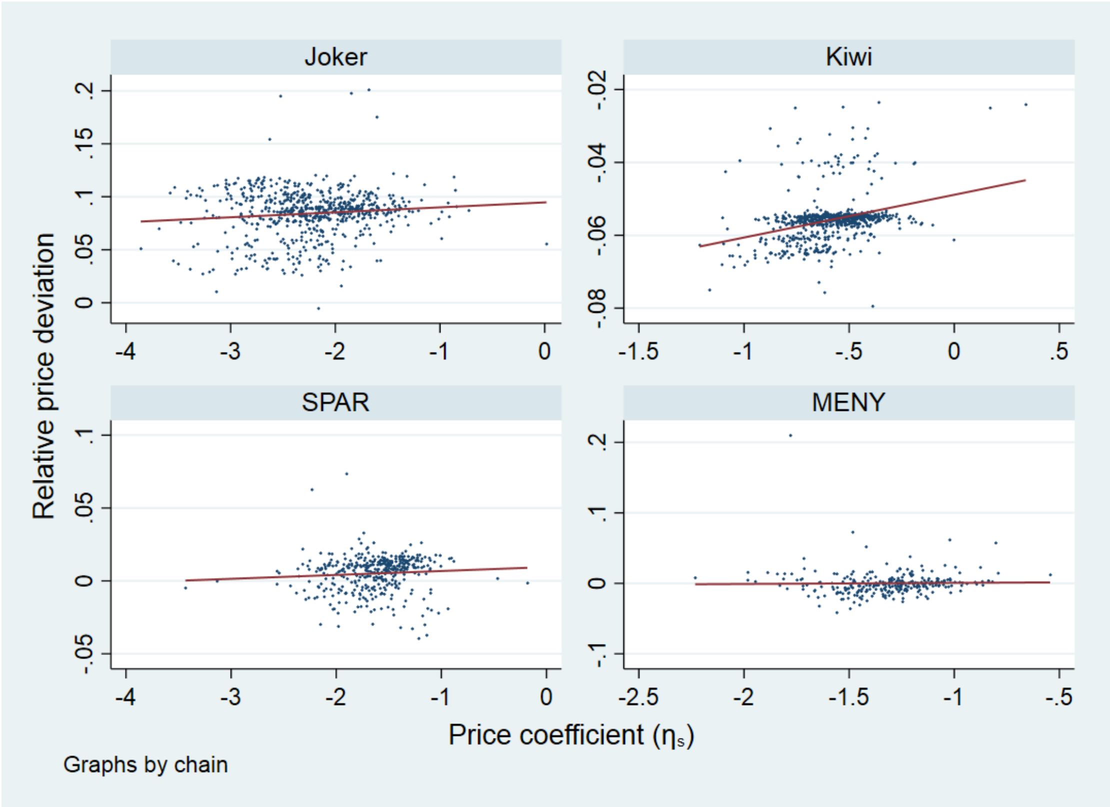


Figure 23: Regression of price deviations and elasticity

Notes: The graph displays the relative price deviations (y-axis) in relation to the price correlation coefficient η_s (x-axis). Each dot represents one store with its corresponding price coefficient η_s (elasticity). See figure 6 for a representation over all stores. In difference to the downwards slope of the general regression, all chains show an upwards sloped regression when only considering the stores of each chain. See table 21 for specific values.

Table 12: Top 10 Municipalities by Median Total Income 2013 - 2018

Rank	Municipality ZIP	Municipality name	Mean total income (in NOK)	Mean number of households	Nearby economic center
1	1142	Rennesøy	845,500	1,856	Stavanger
2	1124	Sola	843,167	10,375	Stavanger
3	0217	Oppegård	829,599	11,005	Oslo
4	0220	Asker	826,500	24,567	Oslo
5	1127	Randaberg	817,833	4,224	Stavanger
6	1244	Austevoll	811,833	1,951	Bergen
7	0219	Bærum	810,833	51,824	Oslo
8	0234	Gjerdum	808,167	2,649	Oslo
9	1114	Bjerkheim	807,000	1,053	Stavanger
10	1122	Gjesdal	806,333	4,511	Stavanger

Table 12: Demographic data: The ten largest municipalities by average median income 2013 - 2018

Notes: The table shows the ten municipalities with the highest average median income 2013 - 2018 as described in chapter 2. The nearby economic centers refer to the closest cities (within 60km radius) when applicable. Nine out of ten of these municipalities are part of the economic areas of Oslo and Stavanger.

Source: Statistisk Sentralbyrå (2019)

Table 13: Top 10 Municipalities by Median Total Households 2013 - 2018

Rank	Municipality ZIP	Municipality name	Mean total income (in NOK)	Mean number of households
1	0301	Oslo municipality	581,500	327,200
2	1201	Bergen	843,167	126,874
3	5001	Trondheim*	626,418	88,264
4	1103	Stavanger	719,301	62,105
5	3024	Bærum	810,833	51,824
6	4204	Kristiansand	618,657	46,392
7	3005	Drammen	605,596	44,761
8	3025	Asker	798,194	37,614
9	3004	Kristiansand	856,500	35,410
10	3030	Lillestrøm	707,966	35,098

Table 13: Demographic data: The 10 largest municipalities by average median number of households 2013 - 2018

Notes: The table shows the ten municipalities with the highest median of households 2013 - 2018 as described in chapter 2.
* Trondheim was part of the municipalities which have seen changes due to the reform in 2017. Values from 2013 - 2018 were added up without further recognizing minor changes in the actual municipality.

Source: Statistisk Sentralbyrå (2019)

Table 14: Summary statistics by chain

Chain	Store income				Households			
	Mean	Median	p25	p75	Mean	Median	p25	p75
Joker	624,101	608,391	581,000	653,557	47,573	5,014	1,610	27,316
Kiwi	636,208	616,833	585,667	676,167	59,840	15,068	6,107	44,761
SPAR	631,208	*618,657*	*590,000*	657,500	23,857	6,131	2,162	16,561
MENY	*645,913*	608,391	586,500	*707,966*	*73,082*	*27,602*	*15,146*	*62,105*
CC-Mat	591,257	585,667	572,000	616,833	13,637	13,918	12,577	14,379

Table 14: Summary statistics by chain

Notes: The table provides some standard statistics for all five chains. For the two variables *Store income* and *Households*, the mean, median, 25th-percentile, and the 75th-percentile are given. "Store income" revers to the median income of a stores postal-code-area as described in chapter 2.1. Similarly, "households" refers to the median households per postal-code-area as also introduced in chapter 2.1. Italic numbers describe the maximum values of each variable.
Differences in each chains' location strategy can be observed. As an example, MENY's stores are mainly located in high-income, urban areas. Joker on the other hand is often located in lower-income areas, also accepting far lower households. This supports the hypothesis, that there is price discrimination trough store localization.

Table 15: Selected Products in Detail

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Table 15: Selected products: product information

Table 16: Selected Products & Categories in Detail

Product Category	Product	Sum of Sales	Product category sum	Product of category	Category of total sales
Soda & mineral water	(1)			7%	9%
Bread (fresh)	(2)			6%	5%
Minced meat (fresh)	(3)			9%	2%
Dressing, Souses & Oils	(4)			36%	0%
Egg	(5)			11%	2%
Ready-made food	(6)			15%	2%
Juice	(7)	This		9%	2%
Coffee	(8)	content		35%	2%
Meat (fresh)	(9)	has		4%	4%
Meat (Sausages)	(10)	been		11%	2%
Milk products	(11)	removed		7%	10%
Cheese	(12)	due		18%	5%
Paper (toilet)	(13)	to		5%	1%
Spread & pate	(14)	confidentiality		6%	2%
Spread (sweet & salty)	(15)			10%	2%
Chocolate	(16)			8%	5%
Butter	(17)			21%	2%
Sweets/ Candy	(18)			94%	1%
Beer	(19)			8%	11%
Sum				7%	69%
Total Sales					

Table 16: Selected products: product categories in detail

Notes: Column one shows the selected product category with their names (translated). Column five shows the percentage, the sales of the selected product covers of the product categories sales. Column six shows the percentage of the total sales of each category in regard to total sales as stated in the last row. Mind that there are other categories not being part of the sample, covering 31% of total sales.

Table 17: Selected Products in Detail

This content has been removed due to confidentiality

Table 17: Selected products: sales data and availability

Table 18: Gross and operating profit margin

	2013	2014	2015	2016	2017	2018
Revenue	64,592,266	68,508,293	72,746,151	76,867,992	82,308,168	84,649,792
Cost of Sales	49,610,047	52,635,629	56,162,847	58,596,019	63,298,903	65,148,516
Gross Profits	14,982,219	15,872,664	16,583,304	18,271,973	19,009,265	19,501,276
Gross profit margin	23.2%	23.2%	22.8%	23.8%	23.1%	23.0%
Operating profit margin	3.9%	4.1%	4.2%	4.1%	3.6%	3.6%

	Period average
Revenue	74,945,444
Cost of Sales	57,575,327
Gross Profits	17,370,117
Gross profit margin	23.2%
Operating profit margin	3.9%

Table 18: *NorgesGruppen's* gross profit margin and operating profit margin

Notes: All values are displayed in TNOK. Gross profits and gross profit margin calculated based on revenue (excluding other revenue) and the cost of sales. Operating profit margin received from annual reports (operating profit/operating revenue).

Source: NorgesGruppen (2019)

Table 19: Pricing differences between counties

County name	Observations	Mean Price Deviation
Oslo	791,542	-.0006276***
Rogaland	618,786	.0012672***
Møre or Romsdal	524,636	.0002863*
Nordland	302,287	.032796***
Viken	1,609,715	-.0176433***
Inland	846,152	-.0024347***
Vestfold og Telemark	798,666	-.00467608***
Agder	598,984	.0110516***
Vestland	1,154,916	.0062662***
Trøndelag	325,433	.0007094***
Troms og Finnmark	282,106	.0277133***
Sum	7,853,223	0

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

Table 19: Price deviation means for all counties

Notes: Values are also shown in graph 4. Significance was tested by using t-tests for sample means, comparing each mean with the hypothesized mean of zero, which is the hypothesized mean in case all counties would show the exact same pricing scheme.

Table 20: Regression of price deviation and income by chains

Chain	Observations	Regression coefficient	F-statistic	R^2
Joker	873	1.59e-8	2.02	0.0023
Kiwi	735	-2.75e-9	0.53	0.0007
SPAR	424	5.29e-9	0.31	0.0007
MENY	292	3.26e-8*	3.91*	0.0133
CC-Mat	3	-1.07e-7	1.03	0.5085
Total	2,327	-4.79e-8***	7.69***	0.0033

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

Table 20: Regression of price deviation and income by chains

Notes: The table shows regressions, using the variables *(between-chains) relative price deviation* and each stores' *household income*. Values are also shown in figure 22. Significance was tested by using F-tests for the explanatory worth of the regression as well as t-tests for the significance of the correlation coefficient. The R^2 value states the degree of representation (0= the linear regression fits the data very bad; 1=the linear regression fits the data perfectly). "Total" shows the regression over all observations as can be seen in figure 5.

Table 21: Regression of elasticity and price deviation by chains

Chain	Observations	Regression coefficient	F-statistic	R^2
Joker	650	.0047***	7.28***	.0111
Kiwi	728	.0117***	82.1**	.1016
SPAR	392	.0027	2.18	.0004
MENY	275	.0016	.11	.0004
CC-Mat	3	-.0133	.01	.0087
Total	2,048	-.0643***	4434***	.6843

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

Table 21: Regression of elasticity and price deviation by chains

Notes: Values are also shown in figure 23. Significance was tested by using F-tests for the explanatory worth of the regression as well as t-tests for the significance of the correlation coefficient. The R^2 value states the degree of representation (0= the linear regression fits the data very bad; 1=the linear regression fits the data perfectly).
"Total" shows the regression over all observations as can be seen in figure 6.
The lower number of observations (stores) is due to restrictions introduced for calculating elasticity. See chapter 3.3 for more information.

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I assert that this paper was written by me personally and that I was not assisted in any way by someone else. Furthermore, I assert that this paper or parts thereof have not been submitted elsewhere, neither by me nor by others. When I consulted print or electronic sources and publications to draw upon the writings or thoughts of others, I cited these sources. All secondary literature and additional sources have been acknowledged and are listed in the bibliography. The same is true for graphs, pictures, and all internet sources. Moreover, I consent that my paper may be screened and saved electronically and anonymously in order to be checked for plagiarism. I am aware that my paper may not be graded if I refuse to agree to these conditions.

Bergen, 20.06.2020

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