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Assortment choice and market power under uniform pricing

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Assortment Choice and Market Power under Uniform Pricing *

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Abstract

This paper studies how retailers strategically use product assortment to respond to local market conditions when prices are set at the national level. When firms are unable to increase the price of a product that is particularly popular in a local market, they can instead replace it with a more expensive substitute. The profitability of these assortment substitutions depends on the degree of market competition. This study uses extensive receipt and store-level data and a structural equilibrium model to evaluate the impact of market power on assortment choices. The findings indicate that firms make use of assortment choices, offering fewer and pricier products in markets with stronger local market power. Counterfactual policy experiments reveal that government intervention in the form of subsidies to consumers or retailers in remote areas can improve total market welfare.

Keywords: non-price competition, uniform pricing, assortment choice, grocery retail market, multi-store firms, market power

JEL classification: L11, L81, L13.

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1 Introduction

Unlike market power over price, there has been little focus on market power when it comes to non-price characteristics. Similar to prices, firms operating in imperfectly competitive industries have the ability to distort non-price attributes from socially optimal levels. Examples include delivery time in online shopping (Ater and Shany, 2021), product downsizing in the retail industry (Yonezawa and Richards, 2016) and product selection in the grocery industry, which is the main focus of this paper, where firms can deliberately restrict consumer choice in stores. Understanding how firms leverage non-price attributes like product selection is crucial for consumer welfare. Restricted product selection can lead to limited access to affordable or preferred products, thereby negatively impacting overall consumer welfare.

The importance of this issue has recently become apparent, as there is increasing evidence that multi-store retailers practise uniform pricing, i.e. charging the same prices for products across markets with different demographics, preferences and levels of competition (DellaVigna and Gentzkow, 2019; Adams and Williams, 2019; Hitsch et al., 2019). This raises the question of whether grocery chains leverage their market dominance through non-price channels when prices are fixed.

When deciding what products to offer, store managers consider the following trade-off. Removing cheap products from a store may cause some consumers to switch to another store, while the remaining consumers are more likely to purchase expensive, higher-margin products. If local competition is intense, the first effect prevails. However, if competition is weak, reducing the product assortment may be profitable. This example highlights how store managers can strategically make assortment decisions to maximise profits based on the level of local competition they face. It also underscores the broader economic principle that firms can exert market power beyond price control, thereby affecting consumer welfare through non-price attributes.

This study focuses on the Norwegian grocery industry, where many supermarkets have substantial local market power. In fact, 22% of grocery stores are considered local monopolies with no competitors within a 5 km radius. I demonstrate that while the price channel is limited due to uniform pricing, firms strategically select the range of products in a store to optimise their profits. Furthermore, I show that the strategic decisions concerning product assortment made by these firms significantly affect consumer welfare. Consequently, this study provides insights for policymakers on potential interventions, such as reducing travel costs for consumers in remote areas or offering subsidies to retailers in high-cost regions to enhance competition and product variety.

The first contribution of this paper is to establish two key stylised facts. Firstly, I show that pricing decisions for individual products are made at the national level, and secondly, that product selection decisions are made at the local level. This supports informal discussions suggesting that the decision-making process for retailers occurs at two levels: each chain sets product-level prices nationally, while regional and store managers determine product selection locally. This two-tiered decision-making process highlights the importance of the assortment channel and allows me to focus solely on assortment decisions while considering product-level prices as given. This observation also aligns with recent discussions on firms delegating different decision-making responsibilities to distinct sub-units within the organisation and the importance of accounting for a firm's organisational structure (Hortaçsu et al., 2024).

To study assortment decisions, I use data from multiple sources. The primary data source is weekly sales at the product and store level for all stores belonging to a large Norwegian retail group. The secondary source is a database provided by Geodata, the primary Norwegian spatial data provider. The database contains information on annual store-level revenue, location and other characteristics for all grocery stores in Norway. I then collect data on the location of distribution centres and the driving distance between stores and distribution centres. Finally, I use detailed information on demographic distribution from Geodata.

To measure assortment at store level, I aggregate individual product items into a composite good. Each store is modelled as making choices regarding two assortment measures characterising a composite good: *price*, which represents the price level of the assortment offered, and *variety*, which quantifies the breadth of assortment. Using a composite good simplifies the assortment analysis while capturing the main factors influencing consumers' store choices, such as shopping costs and product selection.

Based on the stylised facts, I develop and estimate an equilibrium model for the grocery market. On the demand side, I specify a spatial model where consumers decide which store to visit and how much to spend on groceries. In particular, I model how consumers weigh the travel distance against store characteristics, including assortment. On the supply side, each chain makes store-level assortment decisions, determining the price and variety of composite goods to maximise chain profit.

The structural model builds on the novel approach of Ellickson et al. (2020), which allows spatially heterogeneous consumers to have location-specific choice sets, and extends it by introducing an unobserved demand shifter. This framework differs from the conventional isolated markets approach used in previous literature (Bresnahan and Reiss, 1991; Zheng, 2016). In particular, I employ a spatial discrete choice model that explicitly incorporates the distance between consumers and stores, allowing for a more accurate measurement of local competitive pressure. In the model, the set of available stores and the degree of substitution depend on how consumers trade off travel distance and store characteristics, including price level and breadth of assortment. Additionally, I extend the model to allow for a structural unobserved store-level component, significantly improving upon the previous approach by separating unobserved store quality from consumer preferences in specific locations.

Assortment variables could be correlated with the unobserved demand shifter. To obtain consistent estimates of the model parameters, I employ instrumental variables and use the generalised method of moments (GMM) for estimation. In particular, I follow Houde (2012) while bringing the Berry (1994) approach for inverting market shares to the spatial model of Ellickson et al. (2020). As instruments, I leverage differentiation instruments along with exogenous cost shifters. differentiation instruments aim to isolate variation that drives the assortment decisions from the unobserved demand determinants while capturing competitive pressure.

First, by employing the novel approach to demand modelling, I quantify local competition and uncover assortment inequality across different markets. In Norway, most markets are either moderately concentrated (56%) or highly concentrated (41%), and only 3% are considered competitive. Furthermore, I find that residents of large cities have access to more affordable groceries and greater variety, while consumers in remote markets face a more limited and pricier assortment. These findings document the significant variations in market power and product assortment across local markets.

Next, using the model, I separate the impact of local market power from other factors that may affect assortment choice, such as logistics costs, local tastes and store characteristics. In particular, the model allows me to estimate store-level margins, which illustrate stores' ability to raise prices above the marginal cost or limit variety, thus reducing marginal costs – both of which are indicative of local market power. Conversely, factors other than local market power are reflected in the marginal cost. By connecting the choice-weighted margin per person to the localised degree of market concentration, I also quantify the variance of margins associated with differences in market concentration. In the most concentrated markets, consumers spend up to 25% more than in the most competitive markets, constituting around EUR 1,500 annually.

Finally, I use the model to conduct counterfactual experiments. Firstly, the simulation of a uniform assortment strategy indicates that while consumers benefit from increased variety, the policy minimally reduces inequality due to persistent high transport costs in remote areas. Secondly, the analysis shows that maintaining a varied assortment across markets is more profitable for firms, as a uniform assortment strategy could lead to store closures and a further reduction in competition. To address these cost differences across markets, I run additional counterfactual experiments designed to mimic realistic policies. Policy interventions, such as reducing travel costs for remote consumers or providing subsidies to retailers, significantly enhance competition and product variety. Specifically, reducing travel costs increases consumer welfare and firm profits by 11.4% and 5.6%, respectively, while subsidies lead to a 1.8% rise in consumer welfare and a 6.8% increase in firm profits. These findings offer critical insights for policymakers aiming to improve market fairness and consumer access to a diverse selection of products.

The paper speaks to the empirical literature that explores the effects of competition on non-price attributes. Although there is extensive literature on price setting under imperfect competition, much less attention has been paid to the impact of competition on quality and non-price attributes in a more general sense. As with prices, firms in imperfectly competitive industries tend to deviate from socially optimal levels of quality, but unlike prices, the direction of this distortion is not clear (Spence, 1975).

This study is closely related to the work of Argentesi et al. (2021), which examines the effect of a merger between two chains on prices and product assortment. The authors find that after the merger, chains tend to adjust their assortment rather than their prices, suggesting that product selection is a strategic variable for retail chains. Similar to Argentesi et al. (2021), I find empirical evidence that product selection can vary locally. However, this paper differs from theirs in several aspects. Firstly, I use a structural model to separate the impact of local competition from other confounding forces that can impact product assortment decisions. Secondly, the structural model allows me to examine the effects of these assortment differences on consumers across various markets. Lastly, I use the model to simulate counterfactual experiments and propose policy insights on how assortment can be improved in remote areas.

Another closely related paper is Aguirregabiria et al. (2016), who study competition among alcohol retailers in Ontario. Their setting allows for explicit modeling of product-level assortment choices, due to the limited number of products stocked by stores. They find that competitive entry leads to significant adjustments in assortment. While the scale of product assortment in my setting precludes product-level modeling, my approach complements theirs by enabling the estimation of assortment responses in a high-dimensional setting using aggregated variety indices. Both studies underscore the importance of assortment as a competitive margin when prices are regulated or fixed.

This paper also contributes to the growing literature on food prices and assortment inequality between markets with different socio-demographic and economic characteristics (Dubois et al., 2014; Handbury and Weinstein, 2015; Allcott et al., 2019; Handbury, 2019; Eizenberg et al., 2021). The findings in Handbury (2019) suggest that low-income households face different assortment and prices than high-income households, mainly due to their income-specific tastes. In this vein, a higher degree of heterogeneous local tastes can be beneficial for all consumers in a market, leading to increased variety (Quan and Williams, 2018). Additionally, Eizenberg et al. (2021) study price differences across a city's stores and attribute them mainly to spatial frictions. In this paper, I show how, in the context of uniform pricing, firms resort to other strategies to imperfectly segregate the market. Furthermore, I explore how this assortment strategy creates spatial inequalities and affects consumers in urban and rural markets. Similar to Eizenberg et al. (2021), I show that urban residents have better access to a cheaper assortment than residents of rural areas. Using the counterfactual analysis, I also provide policy insights on how to reduce welfare distortions associated with assortment inequality.

Lastly, the paper relates to a growing literature on uniform pricing (Adams and Williams, 2019; DellaVigna and Gentzkow, 2019; Hitsch et al., 2019). In a seminal paper, DellaVigna and Gentzkow (2019) document the use of uniform pricing by a number of US retailers. Adams and Williams (2019) study welfare effects and find that uniform pricing can shield consumers from higher prices in less competitive markets. Similarly, this study confirms the practice of uniform pricing among retailers in Norway. It also complements this strand of literature by showing that when prices are fixed at the national level, firms use other non-price channels, in this case product selection, to respond to changes in market structure.

The paper proceeds as follows. In the next section, I describe the data used in the analysis. Section 3 presents stylised facts and in Section 4, I describe the equilibrium demand and supply framework underlying my empirical model. Section 5 describes the identification of structural parameters and Section 6 presents the estimation results of the demand and supply models. Section 7 presents the results from the counterfactual experiments and, finally, Section 8 concludes.

2 Data and institutional setting

I begin by describing the Norwegian grocery landscape and the data sources used in the study. Next, I explain how I utilise the data to construct the price and variety measures of the composite good.

The Norwegian grocery industry

The Norwegian grocery industry consists of four retail groups: NorgesGruppen (NG), Rema 1000, Coop, and Bunnpris. As of 2018, these four corporations control 99.9% of the market. The first three firms are vertically integrated, controlling their own wholesale and distribution networks, as well as some food production. In contrast, Bunnpris, while operating as a distinct brand, relies on wholesale and distribution services from one of the other corporations.

Table 1 presents selected statistics for the Norwegian grocery market. Three of the retail groups have multiple independent chains representing different grocery formats. For example, the market leader NorgesGruppen has a discount format (Kiwi), a convenience store format (Joker and Nærbutikken), and supermarkets (Spar and Meny). Such differentiation allows a variety of consumer segments to be served. Independent stores not belonging to the four listed retail groups constitute a small part of the market (less than 0.1%). Most of them are located in large cities and usually provide a specific assortment, such as imported products targeted at consumers with non-Norwegian backgrounds.

Table 1: Market structure in the Norwegian grocery industry, 2018

	Market share	Revenue	Number of stores
NorgesGruppen	40.05	72,016	1,758
Kiwi	19.49	35,055	653
Meny	9.85	17,715	187
Spar	6.85	12,320	286
Joker	3.65	6,563	464
Nærbutikken	0.73	1,312	168
Coop	40.87	73,408	1,111
Coop Extra	13.78	24,783	369
Coop Obs	6.59	11,859	30
Coop Prix	5.82	10,472	295
Coop Mega	4.56	8,208	77
Coop Marked	2.27	4,085	244
Matkroken	0.59	1,059	96
Rema 1000	22.16	39,845	589
Bunnpris	3.64	6,552	254
Total	100	179,829	3,712

Note: Market shares are in per cent and revenues are in million Norwegian krone (rounded to the nearest integer). Market shares are computed based on revenue shares.

The Norwegian grocery market, while highly concentrated, exhibits a nuanced decision-making structure that adds complexity to its competitive landscape. Although the three largest groups — NorgesGruppen, Rema 1000, and Coop — maintain integrated ownership over their chains, these chains have a certain degree of autonomy in key operational decisions. Notably, strategic choices such as market entry and store location are typically determined at the group level, ensuring centralized control over long-term expansion and spatial competition. Then, other critical decisions, particularly pricing, are made at the chain level. This structure allows chains within the same retail group to differentiate better from each other. Importantly, some groups even charge different wholesale prices to their chains.

Beyond chain-level pricing, there exists an additional layer of decision-making autonomy at the regional and store level. While overall pricing structures are set centrally, local managers—sometimes at the regional level, other times at the individual store level—have discretion over product assortment. This flexibility enables stores to adjust their offerings locally. Thus, while the Norwegian grocery industry is marked by significant vertical integration and market concentration, the internal decision-making hierarchy introduces important variations that influence competitive dynamics. These structural peculiarities, particularly the distinction between central and decentralized decision-making, will play a key role in formulating assumptions for the model used in this study.

Data

The data comes from multiple sources. The primary data source is receipt data from one large Norwegian retail group, which operates throughout the country and has stores of all existing market formats, including discounters, convenience stores and supermarkets. The data contains item-level transactions on all individual shopping receipts for March 2018 across all stores belonging to the selected retail group. Each item is a unique stock keeping unit (SKU). The dataset contains information about prices with and without discounts for individual items on the receipt, the quantity purchased, store and product IDs. The information about the prices and products offered at the stores obtained from this dataset serves as the foundation for constructing store-level assortment measures, which will be used in subsequent analyses.

The second data source is a geocoded store-level panel provided by Geodata, a Norwegian spatial data provider. Geodata's database contains yearly information on store-level revenue for 2010–2021, as well as information about the location, store ID, store opening date, size and number of employees. Table 2 shows descriptive statistics for the stores.

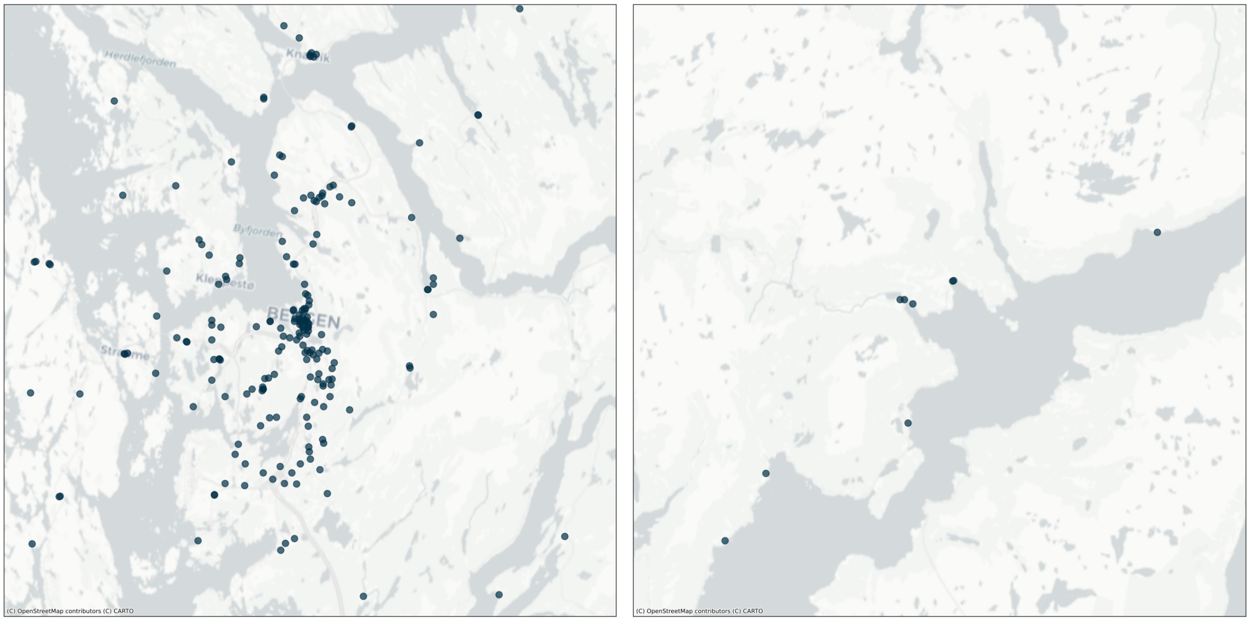
Table 2: Store-level descriptives, 2018

	Mean	SD	Min	Median	Max
Revenue (mln NOK)	48.39	51.43	0.07	39.71	1,249.5
Number of employees	25.21	73.02	1	17	2304
No. hours open	13.95	2.56	3	15	24
Open on Sunday	0.16	-	0	-	1
Location in shopping centre	0.16	-	0	-	1

Source: Geodata.

Geodata's database covers the whole grocery market in Norway, providing a comprehensive overview of the industry. Figure 1 illustrates the spatial distribution of stores in Bergen, the second largest municipality of Norway, and Kvam, a neighbouring municipality with fewer stores. We can see that store density can vary significantly across markets. I use this store location data to measure the degree of spatial competition and to construct choice sets of consumers residing in different locations in the spatial demand model. The unique store ID makes it possible to link Geodata's database on revenues with the receipt data.

Additionally, I use a detailed demographic database provided by Geodata. I use this data



(a) Bergen **(b)** Kvam

Figure 1: Location of stores

at the most granular statistical geographic unit known as a basic unit (BU).[1] To illustrate the spatial distribution, Figure 2 demonstrates how the two largest cities in Norway are divided into basic units. Table 3 shows descriptive statistics of demographic data at the basic unit level.

Similar to other scanner datasets, the receipts do not contain information about the residential location of consumers. It is therefore necessary to make assumptions about which stores consumers can shop at. Since it is likely that consumers residing in a particular basic unit shop in stores located in different basic units, I do not adopt the conventional isolated markets approach inspired by Bresnahan and Reiss (1991). Instead, I link the store-level aggregate revenues to consumer choices using the spatial demand model, exploiting data on store locations and the distribution of consumer demographics. Section 5 provides details of the modelling procedure.

Table 3: Descriptive statistics of demographics data by basic units

	Mean	SD	Min	Median	Max
Area (km^2)	22.98	67.62	0.03	3.44	1,805.21
Population	283.7	314.6	1	179	4,272
Population density (people/km^2)	1248	29,366	0.09	41.9	3,472,394
Average income (thou. NOK)	659.5	546.9	78.8	546.7	18,000

Source: Geodata.

[1] Basic units are generally geographically smaller than postal or zip codes and are similar to census blocks in the US.

(a) Oslo **(b)** Bergen

Figure 2: Division into basic units

Composite Good

An average store in my sample carries several thousand products. For example, Meny, one of Norway's leading supermarket chains, typically offers between 9,000 and 15,000 items.[2] Modeling assortment decisions at the individual product level is therefore infeasible due to the combinatorial complexity. In contrast, some prior studies (e.g., Aguirregabiria et al. (2016)) operate in settings with much smaller assortments, which allows them to model the inclusion or exclusion of specific products. Given the scale of the problem in my context, I adopt a more aggregated approach: I aggregate individual product items into a *composite good* representing a basket of groceries purchased by an average consumer. The composite good is characterised by price and variety measures at the store level. Using the concept of a composite good is common in industrial organisation (Handbury, 2019; DellaVigna and Gentzkow, 2019; Eizenberg et al., 2021; Duarte et al., 2020) and urban economics literature (MacDonald and Nelson Jr, 1991) when it is necessary to compare multi-product stores by relative shopping costs and product selection.

To construct a composite good, I focus on fourteen popular product categories that most households consume daily. The categories are selected based on their sales revenues, excluding fruits and vegetables, as these are not subject to uniform pricing.[3] The final set of product categories comprises cheese, eggs, fresh bread, juice, frozen fish, chocolate bars, beer, jam, dry bread, coffee, milk, yogurt, frozen pizza and canned fish. Each category includes from 10 to 162 products, where a product is identified by a stock-keeping unit ID, which is a consistent identifier across all stores in Norway.

[2] https://meny.no/om-meny/

[3] The suppliers of fruits and vegetables can vary across regions.

Information about products offered in each store and individual product-level prices are collected from the receipt data. As the receipt data records a product's price, quantity purchased and package size, it is possible to calculate a price for a standardised product unit (for example, a kilogram of cheese or a litre of milk).

In line with Eizenberg et al. (2021), I define the price of the composite good as the revenue-weighted average across the chosen categories. In the notation below, i represents a product, c denotes a category and j is the subscript for a store. To aggregate product-level prices p_i into a category-level price p_{cj}, I calculate a revenue-weighted average for products within category c and store j, denoted as Ω_{cj}. I use the relative total product revenue in the retail group as weights, so that more popular products have higher weights in the category-level price. To estimate category costs, I multiply the revenue-weighted average by the average purchased units in the category or the *average basket*. Thus, the revenue-weighted average price for category c in store j is given by:

$$p_{cj} = \text{average basket}_c \times \left(\frac{\sum_{i \in \Omega_{cj}} w_i p_i}{\sum_{i \in \Omega_{cj}} w_i} \right). \tag{1}$$

Note that since product-level prices p_i are fixed, and weights w_i are determined globally and do not vary across stores, variations in the composite good price arise solely from the differences in the product set Ω_{cj} across stores. This difference plays a crucial role in the analysis as it allows us to investigate retailers' strategic assortment decisions.

Finally, I calculate the price of a single unit of the composite good p_j by averaging category-level prices p_{cj} across chosen categories:

$$p_j = \frac{1}{C} \sum_{c=1}^{C} p_{cj}, \tag{2}$$

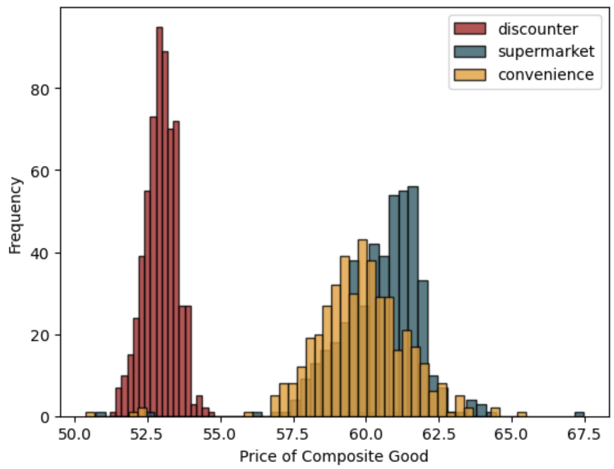
where C is the total number of categories.

To measure the breadth of assortment, I first calculate ν_{cj} as the number of unique products offered in category c of store j. Then, following the approach of Argentesi et al. (2021), I define the variety ν_j of store j as an average number of unique products across chosen categories:

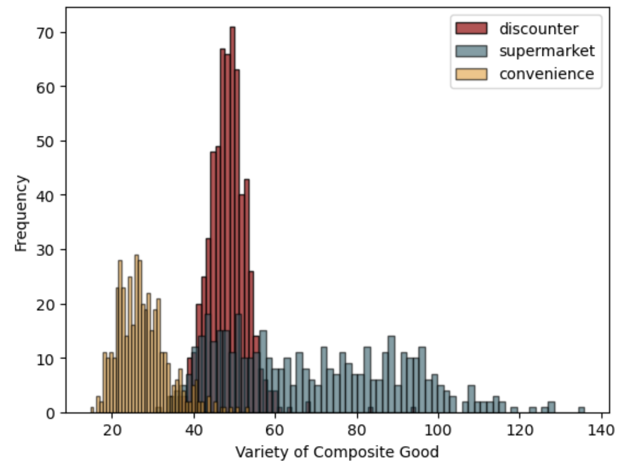
$$\nu_j = \frac{1}{C} \sum_{c=1}^{C} \nu_{cj}. \tag{3}$$

Figures 3a and 3b show the distribution of price and variety across different retail formats. They firstly reveal notable differences in assortment across different retail formats. As expected, discount stores offer a cheaper assortment than supermarkets and convenience stores. Furthermore, the assortment offered by discount stores is more uniform in terms of price and variety measures compared with other formats. Convenience stores offer expensive but a more limited range of products. Finally, supermarkets exhibit greater variation in the assortment breadth compared to other formats.

Table 4 presents descriptive statistics for the price and variety of a composite good across stores. Given that the receipt data is available for one retail group, each format corresponds



(a) Price



(b) Variety

Figure 3: Distribution of price and variety across chains

to a single chain. Additionally, note that the product prices in stores belonging to one chain are the same. Hence, any differences in the price of a composite good only originate from the difference in product selection. Note, furthermore, that this price variation measured in the 95% confidence interval accounts for 10% of the average price of the composite good for convenience stores, 7% for discounters and 9% for supermarkets, which could entail significant welfare effects. Variety also differs noticeably across stores of one format. Aside from market power, this variation could be explained by many confounding factors, including the size of a store and local tastes. I will explore these differences further in the following section.

Table 4: Price and variety summary statistics

	Mean	SD	Min	Median	Max
Price					
Convenience store	59.85	1.44	56.08	59.78	65.48
Discounter	53.02	0.89	51.21	52.98	61.44
Supermarket store	60.6	1.41	52.14	60.79	67.49
Variety					
Convenience store	27.21	6.15	14.64	26.43	53.36
Discounter	48.43	5.19	16.64	48.43	94.36
Supermarket store	69.45	22.04	30.57	66.71	135.93

In this paper, I focus explicitly on the intensive margin of assortment—that is, the number of products (SKUs) offered within a fixed set of categories. All stores in the sample carry the same fourteen product categories, which together account for approximately 70% of total store revenue on average. Therefore, differences in assortment across stores or chains should be interpreted as variation in the depth of assortment within categories (e.g., the number of cereal or dairy SKUs), rather than in the presence or absence of entire categories. This focus avoids conflating assortment differences with broader distinctions in store format (e.g., convenience stores not stocking fresh produce) and instead isolates the strategic within-category assortment decisions that firms make.

It should be noted that assortment information is inferred from the transaction data. Given the limited shelf space in stores, it is plausible to assume that each product displayed in a store has been purchased at least once during the observed month; otherwise, it would not be stocked. Since the transaction data captures one month of purchase activity, any short-term stock-outs are assumed to occur randomly.

It should also be noted that retailers in Norway have three periods per year known as *launch windows* (in February, June and October), when chain managers can introduce changes in the assortment at the central level. The data available for this study covers the period between these launch windows, leading to the assumption that the chains did not alter their assortment during a given month.[4]

3 Stylised Facts

This section uses the data described above to present two stylised facts that support my model assumptions, which are presented in the next section. Firstly, I show that retail chains indeed follow uniform pricing and secondly, I document that product selection can vary locally depending on local market conditions.

Retail Chains Follow Uniform Pricing

Studies by DellaVigna and Gentzkow (2019) and Hitsch et al. (2019) show that national pricing is an industry norm among grocery chains in the US. In contrast, Eizenberg et al. (2021) reveal significant local differences in grocery prices in Israel. Based on the extensive receipt data, I investigate whether there is variation in product prices within chains in Norway.

To begin, I visualise price variation both across all chains and within the stores belonging to one chain. Figure 4 illustrates that price deviations from the mean product price within stores from the same chain are concentrated around zero. Conversely, there is substantial variation in prices for the same product across different chains. Figures A.1 and A.2 in the Appendix present similar plots for product price variation in separate product categories. This result supports the fact that product prices do not vary across stores belonging to one chain.

Additionally, I calculate how often product prices deviate from the mean price both within and between chains. In particular, I look at the share of observations when prices deviate from the mean by more than 1%. The results are summarised in Table 5. The share of non-identical prices within stores of the same chain varies across categories and, on average, amounts to 2.2%. On the other hand, the average share of non-identical prices within all stores is 67.7%. While product prices within chains might differ due to store-specific sales or personal discounts, this variation remains relatively small.

[4]The standardisation committee for the Norwegian grocery industry: https://stand.no/prosess/sortiment/grunndataregistrering-og-produktpresentasjon/

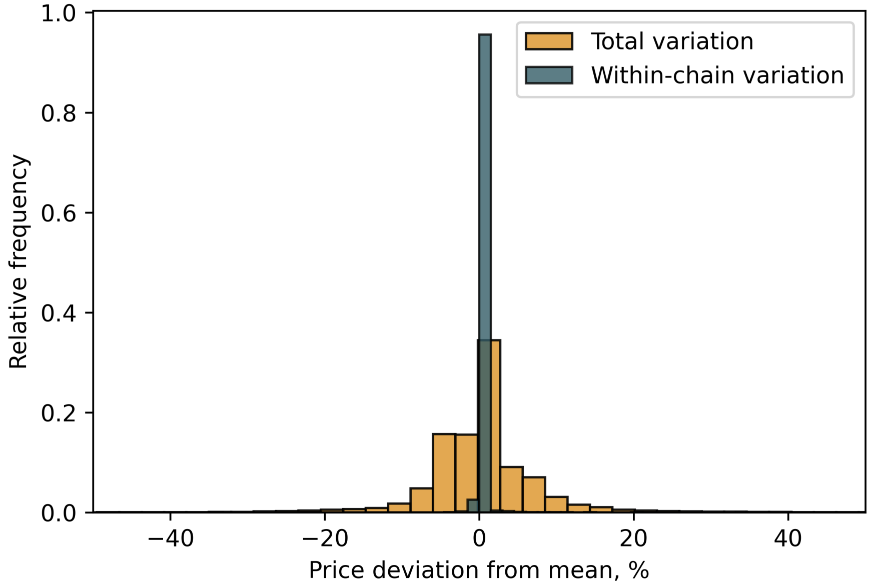


Figure 4: Price variation within and across chains
Note: One observation is one SKU in one store in one day

Table 5: Share of non-identical prices within and between chains

Category	# of obs.	% non-identical prices within SKU-chain-time	% non-identical prices within SKU-time
Milk	107,425	4.9	91.9
Fresh bread	81,185	0.7	64.5
Beer	41,188	0.8	52.3
Chocolate bars	33,600	1.9	66.4
Dry bread	29,109	1.0	48.4
Cheese	21,944	1.1	61.6
Coffee	19,046	6.0	78.4
Juice	18,545	1.3	72.1
Frozen pizza	18,483	0.8	47.5
Jam	15,321	0.7	41.6
Frozen fish	13,359	0.3	42.8
Yogurt	13,327	2.1	60.9
Canned fish	8,054	0.7	67.9
Eggs	3,559	2.7	53.2
Total	424,145	2.2	67.7

Note: One observation is the price for one SKU in one store in one day. Non-identical price refers to deviation from the mean price of more than 1%.

Finally, I explore whether the potential variation in product prices within a chain responds to local market conditions. In particular, I run a regression of product-level prices p_{ijt} on market characteristics z_j, where the store j is located, while controlling for store attributes x_j and including fixed effects for the combination of chain g, product i and day t. After accounting for chain, product and day fixed effects, the remaining variation in product-level prices pertains to the differences between stores of the same chain. The regression looks as follows:

$$p_{ijt} = z_j\alpha + x_j\gamma + \kappa_{igt} + \epsilon_{ijt}, \tag{4}$$

Columns I–III in Table 6 show the results for different specifications, which vary by the size of the market. More specifically, I define a market as the area within a 5, 10 or 30 km driving distance from a store. For each market definition, I calculate the market-specific income as the average income of consumers residing within that distance from a store. Additionally, I calculate a market-specific dummy variable for a store if it belongs to a chain that has no competitors within the given radius. It is important to note that the main purpose of these regressions is to shed additional light on the descriptive patterns in the data; therefore, the estimated coefficients should not be interpreted as causal effects.

Regardless of the size of the market, I find no evidence that prices at the product level respond to local market conditions. Moreover, more than 99% of the variation in p_{ijt} is explained by κ_{igt}. This finding provides further support to the notion that pricing decisions are predominantly made at the national level.

While the evidence presented here strongly supports the assumption of uniform pricing within retail chains, understanding why firms adopt this strategy lies beyond the scope of this paper. A growing literature explores the rationale behind uniform pricing, citing factors such as managerial costs, fairness perceptions, and reputational concerns (e.g., DellaVigna and Gentzkow, 2019; Friberg et al., 2022). This study does not attempt to contribute to that debate. Instead, I take uniform pricing as a feature of the institutional setting and focus on the strategic use of product assortment in response to local market conditions.

Assortment Responds to Changes in Local Market Conditions

Existing literature provides evidence that the assortment of food products can differ among various markets. For instance, Handbury (2019) indicates that retailers tailor their product selection to income-specific preferences. Similarly, Quan and Williams (2018) find that diverse local tastes contribute to an enhanced variety of products within a market. When retailers set prices nationally, product selection can serve as a means to adapt to local market conditions.

To explore the potential variation in assortment within a chain due to local market conditions, I run a regression similar to Equation 4. Specifically, I estimate the following regression equation for the composite good at store level:

$$y_j = z_j\alpha + x_j\gamma + \kappa_g + \epsilon_j, \tag{5}$$

where y_j denotes either the price p_j or variety ν_j of the composite good, z_j represents the market characteristics of store j, x_j is a vector of store attributes and κ_g captures chain fixed effects.

The results are shown in columns IV–IX of Table 6. As the price of the composite good can only vary on the basis of assortment changes, these results indicate that the assortment offered by the different stores in a chain can differ. In particular, after controlling for chain fixed effects, product selection responds to differences in local market conditions. Similar to the findings of Handbury (2019), I find that assortment decisions are correlated with

Table 6: Assortment choice and competition

	I	II	III	IV	V	VI	VII	VIII	IX
	Individual product prices			**Average store price**			**Average store variety**		
	5 km	10 km	30 km	5 km	10 km	30 km	5 km	10 km	30 km
Local monopoly (in radius)	-0.001	-0.001	-0.001	2.27***	2.30***	2.73***	-11.64***	-11.06***	-8.35***
	(0.001)	(0.001)	(0.001)	(0.189)	(0.236)	(0.566)	(0.886)	(1.12)	(2.68)
Average income, 100,000 NOK (in radius)	0.000	0.000	0.000	0.089**	0.126***	0.114	0.797***	1.02***	1.36***
	(0.000)	(0.000)	(0.000)	(0.037)	(0.048)	(0.07)	(0.174)	(0.228)	(0.331)
Location in shopping centre	-0.002	-0.002	-0.002	-0.008	-0.095	-0.212	10.75***	11.26***	11.84***
	(0.001)	(0.001)	(0.001)	(0.22)	(0.223)	(0.229)	(1.036)	(1.06)	(1.09)
Location in city centre	0.001	0.001	0.001	-0.063	-0.33*	-0.522***	3.39***	4.52***	5.31***
	(0.001)	(0.001)	(0.001)	(0.181)	(0.182)	(0.186)	(0.852)	(0.861)	(0.882)
Open on Sunday	-0.000	-0.000	-0.000	2.64***	2.65***	2.63***	-5.43***	-5.42***	-5.07***
	(0.001)	(0.001)	(0.001)	(0.186)	(0.189)	(0.193)	(0.874)	(0.894)	(0.916)
Distance to distribution centre, km	-0.000	-0.000	-0.000	0.002	0.003**	0.006***	-0.051***	-0.052***	-0.061***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.008)	(0.008)	(0.009)
Const.	-0.001	-0.001	-0.001	53.97***	54.00***	54.26***	39.14***	36.20***	32.75***
	(0.001)	(0.001)	(0.001)	(0.274)	(0.339)	(0.485)	(1.29)	(1.61)	(2.30)
FE	Chain-Day-Product			Chain			Chain		
# of obs.	424145	424145	424145	1524	1524	1524	1524	1524	1524
R^2	0.99	0.99	0.99	0.47	0.45	0.42	0.61	0.59	0.56

Note: Significance levels are: *** - 1%, ** - 5%, * - 10%.

income. Product selection is also influenced by store characteristics, such as location in a city centre and location in a shopping centre and, importantly, is associated with distance to the distribution centre. Local market power also tends to play a role in product selection. For instance, when a chain has a local monopoly, it tends to offer a more expensive and narrower assortment.

In summary, this section provides evidence that variation in product-level prices across stores belonging to the same chain is minimal and does not respond to changes in local market competition, indicating the presence of uniform pricing. At the same time, there is evidence that assortment can vary across markets, and that local competition might play a role in these differences. In particular, stores operating in more concentrated markets tend to offer a pricier and narrower assortment. Determining whether these assortment differences stem from local market power or other factors such as logistics costs requires further investigation beyond the ad hoc price and variety measures previously explored. The structural analysis below aims to disentangle the role of market power in product assortment decisions and quantify how this strategic product selection affects consumers residing in urban and remote areas.

4 Model of Spatial Demand and Assortment Choice

In this section, I develop a framework for investigating the role of local market power in assortment decisions. In particular, I specify an empirical model of consumer and firm behaviour suitable for analysing the grocery sector and the available data. The demand side builds on the model of Berry et al. (1995) and expands it by allowing spatial competition as suggested by Davis (2006); Houde (2012). The supply side builds on the framework similar to Crawford et al. (2019), where firms can adjust one or more continuous attributes.

The model captures key mechanisms that drive strategic assortment choice, retailer competition and optimal choices of spatially differentiated consumers. On the demand side, it explicitly accounts for rich heterogeneity in consumer locations, enabling it to accurately capture local market power arising from variations in consumer substitution patterns. On the supply side, the model explains how firms select product assortments in a multi-store oligopoly setting. Additionally, the model facilitates the analysis of the impact of various policies in imperfectly competitive markets, where firms exercise control over store attributes.

Consumers choose the store, maximizing their indirect utility, taking into account store attractiveness based on price, variety, associated travel costs, and other fixed store characteristics, such as store size. The supply side allows firms to compete in the price and variety of the composite goods. I assume that consumers are primarily concerned with the overall selection of products, represented by the composite good, and do not differentiate between individual items within the overall selection. This assumption is based on consumers' limited ability to recall specific prices and the presence of every product. Instead, they base their store choice on a general impression of the store assortment, including its relative price level. I further assume that firms choose the price and variety of the composite goods simultaneously at the store level because, as documented in Section 3, assortment varies within stores of the same chain.

Additionally, I assume that quality difference in product assortment primarily relates to stores of different formats and will, therefore, be captured by format dummies in the model. Within stores of the same chain, differences in product assortment mainly pertain to horizontal differentiation. If stores of one chain have different prices of composite goods, it would mean that the chain replaced some products with others of similar quality but different product prices. However, suppose differences in assortment quality within these stores still exist. In that case, they will be captured by the unobserved store components and later will be accounted for as a cost-shifter on the supply side. Finally, I do not allow for fixed costs in adjusting the assortment. The assortment decisions are modelled here as short-term adjustments after selecting the other attributes. These adjustments mainly affect the marginal costs, which are allowed to depend on variety.

Demand

Before introducing the demand framework, I discuss the main features of the model and provide the reasoning behind them. Given that competition in the grocery industry is localised and market power is confined to a specific geographic area, it is important to incorporate a spatial dimension into the demand model. As consumers choose which store to visit, travel distance appears to be an important factor influencing their decisions. In this study, I use travel distance between consumers and stores to determine the relevant choice set of stores. In spatial competition, available stores and the degree of substitution depend on how consumers trade-off factors such as travel distance and store characteristics, particularly product variety and price. I leverage the flexible demand approach of Ellickson et al. (2020)

to address these considerations. This framework allows us to work with overlapping markets where each consumer has her own choice set instead of isolated markets as seen in Zheng (2016), Handbury (2019) and Argentesi et al. (2021).

I extend the approach of Ellickson et al. (2020) to allow for endogenous unobserved demand shifters. Although the inclusion of the unobserved store-level demand component complicates the computation, it is necessary to incorporate factors determining consumer choices that are unobserved by researchers but may also impact firms' strategic decisions. Examples of such factors may include the overall appearance or the presence of additional amenities or services within or nearby the store, such as a post office or car park. By explicitly addressing these considerations, I account for the potential endogeneity issue, which in turn makes it possible to model firms' strategic incentives when it comes to optimal assortment.

Finally, to model individual consumer expenditures and map them to observed store revenues, I build on previous research on the grocery industry (Duarte et al., 2020; Eizenberg et al., 2021) and use a discrete-continuous choice demand model initially proposed by Hanemann (1984) and later adopted to the aggregate discrete choice framework by Björnerstedt and Verboven (2016). The discrete-continuous choice model offers a more suitable framework for modelling demand in the grocery shopping context than the standard unit demand specification. It provides for consumers to decide which store to shop at and how many units of the composite good to buy. Further details about this model are discussed later in this section.

Each consumer i residing in a location l has Cobb-Douglas preferences over $z_{i(l)}$ units of the numeraire and $q_{i(l)j}$ units of groceries. Since the actual place of residence for each consumer is not observed, the centroid of the basic unit is used as the consumer's location. Each store j offers a basket of groceries characterised by p_j and ν_j. Consumer choices generate the aggregate demand $q_j(p_j, \nu_j)$, representing the total quantity of the composite good sold in store j.

I assume that the demand arises from a constant expenditure model, a special case of the discrete-continuous choice framework of Hanemann (1984), where consumers allocate a constant budget share $\varphi_{i(l)}$ of their income $y_{i(l)}$ to grocery shopping. Consumers then decide in which store $j \in \mathcal{J}_{i(l)}$ to purchase a continuous quantity of grocery goods $q_{i(l)j}$. This specification allows for differences in grocery expenditures between consumers with different incomes. At the same time, the assumption of a constant income share may seem restrictive in the Norwegian context, as we could expect the percentage of income spent on groceries to decline as income grows. However, I observe that this percentage remains relatively constant across different income levels (see Table A.1 in the Appendix). Moreover, as highlighted in other studies of the grocery industry (Duarte et al., 2020; Eizenberg et al., 2021), the constant expenditure assumption appears to be more realistic for the grocery shopping setting than the unit-good assumption.

The conditional direct utility function when choosing store j is defined as:

$$u_{i(l)j} = (1 - \varphi_{i(l)}) \ln z_{i(l)} + \varphi_{i(l)} \ln q_{i(l)j} + \varphi_{i(l)} \ln \psi_{i(l)j}, \tag{6}$$

where $\psi_{i(l)j}$ is the parameter that governs the preferences of consumer i for store j and is specified as:

$$\psi_{i(l)j} = e^{\frac{\theta_j + \rho d_{lj} + \epsilon_{i(l)j}}{\alpha}}. \tag{7}$$

Here, θ_j represents the utility from store characteristics other than price, d_{lj} denotes the distance between location l and store j, $\epsilon_{i(l)j}$ accounts for the consumer-store specific shock with a type-I extreme value distribution, and α is the price sensitivity parameter that governs the relative importance of the utility from the chosen alternative j and the utility from the numeraire.

Maximisation of the conditional direct utility under a budget constraint $p_j q_{i(l)j} + z_i = y_{i(l)}$ will then give the demand functions:

$$q_{i(l)j}(p_j, y_{i(l)}) = \frac{\varphi_{i(l)} y_{i(l)}}{p_j}, \quad z(p_j, y_{i(l)}) = (1 - \varphi_{i(l)}) y_{i(l)}. \tag{8}$$

When substituting the demand functions into the direct utility function, I derive the indirect utility function:

$$\upsilon_{i(l)j} = \frac{\alpha}{\varphi_{i(l)}} \ln y_{i(l)} - \alpha \ln p_j + \theta_j + \rho d_{lj} + \epsilon_{i(l)j}, \tag{9}$$

with θ_j being a linear function of variety ν_j, a vector of observed store characteristics $\mathbf{x}_j$ and an unobserved component of a store's utility ξ_j that captures factors that are not directly accounted for by the observed characteristics of the store.

Finally, I define mean utility δ_j as a linear function of price p_j, variety ν_j, a vector of observed store characteristics $\mathbf{x}_j$ and an unobserved component ξ_j:

$$\delta_j = -\alpha \ln p_j + \theta_j = -\alpha \ln p_j + \gamma \nu_j + \mathbf{x}_j \beta + \xi_j. \tag{10}$$

Inclusion of the structural error ξ_j into the indirect utility function extends the spatial demand approach proposed by Ellickson et al. (2020). This extension makes it possible to address the endogeneity issue that arises when retailers strategically choose certain characteristics, such as, in this case, price and variety of assortment, that enter the utility function. Introducing the structural error makes the estimation process computationally demanding due to the need to solve for ξ_j to evaluate the estimation objective function. However, the extension allows me to account for retailers' strategic decision-making and obtain consistent estimates of the model parameters.

To complete the specification of the demand system, I incorporate an outside option to account for the possibility that some consumers may choose to spend their grocery budget outside of the observed stores:

$$u_{i(l)0} = \frac{\alpha}{\varphi_{i(l)}} \ln y_{i(l)} + \delta_0 + \epsilon_{i(l)0}, \tag{11}$$

where I normalize the mean utility of the outside option to zero, $\delta_0 = 0$.

Finally, the probability that a consumer residing in location l decides to buy groceries from store j takes the usual logit form:

$$\mathbb{P}_{lj}(p_{\cdot}, \nu_{\cdot}, \xi_{\cdot}, d_{l\cdot}; \theta_d) = \frac{\exp(\delta_j(p_j, \nu_j, \xi_j; \theta_d) + \rho d_{lj})}{1 + \sum_{k \in \mathcal{J}} \exp(\delta_k(p_k, \nu_k, \xi_k; \theta_d) + \rho d_{lk})}. \tag{12}$$

The constant expenditure model assumes that a consumer's grocery budget is defined as a constant share of their income. Thus, the total grocery budget of location l is denoted as B_l and defined as:

$$B_l = \int \varphi_{i(l)} y_{i(l)} dF(\varphi, y), \tag{13}$$

where $y_{i(l)}$ represents the consumer's income and $\varphi_{i(l)}$ denotes the fraction of income that the consumer allocates to grocery spending.

Since individual data on grocery expenditure is unavailable, I approximate B_l as the weighted average over the distribution of consumer types in each location, defined by income y_l and the proportion of individual budgets spent on groceries φ_l:

$$B_l \approx \varphi_l \cdot y_l \cdot N_l. \tag{14}$$

Note that information about y_l and N_l is immediately available from the demographics data. Meanwhile, I infer the value for parameter φ_l from the Survey of Consumer Expenditures published by Statistics Norway.[5] The survey provides information about the percentage of household income allocated to food expenditures across various income deciles. Since these food expenditures do not include restaurant spending, they serve as a suitable proxy for grocery expenses. I then assign each basic unit to an income decile based on its average income and utilise the corresponding φ_l value associated with that decile. By incorporating this information, I can account for the variations in consumer behaviour and expenditure patterns across different income levels without estimating φ_l.

As data on grocery expenditure flows between basic units and stores are not available, I aggregate over the model-implied individual choices to connect basic unit-level consumer demographics to store-level market shares. The following describes the steps required to transition from individual choices to observed store-level market shares.

Equation 12 allows me to predict store choice probabilities for a consumer residing in location l for each store in her choice set. The grocery expenditure flow between store j and location l is then computed as the total grocery budget of location l multiplied by the probability of visiting store j:

$$\hat{R}_{lj}(p_{\cdot}, \nu_{\cdot}, \xi_{\cdot}, d_{l\cdot}; \theta_d) = B_l \cdot \mathbb{P}_{lj}(p_{\cdot}, \nu_{\cdot}, \xi_{\cdot}, d_{l\cdot}; \theta_d). \tag{15}$$

To connect the observed store-level market shares and the grocery expenditure flows between locations and stores, I aggregate the grocery expenditure flows $\hat{R}_{jl}$ over locations to formulate the revenue of each store as a function of model parameters:

$$\hat{R}_j(p_{\cdot}, \nu_{\cdot}, \xi_{\cdot}, d_{l\cdot}; \theta_d) = \sum_{l \in L_j} \hat{R}_{lj}(p_{\cdot}, \nu_{\cdot}, \xi_{\cdot}, d_{l\cdot}; \theta_d), \tag{16}$$

[5] https://www.ssb.no/statbank/table/10444/

where L_j is a group of locations that could potentially visit store j. By dividing store revenue by the total grocery budget of locations L_j, I then obtain a store-level market share:

$$\hat{s}_j(p_., \nu_., \xi_., d_{l.}; \theta_d) = \frac{\hat{R}_j(p_., \nu_., \xi_., d_{l.}; \theta_d)}{\sum_{l \in L} B_l}. \tag{17}$$

I assume that consumers' choice sets include all stores within a 30 km radius from the centroid of their basic unit, along with the outside option. Since the demand model explicitly incorporates the disutility of distance, which reflects consumers' preference to shop at nearby stores, the exact radius is not critical. However, it needs to be large enough to encompass the maximum distance consumers are willing to travel.

Finally, I solve the implicit system of equations with respect to $\xi_.$:

$$s_j = \hat{s}_j(p_., \nu_., \xi_., d_{l.}; \theta_d). \tag{18}$$

Note that in the current model specification, substitution patterns within a single location are derived from the standard logit model. However, the actual substitution patterns between stores account for the spatial heterogeneity of consumers, allowing for a higher rate of substitutability between stores located close to each other.

Supply

The entire decision-making process of a retailer can be seen as a two-stage game. In the first stage, multi-store retailers set product-level prices at the national level and in the second, they select the assortment for each store, taking product-level prices as given. This paper does not model the price-setting stage but rather provides empirical evidence of uniform pricing. Instead, the supply model focuses exclusively on the second stage—the store-level assortment choice—treating product prices as given.[6]

Considering the large number of products typically offered by retailers, explicitly modelling each product choice would be computationally complex. The problem is therefore simplified to focus on the two strategic variables: price level of assortment p_j and assortment breadth ν_j. The marginal cost for store j of providing a bundle of goods characterised by p_j and ν_j is defined as:

$$mc_j = mc(\nu_j, \boldsymbol{\omega}_j; \theta_s), \tag{19}$$

where $\boldsymbol{\omega}_j$ denotes a vector of cost shifters and θ_s is a vector of supply-side cost function parameters. Note that in the given specification, I assume that the marginal costs do not change with the quantity of the composite good consumed, indicating no economies of scale. However, I allow the marginal costs to vary with the assortment breadth ν_j to make providing more items on the shelf more costly.

[6] Although some chains belong to the same retail group and share suppliers and distribution networks, they negotiate separate purchase prices, maintain independent management, and compete against one another. Accordingly, the supply model treats each chain as an autonomous profit maximizer.

As such, the multi-store firm's maximisation problem can be represented as follows:

$$\max_{\{p_j,\nu_j\}_{j\in\mathfrak{J}_f}} \sum_{j\in\mathfrak{J}_f} q_j(p_{\cdot},\nu_{\cdot},\xi_{\cdot},d_{\cdot j};\theta_d)(p_j - mc(\nu_j,\boldsymbol{\omega}_j;\theta_s)), \tag{20}$$

where $\mathfrak{J}_f$ is a set of stores belonging to chain f and q_j denotes the demand for store j aggregated over locations, measured in units of the composite good and calculated as follows:

$$q_j = \sum_{l\in L} \frac{\hat{R}_{lj}}{p_j}, \tag{21}$$

with $\hat{R}_{lj}$ being the revenue of store j generated by consumers of location l defined in Equation 15.

The first-order conditions for profit-maximising firms over price and variety are:

$$F.O.C.[p_j] : q_j + \sum_{r\in\mathfrak{J}_f}(p_r - mc_r)\frac{\partial q_r}{\partial p_j} = 0, \tag{22}$$

$$F.O.C.[\nu_j] : -\frac{\partial mc_j}{\partial \nu_j}q_j + \sum_{r\in\mathfrak{J}_f}(p_r - mc_r)\frac{\partial q_r}{\partial \nu_j} = 0. \tag{23}$$

Firms engage in Bertrand competition, simultaneously choosing price and variety of the composite good.[7]

5 Identification and Estimation

In this section, I describe the identification and estimation of demand and supply-side parameters. A key challenge in estimating demand is the potential endogeneity of price and assortment variety, which may be correlated with unobserved store-level demand shocks, ξ_j. For example, stores located in prime areas or offering superior amenities may attract more consumers (i.e., have high ξ_j) and simultaneously offer more expensive or broader assortments. This correlation between regressors and the error term leads to omitted variable bias, resulting in underestimated price sensitivity and overestimated preferences for variety. To address this, I employ instrumental variables to isolate exogenous variation in price and variety and recover parameters $\{\alpha, \gamma, \beta, \rho\}$. I employ the two-step approach developed in Berry (1994) and incorporate the observed spatial consumer heterogeneity, similar to that employed in Davis (2006).

On the supply side, I recover marginal costs $\widehat{mc}_j$ and their sensitivity to assortment size $\partial\widehat{mc}_j/\partial\nu_j$ by solving the firms' first-order conditions for a given set of demand-side parameters. These estimates are then used to identify the supply-side parameters θ_s. Similarly to

[7]The first-order condition with respect to price applies to the composite good sold by the store, rather than to individual product-level prices. Since I do not model individual prices as the outcome of the firm's profit-maximization problem, there is no need to impose a uniform pricing constraint across products at the store level. Instead, I treat the observed composite price as a summary measure that captures the store's pricing decision in equilibrium.

the demand model, supply-side shocks can potentially correlate with cost-shifters. For example, a store located in a high-traffic area may require more staff and incur higher operating costs. It is therefore necessary to account for a potential endogeneity issue in the supply model by employing instrumental variables and using the GMM procedure for estimation. The rest of this section provides details of this estimation procedure.

Demand

To estimate demand-side parameters $\theta_d = \{\alpha, \gamma, \beta, \rho\}$, I begin by selecting an initial value for ρ. Then, I iteratively update the store's mean utility vector, δ, until it converges, using a process similar to the BLP inner loop. In particular, I use the fixed point iterator for the random vector of starting values of δ and iterate the expression: $\delta_j' = \delta_j + \ln(s_j) - \ln(\hat{s}_j(\delta_{\cdot}, \rho))$, where $\hat{s}_j(\delta_{\cdot}, \rho)$ is calculated according to Equation 17. I update the vector of δ until the difference between two consecutive iterations falls below a predetermined tolerance level.[8]

Once the vector δ is obtained, the parameters $\{\alpha, \gamma, \beta\}$ governing preferences for price and variety of the composite good and other observed store characteristics can be identified. Here, I assume that not only price but also variety might correlate with the unobserved store quality.

To address price endogeneity, I employ differentiation instruments proposed by Gandhi and Houde (2019), which are variants of the commonly used BLP instruments. The basic idea is to use each product's exogenous degree of differentiation, in this case, each store in a market, as instruments for price and variety. For a continuous characteristic, the difference for a pair of stores (j, k) is constructed as $\tilde{x}_{jk} = x_j - x_k$. For each store j, I aggregate these differences across competing stores within a 2 km and 5 km radius.

These differentiation instruments help identify the price parameter by shifting store markups: stores facing stronger competition along particular product dimensions will have lower markups, while stores without close substitutes in attribute space can sustain higher markups due to limited diversion. The exclusion restriction is that differentiation instruments do not directly affect demand: consumers do not value the number of similar stores per se, but instead base their decisions solely on product/store attributes and distance. This identification is supported by the structure of the retail group, where decisions about store entry and characteristics (e.g., store size, format, and location) are made centrally by the head office of the retail group, rather than by local managers responding to local conditions. As such, the spatial configuration of stores—and hence their degree of differentiation—is determined independently of local demand shocks. Furthermore, there is a timing separation: key store characteristics are set at the time of entry, often years before the period of analysis. In contrast, demand shocks vary over time. This difference in timing reinforces the assumption that store characteristics—and therefore differentiation measures used as instruments—are uncorrelated with current unobserved demand components.

[8]The share inversion procedure I use follows the standard BLP-type contraction mapping, where I recover the mean utility δ_j that rationalizes observed market shares given the model and the parameter for travel disutility. In my setting, the utility function is additive in the mean utility and consumer-specific deviations. Given this structure, the contraction mapping argument from Berry (1994) and Berry et al. (1995) applies, and guarantees existence and uniqueness of the fixed point.

For variety, I construct two cost-shifting instruments to resolve its endogeneity, both affecting marginal costs. The first instrument is the distance and associated transportation costs between each store and its distribution center. The second instrument is the store's distance to its own chain's logistic hub. Both instruments influence consumer demand exclusively through their effect on assortment size. Distance to the distribution center affects consumer demand only through its impact on the store's assortment size. Consumers are not directly affected by the store's logistics or supply chain costs; they base their choices on observable product offerings, location, and other store attributes.

Then, under the assumption $\mathbb{E}[\xi_j|Z_j^d] = 0$, parameters $\{\alpha, \gamma, \beta\}$ are identified, where Z_j is a vector of instruments and ξ_j is obtained as:

$$\xi_j(\delta, \theta_d) = \delta_j(\rho) + \alpha \ln p_j - \gamma \nu_j - x_j \beta. \tag{24}$$

Assortment information is derived from the receipt data, which is only available for one retail group. To address this, I define a missing indicator d_j that equals one if store j has information about price and variety and zero otherwise, in line with Duarte et al. (2020). The model is then identified under the assumption $\mathbb{E}[\xi_j|Z_j^d, d_j] = \mathbb{E}[\xi_j|Z_j^d] = 0$. This assumption implies that stores with available data are not more or less attractive to consumers than other stores with similar characteristics. This is a plausible assumption as the retail group that provides the data has stores of all types across the country, making it representative of the broader population of stores.

In the final step, I estimate the distance cost parameter ρ. As pointed out by Cao et al. (2024), store location acts as a product characteristic. If retailers choose locations strategically—e.g., placing stores with high unobserved utility ξ_j in densely populated areas—then the average travel distance may be systematically low, leading to a correlation between distance and unobserved utility: $\mathbb{E}[d_j \xi_j] < 0$. This introduces the standard endogeneity problem and leads to overestimated parameter for travel disutility.

To address this source of endogeneity, I need an instrumental variable that is correlated with consumer travel distance but uncorrelated with ξ_j. Following Fan (2013) I use the average distance to consumers for stores of the same retail chain in other similar markets—specifically, municipalities with comparable populations. The rationale is that store entry decisions follow retail group-wide strategic policies rather than local demand conditions. Chains typically maintain consistent strategies for store entries across similar markets, driven primarily by logistical and corporate factors rather than market-specific quality. The instrument influences consumer demand only indirectly through its effect on store distance. Under the exclusion restriction $\mathbb{E}[\xi_j|Z_j^d] = 0$, the parameter ρ can thus be identified.

These steps describe one iteration of the outer loop, and the procedure is repeated with the updated value of ρ until convergence is achieved.

Supply

In line with the approach of Crawford et al. (2019), I specify a function for marginal costs:

$$mc_j = \exp(c_{0j} + c_1 \nu_j). \tag{25}$$

The exponential functional form is chosen to reflect the nature of the retail industry, where store capacity is limited. In the context of limited capacity, the cost per unit of the composite good is expected to be convex. As the assortment breadth increases, the additional cost incurred for providing more items on the shelves becomes progressively higher. By incorporating this convexity into the marginal cost function, the model accounts for the cost implications of expanding the assortment.

Finally, I allow the marginal costs to depend on observed and unobserved cost shifters. In particular, I specify the coefficient c_0 as a linear function of cost shifters $\boldsymbol{\omega}_j$ and a structural error ζ_j:

$$c_{0j} = \boldsymbol{\omega}_j \theta_s + \zeta_j. \tag{26}$$

The vector $\boldsymbol{\omega}_j$ includes characteristics that could potentially affect the costs of running a store, such as the number of employees and whether the store is located in a shopping centre. Marginal costs are allowed to depend on the retail group of a store, as different retail groups might have different input prices. The retail group also determines the distance of a store to a distribution centre, which is relevant in counterfactual experiments where the market structure can change. It is also important to control for the assortment's quality in the marginal costs since, for example, better products tend to have higher input prices. Since direct data on assortment quality is unavailable, I infer the assortment quality from the unobserved component of the demand model ξ_j.

It is worth noting that the unobserved component ξ_j could not only capture assortment-related characteristics but also other factors that make consumers more likely to choose a particular store, such as unobserved store amenities. While recognising that ξ_j serves more as a proxy and might not perfectly capture the true quality of the assortment, it remains important to account for assortment quality when modelling the cost of operating a store, despite the potential noise issue.

Equation 22 allows us to back out the marginal costs mc_j, while Equation 23 enables us to obtain estimates for $\partial \widehat{mc}_j / \partial \nu_j$. Next, substituting these estimates in the functional form for mc_j in Equation 25 makes it possible to derive estimates for c_{0j} and c_1 as follows:

$$\hat{c}_{0j} = \ln(\widehat{mc}_j) - \frac{\partial \widehat{mc}_j / \partial \nu_j}{\widehat{mc}_j} \nu_j, \tag{27}$$

$$\hat{c}_1 = \frac{\partial \widehat{mc}_j / \partial \nu_j}{\widehat{mc}_j}. \tag{28}$$

Intuitively, variation in prices and consumer demand, together with the assumption that firms optimally set prices, identifies marginal costs. When combined with variation in observed cost shifters, this further identifies the parameters governing how marginal costs respond to these shifters. Similarly, variation in assortment variety, coupled with the assumption that firms optimally choose variety, identifies the cost curvature parameter c_1, which captures how marginal costs change with assortment size.

I estimate the vector of supply-side parameters θ_s using a GMM procedure that accounts for the potential endogeneity of cost shifters. In particular, unobserved demand shocks ξ_j, which enter the cost equation as a proxy for assortment quality, may be correlated with the unobserved cost component ζ_j. For example, a store located in a busy area may have high demand (captured by a large ξ_j) while also incurring higher costs (reflected in ζ_j). In such cases, failing to account for this correlation would lead to the overestimated effect of assortment quality on costs.

To address this, I instrument for ξ_j using the average ξ values from other stores in the same retail chain, located in similar but different markets. The identifying assumption is that these values reflect chain-wide assortment policies making them predictive of ξ_j but are uncorrelated with the store-specific cost shock ζ_j. The identification of supply-side parameters therefore relies on this instrumented variation, and the estimation proceeds via GMM, using Equations 27–28 as moment conditions in the minimization problem.

6 Estimation Results

In this section, I present the estimation results of the model. Based on the demand estimates, I compute the market concentration for each consumer location. I additionally leverage the demand estimates to calculate the Average Assortment Consumed (AAC) for each consumer location, allowing me to explore the relationship between assortment differences and variations in market concentration.

Next, I discuss the findings from the supply model. The model provides estimates of marginal costs and markups for each store. I then show the spatial distribution of markups across the country, providing insights into how different areas are affected by the assortment strategies of grocery retailers.

Demand

Table 7 summarises results for the spatial demand model. Both the price and variety coefficients have the expected sign and are statistically significant. As expected, consumers are averse to travelling long distances to stores, reflecting the costliness and inconvenience associated with shopping further from home. Consumers show a strong preference for supermarkets over discounters, and favour stores located in shopping centres.

Localised Concentration and Assortment Measures

The empirical framework of the demand model makes it possible to calculate localised concentration measures. Typically, concentration measures require a predetermined market definition, which has often played a decisive role in antitrust cases. The spatial model employed in this study overcomes this limitation by defining markets based on consumers and their choice sets rather than the geographic locations of stores. This approach measures concentration at a localised level, providing a more accurate representation of local market power.

Based on the demand model, I predict the probability that a consumer residing in location l visits store j $\mathbb{P}_{lj}$, which is not observable in the data and can only be recovered from the model. I then use $\mathbb{P}_{lj}$ to calculate HHI for each location. The distribution of these localised concentration measures across basic units is illustrated in Figure 5. The analysis reveals that most markets in Norway are moderately concentrated (56%), 41% are highly concentrated

Table 7: Demand parameters estimates

Variable	Estimate
Log price	-4.612***
	(1.302)
Variety	0.171*
	(0.008)
Distance	-0.235***
	(0.000)
Supermarket	3.782***
	(0.000)
Number of employees	0.154***
	(0.000)
Shopping centre	11.57***
	(0.000)
Open on Sunday	39.75***
	(0.000)
# of obs.	3718

Note: Significance levels are: *** - 1%, ** - 5%, * - 10%.

and only 3% are considered competitive. Figure 6 shows the spatial distribution of market concentration for *Vestland*, a region of Norway. The key finding is that the area around Bergen is predominantly competitive, with a lower concentration level. However, as we move further away from the city towards more rural areas, the concentration gradually increases.

In Table 8, I compare the classification of basic units based on the HHI calculated using a predefined market definition, in this case the municipality, and based on localised HHI. While the overall composition of markets remains almost the same, there are changes in the level of competition when considering local competition at the basic unit level rather than aggregating the basic units to municipalities. For example, more than half of the competitive markets are estimated to be moderately or highly concentrated. Similarly, when not imposing strict geographical boundaries on the market definition, some markets that were initially attributed to highly concentrated municipalities have access to more competitive markets.

Table 8: Market concentration comparison

		Localised HHI			
		Competitive	Moderately Concentrated	Highly Concentrated	**Total**
Municipality-based HHI	Competitive	331	283	85	699 (5.2%)
	Moderately concentrated	69	5,405	1,466	6,940 (51.5%)
	Highly concentrated	29	1,857	3,950	5,836 (43.3%)
	Total	430 (3.2%)	7,552 (56.0%)	5,502 (40.8%)	

Note: One observation is one basic unit.

Additionally, the estimated demand model allows us to revisit assortment inequality across different regions. As before, the demand model makes it possible to compute the probability that a resident of location l visits store j, $\mathbb{P}_{jl}$. Then, I can calculate the ACC for each location l in terms of price (AAC_l^P) and variety (AAC_l^ν). More specifically, AAC_l^P is calculated as an average price of stores j in the choice set $\mathcal{J}_l$, weighted by the probabilities

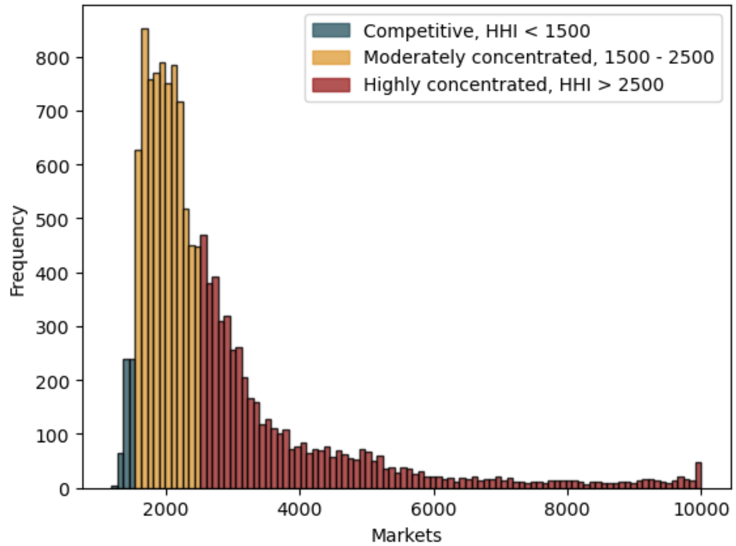


Figure 5: Distribution of localised concentration measures

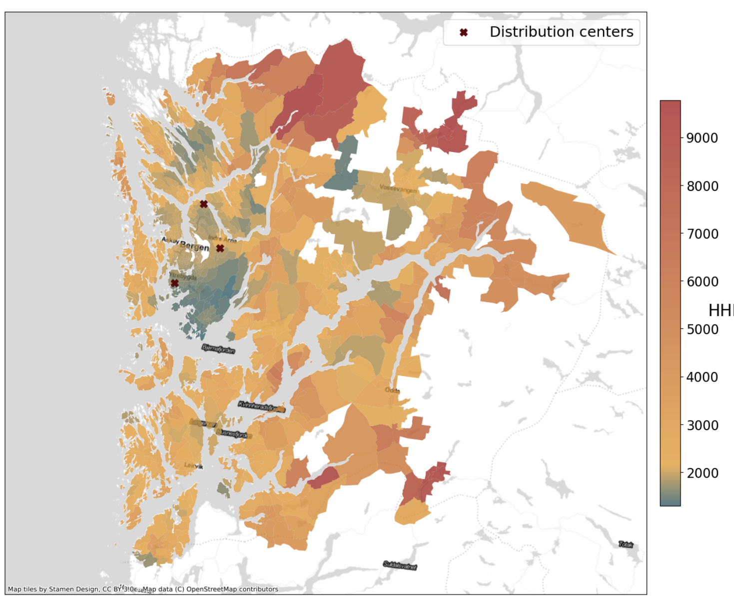
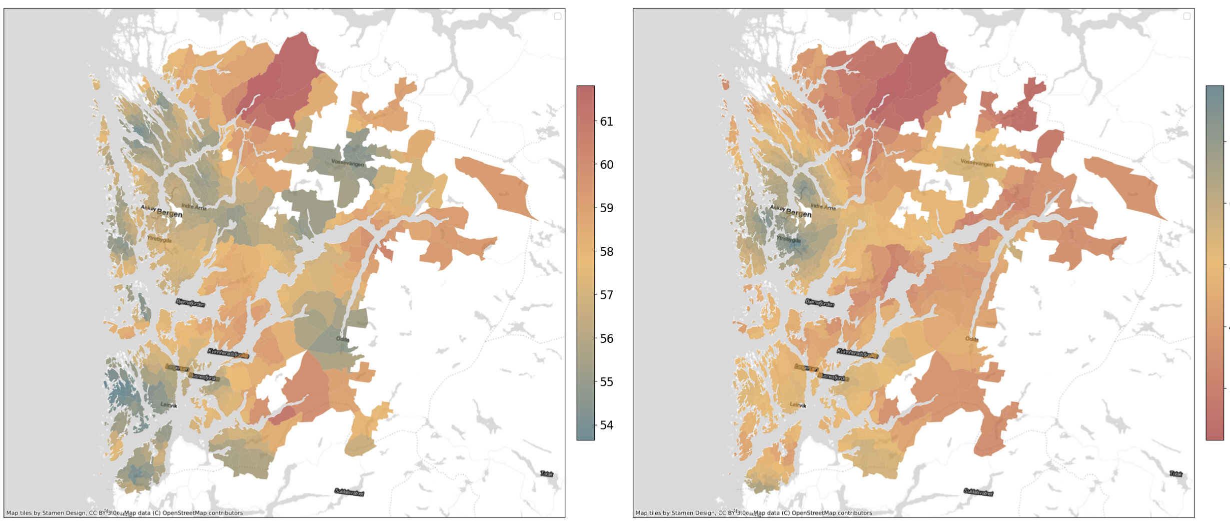


Figure 6: Spatial distribution of market concentration

$\mathbb{P}_{jl}$: $AAC_l^P = \sum_{j \in \mathcal{J}_l} \mathbb{P}_{jl} \cdot p_j$. Similarly, AAC_l^ν is obtained as an average variety of stores weighted by $\mathbb{P}_{jl}$: $AAC_l^\nu = \sum_{j \in \mathcal{J}_l} \mathbb{P}_{jl} \cdot \nu_j$. Therefore, both AAC_l^P and AAC_l^ν represent weighted averages that take into account the shopping behaviour of consumers. Figure 7 illustrates assortment differences across locations. The primary finding is that residents of urban areas, such as Bergen, have access to a more affordable assortment and greater variety, while residents of rural areas have a limited assortment and lack access to cheap products. These results, along with the localised concentration measures, demonstrate that consumers residing in concentrated markets face higher prices and a narrower range of choices.

Lastly, I explore the relationship between the basic unit market concentration and the average assortment consumed in the basic units. As illustrated in Figure 8, the relationship between the HHI and AAC_l^P is not strictly monotone. However, we can see that more concentrated markets have a more expensive assortment (the correlation between HHI and AAC_l^P is 0.12). Conversely, the plot shows a negative monotonic relationship for variety: consumers in competitive markets enjoy a higher variety of products (the correlation between HHI and AAC_l^ν is -0.33).



(a) Price **(b)** Variety

Figure 7: Average assortment consumed

Supply

The descriptive statistics of the marginal costs and markups are shown in Table 9. Figure 9 shows the distribution of marginal costs across formats. As a format providing higher quality and variety, supermarkets have higher marginal costs on average. In contrast, discounters have the lowest marginal costs. As regards markups, there is no noticeable difference between stores of different formats and the estimates of markups are similar to what other studies have obtained when dealing with a composite good (Duarte et al., 2020; Eizenberg et al., 2021).

Table 10 shows the marginal cost function estimates. As expected, providing higher variety and quality is costly for a retailer. Other estimates of the supply-side function also

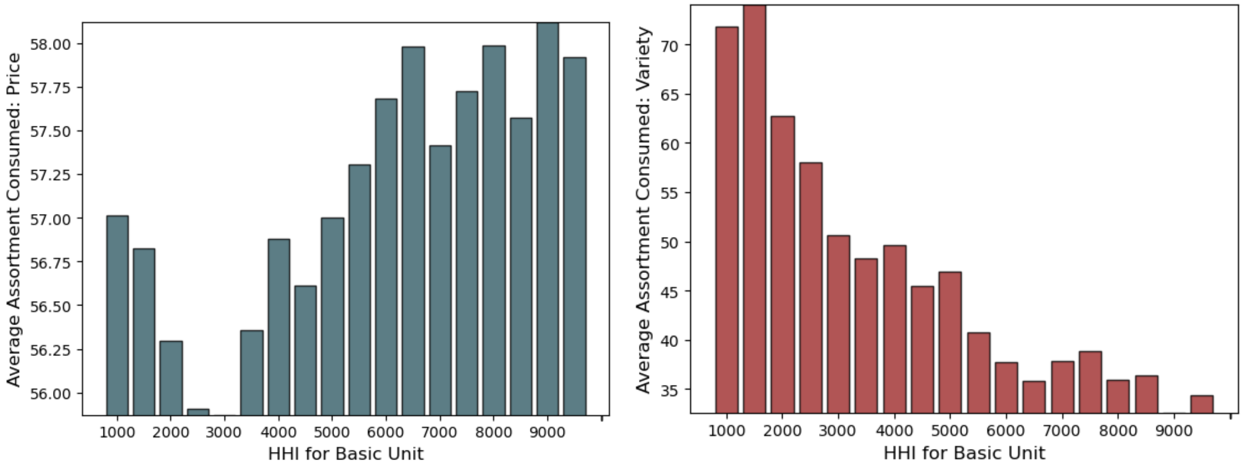


Figure 8: Average assortment consumed and market concentration

Table 9: Summary statistics for costs and margins

	Price	MC	Markup
Mean (all)	56.47	44.54	0.21
Median (all)	55.75	43.95	0.19
By formats			
Median (discounter)	54.15	42.74	0.20
Median (convenience)	58.73	47.02	0.19
Median (supermarket)	60.67	48.66	0.19

Note: Markups are calculated at the store level. Officially reported markups are typically 2-4% and include management and other fixed costs of running a retail group.

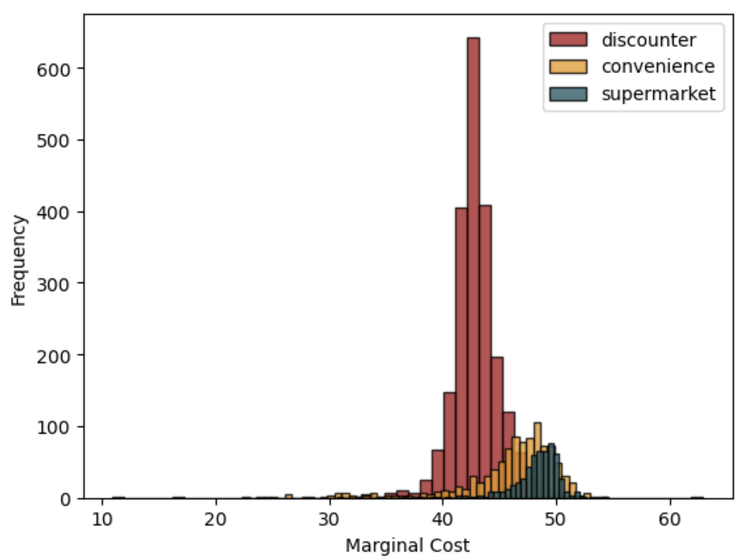


Figure 9: Distribution of marginal costs across formats

have the expected signs. The further the distance to the distribution centre, the more expensive it is to transport goods. It is also more costly to have a store in a shopping centre. Stores that are open on Sundays have higher marginal costs, as they are subject to higher tax rates. Supermarkets have higher marginal costs than discounters and convenience stores as they usually have more employees. Larger retail groups have lower marginal costs, which could be explained by lower input prices and economies of scale. The negative effect of store size and the number of employees could also be attributed to economies of scale.

Table 10: Marginal cost function parameters

Variable	**Estimate**
Const (c_0)	3.645
	(0.137)
Variety (c_1)	0.037
	-
Other observed cost shifters	
Quality of assortment	0.029***
	(0.004)
Supermarket	0.291***
	(0.039)
No. of employees	-0.019***
	(0.001)
Shopping centre	0.276***
	(0.056)
Liquor store	-3.465***
	(0.429)
No. hours open	0.008
	(0.006)
Sunday	1.278***
	(0.145)
Costs of toll roads to dist. centre	0.002**
	(0.001)
Store size	-0.626***
	(0.026)
Retail group A	0.378***
	(0.043)
Retail group B	-0.029
	(0.025)
Retail group C	0.159***
	(0.032)
# of obs.	3639

Note: Retail group D is taken as a base category. Significance levels are: *** - 1%, ** - 5%, * - 10%.

Once the marginal costs are estimated, it is possible to calculate the profit of each store. The demand model provides a more detailed analysis and allows us to calculate the contribution of each location to each store's profit. By then summing across stores, it is possible to calculate the total profit of grocery stores generated by consumers of location l:

$$\Pi_l = \sum_{j \in \mathcal{J}_l} (p_j - mc_j) \cdot q_{jl}, \tag{29}$$

where q_{jl} represents the number of composite goods purchased by consumers of location l in store j, defined as:

$$q_{lj} = \frac{\mathbb{P}_{lj} B_l}{p_j}. \tag{30}$$

Figure 10 displays the spatial distribution of profit Π_l scaled by the number of consumers in location l. The plot suggests that the per capita profits are higher in less densely inhabited areas and lower in large cities. Finally, I examine how profit per capita is related to market concentration. As shown in Figure 11, it is evident that more concentrated markets have higher profits per capita.

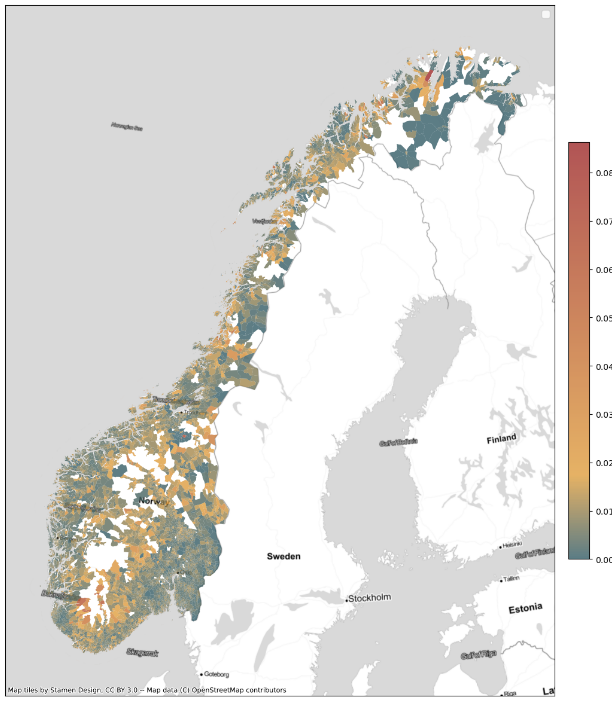


Figure 10: Spatial distribution of profit per person

7 Counterfactual Analysis

The counterfactual analysis begins by summarising the results concerning assortment inequality. I then go on to examine the role of local assortment in generating welfare inequality and consider policies that could improve assortment, such as reducing consumer travel costs and providing cost subsidies to retailers in remote areas.

Assortment Inequality

In the spatial demand model, Figure 7 sheds light on assortment inequality across different locations and indicates that consumers in concentrated areas face limited and more expensive product variety. Figure 10 further emphasises assortment inequality by illustrating that firms charge higher margins in less populated areas even after controlling for logistics costs.

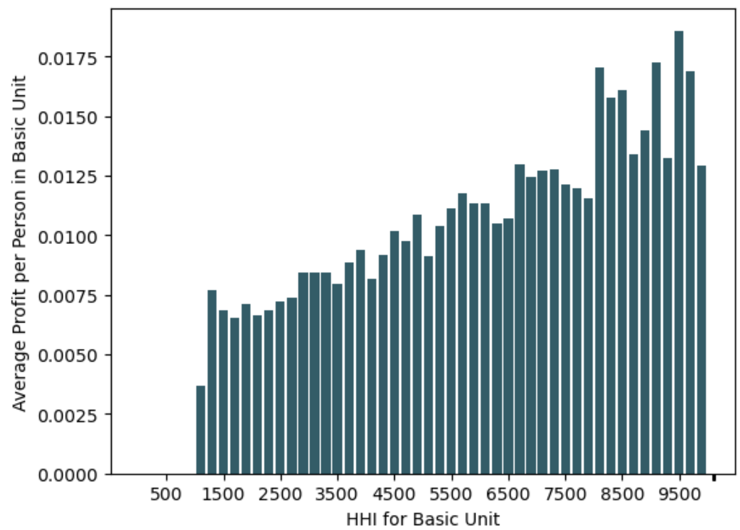


Figure 11: Profit per person and market concentration in basic units

These findings suggest that assortment choice could serve as a strategic channel for firms to maximise their profits.

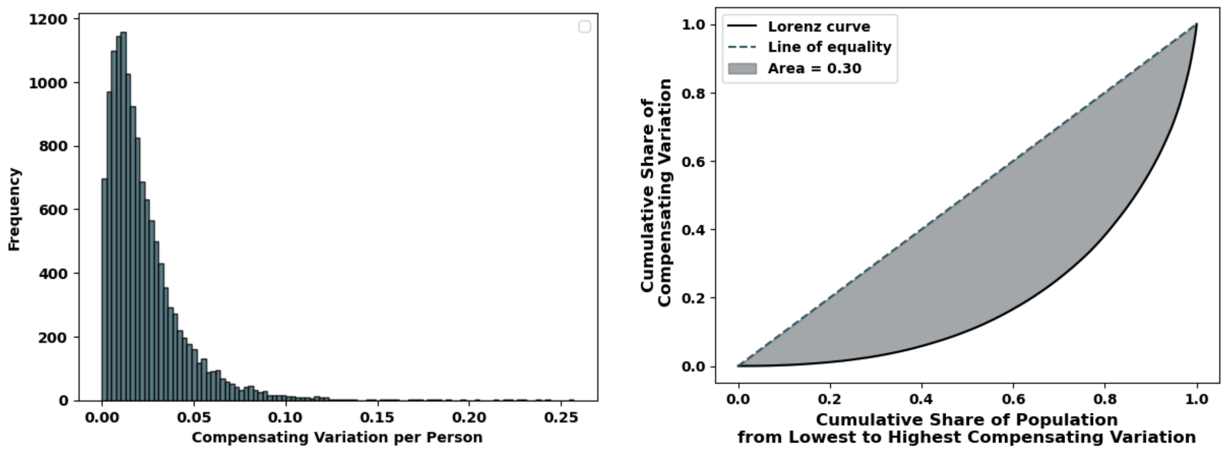
Further, I use a compensating variation metric to compare consumer welfare across different locations. To measure consumer welfare in the benchmark equilibrium, I calculate the compensating variation between the benchmark equilibrium and an alternative environment where only the outside option is available. In line with the approach of Atal et al. (2022), I define compensating variation for consumer i residing in location l as:

$$\max_{j} u\left(y_i, \delta_j, d_{lj}, \epsilon_{i(l)j}\right) = \max_{j'} u\left(y_i - CV_i, \delta_{j'}, d_{lj'}, \epsilon_{i(l)j'}\right). \tag{31}$$

Figure 12a shows the distribution of consumer welfare per person across basic units. To quantify the extent of assortment inequality, I employ the Gini index, computed based on consumer welfare. Figure 12b presents the Lorenz curve for consumer welfare per person, where the cumulative share of the population is plotted against the cumulative share of consumer welfare. The calculated Gini index of 0.3 quantitatively measures assortment inequality and serves as a basis for comparing the benchmark equilibrium with equilibria in counterfactual policies.

Counterfactual Policies

For illustrative purposes, the counterfactual analysis focuses on the Vestland region, with its centre in Bergen. Vestland is a relatively isolated market, and Bergen serves as a central hub for various retail chains, as evidenced by the presence of their distribution centres on the outskirts of the city. As the distance from Bergen increases, the costs associated with logistics for serving stores in remote areas also rise. When it comes to consumer distribution, Bergen is classified as an urban and densely populated area, with a population density of 650.2 people per square kilometre as of 2023. Conversely, there are rural neighbourhoods in



(a) Consumer welfare

(b) Lorenz curve

Figure 12: Inequality in consumer welfare across locations

Note: In the left panel, one observation corresponds to compensating variation for one person in a basic unit, measured in MNOK.

Vestland where the population density can be as low as 0.69 people per square kilometre. Figure 13a illustrates the population density of this region.

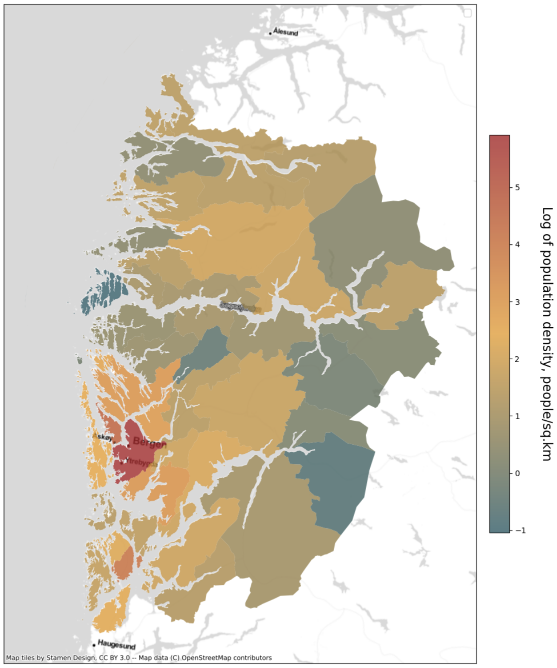
Vestland also has relatively low income inequality, measured in average income across basic units, similar to the overall trend in Norway. Figure 13b shows the spatial distribution of income across municipalities in Vestland, with most municipalities having similar income levels. This region therefore represents a relevant setting for studying assortment decisions across different markets.

Welfare Analysis of Local Assortment. To quantify the welfare effects of the local assortment, I compare the observed assortment with a counterfactual scenario where chains adopt a unified assortment strategy, offering the same bundle of groceries across all their stores. The maximisation problem for a multi-store firm f will then look as follows:

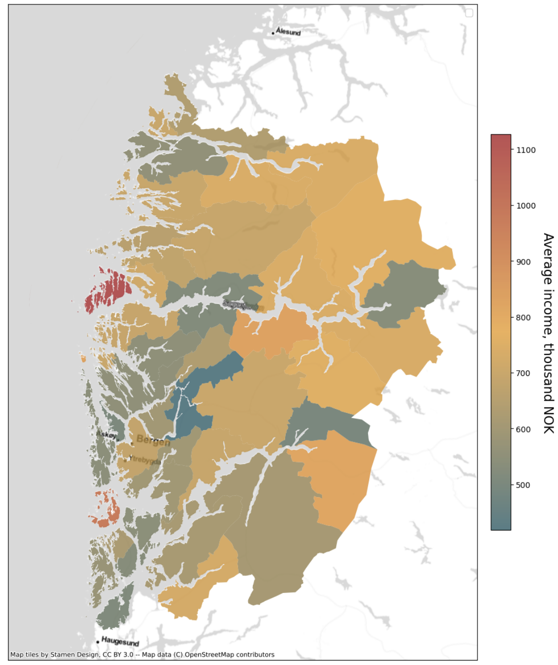
$$\max_{p_f,\nu_f} \sum_{j\in\mathfrak{J}_f} q_j(p_{\cdot},\nu_{\cdot},\xi_{\cdot},d_{\cdot j})(p_f - mc(\nu_f,\boldsymbol{\omega}_j;\theta_s)). \tag{32}$$

Using the first-order conditions for the problem 32, I calculate each firm's new equilibrium price and variety of the composite good. Under uniform assortment, stores offer a wider range of products, resulting in an 11.1% increase in variety. However, this also leads to an average 5.5% increase in the price of goods. Consumers' shopping behaviour reflects similar changes. The average assortment consumed (AAC) experiences a 6.4% increase in price and an 11.6% increase in variety, taking into account changes in both price and variety as well as the probability of shopping at a specific store.

To further understand the welfare implications, I explore how the uniform assortment policy affects markets with different market concentrations. Figure 14 provides a summary of the results, with basic units sorted by the baseline HHI. Across all markets, there is a rise in both the price and variety of AAC. However, markets with higher concentration experience a smaller increase in price and a more significant increase in variety compared



(a) Population density



(b) Average income

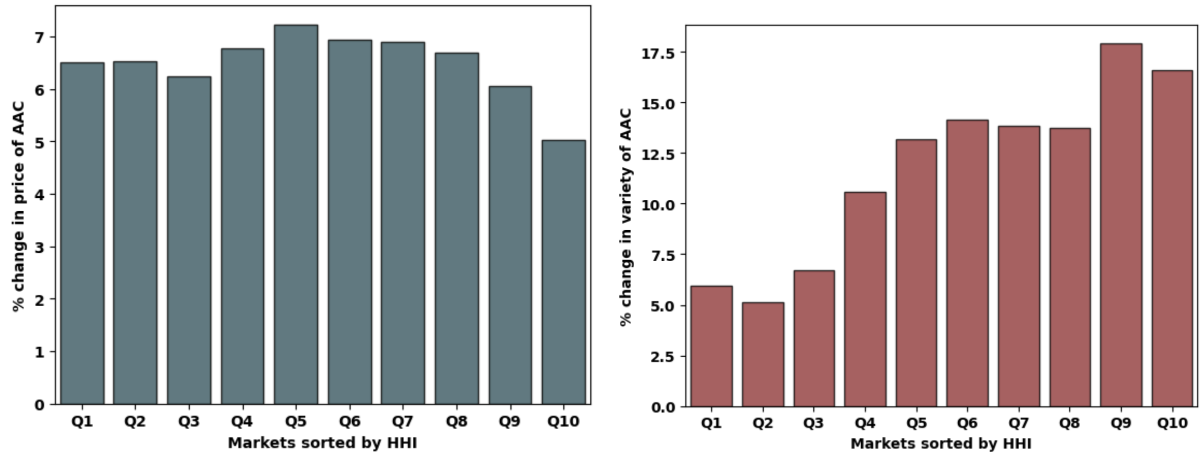
Figure 13: Vestland

to competitive markets. This result indicates that in the benchmark equilibrium, retailers offer a limited and pricier assortment in concentrated markets.

To measure consumer welfare, I use compensating variation between the counterfactual scenario and the benchmark equilibrium. As anticipated, the uniform assortment positively affects consumers, resulting in a remarkable increase in total consumer welfare of 7,756 MNOK. The impact of the policy intervention on the distribution of consumer welfare per person is illustrated in Figure 15a. Additionally, Figure 15b illustrates that while the policy benefits consumers, it does not significantly reduce consumer inequality. Although grocery chains offer an equal assortment across stores, the policy does not address the limited availability of stores in remote markets. Consequently, consumers in these areas continue to face a limited choice of stores and higher transport costs compared to residents of urban areas. This finding highlights the necessity of different interventions to address the disparities in consumer welfare across locations.

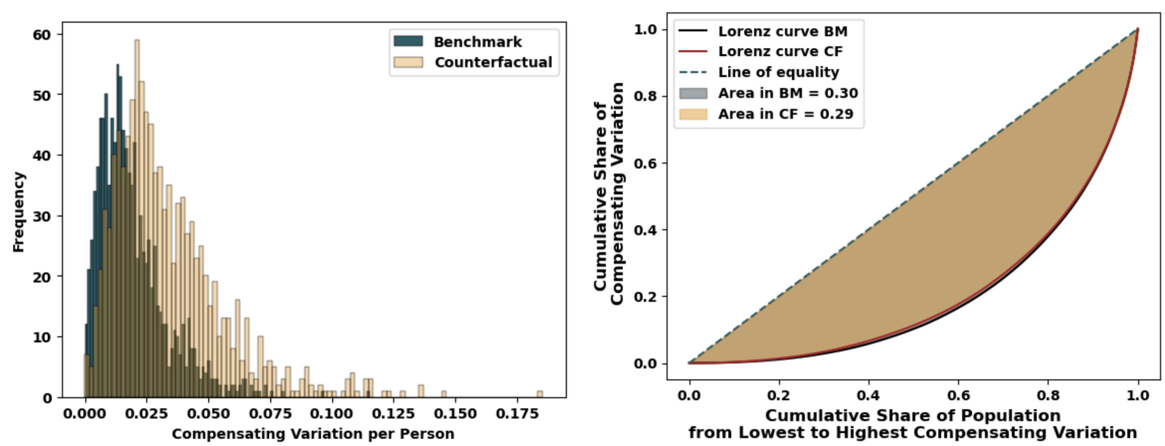
The implementation of the uniform assortment policy has a detrimental effect on firms. The industry's total profit declines significantly by 8,417 MNOK, and a substantial portion of stores, 28%, experience negative profits in the counterfactual equilibrium. This indicates that the policy adversely affects the profitability and viability of some retail outlets.

While consumers benefit from the uniform assortment in the short run, the overall impact on welfare is negative, with a reduction of 660 MNOK, representing a decrease of 4.5%. The decline in profits and the risk of stores becoming unprofitable could lead to store closures in the long run, which would further exacerbate market concentration. With fewer active stores, consumers in certain regions may face even more limited options and potentially



(a) Effect on price **(b)** Effect on variety

Figure 14: Average assortment consumed and market concentration



(a) Consumer welfare **(b)** Lorenz curve

Figure 15: Change in consumer welfare due to uniform assortment

higher prices, ultimately deepening disparities in consumer welfare among different regions. This reinforces the need for a more nuanced approach to tackling assortment inequality.

Reducing travel disutility. In the previous counterfactual experiment, despite grocery chains providing an equal assortment, consumers in remote areas still had to travel further than those in urban areas. In this counterfactual policy, I address disparities in travel disutility across different regions. The policy aims to improve the accessibility and availability of stores for residents of remote areas, which could positively affect consumer welfare. In particular, I investigate the effects of halving the distance disutility for markets that lack stores within a 3 km radius. In reality, this policy could be implemented by reimbursing fuel or electricity costs or reducing public transport fees for individuals living in remote regions.

Firstly, I examine how the reduction in travel disutility affects market concentration. Table 11 summarises changes in market concentration at the basic unit level. Notably, the number of highly concentrated markets decreases by approximately ten percentage points, while the count of moderately concentrated and competitive markets increases by eight and three percentage points, respectively. These findings indicate that reducing travel disutility fosters competition among retailers.

Table 11: Change in market concentration

		HHI Counterfactual			
		Competitive	Moderately Concentrated	Highly Concentrated	**Total**
HHI	Competitive	33	0	0	33 (3.1%)
	Moderately concentrated	27	668	2	697 (65.1%)
	Highly concentrated	4	115	222	341 (31.6%)
	Total	64 (6%)	783 (73.1%)	224 (20.9%)	

Note: One observation is one basic unit.

As a result, the price change varies from -9.3% to 1.3% across stores, with an average decrease of 0.14%. The variety change varies from -0.83% to 4.3% with an average increase of 0.06%. The reduction in travel costs leads to increased competition in most markets, leading to downward pressure on prices and upward pressure on variety.

However, contrary to standard economic intuition, some stores change prices and variety in the opposite direction. This results from a change in demand composition. As travel costs decrease, consumers who continue to shop at expensive stores are those for whom lower travel costs offer little benefit. As such, even though travelling becomes less costly, their choice set does not expand.

To explore this idea, I compare each store's average choice-weighted travelled distance between the benchmark equilibrium and the counterfactual scenario. To compute the average choice-weighted travelled distance, I aggregate the distances travelled from different markets to the store weighted by the choice probabilities derived from the demand model and the share of consumers from each market. The negative correlation of -0.3 confirms the intuition that stores experiencing an increase in prices are those for which the catchment area decreases in the counterfactual scenario. Moreover, as a result of the policy, expenditure by a representative consumer in grocery stores increases as they receive compensation of transport costs. Therefore, in these markets, the retailers encounter a less elastic demand with higher grocery budgets, leading them to raise prices and reduce variety.

Additionally, I investigate how the average choice-weighted HHI at the store level changes as a result of the policy intervention. The average choice-weighted HHI is computed by aggregating HHIs weighted by the share of consumers from each market across locations in the store catchment area. The positive correlation of 0.55 indicates that stores that raise prices in the counterfactual scenario experience an increase in the average weighted HHI. This suggests that these stores now cater to consumers from more concentrated markets with limited choices. This further reinforces the observation that supermarkets face less elastic consumers with higher grocery budgets in these markets, leading them to raise prices and reduce variety. As such, a counterbalancing effect emerges that reduces, and sometimes even neutralises, the competitive pressure exerted on price and variety.

To explore the changes in consumers' shopping behaviour, I calculate changes in the AAC, the weighted average of price and variety consumed by residents of each basic unit, taking into account the probability of shopping at each particular store. The change in the price of AAC varies from -2.6% to 2.6%, with an average increase of 0.2%. The change in the variety of AAC varies to a greater extent, from -16.5% and 22.9%, with an average increase of 1.3%. Figure 16 visually presents the changes in AAC across different basic units in Vestland. The green-coloured areas have a better assortment in the new equilibrium, characterised by lower prices and higher variety.

It is important to note that for some residents, the price and variety of AAC may rise. As travel costs decrease, consumers can reach more competitive areas, such as Bergen, that offer a greater variety with higher prices. To examine this idea deeper, I investigate whether consumers are more inclined to choose stores with lower average choice-weighted HHI in the counterfactual scenario. By aggregating HHIs, weighted by the share of consumers from each market within a store's catchment area, I find a negative correlation of 0.1, indicating that market share increases for stores with lower HHI in the new equilibrium. Finally, for some areas, AAC could change in the opposite direction. This occurs in regions where retailers face a less elastic demand, as discussed earlier, leading them to raise prices and reduce variety.

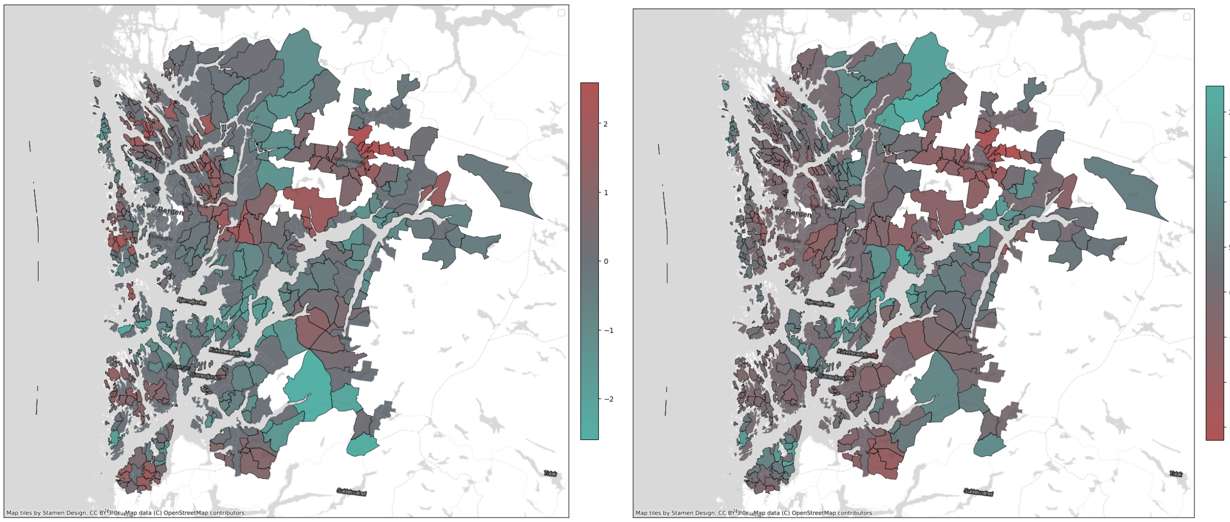
As expected, the policy positively impacts consumer welfare, resulting in a substantial increase of 11.4% or 1,261 MNOK. Figure 17a demonstrates how the distribution of consumer welfare per capita changes due to the policy intervention. The Gini index for the counterfactual scenario illustrates a modest improvement in consumer inequality. The changes are visually depicted with the Lorenz curve in Figure 17b.

The policy also has a positive impact on firms. The industry's total profit increases by 215 MNOK, equivalent to an improvement of 5.6%. The total welfare gain from the policy, calculated as the sum of the change in consumer welfare and change in profits, amounts to 1,476 MNOK, equivalent to an increase of 9.9% compared to the benchmark equilibrium.

Furthermore, I compute the policy cost as the sum of transfers the government needs to provide consumers residing in remote regions in order to offset fifty per cent of their travel disutility. For consumers in remote locations, the transfer is thus defined as follows:

$$u\left(y_{i(l)} + T_{i(l)}, \delta_j, d_{lj}, \rho^{BM}, \epsilon_{i(l)j}\right) = u\left(y_{i(l)}, \delta_j, d_{lj}, \rho^{CF}, \epsilon_{i(l)j}\right), \tag{33}$$

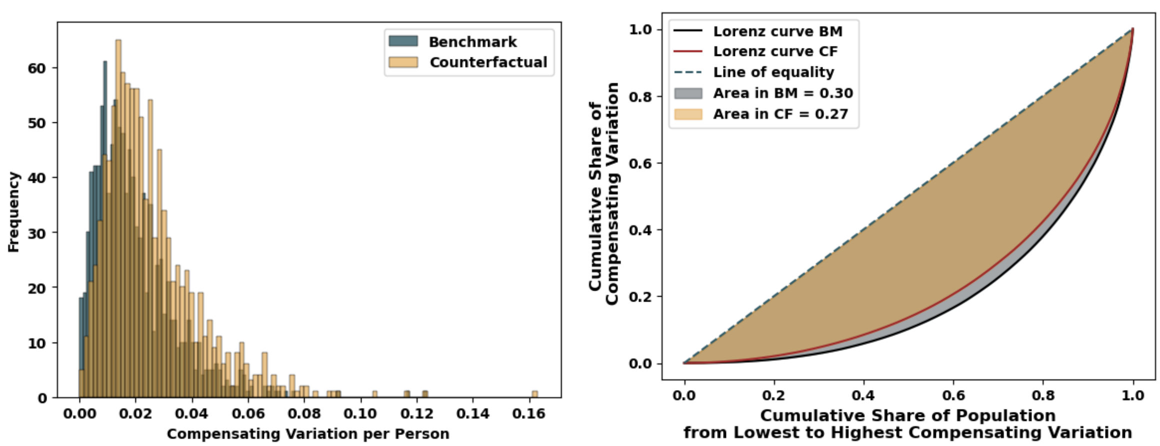
where $j = \arg\max_k u(y_{i(l)}, \delta_k, d_{lk}, \rho^{BM})$, ρ^{BM} represents the parameter for travel disutility in the benchmark equilibrium and ρ^{CF} is the parameter for travel disutility in the counterfactual



(a) Effect on price

(b) Effect on variety

Figure 16: Counterfactual changes in average assortment consumed due to reduced travel disutility



(a) Consumer welfare

(b) Lorenz curve

Figure 17: Change in consumer welfare due to reduced travel disutility

scenario. After aggregating the transfers across markets, the total cost amounts to 1,198 MNOK.

Finally, I calculate the net welfare effect of the counterfactual policy as follows:

$$\Delta W = \sum_i CV_{i(l)} + \sum_j \Delta\Pi_j - \sum_i T_{i(l)} \times MCPF, \tag{34}$$

which includes the compensating variation for consumers $CV_{i(l)}$ and the change in firms' profits $\Delta\Pi_j$. The last term stands for the cost of the policy, which is the total amount of transfers to consumers $T_{i(l)}$ adjusted by the Marginal Cost of Public Funds (MCPF) specific to Norway. By multiplying the transfers by the MCPF, I account for the deadweight loss that may arise from government interventions leading to inefficient allocation of resources. The value of MCPF is adopted from the guidelines outlined in the white paper Principles for profitability assessments in the public sector (NOU 1997:27).[9] As such, the net welfare effect sums up to 38.4 MNOK. The policy demonstrates promising outcomes for consumers and firms, contributing to an overall improvement in total welfare.

Although this counterfactual experiment is somewhat conceptual and not intended to simulate specific policies, it bears some policy relevance. In 2022, a similar policy was implemented in France as a way to support residents of remote regions who were particularly affected by the energy crisis.[10] The government introduced an energy cheque scheme that sought to compensate for increased travel costs. The policy was specifically targeted at the residents of remote areas.

Subsidies for stores located in remote areas. In the experiment on uniform assortment, some stores become unprofitable as they provide the same range of products in all locations, including remote areas. This leads to higher prices as firms must compensate for higher logistics costs. To address this issue in this counterfactual policy, stores in less populated areas receive subsidies to offset logistics costs. This financial aid aims to incentivise chains to offer better and more affordable products in these regions.

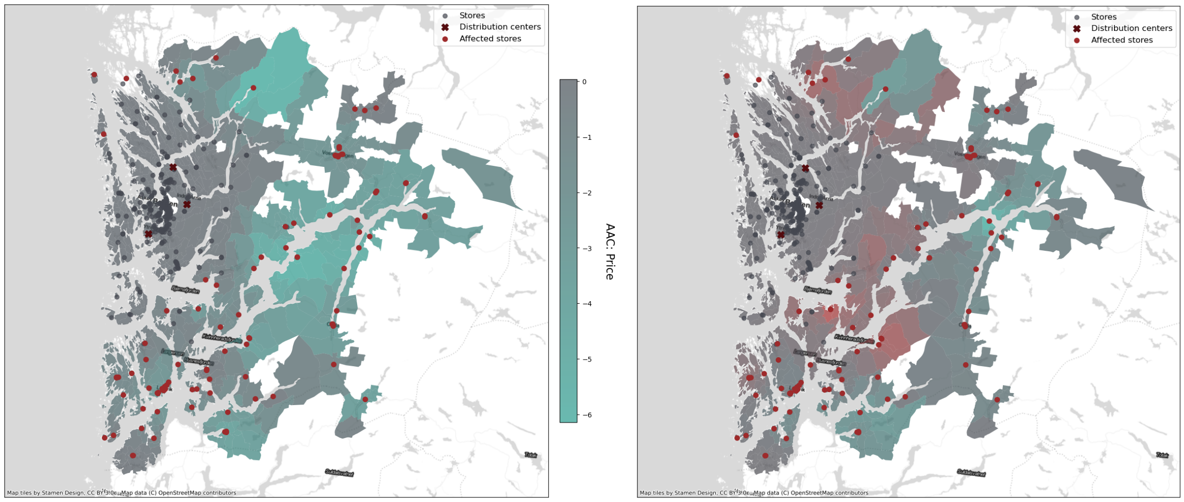
As shown in Figures 6 and 7, regions with limited assortment tend to be further away from distribution centres. In this counterfactual experiment, I examine stores whose distribution centres are located further than 70 km of driving distance, corresponding to the 70th percentile of the driving distance distribution for stores in Vestland. These selected stores receive subsidies to compensate for 10% of their marginal costs. The idea behind this analysis is reminiscent of an actual policy implemented in Sweden that aimed to incentivise stores in rural areas to offer a diverse range of products.[11]

The results indicate that retailers involved in this policy improve their assortment by reducing prices by 1.9% and increasing variety by 0.69%. On the consumer side, the price of the AAC declines by -0.9%, while variety increases by 0.11%. Figure 18 illustrates the spatial distribution of the changes in AAC.

[9] NOU 1997:27, Nyttekostnadsanalyser – Prinsipper for lønnsomhetsvurderinger i offentlig sektor (Utredninger, 1997)

[10] https://www.intereconomics.eu/contents/year/2023/number/1/article/exiting-the-energy-crisis-lessons-learned-from-the-energy-price-cap-policy-in-france

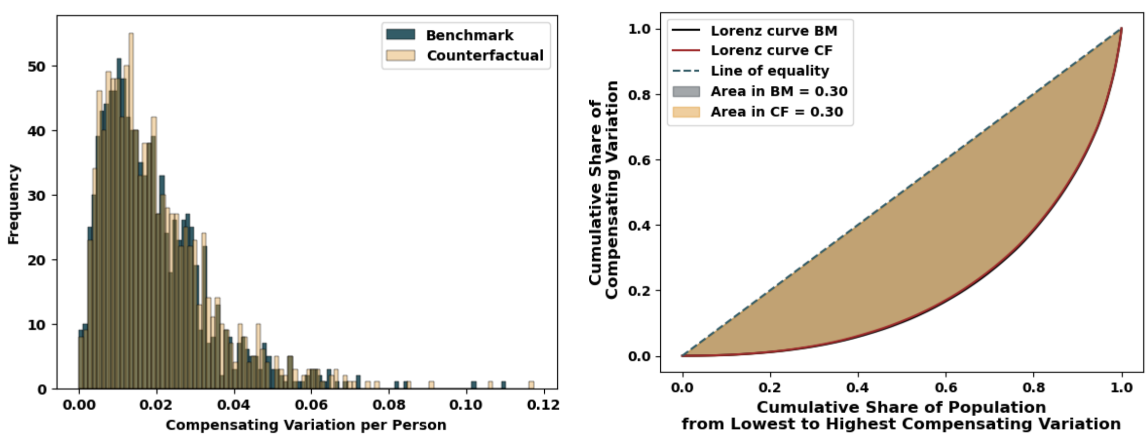
[11] Bill 2001/02:4 A policy for growth and viability for the whole country



(a) Effect on price **(b)** Effect on variety

Figure 18: Counterfactual changes in average assortment consumed due to subsidies to remote stores

The policy exhibits a modest positive impact on consumer welfare, resulting in a slight increase of 1.8% or 199 MNOK. Figures 19a and 19b show that the policy's effectiveness in addressing inequality is limited. Despite the positive changes in consumer welfare, the policy does not significantly contribute to reducing income inequality within the affected markets, as evidenced by the unchanged Gini index.



(a) Consumer welfare **(b)** Lorenz curve

Figure 19: Change in consumer welfare due to subsidies to remote stores

The policy has a notable positive impact on firms, resulting in a total profit increase of 262 MNOK, equivalent to 6.8%. Summing over the change in consumer welfare and firms' profit, I calculate that the welfare gain from the policy amounts to 461 MNOK, equivalent to an increase of 3.1% compared to the benchmark scenario. Firms benefit more from the policy than consumers, primarily because retailers in remote markets have some degree of local market power, allowing them to retain a significant portion of the change in the margin derived from the subsidies on marginal costs. Consequently, despite the modest reduction in price and the slight increase in variety, most of the subsidy is captured in the increased profit margins for retailers.

Additionally, I calculate the policy cost as the product of the number of composite goods purchased in the subsidised stores and the subsidy granted, which is equal to 10% of the marginal costs for each particular store. The resulting cost of the policy is 307 MNOK.

Ultimately, the total welfare effect from the intervention is determined as follows:

$$\Delta W = \sum_i CV_{i(l)} + \sum_j \Delta\Pi_j - MCPF \times 0.1 \sum_{j \in \mathfrak{J}_{sub}} q_j mc_j. \tag{35}$$

Here, $CV_{i(l)}$ represents the compensating variation for consumers and $\Delta\Pi_j$ captures the change in firms' profits. The last term represents the cost of the policy, calculated as the sum of 10% of variable costs across the subsidised stores $\mathfrak{J}_{sub}$ and adjusted by MCPF. Consequently, the net welfare effect accounts for 92.6 MNOK. Based on these figures, it appears that the policy is economically justified, even though the gains experienced by firms drive the majority of the total welfare increase.

Assortment discrimination contributes to welfare inequality by creating disparities in access to affordable products and a wide range of choices, disproportionately affecting consumers in remote markets. To tackle this issue, it is necessary to adopt policies that enhance assortment and minimise welfare disparities. One potential solution could be to incentivise retail chains to provide equal assortments across all their stores within a country. However, as demonstrated earlier, such an approach leads to substantial profit reductions and causes certain stores to become unprofitable, potentially exacerbating market concentration. Implementing this solution in practice also poses practical challenges.

An alternative policy could be to target consumers of areas with a limited assortment. In this study, I examine a policy aimed at reducing travel costs for residents who lack a grocery store within a reasonable distance, which results in increased competition and, in turn, lower prices and greater variety. This policy could be implemented by improving transport infrastructure or providing lump-sum compensations to offset travel expenses. The counterfactual analysis demonstrates that the policy has the potential to effectively enhance competition and improve consumer welfare.

Alternatively, policies can be targeted toward retailers operating in remote areas. This can involve providing cost subsidies or tax deductions to incentivise retailers in remote areas to offer more products at affordable prices. While, technically speaking, this policy may be relatively easier to implement, its effectiveness remains questionable. Although retailers in remote markets improve their assortment with the help of subsidies, local market power enables them to withhold a portion of the subsidy rather than fully pass it on to consumers.

8 Conclusion

In this paper, I study how multi-store firms strategically adjust their product assortment in response to local competition when product-level prices are fixed. Consistent with previous literature (DellaVigna and Gentzkow, 2019; Adams and Williams, 2019; Hitsch et al., 2019), I document that retailers do not adjust product-level prices when the competitive environment changes, but they do adjust their product selection, which could potentially serve as a powerful means of generating margins in the uniform pricing scenario.

Employing a structural, spatial model of consumer and retailer behaviour, I show that product selection can differ significantly across stores belonging to the same chain. The model also allows me to attribute these changes to local market power. This outcome entails substantial assortment inequalities across the country, with urban residents enjoying access to more affordable food options and consumers in remote markets having access to a limited and pricier product selection.

I explore the impact of adopting a uniform assortment policy using counterfactual simulations. While this policy enhances consumer welfare, it would lead to substantial losses for firms. Furthermore, the policy of uniform assortment only partially addresses consumer inequality, with consumers in remote areas still incurring higher transport costs compared to urban residents. On this basis, I explore the potential impact of reducing travel costs for consumers in remote areas. This policy is relatively successful in improving competition in remote markets. The findings reveal improvement in assortment in remote areas and increased total welfare. Lastly, I examine a policy of providing subsidies to retailers in remote areas. The findings show modest improvements in assortment for consumers and an increase in total welfare. Both policies are beneficial for consumers and have a positive net welfare effect.

It is worth noting that the model in the paper focuses on assortment decisions and abstracts from modeling prices for individual products. If, however, market changes lead to a significant increase in market power, a firm might want to revise its entire pricing policy rather than make marginal changes in the assortment. The model nonetheless offers some flexibility in accommodating potential price adjustments by higher or lower optimal price points for the assortment.

Another aspect that remains outside the scope of this study is the choice of formats. When entering new markets, retail groups strategically choose a store format. This choice of format implies a specific store size, prices, location and other characteristics. For the purposes of this research, I take stores' format as a given and analyse assortment decisions conditional on the given format. While this approach allows me to examine marginal changes in the assortment, it is crucial to consider the choice of format in order to gain a comprehensive understanding of the competitive landscape. This would make it possible to explore policies aimed at stimulating more entry into remote markets, which would improve competition and reduce inequality in store access.

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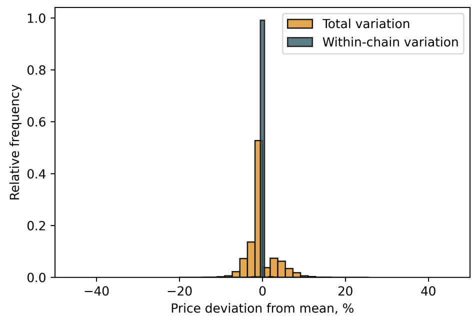
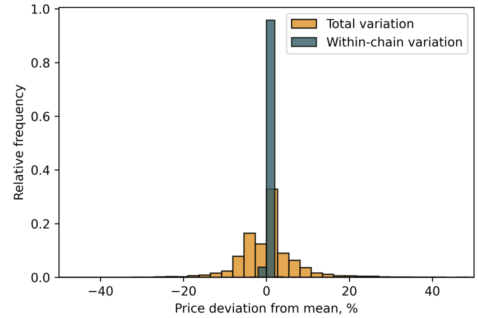
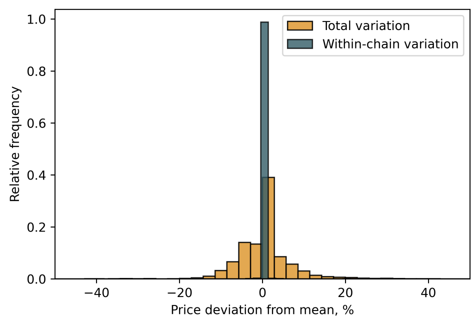
Appendix



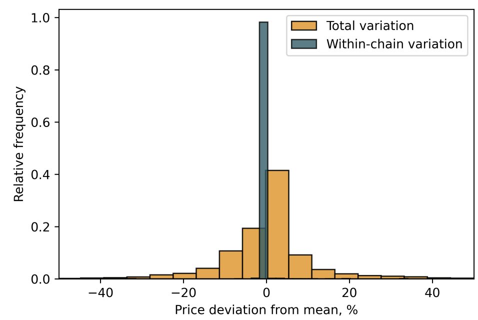
(a) Beer



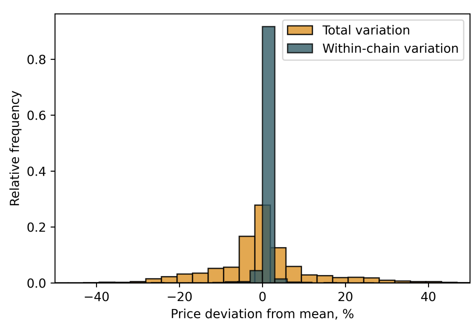
(b) Canned fish



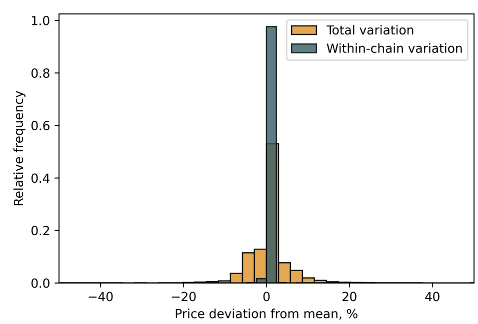
(c) Cheese



(d) Chocolate bars

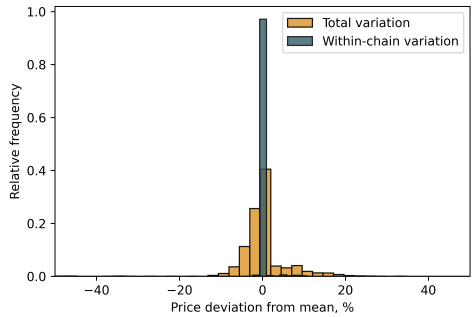


(e) Coffee

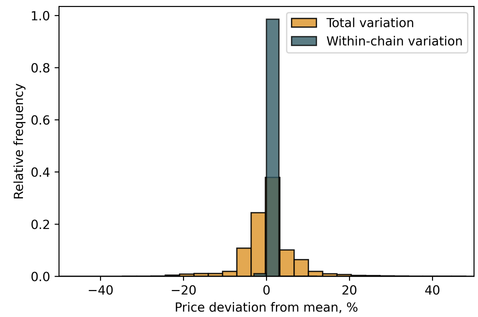


(f) Dry bread

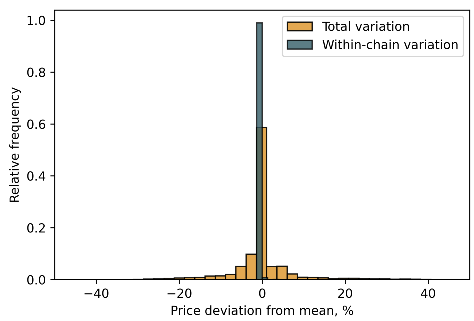
Figure A.1: Price variation within and across chains in different categories (first 6 categories)



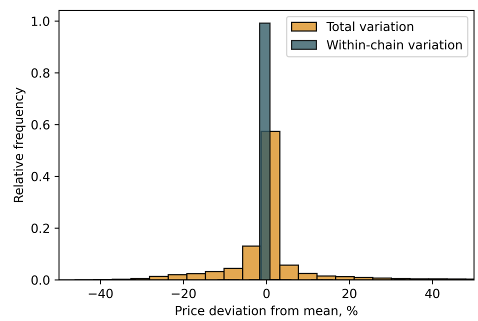
(a) Eggs



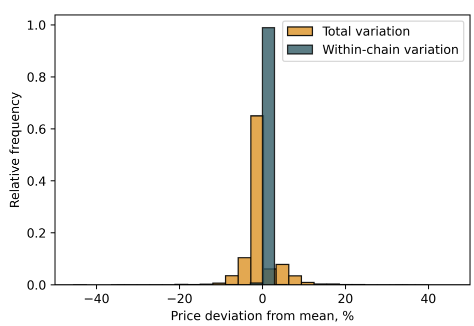
(b) Fresh bread



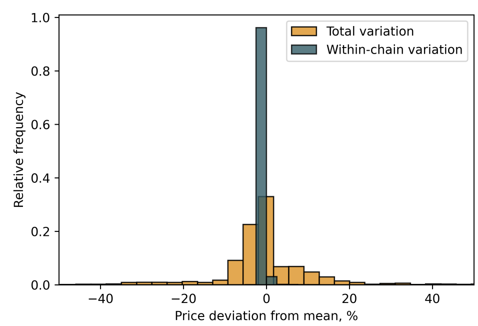
(c) Frozen fish



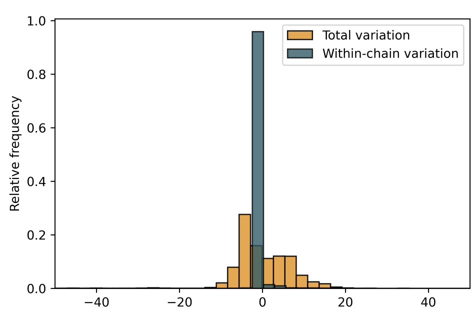
(d) Frozen pizza



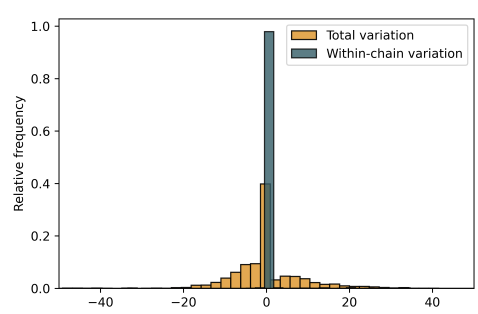
(e) Jam



(f) Juice



(g) Milk



(h) Yoghurt

Figure A.2: Price variation within and across chains in different categories (last 8 categories)

Table A.1: Percentage of income spent on food

Income Decile	0	1	2	3	4	5	6	7	8	9
Percentage	12.3	10.6	10.6	11.6	11.6	12.9	12.9	12.4	12.4	10.7

Source: Statistisk sentralbyrå

Table A.2: Local competition and local tastes

	Profit (I)	Profit (II)	Price (III)	Price (IV)	Variety (V)	Variety (VI)
Const	0.008***	-0.001***	55.756***	55.369***	69.313***	66.964***
	(0.000)	(0.000)	(0.039)	(0.055)	(0.259)	(0.364)
Local HHI	0.012***	0.013***	1.834***	1.875***	-34.614***	-34.365***
	(0.000)	(0.000)	(0.077)	(0.076)	(0.509)	(0.508)
BU Income	-	0.014***	-	0.590***	-	3.579***
		(0.000)		(0.059)		(0.389)
N	13484	13484	13484	13484	13484	13484

Notes: Profit is profit per capita in thousand NOK, calculated based on equation 29. Price and variety are price and variety for Average Assortment Consumed in NOK. Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A.3: Price prediction quality

Format	Chain	p		$\hat{p}$		$\hat{p}$ excl. C.A		$\hat{p}$ excl. S.A	
		Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Convenience	C.A	58.92	1.27	59.01	0.80	58.97	0.81	59.34	0.73
	C.B	59.80	1.63	59.84	1.61	59.84	1.61	59.84	1.61
	C.C	-	-	59.08	0.76	59.09	0.83	59.31	0.76
	C.D	-	-	58.98	1.00	59.01	1.06	59.12	0.98
Discount	D.A	52.99	0.80	52.99	0.79	52.99	0.79	52.99	0.79
	D.B	-	-	54.63	0.71	54.39	0.95	54.83	0.91
	D.C	-	-	54.59	0.83	54.16	0.84	54.47	0.83
	D.D	-	-	54.68	0.73	54.41	1.14	54.88	1.05
	D.E	-	-	54.37	0.78	54.07	0.76	54.34	0.76
Supermarket	S.A	59.87	1.28	59.87	1.27	58.83	1.00	59.84	1.27
	S.B	61.53	0.99	61.52	0.99	61.52	0.98	61.52	0.99
	S.C	-	-	60.43	0.95	60.03	1.08	59.50	1.09
	S.D	-	-	60.26	0.88	59.67	0.99	59.23	0.90

Table A.4: Variety prediction quality

Format	Chain	ν		$\hat{\nu}$		$\hat{\nu}$ excl. C.A		$\hat{\nu}$ excl. S.A	
		Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Convenience	C.A	29.37	24.77	26.34	7.38	26.29	8.01	27.32	3.90
	C.B	27.45	6.24	27.64	6.31	27.64	6.30	27.62	6.33
	C.C	-	-	29.55	7.32	29.62	7.71	31.29	7.22
	C.D	-	-	30.24	7.27	29.56	8.75	31.58	7.17
Discount	D.A	48.46	5.05	48.44	4.99	48.42	4.97	48.42	4.99
	D.B	-	-	46.61	5.52	48.88	7.05	49.53	7.24
	D.C	-	-	56.56	8.94	55.99	8.31	56.64	8.70
	D.D	-	-	46.09	4.69	46.67	6.76	48.14	6.69
	D.E	-	-	53.01	5.81	54.18	5.95	55.22	6.27
Supermarket	S.A	54.40	12.58	54.49	12.60	54.89	10.94	54.48	12.52
	S.B	90.86	12.64	90.68	12.59	90.68	12.59	90.69	12.59
	S.C	-	-	74.63	12.58	79.14	13.91	77.27	13.53
	S.D	-	-	91.30	7.75	95.66	11.86	91.92	11.73