Assortment Choice and Market Power under Uniform Pricing *

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Abstract

This paper examines how retailers adjust product assortments in response to local market conditions when prices are set nationally. Unable to raise prices for locally popular items, firms may instead offer more expensive substitutes. The profitability of these assortment changes depends on market competition. Using detailed receipt and store-level data and a structural equilibrium model, I show that firms in less competitive markets offer fewer, pricier products. Counterfactual policy experiments suggest that consumer subsidies in remote areas can enhance 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 less focus on how firms exercise market power through non-price characteristics. In imperfectly competitive industries firms 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. 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 through assortment choices, thereby affecting consumer welfare through non-price attributes.

This study focuses on the Norwegian grocery industry, where many supermarkets have substantial local market power: 22% of grocery stores have no competitors within a 5 km radius, i.e., are likely local monopolies. 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 to enhance competition and product variety.

The first contribution of this paper is to establish two novel stylised facts. Specifically, I document that product prices are determined at the national level, while product selection decisions occur at the local level. This empirical distinction previously unexamined in the literature reveals a clear separation between centralized pricing policies and decentralized assortment strategies. It also supports informal discussions with industry experts 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 consists of weekly sales data from several independently operated chains that are part of the same 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 representing a typical basket of groceries purchased by an average consumer. While previous studies, such as Aguirregabiria et al. (2016) and Wollmann (2018), explicitly model the inclusion or exclusion of specific products, such an approach would be computationally infeasible given the large assortment scale in my context. Therefore, following recent literature (e.g., Duarte et al., 2020; Eizenberg et al., 2021; Kim and Yeo, 2021), I characterize the composite good using two measures: *price*, representing the overall price level of the store's assortment, and *variety*, capturing the breadth of product offerings. Using a composite good simplifies the assortment analysis while capturing the main factors influencing consumers' store choices, such as shopping costs and product selection.

The second contribution of this paper is to develop and estimate a novel spatial equilibrium model, motivated by the established stylised facts. 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 the 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) and leverage differentiation instruments along with exogenous cost shifters while bringing the Berry (1994) approach for inverting market shares to the spatial model of Ellickson et al. (2020). Differentiation instruments aim to isolate variation that drives the assortment decisions from the unobserved demand determinants while capturing competitive pressure.

Cost shifters, in turn, exploit exogenous variation in product availability driven by cost differences.

The main contribution of this paper is to document and quantify assortment inequality across local markets. Firstly, using the novel approach to demand modelling, I quantify local competition. I find that in Norway, most markets are either moderately concentrated (29%) or highly concentrated (70%), and only 1% are considered competitive. Furthermore, consumers residing in more competitive markets have access to more affordable groceries and greater variety, while consumers in concentrated markets face a more limited and pricier assortment. Specifically, prices in concentrated markets can be up to 3% higher, and the assortment can be up to 37% smaller. These findings document the significant variations in product assortment across local markets.

Next, leveraging the model, I separate the impact of local market power from other factors that may affect assortment choice, such as logistics costs or 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 quantify the variance of margins associated with differences in market concentration. I find that margins in concentrated markets can be up to 130% higher than in competitive markets. These differences translate into substantial consumer expenditure disparities: consumers in more concentrated markets spend up to 20% more than in competitive markets, constituting around EUR 1,000 annually.

Finally, the model facilitates policy-relevant counterfactual analyses. Firstly, I show that disallowing spatial assortment discrimination leads to increased variety in some remote areas, compensating it with reduced variety and increased prices in other, predominantly competitive densely populated areas. The policy leads to consumer welfare loss of 26.4% alongside a 26.5% drop in industry profits. Conversely, targeted interventions, such as reducing travel costs for consumers in markets lacking nearby stores can notably enhance consumer welfare (by 4.7%) and improve firm profitability (by 3.2%). These interventions could be implemented through measures like energy vouchers or subsidized public transport. Overall, these findings demonstrate that unifying assortment can harm consumers in competitive densely populated markets, whereas tailored interventions, such as travel cost subsidies for consumers in remote markets, can effectively address assortment inequality and improve consumer access to a diverse selection of products.

This paper contributes to the empirical literature on non-price competition by providing novel evidence of how retailers strategically adjust their assortments in response to local competition. 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 evidence that product selection can vary locally. However, this paper differs from theirs in several aspects. Firstly, the structural approach allows me to separate the impact of local competition from other confounding forces that can impact product assortment decisions. Secondly, I explicitly quantify how differences in product assortment impact consumers across different local markets. Lastly, I provide policy recommendations informed by counterfactual simulations to mitigate assortment inequality.

Another closely related paper is Aguirregabiria et al. (2016), which studies 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). While previous studies, such as Handbury (2019), highlight assortment inequalities driven primarily by income-specific tastes, this paper shifts the focus to the role of market power rather than local preferences. Specifically, I show that even in settings where prices do not vary locally due to national pricing, retailers still strategically adjust assortment in response to differences in local competition, leading to assortment inequality. My findings also complement those of Eizenberg et al. (2021), who document spatial price differences within a city primarily due to travel frictions. Although prices are uniform in my setting, I similarly demonstrate that urban consumers have better access to cheaper products compared to rural residents. Importantly, I attribute this disparity to strategic assortment decisions rather than variation in prices.

Lastly, the paper relates to a growing literature on uniform pricing (Dobson and Waterson, 2005; Adams and Williams, 2019; DellaVigna and Gentzkow, 2019; Hitsch et al., 2019). In a seminal empirical paper, DellaVigna and Gentzkow (2019) document the widespread use of uniform pricing among major U.S. retailers. Similarly, I provide evidence on the prevalence of uniform pricing in the Norwegian grocery market. One of the earlier studies, Dobson and Waterson (2005), examines the conditions under which uniform pricing can be a profit-maximizing strategy for firms operating in multiple markets. They conclude that uniform pricing can be either consumer-friendly or anti-competitive, depending on the context. Adams and Williams (2019) study welfare effects and find that uniform pricing can shield consumers from higher prices in less competitive markets.

However, unlike previous studies, I highlight an important dimension overlooked in this literature: retailers' strategic use of product assortment. This paper contributes to the literature by showing that when price flexibility is constrained, firms turn to non-price strategies, specifically, product selection, to respond to changes in market structure. Thus, this paper uncovers a previously understudied assortment adjustments that firms use to exploit local market conditions when uniform pricing limits their price flexibility.

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 over 99% 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. Two of the retail groups have multiple independent chains representing different grocery formats. For example, the market leader NorgesGruppen has a discount format (Kiwi), convenience stores (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 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 is highly concentrated but features a complex decision-making structure that influences 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, store location and construction of new distribution centers 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. According to internal discussions with industry experts, chains are independently evaluated based on chain-specific key performance indicators, and some groups even charge different wholesale prices across their individual chains.

Beyond centralized, chain-level pricing, grocery retail chains have an additional layer of decision-making autonomy. Local managers, operating at either regional or individual store levels, possess knowledge of local market conditions, enabling chains to adjust product offerings locally. Therefore, although the Norwegian grocery industry is characterized by significant vertical integration and market concentration, the internal decision-making hierarchy introduces important variations that impact competitive dynamics. These structural features, particularly the distinction between central, group-level, and chain-level 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 several chains within one of Norway's largest retail groups. Importantly, this retail group operates throughout the country and has chains 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 the subsequent analysis.

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.

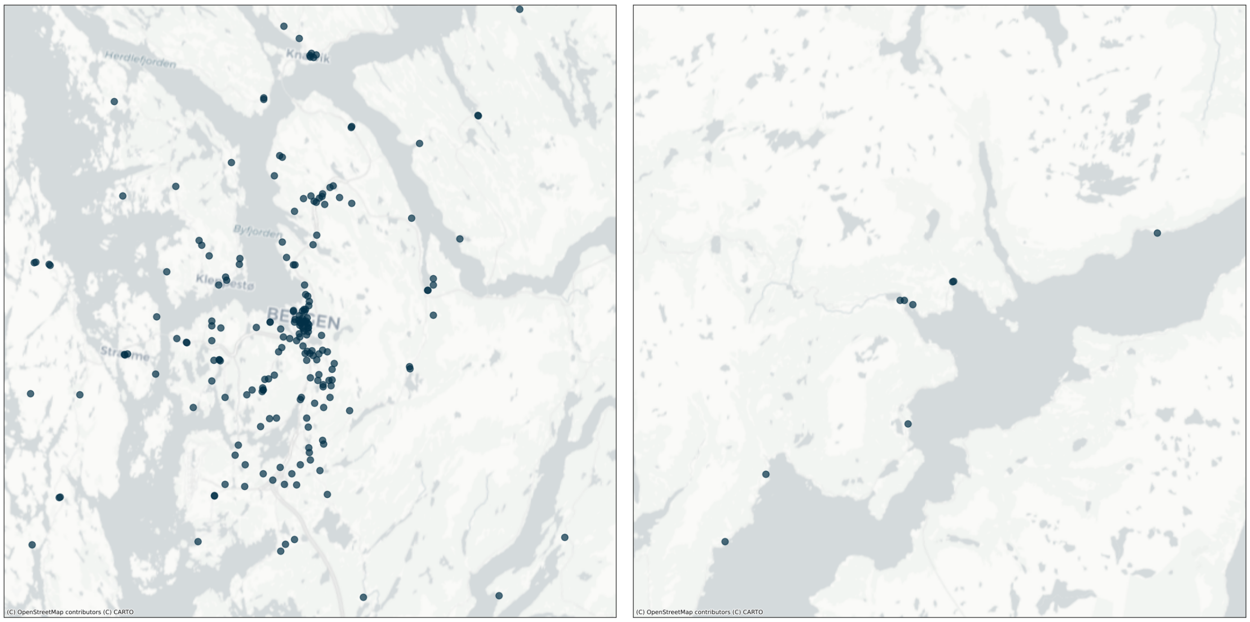
Table 2: Store-level descriptives, 2018

	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.



(a) Bergen

(b) Kvam

Figure 1: Location of stores

Notes: Scale of both maps is 40 X 40 km.

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

[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

Notes: Scale of the left map is 15 X 15 km. Scale of the right map is 8 X 8 km.

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.

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, such as 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 an approach where 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

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

(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.

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). To infer the assortment, I assume that a product was offered in a store in a given month if it was sold at least once; otherwise, it was not offered. While this assumption is driven by data limitations, it is plausible and commonly used in the literature (see, e.g., Handbury and Weinstein, 2015).[4]

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 at a national level 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

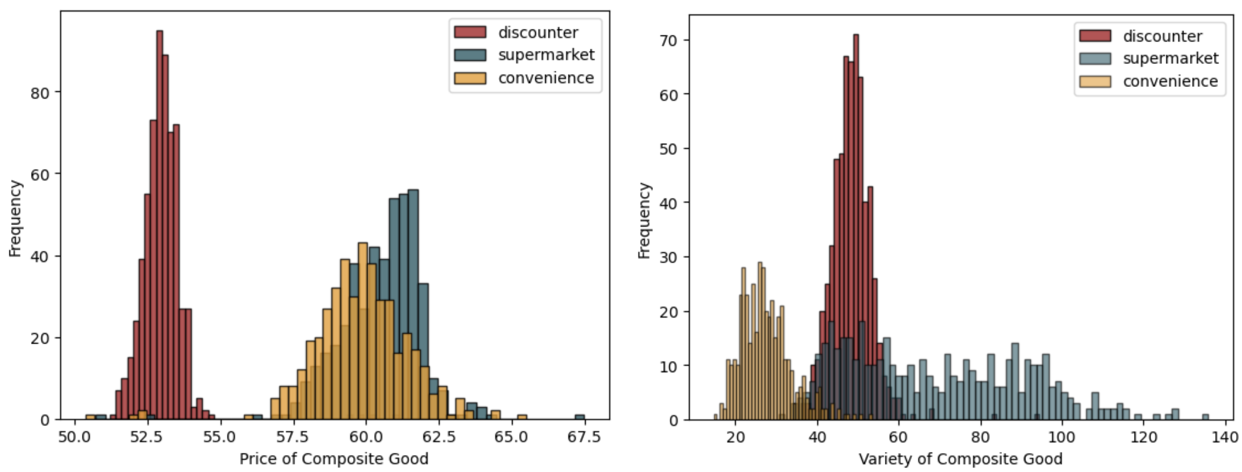
[3]The suppliers of fruits and vegetables can vary across regions.

[4]Since I use sales data to infer assortment, I do not exploit week-to-week variation within a month. Such variation would largely reflect purchasing patterns rather than actual changes in the store's assortment.

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.



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

Figure 3: Distribution of price and variety across chains

Table 4 presents descriptive statistics for the price and variety of a composite good across stores. 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 is equal to 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.

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

Table 4: Price and variety summary statistics

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

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.

Additionaly, retailers in Norway have three periods per year known as *launch windows* (in February, May and September), when chain managers can introduce changes in the assortment at the central level. These launch windows are regulated by the standardization committee (STAND), which plays a key role in coordinating assortment updates by establishing shared timelines and procedures across the supply chain. These launch windows structure when new products can be introduced or delisted. 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.[5]

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

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

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.

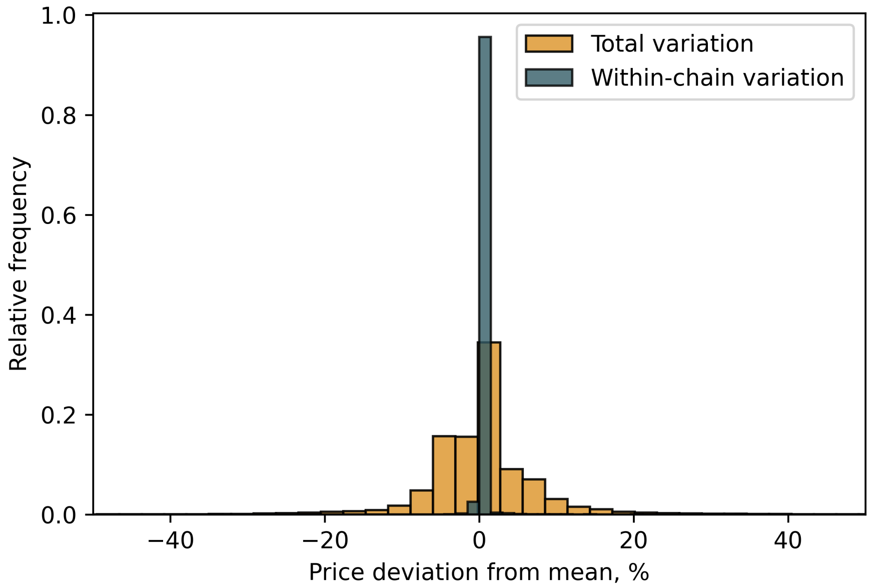


Figure 4: Price variation within and across chains
Note: One observation is one SKU in one store in one day

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.

Finally, I explore whether the variation in product prices within a chain responds to local market conditions. 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:

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%.

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

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 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}, i.e., the chain-day-product fixed effects. 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

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 (0.001)	-0.001 (0.001)	2.27*** (0.189)	2.30*** (0.236)	2.73*** (0.566)	-11.64*** (0.886)	-11.06*** (1.12)	-8.35*** (2.68)
Average income, 100,000 NOK (in radius)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.089** (0.037)	0.126*** (0.048)	0.114 (0.07)	0.797*** (0.174)	1.02*** (0.228)	1.36*** (0.331)
Location in shopping centre	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.008 (0.22)	-0.095 (0.223)	-0.212 (0.229)	10.75*** (1.036)	11.26*** (1.06)	11.84*** (1.09)
Location in city centre	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.063 (0.181)	-0.33* (0.182)	-0.522*** (0.186)	3.39*** (0.852)	4.52*** (0.861)	5.31*** (0.882)
Open on Sunday	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	2.64*** (0.186)	2.65*** (0.189)	2.63*** (0.193)	-5.43*** (0.874)	-5.42*** (0.894)	-5.07*** (0.916)
Distance to distribution centre, km	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.002 (0.002)	0.003** (0.002)	0.006*** (0.002)	-0.051*** (0.008)	-0.052*** (0.008)	-0.061*** (0.009)
Const.	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	53.97*** (0.274)	54.00*** (0.339)	54.26*** (0.485)	39.14*** (1.29)	36.20*** (1.61)	32.75*** (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%.

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 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. The demand side builds on the model of Berry et al. (1995) and expands it by allowing spatial competition as suggested by Davis (2006) and 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 good. 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 (Vanhuele and Drèze, 2002; Loy et al., 2020). 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.

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 me 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 of price and variety, 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:

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

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:

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

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.

As individual grocery expenditure data is not available, I approximate B_l by taking the average consumer's income in location l, scaling it by the local population, and then multiplying by the fraction of the budget that consumers with income y_l allocate to groceries, represented as 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.[6] 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

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

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:

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

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, I then obtain a store-level market share:

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

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. The 30 km threshold also ensures that each basic unit has at least one store in its choice set.

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

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

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.[7]

[7] 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.

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 is defined as:

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

where θ_s is a vector of supply-side cost function parameters. Note that, 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.

The multi-store firm's maximisation problem can be represented as follows:

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

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.[8]

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

[8]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.

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. 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 the distance parameter 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: $\delta_j^{'} = \delta_j + \ln(s_j) - \ln(\hat{s}_j(\delta_., \rho))$, where $\hat{s}_j(\delta_., \rho)$ 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.[9]

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. 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 store's exogenous degree of differentiation, 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 the store 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 market, where decisions about store entry and characteristics (e.g., store size, format, and location) are made centrally by the

[9]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.

head office of the retail group, rather than by local managers responding to local conditions. As such, the spatial configuration of stores and, consequently, their degree of differentiation are 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 strengthens the assumption that store characteristics, and therefore differentiation measures used as instruments, are uncorrelated with current unobserved demand components.

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, which, according to Table 6, is negatively correlated with the assortment size. The second instrument is the store's distance to its closest store of the same chain to account for the logistics network. 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 several independently operated chains of different formats that belong to the same 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 municipalities with comparable populations. The rationale is that store entry decisions follow retail group-wide strategic policies. Chains typically maintain consistent strategies for store entries across similar markets, driven primarily by logistical and corporate factors. 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 marginal costs as:

$$mc_j = \exp(c_{0j} + c_{1j}\nu_j). \tag{25}$$

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.

Equation 22 allows me to back out the marginal costs mc_j, while Equation 23 enables me 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_{1j} as follows:

$$\hat{c}_{0j} = \ln(\widehat{mc}_j) - \frac{\partial\widehat{mc}_j/\partial\nu_j}{\widehat{mc}_j}\nu_j, \tag{26}$$

$$\hat{c}_{1j} = \frac{\partial\widehat{mc}_j/\partial\nu_j}{\widehat{mc}_j}. \tag{27}$$

Intuitively, variation in prices and consumer demand, combined with the assumption that firms optimally set prices, identifies marginal costs. Similarly, variation in assortment variety, coupled with the assumption that firms optimally choose variety, identifies the cost curvature parameter c_{1j}, which captures how marginal costs change with assortment size.

Since prices and variety are observed only for some chains, the inversion of the first-order conditions to recover store-level marginal costs can be implemented only for stores of those chains. However, conducting counterfactual analyses for the entire market requires price and variety data for all chains. To overcome this limitation, I impute assortment information for the remaining chains using data from the observed retail group, which is a largest retailer and includes chains across all store formats.

Store-level prices and varieties are predicted using a set of exogenous store characteristics, along with differentiation instruments derived from these characteristics that were used in the demand estimation. I also include cost-shifting variables such as distance to the retail group's distribution center and proximity to the nearest store of the same chain. This approach leverages variation in observable factors to estimate how unobserved chains would behave under similar conditions.[10]

To validate the quality of this imputation, I perform a leave-one-chain-out cross-validation exercise. In this procedure, I temporarily remove one fully observed chain, re-impute its prices and varieties based on data from the remaining chains, and then compare these predicted values against the withheld true data. Tables B.1 and B.2 in Appendix B confirm

[10]See Appendix B for additional details on the imputation procedure.

that imputed prices and varieties closely match actual observed values across all formats and chains, both in terms of levels and variability. This exercise demonstrates that stores from the observed retail group are representative of similar formats elsewhere, and their locations are structurally comparable to those of unobserved chains.

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. Additionally, I leverage the demand estimates to calculate the Average Assortment Consumed (AAC) for each consumer location (defined later), allowing me to explore the relationship between assortment differences and variations in market concentration.

After discussing the demand estimates, I present 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 signs 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. I also find a strong, positive utility premium for supermarkets relative to discounters—and this premium grows with local income. Consumers show a strong preference for supermarkets over discounters. And this preference is stronger for consumers in wealthier municipalities. Under the constant expenditure specification of the demand model, this indicates that consumers with higher income either purchase larger volumes of grocery bundles or opt for more expensive store formats.

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, 69.7%, are highly concentrated, 28.9% are moderately

Table 7: Demand parameters estimates

Variable	Estimate
Log price	-2.752***
	(0.004)
Variety	0.271***
	(0.004)
Distance	-0.998***
	(0.002)
Supermarket	59.351***
	(0.001)
Supermarket $\times$ log income	5.809***
	(0.001)
Working hours	0.220***
	(0.002)
Open on Sunday	9.102***
	(0.000)
Number of employees	-1.103***
	(0.006)
# of obs.	3712

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

concentrated and only 1.4% 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 or moderately concentrated, with overall lower concentration levels. However, as we move further away from the city towards more rural areas, the concentration gradually increases.

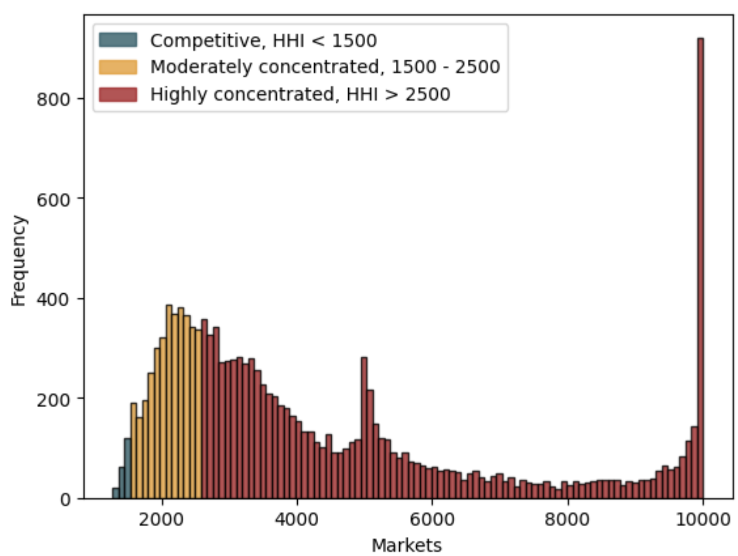


Figure 5: Distribution of localised concentration measures

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. The municipality-based HHI classifies 43.3% of markets as highly concentrated, whereas the more granular, localized HHI flags 69.7% as highly concentrated—showing that the coarser,

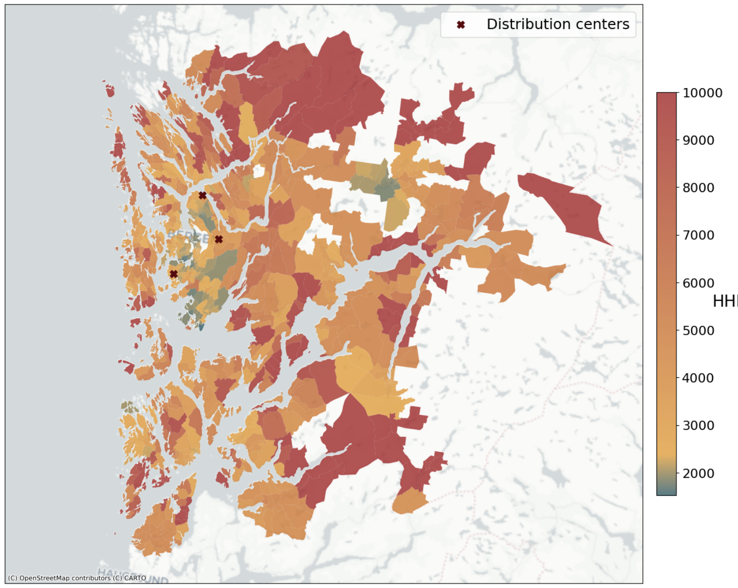


Figure 6: Spatial distribution of market concentration

municipality-level measure systematically understates market concentration. Only 1.4% of markets are classified as competitive under the localized HHI versus 5.2% municipally, and over 4,300 markets shift from "moderately" to "highly" concentrated when examined at a finer scale. This disparity underscores the need for geographically precise concentration metrics to accurately identify concentrated areas.

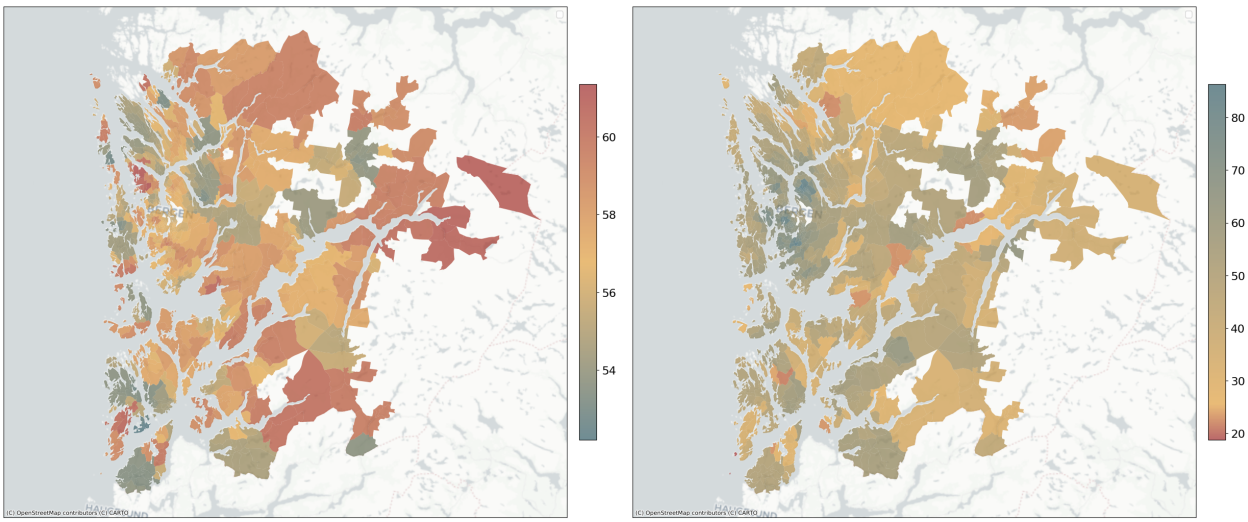
Table 8: Market concentration comparison

		Localised HHI			
		Competitive	Moderately Concentrated	Highly Concentrated	**Total**
Municipality-based HHI	Competitive	89	306	304	699 (5.2%)
	Moderately concentrated	47	2,591	4,302	6,940 (51.5%)
	Highly concentrated	5	439	5,392	5,836 (43.3%)
	Total	141 (1.4%)	3,341 (28.9%)	10,002 (69.7%)	

Note: One observation is one basic unit.

Additionally, the estimated demand model allows me 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). AAC_l^P is calculated as an average price of stores j in the choice set $\mathcal{J}_l$, weighted by the probabilities $\mathbb{P}_{jl}$: $AAC_l^P = \sum_{j \in \mathcal{J}_l} \mathbb{P}_{jl} \cdot p_j$. 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, more concentrated markets tend to offer a more expensive assortment, with price differences reaching up to 3%. Conversely, the plot shows a negative monotonic relationship for variety: consumers in more competitive markets have access to up to 37% more product variety.



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

Figure 7: Average assortment consumed

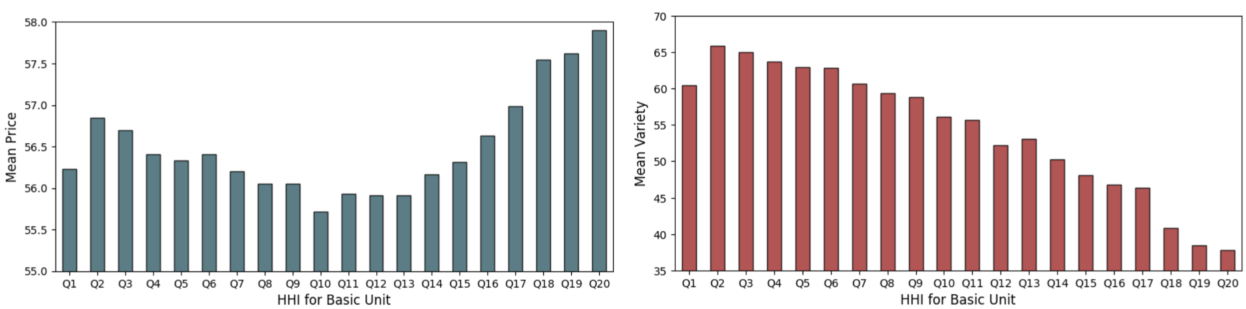


Figure 8: Average assortment consumed and market concentration

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. Regarding markups, supermarkets and discounters display similar levels, whereas convenience stores show notably higher average markups. Overall, these markup estimates align closely with findings from prior studies analyzing composite goods in retail markets (e.g., 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.

Table 9: Summary statistics for costs and margins

	Price	MC	Markup
Mean (all)	56.47	35.97	0.36
Median (all)	55.75	37.39	0.32
By formats			
Median (discounter)	54.15	36.99	0.31
Median (convenience)	58.73	36.89	0.37
Median (supermarket)	60.67	41.97	0.30

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.

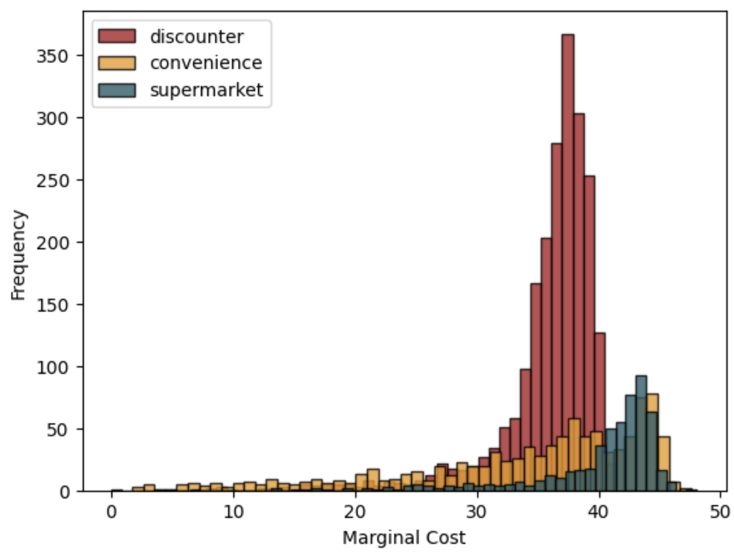


Figure 9: Distribution of marginal costs across formats

Since price and variety data are only available for certain chains within one retail group, marginal costs can be directly recovered via first-order condition inversion for those chains alone. To extend the analysis to the full market, I impute prices and varieties for the remaining chains, which allows me to recover marginal costs for the full sample of stores. Details are provided in Appendix B.

To assess how sensitive marginal cost estimates are to imputation error, I perform a leave-one-chain-out validation exercise. Specifically, for one fully observed chain, I temporarily remove its price and variety data, re-impute these values using the remaining observed chains, and then re-calculate marginal costs. I compare the resulting estimates to those obtained using the full sample. Tables B.3 and B.4 report the quality of these imputations.

Table 10: Marginal cost function parameters

Variable	Estimate
Const (c_0)	-1.159
	(1.203)
Variety (c_1)	0.098***
	(0.023)
# of obs.	3712

Note: Standard errors are obtained via a bootstrap procedure with 1,000 replications, clustered at the chain level. Significance levels are: *** - 1%, ** - 5%, * - 10%.

The resulting errors in both the mean and standard deviation of marginal costs remain small across all store formats. This confirms that the imputation procedure yields robust and unbiased cost estimates, even for stores not covered in the data.

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 me 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:

$$\Pi_l = \sum_{j \in \mathcal{J}_l} (p_j - mc_j) \cdot q_{jl}, \tag{28}$$

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

$$q_{lj} = \frac{\mathbb{P}_{lj} B_l}{p_j}. \tag{29}$$

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. In particular, margins in concentrated markets can be up to 130% higher than in competitive ones. This translates into sizable differences in consumer spending: households in the most concentrated markets spend up to 20% more annually on groceries—approximately EUR 1,000—compared to those in the most competitive areas.

Local competition vs. local tastes

To better understand whether the observed differences in assortment and profit are driven by firms' responses to competitive pressure rather than merely reflecting local demand conditions, I conduct a regression analysis of assortment and profit on local market concentration and income. One concern is that market power and income may be correlated, for instance, high-income consumers may live in remote areas, where markets are also more concentrated. In such cases, it is unclear whether higher prices reflect consumer preferences for more expensive products or retailers exercising market power. This analysis helps disentangle the influence of market structure from that of local preferences. If firms systematically reduce variety and raise prices in less competitive markets even after controlling for income, this

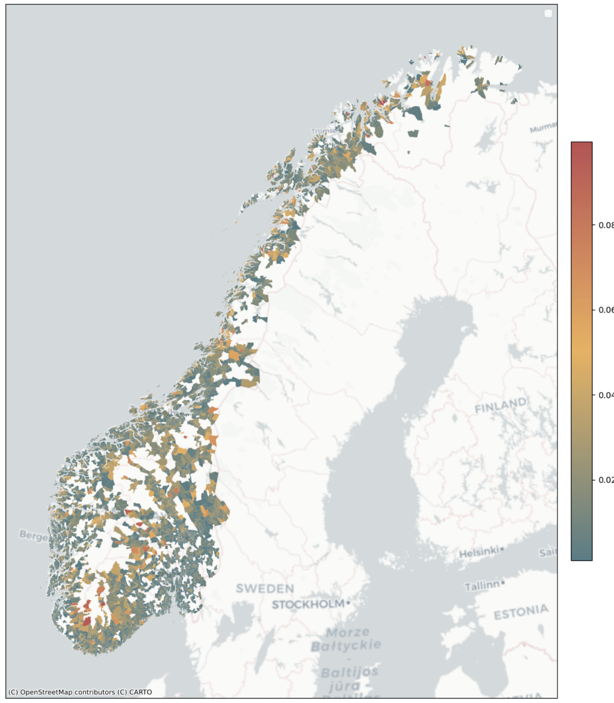


Figure 10: Spatial distribution of profit per capita

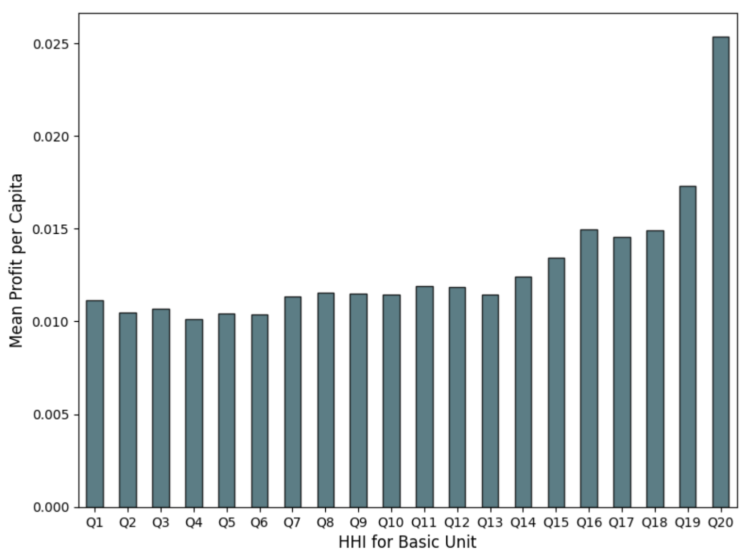


Figure 11: Profit per capita and market concentration in basic units

would suggest that these decisions are shaped not just by demand but also by the degree of competitive pressure.

Table 11 presents the regression results. Local HHI is measured as $\sum_g [\sum_{j \in \mathcal{J}_{lg}} \mathbb{P}_{lj}]^2$, where $\mathbb{P}_{lj}$ is the predicted probability of the consumer residing in l visiting store j. Columns I and II show that profit per capita is strongly and positively associated with local HHI, even after controlling for average income in the basic unit. Columns III and IV indicate that both market concentration and income are associated with higher AAC prices. Finally, columns V and VI confirm that more concentrated markets not only face higher prices but also more limited product offerings. These findings underscore that market structure, independent of local income, contributes to spatial inequality in consumers' access to affordable and broad assortments.

Table 11: Local competition vs. local tastes

	I Profit	II Profit	III Price	IV Price	V Variety	VI Variety
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 28. Price is the Price of the Average Assortment Consumed in NOK, measured as $AAC_l^P = \sum_{j \in \mathcal{J}_l} \mathbb{P}_{jl} \cdot p_j$. Variety is the Variety of the Average Assortment Consumed in NOK, measured as $AAC_l^\nu = \sum_{j \in \mathcal{J}_l} \mathbb{P}_{jl} \cdot \nu_j$. Standard errors in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

7 Counterfactual Analysis

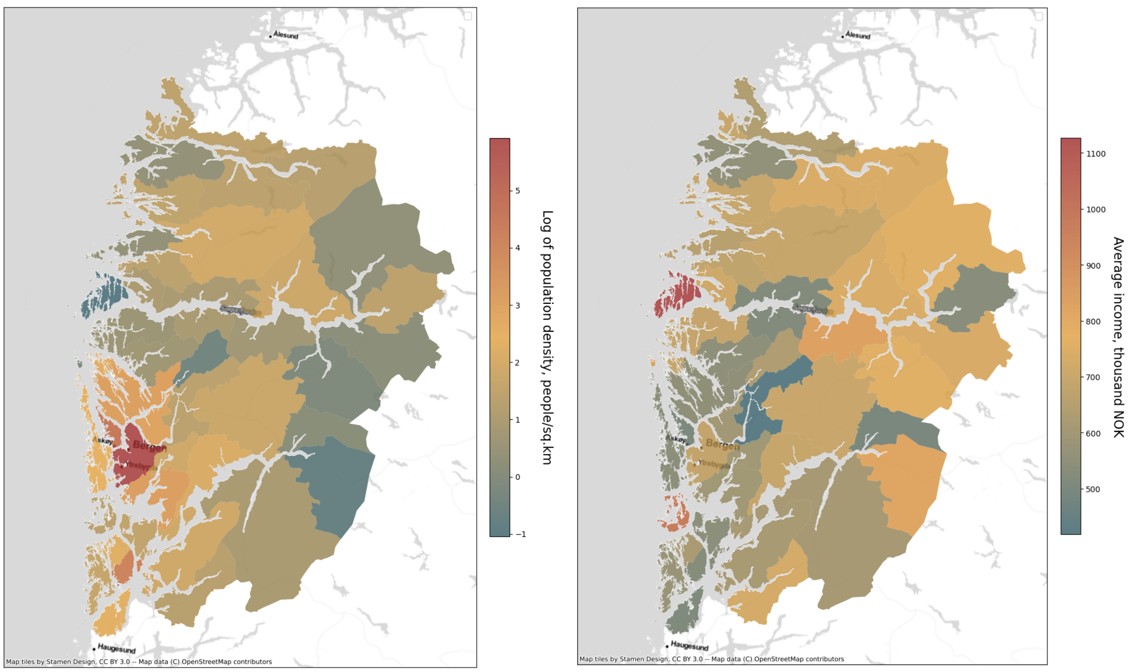
The counterfactual analysis begins by summarising the results concerning assortment inequality. I then go on to examine the role of local assortment in generating welfare inequality and consider a policy that could improve assortment, such as reducing consumer travel costs.

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

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 Vestland where the population density can be as low as 0.69 people per square kilometre. Figure 12a 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 12b 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.



(a) Population density **(b)** Average income

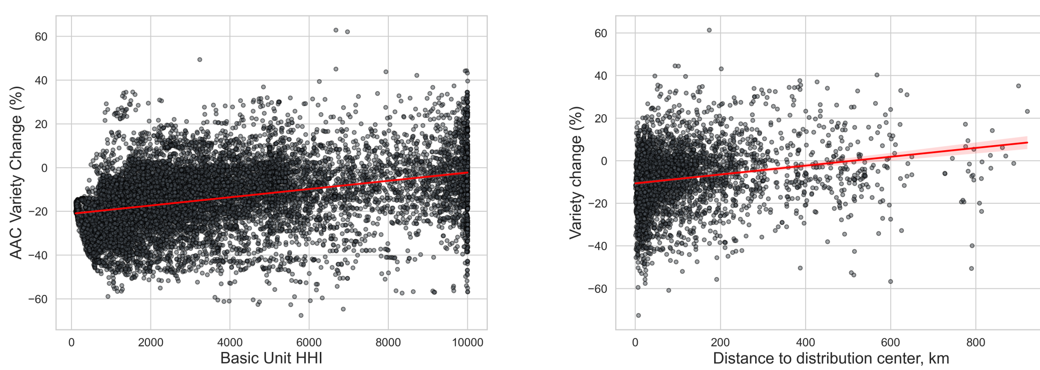
Figure 12: Vestland

Welfare Analysis of Local Assortment. To evaluate the implications of spatial assortment discrimination, 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. In particular, I compute an equilibrium under restriction that each store of the chain offers the same price and variety, taking as given the demand and supply parameter estimates. The maximisation problem for a multi-store firm f will then look as follows:

$$\max_{p_f, \nu_f} \sum_{j \in \mathfrak{J}_f} q_j(p_., \nu_., \xi_., d_{.j})(p_f - mc(\nu_f; \theta_s)). \tag{30}$$

Using the first-order conditions for the problem 30, I calculate each chain's new equilibrium price and variety of the composite good. Under uniform assortment, an average price increases by 2.8% and variety decreases by -8.2%. Consumers' shopping behaviour reflects similar changes. The average assortment consumed (AAC) experiences a 1.3% increase in price and an 14.1% decrease 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 variety on markets with different market concentrations. Figure 13a provides a summary of the results, with basic units sorted by the baseline local HHI. Under uniform assortment, in more competitive areas, stores tend to reduce variety more sharply. In contrast, in more concentrated markets, the reduction in AAC variety is smaller, and in some cases, stores expand variety. I also investigate how variety changes with distance to the distribution center. Stores located in more remote areas tend to experience smaller reductions in variety, and in some instances, slight increases. These patterns are qualitatively similar: stores and markets with limited competition is associated with less reduction in variety, indicating that in the baseline scenario that stores on concentrated markets offer a more limited assortment.



(a) Local HHI and change in variety

(b) Distance to the distribution center and change in variety

Figure 13: Effects on variety

To measure consumer welfare, I use compensating variation between the counterfactual scenario and the benchmark equilibrium. 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:

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

As anticipated, imposing a uniform assortment policy yields heterogeneous effects across markets. Figure 14 displays the distribution of per-capita consumer welfare changes when spatial assortment discrimination is disallowed. Although some markets experience small gains, others incur losses; the population-weighted average effect is a 26.4% decline relative to the baseline. This net welfare loss reflects the fact that the largest assortment cuts occur in competitive and more densely populated markets. These findings are consistent with early theoretical work (Gronberg and Meyer, 1982; Anderson et al., 1989), which shows that the welfare effects of spatial discrimination are theoretically ambiguous and depend on the structure of demand and competition.

The uniform policy also substantially harms firms: total industry profits fall by 26.5%. Under discriminatory assortment, retailers can offer broader assortment where it is cheaper - large, competitive markets not far from the distribution center - and more narrow assortment where costs are higher - remote, low-density areas. The uniform assortment policy leads to decreased average variety and increase in prices in order to compensate increased costs from variety unification. This in turn leads to profits reduction and consumer welfare reduction. Although uniform assortment benefits some isolated consumers, it is, on net, inefficient for both consumers and firms. These results suggest that policymakers should avoid one-size-fits-all solutions and instead consider more targeted interventions, as discussed in the following section.

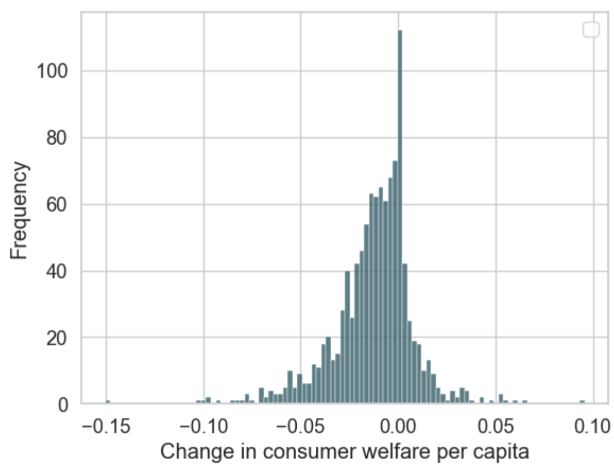


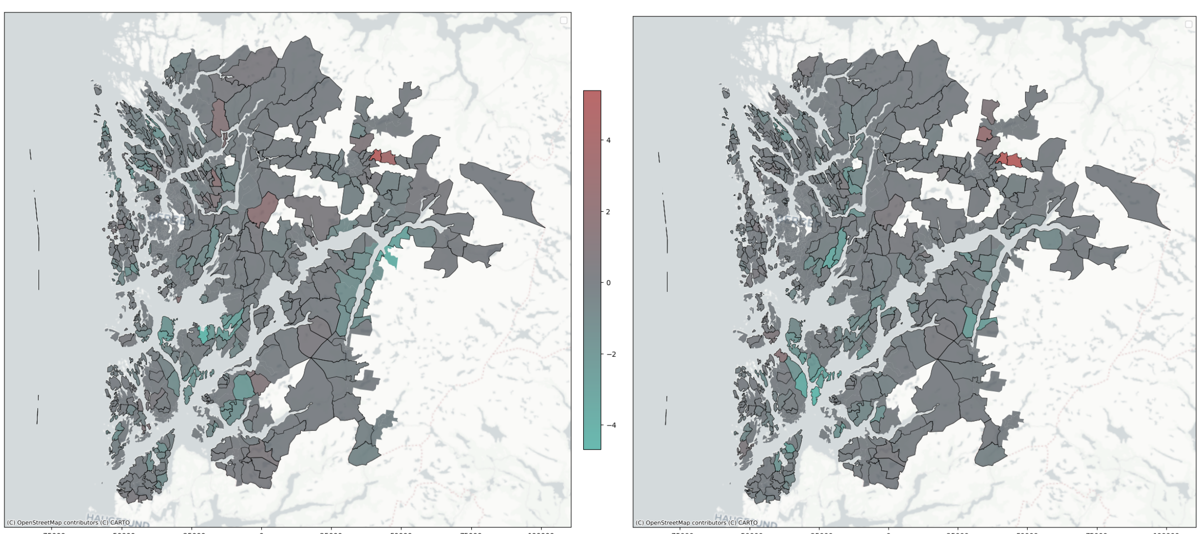
Figure 14: Change in consumer welfare due to uniform assortment

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 the next 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 reducing the distance disutility by 20% 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.

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.[11] The French 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.

The policy generates heterogeneous effects across markets. The price change varies from -6.3% to 5.9% across stores, with an average decrease of 0.01%. The variety change varies from -1.4% to 1.6% with a zero average effect. In theory, the reduction in travel costs should lead to increased competition in 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. For these remaining customers, the effective choice set remains unchanged, making their demand less elastic. Anticipating this, stores in such markets respond by raising prices and narrowing the assortment.

To explore the changes in consumers' shopping behaviour, I calculate changes in the AAC, the weighted average price and variety consumed by residents of each basic unit, taking into account the probability of shopping at each particular store. The change in AAC^p varies from -3.9% to 5.4%, with an average decrease of 0.04%. The change in AAC^ν varies to a greater extent, from -30.8% and 35.9%, with an average increase of 0.43%. Figure 15 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, AAC^p and AAC^ν may rise. As travel costs decrease, consumers can reach more competitive areas, such as Bergen, that offer a greater variety with higher prices.



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

Figure 15: Counterfactual changes in average assortment consumed due to reduced travel disutility

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

As expected, the policy positively impacts consumer welfare, resulting in an increase of 4.7%. The policy also has a positive impact on firms. The industry's total profit increases by 3.2%. The welfare gain from the policy gross of the policy's cost, calculated as the sum of the change in consumer welfare and change in profits, amounts to 4.5% 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 twenty per cent of their travel disutility. For consumers in remote locations, the transfer is thus defined as follows:

$$u\left(y_{i(l)} + T_{i(l)}, \delta_j, d_{lj}, \rho^{BM}, \epsilon_{i(l)j}\right) = u\left(y_{i(l)}, \delta_j, d_{lj}, \rho^{CF}, \epsilon_{i(l)j}\right), \tag{32}$$

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

$$\Delta W = \sum_i CV_{i(l)} + \sum_j \Delta\Pi_j - \sum_i T_{i(l)} \times MCPF, \tag{33}$$

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).[12] As such, the net welfare effect amounts to 4.4% of the baseline total welfare. The policy demonstrates promising outcomes for consumers and firms, contributing to an overall improvement in total welfare.

8 Conclusion

I study how multi-store firms strategically adjust their product assortment in response to local competition when product-level prices are fixed at the national level. Despite national pricing within chains, I document substantial variation in product selection across stores of the same chain. To understand the drivers of this variation, I develop a spatial structural model of consumer and retailer behavior that captures how chains tailor their assortments to local market conditions. The model also allows me to attribute these changes to local market power. This results in 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 modestly improves consumer outcomes in remote areas, it reduces overall welfare by harming consumers in competitive, densely populated markets. I therefore

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

consider a more targeted intervention—reducing travel costs for remote consumers—which proves more effective. This policy improves competition and access in underserved areas and leads to a net gain in total welfare.

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 and location of stores. 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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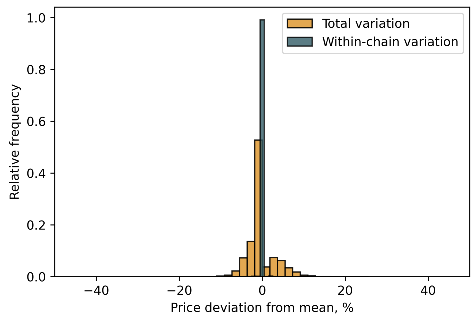
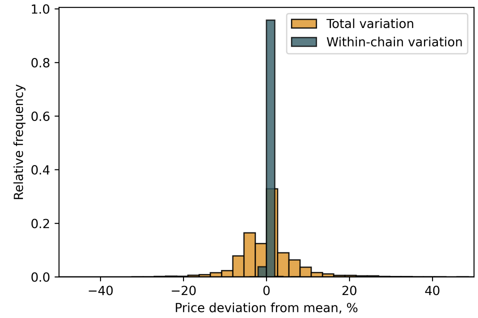
Appendix

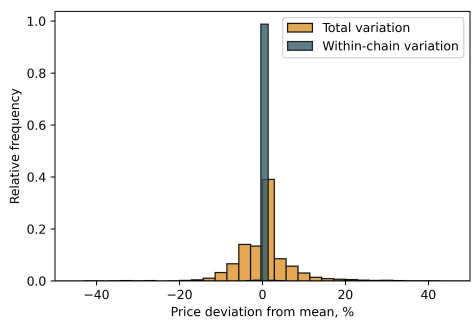
Appendix A



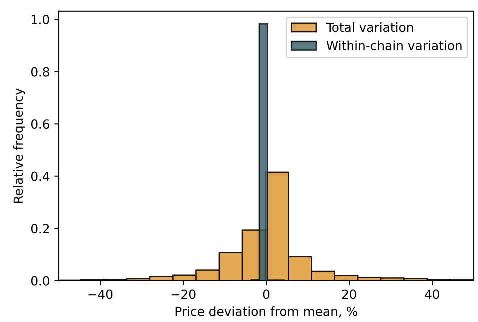
(a) Beer



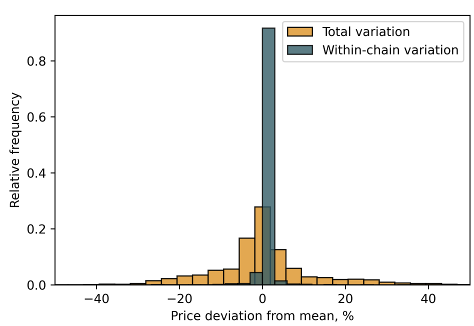
(b) Canned fish



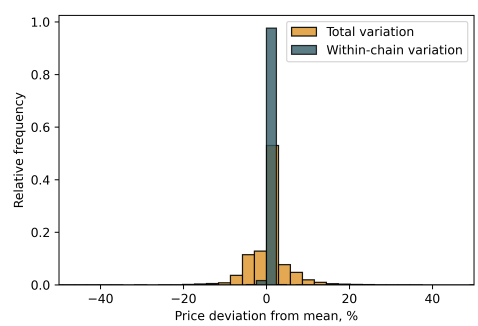
(c) Cheese



(d) Chocolate bars

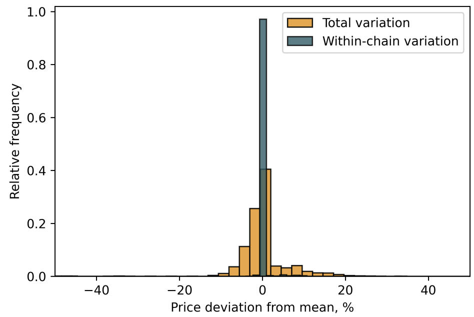


(e) Coffee

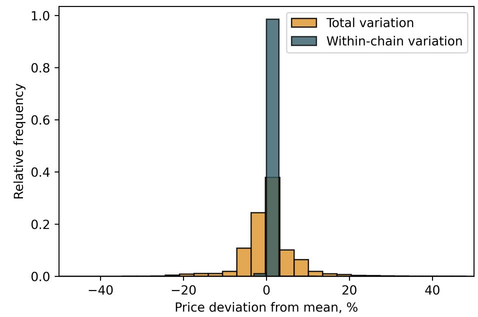


(f) Dry bread

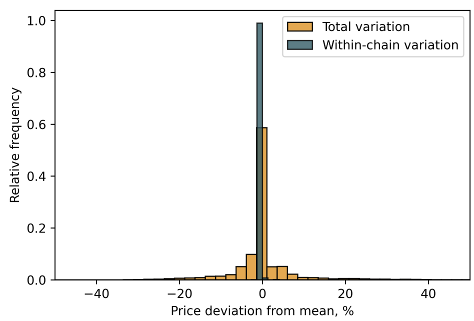
Figure A.1: Price variation within and across chains in different categories (first 6 categories)



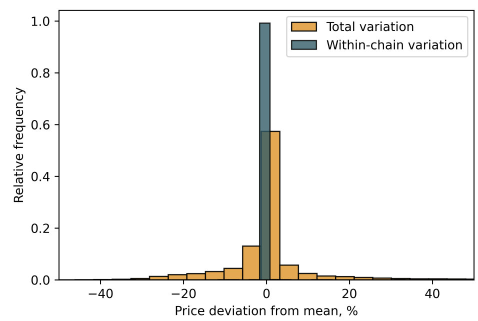
(a) Eggs



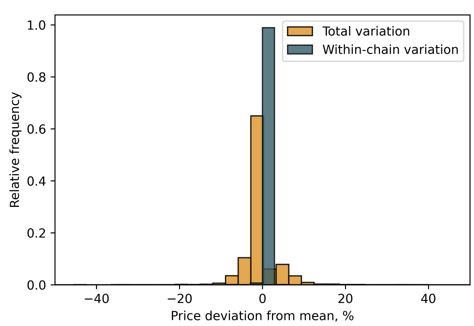
(b) Fresh bread



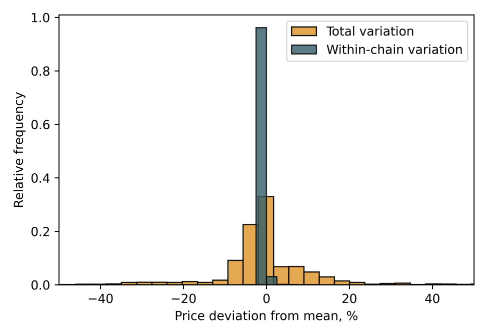
(c) Frozen fish



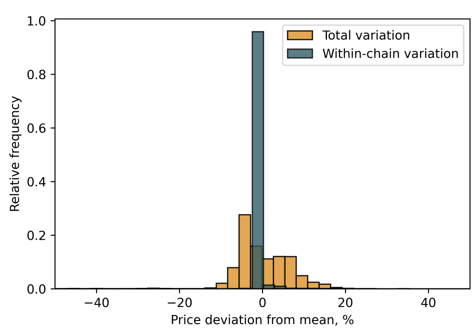
(d) Frozen pizza



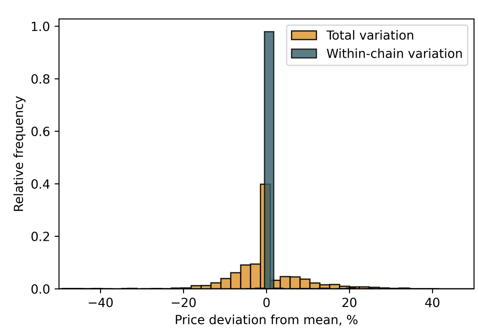
(e) Jam



(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

Appendix B

To conduct a counterfactual analysis for the entire market, I estimate store-level prices and product variety for chains where data is not directly available. This is necessary because the first-order condition inversion used to recover marginal costs can only be applied to the one retail group for which both price and assortment data are available. Given that this group is the largest in Norway and includes chains across all formats, it provides a suitable training sample for predicting outcomes in unobserved chains.

I use a gradient boosting model implemented via the LightGBM package to perform the imputation.[13] The model is trained using a rich set of predictors, including exogenous store characteristics, differentiation instruments used in the demand estimation, and cost-shifting variables such as distance to the distribution center and the nearest same-chain store. The model is trained with the following parameters: 20 leaves, a learning rate of 0.01, 1,000 boosting rounds, and a minimum of 20 observations per leaf. To prevent overfitting, I use subsampling with 30% of features and observations randomly selected in each boosting round. Regularization is applied with both alpha and lambda set to 0.1, and the model is trained using an L2 loss function.

Prediction quality is reported in Tables B.1 and B.2. Column I presents the mean and standard deviation of observed prices and variety, while Column II reports the corresponding predicted values. Column III shows predictions from models trained with one observed chain excluded (leave-one-chain-out). The results indicate that the imputed prices and variety closely replicate the true values across all formats and chains, both in terms of average values and dispersion. This confirms that stores from the observed group are representative of their respective formats and that their locations are structurally similar to those of the unobserved chains.

Table B.1: Price prediction quality

		I		II		III	
Format	Chain	p		$\hat{p}$		$\hat{p}$ excl. S.A	
		Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Convenience	C.A	59.80	1.63	59.84	1.61	59.84	1.61
	C.B	-	-	59.01	0.80	59.34	0.73
	C.C	-	-	59.08	0.76	59.31	0.76
	C.D	-	-	58.98	1.00	59.12	0.98
Discount	D.A	52.99	0.80	52.99	0.79	52.99	0.79
	D.B	-	-	54.63	0.71	54.83	0.91
	D.C	-	-	54.59	0.83	54.47	0.83
	D.D	-	-	54.68	0.73	54.88	1.05
	D.E	-	-	54.37	0.78	54.34	0.76
Supermarket	S.A	59.87	1.28	59.87	1.27	59.84	1.27
	S.B	61.53	0.99	61.52	0.99	61.52	0.99
	S.C	-	-	60.43	0.95	59.50	1.09
	S.D	-	-	60.26	0.88	59.23	0.90

[13] https://lightgbm.readthedocs.io/

Table B.2: Variety prediction quality

Format	Chain	I		II		III	
		ν		$\hat{\nu}$		$\hat{\nu}$ excl. S.A	
		Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Convenience	C.A	27.45	6.24	27.64	6.31	27.62	6.33
	C.B	-	-	26.34	7.38	27.32	3.90
	C.C	-	-	29.55	7.32	31.29	7.22
	C.D	-	-	30.24	7.27	31.58	7.17
Discount	D.A	48.46	5.05	48.44	4.99	48.42	4.99
	D.B	-	-	46.61	5.52	49.53	7.24
	D.C	-	-	56.56	8.94	56.64	8.70
	D.D	-	-	46.09	4.69	48.14	6.69
	D.E	-	-	53.01	5.81	55.22	6.27
Supermarket	S.A	54.40	12.58	54.49	12.60	54.48	12.52
	S.B	90.86	12.64	90.68	12.59	90.69	12.59
	S.C	-	-	74.63	12.58	77.27	13.53
	S.D	-	-	91.30	7.75	91.92	11.73

Next, using observed and imputed prices and variety, I recover estimates of marginal costs and, correspondingly, markups. To assess the sensitivity of marginal cost estimates to imputation error, I conduct a leave-one-chain-out validation exercise. Specifically, for one of the fully observed chains, I temporarily withhold its price and variety data, re-impute these values using the remaining observed chains, and then re-estimate marginal costs based on the imputed inputs. I compare the resulting marginal cost estimates to those obtained using the full data.

Tables B.3 and B.4 summarize the results. Column I reports the mean and standard deviation of "observed" marginal costs and markups (calculated using actual prices and variety). Column II presents the corresponding estimates based on predicted prices and variety. Column III displays the estimates derived from the leave-one-chain-out approach. Across all store formats, the differences in both the mean and standard deviation remain small, confirming that the imputation procedure produces reliable and unbiased estimates—even for chains not directly included in the observed retail group.

Table B.3: Marginal costs prediction quality

Format	Chain	I		II		III	
		$mc(p, \nu)$		$mc(\hat{p}, \hat{\nu})$		$mc(\hat{p}, \hat{\nu})$ excl. S.A	
		Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Convenience	C.A	36.16	9.12	36.54	9.12	36.54	9.13
	C.B	-	-	34.89	8.51	35.06	8.43
	C.C	-	-	28.51	10.76	28.62	10.79
	C.D	-	-	34.70	10.16	34.77	10.16
Discount	D.A	35.30	3.77	35.30	3.77	35.30	3.77
	D.B	-	-	36.83	4.55	36.94	4.44
	D.C	-	-	35.84	4.40	35.76	4.39
	D.D	-	-	34.26	7.97	34.34	7.88
	D.E	-	-	36.64	2.25	36.63	2.25
Supermarket	S.A	37.47	7.12	37.52	7.14	37.51	7.14
	S.B	42.60	2.27	42.63	2.27	42.63	2.27
	S.C	-	-	41.96	2.57	41.31	2.42
	S.D	-	-	39.19	3.15	38.51	3.02

Table B.4: Margin prediction quality

Format	Chain	I		II		III	
		$p - mc(p, \nu)$		$\hat{p} - mc(\hat{p}, \hat{\nu})$		$\hat{p} - mc(\hat{p}, \hat{\nu})$ excl. S.A	
		Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Convenience	C.A	23.64	8.74	23.30	8.71	23.30	8.71
	C.B	-	-	24.12	8.28	24.29	8.42
	C.C	-	-	30.56	10.85	30.69	10.89
	C.D	-	-	24.28	9.66	24.35	9.71
Discount	D.A	17.84	3.81	17.69	3.76	17.69	3.76
	D.B	-	-	17.80	4.65	17.88	4.79
	D.C	-	-	18.74	4.48	18.70	4.47
	D.D	-	-	20.42	8.30	20.53	8.47
	D.E	-	-	17.73	2.15	17.72	2.14
Supermarket	S.A	22.39	6.84	22.35	6.84	22.34	6.85
	S.B	18.93	2.08	18.89	2.09	18.89	2.09
	S.C	-	-	18.47	2.12	18.19	2.18
	S.D	-	-	21.07	2.61	20.72	2.62