Assortment Choice and Market Power under Uniform Pricing

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Abstract

This paper studies how retailers strategically use product assortment to respond to local market conditions when prices are set at the national level. When firms cannot increase the price of a product that is particularly popular in a local market, they can instead replace the product with a more expensive substitute. The profitability of these assortment substitutions depends on the degree of market competition. This study uses extensive receipt and store-level data and a structural equilibrium model to distinguish the impact of market power on assortment choice from other market forces, such as logistics costs. The findings confirm that firms make use of assortment choices, offering fewer and pricier products in markets with stronger local market power. I show that a uniform assortment would benefit consumers but would reduce firm profits. Counterfactual policy experiments reveal that government intervention can improve total market welfare through subsidies to consumers or retailers in remote areas.

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 much less focus on market power regarding non-price characteristics. Similar to prices, firms operating within imperfectly competitive industries have the ability to distort non-price attributes from socially optimal levels. Examples include delivery time in online shopping (Ater and Shany, 2021), product downsizing in the retail industry (Yonezawa and Richards, 2016), or, as the central focus of this paper, product selection in the grocery industry, where firms can deliberately restrict consumer choice in stores.

The importance of this issue has recently become apparent, as there is increasing evidence that multi-store retailers follow uniform pricing. Uniform pricing refers to the practice of 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 study focuses on the Norwegian grocery industry and demonstrates the use of uniform pricing in this context, even though many supermarkets have substantial local market power. In Norway, 22% of grocery stores are considered local monopolies with no competitors within a 5 km radius. This raises the question of whether grocery chains leverage their market dominance through non-price channels when prices are fixed. In this paper, I show that the choice of product assortment offered is one such possible channel and the strategic decisions regarding product assortment made by these firms can significantly affect consumer welfare.

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, then the first effect prevails. However, if competition is weak, reducing product assortment may be profitable. This example highlights how store managers can strategically make assortment decisions to maximize profits based on the level of local competition they face.

Informal discussions with industry experts indicate that the decision-making process occurs at two levels. First, each chain decides on product-level prices, and then regional and store managers make decisions regarding product selection. This two-tiered decision-making process provides informal evidence for the importance of the assortment channel and allows me to focus solely on assortment decisions while considering product-level prices as given. However, to rigorously investigate this process, I establish two key stylized facts. Firstly, I provide evidence that pricing decisions for individual products are made at the national level. Secondly, I show that product selection decisions appear to be made at the local level.

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

Based on the stylized facts, I develop and estimate an equilibrium model for the grocery market. On the demand side, I specify a spatial model where consumers decide which store to visit and how much to spend on groceries. In particular, I model how consumers weigh the travel distance against store characteristics, including assortment. On the supply side, chains decide on assortment in each store. The key tradeoff for a firm is that removing cheap products might discourage some consumers but increases the marginal profit from the remaining consumers. Since local market power tends to be more pronounced in certain areas, e.g. rural areas, where the distance between stores is large, so that consumers are unwilling to switch to a different store, this can result in substantial assortment differences across markets. Therefore, based on the model estimates, I quantify the welfare effects of assortment differences driven by local market power for consumers in different markets.

To measure assortment at a store level, I aggregate individual product items into a composite good. Each store is modeled as making choices regarding two assortment measures characterizing a composite good: *price*, which represents the price level of assortment offered, and *variety*, which quantifies the breadth of assortment. In particular, when designing the price of the composite good, I calculate the average expenditures on a typical shopping basket in each store, similar to Eizenberg et al. (2021). When measuring assortment breadth, I count the number of unique products offered in a particular store, consistent with the approach in previous studies (see, e.g., Argentesi et al., 2021; Kim and Yeo, 2021). Using a composite good, I can simplify the assortment analysis and capture the main factors influencing consumer's store choices, such as shopping costs and product selection.

The structural model builds on the novel approach of Ellickson et al. (2020), which allows spatially heterogeneous consumers to have location-specific choice sets and extends it by introducing an unobserved demand shifter. This framework differs from the conventional isolated markets' approach used in previous literature (Bresnahan and Reiss, 1991; Zheng, 2016). In particular, I employ a spatial discrete choice model that explicitly accounts for the distance between consumers and stores, allowing me to measure local competitive pressure more accurately. 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 structural unobserved store-level component, which is a significant improvement as it allows to separate unobserved store quality from the preferences of consumers residing in a particular location.

On the supply side, each chain makes store-level assortment decisions, determining the price and variety of composite goods to maximize chain profit. In order to account for the higher costs associated with offering a wider variety of products, I specify a cost function that accounts for logistics costs and store characteristics, including assortment breadth.

Since assortment variables could be correlated with the unobserved demand shifter, I have to address the endogeneity problem. To obtain consistent estimates of the model parameters, I employ instrumental variables and use the generalized method of moments (GMM) for estimation. In particular, I follow Houde (2012) and bring the Berry (1994) approach for inverting market shares to the spatial model of Ellickson et al. (2020). As instruments, I leverage differentiation and BLP instruments along with exogenous cost shifters. These instruments aim to isolate variation that drives the assortment decisions from the unobserved demand determinants while capturing competitive pressure. BLP instruments are designed to exploit observed characteristics of competing stores, while differentiation instruments are based on the distance between a store and its competitors in the characteristics space.

Based on the estimates of spatial demand model, I can revisit the market concentration discussion. Dealing with aggregated data, I do not observe grocery expenditure flows between consumers and stores and cannot evaluate the level of competition for all possible consumer locations. However, the model allows me to overcome this limitation and calculate market concentration for each consumer based on their specific location without making strict assumptions about the geographic boundaries of the market. This approach allows me to more accurately quantify local competition, even in small rural areas that would typically be aggregated into larger geographic regions, leading to potentially inaccurate competition assessment. In particular, spatial concentration is calculated based on choice probabilities predicted by the demand model. These localized concentration measures show that most markets in Norway are moderately concentrated (56%) or highly concentrated (41%), and only 3% are considered competitive.[1] Additionally, the market concentration is higher in rural areas compared to urban areas.

Next, the spatial demand model uncovers assortment inequality across different regions. Residents of large cities have access to more affordable groceries and greater variety, while consumers in remote markets face a more limited and pricier assortment.

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

Then, I use the model to conduct three counterfactual experiments. The first experiment is a synthetic one aimed at better understanding the current market equilibrium and quantifying the overall effects of assortment differences across markets. Specifically, I simulate a scenario where grocery chains adopt a uniform assortment strategy, meaning that stores of one chain provide the same composite good. I show that the uniform assortment scenario leads to an increase in the variety and price of the composite good. Additionally, I analyze the effects across different markets in detail. Interestingly, markets with higher concentration experience a relatively smaller price increase but a more significant increase in variety. This finding highlights the current assortment and welfare inequality between competitive and concentrated markets. While, on average, consumers benefit from the uniform assortment, the policy has only a minor effect on consumer inequality across various locations, primarily because consumers in remote areas continue to face higher transportation costs compared to urban residents.

Next, I show that varying assortment across markets is a profitable strategy for firms. If

[1] Standard cutoffs are used here. A market with an HHI of less than 1,500 is considered a competitive marketplace, an HHI of 1,500 to 2,500 is moderately concentrated, and an HHI of 2,500 or greater is highly concentrated.

firms were to provide an equal assortment instead, it would result in lower profits for firms and negative profits for some stores. Thus, imposing a uniform assortment is not a feasible solution due to store closures and reduced competition in some markets.

Therefore, I run counterfactual experiments designed to mimic realistic policies that could mitigate the distortionary effects of assortment choices. In the next counterfactual experiment, I explore the implications of reducing travel costs for consumers in remote areas. Reducing travel costs facilitates better access to stores, consequently enhancing competition in remote areas. Market concentration changes, leading to a lower number of concentrated markets and a higher number of competitive areas, putting downward pressure on prices and upward pressure on variety. As a result, consumer welfare and firms' profits increase by 11.4% and 5.6%, respectively. Considering the cost of implementation, the policy has a positive net welfare effect.

In the last counterfactual scenario, I examine the potential impact of subsidies to retailers in remote areas to compensate for higher logistics costs. The results show that such subsidies lead to a modest reduction in the price of the composite good by 1.92% and a slight increase in variety by 0.69%. This, in turn, leads to a 1.8% increase in consumer welfare and a 6.8% rise in firms' profits. Furthermore, the policy generates a positive net welfare effect, taking into account the costs of its implementation.

The paper speaks to the empirical literature that explores the effects of competition on non-price attributes. Although there is extensive literature on price-setting under imperfect competition, much less attention has been paid to the impact of competition on quality and non-price attributes in a more general sense. As with prices, firms in imperfectly competitive industries tend to deviate from socially optimal levels of quality, but unlike prices, the direction of this distortion is not clear (Spence, 1975). For instance, Crawford et al. (2019) and Fan and Yang (2020) show that under competitive pressure, firms tend to provide higher quality and higher prices than socially optimal. The literature also includes studies exploring the effects of mergers on product offerings in the market, such as the work by Mazzeo et al. (2018) and Sweeting (2010). Additionally, Matsa (2011) studies how competition affects quality in a grocery context, where quality is measured as the number of stockouts.

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 prices, suggesting that product selection is a strategic variable for retail chains. Similar to Argentesi et al. (2021), I find empirical evidence that product selection can vary locally. However, this paper differs from theirs in several aspects. First, I use a structural model to separate the impact of local competition from other forces that can impact product assortment decisions. Second, the structural model allows me to examine the effects of these assortment differences on consumers across various markets. Lastly, using the model, I simulate counterfactual experiments and propose policy insights on improving assortment in remote areas.

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

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

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

2 Data

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

The Norwegian grocery industry consists of four retail groups: NorgesGruppen (NG), Rema1000, Coop, and Bunnpris. As of 2018, these four corporations control 99.9% of the market.[2] Table 1 presents selected statistics for the Norwegian grocery market. Some of the retail groups have multiple chains representing different grocery formats. For example, the market leader NorgesGruppen has a discount format (Kiwi), a convenience store format (Joker), supermarkets (Spar), and high-quality supermarkets (Meny). Such differentiation allows for serving various consumer segments. Independent stores not belonging to the four listed retail groups constitute a small part of the market (less than 0.1%). Most of them are located in large cities and usually provide a specific assortment, such as imported products targeted at consumers with non-Norwegian backgrounds.

The data comes from multiple sources. The primary data source is receipt data from one

[2]Nielsen, Grocery report 2017

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

	Market share	Revenue	Number of stores
NorgesGruppen	42.5	72,614	1,734
Kiwi	20.4	34,892	646
Meny	10.8	18,428	193
Spar/Eurospar	7.1	12,054	282
Joker	3.6	6,156	448
Coop	29.6	50,469	1,114
Coop Extra	13.3	22,726	424
Coop Obs	5.6	9,523	30
Coop Prix	4.4	7,456	254
Coop Mega	3.9	6,716	75
Coop Marked	1.7	2,949	227
Rema 1000	24.1	41,153	589
Bunnpris	3.8	6,510	246
Total	100	79,215	3683

Note: Market shares are in percent, revenues are in million Norwegian krones. Numbers were retrieved from companies' annual reports.

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

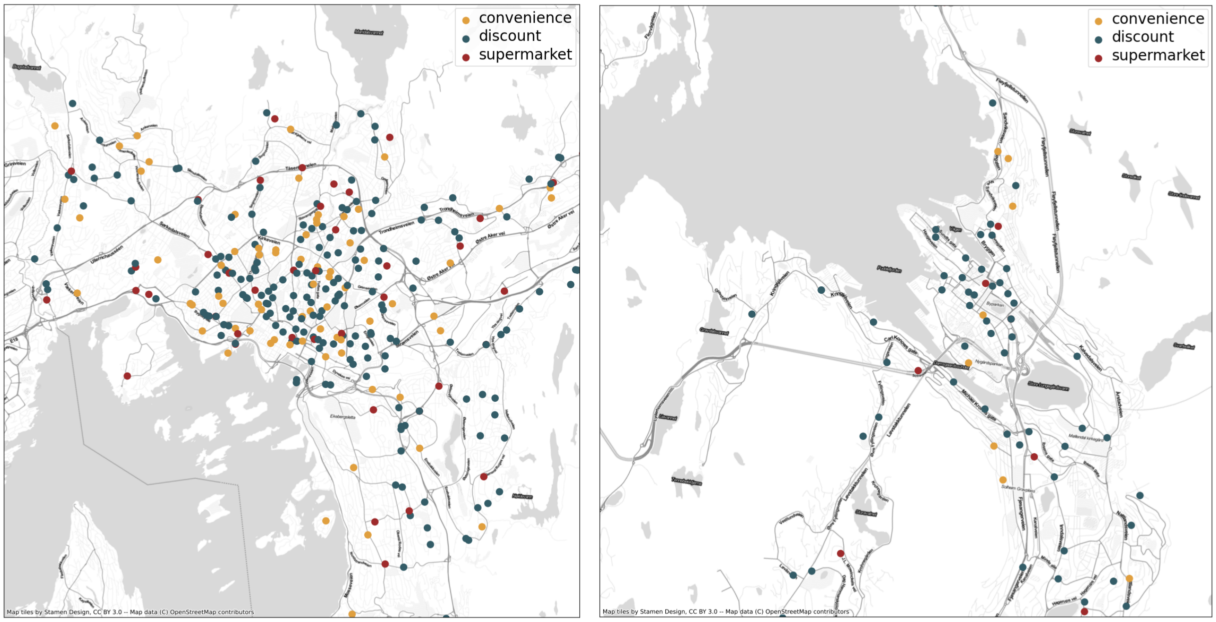
The second data source is a geocoded store-level panel provided by Geodata, a Norwegian spatial data provider. Geodata's database contains yearly information on store-level revenue for 2010-2021. Additionally, it includes information on location, store ID, store opening date, size, and the number of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

Table 2: Store-level descriptives, 2018

	Mean	SD	Min	Median	Max
Revenue (mln NOK)	48.39	51.43	0.07	39.71	1249.5
Number of employees	25.21	73.02	1	17	2304
Open hours	13.95	2.56	3	15	24
Open on Sunday	0.16	-	0	-	1
Location in mall	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 the two largest cities of Norway. I use the information on store locations 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 allows to link Geodata's database on revenues with the receipt data.



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

Figure 1: Location of stores

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).[3] To illustrate the spatial distribution, Figure 2 demonstrates how the two largest cities in Norway are divided into basic units. Table 3 reports descriptive statistics of demographic data at the basic unit level.

Similar to other scanner datasets, the receipts do not contain information on the residential location of consumers. Therefore, I need to assume which stores consumers can visit. 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 modeling procedure.

Table 3: Descriptive statistics of demographics data by basic units

	Mean	SD	Min	Median	Max
Area (km^2)	22.98	67.62	0.03	3.44	1805.21
Population	283.7	314.6	1	179	4272
Population density (people/km^2)	1248	29366	0.09	41.9	3472394
Average income (thou. NOK)	659.5	546.9	78.8	546.7	18000

Source: Geodata.

[3]Basic units are generally geographically smaller than zip codes. Basic units are similar to census blocks in the US.

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

Figure 2: Division into basic units

Composite Good

To document assortment differences across stores in Norway, I aggregate individual product items into a *composite good* representing a basket of groceries purchased by an average consumer. The composite good is characterized by price and variety measures at the store level. Using a composite good is common in industrial organization (Handbury, 2019; DellaVigna and Gentzkow, 2019; Eizenberg et al., 2021; Duarte et al., 2020) and urban economics literature (MacDonald and Nelson Jr, 1991) when one needs to compare multi-products 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 they are not subject to uniform pricing.[4] 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 allows calculating a price for a standardized product unit (for example, a kilogram of cheese or a liter of milk).

Following 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

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

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 relative total product revenue in the retail group as weights, so more popular products have higher weights in the category-level price. To estimate category costs, I multiply the revenue-weighted average by the average purchased units in the category or the *average basket*. Thus, the revenue-weighted average price for category c in store j is given by:

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

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

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

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

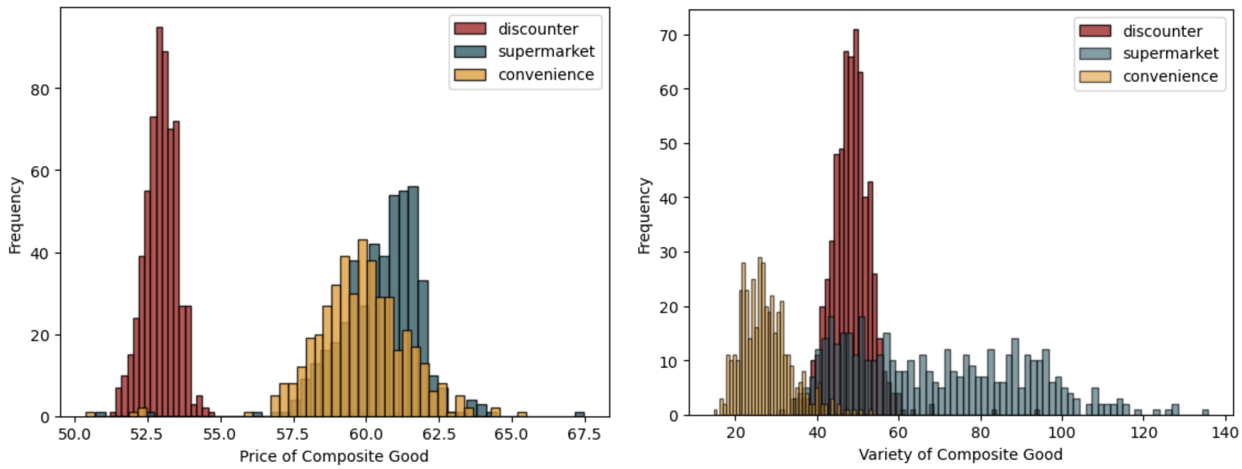
where C is the total number of categories.

To measure the breadth of assortment, I first calculate ν_{cj} as the number of unique products offered in category c of store j. Then following Argentesi et al. (2021), I define 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. First, they 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 within discount stores is more uniform in terms of price and variety measures compared with other formats. Convenience stores offer expensive but a more limited range of products. Finally, supermarkets exhibit greater variation in the assortment breadth compared to other formats.

Table 4 presents descriptive statistics for the price and variety of composite good across stores. Given that the receipt data is available only for one retail group, each format corresponds to a single chain. Additionally note that stores of one chain have the same prices for products. Hence, any differences in the price of composite good originates only from the difference in the product selection. Further notice that this price variation measured in the 95% confidence interval accounts for 10% of the average price of the composite good for convenience stores, 7% for discounters, and 9% for supermarkets, which can result in significant welfare effects. Variety differs noticeably across stores of one format, too. 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.



(a) Price

(b) Variety

Figure 3: Distribution of price and variety across chains

Table 4: Price and variety summary statistics

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

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 stockouts are assumed to occur randomly.

Furthermore, in Norway, retailers have three periods per year, so-called *launch windows* (in February, in June, and October), when chain managers can centrally introduce changes in the assortment. The data available for this study covers the period between these *launch windows*, leading me to assume that the chains did not alter their assortment during a given month.[5]

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

3 Stylized Facts

This section uses the data described before to present two stylized facts that support my model assumptions presented in the next section. First, I show that retail chains indeed follow uniform pricing. Second, 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 price differences in grocery prices in Israel. Given extensive receipt data available, I investigate whether there is variation in product prices within chains.

To begin, I visualize price variation both across all chains and within stores of one chain. Figure 4 illustrates that price deviations from the mean product price within stores of 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 of one chain.

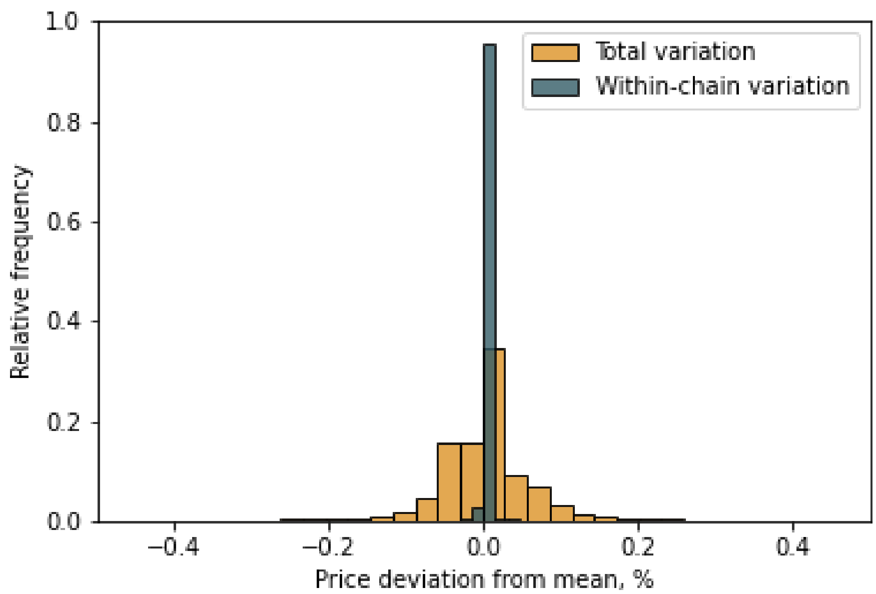


Figure 4: Price variation within and across chains
Note: One observation is one SKU in one store in one day

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 summarized 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 share of non-identical prices within all stores is

67.7% on average. While product prices within chains might differ due to store-specific sales or personal discounts, this variation remains relatively small.

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	107425	4.9	91.9
Fresh bread	81185	0.7	64.5
Beer	41188	0.8	52.3
Chocolade bars	33600	1.9	66.4
Dry bread	29109	1.0	48.4
Cheese	21944	1.1	61.6
Coffee	19046	6.0	78.4
Juice	18545	1.3	72.1
Frozen pizza	18483	0.8	47.5
Jam	15321	0.7	41.6
Frozen fish	13359	0.3	42.8
Yogurt	13327	2.1	60.9
Canned fish	8054	0.7	67.9
Eggs	3559	2.7	53.2
Total	424145	2.2	67.7

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

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

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

Columns I-III in Table 6 show results for different specifications, which vary by the size of the market. In particular, I define a market as the area within 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.

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

Following DellaVigna and Gentzkow (2019), the decision to employ uniform pricing can be attributed to several factors. While setting optimal prices for thousands of products is simply costly for a company, reputation and fairness concerns are often mentioned as an explanation for charging equal prices and seem the most plausible for the Norwegian context (Merker, 2022; Friberg et al., 2022).

Table 6: Assortment choice and competition

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

Assortment Responds to Changes in Local Market Conditions

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

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

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

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

The results are reported in columns IV-IX of Table 6. As the price of the composite good can vary only due to the assortment changes, these results indicate that assortment can differ within stores of the chain. In particular, after controlling for chain fixed effects, product selection responds to differences in local market conditions. Similar to the findings in Handbury (2019), I find that assortment decisions are correlated with income. Furthermore, product selection is influenced by store characteristics, such as location in the city center and location in a mall. Importantly, product selection is associated with the distance to the distribution center. Finally, local market power tends to play a role in product selection as well. For instance, when the 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 of 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. However, 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 studied earlier. The structural analysis below aims to disentangle the role of market power in choosing product offerings and quantify how this strategic product selection affects consumers residing in urban and remote areas.

4 Model of Spatial Demand and Assortment Choice

In this section, I develop a framework for investigating the role of local market power in assortment decisions. In particular, I specify an empirical model of consumer and firm behavior suitable for analyzing the grocery sector and the available data. In the model, spatially heterogeneous consumers choose a store to visit, taking into account store attractiveness based on its characteristics and the associated travel costs. Firms compete in the market for consumers via assortment decisions.

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 localized 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. To address these considerations, I leverage the flexible demand approach of Ellickson et al. (2020). This framework allows working with overlapping markets where each consumer has her own choice set instead of isolated markets as in Zheng (2016), Handbury (2019) or 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 to researchers and 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 postal office or parking lot. By explicitly addressing these considerations, I account for the potential endogeneity problem, which in turn enables modeling firms' strategic incentives regarding 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 Bjornerstedt and Verboven (2016). The discrete-continuous choice model offers a more suitable framework for modeling demand in the grocery shopping context than the standard unit demand specification. It allows consumers first to decide which store to shop at and then 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 characterized by p_j and ν_j. Consumer choice generates aggregate demand $q_j(p_j, \nu_j)$, representing the total quantity of the composite good sold in a store j. I assume that the demand arises from a discrete-continuous choice model in which consumers allocate a constant budget share $\varphi_{i(l)}$ of their income $y_{i(l)}$ to grocery shopping. Then, consumers decide in which store $j \in \mathcal{J}_{i(l)}$ to purchase a continuous quantity of grocery goods $q_{i(l)j}$. As highlighted in other studies of the grocery industry (Duarte et al., 2020; Eizenberg et al., 2021), this assumption appears to be more realistic for the grocery shopping setting as opposed to a 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 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 governs the relative importance of the utility from chosen alternative j and the utility from numeraire.

Then maximization of the conditional direct utility under a budget constraint $p_j q_{i(l)j} + z_i = y_{i(l)}$ gives 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 demand functions into the direct utility function, I derive the indirect utility function:

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

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

Finally, I define mean utility δ_j is 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 allows me to address the endogeneity issue that arises when retailers strategically choose certain characteristics, such as, in this case, the 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, this extension allows me to account for the strategic decision-making of retailers 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 a portion of their grocery budget outside of the observed stores:

$$u_{i(l)0} = \frac{\alpha}{\varphi_{i(l)}} \ln y_{i(l)} + \xi_0 + \epsilon_{i(l)0}, \tag{11}$$

where $\epsilon_{i(l)0}$ is a zero-mean individual store specific shock. The term ξ_0 is normalized to zero.

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

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

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

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

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

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

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

Note that data on y_l and N_l are immediately available from the demographics data. Meanwhile, the value for parameter φ_l I infer from the Survey of Consumer Expenditures published by Statistics Norway.[6] The survey provides information on 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

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

grocery expenses. Then, I assign each basic unit to an income decile based on its average income and utilize the corresponding φ_l value associated with that decile. By incorporating this information, I can account for the variations in consumer behavior and expenditure patterns across different income levels without estimating φ_l.

Estimating φ_l would require an additional structural error at the basic unit level and an additional set of moment conditions. However, an unobserved component driving grocery expenditures in a specific location would contradict the assumption that consumers spend a constant fraction of their income on groceries. In the constant expenditure specification, consumers can have different grocery expenditures across basic units, but these differences should be explained either by differences in income y_l or the fraction of income allocated to grocery spending φ_l. As a result, the model does not incorporate an unobserved component in grocery expenditures, ensuring that the assumption of constant expenditure holds.

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. Next, I describe the steps required to transition from individual choices to observed store-level market shares.

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

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

To connect the observed store 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:

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

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

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

I assume that the consumers' choice set consists of all stores within a 30 km radius from the centroid of the basic unit and the outside option. Since the demand model has an explicit disutility of distance, which should account for consumers' preferences to shop in closer stores, the choice of a particular radius is not critical here. Rather, it has to be no less than how consumers are willing to travel.

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

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

Note that the current specification of the model does not account for unobserved heterogeneity beyond standard logit error. While theoretically, it is possible to incorporate random coefficients into the model to address this limitation, the practical implementation becomes computationally burdensome due to the large number of locations involved (more than 13 thousand) and numerous stores.

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. Then, in the second stage, they select the assortment for each store, taking product-level prices as given. The supply model in this study focuses on the second stage of this decision process.[7]

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

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

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

Then the multi-store firm's maximization problem can be represented as follows:

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

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

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

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

The first-order conditions for profit-maximizing firm over price and variety are:

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

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

Firms engage in Bertrand competition simultaneously choosing price and variety of the composite good.

[7] It is important to note common ownership among some retail chains. Some retail chains are part of a retail group with access to the same producers and shared distribution channels. However, despite this joint ownership, each chain negotiates different purchase prices. Moreover, each chain has its own management and operates independently, treating other group chains as competitors rather than as own-firm stores. Therefore, in the supply model, each chain maximizes its profit independently from other chains within the retail group.

5 Identification and Estimation

In this section, I describe the identification and estimation of demand and supply-side parameters. Estimating demand-side parameters can be problematic due to the endogeneity issue, which is here related to price and variety measures of assortment. Since demand-side shocks realize before the decision on assortment is made, price and variety can be correlated with unobserved demand shocks. Therefore, instruments are needed to account for the endogeneity issue. To estimate the structural parameters governing consumer preferences $\{\alpha, \gamma, \beta, \rho\}$, I employ the two-step approach developed in Berry (1994) and incorporate the observed spatial consumer heterogeneity similar to Davis (2006). By solving the supply-side first-order conditions for a particular set of demand-side parameters, I can estimate $\widehat{mc}_j$ and $\partial\widehat{mc}_j/\partial\nu_j$. Finally, I estimate the supply-side parameters θ_s. Similarly to the demand model, supply-side shocks can potentially correlate with cost-shifters. Therefore, I need to account for potential endogeneity issue in the supply model by employing instrumental variables and using the GMM procedure for estimation. The rest of this section provides details of the estimation procedure.

Demand

To estimate demand-side parameters $\theta_d = \{\alpha, \gamma, \beta, \rho\}$, I begin by selecting an initial value for ρ. Then, I iteratively update the store's mean utility vector, δ, until it converges, using a similar process 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.

Once the vector δ is obtained, the parameters $\{\alpha, \gamma, \beta\}$ governing preferences for price and variety of the composite good and other observed store characteristics can be identified. Here, I assume that not only price but also variety can correlate with the unobserved store quality. Therefore, I use differentiation instruments proposed by Gandhi and Houde (2019) to address this endogeneity issue.

Differentiation instruments are variants of the common BLP instruments and represent differences between own and rival store characteristics. The basic idea is to use each product's exogenous degree of differentiation — in this case, each store in a market — as instruments for price and variety. In particular, 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 in a 2 km and 5 km radius. 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 available only for one retail group. To address this, I define a missing indicator d_j that equals one if store j has information about price and variety and zero otherwise similar to Duarte et al. (2020). Then, the model is 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 last step, I recover the distance cost parameter ρ. Since store location is simply a product characteristic, the estimates will suffer from the standard endogeneity problem if retailers choose it strategically. If, for instance, stores with high ξ_j are located closer to densely populated areas, such that the average travel distance is low, then $\mathbb{E}[d_j \xi_j] < 0$. To correct for this source of endogeneity, one needs to find an instrument that is correlated with the store location or distance to competitors and is not influenced by the store's unobserved factor. For this purpose, I use the average distance to consumers weighted by population for neighboring stores. I define neighboring stores as those within a 1-km radius that can be perceived as immediate competitors. Then under the assumption $\mathbb{E}[\xi_j | Z_j^d] = 0$, parameter ρ is 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

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

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

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

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

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

The vector $\boldsymbol{\omega}_j$ includes characteristics that can potentially affect the costs of running a store, such as the number of employees and whether the store is located within a mall. Marginal costs are allowed to depend on the retail group of a store, as different retail groups might have different input prices. The retail group also determines the distance of a store to a distribution center, which is relevant in counterfactual experiments where the market structure can change.

One also needs to control the assortment's quality in the marginal costs as, for example, better products tend to have higher input prices. Since direct data on assortment quality is unavailable, I infer the assortment quality from the unobserved component of the demand model ξ_j.

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

Equation 22 solely allows to back out the marginal costs mc_j. Having a functional form for mc_j in Equation 25 and first-order conditions for variety ν_j in Equation 23, I can obtain estimates for $\partial\widehat{mc}_j/\partial\nu_j$, which are used to compute c_{0j} and c_{1j}:

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

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

I estimate the vector of supply-side parameters θ_s using GMM, which accounts for the fact that the unobserved store characteristics ξ_j included in $\boldsymbol{\omega}_j$ might be correlated with the unobserved cost component ζ_j. I employ BLP instruments constructed based on ξ_j's of neighboring stores belonging to the same chain, having the same format, or being part of the same retail group. Then, the identification of parameters relies on a GMM procedure where equations 27-28 serve as constraints for the minimization problem.

6 Estimation Results

In this section, I present the estimation results of the demand 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. This allows me to explore the relationship between assortment differences and variations in market concentration.

Next, I discuss the findings of the supply model. Specifically, the model provides estimates of marginal costs and markups for each store. Moreover, I 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 summarizes results for the spatial demand model. Both the price and variety coefficients have the expected sign and are statistically significant. As expected, consumers are averse to traveling long distances to stores, reflecting the costliness and inconvenience associated with longer travel. Consumers show a strong preference for supermarkets over discounters and favor stores located in shopping malls.

Localized Concentration and Assortment Measures

The empirical framework of the demand model allows to calculate localized 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

Table 7: Demand parameters estimates

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

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

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 localized 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 observed in the data and can be recovered only from the model. Then, I use $\mathbb{P}_{lj}$ to calculate HHI for each location. The distribution of these localized concentration measures across basic units is illustrated in Figure 5. The analysis reveals that most markets in Norway are moderately concentrated (56%), 41% are highly concentrated, and only 3% are considered competitive. Figure 6 shows the spatial distribution of market concentration for Vestland, a region in Norway. The key finding is that the area around Bergen is predominantly competitive, with a lower concentration level. However, as we move away from Bergen towards more rural areas, the level of concentration gradually increases.

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

Additionally, the estimated demand model allows revisiting assortment inequality across different regions. As before, the demand model allows me to compute the probability that a resident of location l visits store j, $\mathbb{P}_{jl}$. Then, I can calculate the Average Assortment Consumed for each location l in terms of price (AAC_l^P) and variety (AAC_l^ν). Specifically, 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 behavior of consumers.

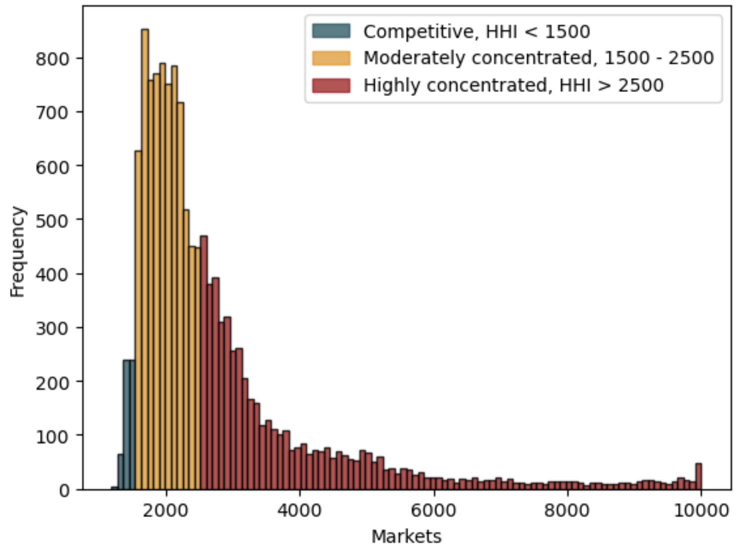


Figure 5: Distribution of localized concentration measures

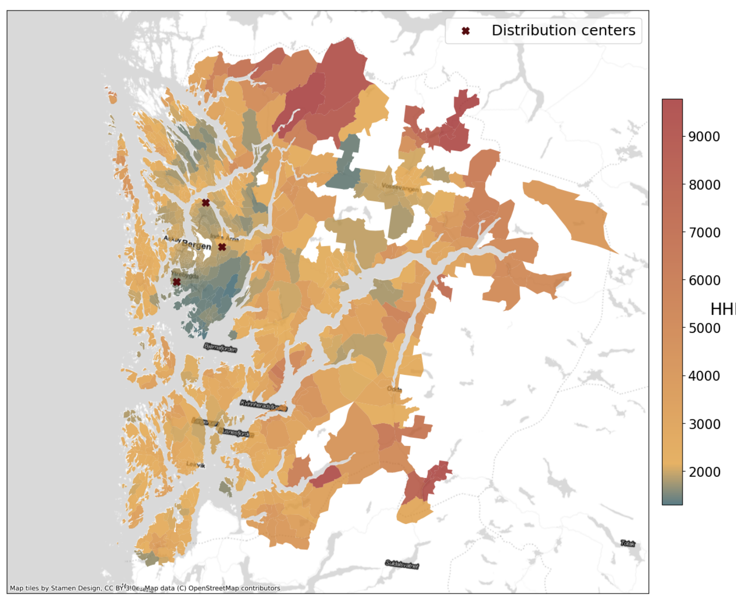


Figure 6: Spatial distribution of market concentration

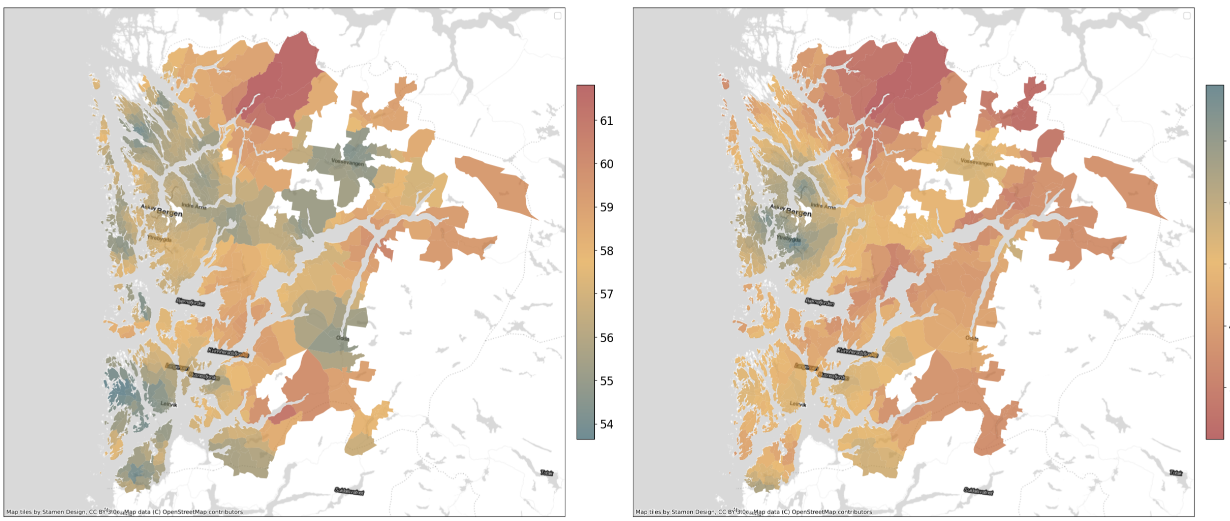
Table 8: Market concentration comparison

		Localized HHI			
		Competitive	Moderately Concentrated	Highly Concentrated	**Total**
Municipality-based HHI	Competitive	331	283	85	699 (5.2%)
	Moderately concentrated	69	5405	1466	6940 (51.5%)
	Highly concentrated	29	1857	3950	5836 (43.3%)
	Total	430 (3.2%)	7552 (56.0%)	5502 (40.8%)	

Note: One observation is one basic unit.

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 with a greater variety. At the same time, residents of rural areas have a limited assortment and lack access to cheap products. These results, along with the localized 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, one can notice that more concentrated markets have more expensive assortment (the correlation between HHI and AAC_l^P is 0.12). Conversely, the plot shows a negative monotonic relationship for variety: consumers in competitive markets enjoy a higher variety of products (correlation between HHI and AAC_l^ν is -0.33).



(a) Price

(b) Variety

Figure 7: Average assortment consumed

Supply

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

Table 10 reports the marginal cost function estimates. As expected, providing higher variety and quality is costly for a retailer. Other estimates of the supply-side function also have expected signs. The further the distance to the distribution center, the more expensive it is to transport goods. It is more costly to have a store in a shopping mall. Stores open

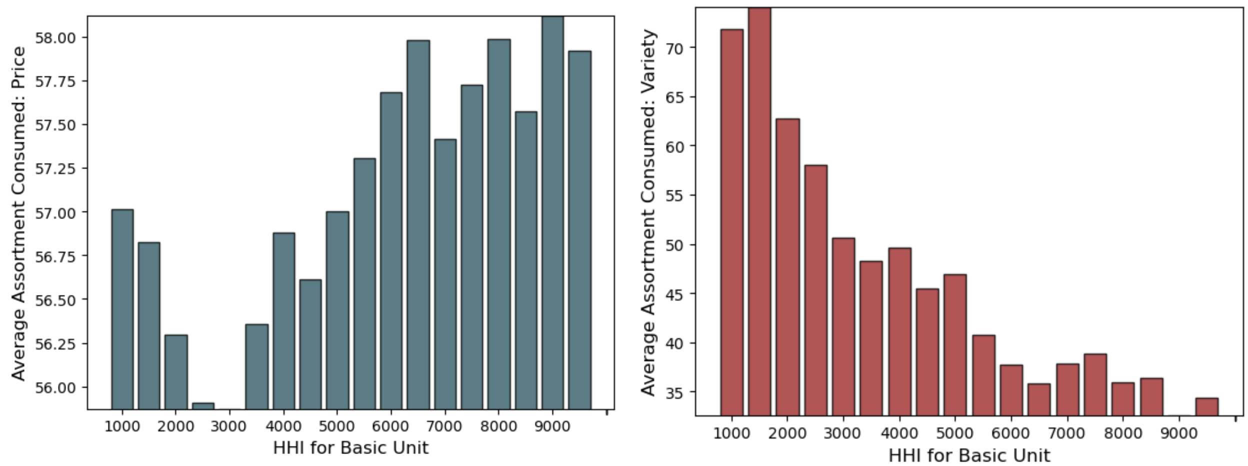


Figure 8: Average assortment consumed and market concentration

Table 9: Summary statistics for costs and margins

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

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

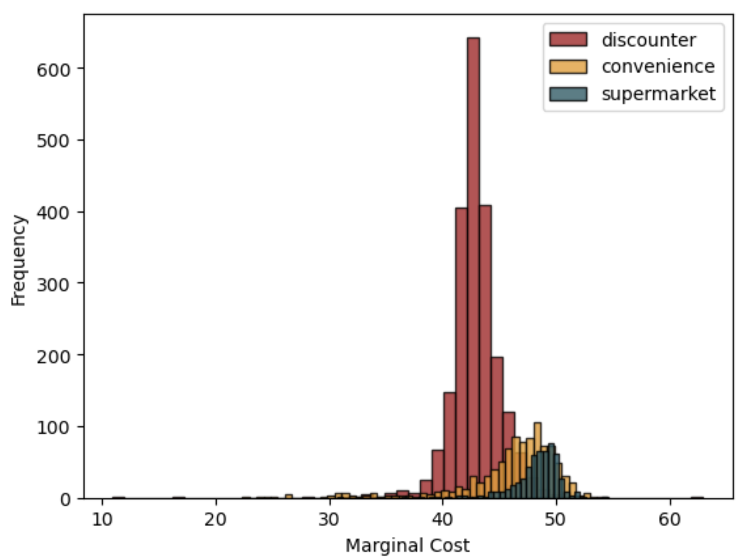


Figure 9: Distribution of marginal costs across formats

on Sundays have higher marginal costs, as by Norwegian legislation, they must pay higher taxes. Supermarkets have higher marginal costs than discounters and convenience stores as they usually have more employees. Larger retail groups have lower marginal costs, which lower input prices and economies of scale could explain. The negative effect of store size and the number of employees could also be attributed to economies of scale.

Table 10: Marginal Cost Function Parameters

Variable	**Estimate**
Const (c_0)	3.645
	(0.137)
Variety (c_1)	0.037
	-
Other observed cost shifters	
Quality of assortment	0.029***
	(0.004)
Supermarket	0.291***
	(0.039)
Number of employees	-0.019***
	(0.001)
Mall	0.276***
	(0.056)
Liquor store	-3.465***
	(0.429)
Open hours	0.008
	(0.006)
Sunday	1.278***
	(0.145)
Costs of toll roads to dist.center	0.002**
	(0.001)
Store size	-0.626***
	(0.026)
Retail group A	0.378***
	(0.043)
Retail group B	-0.029
	(0.025)
Retail group C	0.159***
	(0.032)
# of obs.	3639

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

Once the marginal costs are estimated, it is possible to calculate the profit of each store. The demand model allows for a more detailed analysis and allows to calculate the contribution of each location to each store's profit. Then summing over stores, one can calculate the total profit of grocery stores generated by consumers of location l:

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

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

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

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

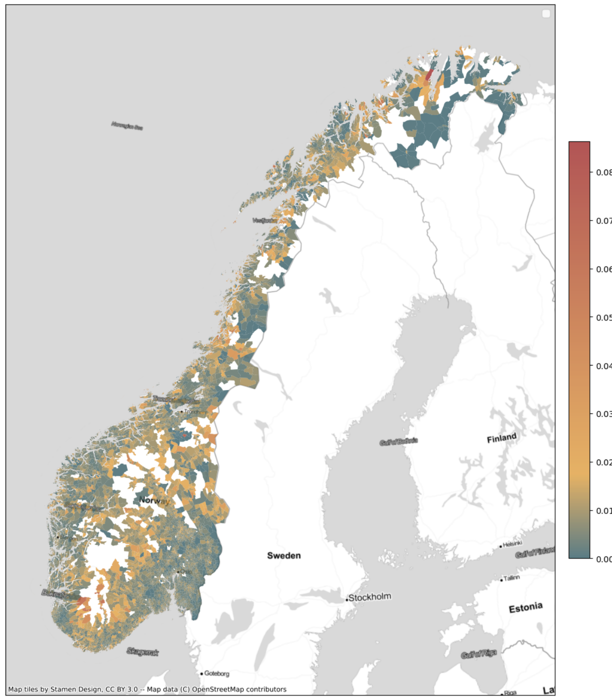


Figure 10: Spatial distribution of profit per person

7 Counterfactual Analysis

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

Assortment Inequality

In the spatial demand model, Figure 7 sheds light on the assortment inequality across different locations. It indicates that consumers in concentrated areas face limited and more expensive product variety. Figure 10 further emphasizes 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 maximize their profits.

Further, I use a compensating variation metric to compare consumer welfare across different locations. To measure consumer welfare in the benchmark equilibrium, I calculate the

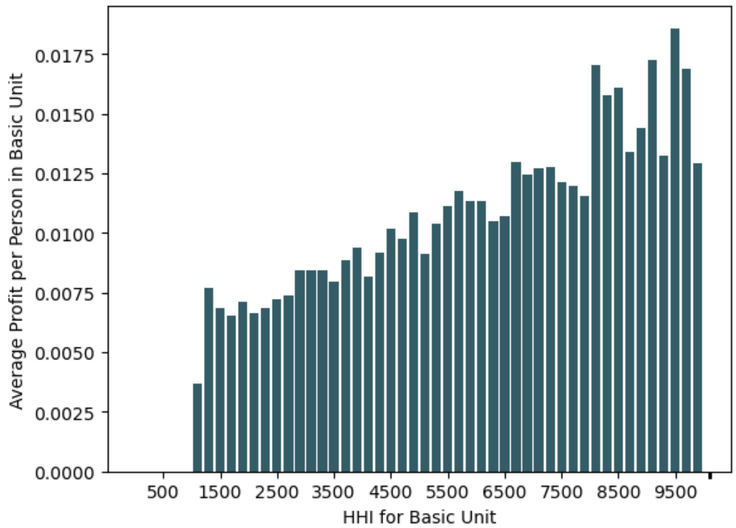


Figure 11: Profit per person and market concentration in basic unit

compensating variation between the benchmark equilibrium and an alternative environment where only the outside option is available. Following the approach by Atal et al. (2022), I define compensating variation for consumer i residing in location l as:

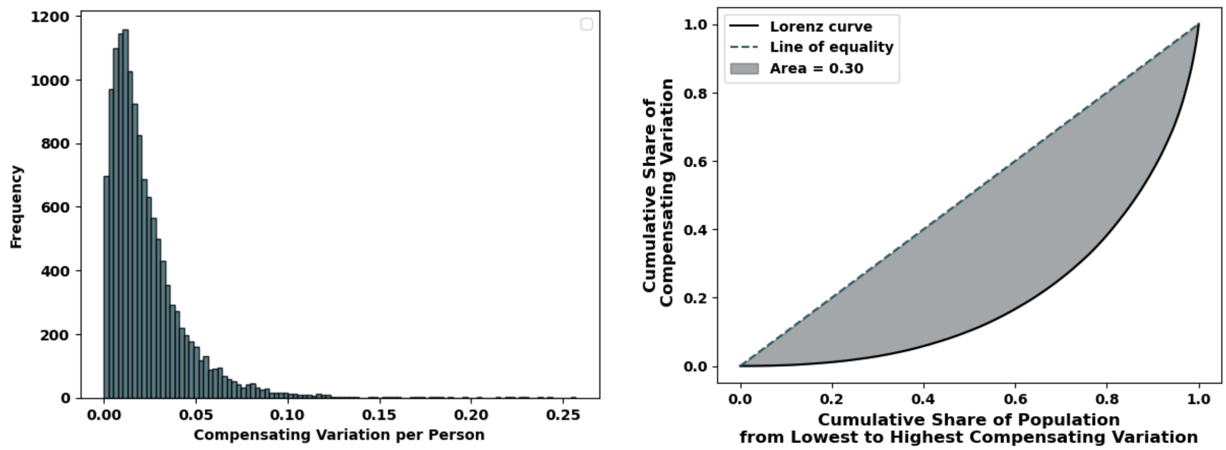
$$\max_{j} u\left(y_i, \delta_j, d_{lj}, \epsilon_{i(l)j}\right) = \max_{j'} u\left(y_i - CV_i, \delta_{j'}, d_{lj'}, \epsilon_{i(l)j'}\right). \tag{31}$$

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

Counterfactual Policies

For illustrative purposes, the counterfactual analysis focuses on the Vestland region with the center 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 centers 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. Regarding consumer distribution, Bergen is classified as an urban and densely populated area, with a population density of 650.2 people per square kilometer as of 2023. Conversely, there are rural neighborhoods in Vestland where the population density can be as low as 0.69 people per square kilometer. Figure 13a illustrates the population density of Vestland.

Additionally, Vestland has relatively low income inequality, measured in average income across basic units, similar to the overall trend in Norway. Figure 13b shows the spatial



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

Figure 12: Inequality in consumer welfare across locations

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

distribution of income across municipalities in Vestland, with most municipalities having similar income levels. Thus, Vestland presents a relevant setting for studying assortment decisions across different markets.

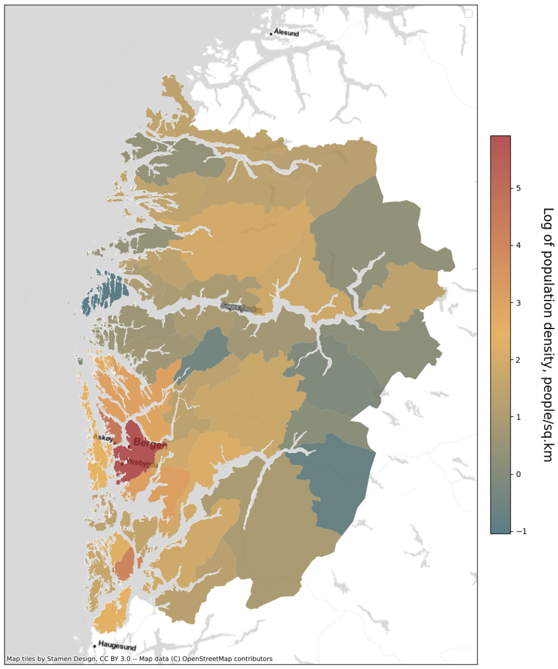
Welfare Analysis of Local Assortment. To quantify the welfare effects of the local assortment, I compare the observed assortment with a counterfactual scenario where chains adopt a unified assortment strategy, offering the same bundle of groceries across all their stores. Then the maximization problem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

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

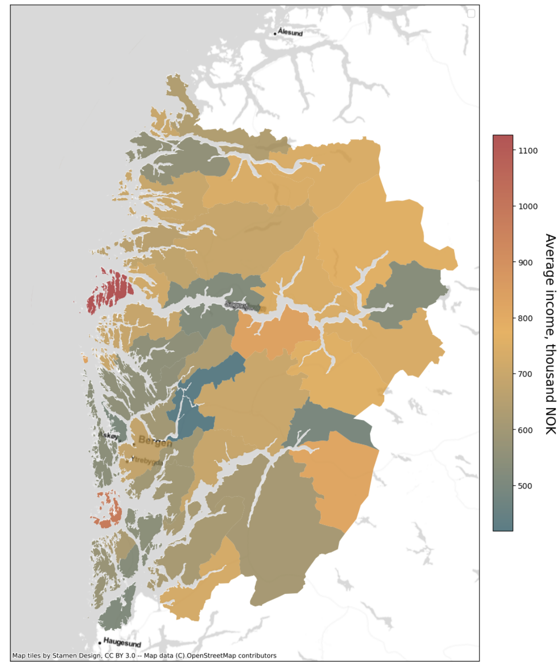
Using the first-order conditions for the problem 32, I calculate each firm's new equilibrium price and variety of the composite good. Under uniform assortment, stores offer a wider range of products, resulting in an 11.1% increase in variety. However, this also leads to an average 5.5% increase in the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

To further understand the welfare implications, I explore how the uniform assortment policy affects markets with different market concentration. Figure 14 provides a summary of the results, with basic units sorted by the baseline HHI. Across all markets, there is a rise in both the price and variety of AAC. However, markets with higher concentration experience a smaller increase in price and a more significant increase in variety compared to competitive markets. This result indicates that in the benchmark equilibrium, retailers offer limited and pricier assortment in concentrated markets.

To measure consumer welfare, I use compensating variation between the counterfactual scenario and the benchmark equilibrium. As anticipated, the uniform assortment positively

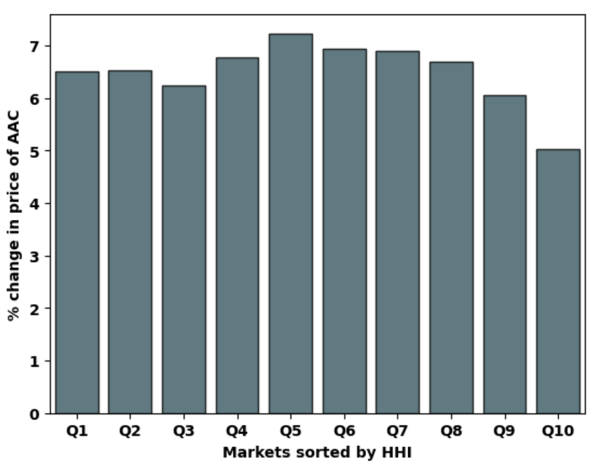


(a) Population density

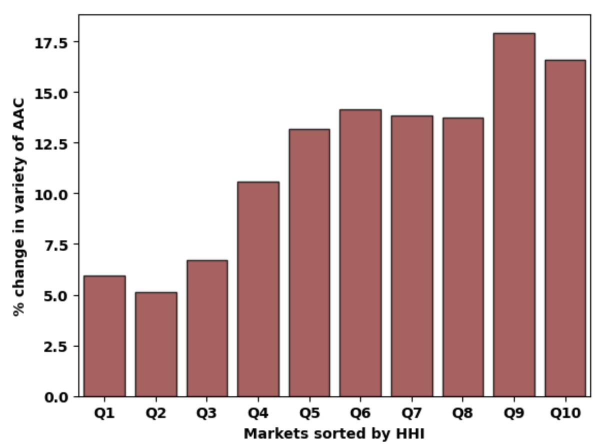


(b) Average income

Figure 13: Vestland



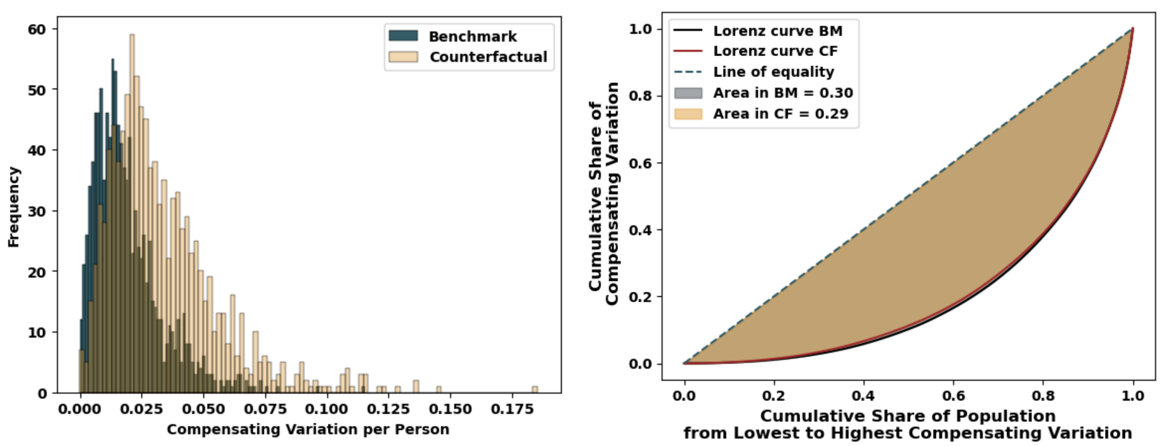
(a) Effect on price



(b) Effect on variety

Figure 14: Average assortment consumed and market concentration

affects consumers, resulting in a remarkable increase in total consumer welfare, amounting to 7756 MNOK. The impact of the policy intervention on the distribution of consumer welfare per person is illustrated in Figure 15a. Additionally, Figure 15b illustrates that while the policy benefits consumers, it does not significantly reduce consumer inequality. Although grocery chains offer an equal assortment across stores, the policy does not address the limited availability of stores in remote markets. Consequently, consumers in these areas continue to face a limited choice of stores and higher transportation costs compared to residents of urban areas. This highlights that different interventions would be necessary to address the disparities in consumer welfare across locations.



(a) Consumer welfare

(b) Lorenz curve

Figure 15: Change in consumer welfare due to uniform assortment

The implementation of the uniform assortment policy has a detrimental effect on firms. The industry's total profit declines significantly by 8417 MNOK, and a substantial portion of stores, 28%, experience negative profits in the counterfactual equilibrium. This indicates that the policy adversely affects the profitability and viability of some retail outlets.

While consumers benefit from the uniform assortment in the short run, the overall impact on welfare is negative, with a reduction of 660 MNOK, representing a decrease of 4.5%. The decline in profits and the risk of stores becoming unprofitable could lead to store closures in the long run, which would further exacerbate market concentration. With fewer active stores, consumers in certain regions may face even more limited options and potentially higher prices, ultimately deepening disparities in consumer welfare among different regions. This reinforces the need for a more nuanced approach to tackle assortment inequality.

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

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

Table 11: Change in Market Concentration

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

Note: One observation is one basic unit.

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

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

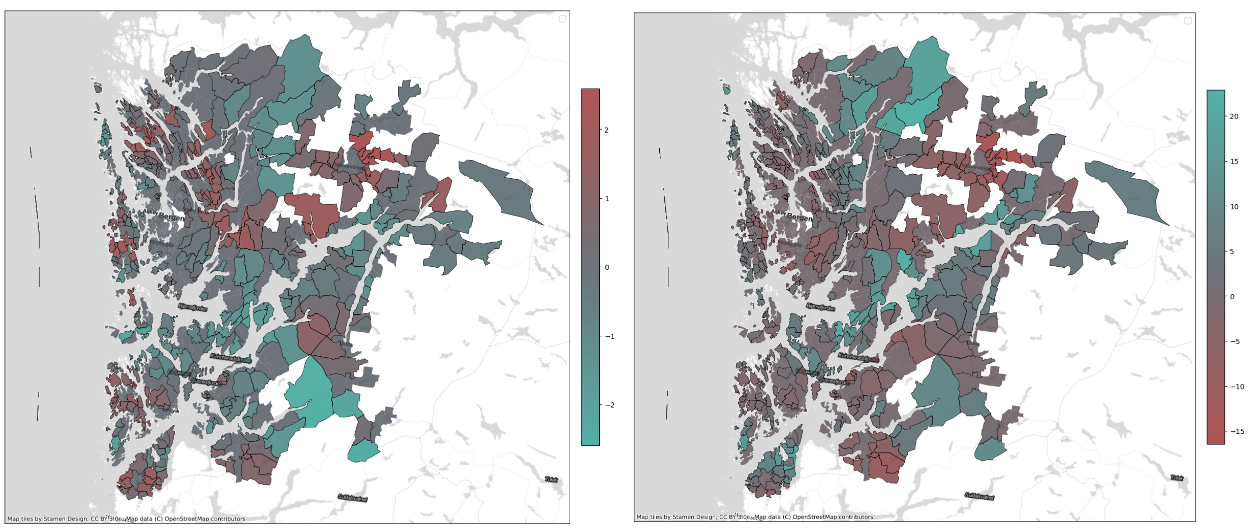
To explore this idea, I compare each store's average choice-weighted traveled distance between the benchmark equilibrium and the counterfactual scenario. To compute the average choice-weighted traveled distance, I aggregate the distances traveled from different markets to the store weighted by the choice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

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

This creates a counterbalancing effect that reduces, and sometimes even neutralizes, the competitive pressure exerted on price and variety.

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

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

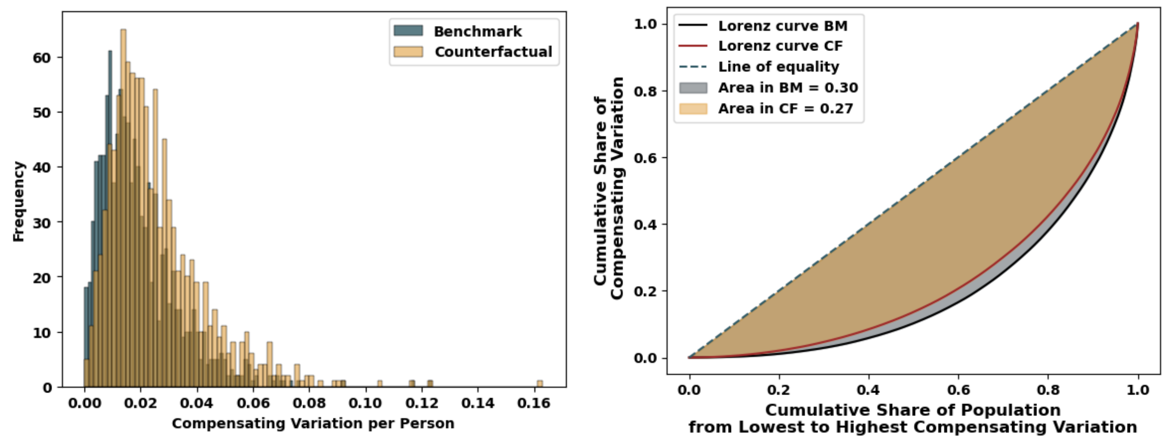


(a) Effect on Price

(b) Effect on Variety

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

As expected, the policy positively impacts consumer welfare, resulting in a substantial increase of 11.4% or 1261 MNOK. Figure 17a demonstrates how the distribution of consumer welfare per person changes due to the policy intervention. The Gini index for the counterfactual scenario illustrates a modest improvement in consumer inequality. The changes are visually depicted with the Lorenz curve in Figure 17b.



(a) Consumer welfare

(b) Lorenz curve

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

The policy also has a positive impact on firms. The industry's total profit increases by 215 MNOK, equivalent to an improvement of 5.6%. The total welfare gain from the policy calculated as a sum of the change in consumer welfare and change in profits amounts to 1476 MNOK, equivalent to an increase of 9.9% compared to the benchmark equilibrium.

Furthermore, I compute the policy cost as the sum of transfers the government needs to provide to consumers residing in remote regions to offset fifty percent of their travel disutility. In other words, for consumers in remote locations, the transfer is defined as follows:

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

where $j = \arg\max_k u(y_{i(l)}, \delta_k, d_{lk}, \rho^{BM})$, ρ^{BM} represents the parameter for travel disutility in the benchmark equilibrium, and ρ^{CF} is the parameter for travel disutility in the counterfactual scenario. After aggregating the transfers across markets, the total cost accounts to 1198 MNOK.

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

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

which includes the compensating variation for consumers $CV_{i(l)}$ and the change in firms' profits $\Delta\Pi_j$. The last term stands for the cost of the policy, which is the total amount of transfers to consumers $T_{i(l)}$ adjusted by the Marginal Cost of Public Funds (MCPF) specific to Norway. By multiplying the transfers by the MCPF, I account for the deadweight loss that may arise due to government interventions leading to inefficient allocation of resources. The value of MCPF is adopted from the guidelines outlined in the Principles for profitability assessments in the public sector (NOU 1997:27).[8] As a result, the net welfare effect sums up to 38.4 MNOK. The policy demonstrates promising outcomes for consumers and firms, contributing to an overall improvement in total welfare.

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

Although this counterfactual experiment is rather conceptual and not meant to simulate specific policies, it bears some policy relevance. In 2022, a similar policy was implemented in France as a way to support residents of remote regions who were particularly affected by the energy crisis.[9] The government introduced an energy cheque scheme aimed at compensating for increased travel costs. The policy was specifically targeted at the residents of remote areas.

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

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

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

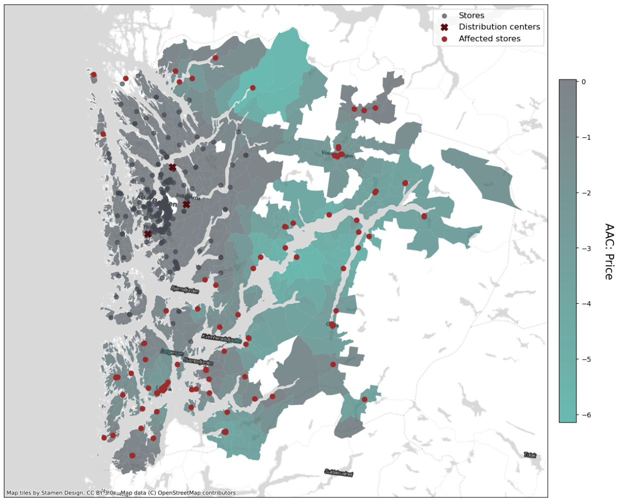
The policy exhibits a modest positive impact on consumer welfare, resulting in a slight increase of 1.8% or 199 MNOK. Figures 19a and 19b show that the policy's effectiveness in addressing inequality is limited. Despite the positive changes in consumer welfare, the policy does not significantly contribute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

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

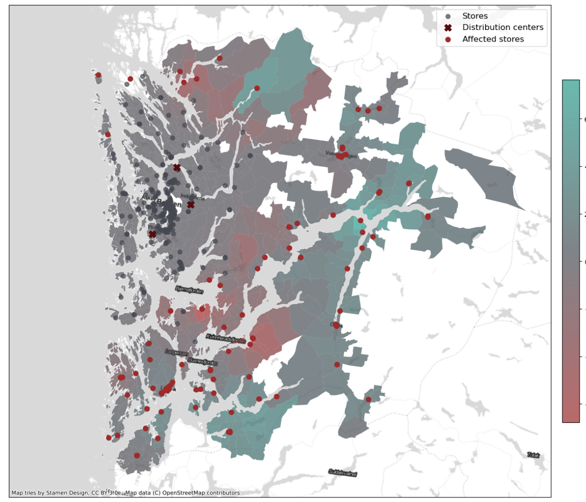
Additionally, I calculate the policy cost as the product of the number of composite goods purchased in the subsidized stores and the subsidy granted, which is equal to 10% of the marginal costs for each particular store. The resulting cost of the policy is 307 MNOK.

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

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

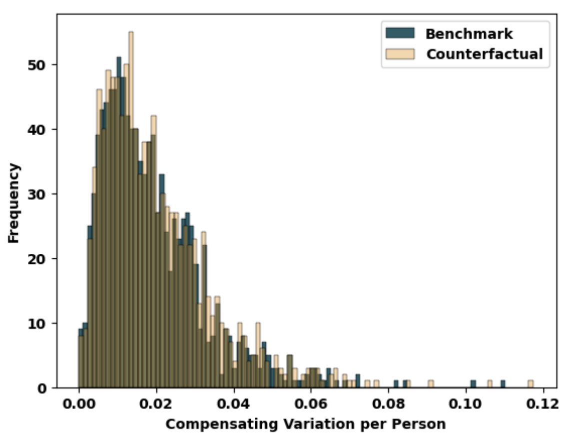


(a) Effect on price

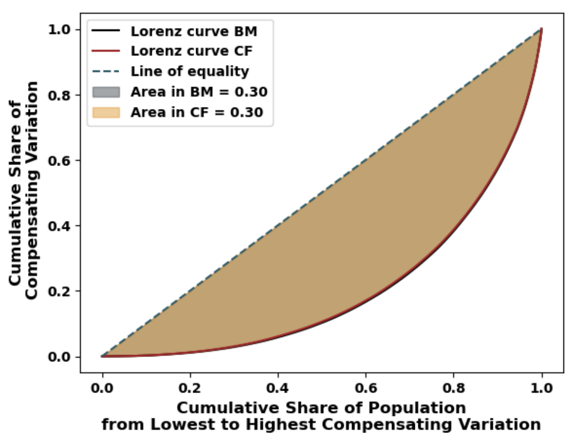


(b) Effect on variety

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



(a) Consumer welfare



(b) Lorenz curve

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

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

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

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

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

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

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

8 Conclusion

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

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

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

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

Another aspect that remains outside the scope of this study is the choice of formats. When entering new markets, retail groups strategically choose a store format. The 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 analyze 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 format choice to gain a comprehensive understanding of the competitive landscape. This would allow exploring policies to stimulate more entry into remote markets that would improve competition and reduce inequality in store access.

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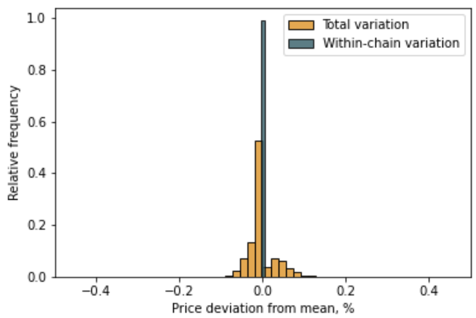
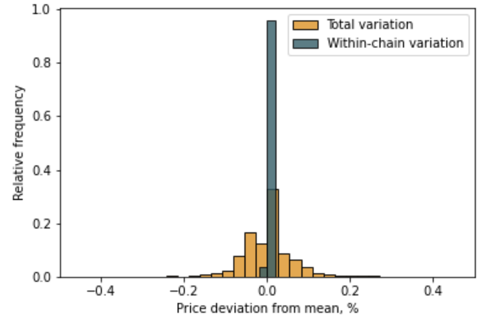
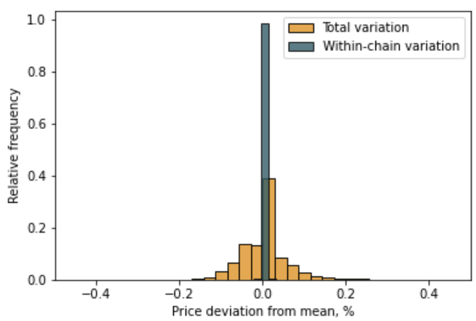
Appendix



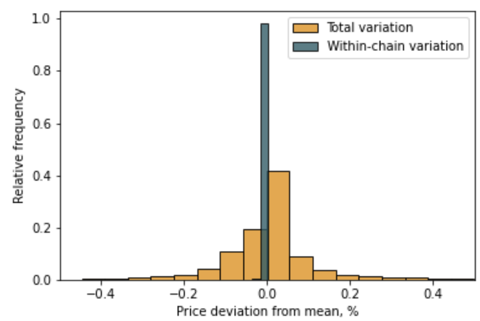
(a) Beer



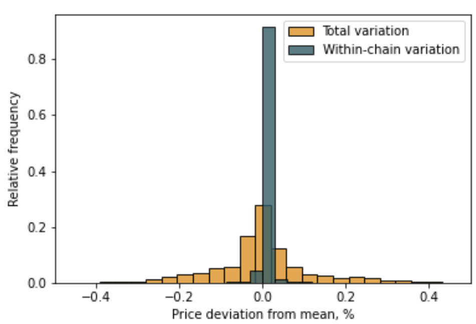
(b) Canned fish



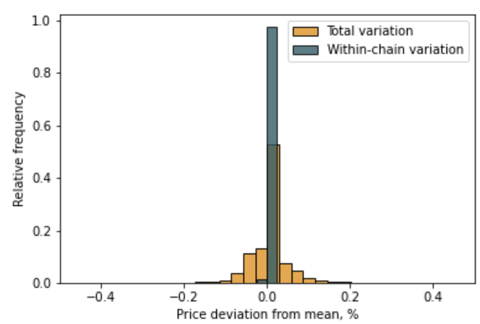
(c) Cheese



(d) Chocolate bars

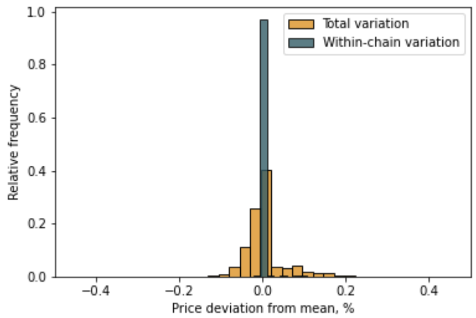


(e) Coffee

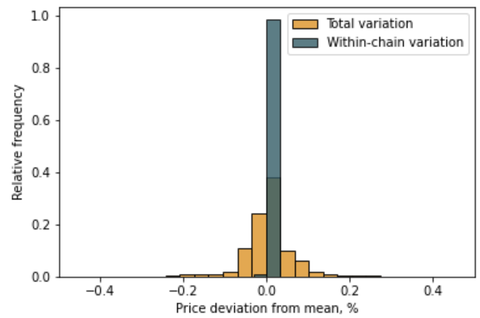


(f) Dry bread

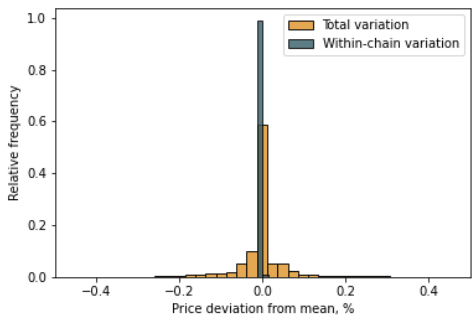
Figure A.1: Price variation within and across chains in different categories (first 6 categories)



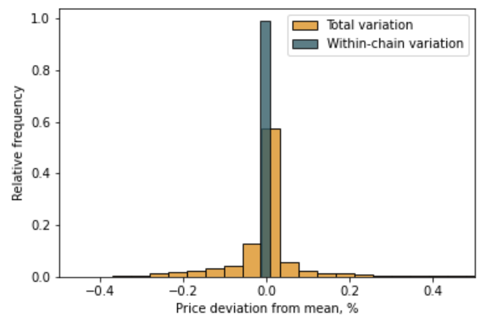
(a) Eggs



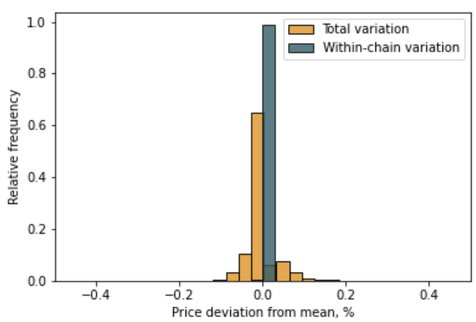
(b) Fresh bread



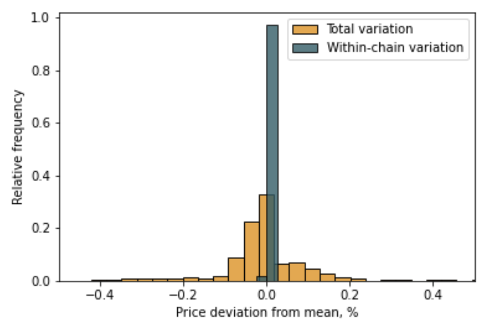
(c) Frozen fish



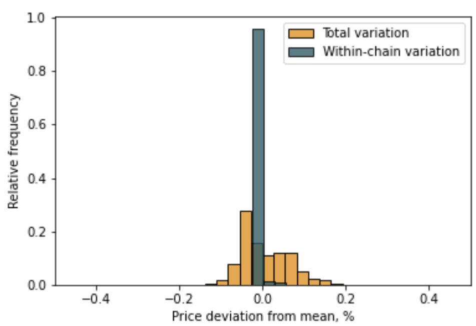
(d) Frozen pizza



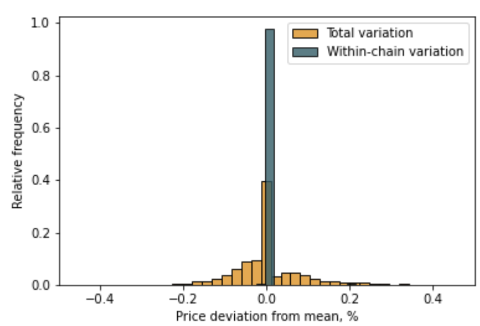
(e) Jam



(f) Juice



(g) Milk



(h) Yoghurt

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