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Restrictive covenants in the Norwegian grocery market: An empirical study

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NORWEGIAN SCHOOL OF ECONOMICS

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Abstract

The Norwegian grocery market has long been characterized by high concentration, posing significant barriers to entry, elevated prices, and limited product selections compared to other European countries (Norwegian Competition Authority, 2022). A key contributing factor to this phenomenon is the use of restrictive covenants by grocery chains, aimed at inhibiting the establishment of competing grocery businesses on certain properties, even following changes in ownership (Ministry of Industry and Fisheries, 2022). Motivated by the newly enforced ban on restrictive covenants issued for anti-competitive purpose, this thesis investigates the extent to which restrictive covenants were used by grocery chains and their impact on the structure of the Norwegian grocery market, focusing on market concentration at the local market level and store distances and turnover at the store level. To our knowledge, no other studies have empirically estimated the impact of restrictive covenants on the grocery market in Norway. Our thesis aims to provide empirical evidence relevant to this policy change, i.e., the ban on restrictive covenants.

Using a dataset of covenants registered in the Norwegian land registration ("Grunnbok"), we identified 568 restricted locations covered under 215 registered documents that are relevant to one of the four main grocery chains. With these identified restrictive covenants, the study employs the Two-Stage Least Squares estimator to estimate the relationship between the number of restrictive covenants imposed by grocery chains within each local market and the market concentration level. Additionally, it uses the standard Ordinary Least Squares estimator to quantify the relationship between the number of same-chain restrictive covenants and store turnover, as well as between the number of same-chain restrictive covenants and store-to-competitor distances. Our models control for various factors related to market characteristics and store attributes. Our results indicate that a higher number of restrictive covenants is associated with higher market concentration and higher store turnover. However, we cannot draw conclusions about the impact of restrictive covenants on store distances.

Keywords – NHH, master thesis, economics, grocery retail, competition, entry barriers, restrictive covenants, market concentration, HHI

Contents

List of Figures

List of Tables

1 Introduction

1.1 Motivation

The grocery market in Norway is highly concentrated, with four main players commanding nearly 100% of the total market share (Nielsen IQ, 2023). This concentration has notably increased over time, prompting growing concerns about competition in the grocery sector (Oslo Economics, 2017). Few new entrants have managed to establish themselves, and there have been no successful new entries into the traditional grocery market with a national presence in the past 20 years (Ministry of Industry and Fisheries, 2022). This insufficient competition among existing players can result in inflated prices, limited product choices and quality, and slower innovation compared to a more competitive market landscape.

In its report, Oslo Economics (2017) identifies a range of entry barriers in the Norwegian grocery market, among which access to premises emerges as the second most significant barrier to entry. Given the pivotal role of a retail store's location in its success (Jaravaza, 2013), and considering Norwegian consumers' strong preference for location when making store choices (Oslo Economics, 2017), a newly established player that only secures unattractive premises may encounter significant disadvantages when competing with established grocery stores. One contributing factor to the limited availability of desirable retail premises is the use of restrictive covenants by grocery chains.

Restrictive covenants, the focal point of our thesis, refer to specific clauses or conditions included in an agreement that impose limitations or restrictions on the use of a property, serving the interests of the party issuing it. In the grocery market, the practice of imposing restrictive covenants is employed by grocery chains to hinder their competitors from establishing rival grocery businesses on a property, extending their influence even after the property changes ownership (Ministry of Industry and Fisheries, 2022). Several countries, namely Australia, Canada, New Zealand, and the United Kingdom, have recognized the adverse effects of restrictive covenants on property controls, particularly within the grocery industry. In Norway, an investigation by the Norwegian Competition Authority revealed 372 restrictive covenants issued, with the four major grocery chains acting as right holders. It also revealed that the use of restrictive covenants as a barrier to entry in the grocery market has persisted for a long time (Ministry of Industry and Fisheries, 2022). Following the investigation's findings, the Ministry of Industry and Fisheries (2023) introduced a regulation prohibiting the use of restrictive covenants with anti-competition purpose, which entered into force in January 2024.

The contribution of our analysis will be twofold. Firstly, there are disagreements surrounding the number of restrictive covenants associated with each grocery chain that are uncovered during the investigation. Additionally, from a policy-making perspective, gathering additional evidence on issued restrictive covenants is crucial to justify the decision to ban them. Hence, our analysis aims to provide an exhaustive list of restrictive covenants imposed by grocery chains for anti-competitive purposes. Secondly, to our knowledge, no other studies have empirically analyzed the effects of restrictive covenants on the grocery market outcomes in Norway to form the basis for the ban. Existing studies on restrictive covenants primarily adopt a descriptive approach, focusing mainly on legal perspectives. Thus, our analysis aims to investigate the extent to which the banned covenants indeed restricted competition, thereby supporting this policy change with empirical evidence.

1.2 Research question

In this thesis, we aim to address the research question:

"How extensively have grocery chains used restrictive covenants for anti-competitive purposes, and what impact have these covenants had on Norway's local grocery markets?"

To answer the research question, we first utilized data on covenants from the land register published on the website of the National Mapping Authority, qualitatively compiling a list of restrictive covenants with relevant wording and relevant grocery chains. Using the list of identified restrictive covenants, along with data on grocery stores in Norway provided by Geodata and demographic data obtained from Statistics Norway, we empirically analyze the impact of restrictive covenants on the market concentration, on the store turnover, and on the distances between grocery stores. In the market concentration model, our methodology involves using the Two-Stage Least Squares (2SLS) estimator. The explanatory variable of interest is the number of all restrictive covenants imposed in a local market, and the dependent variable is the concentration index of that market. The instrumental variable is defined as the number of grocery stores established in the market before the latest covenant date. In the store-turnover and store-distance models, we employ the standard Ordinary Least Squares (OLS) estimator. The explanatory variable of interest is the number of same-chain restrictive covenants imposed in the catchment area of a store, while the dependent variables are the store turnover and the distance from that store to its closest competitor, respectively. We also control for market characteristics and store attributes, which may explain variations in the dependent variables.

Our findings indicate that there are at least 568 properties restricted by the four main grocery chains through covenants in 215 documents. It also reveals that the imposition of restrictive covenants is statistically significant and positively correlated with the concentration level of local grocery markets, as well as with the store turnover. In other words, markets with a higher number of restrictive covenants tend to be more concentrated, and stores associated with a higher number of restrictive covenants is likely to have higher turnover. However, our analysis does not shows a statistically significant relationship between restrictive covenants and store distances. Overall, our findings provide some empirical evidence to the decision of banning covenants used for anti-competitive purposes.

1.3 Outline

The remainder of the thesis is structured as follows: Chapter 2 presents a literature review on entry barriers and restrictive covenants, and offers insights into the Norwegian grocery market, including market characteristics and major grocery chains, and basic information of restrictive covenants. This chapter establishes the background for subsequent sections. Chapter 3 provides an overview of the data sources utilized, outlines the main preprocessing steps, and presents some descriptive statistics for each dataset. Chapter 4 delves into the fundamentals of the regression models, including our model formulations, the definition of local markets, and the subcomponents within our models. Chapter 5 presents the results of the regression analyses, offering interpretations of the findings and discussions on underlying causes, as well as implications of our discoveries. Finally, Chapter 6 comprises concluding remarks and summarizes the key findings of the thesis.

2 Literature review and Background

This section first reviews the literature on entry barriers and restrictive covenants used to limit access to store locations. Then, we provide an overview of the Norwegian grocery retail market, including the market characteristics and the four main grocery chains, and basic information about restrictive covenants. This establishes the background and context for the subsequent discussion.

2.1 Literature review

2.1.1 Barriers to entry

Scholarly interest in barriers to entry has a long history, and the notion of barriers to entry plays a crucial role in economic theory and antitrust litigation (Demsetz, 1982). High entry barriers can impede new competitors, reducing the natural checks on market power. This can lead to fewer firms in the market, weakening competition among existing companies, decreasing socio-economic efficiency, and established companies then exercising greater market power (OECD, 2005; Oslo Economics, 2017).

The types of obstacles considered "barriers to entry" have never been universally agreed upon (OECD, 2005; Oslo Economics, 2017). Bain (1956) defined entry barriers as conditions that allow incumbent firms to achieve long-term economic profits, identifying economies of scale, product differentiation, and absolute cost advantages as key factors. Stigler (1968) offered an alternative definition: a cost of production that entrants must bear but incumbents do not, excluding scale economies or capital requirements if all firms have the same access to technology. McAfee et al. (n.d.) highlighted that sunk costs and uncertainty act as ancillary antitrust entry barriers, which together create a primary barrier. In its report, Oslo Economics (2017) stated that barriers to entry are market structure conditions that make it difficult or unprofitable to enter a market, thereby limiting the number of players.

In the retail setting, several studies have examined the obstacles new entrants may encounter and their impact. Karakaya and Stahl (1989) identified six market entry barriers in consumer and industrial markets, including incumbents' cost advantages, product differentiation, capital requirements, customer switching costs, access to distribution channels, and government policy. Their study of 137 executives in 49 major U.S. corporations found that all six barriers are considered in market entry decisions, with incumbents' cost advantages being the most significant. Furthermore, Gable et al. (1995) compared the impact of exogenous and endogenous market entry barriers in retail. They defined exogenous barriers as those inherent to market conditions and beyond the control of established firms, and endogenous barriers as those created by established firms. Their findings indicate that major entry barriers are exogenous, such as capital requirements, availability of store locations, and qualified personnel. Endogenous barriers, which reinforce exogenous ones, were also significant. In addition, Carree and Thurik (1996), studying entry and exit determinants in 23 Dutch retail sectors in 1981-1988, found that profit ratios, consumer spending growth, and rising unemployment incentivize entry and discourage exit; meanwhile, floor space and professional skill requirements reduce entry rates.

2.1.2 Limited access to store premises

Several studies, some of which are cited above, have pointed to the problem of accessibility to store locations as an entry barrier. The report of Oslo Economics (2017) in grocery retailing uncovered a wide range of entry barriers, among which access to premises is considered the second most significant barrier to entry. Retailing academics and practitioners often emphasize "location, location, location" as the key to success (Grewal et al., 2009). According to the survey of Alfnes et al. (2019b), the convenience of a store's location is crucial for consumers, especially in Norway, where frequent but small-scale shopping is common (Ministry of Industry and Fisheries, 2022). This presents a significant challenge for new entrants in the Norwegian grocery market, particularly in major cities with limited prime locations (Oslo Economics, 2017). The Norwegian Competition Authority has highlighted that, in the grocery sector, difficulty in securing retail locations due to zoning regulations is a public (exogenous) entry barrier, a shortage of suitable business premises can constitute a structural (exogenous) barrier to entry, and the major grocery chains' control of such premises can function as a strategic (endogenous) entry barrier (OECD, 2005).

Legislation and regulations can significantly influence access to premises, hindering market entry (Oslo Economics, 2017). The Norwegian Competition Authority indicated that some municipalities use local building and construction plans to create public barriers to entry, preventing foreign convenience chains from entering the Norwegian market (OECD, 2005). Ellickson (1973) noted that local zoning regulations, from an economic standpoint, are the most significant land use controls, often having a greater effect on land values than other regulatory ordinances. Griffith and Harmgart (2008) investigated the impact of planning regulation on the UK retail market, specifically on the composition of large out-of-town stores and small chain stores. Their structural model of retail competition showed that planning regulations significantly affect the number of firms in a region, although this effect is halved when accounting for differences in population density, employment, and proximity to town centers. Additionally, Sadun (2015) examined the effects of planning regulations on independent retailers in the UK by analyzing data from 303 local authorities between 1993 and 2003. The study used yearly employment data on retail establishments and found that the creation of entry barriers against large shops inadvertently harmed independent retailers. The entry regulations prompted large retail chains to invest in smaller, centrally located stores, which directly competed with independents and accelerated their decline.

In addition, established players themselves may also engage in various landsite-controlling strategies as means of limiting access to premises, hence frustrating competitor entry. In its report, the UK Competition Commission (2008) indicates the four main mechanisms by which grocery retailers are able to control grocery premises, including *i) land bank sites, ii) third-party leases, iii) exclusivity arrangements, and iv) restrictive covenants*. Land banks are sites, or collections of sites, owned by grocery retailers and which are potentially available for development into retail stores or additional retail space. The willingness of a grocery retailer to purchase land to impede competitor entry depends on the costs of acquiring and holding the undeveloped land, along with potential revenue losses if a competitor enters that space (UK Competition Commission, 2008). Instead of keeping land undeveloped as a barrier, another approach is to own or lease a land site and then lease or sub-lease it to a third party that is a non-grocery retailer, limiting the availability of suitable sites for grocery retailing, and therefore, hindering competition (UK Competition Commission, 2008). In addition, exclusivity arrangement is another strategy to discourage competitors or new entrants in the market. An exclusive lease agreement refers to a contractual arrangement that provides a player with the exclusive right to operate its business in one or more specified premises. In this setup, a landowner or developer provides exclusivity to a specific firm, preventing any other firms from operating on the site(s) owned by that landowner. Such exclusivity arrangements are often associated with the development of retail parks or shopping centers (UK Competition Commission, 2008). It is crucial to emphasize that exclusive lease agreements are often undisclosed, making it challenging to estimate their prevalence and assess their impact on competition in the market (Ministry of Industry and Fisheries, 2022), and hence few studies empirically analyzing the consequences of exclusive contracts. One example is Ater (2015) who studied exclusive contracts between hamburger restaurants and Israeli shopping malls, in which mall owners commit to prohibiting additional hamburger restaurants from entering their malls. The paper revealed a negative effect of exclusive contracts on the number of restaurants and on total mall hamburger sales. Finally, another important landsite-controlling strategy is to use a restrictive covenant, which is a constraint commonly applied to the sale of freehold land, dictating the future use of the land.

2.1.3 Restrictive covenants

The use of restrictive covenants to limit access to premises is a significant and common practice (Oslo Economics, 2017) that has been understudied in the literature[1]. Most studies on restrictive covenants utilize qualitative methods and focus on their legal aspects, as seen in the works of Callaway (1951), Berger (1964), Goldschmid (1973), and others. In addition, several empirical studies we found examine the relationship between covenants in private land use contracts and the housing market. For instance, Hughes and Turnbull (1996) evaluates the impact of private deed restrictions on house prices using a hedonic valuation model for deed restrictions and neighborhood covenants. Similarly, Rogers (2006) analyzes 1,487 single-family sales in Colorado, using a unique dataset with information on various use restrictions, building restrictions, and voting rules. The study finds that

[1] In this thesis, we focus exclusively on restrictive covenants in private land use contracts that limit how land sites can be used. While there is extensive literature on restrictive covenants, much of it pertains to different contexts. For instance, Lester (2001) qualitatively examined restrictive covenants in employment contracts that prevent employees from competing with their former employers in a specific geographic area for a set time after leaving the job. Another example is the study of Jones-Correa (2001) on the origins and spread of racial restrictive covenants, which were private agreements preventing non-Caucasians from owning or occupying property in the early 20th–century US. Similar studies include those by Ming (1949), Silva (2010), or Ware (1989). On the quantitative side, most analyses focus on restrictive covenants in public bond contracts or in employment contracts. For example, Reisel (2014) empirically analyzed a dataset of restrictive covenants in public bond contracts to understand how restrictions on investment activities or the issuance of higher priority claims affect the cost of debt. Related studies include those by Nash et al. (2003) or Begley (1994).

building restrictions have no impact on prices, while use restrictions increase prices.

This thesis will specifically focus on the use of restrictive covenants as a strategic tool to raise entry barriers by limiting access to premises for new players in the Norwegian grocery retail market. With the purpose to deter competitors from entering the market, we expect that the use of covenants will result in fewer market participants, leading to increased market concentration. Thus, our first empirical analysis will examine the relationship between restrictive covenants and concentration levels at local markets. Additionally, recent research highlights the importance of proximity to other stores (agglomeration) for multi-stop shopping trips (Grewal et al., 2009). Grocery chains might use restrictive covenants to distance their competitors, aiming to protect their stores by expanding the stores' customer base and hence to increase store turnover. At the same time, this could negatively impact customers by reducing multi-stop shopping options or increasing travel distances. Therefore, at the store level, we will investigate the effect of restrictive covenants on the store turnover as well as on the distance between a store and its competitors, hypothesizing that the use of restrictive covenants will increase this distance and, in turn, boost store turnover.

By combining unique covenant data with grocery store and market characteristics data, we can quantify the impact of restrictive covenants on these metrics. This thesis aims to contribute to the literature on barriers to entry and provide a foundation for the Ministry of Industry and Fisheries' regulation banning restrictive covenants, which lack empirical evidence at the time of its implementation.

2.2 Background

2.2.1 Overview of the grocery market

According to Nielsen IQ (2023), grocery sales in Norway exceeded 224 billion NOK in 2022, with traditional grocery accounting for 89.9% of the total revenue. This amount represents approximately 4% of Norway's total GDP in 2022 (Statistics Norway, n.d.-b).

As of 2022, the Norwegian grocery retail market comprises 3,855 traditional stores (Nielsen IQ, 2023), competing with online retailing operators, restaurants, kiosks and petrol stations, cross-border retail stores, specialty shops, specialized retail stores, duty free stores and others (NorgesGruppen, 2022). The traditional retail stores are usually divided into four different segments, namely convenience store, discount, supermarket, and hypermarket (Wifstad et al., 2018). Regarding store sizes, Nielsen IQ (2016) classifies them into four categories: hypermarkets (larger than 2500 m2), large supermarkets (1000 - 2499 m2), small supermarkets (400 - 999 m2), and superettes/convenience stores (100 - 399 m2 and less than 100 m2).

2.2.1.1 Market characteristics

Norway has a dense retail landscape relative to its population, with the prevalence of smaller retail establishments, particularly those under 1000 m2, compared to other countries (Oslo Economics, 2017; Wifstad et al., 2018). For example, in 2018, Northern Norway had the smallest customer base with 986 people per store, followed by Central Norway with 1,157, Western Norway with 1,317, Vestre Østland with 1,418, Eastern Østland with 1,620, and Oslo with 1,758 people per shop (Alfnes et al., 2019b). Furthermore, 52% of the total stores fell within the mid-size range of 400-999 m2, with 29% between 100 and 399 m2, 15% between 1,000 and 2,499 m2, 3% under 100 m2, and only 1% larger than 2,500 m2 (Alfnes et al., 2019b). The higher store density in Norway is, in part, a result of the population being distributed across areas with fewer concentrated or closely spaced settlements (Oslo Economics, 2017). This high store density often indicates better accessibility, but it also means lower turnover in each individual store and, consequently, a more limited product selection (Oslo Economics, 2017; Alfnes et al., 2019b).

Another special characteristic in the Norwegian grocery market is that consumers shop frequently and little per shopping trip (Oslo Economics, 2017). Bøyum and Hebrok (2019) reveals that Norway leads globally in the frequency of weekly shopping trips, averaging 3.4 times per week. A survey conducted by Amedia Marked (2022) further supports this trend, indicating that 88% of respondents typically visit grocery stores more than once a week, with 57% engaging in shopping activities 2-3 times per week. Despite the growth of e-grocery, a majority of Norwegian consumers favor in-store shopping due to their preference for seeing and physically inspecting the goods (Marcucci et al., 2021). Moreover, Norwegian consumers typically utilize different shops for grocery shopping, and consider store location as the primary factor influencing store selection. Amedia Marked (2022) indicates that 70% of the total respondents say they visit two to three shops for grocery shopping. Meanwhile, the Consumer Council's survey in 2013 shows that for 76% of consumers, proximity to the store is crucial for everyday purchases, whereas a broad product selection becomes more significant for weekend shopping (Bøyum & Hebrok, 2019). While low prices matter, they are generally deemed less important than store proximity and product variety (Oslo Economics, 2017).

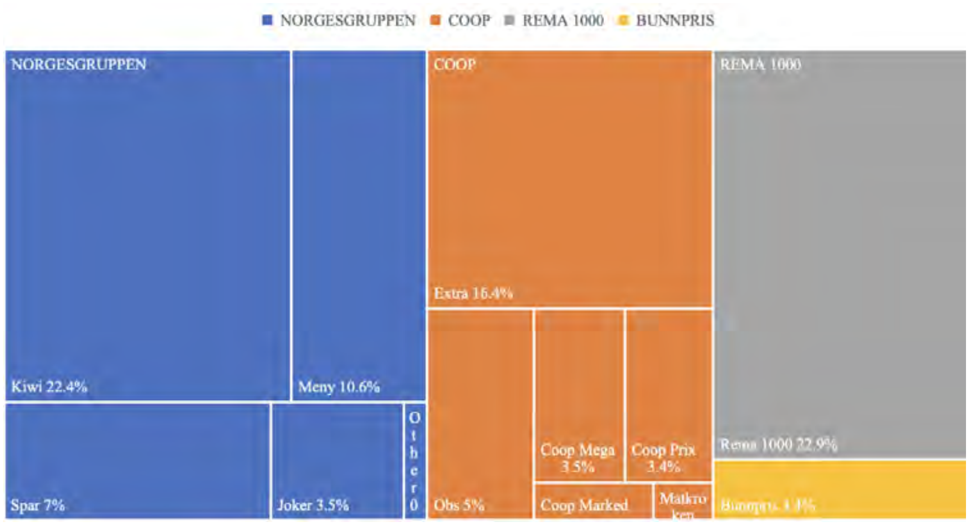
The Norwegian grocery market is also distinct in that it has a limited number of players, and there are no foreign chains present in the market, unlike other Nordic countries (Oslo Economics, 2017). While there are several brands in the grocery retailing sector, almost all of these brands are dominated under the umbrellas of four major chains. These chains, except for Bunnpris, are characterized by a high degree of vertical integration, encompassing functions such as distribution, wholesale, purchasing, and chain operations (Oslo Economics, 2017). That said, independent grocery retailers are compelled to either procure goods directly from grocery suppliers or engage in agreements pertaining to purchasing and distribution with one of the three major grocery chains - NorgesGruppen, Coop, and Rema 1000 (Oslo Economics, 2017).

With few players, the grocery market in Norway is highly concentrated (OECD, 2023), and the concentration has increased significantly over years - especially after the grocery chain Ica sold its Norwegian operations in 2015, leading to increased concern about competition in the market in the long term (Oslo Economics, 2017). In Norway, the combined market share of the top three major players in 2021 hovers at 96.6%, which is higher than that of Sweden with 90.3%, and Danmark with 80.7% (Nielsen IQ, 2022b). According to the UK Competition Commission (2008), high concentration in local markets negatively impacts consumers, as limited competition enables a grocery retailer to diminish the retail offer at its stores and achieve higher profit. In Norway, with fewer grocery players compared to other countries, consumers might miss out on the advantages of heightened competition, including lower prices, improved quality and services, a wider product selection, and increased consumer choice (Norwegian Competition Authority, 2022).

2.2.1.2 Main grocery chains

The Norwegian grocery market structure has undergone substantial changes over time (Oslo Economics, 2017). Currently, the landscape is dominated by three major grocery chains—NorgesGruppen, Coop, and Rema 1000—which collectively contribute to 96% of retail-level turnover[2] and nearly 100% of wholesale-level turnover (wholesale to grocery stores), being vertically integrated along the entire value chain (Oslo Economics, 2017). Together with one smaller grocery retailer - Bunnpris, they form the four umbrellas in the Norwegian grocery market.

Figure 2.1: Market shares of main grocery chains in Norway 2021 (Nielsen IQ, 2022a)



Norgesgruppen

NorgesGruppen is currently the market leader in grocery retail in Norway, with a market share of 44% in 2021 (Nielsen IQ, 2022a). In local markets, Prognosesenteret's calculations in 2021 revealed NorgesGruppen's robust market dominance, holding over 50% market share in 136 Norwegian municipalities, encompassing nearly 1.7 million residents (NRK, 2022). As of 2022, NorgesGruppen has a total of 2,129 stores, in which 44.7% is fully-owned stores and the others are merchant-owned stores (based on franchising), and is present in 88% of the municipalities in Norway. The operating revenue for 2022 reaches NOK 102.7 billion (NorgesGruppen, 2022).

NorgesGruppen operates in several business areas, with retail groceries and wholesale collectively contributing nearly 70% of its total earnings before interest and taxes (Kristiansen et al., 2017). Its retail arm includes well-known grocery brands like Kiwi, Meny, Spar, and Joker, totaling 1,777[3] stores and generating NOK 85.8 billion in 2022

[2] Total net turnover in 2021 is NOK 208 billion (Nielsen IQ, 2022a)

[3] This number includes 50 stores that NorgesGruppen took from ICA in 2015 when ICA was squeezed

(NorgesGruppen, 2022). Additionally, it manages convenience retail chains such as Deli de Luca and Mix, with 335 profiled and 659 associated stores contributing over NOK 3.7 billion (NorgesGruppen, 2022). In 2022, NorgesGruppen expanded by introducing two Gigaboks stores and acquiring Dollarstore. ASKO, its wholesale subsidiary, is Norway's largest grocery wholesaler, contributing NOK 81 billion with extensive logistics operations (NorgesGruppen, 2022). NorgesGruppen also owns UNIL, responsible for its in-house brands, and Bakehuset, with eleven local bakeries, generating approximately NOK 11.7 billion revenue in 2022 (NorgesGruppen, 2022). Additionally, it has interests in Joh. Johannson Coffee, Solberg & Hansen, BAMA, and GrøstadGris, and operates in various other business types, including cross-border retail, tax-free stores, and international ventures through associated companies.

Real estate is also an important business area of Norgesgruppen. NorgesGruppen Eiendom has total revenue of NOK 439 million in 2022 and is in charge of ensuring good locations for Norgesgruppen's stores (NorgesGruppen, 2022). Norgesgruppen currently owns 180 properties - 6 shopping centers, 31 development projects, 115 investment properties and 6 industrial properties (Oslo Economics, 2017). In total, the real estate portfolio is around 800,000 sqm, and Norgesgruppen uses approximately 60% of the area for its own business, while the rest is rented out (Oslo Economics, 2017).

Coop

With the market share of 29.7% (Nielsen IQ, 2022a), Coop is the second largest player in the Norwegian grocery retail market, currently operating 1,227 stores spread over large parts of Norway, and generating a total operating income exceeding NOK 58 billion in 2022 (Coop Norge, 2022). Locally, calculations of Prognosesenteret in 2021 showed that Coop commands a market share exceeding 50% in 100 Norwegian municipalities (NRK, 2022). Functioning as a consumer cooperative, Coop comprises 59 cooperatives with over two million members, collectively forming Coop Norge SA. This member-owned joint organization handles central tasks such as purchasing, logistics, chain management, and marketing for Coop's stores and department stores in Norway (Coop Norge, 2022).

Coop Norge operates in wholesale, industrial operations, real estate, and store management, structured under Coop Norge SA with subsidiaries such as Norsk Butikkdrift, Coop Norge

out of the Norway grocery market (Oslo Economics, 2017)

Industry, Coop Norge Transport AS, and Coop Norge Eiendom (Coop Norge, 2022). Its retail division manages grocery and construction materials stores, with grocery stores generating NOK 59.7 billion in turnover and holding a 29.5% market share in 2022 (Coop Norge, 2022). This includes 1,120 stores across chains like Obs, Extra, Coop Prix, Coop Mega, Coop Marked, and Matkroken. The acquisition of ICA Norway's stores in 2015 significantly boosted Coop's market presence[4]. Coop also leads the private construction market with Obs BYGG and Coop Byggmix stores, achieving NOK 7,166 million turnover and over 37% market share (Coop Norge, 2022). In addition, Coop Norge Industri focuses on in-house production of Coop brands, generating around NOK 2.5 billion turnover (Coop Norge, 2022). For distribution, Coop Norge Logistikk and Coop Norge Transport manage logistics and transport, ensuring efficient nationwide supply chains.

In the real estate area, Coop Norge Eiendom AS is responsible for the development and new establishment of Coop's business - in particular, the purchase and sale, management and development of real estate with strategic interest in Coop (Oslo Economics, 2017). This company currently oversees a retail property portfolio spanning 275,000 m^2, encompassing shopping centers, retail parks, and individual retail properties (Coop Norge, 2022). Additionally, the company holds partial ownership in various property firms, contributing to a combined property mass of around 650,000 m^2 through wholly-owned and partially-owned entities (Coop Norge, 2022).

Rema

Rema holds the third-largest market share at 22.9% among the umbrella chains in 2021, but it is the leading grocery chain concept in the Norwegian market based on net grocery turnover (Nielsen IQ, 2022a). In 2021, Rema obtained the largest shares in 11 local markets, which are small municipalities, according to Prognosesenteret (NRK, 2022). In 2023, the revenue of Rema Norway amounted to NOK 38,267 million, with a total of 674 stores (Reitan Retail, 2023). As the exclusive franchisor for Rema grocery stores operated by franchisees, Rema distinguishes itself as the sole retail operator in the Norwegian grocery market with franchising as its primary operating model (Reitan Retail, 2023).

[4]In 2015, ICA exited the Norwegian grocery market, resulting in the sale of approximately 550 grocery stores under the ICA Supermarked, Rimi, and Matkroken chains to Coop. This acquisition increased Coop´s market share from 22% in 2014 to 29% in 2016, elevating Coop from the third to the second largest player in the Norwegian grocery market (Oslo Economics, 2017). Today, these acquired stores from ICA are managed by Norsk Butikkdrift AS, one of the four subsidiaries of Coop Norge SA

Like other major grocery players, Rema is vertically integrated, encompassing retail, wholesale, distribution, production, and real estate operations. Rema's retail arm includes Rema 1000 in Norway and Denmark, with 674 and 372 stores respectively, and Reitan Convenience with brands like Narvesen and 7-Eleven, and Uno-X Mobility focusing on sustainable mobility solutions (Reitan Retail, 2023). Rema Industrier and Rema Distribusjon ensure smooth goods flow to stores, owning key suppliers and managing exclusive purchasing agreements (Reitan Retail, 2023). Rema Distribusjon operates five distribution branches and collaborates with Servicegrossistene, Kolonial.no, and Circle-K for procurement and distribution (Rema Distribution, n.d.).

In real estate, Reitan Eiendom actively manages a property portfolio to meet Reitan Retail's long-term needs, securing strategic locations for Reitan Retail and its franchisees (Reitan Retail, 2023). Reitan Eiendom has three investment areas: 1) Center property in Trondheim, Bergen and Oslo; 2) Logistics and industrial property in Scandinavia; and 3) Retail property in Scandinavia (Reitan Retail, 2021). With subsidiaries overseeing operations in Trondheim (EC Dahls Eiendom) and Bergen (Vesten-Fjeldske Eiendom), and ongoing development in Oslo, the center property segment achieved an operating profit of NOK 141 million in 2022, and its real estate portfolio's fair value was NOK 4,573 million, covering 116,600 square meters. Meanwhile, the activity within the logistics and industrial property segment is run by RELOG AS, which is a continuation of the businesses of NHP Eiendom and Login Parinvest. In 2021, a larger portfolio has been acquired, and this is organized under the company RELOG Invest AS. Additionally, ownership of commercial property in Norway is handled by REBUS Handelseiendom, while Reitan Eiendom invested in a larger portfolio of retail properties in Denmark through a separate company in Denmark. Reitan Eiendom had as of 2021 ownership interests in 1,522,000 square meters of property (Reitan Retail, 2021).

Bunnpris

Bunnpris is the fourth-largest player in the Norwegian grocery retail segment, boasting a 2022 turnover of almost NOK 7.1 billion, corresponding to a 3.4% market share (Nielsen IQ, 2022a) — approximately one-seventh of the third player. At the end of 2022, there were 241[5] Bunnpris stores in Norway, of which 62 stores are owned by IK. Lykke Drift AS

[5] In 2015, with ICA's exit from the Norwegian grocery market, Bunnpris acquired 43 stores, solidifying its presence (Oslo Economics, 2017).

and the other 179 have a franchise as their mode of operation (Bunnpris, n.d.).

Bunnpris, operated under IK Lykke AS, is headquartered in Trondheim and includes IK Lykke Drift AS, Kløverbakeriet AS, and partial ownership in an egg packing plant, with shares in various companies (Bunnpris, n.d.). IK Lykke Drift AS manages the Bunnpris concept, which focuses on low-priced goods and features Bunnpris & Gourmet for a wider product selection (Bunnpris, n.d.; Wifstad et al., 2018). Unlike the other major chains, Bunnpris lacks its own wholesale business and relies on purchasing partnerships with larger chains, alternating between NorgesGruppen and Rema (Wifstad et al., 2018). Since January 2017, Bunnpris has collaborated with NorgesGruppen for purchasing agreements and distribution, except for Kløverbakeriet AS, which supplies bread and bake-off items to Bunnpris stores (Oslo Economics, 2017).

In real estate, IK Lykke Eiendom Holding, which is a sister group of IK Lykke Drift AS, owned by the Lykke family, oversees the property portfolio within the Bunnpris system, comprising approximately 120,000 square meters in 2020. This includes both wholly owned and partially owned companies, with 75-80 percent of the portfolio dedicated to grocery-related operations (Brown, 2020).

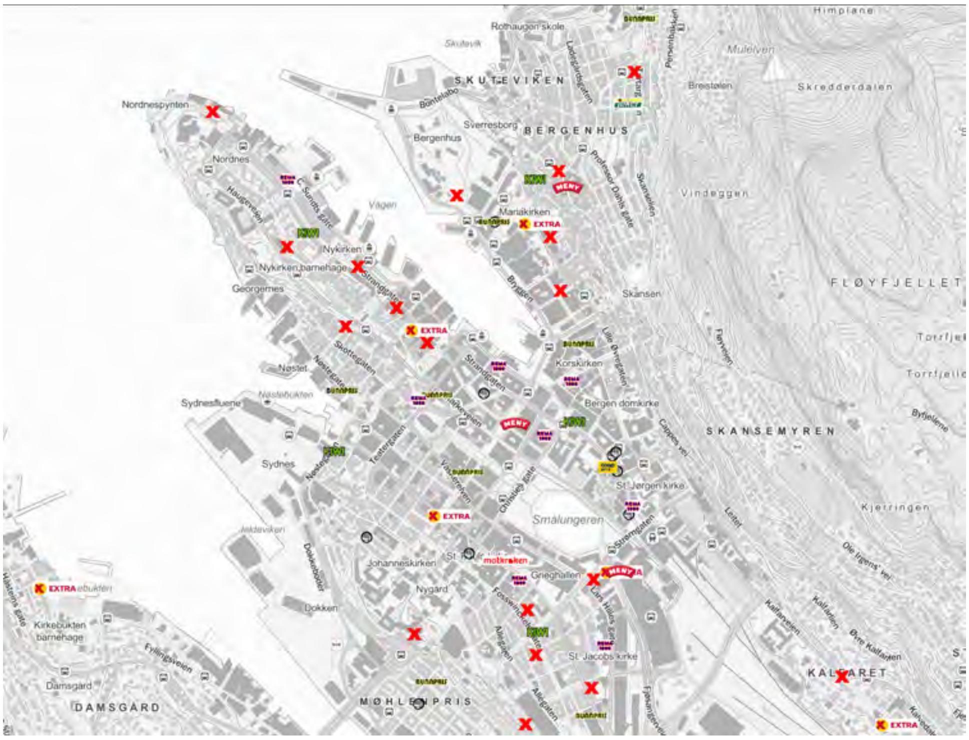
In summary, the four main players in the Norwegian grocery market exhibit a similar structure with a high level of vertical integration, encompassing production, distribution, wholesale, retail, and real estate. Each grocery chain has its own real estate company to manage its property portfolio, ensuring long-term property needs, facilitating growth, and securing access to strategic locations. This underscores the critical importance of store locations for success in grocery retailing and highlights the need to address the barrier of limited access to premises.

2.2.2 Overview of restrictive covenants

In this context, a covenant is defined as a limited right to control someone else's property, with a restrictive covenant specifically granting the right holder the authority to prohibit a specific use of the property (Ministry of Industry and Fisheries, 2022). In Norway, common covenants include the right of first refusal, the right to use a parking space, the right to lease a building, the right of way, the right to occupy, the right to moor a boat, the right to have a water and sewer line over the neighbor's land, building bans, or sale and mortgage bans (Norwegian Mapping Authority, 2022).

Typically, covenants are established through agreements and recorded in the land register[6] to secure legal protection. Restrictive covenants are often negotiated in conjunction with property sales, but they can also be imposed by the property owner or mutually agreed upon by the owner and the right holder independently of a sale (Ministry of Industry and Fisheries, 2022). In addition, covenants can be imposed by local authorities through agreements with the right owners as part of development agreements (UK Competition Commission, 2008; Ministry of Industry and Fisheries, 2022; Rema 1000, 2022). The right holder of a covenant can be persons, properties or companies, and covenants, which are either a time-limited or permanent, can be deleted if rights holders send deletion requests to the Mapping Authority with several exceptions (Norwegian Mapping Authority, 2023b).

Figure 2.2: Illustration of grocery stores and restricted locations in center area of Bergen (Sources: Geodata & Norwegian Mapping Authority)



In the grocery market, restrictive covenants are utilized by grocery chains to impede the establishment of rival grocery businesses on a property, exerting their influence even after the property changes ownership (Ministry of Industry and Fisheries, 2022). These

[6]In Norway, the land register can be accessed through the website of the Mapping Authority: https://www.kartverket.no/eiendom

covenants achieve this by either 1) restricting the use of the land for a specific type of business - selling food for example, or 2) curtailing the landowner's freedom to choose their buying or selling practices and business partnerships (New Zealand Commerce Commission, n.d.). For instance, a covenant might confer preferential rights to a specific grocery wholesaler in supplying products to the landowner. The grocery chains benefiting from the restrictive covenant may experience reduced competition, allowing them to uphold their market share, raise prices, diminish quality, and innovation, and potentially impose unfavorable terms on consumers (New Zealand Commerce Commission, n.d.).

The specific wording of these covenants may vary (UK Competition Commission, 2008), ranging from explicit prohibitions (e.g., "no trade in groceries shall be carried out on this property" or "ban on the operation of grocery stores") to limitations on grocery retailing activities (e.g., "prohibition of competing businesses as long as Coop Rossfjord operates a grocery store"). Additionally, restrictions may be framed as positive obligations (e.g., "the property is only to be used for camping and motels"), effectively preventing land use for grocery retailing. The complexity of these covenants often makes it challenging to ascertain their impact on grocery retailing, especially in cases lacking additional documents (e.g., "prohibition of certain forms of commercial activity with several provisions").

However, it is crucial to acknowledge that not all covenants will function as barriers to entry (UK Competition Commission, 2008). In certain instances, a landsite may have been unsuitable for grocery retailing even without the covenant, although there is a possibility of combining individual land sites with restrictive covenants to create a site suitable for grocery retailing (UK Competition Commission, 2008). Grocery chains may also use covenants to preserve properties currently unavailable for grocery business, ensuring future usage without anti-competitive intent. For example, a grocery operator, unable to secure permission to run a grocery business on a property they own, registers a right upon selling the property. This right ensures the selling grocery operator retains the option to operate a grocery business there in the future if permitted (a type of preferential right). Additionally, grocery retailers might employ covenants to safeguard non-grocery occupants of the land (e.g., block of flats above a store), protect a grocery store's facilities (e.g., car parks), control traffic in an area, maintain the character and use of a property, or secure any increase in value in case of changes in planning prospects or the purchaser's use of the property (UK Competition Commission, 2008; Ministry of Industry and Fisheries, 2022). The implementation of a covenant can be driven by various reasons; however, this paper's main focus is to pinpoint instances where a covenant acts as an entry barrier, allowing dominant grocery retailers to safeguard their position.

Several countries, for example Australia, Canada, New Zealand, and the United Kingdom, have acknowledged the adverse impacts of restrictive covenants for property controls, particularly in the grocery industry (Australian Competition & Consumer Commission, 2008; Canadian Competition Bureau, 2023; New Zealand Commerce Commission, 2022; UK Competition Commission, 2008). In an effort to improve competition in the grocery market, in 2021, the Norwegian Competition Authority conducted an investigation on the use of restrictive covenants as a tool for anti-competition in the market. The findings revealed widespread use of restrictive covenants by grocery chains in Norway, and the practice of establishing negative easements as a barrier to entry in the grocery market has been ongoing for a long time (Ministry of Industry and Fisheries, 2022). The table below displays the count of restrictive covenants held by the four major grocery chains, organized by the year of establishment.

Table 2.1: Count of restrictive covenants (Ministry of Industry and Fisheries, 2022)

	<2000	**2000-2004**	**2005-2009**	**2010-2014**	**2015-2019**	**2020**	**Total**
Norgesgruppen	6	22	6	13	60	1	**108**
Coop	19	28	27	64	45	14	**197**
Rema	0	1	19	6	22	11	**59**
Bunnpris	0	0	0	7	1	0	**8**
Total	**25**	**51**	**52**	**90**	**128**	**26**	**372**

The investigation by the Norwegian Competition Authority has revealed a minimum of 372 relevant restrictive covenants, but the Ministry of Industry and Fisheries (2022) noted the possibility of more undisclosed covenants. The table 2.1 shows that all four major grocery chains have employed restrictive covenants to varying degrees. Coop, contributing to over half of the identified covenants, stands out, while Bunnpris, the smallest chain among the four, has the fewest. Additionally, the three largest chains, namely NorgesGruppen, Coop, and Rema, implemented covenants as recently as 2020. Of the 372 restrictive covenants, 363 valid for more than ten years, with most of the cases being permanent. These chains have established restrictive covenants on land sites nationwide, with a concentration around major cities (Ministry of Industry and Fisheries, 2022).

Assuming that the 372 properties or land sites covered by restrictive covenants are actually suitable for grocery retail, the substantial number of covenants uncovered by this investigation suggests a potential to market foreclosure (Ministry of Industry and Fisheries, 2022). Not only traditional grocery stores but also players in grocery online retailing have encountered barriers due to covenants. Foodora Norway, one of the players in the grocery online retailing, attests to facing obstacles during their nine-month property search because even though not having traditional walk-in stores, they need retail space for their home delivery service (Jordheim, 2023). Given the inherent challenges in establishing new stores in the grocery market, the extensive presence of covenants emerges as a significant barrier for effective competition (Ministry of Industry and Fisheries, 2022).

However, major grocery chains contest the number disclosed by the Norwegian Competition Authority, asserting that it should be smaller and that the covenants were not established for anti-competition purposes (Lorch-Falch et al., 2022). Coop, responsible for 197 of these covenants according to the audit, cites errors and deficiencies in the original proposal (Jordheim, 2022). They argue that the intent behind these covenants is not to create barriers to entry but, for example, to secure their own investments (Lorch-Falch et al., 2022). NorgesGruppen claims, in principle, not to have any covenants, stating that they conducted a review of all contracts a couple of years ago, deleting only three. Also, they deny cases where the right holders of restrictive covenants are companies under NorgesGruppen's brand profiles, asserting that these companies operate independently (Lorch-Falch et al., 2022). Rema contends that they impose covenants to safeguard their right to operate grocery stores on land sites in the future if authorities permit grocery business on those sites (Lorch-Falch et al., 2022).

Objecting to the claims of the grocery chains, the Ministry of Industry and Fisheries (2022) identifies restrictive covenants as a significant issue for competition in the Norwegian grocery market. In response, the Ministry proposed a regulatory ban on the use of restrictive covenants by grocery chains, which underwent a public hearing in 2022. The objective of the proposal was to streamline enforcement and reduce entry barriers in the grocery sector compared to the Competition Act's rules (OECD, 2023). Subsequently, this ban was approved and is effective from January 2024.

3 Data

To answer our research question, we rely on three datasets: 1) the covenant dataset, 2) the grocery store dataset, and 3) the Norwegian demographic dataset. In this section, we will 1) introduce our data sources and outline the key steps taken during the pre-processing phase, and 2) present some descriptive statistics derived from the final datasets.

3.1 Covenant dataset

As mentioned in Section 2.3.2, the investigation conducted by the Ministry of Industry and Fisheries (2022) uncovered 372 restrictive covenants issued by the four main grocery chains, with the possibility of more being present. Due to the ambiguity of many covenants' wordings, difficulties in identifying covenant ownership, and other challenges, we believe that the list of 372 covenants is incomplete. From a policy-making perspective, collecting more evidence is a key in supporting the rationale behind the covenant ban. Therefore, instead of relying solely on the numbers provided by the Ministry in Table 2.1, we will meticulously examine the raw covenant list to identify additional restrictive covenants acting as entry barriers for new players in the local grocery markets of Norway.

3.1.1 Data source and pre-processing

The raw covenant dataset, sourced from the Norwegian Competition Authority, encompasses information on covenants lodged on different properties/land sites. It originally comprises 23,387 observations and 78 variables, providing comprehensive information on properties, including cadastral numbers, owners, and addresses, alongside key covenant details such as right holders, issuance date, document number, and covenant wording. Concerning this dataset, several steps have been implemented, and the main ones are outlined as follows:

3.1.1.1 Mapping covenants with grocery chains

For the analysis in this paper, it is crucial to associate each covenant with its respective grocery chain. This process involves mapping information from right holders, owners, and the wordings of the covenants.

Before commencing the mapping, we compile a comprehensive list of affiliated companies for each grocery chain. This information is sourced from the website of Proff[7], complemented by data from the grocery chains' websites and other sources, including also historical names associated with each grocery chain. It is worth noting that the mapping of covenants to associated grocery chains does not solely hinge on parent-subsidiary relationships. An example is Sporsheim Eiendom AS, identified as a subsidiary of Sporsheim Holding AS, which, in turn, owns Futura Food AS, the legal entity behind Bunnpris Futura. Consequently, Sporsheim Eiendom AS is categorized under the Bunnpris umbrella. Hence, it may lead to disparities with figures provided by grocery chains. For instance, Butikkpartner AS owns stores operating under NorgesGruppen's store profiles Spar, Meny, Kiwi, and Joker (Butikkpartner AS, n.d.), classifying it under NorgesGruppen's umbrella. However, Norgesgruppen refutes any involvement in the Butikkpartner AS case, asserting that Butikkpartner AS operates independently with its own shares and employees - one of the self-employed merchants under NorgesGruppen's brand profiles (NRK, 2022). Despite this, we include these cases under the grocery chains' umbrella in this paper. In summary, we have compiled a list of 359 related names for NorgesGruppen, 123 for Coop, 157 for Rema, and 81 for Bunnpris.

In the covenant dataset, right holders serve as the primary source for mapping covenants to associated grocery chains. However, only 80 distinct right holders are explicitly stated, representing 7.02% (1641 observations) of the total observations in the dataset. It is important to note that, according to the Norwegian Mapping Authority (2023a), the presence or absence of declared right holders in property registrations depends on the nature of the right. Rights tied to a property, enduring over time irrespective of its owner, such as rights of way, are registered without specifying a right holder. Conversely, for personal rights applicable to specific individuals or organizations, for example pre-emption or housing rights, the right holders are explicitly indicated. Out of the 80 right holders, 59 are deemed relevant to one of the four grocery chains.

For observations lacking explicit right holders, our next step involves examining the owners. We posit that, despite the absence of explicitly declared right holders, covenants should favor the grocery chain associated with the property owners. However, a significant

[7]Proff provides the search and evaluation service in the Nordic region, offering comprehensive insights into companies, official company information, roles, and ownership details. (https://www.proff.no/)

portion, 82.4% (19,271 observations), comprises individual owners for whom we lack the means to establish connections with grocery chains. With 17.6% remaining observations, we only identified a mere 27 relevant owners.

Analyzing the wording of covenants offers another avenue to gather information about right holders, especially when the right holders are not explicitly declared. This was accomplished by employing textual analysis techniques to search for names of affiliated companies under grocery chain umbrellas mentioned in the covenant text. Additionally, specific keywords such as “rettighetshaver” (right holders), “AS” (limited company), “handelslag” (commercial cooperative), “samvirkelag” (cooperative), and “bnr” (property unit number) are employed to extract relevant names. This process yields a total of 85 distinct right holders affiliated with one of the four grocery chains.

3.1.1.2 Flagging relevant covenants

Not all entries in the dataset represent restrictive covenants that function as barriers to the entry and expansion of grocery stores. To distinguish their relevance, we categorize covenants based on the type of rights and the wording. Covenants are classified as relevant (restricting the establishment of grocery stores), questionable (requiring additional information for confirmation), or irrelevant (not restricting grocery store establishment).

The dataset comprises 45 different types of rights. In which, "Statement/Agreement"[8] constitutes nearly 50% of the total observations. After analysis, 18 types of rights are identified as relevant to the restriction of grocery store establishment.

There are a total of 3275 different lines of text in the dataset, of which 444 texts are categorized to be relevant. The specific wording of the relevant covenants can vary (Ministry of Industry and Fisheries, 2022). Some of those can take the form of prohibitions on engaging in competitive businesses, specifically in grocery trade, general store operations, or trade in general. On the other hand, several covenants grant exclusive rights to the right holder for operating such businesses or contain provisions related to grocery trade. The language found in the covenants that are categorized as relevant includes expressions such as "Prohibition on grocery business," "Prohibition on activities competing with the right holder," "Prohibition on leasing to grocery stores or related businesses in competition with

[8] "Erklæring/Avtale" in Norwegian

the right holder," "Exclusive rights for the right holder to operate a grocery business," "No grocery business without the consent of the right holder," "The right holder has the unconditional right to be a supplier of all groceries and associated products to the grocery business that is operated on the property," and similar statements.

It is important to note that one phrase can be categorized differently depending on the context. For instance, "prohibition of certain forms of commercial activities with several provisions" is deemed relevant if the right holders are affiliated with a grocery chain, otherwise, it is considered questionable, requiring more information to determine if grocery stores are restricted from operating in the land sites. The assumption here is that if the right holders are relevant, the commercial activities mentioned include grocery business.

Additionally, in some cases, relying solely on the wording of the covenant written on the land registration book[9] is insufficient to determine its relevance. Hence, we obtained and examined 15 registered documents[10] from the Norwegian Mapping Authority to gain deeper insights into the content of the registered covenants. For instance, a phrase initially categorized as questionable, such as "provision on the operation of grocery stores," was clarified by the registered document, stating that "NorgesGruppen Eiendom Midt-Norge AS, corporate no. 935480507, or the one NorgesGruppen Eiendom Midt-Norge AS designates, is given an exclusive, compensation-free and perpetual right to operate grocery trade within section 16. bn. 115, 371, 372, 510, 511 and 512 in Trondheim municipality". Another example is the phrase "provision on the establishment or leasing of the premises for grocery trade for 20 years from 01.02.2005". Examination of the registered document revealed more details about the covenant and its association with Coop: "Future owners of the property do not have the opportunity to establish or rent out the premises for grocery trade within a period of 20 years from 01/02/2006. Transferred from: Coop Innlandet BA - 947771744". It is important to note that due to the associated cost per ordered document, we could not verify all cases categorized as questionable, potentially leading to under-reporting of relevant covenants and associated grocery chains.

[9] "Grunnbok", which provides an overview of who has registered ownership of the property, and what has been registered of encumbrances and obligations on the property. More information here: https://www.kartverket.no/eiendom/bestille-fra-grunnboken/grbutskr-fe

[10] "Tinglyst" documents, for example a deed - document used to transfer real estate to a new owner, which can be ordered through the website of the Norwegian Mapping Authority. More information here: https://www.kartverket.no/eiendom/bestille-fra-grunnboken/kopi-dok

3.1.1.3 Retrieving addresses of land sites

A land site may undergo sectioning, re-sectioning, or changes over time. To maintain up-to-date information about the land sites, we retrieve addresses from the website of the Norwegian Mapping Authority[11] using cadastral numbers. A cadastral number (e.g., 5036/78/25/0/0) for a land site consists of numbers in the following order: municipality number, farm number, utility number, and possibly attachment number and/or section number (Norwegian Mapping Authority, n.d.).

In Norway, the official address of a land site can take the form of a road address or a cadastral address. As of January 2021, road addresses constitute 97% of the total addresses (Norwegian Mapping Authority, 2021). All buildings planned for residential purposes, cottages, and buildings planned for business or public activities, are required to be assigned a road address (Norwegian Mapping Authority, 2023c). According to the Regulations on property registration (Ministry of Local Government and Districts, 2023), a typical road address (e.g., Svaneviksveien 87) includes an address name, representing the street, road, path, place, or area, and an address number, a unique identifier for properties within that addressable location. Additional address names, such as a farm name or the name of a well-known institution or building, may also be required in specific cases (e.g., Sangereid gård, Justøyveien 10), or in some instances, municipalities may assign common address extension names to smaller demarcated areas. Moreover, a road address may incorporate a utility unit number, consisting of a capital letter (L, H, U, or K) and four digits, indicating the floor code, floor number, and utility unit's number on the floor (e.g., Bjørn Farmanns gate 15-H0502).

For land sites without a road address, the official address is a cadastral address, a series of numbers based on farm and utility numbers. The cadastral address is utilized when road addresses are not available, and municipalities may decide to use cadastral addresses temporarily or permanently based on specific circumstances in an area (Norwegian Mapping Authority, 2023c). However, it should be highlighted that a land site cannot be found on Google Map using the cadastral addresses, making it impossible to assign a land site to the appropriate local market or extract longitude and latitude information via GoogleAPI. Hence, these cadastral addresses cannot be utilized for information extraction.

[11] https://seeiendom.kartverket.no/

Figure 3.1: Illustration of a land site without road address
(Source: Norwegian Mapping Authority)

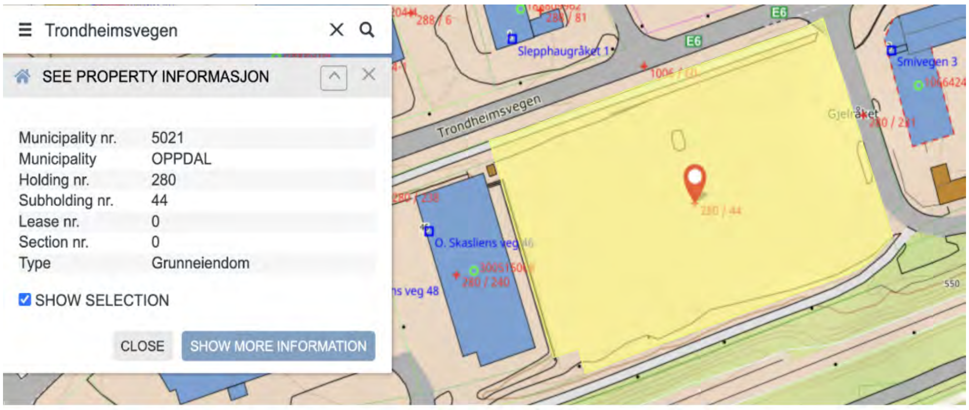
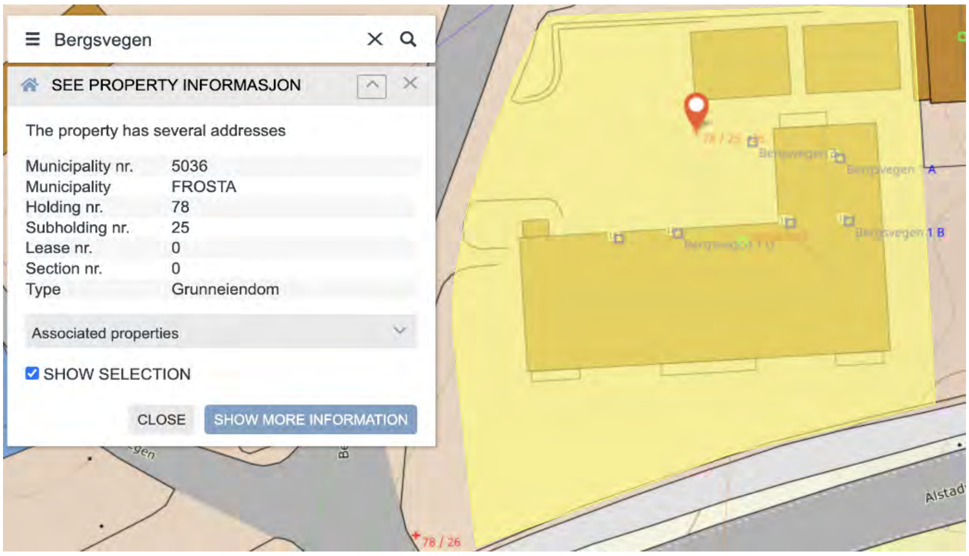


Figure 3.2: Illustration of a land site with multiple road addresses
(Source: Norwegian Mapping Authority)



When retrieving addresses, various decisions impact the final results. First, in cases that the central cadastre database[12] indicates no road address for a land site, we opt to use the address of the closest land site with an address (e.g., Skasliens Veg 46 in Figure 3.1), determined based on the cadastral map. If no address is registered and no map is provided (e.g., the land site with cadastral number 0301/521/2/0/0), the observation is removed. On the other hand, for land sites with multiple addresses, only road addresses with name and number are retained, excluding utility unit numbers. For example, the addresses of the land site illustrated in Figure 3.2, including Bergsvegen 1A–1E and Bergsvegen 3-H0201–H0205, are consolidated to Bergsvegen 1A–1E and Bergsvegen 3.

[12]"Matrikkelen" in Norwegian

This assumption is made considering that residential apartments above the first floor are not deemed suitable for operating a grocery store, and therefore should not be counted as multiple restrictive covenants. Finally, observations with cadastral numbers no longer accessible on the Norwegian Mapping Authority website are removed (e.g., the land site with cadastral number 1103/57/1882/0/0), possibly due to land site changes or merges. In total, we have removed 115 cadastral numbers.

An additional step involves obtaining the longitude and latitude coordinates of each landsite. These coordinates are crucial for calculating distances among stores in local markets. While acknowledging that using coordinates from the Norwegian Mapping Authority database might offer more precise data, especially for land sites with only cadastral addresses (for which we currently rely on nearby land sites), we opt for GoogleAPI due to its simpler and faster data extraction process, considering the complexities associated with handling personal data as a requirement from the Norwegian Mapping Authority.

3.1.1.4 Retrieving areas of land sites

After compiling a list of covenants that are associated with one of the four main grocery chains and that are categorized as having relevant wording, we conduct an additional step to enhance the accuracy of data related to restricted land sites. Specifically, we obtain information about the area of land sites covered by these covenants and exclude sites that appear unsuitable for opening a grocery store even without the application of covenants, meaning that the presence of these covenants does not act as a deterrent to entry.

The land sites exhibit considerable variation in size and shape. In situations where land sites are sectioned into multiple addresses or smaller sites, and the area is registered as a whole for all sections under the same cadastral number, we assume that the area of each section is equal to the total area of a landsite divided by the number of sections[13].

We opt to exclude sites with an area smaller than 50[14] square meters, irregular shapes,

[13] While this method may not precisely reflect the actual sizes of individual sections, as they may vary, we lack access to additional documentation beyond the public land register to obtain precise area measurements. However, we believe that any variations in actual area measurements would likely have a minor impact on the final number of restricted locations as we employ additional criteria beside the area figures, such as consulting cadastral maps and actual images from Google Maps, to further refine our decisions regarding the inclusion or exclusion of land sites.

[14] We set the minimum area threshold for a land site at 50 square meters, aligning with the smallest area of a grocery store as indicated in the grocery store dataset obtained from Geodata.

coverage of roads, or limited to the surrounding area of a building or a cluster of buildings (excluding the buildings themselves). For sites with an area exceeding 50 square meters with seemingly unsuitable shapes or coverage, we conduct further assessments using actual images from Google Maps to determine their suitability for grocery store operations. Figure 3.3 illustrates instances where we have deemed land sites unsuitable, prompting their exclusion from consideration as restricted sites.

Figure 3.3: Illustrations of excluded land sites. (From left to right: a small area with irregular shape, coverage of road, limited to the surrounding area of a building) (Source: Norwegian Mapping Authority)

3.1.1.5 Determining expiration dates of covenants

In addition, we consider the expiration date of covenants as an important factor and extract this information from the covenant wordings. This information is essential for counting valid restricted land sites as a variable in our models.

The wording regarding expiration dates varies. For covenants without a specified expiration date, we assume they are permanent unless removed by the right holders. In cases where the wording includes conditions such as "Apply for 10 (ten) years from the date of registration, unless it can be made permanent," or "This clause applies for 10 years from the date of issue, but must be permanent if the competition act and/or regulations are changed so that permanent non-competition clauses can legally be enforced," we treat them as expired after the mentioned period. Additionally, for covenants referring to the commercial activities of specific stores (e.g., “No opportunity to operate grocery business as long as Coop Høyland and Jæren BA have commercial activities in the area.”), we verify the operational status of those stores to determine if the covenants have expired or remain in force.

3.1.2 Descriptive statistics

The final covenant dataset comprises information of 568[15] restricted land sites, covered by 215 unique registered documents and 1241 cadastral numbers. Among those identified, 11 registered documents expired before the end of 2020.

Table 3.1: Numbers of restricted land sites by grocery chains and registration years

Period	Grocery chains				Total
	Bunnpris	Coop	Norgesgruppen	Rema	
1960 - 1964		2			2
1965 - 1969		1			1
1970 - 1974		1			1
1975 - 1979		2			2
1980 - 1984		13			13
1985 - 1989		15	5		20
1990 - 1994		15			15
1995 - 1999	3	32	22		57
2000 - 2004		108	41	1	150
2005 - 2009		27	12	15	54
2010 - 2014	20	43	20	8	91
2015 - 2019	1	35	91	13	140
2020		14	3	5	22
Total	**24**	**308**	**194**	**42**	**568**

Table 3.1 presents the catalog of restricted land sites linked to the four major grocery chains, categorized by registration periods of 5 years each. Our analysis revealed a total of 568 restricted locations. Notably, Coop encompasses roughly half of these restricted locations, in line with the Norwegian Competition Authority's observations. Furthermore, our analysis unveiled that the earliest covenants we identified were registered during the 1960-1964 period, with a substantial increase in registrations occurring after 2000.

[15]As mentioned in section 2.1.5, the Norwegian Competition Authority identified 372 restrictive covenants associated with the four major grocery chains. However, the specific methodology employed by the authority to arrive at this number was not explicitly provided. For example, it remains unclear whether the count is based on unique cadastral numbers, registered documents, or locations. Additionally, the definition of a location could vary, such as counting an entire building as one location, considering each section/apartment as a separate location, or counting each address associated with a building as a distinct location. The lack of clarity on these methodological aspects introduces potential variability in the reported number of restrictive covenants. In our analysis, prioritizing the concerns of potential new entrants who seek suitable locations for opening grocery stores—locations that are accessible, have sufficient area, and necessary facilities—we focused on counting the number of restricted locations. Through this approach, we identified a total of 568 restricted locations.

Figure 3.4: Distribution of restricted locations by municipalities in 2020

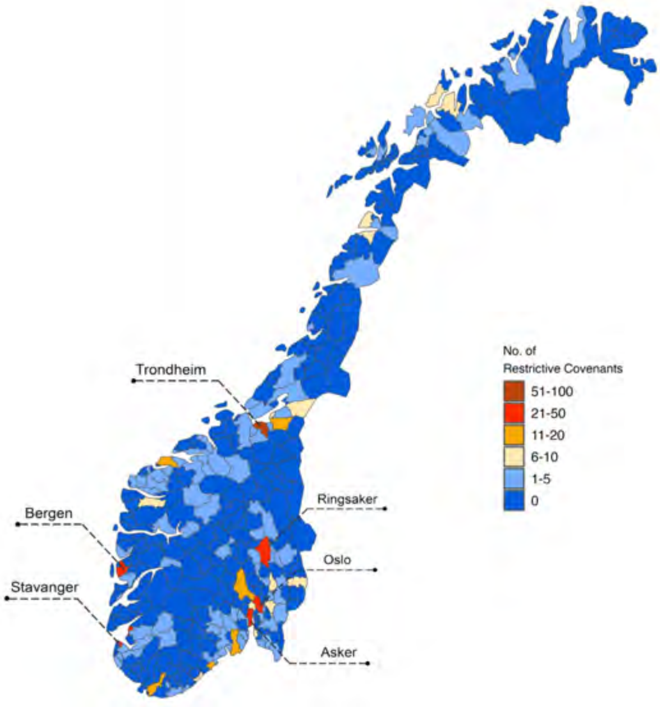


Table 3.2: Top municipalities with high number of restrictive covenants

Municipality	No. covenants	Population	Area (km2)	Population Density	Income (NOK)
Trondheim	98	205,163	496	413.64	534,000
Stavanger	26	143,574	257	558.65	585,000
Ringsaker	26	34,768	1,123	30.96	525,000
Oslo	24	693,494	426	1,627.92	501,000
Asker	24	94,441	364	259.45	663,000
Bergen	21	283,929	445	638.04	532,000

Notes: Demographics data in this table is sourced from Statistics Norway

Not surprisingly, a significant concentration of restricted land sites is observed in large cities or areas characterized by high population density. Figure 3.4 illustrates the distribution of restricted locations across municipalities in 2020. Specifically, many municipalities have no locations subject to covenants acting as entry deterrents in the grocery retail sector. In contrast, Trondheim emerges as the municipality with the highest count of restricted locations, totaling up to 98.

3.2 Grocery store dataset

3.2.1 Data source and pre-processing

We also leverage the store-level panel data[16] from Geodata, the Norwegian spatial data provider. The Geodata dataset covers the entire Norwegian grocery market with 4,117 observations, each representing a grocery store, some of which were permanently closed before 2020. It provides comprehensive details on yearly turnover for 2010-2020, location, store opening dates, store size, working hours, distribution centers, store formats, and other relevant dummy variables for store characteristics. The dataset predominantly features grocery stores that fall under the four main grocery chains' umbrellas, and only a small proportion of stores that do not.

After removing permanently closed grocery stores before 2020, our dataset was reduced to 3,798 stores. Subsequently, minor modifications were made to this dataset, along with calculating distances between stores and from stores to restricted land sites.

3.2.1.1 Retrieving distances from stores to stores

In our models, the distances between grocery stores serve a crucial role, aiding in the assessment of local market competition.

The 3,798 different grocery stores are grouped by counties, and combinations of stores are created within each county. Subsequently, we identify nearby pairs of counties and compile combinations of stores in the municipalities either bordering or close to the border of these counties. By considering geographical proximity, we can mitigate the impact of geographical borders on a store's local market, acknowledging the fact that people from one county may shop at stores in its neighboring county if the distances are sufficiently short. Finally, the two lists of combinations are consolidated, and any duplicates are eliminated, yielding a streamlined and condensed list of combinations.

Once the combinations are established, the subsequent task involves computing the distances between stores using two metrics: Euclidean distance[17] and Driving time

[16] We would like to thank Alina Ozhegova for generously providing us with access to this dataset.

[17] A similar metric to Euclidean distance is the Haversine distance. Haversine distance calculates the angular distance between two points on the surface of a sphere, with latitude and longitude given in radians. As the Earth is nearly spherical, the Haversine formula offers a reliable approximation of the

obtained from Google Distance Matrix API[18] and from the Route Planning Service[19] provided by the Norwegian Public Roads Administration (NPRA). Euclidean distance represents the straight-line distance between two points (Black, 2004), calculated directly using their longitude and latitude coordinates. In contrast to Euclidean, driving time provides a more precise measure for defining the local market around a specific store, reflecting the actual time people spend on roads.

3.2.1.2 Retrieving distances from stores to restricted locations

Including the distances between grocery stores and locations restricted by covenants is also important for our analysis. This information enables us to associate restricted locations with the specific local markets.

The process of calculating distances from stores to locations restricted by covenants mirrors that of determining distances between stores. The same two distance metrics—Euclidean distance and Driving time—are employed. The key distinction lies in the method of obtaining combinations. Each location restricted by covenants is assigned a unique ID formed by combining the associated grocery chain name with a distinct number. Subsequently, we generate a list of unique combinations, pairing each store with a restricted location. More details is presented in Appendix A.

3.2.2 Descriptive statistics

The final dataset for grocery stores in Norway comprises 3,798 observations, representing 3,798 stores normally operated in 2020.

Figure 3.5 illustrates the distribution of grocery stores across different grocery chains

Earth's surface distance, with an average error of less than 1 percent (Scikit–learn, 2007). However, in the context of this paper, the distances between stores or from stores to restricted land sites are not significant enough for the distinction between Euclidean distance and Haversine distance to be substantial. Hence, we opt to use Euclidean distance due to its simpler formula and adequate representation for the purposes of this analysis.

[18]Google provides the Distance Matrix API, a service that accepts an HTTPS request containing origins and destinations for a given mode of transport. For each combination of origin and destination, it returns the travel distance and duration. More information on: https://developers.google.com/maps/documentation/distance-matrix

[19]The Route Planning Service, an API service by the Norwegian Public Roads Administration, will adjust the start and end point to the nearest point on the drivable road network, and calculate the route in between. More information on: https://github.com/LtGlahn/adhocanalyser/tree/fattigmanns_nettverkanalyse and https://www.vegvesen.no/ws/no/vegvesen/ruteplan/routingservice_v3_0/open/routingService/openapi

(Bunnpris, Coop, Norgesgruppen, Rema, and others) and store formats (convenience store, discount store, supermarket, hypermarket, and others). Notably, Norgesgruppen owns the highest number of stores in different formats, accounting for 46% of the total stores. Additionally, 50 grocery stores, equivalent to merely 1.3% of the total, fall outside the umbrellas of the four main grocery chains. Furthermore, the majority of grocery stores belong to the discount store format, constituting approximately 59.5% of the total.

Figure 3.5: Distribution of grocery stores across various grocery chains and store formats

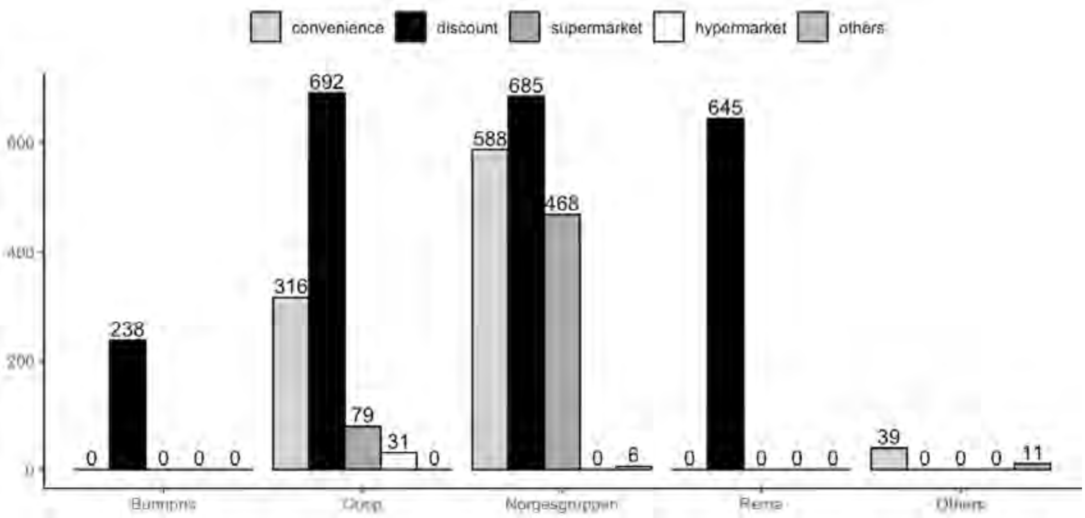


Table 3.3: Annual turnover of grocery stores in 2020 (in million NOK)

Grocery chain	N. stores	Annual turnover				
		Min	Mean	Median	Max	Total
Norgesgruppen	1,747	0.324	47.146	43.511	425.998	82,364.010
Coop	1,118	0.973	51.418	35.143	1,728.654	57,485.669
Rema	645	3.665	69.546	65.815	230.441	44,856.867
Bunnpris	238	0.001	27.494	25.309	88.272	6,543.515
Others	50	1.618	6.104	5.815	13.444	305.209

Table 3.3 displays key statistics on the annual turnover of grocery stores in 2020. Not surprisingly, Norgesgruppen has the highest total turnover in 2020, followed by Coop. Due to its hypermarkets, Coop has the highest maximum turnover, which is far larger than that of Norgesgruppen. However, in terms of average and median turnover, Rema stores have higher values. Bunnpris has a relatively small turnover compared to the other three major players, but it is still much larger than the aggregate numbers of other minor ones in the Norwegian grocery retail market.

3.3 Demographic dataset

3.3.1 Data source and pre-processing

Demographic characteristics are crucial in accounting for variations in local market conditions, thus playing a significant role in our analysis. We obtained demographic data from Statistics Norway and Geodata websites, focusing on: 1) Municipal centrality index, 2) Urban settlement population, 3) Other demographics. It should be highlighted that, given the store turnover data is available only until 2020, we extracted demographic data for the same year to ensure alignment.

3.3.1.1 Municipal centrality index

The centrality index, as described by Statistics Norway (2020a), is a value assigned to each individual municipality based on access to workplaces and service functions from approximately 13,500 inhabited basic statistical units[20] in the country. This index is calculated by aggregating data at the level of basic statistical units up to the municipality level, with weighting according to the number of residents in the basic statistical units.

Specifically, the centrality index is composed of two sub-indices: 1) How many workplaces can people who live in each basic statistical unit reach by car within 90 minutes; and 2) How many service functions can those who live in each basic statistical unit reach by car within 90 minutes[21] (Statistics Norway, 2020a). The calculation incorporates a weighting system so that proximity to the place of residence increases the count for a workplace or service function, acknowledging that distance entails a cost or resistance. For each of the two sub-indices, the average is then calculated for each municipality based on the population in the municipality's basic statistical units (Statistics Norway, 2020a). Finally, the combined indices yield the overall centrality index for the specific municipality.

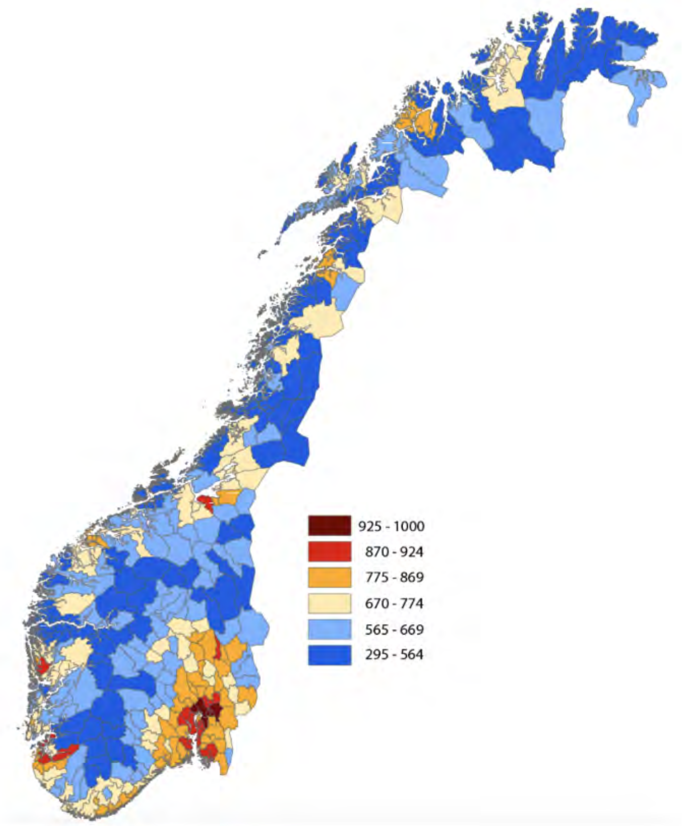
The centrality index ranges theoretically from 0 to 1000, with the most central municipality consistently assigned a value of 1000 (Oslo), while the least central municipality can

[20]"Grunnkrets" in Norwegian. It is the smallest administrative unit. The next levels (in ascending order) are: statistical tracts (delområde), municipalities (kommune), and counties (fylke) (Statistics Norway, 2021).

[21]Workplaces and service functions situated more than 90 minutes from the place of residence are excluded from consideration as the findings of the Travel Habits Survey (Hjorthol et al., 2021) indicates that less than 1 percent of individuals nationally have a work journey exceeding 90 minutes.

have values as low as 300. These values are categorized into six classes, with Group 1 representing the most central municipalities (highest centrality indices) and Group 6 comprising the least central municipalities (lowest centrality indices). The centrality classes of municipalities in Norway are illustrated in Figure 3.6.

Figure 3.6: Municipalities by centrality class (Statistics Norway, 2020a)



We obtain the data of municipal centrality classes from Statistics Norway, integrate it with our grocery store dataset so that each grocery store is assigned a municipal centrality class based on the municipality it is situated in, and subsequently employ it to define the local market for each particular grocery store. For the purpose of our analysis, we opted to merge the six classes of centrality into four broader classes:

1. "Most centrality": include groups 1, 2, and 3
2. "Moderate centrality": include group 4
3. "Low centrality": include group 5
4. "Least centrality": include group 6

3.3.1.2 Urban settlement population

Population in urban settlements is a vital demographic characteristic that, when combined with the municipal centrality index, allows us to define the local market for each store. Urban settlements are dynamic geographical areas with the number of urban settlements and their outer limits subject to change over time based on building activity and population development (GeoNorge, 2020). An urban settlement includes a cluster of buildings that is inhabited by at least 200 persons, with the distance between buildings normally not exceeding 50 meters[22] (Statistics Norway, 2020b).

The data obtained from Geodata's website includes details about urban settlements, such as unique IDs, settlement names, population, land area in square kilometers, and population density. This information is integrated with our store dataset using the store's longitude and latitude coordinates to determine the urban settlement to which each store belongs. Each store is then assigned one level of urban settlement:

1. "No settlement": If the store is not located in an urban settlement or if it locates in the urban settlement that has less than 200 people;
2. "Small settlement": If the store is in an urban settlement with a population ranging from 200 to 1,999 people;
3. "Settlement": If the store is in an urban settlement with 2,000 to 99,999 people;
4. "Big settlement": If the store is in an urban settlement with over 100,000 people.

3.3.1.3 Other demographics

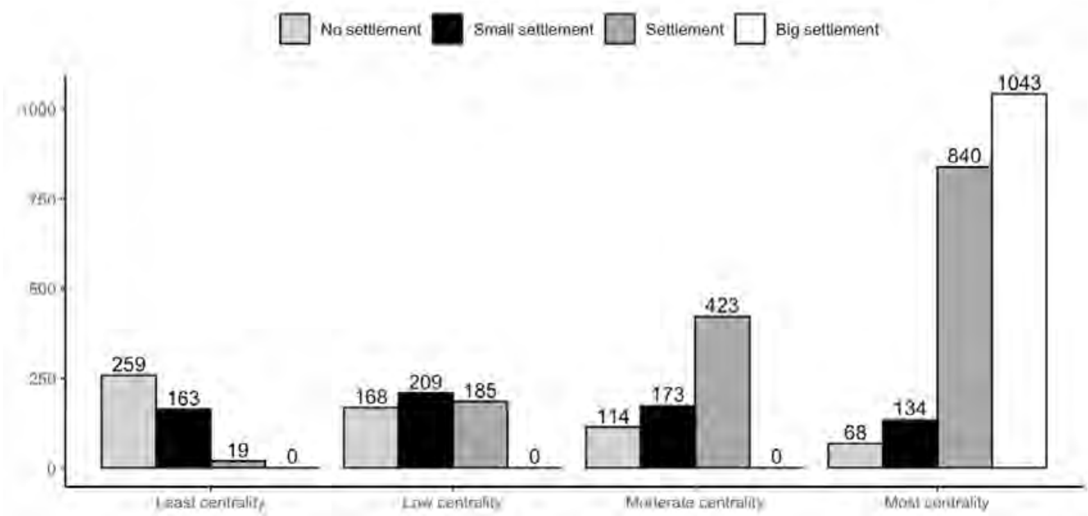
In addition to the municipal centrality index and urban settlements, we collect data on other demographic characteristics, including population, area in square kilometers, average household income after tax, and number of people in each age group from Statistics Norway. This data is retrieved at the level of basic statistical units and aggregated to higher levels when necessary. These data will be utilized in our models as control variables to account for variations in local market conditions.

[22]Exceptions to the 50-meter rule are allowed in areas that cannot or should not be built up, such as parks, sports facilities, industrial areas, and natural barriers like rivers or arable land. Additionally, smaller clusters of buildings that naturally belong to the urban settlement should be included if situated within a distance of up to 400 meters from the main urban settlement.

3.3.2 Descriptive statistics

Figure 3.7 illustrates the distribution of grocery stores across various combinations of municipal centrality classes and urban settlement levels. A substantial portion of stores (approximately 50%) is situated in municipalities with the highest centrality, paired with either an urban settlement or a big urban settlement level.

Figure 3.7: Store distribution by municipal centrality classes and urban settlement levels



In Table 3.4, we present the summary of demographics information at basic statistical unit level in 2020. The data highlights significant variation in each characteristic across different geographical locations.

Table 3.4: Demographics summary in 2020 - Basic statistical unit level

	Min	Median	Mean	Max
Population	1	243	387	6,354
Land area	0.01	3.35	21.57	1,683.41
Household income aft. tax	329,000	549,000	557,199	952,000
Age group 0-19	0	51	88.66	1,954
Age group 20-66	3	142	233.3	3,934
Age group >67	0	37	58.74	856

4 Methodology

In this section, we provide an overview of our methodology for constructing the models to address our research questions. This includes: 1) selecting regression models, 2) defining local markets, 3) establishing main variables, 4) determining relevant control variables.

4.1 Regression models

In this thesis, we examine the impact of restrictive covenants on the local grocery markets using three metrics: 1) market concentration (market level), 2) store turnover (store level), and 3) distance from a store to its closest competitor (store level).

4.1.1 Regression model for market concentration

4.1.1.1 Model formulation

To quantify the relationship between restrictive covenants and market concentration at the local market level, we employ the 2SLS method with one instrumental variable (IV).

In the initial stage, we conduct a regression where the variable of restrictive covenants is regressed against the IV and control variables to derive the fitted value of the number of restrictive covenants. Our first-stage model takes the following form:

$$C_m = \alpha_1 + \beta_1 * S_{md} + \gamma_1 * X_m + {\varepsilon_m}^C \tag{4.1}$$

In which, C_m is the variable indicating the total number of restrictive covenants imposed in a local market m, regardless of which grocery chain issued the covenants. S_{md} is the IV in our model, which represents the number of grocery stores established before the imposition date d of the last restrictive covenant in a local market m. X_m is a vector of the control variables in a local market m, and ${\varepsilon_m}^C$ is the error term.

In the second stage, we regress the market concentration on the fitted value of the variable of restrictive covenants and the control variables to ensure consistent estimation of the structural parameter. It is noted that the fitted value of the variable of restrictive covenants retains partial information about market concentration while remaining uncorrelated with the error term, owing to its dependence on the IV that is itself uncorrelated with the error term (Shin et al., 2021). Leveraging the fitted variable of restrictive covenants, the second stage estimates the structural parameter through a straightforward regression of market concentration on the fitted number of covenants and the control variables. Our second-stage model is outlined below:

$$HHI_m = \alpha_2 + \beta_2 * \hat{C}_m + \gamma_2 * X_m + {\varepsilon_m}^{HHI} \tag{4.2}$$

In which, HHI_m is the market concentration level of a local market m. $\hat{C}_m$ is the fitted value of the number of restrictive covenants resulted from the first-stage regression. X_m is the same vector of the control variables in a local market m, and ${\varepsilon_m}^{HHI}$ is the error term.

4.1.1.2 OLS versus 2SLS

Examining the relationship between the use of restrictive covenants and the concentration of local markets reveals that there exists an endogeneity issue for which using OLS estimator may lead to bias and inconsistent estimates, and therefore, employing 2SLS method appears to be a suitable approach.

The use of OLS estimator may not be suitable in our case due to the problem of endogeneity, which could introduce some level of inconsistency and bias into the estimates of our parameters. Endogeneity arises in OLS regression when predictors are correlated with the error term (James and Singh, 1977; Blalock et al., 1970). This issue can result from omitted variables, reverse causality, selection bias, or measurement error (Alfnes et al., 2019a). The decision to impose a covenant in a local market is strategic, created and maintained by established firms based on factors such as market demand and associated costs, rather than randomly assigned, potentially leading to selection bias. Moreover, as noted by Singh and Zhu (2008), market structures result from strategic decisions by firms, which take into account demand, cost conditions, and potential competitors when entering a market, so unobserved demand and cost shocks in a market may influence both the imposition of restrictive covenants and market concentration, leading to omitted variable bias. For instance, markets with unobserved high costs may attract fewer entrants, leading to higher concentration. Grocery chains might also opt not to impose covenants in these markets due to the high costs. Consequently, a regression of market concentration on the number of restrictive covenants could erroneously suggest that higher concentration is associated with fewer covenants, driven partially by unobserved costs. Conversely, unobserved positive demand shocks, like new building projects, may lead to more covenants and a higher number of players in a market, probably leading to an inaccurate evaluation of the impact of covenants on market concentration. In short, with potential selection bias and omitted variable bias associated with the imposition of covenants and the market concentration, employing an OLS estimator in this case may result in endogeneity issues.

Generally regarded as powerful as more complex methods (Theil, 1971; James and Singh, 1977), 2SLS with instrumental variables offers an estimation approach capable of addressing the endogeneity problems across a broad spectrum of single-equation regression scenarios (Angrist & Imben, 1995). For instance, Ater (2015) examined how exclusive contracts between hamburger restaurants and Israeli shopping malls affect the number of hamburger restaurants and their sales, recognizing that the decision to establish exclusive contracts may be correlated with unobserved demand conditions at the mall level, potentially biasing estimated coefficients. Therefore, Ater (2015) employed 2SLS regression with an IV to address this issue. The 2SLS regression focuses on the variations in the endogenous regressor that are uncorrelated with the error term and disregard the variations in the endogenous regressor that bias the OLS coefficients (Bascle, 2008). Given the similarities between exclusive contracts and restrictive covenants, as well as the potential for endogeneity due to omitted variable bias or selection bias, we find that the 2SLS method is a suitable approach for examining the relationship between the use of restrictive covenants and the concentration of local markets.

4.1.1.3 Instrumental variable

Instrumental variables (IVs) are variables that are related to the outcome variable solely through the independent variable of interest (Angrist & Imben, 1995). According to Alfnes et al. (2019a), to be considered a valid instrument, a potential IV must meet two criteria:

(a) it should be uncorrelated with the error term, referred to as *instrument exogeneity*,

(b) it should exhibit a non-zero partial correlation with the independent variable of interest (e.g., restrictive covenants), given the observed control variables, referred to as *instrument relevance*.

Fulfilling these conditions allows the IV to isolate the exogenous variation in the independent variable of interest, thereby facilitating the consistent identification of the coefficient of interest (Alfnes et al., 2019a).

In our analysis, we define the IV as the count of grocery stores established before the imposition date of the last restrictive covenant in the local market under scrutiny. Our rationale is that a grocery chain may opt for a restrictive covenant if they perceive the market as still profitable for new entrants. This decision hinges on assessing the market's customer base in relation to the current number of stores, with the expectation that potential new entrants would conduct a similar analysis. Consequently, it becomes unnecessary to impose covenants in markets where the ratio of grocery stores to customer base is already high. Therefore, the count of stores already existing in a market is pertinent to the decision of whether to impose a covenant. Additionally, in markets with multiple covenants, determining which date to use for counting stores becomes crucial. We select the imposition date of the last restrictive covenant as it represents the highest number of stores where all current covenants are in effect, likely indicating the maximum number of profitable stores in the market with the current customer base. Furthermore, we choose the number of stores established before the imposition date of the last covenant as our IV because it is unlikely to be directly linked to market concentration. This count may not capture all stores due to population changes or urbanization for example, and the total number of stores does not necessarily reflect the number of players in the market as all stores might belong to the same chain. In summary, we consider this IV to be valid for our models, and we will further examine its robustness in Section 5.

4.1.2 Regression model for store turnover

To assess the association between restrictive covenants and store turnover, we utilize the OLS method, as no evidence of an endogeneity problem was found. Our model is structured as follows:

$$T_i = \alpha_3 + \beta_3 * C_i + \gamma_3 * X_i + \delta_3 * Y_i + {\varepsilon_i}^T \tag{4.3}$$

In which, T_i is the variable indicating the turnover of grocery store i in the year 2020, measured in millions of NOK. C_i is the variable indicating the number of same-chain restrictive covenants (i.e., restrictive covenants that are imposed on locations within the coverage area of store i, and that are issued by the same grocery chain that owns store i). We assume that all the covenants placed by the grocery chain that owns store i and imposed in the store's coverage area could have benefited store i. X_i is the vector of market characteristics of the local market where store i is located. Y_i is a vector of store characteristics of store i. X_i and and Y_i are used as control variables in our models. Finally, ${\varepsilon_i}^T$ is the error term.

4.1.3 Regression model for store distances

To quantify the relationship between restrictive covenants and store distances, we also employ the OLS method as we found no sign of endogeneity problem. Our model takes the following form:

$$D_i = \alpha_4 + \beta_4 * C_i + \gamma_4 * X_i + \delta_4 * Y_i + {\varepsilon_i}^D \tag{4.4}$$

In which, D_i is the variable indicating the minimum driving time from store i to its closest competitor. C_i is the variable indicating the number of same-chain restrictive covenants (i.e., restrictive covenants that are imposed on locations within the coverage area of store i, and that are issued by the same grocery chain that owns store i). Similar to store turnover model, we assume that all the covenants placed by the grocery chain that owns store i in its coverage area could have benefited store i. X_i is the vector of market characteristics of the local market where store i is located. Y_i is a vector of store characteristics of store i. X_i and and Y_i are used as control variables in our models. Finally, ${\varepsilon_i}^D$ is the error term.

4.2 Local markets

To assess the impact of restrictive covenants on local markets, we must delineate these markets effectively. In the Geographical Information Systems (GIS) literature [23], defining the catchment area of a retail store involves estimating how far consumers are willing to travel to the store, either a distance or a travel time, and then marking the area centered

[23] Beaumont, 1991 ,Elliot, 1991, Howe, 1991, Reid, 1993, Ireland, 1994

around that store and within the limit of that time or distance factor (Benoit & Clarke, 1997). Relying on this idea, our paper considers two potential approaches to define the local market (or catchment area) of a store: 1) Geographical border, and 2) Driving time

4.2.1 Geographical border

Instead of establishing a specific distance threshold and using it as a radius to limit the local market of a grocery store, the first approach opts for a simplified and straightforward method. This involves utilizing the borders of the geographical unit where the store is situated to delineate its market. The chosen geographical level is either the statistical tract or the municipality, depending on the population.

Table 4.1: Summary of population (Statistics Norway, n.d.-c)

Geographical level	Min	Q1	Median	Mean	Q3	Max
Basic statistical units	1	111	251	396.3	524.5	6354
Statistical tracts	7	1,668	3,217	4,672	5,727	32,344
Municipalities	198	6,809	23,046	73,257	63,764	693,494
Counties	241,235	286,234	419,396	487,962	558,212	1,241,165

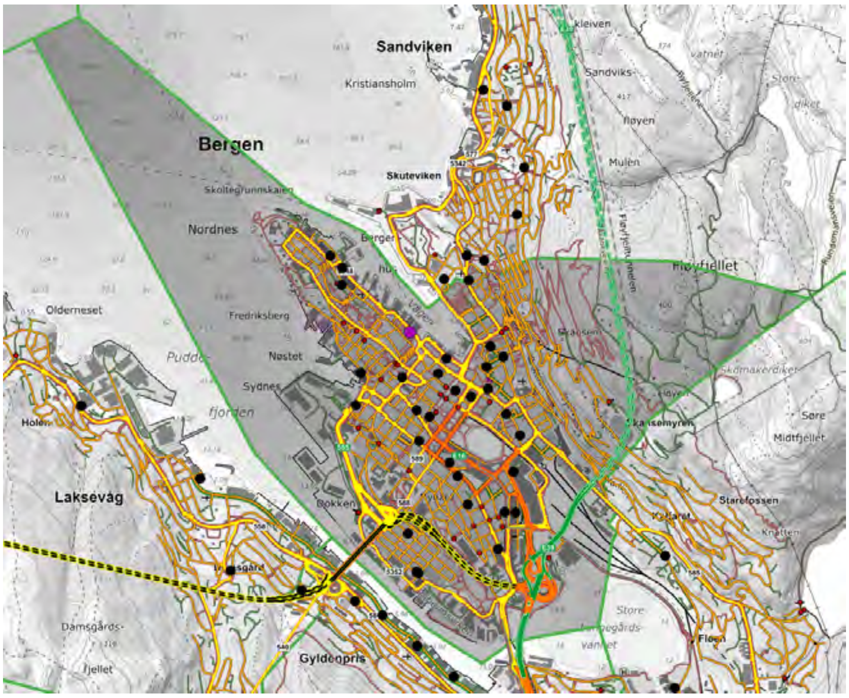
The selection of these two levels for defining local markets is based on an examination of the four geographical units in Norway, including basic statistical units, statistical tracts, municipalities, and counties. This analysis, utilizing both population statistics (summarized in Table 4.1) and administrative border maps[24] provided by Statistics Norway, reveals that statistical tracts and municipalities are deemed suitable for defining local markets, not being too small as basic statistical units or too big as counties for consumers traveling for grocery shopping. In addition, considering the variety of the population distribution in Norway, we choose a threshold of 50,000 headcount to decide which geographical level is used as the market of a store. Specifically, if a store is located in a municipality with over 50,000 headcount, its catchment area is defined as its statistical tract; otherwise, the municipality is chosen. This approach ensures a balanced consideration of population density and administrative divisions.

Figure 4.1 depicts the local market (the dark grey area inside the green lines, which is the border of the statistical tract, with the yellow and orange lines indicating the road

[24] Available at https://kart.ssb.no/

network) of a store (represented by the purple dot, with other stores shown in black dots) situated in the center of Bergen using method 1. Bergen, a sizable municipality in Norway with a population exceeding 280,000 as of 2020, hosts numerous grocery stores within the reach of local residents. Consequently, it is reasonable to infer that residents in this area prefer shorter distances for their grocery shopping needs. Hence, the statistical tract level is selected over the municipality level.

Figure 4.1: Illustration of a store's local market defined by method 1



The primary advantage of defining local markets based on geographical borders is its accuracy and ease of controlling and calculating several variables in the models, such as population, land area, and other demographic factors. In simple words, with available data sourced from Statistics Norway for each geographical unit, we can easily and accurately calculate these variables for each local market defined using this method without making any assumption.

However, it is essential to recognize some limitations of this approach. Firstly, the fixed borders of geographical units may not always align with real-world consumer behavior. For example, stores located near the border of two units may draw customers from both areas due to proximity, leading to a more fluid catchment area. By rigidly adhering to these borders, our models may introduce bias and overlook important market dynamics.

Secondly, using a single threshold, such as a population count of 50,000, to determine the market level (municipality or statistical tract) may also introduce bias to our analysis, especially for those municipalities with populations slightly above or below this threshold.

4.2.2 Driving time

The second method to define the catchment area of a grocery store takes into account the travel time factor. In other words, based on a combination of the municipal centrality index and the urban settlement population of the area where a store is located, a threshold of driving time is applied and the store's catchment area is marked using this threshold.

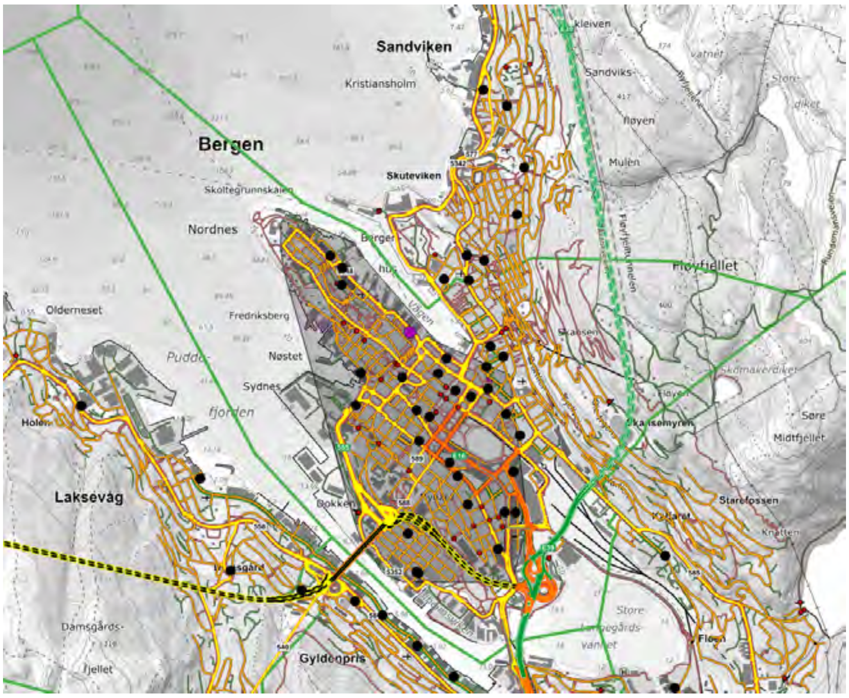
To set the thresholds for driving time, we rely on the list of thresholds proposed by the Norwegian Competition Authority, as detailed in Table 4.2. The Norwegian Competition Authority (2023) has considered that people have varying tolerances for travel time to grocery stores, depending on their residential locations, and that the store's catchment area is defined as the maximum driving time for its customers who account for at least 80% of the store's turnover (Norwegian Competition Authority, 2015). Consequently, the authority has mapped grocery store locations with the municipal centrality index and the population data of urban settlements, and computed the catchment areas for these stores (Norwegian Competition Authority, 2023). The suitable driving time may differ, with shorter driving times being pertinent in densely populated areas, while broader delineations may be appropriate in more remote regions (Ministry of Industry and Fisheries, 2022).

Table 4.2: Driving time thresholds (minutes) (Norwegian Competition Authority, 2023)

Urban settlement levels	Municipal centrality classes			
	Least	Low	Moderate	Most
No settlement (0-199)	20	15	15	15
Small settlement (200-1999)	15	15	15	10
Settlement (2000-99 999)	15	10	10	10
Big settlement (>100 000)			10	5

Figure 4.2 also depicts the local market (the dark grey area) of a store (the purple dot) in the center of Bergen as in Figure 4.1 but using the driving-time approach. In this case, the driving time threshold is 5 minutes. It can be seen that the catchment areas of this store in Bergen center defined by method 1 and method 2 are quite comparable.

Figure 4.2: Illustration of a store's local market defined by method 2



Similar to the geographical border approach, the driving time approach also presents both advantages and disadvantages, albeit in the opposite order. The main advantage is that it more accurately defines a store's competitors as well as its consumers who are reachable from the store location, not limited by the invisible geographical borders. However, this method complicates the calculation of some variables in our models as there is no ready-to-use data available, especially control variables (i.e., market characteristics). Specifically, we need to make certain assumptions to be able to calculate some variables (more details in subsequent sections), introducing variance into our calculation results.

Considering advantages and disadvantages of both methods, we opt for the driving-time approach. While this method comes with a trade-off in terms of potential variance in market characteristics, it more closely simulates how the actual markets operate.

4.3 Main variables

With the chosen method to define local markets of grocery stores, the main variables in our models, including the restrictive covenants, market concentration, store turnover, and store distances are then calculated.

4.3.1 Restrictive covenants

As mentioned in Section 3.1.2, we found 568 restricted land sites, covered by 215 unique registered documents and registered under 1,241 cadastral numbers. The choice of measurement unit for counting restrictive covenants could impact our model results due to the wide range of these numbers. In our analysis, prioritizing the concerns of potential new entrants who seek suitable locations for opening grocery stores—locations that are accessible and that have sufficient area and necessary facilities—we opt for modeling the restricted land sites instead of the registered documents or cadastral numbers.

4.3.1.1 At market level

To assess the impact of restrictive covenants on market concentration level, we use the total number of restrictive covenants imposed in a local market as the explanatory variable of interest C_m.

Utilizing the distance matrix, we group store-to-covenant combinations by store IDs. Within each group (i.e., each store), only combinations where the driving time from the store to covenants is equal to or less than the store's assigned driving time threshold (refer to Table 4.2) are retained. This defines all covenants within the catchment area of the store - i.e., the local market of interest.

Figure 4.3: Restrictive covenants at market level

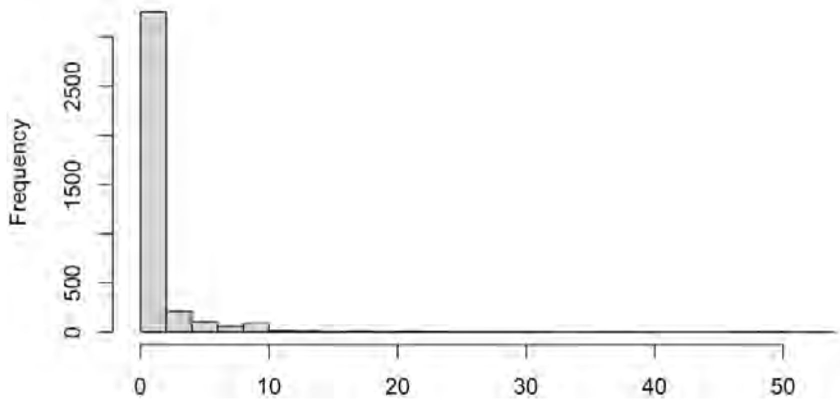


Figure 4.3 shows the distribution of the number of restrictive covenants imposed in each local market in our dataset. It can be seen that the dataset is skewed to the right, in which approximately 60% of the local markets are not mapped with any restrictive covenants.

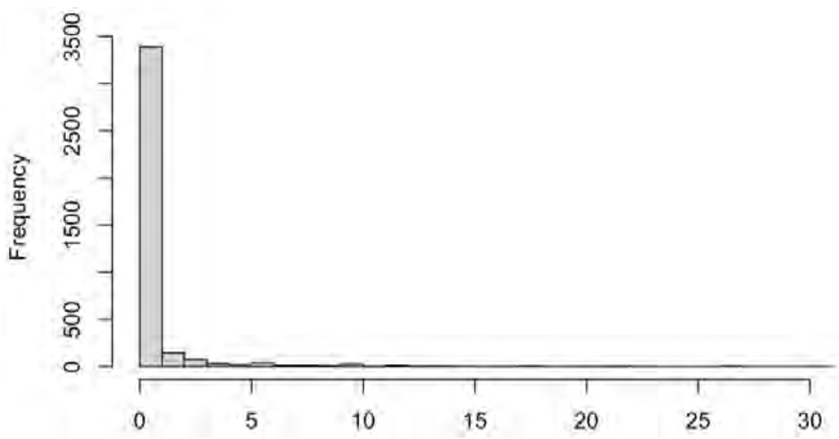
4.3.1.2 At store level

To model the impact of restrictive covenants on store turnover and on distances between grocery stores at store level, we use the number of same-chain restrictive covenants as the explanatory variable of interest. The number of same-chain restrictive covenants is defined as the count of covenants that are imposed on locations within the coverage area of a store, and that are issued by the same grocery chain that owns the store.

Similar when counting covenants at market level, we also utilize the distance matrix to define all elements within the catchment area of a store. The remaining covenants undergo another filtering step to retain only those associated with the same chain as the store. Assuming that all these covenants have an effect on the store if they are in its coverage area, we assign this counted number of same-chain covenants to the store accordingly.

The distribution of the number of same-chain restrictive covenants associated with each grocery store is presented in Figure 4.4. We can see a highly skewed dataset to the right with about 85% of the stores are not mapped with any restrictive covenants.

Figure 4.4: Restrictive covenants at store level



4.3.2 Market concentration

Market concentration assesses the degree to which market shares are centralized among a small number of firms, and this metric is commonly used as an indicator of the level of competition in the market (OECD, n.d.). In industries characterized by high market concentration, companies often engage in profitable mergers and acquisitions, allocate significant resources to lobbying, and enjoy sustained excess profits due to diminished competition (Philippon, 2019). Diminished competition allows leading firms to preserve pricing power and profit margins, while barriers to entry and limited free entry hinder new competitors from effectively entering and challenging existing firms (Cowling and Waterson, 1976; Philippon, 2019). Market concentration can be assessed through various indicators, such as the Herfindahl - Hirschman Index (HHI) and concentration ratio (CR).

The HHI is a commonly accepted measure of market concentration, calculated by summing the squares of the market shares of all players in the market (Antitrust Division, n.d.). The formula is expressed as:

$$HHI_m = \sum_{i=1}^{N} s_{im}^2 \tag{4.5}$$

where $s_{im} \in [0, 100]$ represents the market share of player i in a local market m, N is the total number of players in that local market m, and HHI_m is the concentration index of the local market m (Eide et al., 2022). The resulting index ranges from 0 to 10,000, with 0 when a market is occupied by a large number of firms of relatively equal size and 10,000 indicating that a single player holds a 100 percent market share. According to practice of the Norwegian Competition Authority and European Commission, an HHI of over 2,000 is an indication that the market has high concentration (Midttømme et al., 2022).

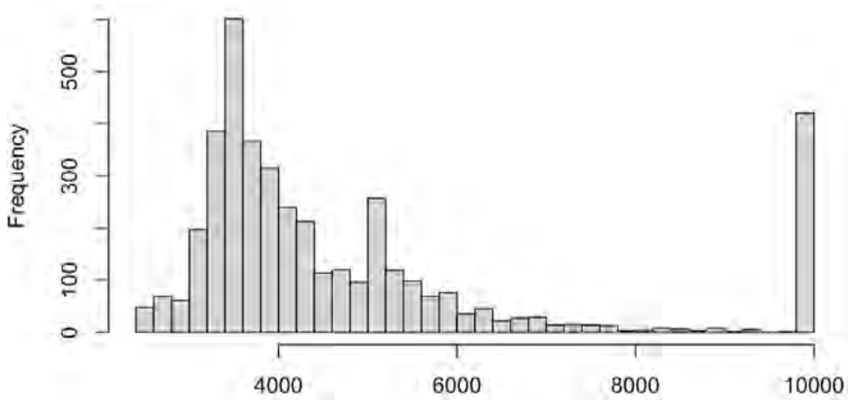
An alternative approach to measure market concentration is CR, which involves examining the market share of the major players. CR requires information on the number of firms and the market shares of the largest firms, and the N-firm concentration ratio measures the market share of the top N firms in the market, such as C3, C5, and C10 (OECD, 2023). The index approaches zero for an infinite number of equally sized firms and equals 1 if the firms included in the calculation make up the entire market; however, by focusing only on the market share of the top N firms, CR takes no account of the market share distribution of the remaining firms (OECD, 2023).

The suitability of HHI or other concentration metrics for assessing the competitive landscape depends on the prevailing market competition dynamics, with a particularly strong correlation in Cournot markets characterized by quantity competition (Oslo Economics, 2017). According to Pavic et al. (2016), there exists a specific relationship between CR and HHI, suggesting no distinction between them. This relationship allows for converting values of one indicator into corresponding values of the other, enabling conclusions to be drawn based on either indicator. In our scenario, with only four main grocery chains and some other stores, the difference between these two indicators would likely be negligible, and we choose HHI to measure market concentration level.

$$s_i = \frac{\sum_{j=1}^{J} T_{ij}}{\sum_{i=1}^{N} \sum_{j=1}^{J} T_{ij}} \tag{4.6}$$

To calculate the market share of each grocery chain in a local market, we utilize the equation 4.6. In this equation, the market share of a grocery chain i in a local market m is computed as the total turnover of all stores j belonging to that chain in the local market m, divided by the total turnover of all chains in the same market. Subsequently, we calculate the HHI of the local market m using equation 4.5. Figure 4.5 shows the distribution of HHIs across local markets. Notably, almost all markets exhibit high concentration level ($HHI > 2,000$), with some markets characterized by a monopoly ($HHI = 10,000$).

Figure 4.5: Distribution of HHI of local markets



4.3.3 Store turnover

In our analysis, store turnover refers to the sales generated by each store in the year 2020. We model turnover at the store level without aggregating to chain or market-wide turnovers. Descriptive statistics of store turnover can be found in section 3.2.2.

4.3.4 Store distances

To quantify the distance between two points, various measurement units exist, such as Euclidean distance, Haversine distance, driving time, or walking time. In our analysis, we use driving time to represent distances, reflecting the actual time customers travel from one store to another. Notably, there are several cases where no driving route from a store to others exists (e.g., stores located on islands). Hence, we opt for removing these cases.

Additionally, we distinguish between (i) distances from one store to other same-chain stores and (ii) distances from one store to competitors' stores. Restrictive covenants set by a grocery chain are commonly used to deter competitors (i.e., stores under different grocery chains) from opening establishments at certain addresses. Consequently, competing chains may need to relocate their stores further from their desired locations due to these covenants. On the other hand, the impact of restrictive covenants on stores under the same chain varies depending on the covenant's wording[25]. Therefore, we anticipate that covenants imposed by one grocery chain may have a different and more complicated impact on the distances between same-chain stores than on the distances to its competitors. In our analysis, we will focus on the distance between a store and its competitor only.

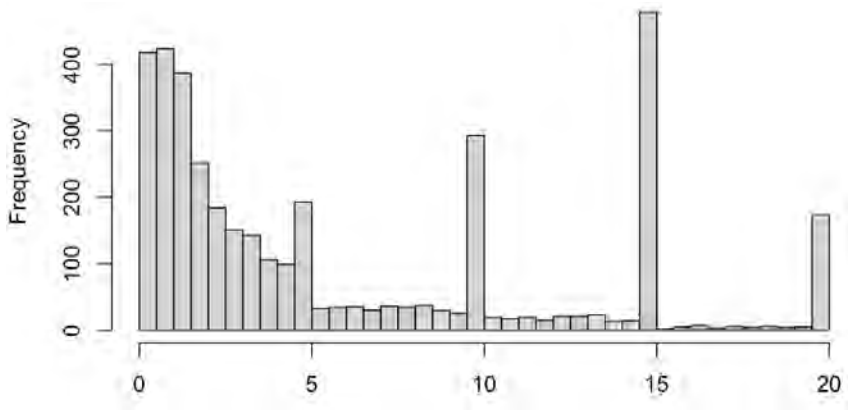
In our model, each observation represents a single store within its local market, with multiple distances linking that store to others in the same market. The challenge lies in selecting a single representative distance for each store in our model. We choose the minimum distance, which reflects the proximity of the store to its closest competitor. For instance, we consider Store i situated in a densely populated area, where competitors aim to establish new stores nearby. However, due to covenants imposed by store i, competitors are compelled to select locations farther away. Subsequent competitors entering the market may consider various factors influencing their location decisions, aside from covenants placed by store i (e.g., covenants issued by other chains, nearby residential developments). Hence, we posit that restrictive covenants exert the strongest influence on the location decision of its closest store, represented by the minimum distance. Additionally, customer surveys conducted by Coop in 2015 (Norwegian Competition Authority, 2015) reveal that nearly half of the average income diversion is directed to the two nearest shops, with the diversion to the nearest store being significantly higher compared to the second one. This underscores the importance for a store to strategically impose covenants in proximity to

[25] For instance, if a covenant states "Prohibition on grocery business," stores under the same chain might also face restrictions on opening in that area. Conversely, if the covenant specifies "Prohibition on activities competing with the right holder," it is more probable that a store under the same chain can be established. However, the decision to open another store in that area to compete with the current store under the same chain could be influenced by additional factors that the chain must take into account.

their own establishments, potentially influencing the location of its closest competitor.

Utilizing a distance matrix among grocery stores generated from our route calculations, for each store, we extract the list of distances between that store and all other stores located in its local market (i.e., within the store's driving time threshold). Subsequently, we exclude distances to other stores that were established prior to the store of interest. From the remaining distances, we identify the minimum distance. If there is no competitor in the store's catchment area, we use the driving time threshold of that store as the minimum distance. Figure 4.6 below illustrates the distribution of minimum distances.

Figure 4.6: Distribution of minimum driving time to competitor (in minutes)



4.4 Control variables

Each local market is characterized by its own set of demographic factors, and each store has its own set of attributes. To draw conclusions regarding the impact of restrictive covenants, it is essential to control for these factors. Identifying and managing other relevant variables that may inadvertently influence the relationships being examined not only ensures methodological rigor but also enhances the generalizability of findings (Bernerth & Aguinis, 2016). In our analysis, we incorporate several market demographic characteristics X_m as well as store attributes Y_i as control variables.

$$X_m = (Pop_m, Area_m, Income_m, Age_m) \tag{4.7}$$

$$Y_i = (Area_i, Center_i, Mall_i) \tag{4.8}$$

The vector of market characteristics includes total population Pop_m, total land area in square kilometers $Area_m$, average household income after tax $Income_m$, and proportion of each age group Age_m. To gather data on market characteristics, we utilize the Isochrones service[26]. This service offers a tool to determine areas reachable from specific locations (i.e., grocery stores in our case), using driving time thresholds. Once the catchment area is established, we compile a list of basic statistical units that intersect the store's catchment area. Then, market characteristics are computed by aggregating the data from each basic statistical unit. There are instances where the Isochrones service fails to return catchment areas or provides "seemingly unreliable" areas, which typically due to stores are located in isolated islands or restrictive areas with little access to roads. Our approach to handle those is presented in Appendix B.

It is worth noting that we had the option to utilize demographic data directly from the Isochrones service. However, we opted for the method described above for two main reasons. Firstly, as mentioned above, the Isochrones could sometimes fail to return or provide unrealistic catchment areas, leading to unreliable land area data. Secondly, the Isochrones data provides only population and area information for a reachable area. To incorporate additional variables, we need to either calculate them using the method above or assume demographic data by geographical border. Therefore, aggregating data from basic statistical units appears to be a logical and reliable approach.

However, it is important to acknowledge that our method has its limitations. There are instances where not all basic statistical units are entirely contained within the borders of the catchment areas. Consequently, by aggregating data from all basic statistical units returned by the Isochrones service, regardless of whether they lie entirely within the catchment area or not, we may introduce some variance into the dataset.

In term of store attributes, we include store area $Area_i$ in square meters, a binary variable of whether the store of interest is located in center $Center_i$, and a binary variable of whether the store of interest is located in a shopping mall $Mall_i$ as control variables. These variables are available in the original store dataset.

[26]The Isochrones service is provided by Openrouteservice, which offers global spatial services using user-generated and collaboratively collected free geographic data from OpenStreetMap. The Isochrone Service supports time and distance analyses for one or multiple locations. More information on: https://openrouteservice.org/

5 Analysis

In this section we present the results of our empirical analysis, discuss robustness checks and the validity of our models, as well as the limitations in our analysis and implications for future research.

Overall, at market level, our analysis reveals a positive relationship between restrictive covenants and the level of local market concentration. This indicates that in local markets where a greater number of restrictive covenants are imposed, there tend to be higher HHI values, suggesting increased market concentration. At store level, there exists a statistically significant positive relationship between restrictive covenants and store turnover, indicating that a grocery store associated with more same-chain restrictive covenants tends to have higher turnover. However, the null hypothesis that restrictive covenants have no impact on store distances cannot be rejected. By employing various robustness checks and validating the IV, we found our results are relatively robust.

5.1 Results

5.1.1 Market concentration

Table 5.1 presents the regression outcome of the second-stage regression for our model M1. The independent variable of interest is the fitted value of the number of restrictive covenants in each local market obtained from the first-stage regression, with the number of grocery stores established before the imposition date of the last restrictive covenant acting as the IV. The dependent variable is the market concentration level, represented by HHI.

In model M1, employing the 2SLS method, we observe a positive and statistically significant relationship between the number of restrictive covenants and the HHI index of the local market, significant at the 0.1% level. This implies that in local markets with a greater number of restrictive covenants, there tends to be higher level of market concentration. Given that restrictive covenants aim to deter competitors of a grocery chain from entering or expanding within a local market, this result obtained for model M1 using 2SLS with one IV aligns with our expectation.

For comparison, we present the regression result of our model M1 using the standard OLS estimator in Table 5.1. Interestingly, the results show a shift in the relationship direction depending on the method used. As mentioned above, the 2SLS method returns a positive relationship, statistically significant at the 0.1% level. Meanwhile, the OLS model yields a contradictory result, showing a negative relationship between restrictive covenants in a local market and the level of concentration, with statistical significance at the 0.1% level. This suggests that, according to the OLS model, local markets with higher number of restrictive covenants tend to exhibit a lower level of market concentration. This result is contradict to that of our 2SLS model as well as our expectation considering the anti-competitive purpose of covenant. Additionally, the magnitude of the coefficients obtained from 2SLS and OLS methods is markedly different. This disparity suggest that there might exist bias in the model using OLS estimator.

Table 5.1: M1 Regression results – Market concentration

	(M1)	
	2SLS	OLS
Number of restrictive covenants	188.0894***	-38.7987***
	(51.5448)	(8.2241)
Land area	1.4315***	1.2943***
(sqkm)	(0.1368)	(0.1331)
Population	-21.5149***	-16.0797***
(1000 people)	(2.0138)	(1.6012)
Household income after tax	5.7431***	5.6672***
(1000 NOK)	(0.5783)	(0.5774)
Proportion of Age group 0-19	-72.4512***	-92.1774***
(%)	(12.0038)	(11.1458)
Proportion of Age group >67	83.5779***	69.9715***
(%)	(8.3169)	(7.7278)
Constant	1,860.3773***	2,789.0127***
	(391.2350)	(330.8102)
No. Observations	3,798	3,798
R-squared	0.2000	0.2019

Standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001

5.1.2 Store turnover

As presented in Section 4.1.2, we use the OLS method to quantify the relationship between restrictive covenants and store turnover. We examine model M2 at store level, in which the independent variable of interest is the number of same-chain covenants associated with a grocery store and the dependent variable is the turnover of that store.

Table 5.2: M2 Regression results – Store turnover (Million NOK)

	(M2)	
	All stores	Store with covenants
Number of same-chain covenants	0.7219**	0.1312
	(0.2765)	(0.6712)
Store area (sqm)	0.0687***	0.0865***
	(0.0013)	(0.0051)
Binary of center location	2.8372	2.6228
	(1.5481)	(6.7052)
Binary of shopping mall location	9.6320***	8.6274
	(2.1195)	(8.6261)
Land area (sqkm)	-0.0046	-0.0056
	(0.0026)	(0.0159)
Population (1000 people)	0.0870**	0.0993
	(0.0320)	(0.1165)
Household income after tax (1000 NOK)	0.0521***	0.1085
	(0.0114)	(0.0562)
Proportion of Age group 0-19 (%)	-0.5191*	-2.1158*
	(0.2255)	(1.0556)
Proportion of Age group >67 (%)	-0.2545	-0.1625
	(0.1520)	(0.6726)
Constant	-13.0158	-21.9858
	(6.6613)	(28.9538)
No. Observations	3,798	644
R-squared	0.500	0.3712

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The regression result of our turnover model M2 is presented in Table 5.2. It can be seen that there exists a positive relationship between restrictive covenants and the turnover of a store, statistically significant at 1% level. Specifically, a grocery store associated with a higher number of same-chain covenants is likely to have higher turnover. Given that restrictive covenants aim to deter competitors from entering the coverage area of a store, this result aligns with our expectation for the impact of restrictive covenants.

Our independent variable of interest, the number of same-chain restrictive covenants, is highly skewed as shown in Figure 4.4, with around 85% of stores associated with no covenants. Hence, we re-ran our model M2 using only grocery stores that are associated with at least one restrictive covenant each. The result still shows a positive relationship but it is no longer statistically significant, meaning that we cannot reject the null hypothesis that the number of same-chain restrictive covenants do not affect the turnover of a grocery store. Excluding stores associated with no restrictive covenants might have lowered the statistical power, making it harder to detect a significant relationship.

5.1.3 Store distances

In store turnover model, we use OLS estimator, with the same explanatory variable of interest as in store turnover model - which is the number of same-chain covenants imposed in the catchment area of a store. The dependent variable now is the driving time from that store to its closest competitor.

Table 5.3 presents the regression outcomes of our model M3. We observe no statistically significant relationship between same-chain restrictive covenants and minimum store distances, meaning that we cannot reject the null hypothesis that the number of same-chain restrictive covenants does not impact the distance of the store of interest and its closest competitor. Given that restrictive covenants aim to deter competitors from entering the coverage area of a store, this result is differ from what we expected.

Similar to our store turnover model, due to the high skewness of the number of same-chain covenants, we also re-ran model M3, including only stores that have at least one covenant, to see how the model perform under this condition. The result is similar to that of model M3 when regressed on all stores: we cannot reject the null hypothesis that the number of same-chain covenants do not affect the distance between a store and its closest competitor.

Table 5.3: M3 Regression results – Store distances (Minutes)

	(M3)	
	All stores	Store with covenants
Number of same-chain covenants	-0.0449	-0.0208
	(0.0376)	(0.0354)
Binary of center location	-2.8134***	-2.0098***
	(0.2080)	(0.3509)
Binary of shopping mall location	-1.0030***	-0.1547
	(0.2804)	(0.4368)
Land area (sqkm)	0.0054***	0.0081***
	(0.0004)	(0.0008)
Population (1000 people)	-0.0454***	-0.0218***
	(0.0044)	(0.0061)
Household income after tax (1000 NOK)	0.0125***	0.0122***
	(0.0015)	(0.0029)
Proportion of Age group 0-19 (%)	-0.2362***	-0.1936***
	(0.0301)	(0.0544)
Proportion of Age group > 67 (%)	0.1879***	-0.0255
	(0.0207)	(0.0354)
Constant	2.0459*	2.3125
	(0.9060)	(1.5274)
No. Observations	3,798	644
R-squared	0.3216	0.3004

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Robustness check and validity

In addition to examining the significance and direction of the relationship between restrictive covenants and outcome variables as outlined in section 5.1, we also assess its sensitivity to changes in the models and sample. This is done to ascertain whether our findings hinge heavily on specific assumptions and constraints or if they remain consistent across various contexts, and to confirm the validity of our findings.

5.2.1 Market concentration

In this part, we first present the results of our robustness check for our market concentration model. Later, we will discuss the validity of the IV in our model.

5.2.1.1 Robustness check

For the market concentration model M1, we conduct the robustness check by examining three different tests, each differing by one element from the original model to observe how the results change accordingly.

1. Altering the count of covenants from unique addresses to unique documents.
2. Modifying the market definition from driving time thresholds to geographical borders.
3. Eliminating local markets with HHI = 10,000 (monopoly).

M11 - Unique documents:

As previously mentioned, we measure the number of restrictive covenants in each local market by counting the distinct addresses where these covenants are imposed. However, there is a significant difference in this count depending on whether we consider unique addresses or unique documents. Here, the documents refer to contracts or agreements containing the restrictive covenants, which may apply to entire building or even multiple buildings rather than individual addresses within each building. Consequently, the count of documents is typically lower than the count of addresses. In total, we have 204 restrictive covenants based on this new counting, as opposed to the 531[27] covenants observed in model M1. To evaluate the robustness of our model, we adjust the count of covenants from distinct addresses to distinct documents to observe any variations in model behavior.

M12 - Market definition 1:

In Section 4.2, we outlined two methods for defining local markets, ultimately opting for the driving time threshold method due to its closer alignment with real-world dynamics. However, it is important to note that this method relies on assumptions about the demographic data of the local markets. For our second robustness check, we wanted to

[27] As stated in Section 3.1, we initially identified 568 restrictive covenants associated with one of the four main grocery chains. However, for our models, we considered only 531 of these covenants, excluding those that had expired before 2020.

assess the impact of these assumptions on the result of our regression model. Therefore, we altered the definition of local markets to the geographical border method to observe any differences in our findings. By changing the definition of local markets, we significantly reduce the number of observations from 3,798 to only 672 local markets.

M13 - Exclude HHI 10,000:

Our third robustness check involves excluding outlier observations from our dataset that is then fed to the models. As depicted in Figure 4.5, there are several local markets where a single player dominates the market, resulting in an HHI of 10,000. We aimed to exclude these outliers to determine if our results are driven by a few extreme cases.

Table 5.4: M1 Robustness check results - Market concentration

	(M11) Unique documents	(M12) Market option 1	(M13) Exclude HHI10,000
Number of restrictive covenants	861.8284***	676.3509***	84.5226**
	(236.1792)	(87.1779)	(29.4138)
Land area (sqkm)	1.5517***	-0.4077***	0.9114***
	(0.1478)	(0.1057)	(0.0917)
Population (1000 people)	-23.8720***	-191.0067***	-6.7937***
	(2.4633)	(13.1519)	(1.1579)
Household income after tax (1000 NOK)	6.4320***	2.9021*	3.0729***
	(0.6137)	(1.4006)	(0.3586)
Proportion of Age group 0-19 (%)	-104.0756***	64.6002*	-25.5594***
	(11.8964)	(28.1857)	(7.5670)
Proportion of Age group >67 (%)	68.4201***	4.4931	50.4248***
	(7.7939)	(18.1927)	(5.0757)
Constant	2,302.6416***	3,760.6698***	2,224.2400***
	(341.4899)	(719.1883)	(234.4000)
No. Observations	3,798	672	3,410
R-squared	0.2000	0.2849	0.1468

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.4 presents the regression results obtained from the second-stage regression of our robustness check, in which the independent variable of interest is the fitted value of the number of restrictive covenants imposed in a local market from the first-stage, with the IV defined as the number of grocery stores established before the latest covenant date. The dependent variable is the concentration level of local markets - HHI. It can be seen that all models consistently show a positive relationship between restrictive covenants in a local market and the level of market concentration, indicating that a local market with a higher number of restrictive covenants tends to be more concentrated. In model M13, where we change exclude markets with HHI 10,000, the estimated coefficient is statistically significant at the 1% level, while in the other two models, it is significant at the 0.1% level.

5.2.1.2 Validity of IV estimates

Since 2SLS estimates can have large standard errors and are less efficient than OLS when explanatory variables are exogenous, testing for endogeneity is essential to determine the necessity of 2SLS (Wooldridge, 2013). We choose 2SLS estimator for our models of market concentration due to the suspected endogeneity problem based on the literature, but we want to empirically test for the endogeneity of the explanatory variable of interest. Following a regression test for endogeneity described by Wooldridge (2013), we test for the endogeneity of restrictive covenants by obtaining the residuals $\hat{\varepsilon}_m^C$ from estimating the number of restrictive covenants (see equation 4.1) and including the obtained residuals in equation 5.1 below to test for the significance of the residuals.

$$HHI_m = \alpha_2 + \beta_2 * C_m + \gamma_2 * X_m + \delta_2 * \hat{\varepsilon}_m^C + {\varepsilon_m}^{HHI} \tag{5.1}$$

When we do this, the coefficient on $\hat{\varepsilon}_m^C$ is $\hat{\delta_2} = -233.2708 * **$ with $t = -4.487$, statistically different from zero. This is moderate evidence of negative correlation between ${\varepsilon_m}^{HHI}$ and ${\varepsilon_m}^C$, indicating that our explanatory variable of interest C_m is endogenous. The validity of our findings now depends on whether the number of grocery stores established before the issued date of the latest restrictive covenant in each local market is a valid instrument. The conditions for an IV to be valid, as presented in section 4.4, include *instrument exogeneity* and *instrument relevance.*

The first concern is the violation of the instrument exogeneity condition. Essentially, this refers to a scenario where the number of stores established before the latest covenant date becomes correlated with the omitted variables (or the error term in the equation of interest). Such correlation can introduce bias into the resulting estimates, potentially greater than that observed in OLS estimates (Angrist & Krueger, 2001). Unfortunately, this condition is inherently untestable due to the unobservability of the error term, making it impossible to distinguish between direct and indirect effects through the independent variable of interest, namely, the use of restrictive covenants (Sæthre, 2022). However, as detailed in Section 4.4, we have good reasons to believe that our IV does not contravene the instrument exogeneity condition.

The second concern is the violation of the instrument relevance condition. Table 5.5 displays the resulting coefficient of the IV in the first-stage regression of our market concentration model in different scenarios, which are different from zero and statistically significant at the 0.1% level in all cases. The negative sign of the coefficient indicates a negative relationship between the IV and restrictive covenants. This aligns with our intuition that the presence of more grocery stores in a market likely reduces the necessity of imposing covenants in that market.

Table 5.5: Coefficients & F-statistics of IV in 1st-stage regression

	Coefficient β_1	Std. Error	t-value	F-statistics	R-squared
Model M1	-0.0750***	0.0075	-9.962	99.2414	0.0986
Model M11	-0.0164***	0.0018	-9.007	81.1260	0.0800
Model M12	-0.3298***	0.0358	-9.2248	85.0975	0.2849
Model M13	-0.0785***	0.0080	-9.828	96,5896	0.0918

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

Notes: In the first-stage regression, there are both IV and other exogenous control variables. In this table, we report only the coefficient of interest, i.e., the coefficient of the IV.

Another concern involves the potential for bias when the IV is only weakly correlated with the endogenous regressor (Angrist & Krueger, 2001). In this context, it means that the number of grocery stores established before the imposition date of the last covenant may be weakly correlated with the number of restrictive covenants imposed in that market. Assuming the IV is valid (meeting both exogeneity and relevance conditions), but the covariance between the IV and the independent variable of interest (i.e., restrictive covenants) is "close to" zero - indicating a weak instrument problem - it can result in poor estimator performance. Notably, finite-sample bias and sampling variance are likely to be larger in such cases (Sæthre, 2022). Estimates derived from IVs with very weak instruments tend to converge towards the corresponding OLS estimate (Sawa, 1969).

According to Staiger and Stock (1997), the rule of thumb to consider if level of correlation is not “too low” is that the F-statistic on the instrument is at least 10. For a single instrument as in our case, this translates to a t-statistic greater than 3.16. Table 5.5 presents the reported t-statistics and F-statistics of the first-stage regression for our main model M1, as well as the models from the robustness check (M11, M12, and M13). It is evident that all statistics in each model significantly exceed the mentioned threshold, indicating that our models do not suffer from the issue of weak instruments.

In addition, Angrist and Krueger (2001) described a solution to the weak instruments problem, which is to use fewer instruments. Angrist and Krueger (2001) explained that the bias of the 2SLS estimator is proportional to the degree of over-identification. Specifically, if K instruments are used to estimate the effect of G endogenous variables, the bias is proportional to K - G; therefore, using fewer instruments can help reduce bias. In fact, if the number of instruments is equal to the number of endogenous variables, the bias is approximately zero (Angrist & Krueger, 2001). Since our models only involve one endogenous variable with one IV, it is unlikely that our models suffer from bias caused by weak instruments.

Angrist and Krueger (2001) also mentioned that various technical fixes and diagnostic tests have been proposed for the weak instrument problem. One such method is the use of the Limited Information Maximum Likelihood (LIML) estimator. Although LIML and 2SLS have the same asymptotic distribution and are algebraically equivalent in just-identified models, their finite-sample distributions can differ significantly in over-identified models (Angrist & Krueger, 2001). Importantly, LIML is approximately unbiased in the sense that the median of its sampling distribution is generally close to the population parameter being estimated (Anderson et al., 1982). Testing our model M1 with the LIML estimator, the result - presented in Table 5.6 - is nearly identical to that of our 2SLS model, indicating that our estimations are not biased due to weak instruments.

Table 5.6: Regression results - LIML estimator

	(M1)	
	LIML	2SLS
Number of restrictive covenants	188.0894***	188.0894***
	(56.41637)	(51.5448)
Land area	1.4315***	1.4315***
(sqkm)	(0.1497)	(0.1368)
Population	-21.5149***	-21.5149***
(1000 people)	(2.2042)	(2.0138)
Household income after tax	5.7431***	5.7431***
(1000 NOK)	(0.6330)	(0.5783)
Proportion of Age group 0-19	-72.4512***	-72.4512***
(%)	(13.1383)	(12.0038)
Proportion of Age group >67	83.5779***	83.5779***
(%)	(9.1029)	(8.3169)
Constant	1,860.3770***	1,860.3773***
	(428.2108)	(391.2350)
No. Observations	3,798	3,798
R-squared		0.2000

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2.2 Store turnover

For the store turnover model M2, we conduct the robustness check by examining three different tests:

1. Altering the count of covenants from unique addresses to unique documents
2. Modifying the market definition from driving time thresholds to geographical borders
3. Counting only closest covenant instead of same-chain covenants

M21 - Unique documents:

Similar to our market concentration model, our first robustness check of our store turnover model M2 is to change the counting of restrictive covenants. Instead of using 531 unique addresses, we have 204 unique documents as covenants. By doing this, we wanted to assess how the counting assumption of covenants affect the result of our turnover model.

M22 - Market option 1:

For the second robustness check, we define the market of a store using geographical borders instead of driving time thresholds. With this change in market definition, the number of same-chain covenants associated with a grocery store, as well as control variables related to market characteristics, are adjusted. We aim to assess how the choice of market definition affects the result of our store turnover model.

M23 - Closest covenants:

As previously mentioned, we quantify the relationship between restrictive covenants and store turnover, in which restrictive covenants are represented by the number of all same-chain restrictive covenants that are issued by the grocery chain owning the store and that are imposed on locations within the coverage area of the store. Instead, our third robustness check involves counting only the number of restrictive covenants that are imposed on locations to which the driving time from the store of interest is the shortest, and that the locations are within a store's coverage area. We aim to include only closest restrictive covenants to determine if our results are driven by the assumption that all same-chain restrictive covenants in the market have an effect on the store of interest.

Table 5.7 presents the results of our robustness check for the store-turnover model. Similar to our main model M2, the robustness check reveals a statistically significant and positive relationship between same-chain restrictive covenants and store turnover. It indicates that a grocery store associated with a higher number of same-chain covenants is likely to have higher turnover.

As shown in Table 5.2, the coefficient of restrictive covenants in model M2 is no longer statistically significant when we regressed only on stores associated with at least one same-chain covenant. To further investigate, we perform the robustness check using a subset of the dataset, including only stores with at least one same-chain covenant, to observe how the results in Table 5.7 would change. With this new setting, the resulting coefficients[28] of the explanatory variable of interest (i.e., the number of restrictive covenants) are no longer statistically significant in all three models M21 (Unique documents), M22 (Market

[28] see Appendix C for full regression results

option 1), and M23 (Closest covenants). This may be because excluding stores with no restrictive covenants reduces the statistical power, making it harder to detect a significant relationship. In other words, removing a large portion of the dataset leaves the remaining stores with at least one covenant not significantly different enough to show a distinction between stores with higher numbers of covenants and those with lower numbers. However, there is a significant difference between stores with covenants and those with none.

Table 5.7: M2 Robustness check results - Store turnover

	(M21) Unique documents	(M22) Market option 1	(M23) Closest covenants
Number of restrictive covenants	2.2559* (1.0749)	0.9094*** (0.2741)	2.8204*** (0.5454)
Store area (sqm)	0.0686*** (0.0013)	0.0692*** (0.0013)	0.0685*** (0.0013)
Binary of center location	2.8706 (1.5490)	2.2385 (1.5264)	2.5841 (1.5444)
Binary of shopping mall location	9.6251*** (2.1202)	9.5344*** (2.1169)	9.6366*** (2.1140)
Land area (sqkm)	-0.0045 (0.0026)	-0.0029*** (0.0008)	-0.0044 (0.0026)
Population (1000 people)	0.0904** (0.0320)	-0.0444 (0.0568)	0.1057*** (0.0315)
Household income after tax (1000 NOK)	0.0531*** (0.0114)	0.0682*** (0.0134)	0.0523*** (0.0114)
Proportion of Age group 0-19 (%)	-0.5642* (0.2249)	-1.0747*** (0.2442)	-0.5338* (0.2244)
Proportion of Age group >67 (%)	-0.2752 (0.1519)	-0.5833*** (0.1479)	-0.2551 (0.1515)
Constant	-12.2889 (6.6552)	-0.9872 (5.9134)	-12.9888 (6.6373)
No. Observations	3,798	3,798	3,798
R-squared	0.4997	0.5012	0.5026

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Besides the robustness check mentioned above, we also wanted to test if there exists a potential endogeneity problem in our model. Therefore, we conducted an endogeneity test for our store turnover model, similar to the approach used in Section 5.2.1 for validating IV estimates in the market concentration model. We used the following two equations:

$$C_i = \alpha_5 + \beta_5 * P_i + \gamma_5 * X_i + \delta_5 * Y_i + \varepsilon_i{}^C \tag{5.2}$$

$$T_i = \alpha_6 + \beta_6 * C_i + \gamma_6 * X_i + \delta_6 * Y_i + \theta_6 * \hat{\varepsilon}_i^C + \varepsilon_i{}^T \tag{5.3}$$

Table 5.8: Endogeneity test of store turnover model

		Coefficient	(Std. Err)	t value
Equation 5.2	Binary of property companies	1.024***	0.1401	7.311
Equation 5.3	No. same-chain covenants	2.3332	2.3442	0.995
	Residuals $\hat{\epsilon}^C$	-1.6335	2.3607	-0.6920

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

In Equation 5.2, we regressed the number of same-chain covenants C_i on a binary variable indicating whether there is any property management company under the same chain located in a store's coverage area[29][30] P_i, as well as control variables X_1 and Y_i. We posit that P_i is exogenous, meaning it is not directly correlated with the turnover of a store. We then obtained the residuals $\hat{\varepsilon_i}^C$ and added them to Equation 5.3, testing for the significance of $\hat{\varepsilon_i}^C$ using an OLS regression. In Equation 5.3, the outcome variable T_i is the turnover of store i.

[29]In the market concentration model, we used the number of grocery stores established before the latest covenant date as the IV. However, we found this IV unsuitable for our store turnover model because it correlates with store turnover, i.e., markets with more stores are likely to have lower turnover for each individual store. Thus, we tried a different IV: a binary variable indicating whether a property management company under the same chain is in a store's coverage area. This variable should not relate to store turnover but should relate to the number of covenants, as such companies can facilitate the covenant imposition. We compiled a list of relevant property management companies by webscraping Proff.no using stores' organization numbers to find all related companies to the store of interest, kept only those with relevant sector code, and assigning them to local markets using the Isochrone service.

[30]It should also be noted that we found this new IV (the presence of a property management company under the same chain) unsuitable for our market concentration model because it is likely correlated with the number of grocery chains in that market.

The results[31] are shown in Table 5.8. Our IV P_i is correlated with the number of same-chain covenants C_i, with statistical significance at the 0.1% level and a t-value greater than 3.16. In Equation 5.3, the coefficient for the residuals $\hat{\varepsilon}_i^C$ is not statistically significant, indicating that ${\varepsilon_i}^C$ and ${\varepsilon_i}^T$ is not correlated, thus C_i is not endogenous. In addition, according to Wooldridge (2013), estimating Equation 5.3 by OLS produces the same β_2 as estimating by 2SLS. Therefore, if we run the store turnover model using 2SLS estimator, we will observe a positive relationship between the number of same-chain covenants C_i and store turnover T_i, but no longer statistically significant.

5.2.3 Store distances

For store distance model, we also conduct the robustness check by examining four tests:

1. Altering the count of covenants from unique addresses to unique documents.
2. Modifying the market definition from driving time thresholds to geographical borders.
3. Using Euclidean distance instead of driving time.
4. Altering the minimum driving time to competitors to the median driving time

M31 - Unique documents:

We repeat the same test as our previous two models by using 204 unique documents as restrictive covenants instead of using 531 unique addresses to assess how the counting assumption of restrictive covenants affects the result of our store distance model.

M32 - Market option 1:

For the second robustness check, we also change the market definition of a store using geographical borders instead of driving time thresholds, aiming to assess the influence of the choice of market definition on the result of our store distance model.

M33 - Euclidean distance:

Among different metrics to represent distance, we chose driving time as it seems to more closely resemble real-world scenarios. For this robustness check, we change the metric from driving time to Euclidean distance to observe any variation in the model behavior.

[31] We show only the estimates of some variables of interest; estimates for control variables X_i and Y_i are not presented.

M34 - Median distance:

In our store distance model M3, we use the minimum driving time between a store and its closest competitor as the outcome variable, assuming the effect of covenants, if any, will be largest on its closest competitor. In this robustness check, we instead use the median distance between a store and the competitors in its coverage area to see how the results change. We aim to assess whether our result is driven by the assumption that covenants benefiting a store affect the location of its closest competitor only.

Table 5.9: M3 Robustness check results - Store distances

	(M31) Unique documents	(M32) Market option 1	(M33) Euclidean distance	(M34) Median distance
Number of restrictive covenants	-0.6304***	-0.4130	-93.2452	-0.0312
	(0.1452)	(0.4584)	(72.5938)	(0.0338)
Binary of center location	-2.8221***	-11.4725***	-3,879.7056***	-2.6096***
	(0.2075)	(2.5135)	(402.0041)	(0.1871)
Binary of shopping mall location	-0.9840***	-1.8553	-1,585.3348**	-0.8399***
	(0.2798)	(3.4450)	(541.9569)	(0.2522)
Land area (sqkm)	0.0053***	-0.0002	9.5797***	0.0049***
	(0.0004)	(0.0013)	(0.6903)	(0.0003)
Population (1000 people)	-0.0432***	-1.3615***	-85.3821***	-0.0250***
	(0.0043)	(0.0941)	(8.4175)	(0.0039)
Household income after tax (1000 NOK)	0.0124***	0.0480*	21.7168***	0.0102***
	(0.0015)	(0.0225)	(2.9948)	(0.0014)
Proportion of Age group 0-19 (%)	-0.2313***	0.3174	-477.7646***	-0.1754***
	(0.0299)	(0.4066)	(58.1114)	(0.0270)
Proportion of Age group >67 (%)	0.1901***	0.1282	355.4559***	0.1954***
	(0.0206)	(0.2474)	(39.9763)	(0.0186)
Constant	2.0506*	25.6901**	1,951.1482	2.8690***
	(0.9027)	(9.8867)	(1,750.9140)	(0.8149)
No. Observations	3,798	3,798	3,798	3,798
R-squared	0.3247	0.0767	0.2774	0.2972

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.9 presents the results of our robustness check for the store-distance model. Similar to our main model M3, the robustness check reveals that the coefficient for the number of same-chain covenants is negative but not statistically significant, except in model M31, where the count of covenants is changed from unique addresses to unique documents. The relationship between number of same-chain covenants, which is counted by number of unique covenant documents, and the distance from a store to its closest competitor in model M31 is negative and statistically significant at 0.1% level. This result is contradict to our expectation, given the purpose of covenants to deter competitors farther away.

We also re-ran models M31 (Unique documents), M32 (Market option 1), M33 (Euclidean distance), and M34 (Median distance) using only stores with at least one same-chain restrictive covenant in their coverage area to see if the results change. Excluding grocery stores that are associated with no covenants in the original dataset, we then regressed these three models on the remaining stores. The obtained coefficients[32] of the explanatory variable of interest (i.e., the number of same-chain covenants) stay negative and not statistically significant in all cases, consistent with the result of our main model M3.

Given the unexpected results, we wanted to check for any endogeneity problems in our model. We conducted an endogeneity test for the store distance model, similar to the approach used in our market concentration and store turnover models. We utilized the same IV as in the endogeneity test for our store turnover model: a binary variable indicating the presence of any property management company under the same chain located within a store's coverage area. We regressed the number of same-chain covenants C_i on this IV P_i, as well as control variables X_i and Y_i, as specified in Equation 5.2. The residuals $\hat{\varepsilon}_i^C$ were then obtained and added to Equation 5.3 below, where the outcome variable D_i is the minimum distance from store i to its competitors.

$$D_i = \alpha_7 + \beta_7 * C_i + \gamma_7 * X_i + \delta_7 * Y_i + \theta_7 * \hat{\varepsilon}_i^C + {\varepsilon_i}^D \quad (5.4)$$

The results[33] are presented in Table 5.10. As demonstrated in the endogeneity test for our store turnover model, our IV P_i is correlated with the number of same-chain covenants

[32] see Appendix C for full regression results

[33] We show only the estimates of some variables of interest, and there are also estimates for control variables X_i and Y_i which are not presented.

C_i, statistically significant at the 0.1% level with a t-value > 3.16. In Equation 5.4, the coefficient of residuals ($\hat{\varepsilon}_i^C$) is not statistically significant, indicating that ${\varepsilon_i}^C$ and ${\varepsilon_i}^D$ is not correlated, hence C_i is not endogenous. If we run our distance model using 2SLS estimator, we would observe a statistically insignificant relationship between the number of covenants and the store distance D_i, aligning with our OLS result in Table 5.3.

Table 5.10: Endogeneity test of store distance model

		Coefficient	(Std. Err)	t value
Equation 5.2	Binary of property companies	1.0400***	0.1403	7.412
Equation 5.4	No. of same-chain covenants	-0.3457	0.3140	-1.101
	Residuals $\hat{\epsilon}^C$	0.3060	0.3163	0.968

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

5.3 Discussion

In this part, we will first summarise our findings, then discuss the limitations of our analysis as well as present the implications of our findings.

5.3.1 Summary of findings

In the first part of our analysis, we re-checked the number of restrictive covenants imposed by the four main grocery chains that were published through the investigation of the Norwegian Competition Authority, and found a slightly higher number (568 restricted land sites, registered under 215 unique documents, with 11 documents expiring before the end of 2020). This suggests that the actual entry barrier due to limited access to store premises is even higher than previously estimated. In the second part, we empirically analyzed the impact of covenants on local market concentration at market level and on store turnover and store distances at store level.

At local market level, the finding of our main model M1 and the results of the models in robustness checks are consistent, highlighting the robustness of our approach using 2SLS estimator across various scenarios. This consistency confirms that the imposition of restrictive covenants influences the concentration at the local market level, with local markets featuring a higher number of restrictive covenants tending to be more concentrated. This finding provides support to the decision of the Ministry of Industry and Fisheries on banning anti-competitive restrictive covenants.

At the store level, our store revenue model M2 reveals a statistically significant and positive relationship between same-chain restrictive covenants and store turnover. This suggests that when a grocery chain imposes restrictive covenants on locations within the coverage area of its store, their store is likely to have higher turnover. Interestingly, our robustness check suggests that there is a significant distinction between stores associated with at least one covenant and stores with none, while the distinction is not significant among stores that are all associated with at least one covenant.

In contrast, the findings from our store distance model M3 and its robustness check indicate that we cannot reject the null hypothesis that the number of same-chain covenants does not affect the distance between a store and its closest competitor. There is one exception: model M31, where we change the count of covenants from the number of unique restricted addresses to the number of unique documents. In which, the relationship between the number of same-chain covenants and the distance from a store to its closest competitor is negative and statistically significant at 0.1% level, contradicting to our expectation. However, when using the subset of grocery stores associated with at least one covenant, the coefficient of interest in model M31 is no longer statistically significant.

As discussed in the literature review, the intended purpose of restrictive covenants imposed by grocery chains is to deter competitors from entering the market and to keep them farther away. Therefore, we expected that the imposition of restrictive covenants would increase the HHI (market concentration index), increase the turnover of a store, and increase the distances between a store and its competitors - which to some extent explain for the increase of store turnover. The results of our analysis align with these expectations, except for the result of our store distance model, where we cannot conclude that restrictive covenants affect store distances. Overall, our findings, to some extent, support the policy change of banning restrictive covenants, as we initially aimed for. We believe the unexpected result in our store distance model may be due to limitations in our analysis, which we will discuss in more detail in the next section.

5.3.2 Limitations

Due to various reasons, our thesis has some limitations that may affect our results.

5.3.2.1 Regarding our restrictive covenant dataset

Firstly, when mapping restrictive covenants with the grocery chains, we may have excluded several relevant restrictive covenants, leading to an underestimation of their effect on grocery markets. One reason for this limitation might be the absence of a clear right holder associated with the restrictive covenant under examination. As discussed in Section 3.1, this could occur if the covenant was imposed permanently on the property long ago without stating the right holders, or if we lack the means to access more information about it. Obtaining additional documents about restrictive covenants ("Tinglyst" documents) could provide useful information about the right holders; however, each copy of these documents costs NOK 240 and is sent by post in hard copy format, making it challenging to review thousands of documents, especially given our limited resources. Another reason for the exclusion of relevant restrictive covenants is our inability to determine whether the right holders or owners of the properties are associated with any of the grocery chains. In many cases, the owners or right holders are individuals, making it difficult to map their relationships with grocery chains. It is possible that properties registered under individuals actually belong to a grocery chain, and the individual has a special relationship with a grocery chain (for example, being a relative of the owners of a grocery chain).

Secondly, the process of flagging covenant wording is subjective, potentially introducing bias to our dataset. When categorizing restrictive covenants as irrelevant, questionable, or relevant, we designated a covenant as relevant only if it explicitly prohibited the operation of grocery stores, unless additional information was available. Consequently, it is possible that many covenants were classified as "questionable," potentially resulting in the omission of relevant restrictive covenants. For instance, some covenants may not directly restrict grocery business but instead impose limitations on specific product types (e.g., "adjustment of the non-competition clause regarding restrictions on trade in home electronics"), or restrict access to other essential facilities required for operating a grocery store, such as parking space (e.g., "case no. 15-198423, no. 11, the use arrangement for parking spaces applies"). These covenants are categorized as questionable and thus excluded from the counting. Similar to the first limitation regarding mapping right holders, this limitation of over-counted "questionable" covenants could be minimized if further information were accessible in "Tinglyst" documents, but unfortunately, we lack such access. Conversely, we might have counted both anti-competitive and non-anti-competitive covenants as relevant, because it is difficult to distinguish the underlying intention of a grocery chain issuing the covenants—either to deter its competitors or to protect its locations for future development. Hence, we may inflate the number of relevant covenants.

Thirdly, the absence of road addresses in some cases could introduce variance into our dataset. When obtaining addresses for restrictive covenants, there are instances where land sites lack specific road addresses. Consequently, we must select a nearby address to obtain longitude and latitude coordinates, allowing us to calculate distances to other objects in the market. This may pose a challenge if the selected nearby address is considerably distant from the original address, particularly in areas with low population density. One potential solution to this issue is to utilize API data directly from the Norwegian Mapping Authority, which would enable us to get coordinate data using cadastral addresses. However, due to the complexity of complying with the requirements for handling personal data from the Norwegian Mapping Authority, we are unable to obtain access to this API data.

Finally, the threshold we established for the minimum area of a land site could introduce some variance into our dataset. For sectionalized land sites, there is often missing data regarding the area of each individual section, leading us to assume uniform size across all sections. However, in reality, these sections can vary significantly in size, and it is possible that a land site where we marked a covenant as relevant may not actually be large enough to accommodate a grocery store. This inconsistency could impact our analysis by misrepresenting the feasibility of opening a grocery store in certain locations.

5.3.2.2 Regarding our analysis method

In our analysis, we are working with cross-sectional data fixed for the year of 2020. Restrictive covenants may have been imposed in an area with the purpose of deterring competitors; however, real-world dynamics like population shifts, construction projects, or urban development in that area over time might have partly covered the initial impact of these covenants, influencing our estimations. Consider this example: A grocery chain might have imposed a restrictive covenant in a particular location, causing competitors to establish themselves farther away. However, as new buildings emerge, residential areas spring up in between, and new competitors can set up stores in these new locations, regardless of whether the initial location is still restricted or not. This may shorten the distances between the chain's store and its competitor. Given the limitations of our thesis scope and the available data, we have not been able to incorporate these dynamic changes. Therefore, our cross-sectional analysis may not fully capture how the impact of restrictive covenants, especially considering that each covenant might have been issued at different points in time.

In addition, our analysis method has not accounted for the factor of who is the right holder of covenants in a market. In other words, in a local market, the impact of covenants issued by an incumbent could be much different from that of covenants issued by a new or small player. For instance, when a small player issues covenants, either with an anti-competitive purpose or not, the imposition of covenants could help this small player to limit the expansion of the incumbent in that market, providing an opportunity for this new player to grow stronger and somehow reducing market concentration. However, in a local market, the position of its market leaders could also change over time. As mentioned earlier, we cannot include time-variant factors in our models with currently available data, so we cannot account for this factor as well.

Finally, there is a risk that our IV used in our market concentration model, which is the number of grocery stores established before the imposition date of the last restrictive covenant, is not valid. Although we have conducted various tests to check if our IV meets the necessary conditions as presented in previous sections, one condition, which is instrument exogeneity, remains untestable empirically.

5.3.3 Implications

Given the limitations outlined above, future research aiming to determine the precise number of restrictive covenants in a market could consider leveraging additional resources, such as "Tinglyst" documents and API data from the Norwegian Mapping Authority. This could help mitigate bias introduced into the dataset and allow for a more precise estimation of the impact of restrictive covenants on the structure of the grocery market.

Future research could broaden its scope by exploring alternative methods to see how the results would change. Currently, our analysis utilizes the 2SLS estimator for market concentration models and the OLS estimator for store distance and store turnover models. Gathering more extensive data about grocery stores across different years from sources like Geodata and exploring alternative methods could enhance our understanding. For example, using panel data with time series analysis could allow researchers to examine the effects of restrictive covenants before and after their issuance.

Furthermore, future research could conduct a more comprehensive analysis of the policy change—the ban on covenants—that would supplement our findings. For example, in a few years from now, researchers should be able to see whether banning covenants leads to more entries in markets with higher covenant intensity to conclude about the impact of restrictive covenants as well as the effectiveness of the policy change. However, we currently do not have the necessary data.

In addition, future research could consider additional market outcomes to provide further insights into the dynamics influenced by restrictive covenants in the grocery market landscape. Currently, our analysis focuses on the concentration level of local markets and on the store turnover as well as store distances due to constraints related to time and resources. Exploring market outcomes beyond these three metrics, such as the number of new entries into a market each year, could offer a more nuanced understanding of the impact of restrictive covenants on the grocery market.

In summary, pinpointing the exact number of restrictive covenants imposed in a market is challenging due to various influencing factors. Our analysis of the limitations suggests that the actual number of covenants aimed at limiting access to premises for newcomers could be even higher than our estimates indicate, and that there might be some limitations in our empirical method that explain for the unexpected result in our store distance model. Despite limitations in our analysis, our findings regarding the impact of restrictive covenants on the concentration of local markets, on store turnover, and on the distances between grocery stores remain relatively robust. Overall, our findings support the decision of the Ministry of Industry and Fisheries to ban restrictive covenants imposed with anti-competitive purposes, as we expected at the beginning.

6 Conclusion

Aiming at providing empirical evidence to support the recent ban of restrictive covenants by the Ministry of Industry and Fisheries, this thesis examine how extensively restrictive covenants are utilized by grocery chains in Norway and analyze their impact on the structure of local grocery markets. With only four players controlling nearly 100% of the total market share and high market concentration observed in numerous local markets, the issue of insufficient competition among existing players has become a major concern for government authorities. However, the use of restrictive covenants as a means to deter competitors and consequently reduce competition among grocery chains remains relatively understudied. Conducting an empirical analysis of the effect of restrictive covenants on the grocery market could offer valuable insights and lay a research foundation for informed decision-making.

With exclusive access to a covenants dataset obtained from the land register published on the website of the Norwegian Mapping Authority, our first focus is on identifying restrictive covenants issued by grocery chains to deter competitors from opening stores. We then quantify the relationship between these restrictive covenants and local market concentration, using the 2SLS estimator with an instrumental variable to address endogeneity problems. Furthermore, we quantify the relationship between restrictive covenants and store turnover to assess how these covenants benefit the stores of the issuing grocery chain. Additionally, we examine the relationship between restrictive covenants and the minimum distance between a store and its competitors to see if covenants increase this distance. In other words, we want to assess if covenants placed by a grocery chain help its store expand the customer base and increase the store turnover, while reducing customers' store choices for multi-stop shopping. Our store turnover and store distance models are estimated using the OLS estimator, as we found no signs of endogeneity.

Our analysis reveal a list of 568 land sites restricted by covenants that were issued by grocery chains under 215 documents. In addition, the results show a positive relationship between restrictive covenants imposed in a local market and the level of concentration in that market - statistically significant in all scenarios, as well as a positive relationship between same-chain restrictive covenants and store turnover - statistically significant in all cases except for one case where we regress only on stores associated with at least one covenant. This indicates that local markets with a higher number of properties restricted by covenants are likely to be more concentrated, and that stores associated with same-chain restrictive covenants tend to have higher turnover. These findings align with the expected impact of restrictive covenants, which are designed to deter competitors. However, for our store distance model where we regress the minimum distance between a store and its competitor on the number of same-chain restrictive covenants, the results are contrary to our expectations as the relationship is not statistically significant in most scenarios.

Our analysis is subject to several limitations primarily due to resource constraints, which may have led to under-reporting the number of restrictive covenants and consequently underestimating their effects. Future research could address these limitations by conducting more thorough investigations to gather additional information from reliable sources, such as registered documents about covenants on properties and other data about property characteristics from the Norwegian Mapping Authority. This would enable a more precise and updated assessment of the number of restrictive covenants. Additionally, we encourage further analyses to explore other methods and other aspects of grocery market outcomes, such as the number of new entries in each market, to supplement our findings. These analyses would contribute to a more comprehensive understanding of the impact of restrictive covenants on the grocery market and strengthen the grounds for decision-making.

Overall, despite some limitations, the findings of this thesis provide support, to some extent, for the regulation aimed at banning the utilization of restrictive covenants as a tool for anti-competition, aligning with our initial objectives.

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Appendices

A Route calculation

Route calculation plays an important role in our analysis. The resulting driving time between two points is used either to define the elements in the local market of a grocery store or as the outcome variable in our store distance model. In this part, we will first introduce briefly the route calculation tools used in our analysis and then summarize how we handle error in the analysis process.

A.1 Route calculation tools

The driving times for most store-to-store and store-to-covenant combinations are calculated using the Route Planning Service provided by the Norwegian Public Roads Administration (NPRA). A small portion of these combinations is calculated through the Google Distance Matrix API.

The route calculation process using the Route Planning Service of the NPRA was conducted by Jan Kristian Jensen, a chief engineer at NPRA. First, our dataset, comprising over 200,000 combinations with longitude and latitude coordinates, was processed. A line geometry was created from the start point to the end point for each combination and converted to UTM zone 33 (EPSG:25833) to prepare for route calculation (Jensen, 2024). A request was then made to the NPRA route planning service for each combination of starting and ending points. The route planning service adjusted the specified starting and ending points to the nearest drivable points on the road network and calculated the route between those adjusted points (Jensen, 2024). A list of one to three route suggestions was provided, with the first suggestion, usually the most efficient or shortest route, consistently chosen for further analysis. Along with the chosen route, the data included the distance traveled by ferry (if applicable) and the total distance between the adjusted starting and ending points on the road network (Jensen, 2024).

Figure A.1 shows all the driving routes for the store-to-store and store-to-covenant combinations in our dataset, depicted by green strings, and Table A.1 below provides the distribution of the retrieved data for store-to-store combinations (Panel A) and for store-to-covenant combinations (Panel B).

Figure A.1: Driving routes from store to store (left) and from store to covenant (right)

Table A.1: Distribution of driving time returned by NPRA

	No. of Obs	No. of NA	Min	Median	Mean	Max
A: Store-to-store combinations						
Airline distance (meters)	193,896	0	0	6,987	9,043	36,666
Driving time (minutes)	193,480	416	0	12.12	18.46	541.87
Total route (meters)	193,480	416	0	9,954	15,764	387,888
B: Store-to-covenant combinations						
Airline distance (meters)	14,097	0	0	6,430	8,440	36,626
Driving time (minutes)	14,078	19	0	11.32	16.09	133.10
Total route (meters)	14,078	19	0	9,318	13,973	149,103

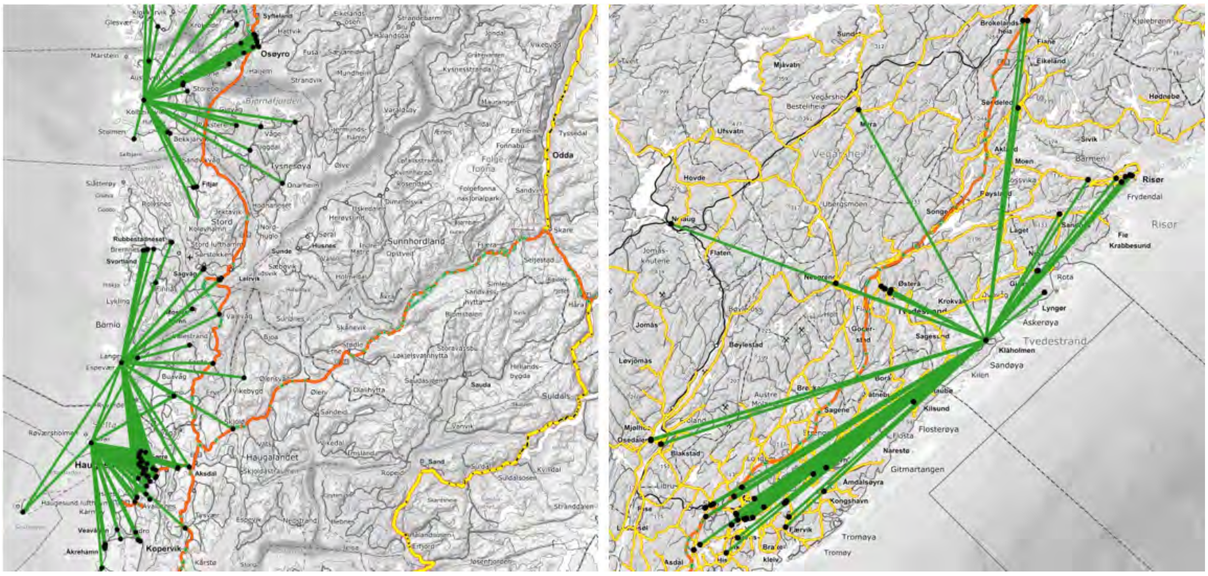
In addition to the Route Planning Service by NPRA, the Google Distance Matrix API is also utilized in our route calculation process. This API retrieves distance and travel time between two points from Google Maps, offering four possible modes of transportation: bicycling, walking, driving, and public transportation (Melo & Zarruk, 2023). The calculation process is straightforward, using the gmapsdistance function. To use this function, an API key is required, and the Distance Matrix API must be enabled in the

Google Developers Console (Melo & Zarruk, 2023). While the process to extract distance and time for each combination is simple, it incurs a cost for each request. Therefore, we use this service for a small portion of our combination dataset and to handle some error routes returned by NPRA.

A.2 Error handling

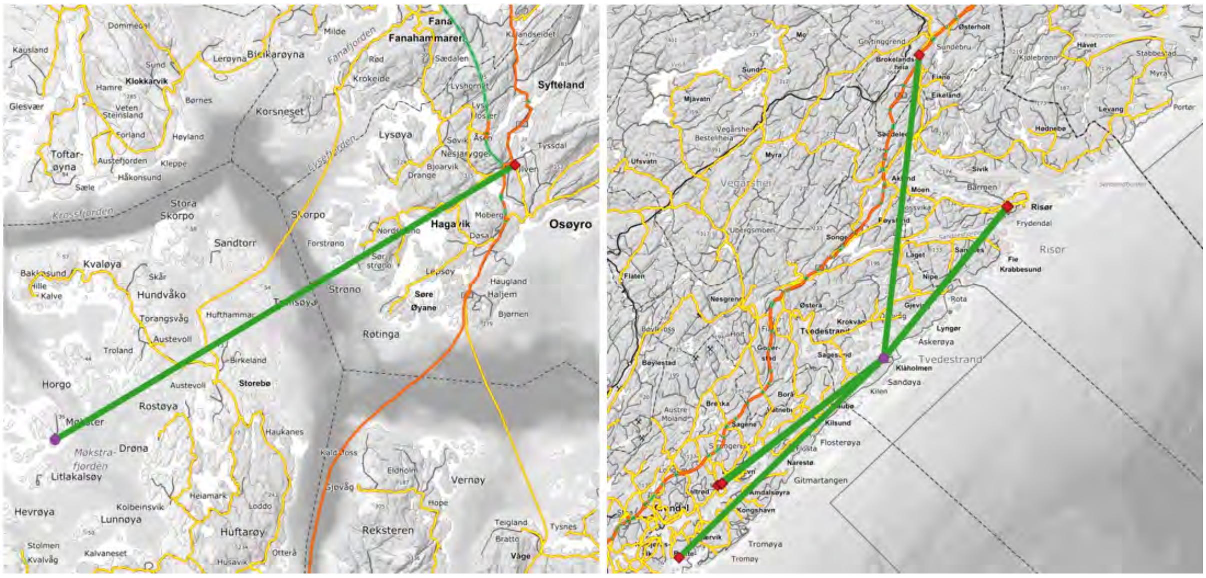
Out of the 193,896 store-to-store combinations calculated by NPRA, 193,480 routes were successfully retrieved, with a total of 8,906 routes including travel time on a ferry. Driving routes were not found for 416 combinations. According to (Jensen, 2024), this is because the starting or ending points are sometimes located on islands separated from the main road network or on restricted areas with drivable roads that are not accessible to the public, such as squares or service roads in shopping centers, usually blocked by a roadblock or a 'No Entry' sign.

Figure A.2: Illustration of stores with no driving routes to other stores



For the 416 combinations with missing route information, the Google Distance Matrix API was used to attempt retrieving the distance and time. This process yielded 83 additional routes. Additionally, there were 333 combinations for which neither the NPRA Route Planning Service nor the Google Distance Matrix API could find a route. A common feature of these combinations is that at least one of the stores in each combination is located on an isolated area. Figure A.2 highlights the Euclidean distances (green lines) for some of the stores that route information to other stores was not able to be retrieved, confirming that some stores are located on islands. Considering all stores located on islands and the Euclidean distances of the store combinations, the remaining 333 combinations with routes not found were removed from the dataset.

Figure A.3: Illustration of stores with no driving routes to restricted landsites



For store-to-covenant combinations, from the original 14,097 combinations, the NPRA Route Planning Service was unable to retrieve route information for 21 of them. Similar to the process used for store-to-store combinations, the Google Distance Matrix API was used to retrieve information for these combinations, resulting in route information for 12 additional combinations. The 9 store-to-covenant combinations where it was not possible to retrieve route information involved two stores and 9 covenants. One of the stores was linked to one restrictive covenant, as illustrated on the left side of Figure A.3, which shows the Euclidean distance (green lines) between the store (purple dot) and the land site restricted by the covenant (red dot). The other store was linked to the remaining 8 restrictive covenants, and the right side of Figure A.3 illustrates the Euclidean distances between this store and the 8 land sites restricted by these covenants. It can be seen from this figure that the stores with missing routes to restrictive covenants are both located on islands. Consequently, none of the 9 store-to-covenant combinations with missing route information were retained.

B Catchment areas

Defining the catchment area of a grocery store is crucial for our analysis, as it allows us to calculate all variables of interest in our models as well as the demographic data used as control variables. In this section, we briefly describe how these catchment areas were defined, how errors were handled, and how we retrieved demographic data from these catchment areas.

B.1 Defining catchment areas

In our analysis, the catchment area of a store was created using the Isochrone Service of Openrouteservice, which utilizes data directly from OpenStreetMap (Openrouteservice, n.d.). This service provides isochrone maps, representing areas of reachability from given locations within specified times or distances.

Each grocery store is assigned a driving time threshold based on the combination of the municipal centrality index and the urban settlement population of the area where the store is located. This driving time threshold is set to ensure that at least 80% of the store's turnover is from customers living within the catchment area (Norwegian Competition Authority, 2015). With this driving time threshold set, we input the coordinates of the store of interest and its corresponding time limit to extract the isochrone map of that store. The attribute "driving-car" is set so that the catchment area is defined by driving time, not by other modes of transport. An isochrone map captures all driving routes within the maximum driving-time threshold of a store, retaining demographic data, specifically population and land area data.

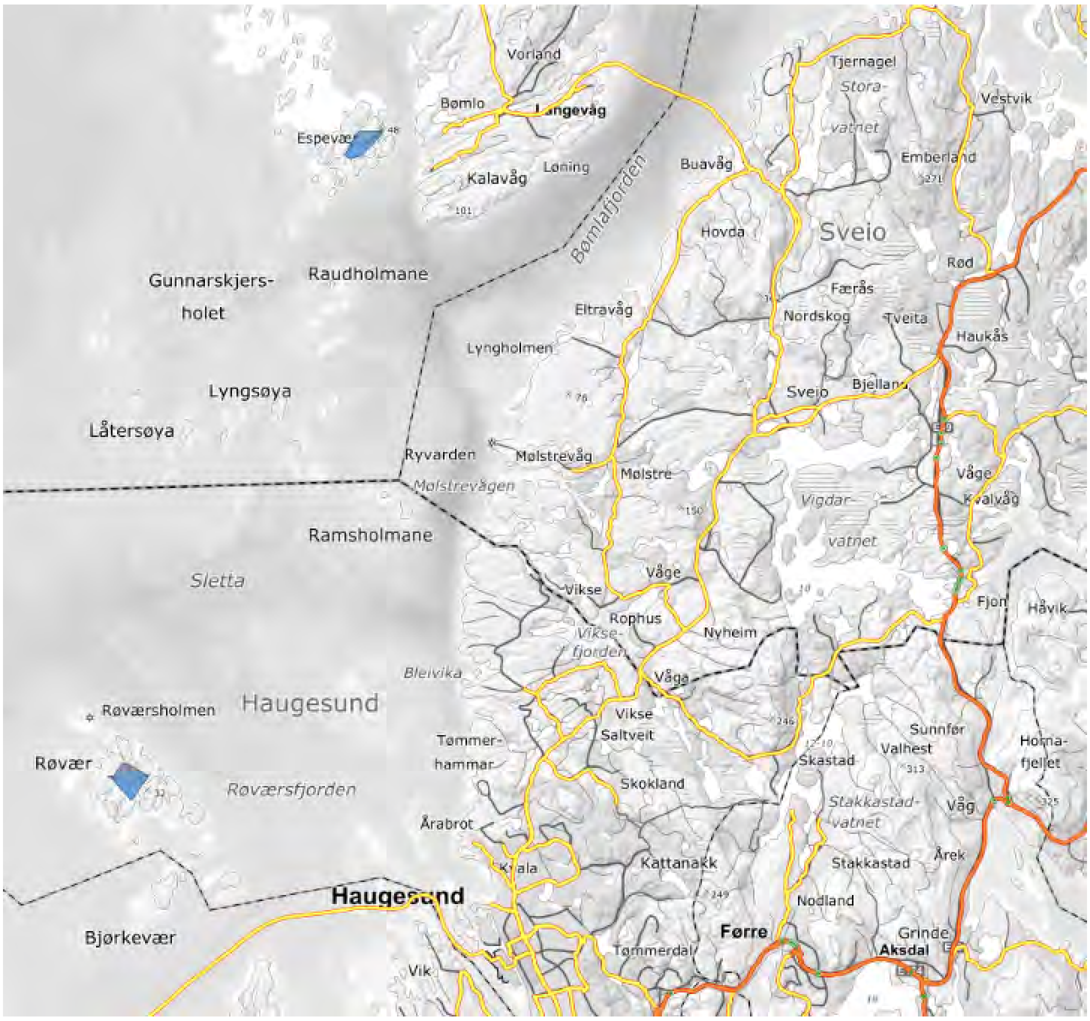
In total, we have retrieved isochrone maps for 3,785 out of 3,798 stores. However, there were multiple cases where the isochrones appeared unrealistically small in size.

B.2 Error handling

As mentioned, there are 13 cases where we were not able to retrieve isochrone maps from the Isochrone Service. Additionally, among those successfully retrieved, many cases had unrealistically small catchment areas, necessitating further investigation.

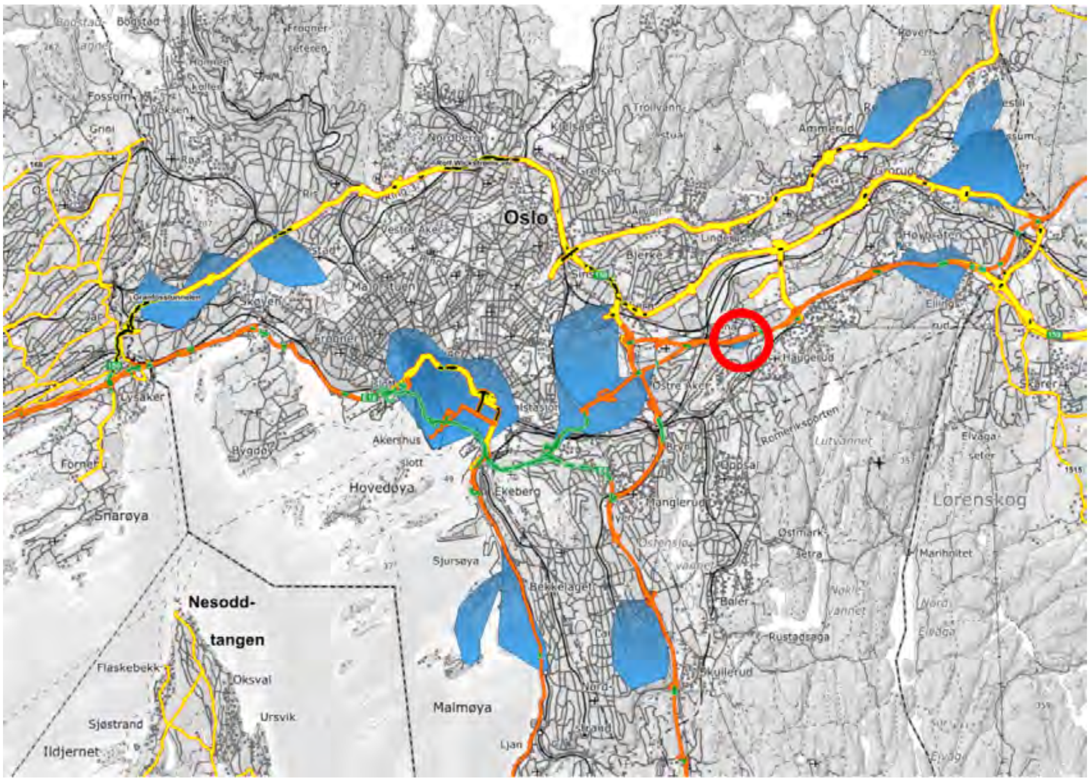
Using a threshold of 2,000,000 square meters, the catchment areas of 82 stores were examined. Of these, the original catchment areas were retained for 58 stores, as their sizes seemed reasonable given their locations. For example, some stores are located on islands or in the centers of the largest cities in Norway. Among these, 29 cases were identified where the small size of the catchment areas could be attributed to the stores being located on islands. In these instances, the original isochrones were retained. Figure B.1 displays the catchment areas (depicted by the blue areas) for two stores on separate islands.

Figure B.1: Illustration of catchment areas of stores located in islands



In Oslo municipality, there were 29 stores with catchment areas below the threshold of 2,000,000 square meters. Figure B.2 shows maps of some of these isochrones. Most of them seemed reasonable in terms of land area coverage. However, one catchment area was considered too small to be classified as reasonable, marked with a red circle in Figure B.2.

Figure B.2: Illustration of catchment areas of stores in Oslo



In total, there exist 37 stores with either missing or invalid catchment areas. In which, there are 24 stores in the dataset that were considered to have invalid catchment areas, and 13 stores that we were not able to retrieve catchment areas. For these stores, the catchment areas were replaced by the valid catchment areas of their closest stores. Among those, 33 stores have their closest stores located within less than 3 minutes of driving and within the Euclidean distance less than 1,000 meters. Thus, they are assumed to share the same demographic characteristics, and their new catchment areas seem to be plausible replacements.

The left side of Figure B.3 shows an example of a store (depicted by the purple dot) located in a shopping mall with an invalid catchment area (depicted by the blue area). This issue aligns with the explanation by Jensen (2024) regarding why the NPRA Route Planning Services were unable to find routes between certain stores. The right side of Figure B.3 shows the new catchment area (depicted by the blue area) of the store depicted on the left side of the figure. The new catchment area is defined using the catchment area of its closest store (depicted by the orange dot). It can be seen that the new catchment area is much larger than the previous one.

Figure B.3: Illustration of catchment areas of stores in shopping mall

B.3 Demographics data

The store's catchment areas were used to identify intersections with basic statistical units, and then the demographic data of these basic statistical units from Statistics Norway were aggregated to form the final numbers for each catchment area. This data was then compared to the population and land area obtained directly from Openrouteservice, where the source of the population data is the Global Human Settlement Layer (GHSL) project[34] to decide which data should be used.

Figure B.4 compares the distributions of land area (in square kilometers) and population of the catchment areas returned directly from the Isochrones Service and those resulting from aggregating data of the intersecting basic statistical units. The distributions indicate that the aggregated population of the intersecting basic statistical units is higher than the data obtained directly from Openrouteservice. This suggests that the demographic population data retrieved from Openrouteservice could be reliable, as it is expected to be lower than the aggregated values of the intersecting basic statistical units. After adjusting for the replaced isochrones, the population data retrieved from Openrouteservice was higher in 571 out of 3,798 cases. While there is not a substantial difference in the population distributions in Figure B.4, there is a more significant difference between the distributions of land area.

[34]More information on: https://human-settlement.emergency.copernicus.eu/about.php

Figure B.4: Comparison of demographic data returned by two methods

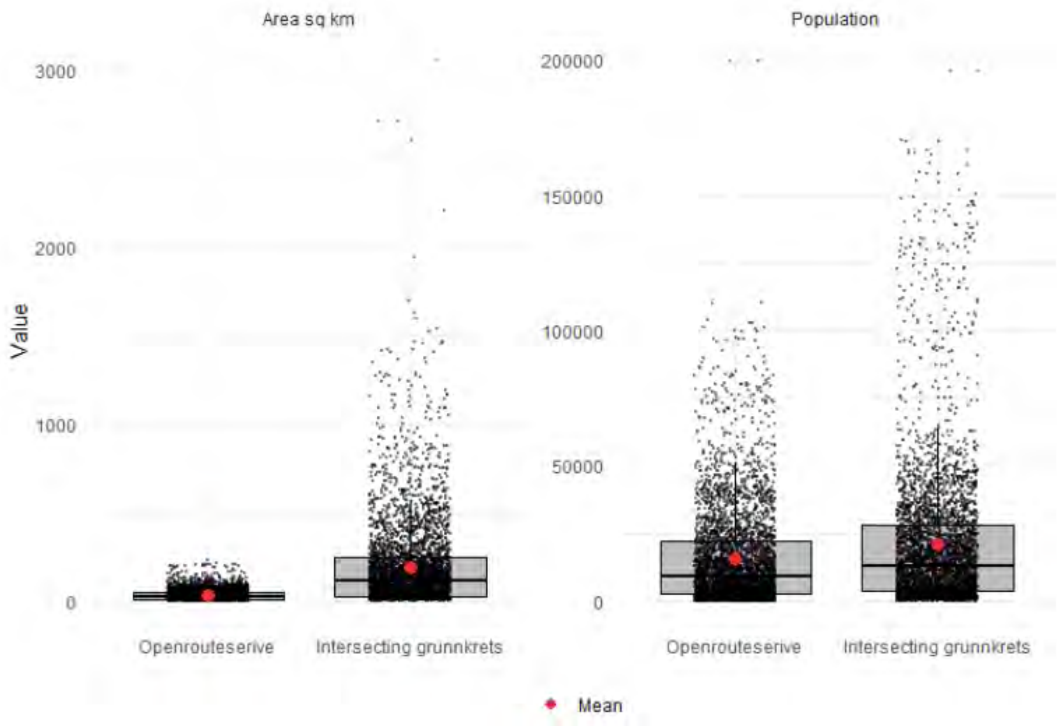


Table B.1: Demographics data comparison

Store ID	Figure	Area		Population		Population density	
		Opt1	Opt2	Opt1	Opt2	Opt1	Opt2
coop::4570	B.5	1.72	2.45	17,797	16,749	10,322.62	6,836.33
coop::1969	B.6	4.23	213.34	648	640	153.01	3.00
meny::7080000005918	B.6	28.91	482.54	4,335	4,506	149.91	9.33

Opt1: Retrieving data directly from Isochrones Service
Opt2: Aggregating data from intersecting basic statistical units

Table B.1 shows the comparison of the demographic data obtained by the two methods for three different stores. The first store is located in an urban area, visualized in Figure B.5. The other stores are located in more remote areas, visualized in Figure B.6 left side and right side respectively. It can be observed from the table that the population data returned by these two methods are quite comparable. Meanwhile, the land area data is quite similar for stores located in urban areas, but it exhibits significant differences in remote areas.

Figures B.5 and B.6 illustrate significant differences in land area when comparing data retrieved directly from Openrouteservice (depicted by the blue areas) to data aggregated from the intersecting basic statistical units (depicted by the grey areas). The size of a store's catchment area retrieved from Openrouteservice depends on the road network, with a more complex road network resulting in a larger catchment area.

Figure B.5: Comparison of catchment areas of store in urban areas

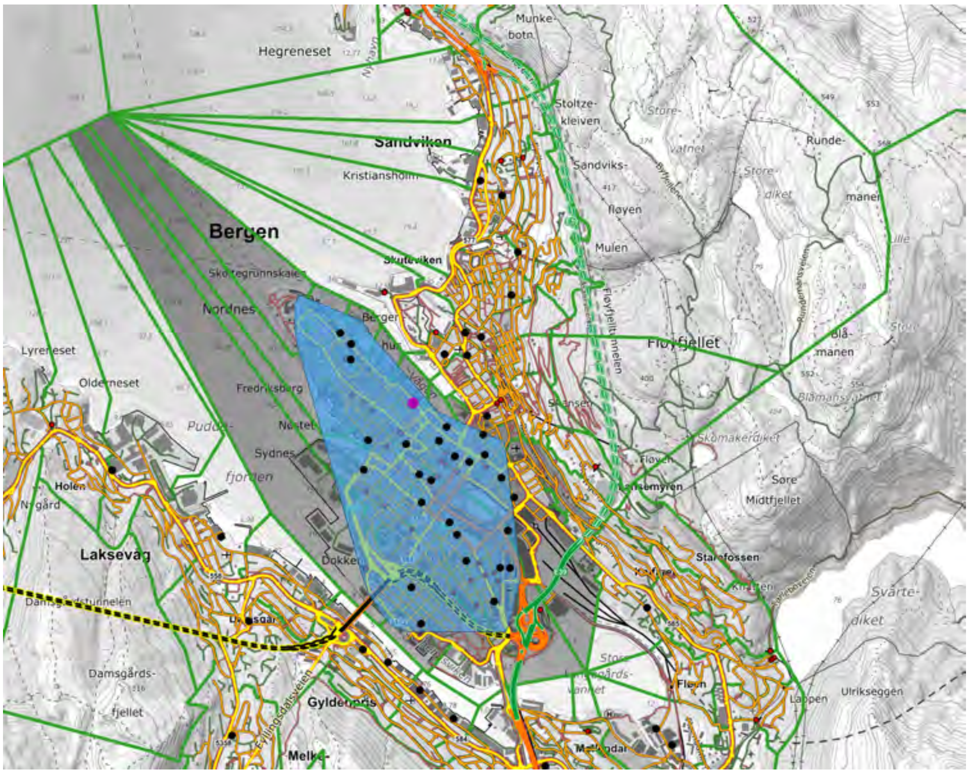


Figure B.6: Comparison of catchment areas of store in remote areas

In urban locations, the road networks are more complex, covering more directions, while the land area of the basic statistical units tends to be smaller compared to less central areas. Consequently, there is less deviation in land area between the two different data sources, as shown in Figure B.5. In more remote places, the catchment area of a store could become quite small due to the simple road network where the store is located, as illustrated in Figure B.6. In these cases, the size of the catchment areas from Openrouteservice does a poor job of capturing how remote these places are.

This thesis utilizes demographic data (e.g., population, land area) obtained by aggregating values from intersecting basic statistical units within the catchment area of a store. This method includes all intersecting basic statistical units, meaning that even if only 1% of the area of a basic statistical unit is covered within the catchment area of a store, 100% of its values will be used. It should be mentioned that we had explored different thresholds for the overlapping rate to decide whether to include a basic statistical unit in the aggregation. Specifically, we considered including values only if the basic statistical unit intersected with the catchment area of a store by at least 20%, 10%, or 5% of its total area. However, some basic statistical units are very large in area but have a small and simple road network, resulting in the catchment area of a store covering only a small proportion of the unit — sometimes less than the smallest threshold we used — even if the catchment area lies entirely within the basic statistical unit. Consequently, these basic statistical units might not have been adequately captured, and these stores would not have been assigned to any basic statistical unit using the overlapping threshold method. Therefore, we decided not to employ this method.

C Robustness check and validity

Table C.1: M2 Robustness check results - Store turnover - Stores with covenants

	(M21) Unique documents	(M22) Market Option 1	(M23) Closest covenants
Number of restrictive covenants	-0.7875	0.7797	2.5054
	(3.9681)	(0.6415)	(2.1268)
Store area (sqm)	0.0866***	0.0887***	0.1257***
	(0.0051)	(0.0060)	(0.0160)
Binary of center location	2.9203	2.1156	-1.6322
	(6.8017)	(7.8325)	(18.7667)
Binary of shopping mall location	8.6186	7.9863	26.7248
	(8.7109)	(9.8709)	(23.8872)
Land area (sqkm)	-0.0054	-0.0061	-0.0130
	(0.0160)	(0.0047)	(0.0419)
Population (1000 people)	0.1131	-0.2958	-0.5572
	(0.1178)	(0.2307)	(0.5920)
Household income after tax (1000 NOK)	0.1104	0.1496	0.2279
	(0.0564)	(0.0968)	(0.1659)
Proportion of Age group 0-19 (%)	-2.0972*	-3.6335*	-6.6321*
	(1.0557)	(1.7373)	(3.2671)
Proportion of Age group >67 (%)	-0.1421	0.0442	-1.9328
	(0.6702)	(1.0993)	(2.1733)
Constant	-22.9813	-4.1500	15.5804
	(29.2459)	(43.4444)	(99.9858)
No. Observations	639	554	195
R-squared	0.3707	0.3541	0.3279

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.2: Testing for endogeneity - Store turnover

	OLS1 DV: No. of Covenants	OLS2 DV: Store Turnover
Binary of property company	1.0240***	
	(0.1401)	
Number of same-chain covenants		2.3332
		(2.3442)
Residuals of OLS1		-1.6335
		(2.3607)
Store area	0.0003***	0.0682***
(sqm)	(0.00008)	(0.0015)
Binary of center location	-0.0739	2.8808
	(0.0907)	(1.5629)
Binary of shopping mall location	-0.0396	9.6380***
	(0.1241)	(2.1292)
Land area	0.0001	-0.0047
(sqkm)	(0.0002)	(0.0027)
Population	0.0185***	0.0550
(1000 people)	(0.0019)	(0.0554)
Household income after tax	0.0011	0.0504***
(1000 NOK)	(0.0007)	(0.0118)
Proportion of Age group 0-19	-0.0464***	-0.4204
(%)	(0.0135)	(0.2718)
Proportion of Age group >67	-0.0155	-0.2177
(%)	(0.0090)	(0.1631)
Constant	0.6763	-14.8866*
	(0.3962)	(7.2576)
No. Observations	3,785	3,785
R-squared	0.1046	0.4991

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.3: M3 Robustness check results - Store distances - Stores with covenants

	(M31) Unique documents	(M32) Market option 1	(M33) Euclidean distance	(M34) Median distance
Number of restrictive covenants	-0.2788	-0.2407	-12.2013	-0.0239
	(0.2094)	(0.4476)	(61.9971)	(0.0315)
Binary of center location	-1.9991***	-14.7369**	-2602.5651***	-2.0771***
	(0.3553)	(5.3311)	(614.5842)	(0.3127)
Binary of shopping mall location	-0.1756	0.8264	-108.6613	-0.1733
	(0.4396)	(6.5961)	(765.0476)	(0.3892)
Land area (sqkm)	0.0079***	0.0033	13.5467***	0.0070***
	(0.0008)	(0.0033)	(1.4526)	(0.0007)
Population (1000 people)	-0.0230***	-0.7237***	-30.7136**	-0.0029
	(0.0062)	(0.1594)	(10.7682)	(0.0055)
Household income after tax (1000 NOK)	0.0121***	-0.0042	16.1828**	0.0084**
	(0.0029)	(0.0676)	(5.1571)	(0.0026)
Proportion of Age group 0-19 (%)	-0.1887***	0.6382	-324.8850***	-0.0917
	(0.0544)	(1.2095)	(95.2718)	(0.0485)
Proportion of Age group >67 (%)	-0.0262	-1.1933	-18.9634	0.0112
	(0.0352)	(0.7636)	(61.9435)	(0.0315)
Constant	2.6389	49.8380	2625.3109	3.0866*
	(1.5382)	(30.2376)	(2675.1943)	(1.3610)
No. Observations	639	554	644	644
R-squared	0.3025	0.0628	0.2368	0.2776

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.4: Testing for endogeneity - Store distance

	OLS1 DV: No. of Covenants	OLS2 DV: Store Distances
Binary of property company	1.0400***	
	(0.1403)	
Number of same-chain covenants		-0.3457
		(0.3140)
Residuals of OLS1		0.3060
		(0.3163)
Binary of center location	-0.0186	-2.8067***
	(0.0900)	(0.2087)
Binary of shopping mall location	0.0727	-0.9911***
	(0.1207)	(0.2818)
Land area	0.00006***	0.0053***
(sqkm)	(0.0002)	(0.0004)
Population	0.0190***	-0.0396***
(1000 people)	(0.0019)	(0.0076)
Household income after tax	0.0008	0.0129***
(1000 NOK)	(0.0007)	(0.0016)
Proportion of Age group 0-19	-0.0361**	-0.2543***
(%)	(0.0132)	(0.0346)
Proportion of Age group >67	-0.0142	0.1806***
(%)	(0.0090)	(0.0220)
Constant	0.7403	2.4443*
	(0.3966)	(0.9937)
No. Observations	3,785	3,785
R-squared	0.1011	0.3207

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$