Misaligned Objectives and Within-Firm Competition in Retail Chains*

Francis Guiton†

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Abstract

In large retail organizations, the objectives of store managers can be misaligned with the objectives of the firm. In particular, competitive interactions between store managers driven by performance-based incentives can lead to sub-optimal outcomes from the point of view of the organization. This paper examines this potential misalignment in the context of a large Canadian retail chain, in which store managers oversee the inventory management of their store under the supervision of a district manager. Leveraging a unique and highly-detailed dataset describing the inventories, sales, and prices of all products carried by stores in the retail chain, the structural estimation of a game of product assortment decisions shows that store managers do not fully internalize the outcomes of other stores in their district. Results also show that the extent to which store managers behave in their own self-interest is correlated with the size of their store and the number of same-district stores in their neighbourhood. Counterfactual experiments reveal that this misalignment of objectives implies a substantial loss in profit for the firm, but an ambiguous effect on consumer welfare. Aligning the objectives of store managers with the objectives of the organization is shown to mitigate these cannibalization effects and provide consumers with greater product variety.

Keywords: Managerial decision-making; Competition; Cannibalization; Retail chain; Store managers; Inventory management.

JEL codes: D22, L21, L81.

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†Ph.D. Candidate, Department of Economics, University of Toronto. 150 St. George Street, Toronto, ON, M5S 3G7, Canada, francis.guiton@mail.utoronto.ca.

1 Introduction

Store managers play a central role in retail organizations, and their decisions can have a substantial impact on firm-level outcomes. However, if these decisions are not aligned with the firm's objectives, or in other words do not fully take into account the outcomes of the organization, then they can generate a significant loss in profit for the organization. Notably, performance-based incentives can drive store managers to behave in their own self-interest in order to maximize their own store's profits, disregarding the outcomes of the firm and creating within-firm competition in the retail chain. Increasing the extent to which store managers internalize the impacts of their decisions on neighbouring stores can align the goals of the firm with the goals of store managers, thereby mitigating the resulting cannibalization effects from within-firm competition.

This paper explores managerial decision-making in large organizations and the cannibalization effects of within-firm competition using a structural approach. Specifically, the paper examines the *Liquor Control Board of Ontario* (LCBO), a large Canadian retail chain in the beverage alcohol market. The LCBO presents an interesting setting for studying managerial decision-making and within-firm competition. Store-level inventory management at the LCBO is delegated to its store managers, such that individual store managers have the ability to choose which products to carry at their store. In the context of this paper, district managers encourage store managers to take into account the impact of these inventory decisions on profits of other stores in their district. At the same time, pricing decisions are centralized and uniform across stores in the retail chain, such that store managers take retail prices as given when making their inventory decisions. Finally, in terms of incentives, the LCBO provides annual bonuses to store managers based on the performance of their store. Store managers are therefore encouraged to exert effort in their inventory decisions through annual performance-based incentives.

The analysis relies on a unique and rich dataset from the LCBO containing daily information on inventories, sales, and prices at every store and for every product in the retail chain from October 2011 to October 2013. Importantly, the dataset also includes information relating to product assortments: the set of products carried by each store during the week, new product arrivals at the warehouse, and chain-wide product de-listings. This main dataset is complemented with two secondary datasets: Enhanced Points of Interest data from DMTI Spatial, containing location information for LCBO's main competitors in the wine market, Wine Rack and Wine Shop; and the 2011 and 2016 Canadian Census of Population, containing socioeconomic characteristics of consumers across Ontario as well as their average commuting distances.

In order to understand how own-store profit-maximizing behaviour can lead to sub-optimal outcomes from the point of view of the firm, a stylized model of assortment decisions is first explored. Relying on a simple setting in which two stores must choose which product to carry, the model shows that if both store managers are solely own-store profit maximizing, then the best response of each manager is to carry the same product as their competitor. However, under some conditions on demand regarding the willingness of consumers to substitute between stores, the optimal outcome from the point of view of the firm is instead for each store manager to carry a different product.

As shown by the stylized model, consumers' willingness to substitute across stores plays a pivotal role in influencing the competitive interactions between store managers and the cannibalization effects resulting from the misalignment between the firm and its store managers. To measure the extent of consumers' spatial substitution between stores in the Ontario alcohol market, a consumer demand system is proposed and estimated. Relying on a nested model in which consumers sequentially choose a store, a product category, and a product, the estimated demand system reveals that product assortment decisions have a significant impact on which store consumers choose to visit. Using the demand estimates, a simple counterfactual experiment shows that from the point of view of a store manager, if consumers choose to substitute towards other LCBO stores, then store profits can be significantly impacted, creating an avenue for within-firm competition.

A structural game of product assortment decisions is then proposed, in which store managers choose the combination of products to carry at their store given the actions of all neighbouring stores. Importantly, the objective function of the store manager incorporates the role of district managers: the objective function includes a weight that captures the degree to which the store manager internalizes the outcomes of neighbouring stores from their district. In order to estimate this combinatorial decision problem, a revealed-preference approach to partial identification is considered. Results show that on average, managers do not fully account for the impact of their inventory decisions on profits of neighbouring stores in their district, providing evidence of within-firm competition. Interestingly, results also reveal that the degree to which store managers behave in their own self-interest varies significantly across stores, and that in particular managers of larger stores (i.e. AAA, AA, and A stores) and stores in neighbourhoods with fewer same-district stores seem to demonstrate greater self-interest in their decision-making.

Finally, counterfactual experiments explore how changing the weight that store managers place on other LCBO stores when making their inventory decisions can affect firm outcomes. Perfectly aligning the objectives of the firm with the objectives of store managers (i.e. store managers placing equal weight on own-store profits and neighbouring-store profits, regardless of district) generates an increase in firm profits of approximately 16%, a reduction in the product assortment overlap between stores of approximately 10%, and an increase in the variety of products available to consumers of approximately 15%. However, results show that the effects on consumer surplus are small, the result of counteracting effects from greater product variety and higher travelling cost, and that they vary significantly across census tracts/subdivisions. In the other extreme case of each store manager focusing instead solely on own-store profits (i.e. fully disregarding the firm's outcomes), counterfactual results reveal that cannibalization effects are equivalent to a 15% loss in firm profits, and consumers have access to 11% lower product variety on average. Overall, the counterfactual experiments therefore suggest that increasing the degree to which store managers internalize firm outcomes could offer benefits to an organization by mitigating potential cannibalization effects from within-firm competition.

This paper relates and contributes to several literatures. First, this paper relates to the recent literature in empirical industrial organization exploring how inefficiencies within large, multi-divisional companies can occur. DellaVigna and Gentzkow (2019) show how within most large U.S. retail chains, prices are nearly uniform across outlets, potentially the result of managerial inertia. They find that in charging these uniform prices, retail chains sacrifice significant profit relative to an optimal pricing strategy. Hortaçsu et al. (2022) examine the pricing dynamics within a large U.S. airline. The authors find that observed prices are the result of a game played by the different airline departments, and involve significant coordination failure driven by the airline's decentralized decision rights. Aguirregabiria and Guiton (2023) study the ordering decisions of store managers within a large Canadian retail chain. Through a single-agent dynamic framework, they find that managers have heterogeneous perceptions about store-level costs, resulting in inefficiencies for the firm through higher inventory costs. They also find that these different perceptions are correlated with education and experience of managers. The current paper contributes to this literature by exploring how misaligned objectives between a firm and its store managers can create inefficiencies for the organization. Specifically, the current paper shows that within-firm competition between store managers can result in store-level decision-making not fully internalizing the outcomes of the organization.

Second, this paper relates and contributes to the vast literature in organizational economics concerning franchising and vertical relationships. Although the LCBO does not constitute a franchise, many similarities can be drawn from the franchising literature. Kalnins and Mayer (2004) study the survival rates of pizza restaurants in Texas, and find that the franchisor's local experience plays an important role in the success of its business units. Similarly, using microdata, Lafontaine et al. (2019) find that the transfer of business know-how from franchisor to franchisee has a positive effect on the survival rate of new businesses. Lo et al. (2016) examine the role of performance-based incentives in the sales industry, and find that the delegation of decision-making to salespersons is increasing in the intensity of performance pay. Other notable papers in this literature studying the trade-offs faced by a franchising firm include Brickley and Dark

(1987), Lafontaine et al. (2017), and Lafontaine (2021). The current paper contributes to this literature by exploring the vertical relationship between a retail chain's head office and its store managers in an organization where store managers have decision-making power. This franchise-like setting also incorporates performance-based incentives provided by the firm's headquarters and how they can affect the extent to which store managers consider the firm's objectives in their decision-making, creating a misalignment of objectives within the organization.

Finally, this paper relates to the theoretical management literature regarding the delegation of decision-making rights within organizations. Papers in this literature include Alonso et al. (2008), Bester and Krähmer (2008), and Friebel and Raith (2010), among others. Overall, the literature assesses the trade-offs associated with decentralizing decision-making in an organization, which can depend among other factors on the cost of providing effort incentives (Bester and Krähmer (2008)), the value of local information (Alonso et al. (2008)), and the allocation of firm-specific resources (Friebel and Raith (2010)). The current paper contributes to this literature by examining an empirical setting in which inventory decision-making is assigned to store managers in a decentralized retail chain. In particular, the current paper provides further evidence of the trade-offs associated with decentralizing decision-making – that decisions may not necessarily be aligned with the firm's objectives if there are competitive interactions between decision-making agents within the firm.

The rest of the paper is organized as follows. Section 2 presents institutional details about the LCBO, as well as a summary of the main datasets used in the paper. Section 3 presents a stylized model of product assortment decisions, and describes the mechanism through which cannibalization effects can occur due to within-firm competition. Section 4 presents a consumer demand system, and in Section 5 a structural game of product assortment decisions is proposed and estimated. Section 6 explores the counterfactual experiments, and Section 7 concludes.

2 The LCBO Retail Chain

2.1 Institutional Details

The LCBO. The LCBO is a crown corporation of the provincial government of Ontario. It operates through its network of 634 retail stores (as of 2013), and provides consumers with three main categories of products: wine, beer, and spirits. The company aims to "offer customers a broad product selection and value at all price points [and to] generat[e] maximum profits to fund government programs and priorities",[1] making it a profit-maximizing firm. The LCBO

[1]See https://www.lcbo.com/content/lcbo/en/corporate-pages/about/aboutourbusiness.html.

competes with three retail chains in Ontario: The Beer Store in the beer market, and Wine Rack and Wine Shop in the wine market.[2] In the spirits market, LCBO has a monopoly.[3]

Retail Stores. LCBO stores are classified into six groups (i.e. store classifications): AAA, AA, A, B, C, and D. Overall, a store's classification is strongly correlated with its physical size (i.e. floor space). Additionally, higher-classified stores (i.e. larger stores) are located predominantly in Ontario's largest cities. Out of the 634 LCBO stores, most outlets are located in the southern region of the province (from Windsor in the South-West to Ottawa in the South-East).[4]

Pricing. LCBO and its competitors are subject to strict pricing restrictions: retail prices must be the same across all stores in all markets for a given product. Specifically, retail prices are determined as a fixed markup over the wholesale price.[5] Therefore, there is no price variation both within the LCBO and between the LCBO and its competitors.

Store managers. Stores in the retail chain are operated by a single manager. Store managers at the LCBO are responsible for the inventory management of their store, which involves two responsibilities: choosing which products to carry at their store (i.e. the *assortment decision*), and maintaining the level of inventory of these products (i.e. the *ordering decision*). For direct incentive purposes, annual bonuses provided to store managers are linked to their store's yearly profits. The LCBO therefore presents a particularly interesting setting for studying managerial incentives and within-firm competition, as managers have an incentive to compete with neighbouring LCBO stores for greater bonus pay.[6]

District managers. Stores at the LCBO are grouped into 25 distinct districts, each under the supervision of a single district manager. District managers are tasked with overseeing the overall operations within their district. In the context of this paper, district managers aim to maximize district profits by encouraging store managers to take into account the impact of their inventory decisions on neighbouring stores within their district.

2.2 Data from LCBO

The unique and rich dataset from LCBO provides daily information on inventories, sales, and prices of every product sold at every LCBO store from October 2011 to October 2013. In

[2]Wine Rack and Wine Shop outlets are reticted to selling Ontario wines, meaning that they can only sell a subset of LCBO products.

[3]See Appendix A.1 for the market shares of each firm in the alcohol market across the sample period.

[4]See Appendix A.2 for the location of LCBO stores across the province, as well as the four distribution centres in Thunder Bay, London, Durham, and Ottawa.

[5]See Aguirregabiria et al. (2016) for details regarding LCBO's pricing policy.

[6]An interview conducted with an LCBO store manager at a downtown Toronto store confirmed that stores are competitive with each other.

total, the raw dataset includes over 700 million observations and more than 20,000 unique products. The working sample considered in this paper consists of the set of all wine and spirit products offered at the LCBO, aggregated at the weekly level.[7] This working sample consists of approximately 70 million observations in total. Table 1 below presents summary statistics for this working sample. On average, LCBO stores have an assortment size of 1,139, sell 5,823 units per week, and generate $99,474 of weekly revenue. Wine products represent the largest portion of product assortments on average, with 667 wine products at the average store. Stores of higher classifications (i.e. AAA, AA, and A stores) have the highest weekly sales on average, and carry the greatest number of products. For example, relative to the average D store that sells 743 units per week and carries 465 products, the average AAA store sells 25,559 units per week and carries 2,577 products. In addition to differences across store classifications, Table 1 also reports significant heterogeneity within store classification in terms of product assortments. For instance, the average B store carries 769 wine products, but the standard deviation of product assortment size within that store classification is 233. The working sample therefore exhibits significant heterogeneity both within and across store classifications in terms of product assortments.

Table 1: Working Sample

	Store Classification						
	All	*AAA*	*AA*	*A*	*B*	*C*	*D*
	Mean (st.dev)	*Mean (st.dev)*	*Mean (st.dev)*	*Mean (st.dev)*	*Mean (st.dev)*	*Mean (st.dev)*	*Mean (st.dev)*
Number of Observations							
Number of stores	634	5	25	148	157	164	135
Revenues & Sales Per Store							
Revenue per week ($)	99,474	434,481	293,950	194,447	104,787	39,186	13,993
	(88,086)	(101,080)	(43,214)	(37,796)	(29,002)	(17,176)	(7,715)
Units sold per week	5,823	25,559	17,255	11,521	6,223	2,135	743
	(5,281)	(5,624)	(2,581)	(2,529)	(1,777)	(972)	(415)
Assortment Size Per Store							
All product categories	1,139	2,577	2,278	1,852	1,277	700	465
	(639)	(337)	(262)	(303)	(346)	(177)	(135)
Wine products	667	1,587	1,407	1,126	769	374	231
	(419)	(119)	(171)	(233)	(233)	(121)	(81)
Spirit products	402	786	717	605	435	290	205
	(186)	(92)	(98)	(100)	(117)	(66)	(58)

[7] Beer is excluded from the analysis for two reasons. First, contrary to wine and spirits, most beer products are sold in 6-packs or 12-packs, making demand for these products significantly different than for wine and spirits. Second, contrary to Wine Rack and Wine Shop, detailed information about product assortments at The Beer Store locations is unavailable.

Among other factors, store managers at the LCBO have an incentive to periodically update their product assortments due to the introduction of new products to the retail chain. Specifically, throughout the year, the LCBO issues product calls (or in the LCBO's internal jargon, *Product Needs Letters*) to manufacturers describing the types of products it wishes to introduce to the retail chain, including the desired product characteristics (e.g. price, alcohol content, country of origin).[8] Once new products are chosen and become available at the distribution centres, store managers decide whether or not to include these new products in their store's assortment.[9] Table 2 below presents summary statistics describing the new listings at LCBO over the sample period. In total, there are 897 new products introduced throughout the sample period. Most new products are red and white wines, jointly accounting for approximately 41% of new listings. However, contrary to the red and white wine product categories, vodka products have the largest store take-up rate, with 422 stores in the retail chain introducing a newly-listed vodka product to their product assortment on average over the sample period. Table 2 also reveals how observable characteristics of products vary by product category. For instance, whisky, vodka, and rum products have the highest retail price, highest alcohol content, and lowest sugar content on average, while cocktail products have the lowest retail price, lowest alcohol content and highest sugar content on average.

Table 2: New Product Listings at the LCBO

	Product Category						
	Red wine	*White wine*	*Sparkling wine*	*Whisky*	*Vodka*	*Rum*	*Cocktails*
	Mean (st.dev)	*Mean (st.dev)*	*Mean (st.dev)*	*Mean (st.dev)*	*Mean (st.dev)*	*Mean (st.dev)*	*Mean (st.dev)*
Number of Observations							
New listings	192	181	105	166	58	145	50
New listings per week	2.74	2.41	2.84	3.53	2.23	2.90	2.5
	(2.07)	(1.82)	(3.16)	(3.96)	(1.70)	(3.04)	(2.42)
Stores introducing new products	348	359	360	379	422	390	404
	(124)	(130)	(140)	(169)	(134)	(151)	(144)
Product Characteristics							
Retail price ($)	15	14	17	77	37	74	7
	(5)	(4)	(17)	(121)	(21)	(413)	(7)
Alcohol content (%)	13	12	12	43	37	36	9
	(1)	(1)	(2)	(5)	(4)	(10)	(10)
Sugar content (g/L)	10	12	30	6	6	5	32
	(15)	(18)	(51)	(2)	(2)	(2)	(36)

[8] Appendix A.3 presents a sample Product Needs Letter sent out by LCBO in 2011 for wine products.

[9] In order to persuade managers to include their product in their assortment, manufacturers can visit LCBO stores and "discuss the product's benefits to the store's selection", a process known as detailing.

2.3 Consumer Consideration Sets and Store Clusters

An important element of this paper is capturing the spatial substitution patterns of consumers between stores in their consideration set. Relying on information from the 2011 Census of Population, we first geographically separate the Ontario market into census tracts (urban areas) and census subdivisions (rural areas). Given the absence of location information at the household level, the entire mass of consumers is assumed to be concentrated at the centroid of each urban/rural area. Consumers can then travel to any alcohol retailer within their radius of search. This radius is defined using information on commuting distances in the 2016 Census of Population, which describes the average daily commuting distance within each census tract or census subdivision.[10] It is important to note that the average daily commuting distance does not directly equate to the average distance a consumer is willing to travel to visit a liquor store, as commuting distance constitutes a wider radius. However, this measure gives us the maximum possible distance that a consumer would be able to travel in order to purchase an alcohol product, which is exactly the information required to construct consumer consideration sets. A consumer's *consideration set* is then defined as the set of stores within each consumer's radius of search. Table 3 below presents summary statistics regarding census tracts/subdivisions in the sample, including the consideration sets of consumers.

Table 3: Census tract/sudivision summary statistics

	All	*Urban*	*Rural*
	Mean *(st.dev)*	*Mean* *(st.dev)*	*Mean* *(st.dev)*
Number of observations	2,698	2,271	427
Population (as of 2011)	4,746	4,665	5,180
	(4,121)	(2,035)	(9,233)
Median individual income (as of 2011, in CAD)	31,929	32,473	27,616
	(8,695)	(8,773)	(6,634)
Average daily commuting distance (in kilometres)	5.89	4.71	12.17
	(3.17)	(1.27)	(2.84)
Number of stores in consideration set	5.42	5.88	1.44
	(5.60)	(5.74)	(0.84)

Another important element of this paper is capturing the potential competitors of stores at the LCBO. Given consumer consideration sets, we can define *store clusters*. A store cluster is defined as a group of stores with overlapping consumer consideration sets, and where potential

[10]Here, the radius of search is based on Census data, and therefore varies geographically at the census tract/subdivision level.

competition can occur. However, not all stores within a cluster are potential competitors. Stores within a cluster are potential competitors if they belong to at least one common consumer consideration set (i.e. consumers can substitute between these stores). The set of potential competitors of a store is defined as its *neighbourhood*. Importantly, store clusters can also include stores from several districts, such that different district managers can be supervising within a cluster. This entails that stores within a cluster can be in potential competition with stores from other districts. Table 4 below provides summary statistics regarding store clusters in the working sample, and how districts and store clusters can overlap. Additionally, Appendix A.4 provides graphical examples of store clusters in the sample and how their structure can vary.

Table 4: Store Clusters

	Mean	*Standard Deviation*	*Minimum*	*Maximum*
Number of clusters	232	-	-	-
Districts per cluster	1.30	0.52	1	4
Census tracts/subdivisions per cluster	11.97	39.55	1	289
LCBO stores per cluster	2.37	3.81	1	22
Wine Rack stores per cluster	0.67	1.97	0	15
Wine Shop stores per cluster	0.37	1.17	0	6

3 Stylized Model of Assortment Decisions

In this section, a stylized model of managerial decision-making in a retail chain is explored, in which managers must choose the product assortment to carry at their store. The goal of this section is to find conditions on demand under which within-firm competition can create a misalignment of objectives between the firm and its managers, potentially leading to cannibalization effects.

Suppose a retail chain produces two products, A and B, which it sells at its two retail locations, store 0 and store 1. Both goods A and B are assumed to have a price-cost margin equal to 1 for notational simplicity. The two stores are located at the extremes of the unit line, along which consumers are uniformly distributed. Managers play a game of product assortment decisions. That is, store 0 must choose its product assortment given the choice of store 1, and vice-versa. However, each store has a capacity constraint of one, meaning that they must choose whether to carry product A or product B. Furthermore, assume that the firm provides large performance-based incentives to its store managers, such that they solely maximize own-store profits and do not internalize firm outcomes.

Consumers in the market are classified into two types based on their preferences. Type-A consumers, representing a proportion $\rho > \frac{1}{2}$ of total consumers, value product A at $v > 0$, and product B at 0. On the other hand, type-B consumers, representing a proportion $(1 - \rho)$ of total consumers, value product B at $v > 0$, and product A at 0. Consumers choose whether to visit store 0, store 1, or an outside option that generates a utility of 0. Finally, consumers face a travelling cost of $t > 0$ per unit of distance.[11]

We assume that stores compete for a fraction of consumers, such that there is within-firm competition. Let x_0^* be the location of the marginal consumer that is indifferent between visiting store 0 and the outside option. Formally,

$$v - t\mathrm{x}_0^* - 1 = 0$$
$$\implies \mathrm{x}_0^* = \frac{v-1}{t}$$

Similarly, let x_1^* be the location of the marginal consumer that is indifferent between visiting store 1 and the outside option:

$$v - t(1 - \mathrm{x}_1^*) - 1 = 0$$
$$\implies \mathrm{x}_1^* = \frac{1 - v + t}{t}$$

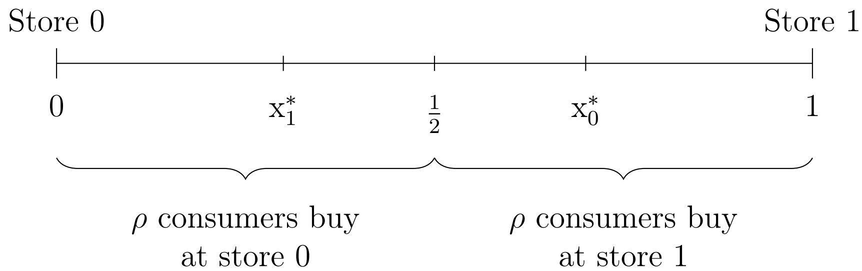
Under the assumption of within-firm competition, a fraction of consumers must have both stores in their consideration sets. In other words, we need $0 < \mathrm{x}_1^* < \mathrm{x}_0^* < 1$. Relying on the locations of the marginal consumers x_0^* and x_1^*, this implies the restrictions:

$$0 < \frac{1 - v + t}{t} < \frac{v - 1}{t} < 1$$
$$\implies 1 + \frac{t}{2} < v < \min\{1 + t, 2\}$$

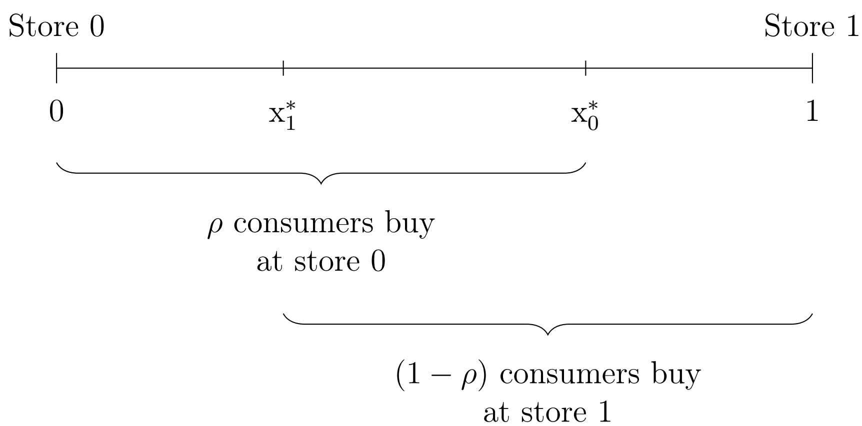
We now examine the profits of each store under the four possible strategy profiles of product assortment choices: (A,A), (A,B), (B,A), (B,B). Given the store profits for each strategy profile, we will find the optimal product assortments under two scenarios: the Nash equilibrium of the game, and the firm's solution.

[11]The stylized model presented in this section draws on important previous work studying Hotelling spatial competition with discrete product choice. Such papers include Lancaster (1975), Spence (1976), Klemperer (1992), and Irmen and Thisse (1998).

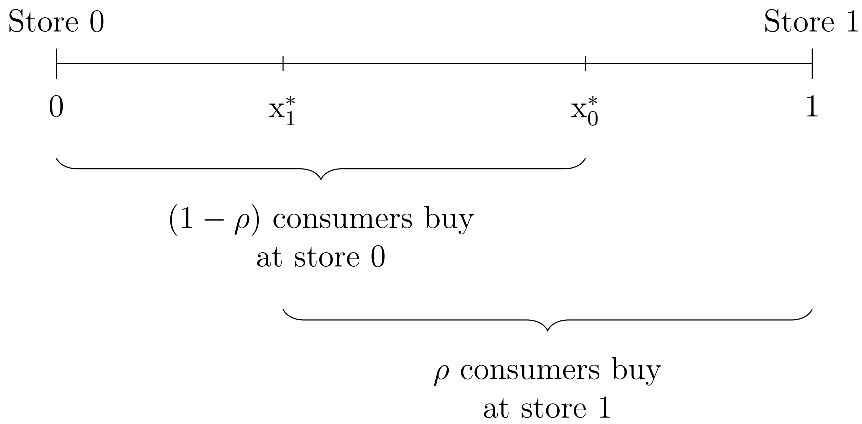
Store profits under (A,A). In this strategy profile, the market will be evenly split between the two stores: type-A consumers on $[0, \frac{1}{2}]$ will visit store 0 and purchase product A, and type-A consumers on $[\frac{1}{2}, 1]$ will visit store 1 and purchase product A. Store 0 will generate a profit of $\pi_0 = \frac{\rho}{2}$ and Store 1 will generate a profit of $\pi_1 = \frac{\rho}{2}$.



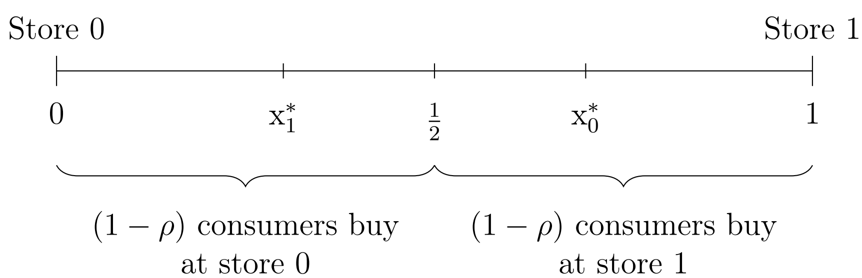
Store profits under (A,B). In this strategy profile, on the interval $[0, x_1^*]$, consumers of type A will visit store 0 and consumers of type B will take the outside option. On the interval $[x_1^*, x_0^*]$, consumers of type A will visit store 0 while consumers of type B will visit store 1. Finally, on the interval $[x_0^*, 1]$, consumers of type B will visit store 1 while consumers of type A will take the outside option. Store 0 will generate profit $\pi_0 = \rho x_0^* = \rho(\frac{v-1}{t})$ and store 1 will generate profit $\pi_1 = (1-\rho)(1-x_1^*) = (1-\rho)(\frac{v-1}{t})$.



Store profits under (B,A). The outcome of this strategy profile is symmetric to the profile (A,B). On the interval $[0, x_1^*]$, consumers of type B will visit store 0 and consumers of type A will take the outside option. On the interval $[x_1^*, x_0^*]$, consumers of type B will visit store 0 while consumers of type A will visit store 1. Finally, on the interval $[x_0^*, 1]$, consumers of type A will visit store 1 while consumers of type B will take the outside option. Store 0 will generate profit $\pi_0 = (1-\rho)x_0^* = (1-\rho)(\frac{v-1}{t})$ and store 1 will generate profit $\pi_1 = \rho(1-x_1^*) = \rho(\frac{v-1}{t})$.



Store profits under (B,B). The outcome of this strategy profile is symmetric to the profile (A,A). The market will be evenly split between the two stores: type-B consumers on $[0, \frac{1}{2}]$ will visit store 0 and purchase product B, and type-B consumers on $[\frac{1}{2}, 1]$ will visit store 1 and purchase product B. Store 0 will generate a profit of $\pi_0 = \frac{(1-\rho)}{2}$ and store 1 will generate a profit of $\pi_1 = \frac{(1-\rho)}{2}$.



Nash equilibrium. Given store profits under the four strategy profiles, we can construct the matrix of payoffs resulting from the game of assortment decisions between store 0 and store 1. The payoffs are depicted below:

		Store 1	
		A	B
Store 0	A	$\frac{\rho}{2}, \frac{\rho}{2}$	$\frac{\rho(v-1)}{t}, \frac{(1-\rho)(v-1)}{t}$
	B	$\frac{(1-\rho)(v-1)}{t}, \frac{\rho(v-1)}{t}$	$\frac{(1-\rho)}{2}, \frac{(1-\rho)}{2}$

Relying on the payoff matrix, the profile (A,A) is the Nash Equilibrium of the game if $\frac{\rho}{2} > \frac{(1-\rho)(v-1)}{t}$. Notice that this restriction is feasible under the model's assumptions since we have that $\rho > (1-\rho)$. However it is not necessarily satisfied. Recall that $\frac{(v-1)}{t} = \mathrm{x}_0^* > \frac{1}{2}$, which entails that we need the restriction

$$\frac{\rho}{(1-\rho)} > 2\mathrm{x}_0^* \tag{1}$$

Firm solution. From the firm's point of view, only the aggregate profits matter. Therefore, we explore the total profits below for each strategy profile of the product assortment game, denoting Π as the aggregate profits from the point of view of the firm:

$$\begin{cases} \Pi(\text{A,A}) = \frac{\rho}{2} + \frac{\rho}{2} = \rho \\ \Pi(\text{A,B}) = \frac{\rho(v-1)}{t} + \frac{(1-\rho)(v-1)}{t} = \frac{(v-1)}{t} \\ \Pi(\text{B,A}) = \frac{(1-\rho)(v-1)}{t} + \frac{\rho(v-1)}{t} = \frac{(v-1)}{t} \\ \Pi(\text{B,B}) = \frac{(1-\rho)}{2} + \frac{(1-\rho)}{2} = (1-\rho) \end{cases}$$

From the firm's point of view, the outcomes (A,B) and (B,A) generate the highest aggregate profits if $\rho < \frac{(v-1)}{t}$. Notice that this restriction is feasible under the model's assumptions since we have that $x_0^* > \frac{1}{2}$. In other words, we need the restriction:

$$\rho < \mathrm{x}_0^* \tag{2}$$

Therefore, combining conditions (1) and (2), we have that from the point of view of the firm, the Nash equilibrium outcome (A,A) results in sub-optimal firm profits compared to the firm's solution (A,B) or (B,A) if $\mathrm{x}_0^* \in (\rho, \frac{\rho}{2(1-\rho)})$. Specifically, own-store profit maximizing behaviour creates an overlap in product assortments offered by the stores (i.e. both stores carry product A in equilibrium), which leads to cannibalization effects from the point of view of the firm. Crucially, the misalignment between the firm's outcome and the Nash equilibrium of the game depends on the consumers' willingness to substitute across stores (i.e. the location of the marginal consumer x_0^*).[12] In order to capture this willingness to substitute in the case of the LCBO, a consumer demand system is proposed and estimated in the next section.

[12]The region of x_0^* under which this misalignment can occur in the model is illustrated in Appendix A.5.

4 Demand System

In this section, a demand system is proposed in which consumers are assumed to purchase a single alcohol product in three stages. First, consumers choose a store to visit. This choice set includes every LCBO store in the consumer's radius, as well as stores from competing chains (Wine Rack and Wine Shop). Then, consumers choose among product groups (or "shelves"), before deciding which product to purchase. The demand system is therefore modeled according to a three-tier nested choice model, as it combines the traditional two-tier nested choice structure with a spatial component.[13] In the model description below, time index t is omitted for notational simplicity.

4.1 Utility Maximization

Consumers are assumed to have preferences over product characteristics. In the model described below, a product j can therefore be thought of as a vector (or bundle) of product characteristics. The set of products available to a consumer visiting store i is determined by the product assortment chosen by the store manager at the beginning of the week, which we will denote as $\boldsymbol{a}_i$. Products are partitioned into G mutually exclusive groups, indexed by $g \in \{1, 2, ..., G\}$. These groups are determined according to the LCBO's own 7-group partition (i.e. $G = 7$): red wine, white wine, sparkling wine, whisky, vodka, rum, and cocktails. For notational purposes, the set of products in group g included in a store's assortment is denoted by $\mathcal{J}_g$, and these products are indexed by $j \in \{1, 2, ..., J_g\}$.

Consumers can choose to visit any LCBO, Wine Rack, or Wine Shop store within their consideration set (see Section 2.3 for a description of the consumer's consideration set). However, relying on Section 2.1, consumers visiting a competing chain (i.e. Wine Rack or Wine Shop) have restricted choice sets relative to visiting an LCBO store. If consumer h visits store i, the utility she derives from purchasing product j belonging to group g is:

$$u_{h,i,j} = X_j\beta + \alpha p_j + Z_{i,h}\gamma + \xi_j + \zeta_i + \sigma_1\eta_{h,i}^{(1)} + \sigma_2\eta_{h,i,g}^{(2)} + \sigma_3\eta_{h,i,j}^{(3)},$$

where $\boldsymbol{\eta} = (\eta_{h,i}^{(1)}, \eta_{h,i,g}^{(2)}, \eta_{h,i,j}^{(3)})$ are i.i.d. Extreme Value Type 1 distributed variables, and σ_1, σ_2, and σ_3 are dissimilarity parameters that measure consumers' preference heterogeneity across stores, groups of products, and products, respectively. Matrix X_j includes characteristics of product j, matrix $Z_{i,h}$ includes characteristics of store i and location h, and terms ξ_j and ζ_i capture the unobserved consumer tastes for product j and store i, respectively. Crucially,

[13] Recent empirical applications of spatial demand models in the retail industry include Smith (2004), Davis (2006), Houde (2012), Seim and Waldfogel (2013), Miller and Osborne (2014), and Thomassen et al. (2017).

matrix $Z_{i,h}$ includes the distance in kilometres between consumer location h and store i. Vector $\boldsymbol{\theta} = (\beta, \alpha, \gamma, \sigma_1, \sigma_2, \sigma_3)$ is the vector of parameters to be estimated.

Product Choice. Relying on the approach outlined in Berry (1994) and Berry et al. (1995), mean utility associated with purchasing product j (at the average store) can be denoted as:

$$\delta_j(\boldsymbol{\theta}) = X_j\beta + \alpha p_j + \xi_j$$

Given $\delta_j(\boldsymbol{\theta})$ and the distributional assumption regarding the unobservables $\boldsymbol{\eta}$, we can derive the market share functions associated with the product choice of consumers.[14] For a given store i, the conditional market share function of product j belonging to group g is given by:

$$s_{i,j|g}(\boldsymbol{a}_i;\boldsymbol{\theta}) = \frac{a_{i,j} \times \exp\left\{\frac{\delta_j(\boldsymbol{\theta})}{\sigma_3}\right\}}{\sum_{k=1}^{J_g} a_{i,k} \times \exp\left\{\frac{\delta_k(\boldsymbol{\theta})}{\sigma_3}\right\}}, \tag{3}$$

where $a_{i,j}$ is equal to 1 if product j is carried at store i, such that the market share function $s_{i,j|g}(\boldsymbol{a}_i;\boldsymbol{\theta})$ depends on the product assortment $\boldsymbol{a}_i$ chosen by the store manager. Denoting $U_g^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta})$ as the consumer's expected utility of choosing alternatives in group g before the realization of shock $\eta_{h,i,j}^{(3)}$ (or the *inclusive value* associated with product group g), we have by the distributional assumption of the unobservables $\boldsymbol{\eta}$ that:

$$U_{i,g}^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta}) = \log\left(\sum_{j=1}^{J_g} a_{i,j} \times \exp\left\{\frac{\delta_j(\boldsymbol{\theta})}{\sigma_3}\right\}\right)$$

Again, the expected utility of choosing alternatives in group g is a function of the assortment $\boldsymbol{a}_i$. Given $U_g^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta})$, we can then obtain the market share function for product group g:

$$s_{i,g}(\boldsymbol{a}_i;\boldsymbol{\theta}) = \frac{\exp\left\{\frac{\sigma_3}{\sigma_2}U_g^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta})\right\}}{1 + \sum_{g'=1}^{G}\exp\left\{\frac{\sigma_3}{\sigma_2}U_{g'}^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta})\right\}}$$

Finally, by construction, $s_{i,j}(\boldsymbol{a}_i;\boldsymbol{\theta}) = s_{i,j|g}(\boldsymbol{a}_i;\boldsymbol{\theta}) \times s_{i,g}(\boldsymbol{a}_i;\boldsymbol{\theta})$. Therefore, the unconditional market share function of product j is given by:

$$s_{i,j}(\boldsymbol{a}_i;\boldsymbol{\theta}) = \left(\frac{a_{i,j} \times \exp\left\{\frac{\delta_j(\boldsymbol{\theta})}{\sigma_3}\right\}}{\sum_{k=1}^{J_g} a_{i,k} \times \exp\left\{\frac{\delta_k(\boldsymbol{\theta})}{\sigma_3}\right\}}\right) \times \left(\frac{\exp\left\{\frac{\sigma_3}{\sigma_2}U_{i,g}^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta})\right\}}{1 + \sum_{g'=1}^{G}\exp\left\{\frac{\sigma_3}{\sigma_2}U_{i,g'}^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta})\right\}}\right)$$

[14]See Appendix A.7 for details.

We define the outside option $s_{i,0}(\boldsymbol{a}_i;\boldsymbol{\theta})$ as purchasing a non-alcohol related item, such as a gift card. The share of this outside option is observable in the data for each store in the sample. Normalizing the mean utility of this outside option to $\delta_0(\boldsymbol{\theta}) = 0$, we have:

$$s_{i,0}(\boldsymbol{a}_i;\boldsymbol{\theta}) = \frac{1}{1 + \sum_{g'=1}^{G} \exp\left\{\frac{\sigma_3}{\sigma_2} U_{i,g'}^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta})\right\}}$$

Store Choice. Denoting $U_i^{(1)}(\boldsymbol{a}_i;\boldsymbol{\theta})$ as the consumer's expected utility of visiting store i before the realization of shocks $\eta_{h,i,j}^{(3)}$ and $\eta_{h,i,g}^{(2)}$ (or the *inclusive value* associated with store i), we have by the distributional assumption of the unobervables $\boldsymbol{\eta}$ that:

$$U_i^{(1)}(\boldsymbol{\theta}) = \sum_{\boldsymbol{a}_i} B_i(\boldsymbol{a}_i) \times \log\left(1 + \sum_{g'=1}^{G} \exp\left\{\frac{\sigma_3}{\sigma_2} U_{i,g'}^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta})\right\}\right),$$

where $B_i(\boldsymbol{a}_i)$ denotes the belief of consumers regarding product assortment $\boldsymbol{a}_i$. We will assume that these product assortments are perfectly known to consumers when making their store choice, such that $B_i(\boldsymbol{a}_i)$ captures perfect information.[15] Finally, given $U_i^{(1)}(\boldsymbol{a}_i;\boldsymbol{\theta})$, the unconditional market share function of store i in location h is derived as:[16]

$$s_{i,h}(\boldsymbol{a}_i, \boldsymbol{a}_{-i};\boldsymbol{\theta}) = \frac{\exp\left\{\frac{\sigma_2}{\sigma_1}\left(\frac{\sigma_2 U_i^{(1)}(\boldsymbol{a}_i;\boldsymbol{\theta}) + Z_{i,h}\gamma + \zeta_i}{\sigma_2}\right)\right\}}{1 + \sum_{m\in\mathcal{R}(h)} \exp\left\{\frac{\sigma_2}{\sigma_1}\left(\frac{\sigma_2 U_m^{(1)}(\boldsymbol{a}_m;\boldsymbol{\theta}) + Z_{m,h}\gamma + \zeta_m}{\sigma_2}\right)\right\}}, \tag{4}$$

where importantly, the market share function of store i depends on the assortment decisions of other stores in its neighbourhood $\boldsymbol{a}_{-i}$, and relying on Section 2.3 the set $R(h)$ denotes the set of stores in consumer h's consideration set. Finally, the outside option for consumer h is defined as staying home. Normalizing the mean utility of this outside alternative to zero, we can obtain the following market share function in location h:

$$s_{0,h}(\boldsymbol{a}_i, \boldsymbol{a}_{-i};\boldsymbol{\theta}) = \frac{1}{1 + \sum_{m\in\mathcal{R}(h)} \exp\left\{\frac{\sigma_2}{\sigma_1}\left(\frac{\sigma_2 U_m^{(1)}(\boldsymbol{a}_m;\boldsymbol{\theta}) + Z_{m,h}\gamma + \zeta_m}{\sigma_2}\right)\right\}}$$

[15] A sensitivity analysis is conducted in Appendix A.6 where this assumption is relaxed. Results show that the current specification of perfect information does not overestimate the degree of substitution of consumers across stores relative to consumers having imperfect information about product assortments.

[16] See Appendix A.7 for details.

4.2 Estimation

Product Choice Estimates. We begin by computing the observable shares $s_{i,j|g,t}$ and $s_{i,g,t}$:

$$s_{i,j|g,t} = \frac{q_{i,j,t}}{\sum_{k=1}^{J_g} q_{i,k,t}}; \qquad s_{i,g,t} = \frac{\sum_{j=1}^{J_g} q_{i,j,t}}{\sum_{g'=0}^{G} \sum_{k=1}^{J_{g'}} q_{i,k,t}},$$

where $q_{i,j,t}$ denotes units sold of product j at store i during week t, which is observed in our dataset. Given these observable market shares, and denoting $s_{0,i,t}$ as the observable group share for group $g = 0$, we can invert the market share function (3) in order to obtain the product choice equation:[17]

$$\log(s_{i,j|g,t}) = X_j\tilde{\beta} + \tilde{\alpha}p_{j,t} - \tilde{\sigma}_2\Big(\log(s_{i,g,t}) - \log(s_{i,0,t})\Big) + \tilde{\xi}_{i,j,t}, \tag{5}$$

where $\tilde{\beta} = \frac{\beta}{\sigma_3}$, $\tilde{\alpha} = \frac{\alpha}{\sigma_3}$, $\tilde{\sigma}_2 = \frac{\sigma_2}{\sigma_3}$, and $\tilde{\xi}_{i,j,t} = \frac{\xi_{i,j,t}}{\sigma_3}$. The unobservable term $\xi_{i,j,t}$ is assumed to have the following structure: $\xi_{i,j,t} = \xi_i + \xi_j + \xi_t + \xi^*_{i,j,t}$, where retail price $p_{j,t}$ and group share $s_{g,i,t}$ are potentially correlated with the unobserved taste parameters ξ_i, ξ_j, ξ_t, but not correlated with $\xi^*_{i,j,t}$. In order to obtain consistent estimates of parameters $(\tilde{\beta}, \tilde{\alpha}, \tilde{\sigma}_2)$, we begin by first assuming that retail price $p_{j,t}$ is independent of unobservable ξ_t. Given that the majority of within-group price variation occurs during holiday seasons, after controlling for seasonal effects we can plausibly assume that $p_{j,t}$ is independent of ξ_t. On the other hand, we need to explicitly control for the potential endogeneity from unobservable ξ_j as this term is likely correlated with $p_{j,t}$. Using a within-group transformation of equation (5) (i.e. including store-product fixed effects), time-invariant factors are cancelled-out, including X_j and ξ_j. Under this transformation, parameter $\tilde{\alpha}$ can be consistently estimated. In a second step, BLP-type instruments are constructed based on observable product characteristics. Specifically, three sets of instruments are constructed: the total alcohol contents of products in group g excluding product j, the total sugar contents of products in group g excluding product j, and the total container sizes of products in group g excluding product j.[18]

Using the within-group transformation in step 1 and the instruments constructed in step 2, parameters $\tilde{\alpha}$ and $\tilde{\sigma}_2$ are estimated by maximum likelihood. We allow for flexibility in the estimation by having both parameters $\tilde{\alpha}$ and $\tilde{\sigma}_2$ vary by product category.[19] Estimates are presented in Table 5 below, separately for each of the seven main product categories.

[17] See Appendix A.8 for details.

[18] Notice that these instruments have explanatory power in predicting group share $s_{g,i,t}$ as they vary with the product assortment offered by the store; however they do not directly affect the within-group market share $s_{j|g,i,t}$.

[19] Since σ_2 is constant across product categories by definition, letting $\tilde{\sigma}_2$ vary by product category is equivalent to allowing σ_3 to vary by product category.

Table 5: Product Choice Regressions

	(1) Red Wine	(2) White Wine	(3) Sparkling Wine	(4) Whisky	(5) Vodka	(6) Rum	(7) Cocktails
Variable	*Est.*	*Est.*	*Est.*	*Est.*	*Est.*	*Est.*	*Est.*
	(s.e.)	*(s.e.)*	*(s.e.)*	*(s.e.)*	*(s.e.)*	*(s.e.)*	*(s.e.)*
Retail price	–0.3374***	–0.3117***	–0.0889***	–0.0323***	–0.0500***	–0.0331**	–0.1463***
	(0.0153)	(0.0106)	(0.0154)	(0.0113)	(0.0111)	(0.0110)	(0.0379)
Median price elasticity	–4.6621***	–4.0308***	–1.1466***	–1.6399***	–1.3196***	–0.9222***	–0.7491***
	(0.2109)	(0.1373)	(0.1993)	(0.5722)	(0.2935)	(0.3065)	(0.1941)
(–) Group share	1.4205***	0.6164***	1.6348***	0.4704***	0.8201***	2.9076***	1.3071***
	(0.0466)	(0.0567)	(0.0513)	(0.0635)	(0.0814)	(0.0698)	(0.0418)
Store × Product F.E.	✓	✓	✓	✓	✓	✓	✓
Observations	14,692,309	10,175,481	4,317,886	5,503,549	3,547,474	9,049,164	967,649

(1) Standard errors clustered at the product level in parentheses

(2) * $p-value < 0.10$, ** $p-value < 0.05$, *** $p-value < 0.01$

(3) Month dummies and holiday dummies are included in all regressions in order to account for seasonal factors.

Table 5 above shows that allowing parameters to vary across product categories captures significant heterogeneity in the factors affecting the consumer's product choice. Namely, the results show that demand elasticities vary substantially across product categories: the highest own-price elasticity is for the red wine category, with an elasticity of -4.66, and the lowest elasticity is -0.75 for the cocktail category. On average, the own-price elasticity across categories is approximately -2.05, which is in line with previous estimates in the literature.[20]

Store Choice Estimates. The observable market share of store i in location h during week t can be computed as:

$$s_{i,h,t} = \frac{q_{i,h,t}}{M_h},$$

where $q_{i,h,t}$ denotes total units sold at store i during week t to consumers living in location h, and $M_{h,t}$ represents the market size in location h. Denoting $s_{0,h,t}$ and $U^{(1)}_{i,t}(\tilde{\alpha}, \tilde{\sigma}_2)$ as the observable share of the outside option and the observable store-level expected utility respectively, we can invert market share function (4) to obtain the store choice equation:[21]

$$\log(s_{i,h,t}) - \log(s_{0,h,t}) = Z_{i,h}\gamma^* + \sigma_2^* U^{(1)}_{i,t}(\tilde{\alpha}, \tilde{\sigma}_2) + \zeta^*_{i,t}, \tag{6}$$

[20]Among other empirical studies, see Aguirregabiria et al. (2016), Conlon and Rao (2015), Illanes and Moshary (2020), and Miravete et al. (2020) for estimates of price elasticities in the beverage alcohol market.

[21]See Appendix A.8 for details.

where $\sigma_2^* = \frac{\sigma_2}{\sigma_1}$, $\gamma^* = \frac{\gamma}{\sigma_1}$, and $\zeta_{i,t}^* = \frac{\zeta_{i,t}}{\sigma_1}$. An important issue arises in the estimation of the store choice parameters: sales at the store-location level $q_{i,h,t}$ are in principle not observed in the dataset. However, we can leverage the fact that store-location level sales $q_{i,h,t}$ are equivalent to store level sales $q_{i,t}$ if store i belongs to only one consumer consideration set. Therefore, we estimate equation (6) using only the sub-sample of store clusters containing one consumer location.[22] However, we need to account for selection in the estimation, as these store clusters are mostly located in rural regions. Leveraging the fact that in our model, the degree of inter-chain competition in a given location h (measured as the number of Wine Rack and Wine Shop stores relative to the number of LCBO stores) does not directly affect $s_{i,h,t}$, but is potentially correlated with regional factors, we can use a two-step Heckman approach to correct for sample selection in the estimation of equation (6). Results are depicted in Table 6 below.

Table 6: Store Choice Regression

	OLS
	Est. *(s.e.)*
Store inclusive value	2.5883*** (0.0977)
Distance traveled	-0.1301*** (0.0108)
Store classification	
B	-0.7621*** (0.0935)
C	-1.9470*** (0.2120)
D	-2.0524*** (0.2772)
Retail Chain F.E.	✓
Location × Time F.E.	✓
Observations	9,736

(1) Standard errors clustered at the location-time level in parentheses
(2) * $p-value < 0.10$, ** $p-value < 0.05$, *** $p-value < 0.01$

[22] This sub-sample consists of 150 stores in total (approximately 20% of all stores).

As expected, a store's market share is positively correlated with the expected utility to the consumer of visiting the store. Importantly, this variable is a function of the product assortment offered by the store manager, such that consumers are willing to respond to the assortment decisions of managers. The results also show that consumers value the type of store they visit, and that they prefer visiting larger, flagship stores. Relative to the omitted categories (i.e. AAA, AA, and A stores), stores of lower classifications are associated with lower market shares on average. Finally, Table 6 shows that consumers have a disutility associated with travelling (i.e. they incur a travelling cost). This disutility, as well as the extent to which consumers respond to the assortment decisions of store managers, are quantified in the next section.

4.3 Willingness to Pay and Substitute

Given the estimates of $\boldsymbol{\theta}$ in Tables 5 and 6, we can compute consumers' travelling cost for purchasing an alcohol product. This cost is estimated at \$0.4613 per kilometre. The magnitude of this travelling disutility is broadly consistent with other estimates in the literature.[23]

Importantly, we can also examine the extent to which consumers are willing to substitute between stores in response to the assortment decisions of managers. Using the estimates of $\boldsymbol{\theta}$, the average consumer is willing to travel approximately 0.6 kilometres in response to an increase of 1% in consumer store-level expected utility (i.e. $U_i^{(1)}$). In other words, a consumer is willing to travel to a store that is 0.6 kilometres further away if that store has 1% greater expected utility for the consumer. To put this change in expected utility into perspective, a 1% increase in $U_i^{(1)}$ represents the gain in expected utility from adding approximately 100 additional average products to a store's assortment, representing a 10% increase in the size of the average store's product assortment. Given that we have allowed parameters to vary at the product category level, we can also explore the degree of consumer substitution in response to changes in $U_{i,g}^{(2)}$. Table 12 below presents consumer's willingness to travel in response to a 1% increase in $U_{i,g}^{(2)}$.

Table 7: Responses to Assortment Decisions by Product Category

	(1) Red Wine	(2) White Wine	(3) Sparkling Wine	(4) Whisky	(5) Vodka	(6) Rum	(7) Cocktails
Willingness to travel (in km.)	0.4192	0.0754	0.0136	0.0118	0.0151	0.0442	0.0010

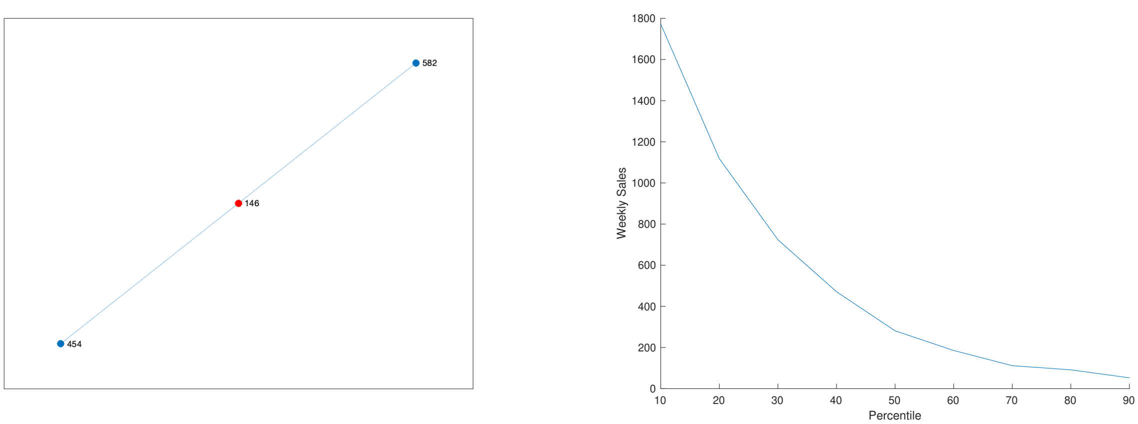
[23] Among other empirical studies, see Davis (2006), Houde (2012), McManus (2007), Seim and Waldfogel (2013), and Thomadsen (2005) for estimates of consumers' disutility of travelling.

The results above show that consumers are most responsive to changes in product assortments when they involve the red wine and white wine categories: consumers are willing to travel approximately 0.4 kilometres and 0.1 kilometres for a 1% increase in the expected utilities of the red wine and white wine categories, respectively. On the other hand, consumers respond the least to changes involving the cocktails category. Importantly, we can also check whether consumers' willingness to substitute implied by our estimates match with what we see in the data. In Appendix A.9, we leverage an exogenous product assortment variation from a new store opening during the sample period. Results show that our demand system predicts the substitution patterns of consumers in response to changes in product assortments very well.

Given the evidence of consumers being willing to substitute between stores in response to product assortment decisions, we can examine the impact on store sales from these substitution effects. We consider below a simple counterfactual experiment focusing on a specific group of stores, LCBO store #146 and competing LCBO stores #454 and #582, depicted in Panel (a) of Figure 1 below.[24] If store #146's neighbours decide to provide better product assortments to consumers, then holding everything else constant, consumers should be willing to substitute towards these stores, impacting demand faced by store #146. In the experiment, competing stores are gradually assigned the product assortments of stores from the 10th to the 90th percentile in the empirical distribution of consumers' store-level expected utility. The impact on weekly demand at store #146 is then examined in each of these cases according to the model depicted in Section 4.1, and presented in Panel (b) of Figure 1 below.

Figure 1: Consumer Substitution and Store Sales

(a) (b)



[24]In this example, there are two consumer consideration sets: one that includes stores #146 and #454, and one that includes stores #146, #582.

Figure 1 above provides evidence of the significant impact on store demand from the assortment decisions of its neighbouring stores: as consumers' expected utility from visiting competing stores increases, consumers substitute towards these stores. Specifically, the illustrative example in Panel (b) shows that if the expected utility generated by assortments of neighbouring stores increased from the 10^{th} percentile to the 90^{th} percentile of the distribution, then overall weekly demand at store #146 would fall by approximately 97% (from 1,772 to 53). Additionally, even a relatively small increase in the expected utility to consumers of visiting these competing stores would generate non-negligible effects on demand – a 34% decrease in demand from improving the assortments of neighbouring stores from the 50^{th} percentile to the 60^{th} percentile of the expected utility distribution.

These effects can also be decomposed across product categories. In Table 8 below, the effect of increasing category-level expected utility in competing stores on demand at store #146 is depicted. Similarly to Figure 1 above, demand at store #146 falls as consumers substitute towards other stores. However, the magnitude of this effect varies significantly across product categories. The effect is greater for red wine and white wine products (66% and 65% reductions in demand from increasing expected utility from the 10^{th} percentile to the 90^{th} percentile of the category-specific distribution), and is the smallest for cocktail products.

Table 8: Consumer Substitution and Store Sales by Product Category

	(1) Red Wine	(2) White Wine	(3) Sparkling Wine	(4) Whisky	(5) Vodka	(6) Rum	(7) Cocktails
P90-P10 spread (in %)	–66	–65	–15	–28	–22	–18	–6

(1) Figures in table represent demand at LCBO store #146.

A key takeaway from this section is that the assortment decisions of managers have significant and tangible effects on the store choice of consumers, as they are willing to respond to these decisions. Therefore, if managers provide better product assortments to consumers in terms of expected utility, then their market share will increase relative to other stores in their neighbourhood, which has a significant impact on sales and profits. In the next section, we explore to what extent store managers internalize these externalities on neighbouring stores.

5 Game of Product Assortment Decisions

In this section, a structural game of store manager product assortment decisions is proposed and estimated.[25] A store manager chooses which products to carry at their store at the beginning of each week given the decisions of stores in their neighbourhood, demand for all available products, and assortment costs. Importantly, the model allows for store managers to potentially internalize the impact of their assortment decisions on the profits of neighbouring stores from their district. For notational simplicity, the time index is omitted below.

5.1 Store Manager Decision Problem

At the beginning of each week, store managers play a game of product assortment decisions. Given the choices of all stores in their neighbourhood, store managers decide which products to carry in order to maximize own-store profits while (potentially) internalizing the impact of these decisions on the profits of neighbouring stores from their district. Product assortment decisions are assumed to occur simultaneously, and under complete information.

The vector of state variables is given by $\boldsymbol{\omega} = (\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{\epsilon})$, where $\boldsymbol{X}$ represents the full matrix of product characteristics, $\boldsymbol{Z}$ captures characteristics of all stores in the neighbourhood, and $\boldsymbol{\epsilon}$ denotes stochastic mean-zero shocks affecting assortment costs. Note that variables $\boldsymbol{\epsilon}$ are unobservable to the researcher, but known to the store managers at the time of their assortment decisions under the assumption of complete information. Given the actions of all neighbouring stores $\boldsymbol{a}_{-i}$ and the vector of state variables $\boldsymbol{\omega}$, manager i chooses product assortment $\boldsymbol{a}_i$ to maximize her store's profits (while potentially taking into account the externalities of her decision on profits of neighbouring stores in her district).

The choice variable of the store manager in this game is a binary vector $\boldsymbol{a}_i$ describing which products are carried at the store. Entry $a_{i,j}$ equals 1 if product j is carried at store i, and 0 otherwise. This is a combinatorial problem: for a given number J of potential products, the store manager must choose which combination $\boldsymbol{a}_i$ of products to offer.[26] These potential combinations represent an extremely large choice space. We will therefore see that although point identification is infeasible in this context, we will be able to partially identify our parameters of interest.

For any own-store product assortment $\boldsymbol{a}_i$ and set of all neighbouring-store product assortments $\boldsymbol{a}_{-i}$, define function $v_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i)$ as the objective function of store manager i:

[25] There is a vast empirical literature examining models of firm product assortment and product positioning strategies, including Berry and Waldfogel (2001), Mazzeo (2002), and Draganska et al. (2009). See also Blinder (1981), Rust (1987), Aguirregabiria (1999), Bray et al. (2019), and Bray and Stamatopoulos (2021) for models exploring the inventory decisions of retailing firms.

[26] In any given week, the average store has upwards of 2^{2000} possible combinations of $\boldsymbol{a}_i$ to choose from.

$$v_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i) = (1-\lambda_i)\pi_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \gamma_i) + \lambda_i \sum_{m \in \mathcal{M}(i)} \mathbb{1}\Big\{m \in \mathcal{M}_d(i)\Big\}\pi_m(\boldsymbol{a}_m, \boldsymbol{a}_{-m}, \boldsymbol{\omega}; \boldsymbol{\theta}, \gamma_m),$$

where $\pi_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \gamma_i)$ is the store's one-period profit function, $\mathcal{M}(i)$ denotes the set of all neighbouring stores to store i, $\mathcal{M}_d(i)$ denotes the subset of this group for which stores belong to the same district as store i, and γ_i and λ_i are parameters. Notably, parameter λ_i is the parameter of interest in the store manager's objective function, as it captures the extent to which store manager i internalizes the outcomes of the firm. If $\lambda_i = 0$, the store manager solely values own-store profits, disregarding the impact of her assortment decisions on the firm's outcomes. If $\lambda_i = 0.5$, the store manager perfectly internalizes how her assortment decisions can affect the profits of neighbouring stores in her district. Notice that the specification of the objective function of a store manager incorporates the role of the district manager at the LCBO: in the context of this paper, the district manager encourages store managers to internalize the impact of their decisions on profits of neighbouring stores belonging to their district (i.e. upward pressure on λ_i), but not on neighbouring stores from other districts. This entails that store i places zero weight on the profits of neighbouring stores if they belong to other districts (i.e. $\lambda_i = 0$). The store's one-period profit function is given by:

$$\pi_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \gamma_i) = \Big(\sum_{j=1}^{J}(p_j - c_j) \times q_{i,j}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta})\Big) - f(\boldsymbol{a}_i, \epsilon_i; \gamma_i), \tag{7}$$

where demand for product j depends on the markets share functions derived in Section 4.1:

$$q_{i,j}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}) = \Big(\sum_{h:\, i \in \mathcal{R}(h)} M_h \times s_{i,h}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta})\Big) \times s_{i,g}(\boldsymbol{a}_i, \boldsymbol{\omega}; \boldsymbol{\theta}) \times s_{i,j|g}(\boldsymbol{a}_i, \boldsymbol{\omega}; \boldsymbol{\theta})$$

Importantly, function $f(\boldsymbol{a}_i, \epsilon_i; \gamma_i)$ in equation (7) represents the weekly assortment cost incurred by store i from carrying product assortment $\boldsymbol{a}_i$. Assortment cost is assumed to depend on a store-specific parameter γ_i and an unobservable variable ϵ_i, and has the following restriction: for any assortment $\boldsymbol{a}'_i$ such that $\sum_{j=1}^{J} a'_{i,j} = \sum_{j=1}^{J} a_{i,j}$, we have that $f(\boldsymbol{a}'_i, \epsilon_i; \gamma_i) = f(\boldsymbol{a}_i, \epsilon_i; \gamma_i)$. In other words, we impose the restriction that two product assortments containing the same number of products generate the same weekly assortment cost.[27]

[27] This restriction is equivalent to assuming that assortment cost captures a storage cost, and that storage cost is constant across products. In the current specification of the profit function, all product-specific costs are therefore captured by wholesale price c. This profit function could eventually be extended to include an explicit product-specific assortment cost, for example by including a parameter that varies with the number of units sold.

For notational purposes, the set of assortments with the same number of products as assortment $\boldsymbol{a}_i$ is denoted as $\mathcal{A}_i$. We will consider in the model below that the choice space of store manager i is given by this set $\mathcal{A}_i$: store managers choose which products to carry at their store, holding the total number of products in their assortments fixed. This simplifying assumption is made for two reasons: first, given that product assortment decisions imply a combinatorial problem, considering $\mathcal{A}_i$ as the choice space of store manager i significantly reduces the set of possible vectors in the store manager's choice set, and therefore the dimension of the problem. Second, under the restriction imposed on function $f(\boldsymbol{a}_i, \epsilon_i; \gamma_i)$, parameters $\boldsymbol{\gamma}$ do not need to be jointly estimated with λ_i, since the assortment cost generated by any assortment $\boldsymbol{a}_i \in \mathcal{A}_i$ is the same. This again significantly reduces the computational cost of estimating parameters λ_i.

Given the objective function, we can define the strategy function of store manager i in the game of product assortment decisions in equation (8) below:

$$\sigma_i(\boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i) = \underset{\boldsymbol{a}_i \in \mathcal{A}_i}{\operatorname{argmax}} \Big\{ v_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i) \Big\}, \tag{8}$$

where store manager i chooses the product assortment $\boldsymbol{a}_i$ from the set $\mathcal{A}_i$ in order to maximize her objective function given the actions of all neighbouring stores. Finally, an equilibrium of the game of product assortment decisions is a set of strategy function $\boldsymbol{\sigma}$ such that each store manager is maximizing their objective function given the strategies of other stores:

$$\boldsymbol{\sigma} = \Big\{ \sigma_i(\boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i) : i \in \{1, 2, ..., I\} \Big\}$$

5.2 Partial Identification of λ

Given the decision problem presented above, we now want to estimate the extent to which store managers internalize the impact of their assortment decisions on the firm. Although we have imposed a restricted choice space $\mathcal{A}_i$ on store managers, point identification of λ_i remains computationally infeasible due to the size that $\mathcal{A}_i$ still represents. Below, we therefore describe a partial identification approach for parameters λ_i.[28]

Relying on the framework outlined by Pakes (2010) and Pakes et al. (2015), we proceed using a revealed preference approach to partial identification. For any counterfactual assortment $\boldsymbol{a}'_i \neq \boldsymbol{a}_i, \in \mathcal{A}_i$, where $\boldsymbol{a}_i$ denotes the assortment chosen by store manager i, we have that by revealed preference:

[28] For examples of the moment inequality approach in empirical industrial organization, see Varian (1982), Haile and Tamer (2003), Ciliberto and Tamer (2009), Ho (2009), Holmes (2011), and Ho and Pakes (2014), among others. See also Kline et al. (2021) for a review of partial identification in empirical industrial organization.

$$v_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i) - v_i(\boldsymbol{a}'_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i) \geq 0 \tag{9}$$

That is, under revealed preference, any counterfactual assortment $\boldsymbol{a}'_i$ generates a value to store manager i that is no greater than the value under $\boldsymbol{a}_i$. Next, we define two functions $\Delta R_i(\boldsymbol{a}'_i)$ and $\Delta R_{-i}(\boldsymbol{a}'_i)$ that depend on counterfactual assortment $\boldsymbol{a}'_i$, describing the change in own-store variable profits and the change in variable profits for neighbouring stores belonging to store i's district respectively:

$$\Delta R_i(\boldsymbol{a}'_i) = \sum_{j=1}^{J} (p_j - c_j) \times \Big(q_{i,j}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}) - q_{i,j}(\boldsymbol{a}'_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta})\Big)$$

$$\Delta R_{-i}(\boldsymbol{a}'_i) = \sum_{m \in \mathcal{M}(i)} \mathbb{1}\Big\{m \in \mathcal{M}_d(i)\Big\} \sum_{j=1}^{J} (p_j - c_j) \times \Big(q_{m,j}(\boldsymbol{a}_m, \boldsymbol{a}_{-m}, \boldsymbol{\omega}; \boldsymbol{\theta}) - q_{m,j}(\boldsymbol{a}_m, \boldsymbol{a}'_{-m}, \boldsymbol{\omega}; \boldsymbol{\theta})\Big),$$

where $\boldsymbol{a}'_{-m}$ denotes the vector of neighbouring-store product assortments from the point of view of store m under counterfactual assortment $\boldsymbol{a}'_i$. Relying on the revealed preference condition in equation (9), we can combine functions $\Delta R_i(\boldsymbol{a}'_i)$ and $\Delta R_{-i}(\boldsymbol{a}'_i)$ in order to obtain:

$$(1 - \lambda_i)\Delta R_i(\boldsymbol{a}'_i) + \lambda_i \Delta R_{-i}(\boldsymbol{a}'_i) \geq 0$$

Finally, re-arranging the above condition in order to isolate λ_i yields sharp bounds on the parameter:

$$\lambda_i \geq \max_{\boldsymbol{a}'_i \in \mathcal{A}_i} \left\{ - \frac{\Delta R_i(\boldsymbol{a}'_i)}{\Big(\Delta R_{-i}(\boldsymbol{a}'_i) - \Delta R_i(\boldsymbol{a}'_i)\Big)} \;\Big|\; \Big(\Delta R_{-i}(\boldsymbol{a}'_i) - \Delta R_i(\boldsymbol{a}'_i)\Big) > 0 \right\} \equiv \lambda_{i,L}$$

$$\lambda_i \leq \min_{\boldsymbol{a}'_i \in \mathcal{A}_i} \left\{ - \frac{\Delta R_i(\boldsymbol{a}'_i)}{\Big(\Delta R_{-i}(\boldsymbol{a}'_i) - \Delta R_i(\boldsymbol{a}'_i)\Big)} \;\Big|\; \Big(\Delta R_{-i}(\boldsymbol{a}'_i) - \Delta R_i(\boldsymbol{a}'_i)\Big) < 0 \right\} \equiv \lambda_{i,U},$$

where $\lambda_{i,L}$ denotes the expression for the lower bound, and $\lambda_{i,U}$ denotes the expression for the upper bound. Given these bounds, we have that the identified set of λ_i for store manager i is defined as:

$$\Lambda_i = \{\lambda_i : \lambda_{i,L} \leq \lambda_i \leq \lambda_{i,U}\}$$

5.3 Estimation

Given the partial identification of λ_i above, we can estimate the bounds $\lambda_{i,L}$ and $\lambda_{i,U}$ that define set Λ_i for each store manager i.[29] As a direct result of the demand system, the conditions $\left(\Delta R_{-i}(\boldsymbol{a}_i') - \Delta R_i(\boldsymbol{a}_i')\right) > 0$ and $\left(\Delta R_{-i}(\boldsymbol{a}_i') - \Delta R_i(\boldsymbol{a}_i')\right) < 0$ in the expressions for $\lambda_{i,L}$ and $\lambda_{i,U}$ respectively are equivalent to the conditions $\Delta R_i(\boldsymbol{a}_i') < 0$ and $\Delta R_i(\boldsymbol{a}_i') > 0$: counterfactual assortments $\boldsymbol{a}_i'$ that drive consumers away from neighbouring stores in store i's district towards store i entail that $\Delta R_i(\boldsymbol{a}_i') < 0$, and vice-versa. The externalities generated by these substitution effects are depicted in Section 4.3. The idea of this revealed preference approach is therefore to find counterfactual assortments that would have made neighbouring stores belonging to store i's district worse off (i.e. $\Delta R_i(\boldsymbol{a}_i') < 0$) and counterfactual assortments that would have made them better off (i.e. $\Delta R_i(\boldsymbol{a}_i') > 0$), and to examine the ensuing changes in variable profits.

First, doing inference on bounds $\lambda_{i,L}$ and $\lambda_{i,U}$ entails choosing appropriate counterfactual assortments that yield $\Delta R_i(\boldsymbol{a}_i') < 0$ and $\Delta R_i(\boldsymbol{a}_i') > 0$ for each store i. In order to choose counterfactual assortments $\boldsymbol{a}_i'$ that yield these conditions, the following algorithm is proposed, applicable to any store i in the sample. For a given choice of integer $n > 0$:

1. Replace the n least (most) popular products in store i's assortment $\boldsymbol{a}_i$ with the n most (least) popular products available at the warehouse, but not belonging to assortment $\boldsymbol{a}_i$.
2. Denote the resulting counterfactual assortment as $\boldsymbol{a}_i'^{(n)}$.
3. Compute the change in own-store profits and profits of neighbouring stores from the same district, $\Delta R_i(\boldsymbol{a}_i'^{(n)})$ and $\Delta R_{-i}(\boldsymbol{a}_i'^{(n)})$.

Repeating the above steps for different values of n yields a set of functions $\Delta R_i(\boldsymbol{a}_i'^{(n)})$ and $\Delta R_{-i}(\boldsymbol{a}_i'^{(n)})$ for store i. Extending the above algorithm to each store i and week t in the sample, we can define the sample averages $m_i(n)$ and $M_i(n)$ as follows:

$$m_i(n) = \frac{1}{T}\sum_{t=1}^{T} \Delta R_{i,t}(\boldsymbol{a}_{i,t}'^{(n)})$$

$$M_i(n) = \frac{1}{T}\sum_{t=1}^{T} \Delta R_{-i,t}(\boldsymbol{a}_{i,t}'^{(n)}),$$

[29] For further details regarding inference in partially-identified models, see Manski and Tamer (2002), Chernozhukov et al. (2007), and Romano and Shaikh (2010).

where T denotes the total number of weeks in the sample. Finally, given sample averages $m_i(n)$ and $M_i(n)$, the following estimator is proposed for bounds $\lambda_{i,L}$ and $\lambda_{i,U}$:[30]

$$\widehat{\lambda_{i,L}} = \max_n \left\{ -\frac{m_i(n)}{\Big(M_i(n) - m_i(n)\Big)} \;\Big|\; \Big(M_i(n) - m_i(n)\Big) > 0 \right\}$$

$$\widehat{\lambda_{i,U}} = \min_n \left\{ -\frac{m_i(n)}{\Big(M_i(n) - m_i(n)\Big)} \;\Big|\; \Big(M_i(n) - m_i(n)\Big) < 0 \right\}$$

Using the estimated bounds, we can define the store-level estimate $\widehat{\lambda_i}$ as the midpoint value of the confidence interval $\left[\widehat{\lambda_{i,L}}, \widehat{\lambda_{i,U}}\right]$. In particular, we will consider $\widehat{\lambda_i}$ as the midpoint value of a 95% normally-distributed confidence interval around the true parameter λ_i. Estimates from running the proposed algorithm are provided in Table 9 below.

Table 9: Estimates of λ_i

	Median est. (*Median s.e.*)
λ_i: *Midpoint Estimate*	0.3862 (0.0122)
$\lambda_{i,U}$: *Upper Bound*	0.4203
$\lambda_{i,L}$: *Lower Bound*	0.3575

(1) Standard errors based on 95% confidence intervals around λ_i.

Estimates in Table 9 show that on average, store managers at the LCBO do not fully internalize the outcomes of neighbouring stores in their district when making their product assortment decisions, providing evidence of within-firm competition. Specifically, Table 9 shows that the median store manager places a weight of approximately 61% on own-store profits, meaning that the median store manager only places a weight of 39% on profits of neighbouring stores in their

[30]Notice that the proposed estimator is a ratio of sample averages as opposed to a sample average of ratios. This distinction is noted by Pakes (2010), and follows from the specification of the store manager's objective function. See Appendix A.10 for details regarding the asymptotics of this estimator.

district. To put these numbers into perspective, from the point of view of the LCBO, store managers should be placing equal weight on both own-store profits and profits of neighbouring stores in their district. These estimates therefore provide evidence of a misalignment between the objectives of the firm and the objectives of store managers: relative to the firm's objective, the median store manager places 23% less weight on profits of neighbouring stores from their district, resulting in within-firm competition.

Given that we have estimates λ_i at the store level, we can also explore the extent of this misalignment across the retail chain by examining how λ_i varies across stores in the sample. In order to correct for excess dispersion in these store-level estimates, a shrinkage estimator is first applied to parameters λ_i.[31] In Figure 2 below, the store-level shrinkage estimates of λ_i are presented, with the vertical red-dotted line representing the median-store estimate.

Figure 2: λ_i Shrinkage Estimates

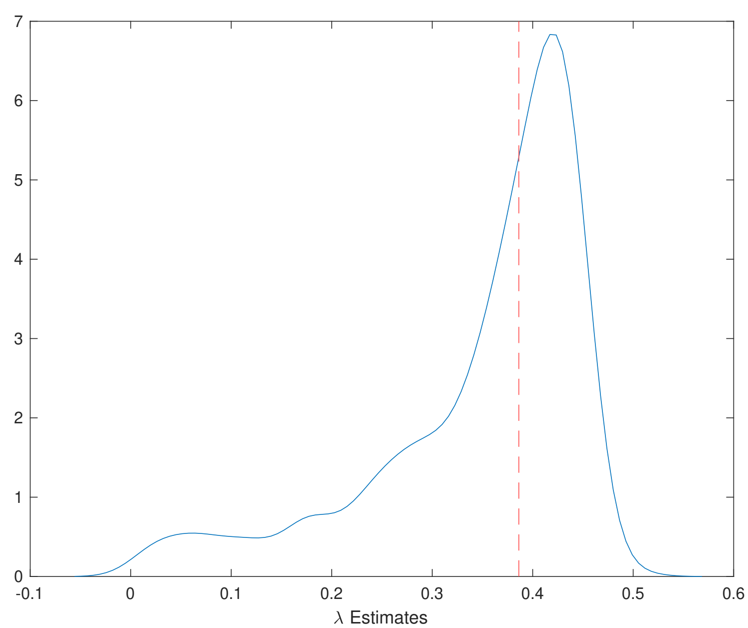


Figure 2 above shows that estimates of λ_i vary significantly across store managers at the LCBO. Indeed, while the median estimate of this empirical distribution is approximately 0.39, the standard deviation is around 0.11, which represents a significant spread in estimates. The distribution also displays a long left-tail, evidence that some store managers place very little weight on profits of neighbouring stores in their district. At least two store characteristics can

[31] See Ashley (1990), Gu and Koenker (2017a), and Gu and Koenker (2017b) for details regarding shrinkage estimators.

potentially explain these differences across stores:[32] (1) store classification. Driven by higher sales potential and better managerial experience, managers in charge of larger AAA stores may have a stronger incentive to behave in their own self-interest relative to managers at smaller D stores;[33] (2) number of same-district stores in the neighbourhood. Neighbourhoods with greater numbers of same-district stores may provide a stronger influence on the store manager to internalize firm outcomes through the district manager effect. Given these two channels, we explore how estimates of λ_i vary according to these factors in Table 10, controlling for district.

Table 10: λ_i Regressions

	OLS
	Est. *(s.e.)*
Same-district stores in neighbourhood	0.0136***
	(0.0028)
Store classification	
B	0.0756***
	(0.0126)
C	0.1010***
	(0.0214)
D	0.1357***
	(0.0249)
District F.E.	✓
R-squared	0.3191
Observations	275

(1) Standard errors clustered at the store level in parentheses
(2) * $p-value < 0.10$, ** $p-value < 0.05$, *** $p-value < 0.01$

First, Table 10 reveals that estimates of λ_i are strongly correlated with store classification. Relative to the omitted categories AAA, AA, and A, estimates of λ_i are significantly higher for B, C, and D stores on average. In other words, managers of smaller stores seem to place higher weight on profits of neighbouring stores from the same district – or conversely, managers in larger stores place lower weight on the firm's outcomes. Second, results show that the number of

[32] Among other empirical studies, see Goldfarb and Xiao (2011), Ellison et al. (2018), and Hortaçsu et al. (2019) for papers studying how store and manager characteristics can affect strategic ability in decision-making.

[33] According to internal documents, managers assigned to stores of higher classification have greater experience and education on average.

same-district stores in the neighbourhood is correlated with λ_i. Stores located in neighbourhoods with a higher number of stores from the same district seem to place greater weight on the profits of these stores on average. The degree to which store managers internalize firm outcomes in their decision-making is therefore positively correlated with the number of same-district LCBO stores in their neighbourhood. For illustration purposes, Appendix A.11 presents scatter plots of λ_i against store classification and number of same-district stores in the neighbourhood.

Given the evidence of heterogeneity across stores in parameters λ_i, and the factors determining these differences, we now move on to counterfactual experiments in which we examine how redefining the objectives of store managers can have significant effects on firm outcomes.

6 Counterfactual Experiments

In this section, we conduct a series of counterfactual experiments in which we examine how re-defining the objective functions of store managers – and particularly, changing the weight placed by store managers on neighbouring stores – can affect firm outcomes. Importantly, we want our counterfactual experiments to be conditional on the current managerial incentives being provided by the firm. We will therefore assume that effort is associated with the number of products carried by a store, such that greater effort involves carrying a higher number of products, and keep this measure constant throughout the counterfactual experiments. Keeping effort of store managers constant therefore entails keeping the number of products fixed in the product assortments of stores, and focusing solely on which products are carried.

6.1 Approximating the Counterfactual Equilibrium

In the following counterfactual experiments, we fix parameters λ_i to some counterfactual value $\tilde{\lambda}$, and solve for the new equilibrium strategies under this restriction. Two (extreme) cases for the value of $\tilde{\lambda}$ are considered below: (1) perfect alignment with the firm. In this experiment, each store manager places weight $\tilde{\lambda} = 0.5$ on neighbouring-store profits, regardless of district, and perfectly internalizes the impact of their assortment decisions on the outcomes of the firm. (2) complete self-interest. This involves setting $\tilde{\lambda} = 0$ for each store manager, such that store managers care solely about own-store profits. In general, for a given value of $\tilde{\lambda}$, the counterfactual strategy function of store i is given by:

$$\sigma_i(\boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \tilde{\lambda}) = \underset{\boldsymbol{a}_i \in \mathcal{A}_i}{\operatorname{argmax}} \Big\{ (1-\tilde{\lambda})\pi_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \gamma_i) + \tilde{\lambda} \sum_{m \in \mathcal{M}(i)} \pi_m(\boldsymbol{a}_m, \boldsymbol{a}_{-m}, \boldsymbol{\omega}; \boldsymbol{\theta}, \gamma_m) \Big\},$$

where the counterfactual objective function of store manager i no longer includes own-district considerations $\mathcal{M}_d(i)$, and now depends on the counterfactual parameter $\tilde{\lambda}$. The new equilibrium of the game of product assortment decisions is then given by the set of strategy functions $\tilde{\boldsymbol{\sigma}}$:

$$\tilde{\boldsymbol{\sigma}} = \left\{ \sigma_i(\boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \tilde{\lambda}) : i \in \{1, 2, ..., I\} \right\}$$

As described in Section 5.1, the size of the choice space $\mathcal{A}_i$ of store managers in the game of assortment decisions is extremely large. Therefore, we will approximate the counterfactual equilibrium $\tilde{\boldsymbol{\sigma}}$ by using Monte Carlo simulation: drawing random sets of product assortments in each store cluster, we will approximate the best response functions of store managers by exploring deviations in the region of each store manager's drawn product assortment and finding the set of product assortments that jointly minimize these deviations of each store within the cluster. Denoting $\tilde{v}_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \tilde{\lambda})$ as the counterfactual objective function of store manager i, the following algorithm is proposed, which can be applied to each store cluster separately:[34]

1. In iteration r, draw a random binary matrix describing the product assortments $\boldsymbol{a}_i$ of each store i, under the restriction $\boldsymbol{a}_i \in \mathcal{A}_i, \forall i$.

2. For each store i, compute value $\tilde{v}_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \tilde{\lambda})$.

3. Draw a set of random deviations in the region of $\boldsymbol{a}_i$ for each store i, denoting the resulting product assortment from deviation l as $\boldsymbol{a}_i^{(l)}$, and compute the set of deviation values $\tilde{v}_i(\boldsymbol{a}_i^{(l)}, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \tilde{\lambda}) - \tilde{v}_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \tilde{\lambda})$ for each store manager i.

4. After R iterations, an approximation of equilibrium $\tilde{\boldsymbol{\sigma}}$ is the matrix of assortments that minimizes deviation values $\tilde{v}_i(\boldsymbol{a}_i^{(l)}, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \tilde{\lambda}) - \tilde{v}_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \tilde{\lambda})$ for each store i.

Notice that considering the counterfactual value $\tilde{\lambda} = 0.5$ is a special case of the algorithm, as it coincides with the firm's objective function. From the point of view of the firm, maximizing aggregate profits entails maximizing the sum of store-level profits across the retail chain. Therefore solving for the counterfactual equilibrium in which store managers place equal weight on own-store profits and neighbouring-store profits, regardless of district, is equivalent to solving the firm's maximization problem:

[34] The algorithm can be separated by store cluster given that in the model, competitive interactions occur only within store clusters.

$$\max_{\{\boldsymbol{a}_i \in \mathcal{A}_i\}_{i\in\mathcal{I}}} \quad \sum_{i=1}^{I} \pi_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \gamma_i)$$

$$\text{s.t.} \quad (1)\ \ \pi_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \gamma_i) = \Big(\sum_{j=1}^{J} (p_j - c_j) \times q_{i,j}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta})\Big) - f(\boldsymbol{a}_i, \epsilon_i; \gamma_i)$$

$$(2)\ \ q_{i,j}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}) = \Big(\sum_{h:\, i\in\mathcal{R}(h)} M_h \times s_{i,h}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta})\Big) \times s_{i,g}(\boldsymbol{a}_i, \boldsymbol{\omega}; \boldsymbol{\theta}) \times s_{i,j|g}(\boldsymbol{a}_i, \boldsymbol{\omega}; \boldsymbol{\theta}),$$

In terms of the proposed algorithm, Monte Carlo simulation under $\tilde{\lambda} = 0.5$ substantially reduces the computational burden of approximating the counterfactual equilibrium. Instead of approximating the best response functions of each store manager, we can draw random product assortment matrices for each store cluster and iterate until we find the set of product assortments that maximize total profits in that cluster. Results from running our Monte Carlo simulations under $\tilde{\lambda} = 0.5$ and $\tilde{\lambda} = 0$ are presented in Section 6.2 below.

6.2 Counterfactual Results

Table 11: Results of Monte Carlo Simulations

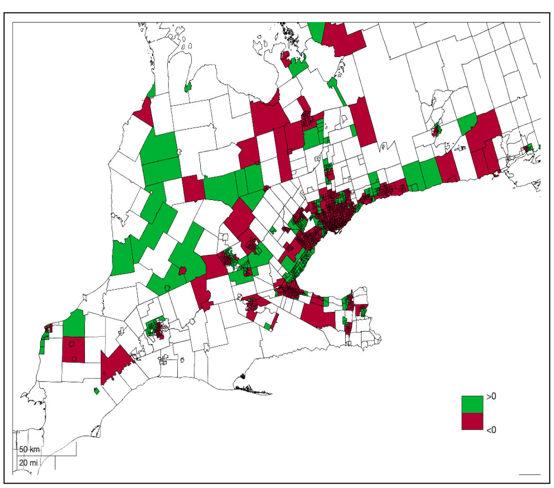
	Perfect alignment $\tilde{\lambda} = 0.5$	Complete self-interest $\tilde{\lambda} = 0$
Δ Firm Profits	+ 15.80%	– 14.72%
Δ Consumer Surplus	– 2.45%	+ 0.58%
Δ Products in Circulation	+ 14.58%	– 11.19%
Δ Product Assortment Overlap	– 10.50%	+ 13.43%

(1) Figures in table represent the percentage difference between the counterfactual equilibrium and the actual solution.
(2) Firm profits and consumer surplus are computed as sums over store clusters.
(3) Products in circulation and product assortment overlap are computed as averages over store clusters.

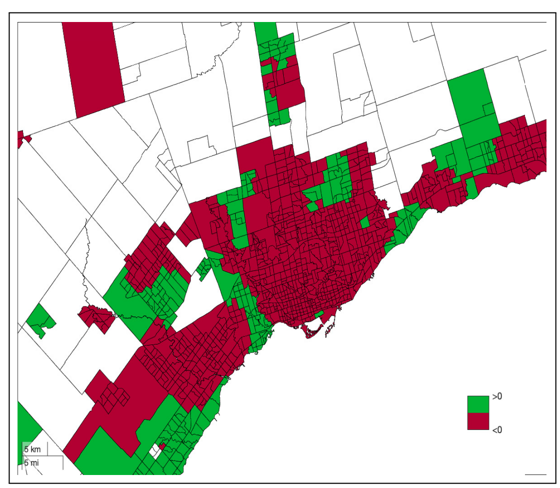
Overall, Table 11 above shows that conditional on the current managerial incentives, changing the degree to which store managers internalize firm outcomes results in significant impacts on the retail chain. Focusing on the first column, if store managers were to perfectly internalize the impact of their actions on firm outcomes, then the firm could increase aggregate profits by approximately 16%. Additionally, the average product overlap between stores would fall by approximately 10%, subsequently providing approximately 15% more products to consumers on average. Relying on the stylized model in Section 3, these findings therefore show that reducing the degree of competitive behaviour between store managers can reduce their strategic incentives to offer the same products as neighbouring stores. In terms of consumer surplus, a higher number of products in circulation provides consumers with greater choice. However, given that the degree of product assortment overlap is lower in the counterfactual solution, consumers must also travel further on average to purchase a specific product, increasing the disutility related to travelling. Combining these two effects results in a small negative change in total consumer surplus of approximately 2% in the counterfactual solution. Interestingly, the resulting changes in consumer welfare vary significantly across census tracts/subdivisions, such that some areas benefit from within-firm competition while others do not. Figure 3 below depicts the distribution of changes in consumer welfare across Ontario in the counterfactual solution under $\tilde{\lambda} = 0.5$.

Figure 3: Distribution of Welfare Gains (under $\tilde{\lambda}$=0.5)

(a) Southern Ontario



(b) Greater Toronto Area



Panel (a) shows that many regions in Southwestern Ontario have a positive change in consumer welfare under the counterfactual solution with $\tilde{\lambda} = 0.5$, meaning that they benefit from the firm aligning its objectives with the objectives of store managers. However, panel (b) also shows that many consumers in the Toronto-core area are made worse off under the counterfactual solution, and are therefore better off under within-firm competition.

At the other extreme, the second column of Table 11 describes the extent to which within-firm competition could potentially harm the firm. Holding managerial incentives constant, if all store managers in the retail chain were driven to be solely own-store profit maximizing, then firm profits would fall by approximately 15% relative to current profits. Completely misaligned objectives between the firm and its store managers would therefore generate substantial cannibalization effects from the point of view of the firm. Table 11 shows that these cannibalization effects effects would be driven by an increase of approximately 13% in the product assortment overlap between stores, resulting in 11% less products in circulation for consumers. Again, relying on the stylized model in Section 3, within-firm competition therefore entails that store managers have an incentive to offer similar products as their neighbours. However, under $\tilde{\lambda} = 0$, consumer surplus would slightly increase by approximately 1%: the reduction in travelling costs from higher product assortment overlap would outweigh the negative effects from a reduction in products in circulation in the aggregate.

In general, the results from the counterfactual experiments provide evidence of the trade-offs a firm faces when decision-making is delegated to store managers. On one hand, the firm wants to motivate store managers to exert effort in their decision-making by providing performance-based incentives. However, increasing individual performance can negatively impact neighbouring stores, eventually creating a misalignment between the objectives of the firm and the objectives of its store managers. In this respect, the findings from the counterfactual experiments show that increasing the degree to which store managers internalize the impact of their decisions on neighbouring stores can improve firm outcomes and mitigate cannibalization effects from within-firm competition.

In terms of policy implication, the district manager channel presents an interesting avenue for the LCBO to potentially achieve the optimal product allocation across stores. The LCBO may want to consider enhancing the influence of district managers on store-level decision-making, for instance by further encouraging district managers to maximize total profits across stores in their district. However, in doing so, these policies should avoid reducing managerial effort in the inventory decisions of store managers. The LCBO could therefore consider combining some form of enhanced district-manager policies with appropriate adjustments to the performance-based incentives provided to store managers.

7 Conclusion

This paper has examined how competitive interactions between managers can have significant impacts on firm outcomes. First, the paper presents a simple stylized model of assortment decisions that illustrates how own-store profit maximizing behaviour can create a misalignment between the objectives of the firm and the objectives of store managers, generating cannibalization effects from the point of view of the organization. Second, relying on the estimation of a nested demand system, findings show that consumers are willing to substitute across stores in their consideration sets in response to the product assortment decisions of store managers. Exploring this mechanism using a simple counterfactual experiment shows that consumer substitution between stores has a substantial effect on store profits, driving managers to engage in within-firm competition. A game of product assortment decisions is then estimated in which store managers strategically choose which products to carry at their store. The results show that the median store manager places lower weight on profits of neighbours from their district relative to the firm's objective. However these weights vary across the retail chain. Specifically, regression analysis reveals that store size and number of same-district stores in the neighbourhood seem to be correlated with the degree to which managers internalize the profits of neighbouring stores in their district. Finally, counterfactual experiments are explored in which the objective functions of store managers are re-defined in order to change the degree to which they internalize the outcomes of the firm in their inventory decisions. Holding the current managerial incentives constant, findings reveal that perfectly aligning the objectives of the firm with the objectives of store managers would significantly increase firm profits, with a small negative effect on consumer welfare. On the other hand, results also show that if store managers care only about own-store profits, then substantial cannibalization effects are generated, with a negligible effect on consumer welfare. In general, the counterfactual experiments suggest that increasing the degree to which store managers internalize the impact of their decisions on neighbouring stores can mitigate the cannibalization effects from within-firm competition, and improve firm outcomes. To put this policy into practice, the LCBO can potentially consider enhancing the influence of district managers while also adjusting store-level performance-based incentives.

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A Appendix

A.1 Ontario Alcohol Market Shares[35]

Market Participants	2011 Market Share	2012 Market Share	2013 Market Share
LCBO	34.1	34.7	35.7
The Beer Store	54.8	53.9	52.9
Wine Rack	0.90	0.85	0.95
Wine Shop	0.90	0.85	0.95
Other	9.3	9.7	9.5

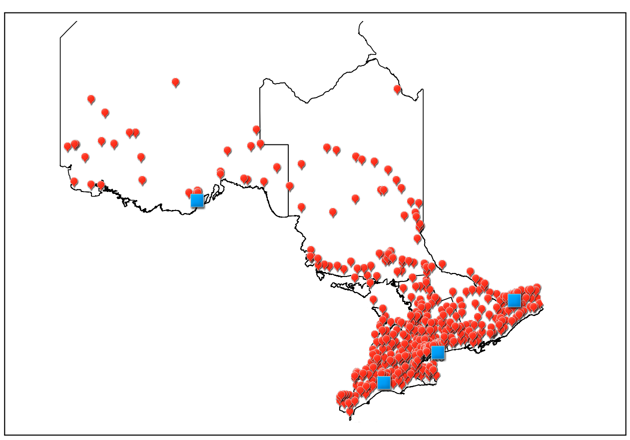
(1) Market shares expressed in terms of total litres sold.

(2) Category "Other" includes third party legal and illegal retailers.

(3) In the beer market, the LCBO has approximately a 20% market share.

A.2 Store and Warehouse Locations at the LCBO

Note: retail stores in red; distribution centres in blue



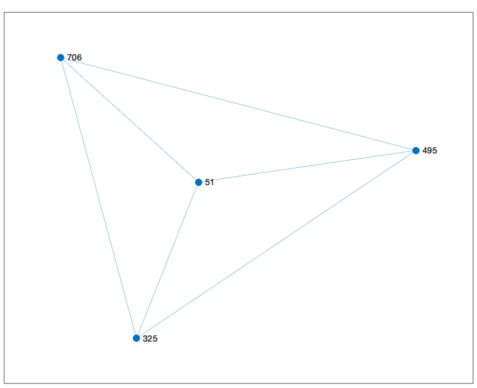
[35]Information originates from LCBO's Annual Reports. See Liquor Control Board of Ontario (2012) and Liquor Control Board of Ontario (2013).

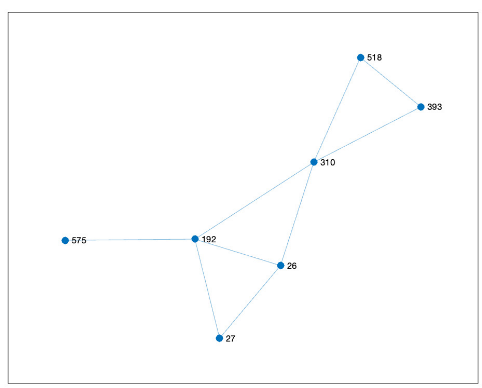
A.3 Sample Wine Product Needs Letter

LCBO WINES 2011 PRODUCT NEEDS

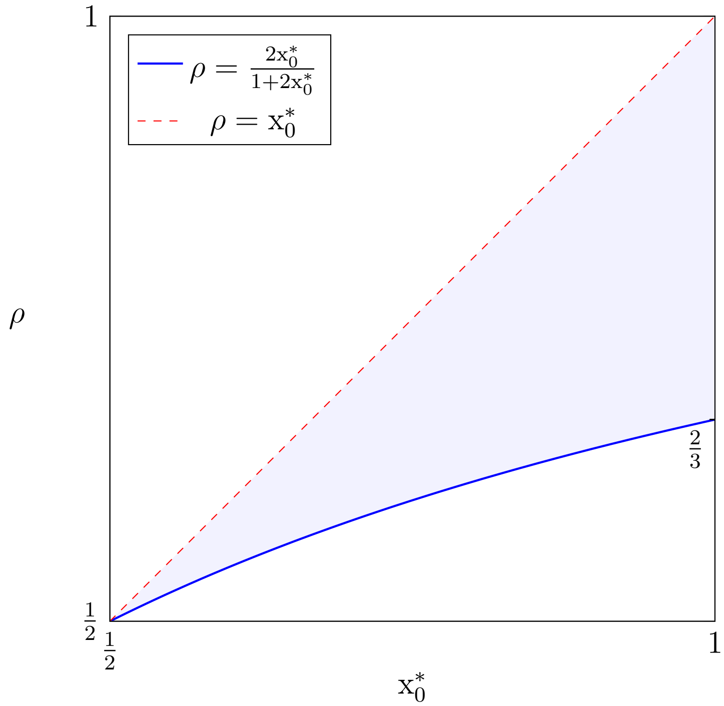
Product Category	ID #	Product Specifications	Price Range	Buyer	Pre-sub Deadline (Friday)	Call Back Deadline	Sample Deadline (Friday)	Tasting Date
Ontario	935	Ontario VQA - Wines to Watch	$12-$20.00	Ontario	March 25, 2011	April 1, 2011	April 15, 2011	April 21, 2011
Sparkling	936	New World All Countries	$10+	New World	March 25, 2011	April 1, 2011	April 29, 2011	May 5, 2011
	937	European Wines Champagne Rose & Prosecco	Champagne Rose $39.95 to $59.95 and Processo $13.95 to $16.95	European Wines				
Sauvignon Blanc	938	South Africa	$12-$18.00	New World	April 8, 2011	April 15, 2011	May 13, 2011	May 19, 2011
	939	Chile	$12+	New World				
Moscato	940	New World Wines - Open to all countries	$9.95 to $15.95	New World				
	941	European Wines - Open to all countries/ Regions	$9.95 to $15.95	European Wines				
Gruner Veltliner	942	Austria Primarily Gruner Veltliner, can include Zweigelt (Red)	$11.95 to $14.95	European Wines				
Various White Varietals (1 of 2)	943	South Africa (Excluding Sauv Blanc)	$10+	New World	April 22, 2011	April 29, 2011	May 27, 2011	June 2, 2011
	944	New Zealand (Excluding Sauv Blanc)	$13+	New World				
	945	BC VQA	$12+	New World				
	946	Italy Primarily Grillo, Verdicchio, Chardonnay, Spain Primarily Albarino	$11.95 to $14.95	European Wines				
Eastern Europe White & Red	947	Eastern Countries including Greece - Red & White	$9.95 to $14.95	European Wines	May 6, 2011	May 13, 2011	June 10, 2011	June 16, 2011
Fortified European Wines	948	Ruby and Tawny Ports, Sherry Dry	Ruby $13.95 to $14.95 and Tawny Port to $24.95, Sherry $10.95+	European Wines				
Chardonnay	949	California	$18+	New World	May 27, 2011	June 3, 2011	June 30, 2011	July 7, 2011
	950	Australia	$18+	New World				
	951	Argentina	$10+	New World				
	964	Chile	$12+	New World				

A.4 Examples of Store Clusters





A.5 Misalignment Region of x_0^*



A.6 Sensitivity Analysis

Several papers in the marketing and business economics literatures, including Seiler (2013), Giulietti et al. (2014), Morozov et al. (2021), and Natan (2023), study consumer purchasing decisions by explicitly modelling consumer search patterns and search costs. In the current paper's approach, an equivalent approach would entail relaxing the assumption of consumers being perfectly aware of the product assortments offered by stores when making their store decision. In order to assess this change, we can introduce weights into the calculation of inclusive values at the product category level. More specifically, denoting $w_{i,j}$ as the weight given to product j, which is increasing in the number of consecutive periods that the product has been in the assortment of store i, we can compute the inclusive value $U_{i,g}^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta})$ as:

$$U_{i,g}^{(2)}(\boldsymbol{a}_i;\boldsymbol{\theta}) = \log\left(\sum_{j=1}^{J_g} a_{i,j} \times w_{i,j} \times \exp\left\{\frac{\delta_j(\boldsymbol{\theta})}{\sigma_3}\right\}\right)$$

Notice that including weights $w_{i,j}$ accounts for the fact that consumers may not be perfectly aware of the product assortments chosen by store managers at the beginning of the week. Products that have recently been introduced have a lower weight in the summation term, while products that have been in the store's assortment for longer periods of time have a higher weight. Using the inclusive values $U_{i,g}^{(2)}$ above, we can then calculate the willingness of consumers to substitute between stores and compare the findings to those reported in the paper. Overall, consumers are willing to travel approximately 0.64 kilometres in response to a 1% increase in store-level expected utility, which is approximately equal to what we find without including weights $w_{i,j}$. Additionally, the effects by product category depicted below are very similar to the values reported in Table 12, confirming that the assumption of perfect information about product assortments does not significantly impact the estimated substitution patterns of consumers.

Table 12: Responses to Assortment Decisions by Product Category

	(1) Red Wine	(2) White Wine	(3) Sparkling Wine	(4) Whisky	(5) Vodka	(6) Rum	(7) Cocktails
Willingness to travel (in km.)	0.4464	0.0817	0.0140	0.0163	0.0181	0.0439	0.0009

A.7 Deriving Market Shares

In a given store, consumer h chooses product j iff $u_{hj} > u_{hk}, \forall k \neq j$. Re-arranging the inequality, the probability that consumer h chooses product j is equal to

$$P_{h,j} = \Pr\Big[\sigma_3 \eta_{h,k} < \sigma_3 \eta_{h,j} + \delta_j(\boldsymbol{\theta}) - \delta_k(\boldsymbol{\theta}), \forall k \neq j\Big]$$

Denoting $\mathrm{Var}(\eta_{h,j}) = \sigma_\eta^2$ and $\mathrm{Cov}(\eta_{h,j}, \eta_{h,k}) = \rho$,

$$\mathrm{Var}(\eta_{h,j} - \eta_{h,k}) = 2\sigma_\eta^2(1-\rho)$$

Using the standard definition of the dissimilarity parameter, $\sigma_3 = \sqrt{1-\rho}$, we obtain

$$\mathrm{Var}(\eta_{h,j} - \eta_{h,k}) = 2\sigma_\eta^2(\sigma_3)^2$$

In order to compare utilities in different groups g, we must therefore scale the utility function by the factor $\frac{1}{\sigma_3}$. Relying on the distributional assumption of the unobservables $\boldsymbol{\eta}$, the probability of consumer h choosing product j then yields:

$$P_{h,j} = \int \prod_{k \neq j} \exp\left\{ - \exp\left\{ - (\eta_j + \frac{\delta_j(\boldsymbol{\theta}) - \delta_k(\boldsymbol{\theta})}{\sigma_3}) \right\} \right\} f(\eta_j) d\eta_j$$

Solving the integral yields the conditional market share $s_{i,j|g}$:

$$s_{i,j|g}(\boldsymbol{a}_i; \boldsymbol{\theta}) = \frac{a_{i,j} \times \exp\left\{ \frac{\delta_j(\boldsymbol{\theta})}{\sigma_3} \right\}}{\sum_{k=1}^{J_g} a_{i,k} \times \exp\left\{ \frac{\delta_k(\boldsymbol{\theta})}{\sigma_3} \right\}}$$

Expressions for the group share s_g and the store share s_i are obtained in a similar fashion, with the exception that these two market shares are a function of the consumer's expected utilities of "visiting" the nests (i.e. of the inclusive values $U_g^{(2)}$ and $U_i^{(1)}$, respectively).

A.8 Inverting Market Shares

Product Choice. Taking the logarithm of market shares $s_{j|g}$, s_g, and s_0:

$$\log\Big(s_{j|g}(\boldsymbol{a}_i; \boldsymbol{\theta}) \Big) = \frac{\delta_j(\boldsymbol{\theta})}{\sigma_3} - U_g^{(2)}(\boldsymbol{a}_i; \boldsymbol{\theta}) \tag{10}$$

$$\log\Big(s_g(\boldsymbol{a}_i; \boldsymbol{\theta}) \Big) = \frac{\sigma_3}{\sigma_2} U_g^{(2)}(\boldsymbol{a}_i; \boldsymbol{\theta}) - \log\left(1 + \sum_{g'=1}^{G} \exp\left\{ \frac{\sigma_3}{\sigma_2} U_{g'}^{(2)}(\boldsymbol{a}_i; \boldsymbol{\theta}) \right\} \right) \tag{11}$$

$$\log\Big(s_0(\boldsymbol{a}_i; \boldsymbol{\theta}) \Big) = -\log\left(1 + \sum_{g'=1}^{G} \exp\left\{ \frac{\sigma_3}{\sigma_2} U_{g'}^{(2)}(\boldsymbol{a}_i; \boldsymbol{\theta}) \right\} \right) \tag{12}$$

Substituting (12) into (11) yields

$$U_g^{(2)}(\boldsymbol{a}_i; \boldsymbol{\theta}) = \frac{\sigma_2}{\sigma_3} \left(\log\Big(s_g(\boldsymbol{a}_i; \boldsymbol{\theta}) \Big) - \log\Big(s_0(\boldsymbol{a}_i; \boldsymbol{\theta}) \Big) \right)$$

Finally, substituting (13) back into (10) yields the mean utility function:

$$\delta_j(\boldsymbol{\theta}) = \sigma_3 \log\Big(s_{j|g}(\boldsymbol{a}_i; \boldsymbol{\theta}) \Big) + \sigma_2 \left(\log\Big(s_g(\boldsymbol{a}_i; \boldsymbol{\theta}) \Big) - \log\Big(s_0(\boldsymbol{a}_i; \boldsymbol{\theta}) \Big) \right)$$

Store Choice. Taking the logarithm of the market shares $s_{i,h}$ and $s_{0,h}$,

$$\log\Big(s_{i,h}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}; \boldsymbol{\theta})\Big) = \frac{\sigma_2}{\sigma_1}\Big(\frac{\sigma_2 U_i^{(1)}(\boldsymbol{a}_i; \boldsymbol{\theta}) + Z_{i,h}\gamma + \zeta_i}{\sigma_2}\Big) - \log\left(1 + \sum_{m \in \mathcal{R}(h)} \exp\left\{\frac{\sigma_2}{\sigma_1}\Big(\frac{\sigma_2 U_m^{(1)}(\boldsymbol{a}_m; \boldsymbol{\theta}) + Z_{m,h}\gamma + \zeta_m}{\sigma_2}\Big)\right\}\right)$$

$$\log\Big(s_{0,h}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}; \boldsymbol{\theta})\Big) = -\log\left(1 + \sum_{m \in \mathcal{R}(h)} \exp\left\{\frac{\sigma_2}{\sigma_1}\Big(\frac{\sigma_2 U_m^{(1)}(\boldsymbol{a}_m; \boldsymbol{\theta}) + Z_{m,h}\gamma + \zeta_m}{\sigma_2}\Big)\right\}\right)$$

Subtracting $\log(s_{0,h})$ from $\log(s_{i,h})$ and re-arranging the terms, we obtain the mean utility function:

$$Z_{i,h}\gamma + \zeta_i = \sigma_1\left(\log\Big(s_{i,h}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}; \boldsymbol{\theta})\Big) - \log\Big(s_{0,h}(\boldsymbol{a}_i, \boldsymbol{a}_{-i}; \boldsymbol{\theta})\Big)\right) - \sigma_2 U_i^{(1)}(\boldsymbol{a}_i; \boldsymbol{\theta})$$

A.9 Robustness Check: New Store Opening

	Change in average weekly demand at LCBO store #499
Actual change	– 3.51%
Predicted change	– 3.39%

(1) Table reports change in average weekly demand at store #499 before and after April 2013.

A.10 Partial Identification of λ

By revealed preference, for any $\boldsymbol{a}_i' \neq \boldsymbol{a}_i, \in \mathcal{A}_i$, we have that:

$$\mathbb{E}\Big[\Delta v_i(\boldsymbol{a}_i', \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i)\Big] = \mathbb{E}\Big[v_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i)\Big] - \mathbb{E}\Big[v_i(\boldsymbol{a}_i', \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i)\Big] \geq 0$$

By the L.L.N., and defining N as the sample size,

$$\frac{1}{N}\sum_{i=1}^{N}\left(\Delta v_i(\boldsymbol{a}_i', \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i) - \mathbb{E}\Big[\Delta v_i(\boldsymbol{a}_i', \boldsymbol{a}_{-i}, \boldsymbol{\omega}; \boldsymbol{\theta}, \boldsymbol{\gamma}, \lambda_i)\Big]\right) \xrightarrow{p} 0$$

Using our specification of the objective function, and combining the last two expressions, we can obtain the following asymptotics for parameter λ_i:

$$\frac{\frac{1}{N}\sum_{i=1}^{N}(\boldsymbol{p}-\boldsymbol{c})\times\Delta\boldsymbol{q}_i(\boldsymbol{a}_i',\boldsymbol{a}_{-i},\boldsymbol{\omega};\boldsymbol{\theta})}{(\frac{1}{N}\sum_{i=1}^{N}\sum_{m\in\mathcal{M}_d(i)}(\boldsymbol{p}-\boldsymbol{c})\times\Delta\boldsymbol{q}_m(\boldsymbol{a}_m,\boldsymbol{a}_{-m}',\boldsymbol{\omega};\boldsymbol{\theta}))-(\frac{1}{N}\sum_{i=1}^{N}(\boldsymbol{p}-\boldsymbol{c})\times\Delta\boldsymbol{q}_i(\boldsymbol{a}_i',\boldsymbol{a}_{-i},\boldsymbol{\omega};\boldsymbol{\theta}))}$$

$$\xrightarrow{p} -\lambda+\frac{\frac{1}{N}\sum_{i=1}^{N}\mathbb{E}\Big[\Delta v_i(\boldsymbol{a}_i',\boldsymbol{a}_{-i},\boldsymbol{\omega};\boldsymbol{\theta},\boldsymbol{\gamma},\lambda_i)\Big]}{(\frac{1}{N}\sum_{i=1}^{N}\sum_{m\in\mathcal{M}_d(i)}(\boldsymbol{p}-\boldsymbol{c})\times\Delta\boldsymbol{q}_m(\boldsymbol{a}_m,\boldsymbol{a}_{-m}',\boldsymbol{\omega};\boldsymbol{\theta}))-(\frac{1}{N}\sum_{i=1}^{N}(\boldsymbol{p}-\boldsymbol{c})\times\Delta\boldsymbol{q}_i(\boldsymbol{a}_i',\boldsymbol{a}_{-i},\boldsymbol{\omega};\boldsymbol{\theta}))},$$

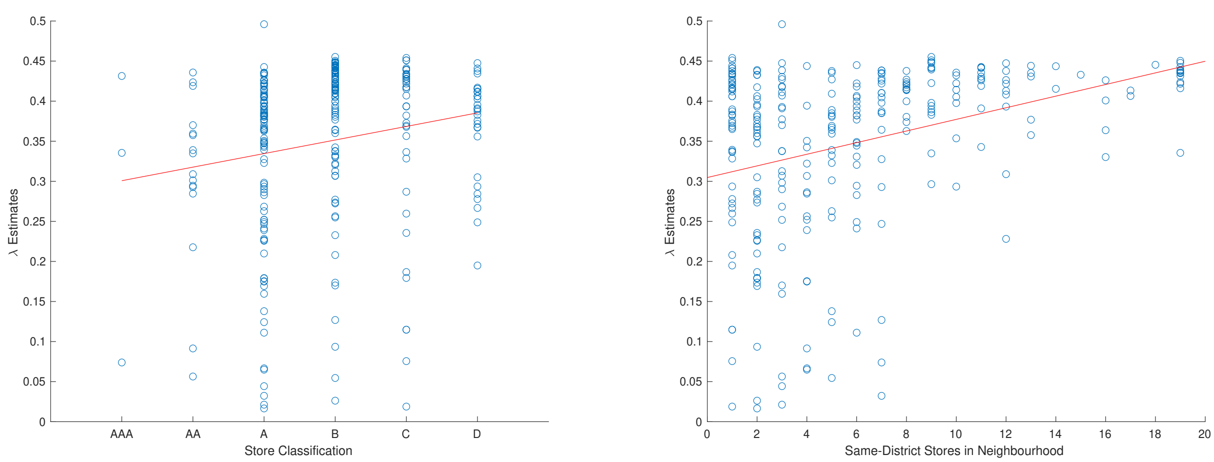
where the term $\Delta\boldsymbol{q}_i(\boldsymbol{a}_i',\boldsymbol{a}_{-i},\boldsymbol{\omega};\boldsymbol{\theta})$ is defined as

$$\Delta\boldsymbol{q}_i(\boldsymbol{a}_i',\boldsymbol{a}_{-i},\boldsymbol{\omega};\boldsymbol{\theta})=\Big(q_{i,j}(\boldsymbol{a}_i,\boldsymbol{a}_{-i},\boldsymbol{\omega};\boldsymbol{\theta})-q_{i,j}(\boldsymbol{a}_i',\boldsymbol{a}_{-i},\boldsymbol{\omega};\boldsymbol{\theta})\Big)$$

A.11 λ_i and Covariates

(a) Store Classification

(b) Same-District Stores in Neighbourhood



The figures above show that λ_i varies significantly both across store classifications and number of stores in the neighbourhood. Panel (a) shows that larger stores (i.e. AAA, AA and A stores) seem to be associated with lower values of λ_i relative to smaller stores. Panel (b) shows that stores belonging to neighbourhoods with a greater number of same-district stores seem to be associated with higher values of λ_i.