Winning Big: Scale and Success in Retail Entrepreneurship

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Abstract

In 2014, Washington State used a lottery system to allocate licenses to firms in the newly legalized retail cannabis industry, generating random variation in how many stores entrepreneurs were able to own. We observe highly detailed data on all subsequent industry transactions, including prices, wholesale costs, markups, and product assortments. We find that entrepreneurs who are randomly allocated more store licenses ultimately earn substantially higher per store profits than do single-store firms, suggesting that the returns to scale in the mom-and-pop retail sector are quite large. Despite these firms having less local competition, this increase in profits does not come at the expense of consumers. Rather, retailers in multi-store chains ultimately charge significantly lower prices and margins and offer greater product variety. This gap in prices is not initially present but grows substantially over time, as does the difference in assortment size and profits between stores in multi-store chains and stores operating alone, consistent with firm learning. Using the full history of outcomes, we track the evolution of firms in this new market and show that multi-store retailers use an initial advantage in offering larger assortments to position themselves as the low-price, large-assortment retail option and attract a larger but more price-sensitive set of customers. These results have implications for the study of retail concentration and mergers, countervailing buyer power, and consumer search. Our results suggest that policies to help entrepreneurs expand in retail may have large benefits to both firms and consumers.

Keywords: Economies of scale, entrepreneurship, retail, entry regulation, firm learning, cannabis policy

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The factors that determine the success or failure of new small businesses have attracted substantial interest from the academic literature on entrepreneurship and from policymakers interested in promoting entrepreneurship and small businesses.[1] Retail plays an outsized role in this debate because mom-and-pop retail firms, those with either one or several outlets in a local area, account for 88% of all retail firms and retail is the 2nd most common occupation for the self-employed.[2] This paper studies several open questions regarding the size and nature of economies of scale for small, "mom-and-pop" style retailers, the determinants of entrepreneurial success, the effects of retail concentration on consumers, and the evolution of firm outcomes and strategies in new industries.

We do so using a novel setting where entrepreneurs were randomly allocated different numbers of retail stores in a new industry. A retail chain's size or scale both caused and are determined by its pricing policies, its assortment choices, its managerial quality, its capitalization, its brand positioning, its set of upstream relationships, its degree of competition with rivals, and so on. As such, it is particularly difficult to separately identify cause and effect relationships between strategies and outcomes that are jointly determined in equilibrium. Studying retail entrepreneurship using the random allocation of retail stores to entrepreneurs as essentially a laboratory allows us to cleanly measure aspects of retailing where there has traditionally not been any way to separately identify cause and effect relationships.

The setting we study is the newly legalized retail cannabis industry in Washington state, which began in 2014 and features a number of advantages as a laboratory for the study of retail strategy, entrepreneurship, firm size, and competition. First, the number of new firms allowed to enter was capped by regulatory design and excess demand for entry licenses by entrepreneurs led to a lottery to allocate them. Firms could win multiple licenses in this lottery such that two firms applying for the same number of licenses would, purely by random draw, end up with different numbers of stores. This lottery that allocated licenses to own and operate retail stores is essentially unprecedented and offers a unique opportunity to study the role of retail chain scale on outcomes in a transparent way.

Second, because this market is closely monitored by regulators, there exists exceptionally good data on both lottery applications and post-entry outcomes. We observe every transaction conducted

[1] See Jovanovich (1982) or Holmes and Schmitz (1995) for reviews of research on barriers to firm expansion faced by entrepreneurs. Pozzi and Schivardi (2015) provides an extensive overview of the types of regulations and measures used by governments to restrict retail entry as well as trends in these regulations and empirical evidence on their effects on consumers and firms.

[2] See Hurst and Pugsley (2011) for the share of retail firms that are "small businesses", defined as having 20 or fewer total employees. For occupation data on the self-employed see IRS (2019), the most common occupation is construction services and other personal services.

in the industry starting with the first sales, including upstream transactions. This means we directly observe retail prices, store product assortments, vertical arrangements between retailers and manufacturers, wholesale prices, and markups, all at the transaction level. These stores do substantial amounts of sales, averaging $2.2 million per year in revenue.

Third, the industry is new and therefore we have the unique opportunity to observe and describe the full evolution of firm choices and outcomes over time. The novelty of the market as a whole also means retailers are especially important. Consumers must discover what products they value, producers must decide what products to make and how, and retailers act as the intermediaries between these two groups, deciding what products to stock, what prices to charge, what manufacturers to purchase from, and how to position themselves to best compete with rivals. By 2021, 15 states had voted to create legal retail industries for cannabis products, with many unresolved policy questions and little evidence to guide policymakers who are writing the rules for what is a large and growing industry.[3] These unresolved policy questions include whether to allow vertical integration between retailers and manufacturers, how much to tax cannabis and at what level (retail sales or upstream), and of course whether to restrict retail entry or restrict the size of retail chains.[4]

Our identification strategy relies on the assumption that condition on the number of applications submitted by each firm, lottery outcomes are exogenous.[5] We find that stores that win multiple licenses and are thus part of multi-store firms grow to be substantially more profitable than stores operating alone. Their variable profits are higher by an average of $290,000 per store per year in the last year of the data, roughly 20% more than single-store operations. If we simply compared these retailer profits in cross-sectional data, we would see this positive correlation between number of outlets and profits, and therefore we might conclude that stores owned by higher quality entrepreneurs earn higher profits and their higher quality also allows them to grow and open more outlets. While this effect is generally likely to be true, our first contribution is to show that there is a direct causal

[3] Retail sales of cannabis products surpassed $20 billion in 2020 and are expected to grow to roughly $60 billion by 2025, see https://www.bloomberg.com/press-releases/2019-10-30/legal-marijuana-market-value-to-hit-59-billion-by-2025-global-market-insights-inc

[4] See Thomas (2019), who studies the efficiency implications of the retail license cap and estimates a counterfactual with free entry of retailers, but does not study the issue of multi-store retail chains. Hollenbeck and Uetake (2021) and Hansen, Miller, Seo, and Weber (2020) study tax policy and how it interacts with retailer market power and the vertical structure between manufacturers and retailers.

[5] In related work, Cirik and Makadok (2020) use the same cannabis store lottery to measure the effect of entry order on subsequent store profits and how this first-mover effect is moderated by availability of online reviews. Giroldo and Hollenbeck (2021) use the same setting and identification strategy to examine the relationship between market level concentration and retail markups. Our approach is also similar to that of Rao (2020) who uses the partially random nature of FDA approvals for new drugs to generate exogenous changes to market structure and measure how investment decisions in the Pharmaceutical industry respond to competition.

effect in the opposite direction as well. Retail firm size matters, and having more outlets causes higher profits directly. Moreover, for the type of entrepreneur operating a mom-and-pop style retail outlet, the returns to scale are quite large.

Our second contribution is to study whether this increase in profits comes at the expense of consumers and more broadly what mechanism is driving it. We are particularly interested in prices and whether multi-store firms use their lower level of local competition and greater brand awareness to earn higher profits by charging higher prices to consumers or if they increase profits using other strategies.[6] We also investigate whether greater scale leads multi-store firms to restrict the product variety available to consumers. We first show that multi-store chains charge substantially lower retail prices than smaller firms, including for the same products. Because we observe wholesale prices, we can rule out that this is merely the result of cost-side economies of scale. While we do find evidence of traditional cost-side retail economies of scale, in that the multi-store firms pay lower wholesale prices for the same products as smaller firms, the difference in retail prices is substantially larger. In other words, chain retailers charge both lower prices and lower margins. This is despite enjoying higher awareness or reputation and having lower competition. We also find that multi-store retailers offer larger assortments, both in number of brands carried and number of products. We find that the difference in prices and assortment sizes is not initially present but grows over time, consistent with firms learning to play the optimal strategies. In this context, the combination of lower prices and larger product variety suggest that a more concentrated retail sector with larger retailers provides significant benefits to consumers as well as to the retailers themselves.[7]

Studying the relationship between prices and retail firm size in this clean setting also helps shed light on several ongoing debates. In particular, the theoretical study of consumer search and retail competition has made great progress in advancing our understanding of the role of the retail sector in markets with consumer search costs, but fundamental issues still remain unresolved. One of these is why different retail stores charge different prices for the same product, and in particular whether larger retailers will ultimately charge higher or lower prices, holding costs and other factors

[6]Thomadsen (2005) shows that co-owned fast food outlets do charge significantly higher prices when located relatively close to each other. In a related work, Pancras, Sriram, and Kumar (2012) develop a demand model that accounts for location endogeneity and spatial competition to measure the net impact of store openings on chain outlet sales in the fast food industry. They use this model to identify what stores provide more or less value to their chain partners and to measure cannibalization between franchised chain outlets.

[7]These results are also consistent with new work by Bronnenberg (2018), which studies the role of retail in a general equilibrium setting and shows how the retail sector as a whole benefits consumers by increasing product variety.

fixed. The disagreement stems from different ways of modeling the nature of consumer search and demand and how these effect retailer pricing incentives.

One view, shown in models such as McAfee (1994) and Armstrong and Vickers (2020) is that larger or multi-store firms should have more "captive" customers who do not price search and therefore they should charge higher prices than smaller firms.[8] Another key aspect of economies of scale in retail is that larger chains can spread the fixed costs of contracting with manufacturers over more stores and this allows them to stock more brands and offer larger assortments. If retailers with more outlets can offer larger assortments, their pricing and positioning should adjust as well. Anderson and De Palma (2006) show that larger assortments should result in higher prices under standard demand conditions. Kim, Allenby, and Rossi (2002) also show that preference for variety should lead retailers with larger assortments to offer higher average prices. A final force that would cause stores in multi-store firms to set higher prices is that most co-owned stores are located near each other, and therefore these firms have less local competition, which should result in higher markups (Thomadsen (2005)).

On the other hand, if the firm with multiple outlets has greater awareness but its customers are not "captive", it should have an incentive to charge lower prices to prevent them from searching at rivals (Armstrong, Vickers, and Zhou (2009), Zhou (2014)). As noted above, multi-store retailers should be able to offer more products than single-store retailers if it is profitable to do so. Retail stores that offer more products may attract a larger but more price-sensitive "mass market" set of consumers while small firms are left to offer a more niche assortment but sell at higher prices to high value consumers (Rhodes (2015), Rhodes and Zhou (2019)). Kuksov and Lin (2017) also show how a larger assortment can be used to signal low prices to prevent customer search. This assortment effect would result in multi-store retailers charging lower prices but earning higher profits.

Our results show a clear causal relationship that larger retailers with more stores do charge lower prices and combine their lower prices with larger assortments.[9] The literature makes different

[8] Prior work has found that both hotel chains and chain restaurants benefit from reputation effects that allow them to charge significantly higher overall prices in this way, see Hollenbeck (2017) and Klopack (2018). Hollenbeck (2017) finds that chain hotels earn roughly 25% higher revenues than otherwise identical independent hotels and attributes this to greater consumer information on chain hotel quality due to their ability to build reputation over multiple outlets. Klopack (2018) finds a similar demand side advantage in the restaurant industry.

[9] These results show evidence for countervailing buyer power, that is the idea that an increase in market power downstream might benefit consumers by increasing retailer buyer power relative to suppliers, decreasing input prices, and passing a portion of the savings along to consumers. It is a theoretical debate in what conditions a downstream merger can improve social surplus (Inderst and Shaffer (2007) , Symeonidis (2010), Loertscher and Marx (2019)) and this has limited empirical evidence (Barrette, Gowrisankaran, and Town (2020)).

predictions on the direction of these effects and so it is an empirical question what forces will dominate. Our evidence suggests larger retailers do not exploit captive customers and that their larger product variety is not associated with higher prices. Among the models predicting lower prices for larger or multi-store firms, we find that the evidence is more consistent with the view that larger assortments attract more price-sensitive customers (Rhodes (2015), Kuksov and Lin (2017), Rhodes and Zhou (2019)) as opposed to them pricing lower due to a simple prominence effect. The gap in prices between multi-store and single-store firms is not initially present but grows substantially over time, as does the difference in assortment size between stores in multi-store chains and stores operating alone.[10] We also find, consistent with Rhodes (2015), that customers at multi-store retailers are more likely to purchase baskets of products containing products from multiple brands and multiple categories.

Finally, we estimate a model of consumer demand and find that multi-store firms face significantly more price sensitive customers than do single-store firms and that this difference is also growing over time. This suggests that consumer demand shifts outwards for multi-store firms, as evidenced by their higher profits and sales, but the marginal consumer visiting a multi-store firm is substantially more price sensitive than the marginal consumer faced by a single-store firm.

These results together suggest that, multi-store firms turn a small initial advantage in their ability to offer larger assortments to cumulatively build a large profit advantage by learning to position themselves as the large-assortment, low-cost retail option that attracts the largest segment of customers. As shown in Rhodes (2015), this result is quite general and does not depend on strong assumptions about the shape of demand. This is consistent with work in the marketing literature on the important role for assortment in retail store choice, which has shown that retailer assortment is more important than pricing in store choice decisions (Fox, Montgomery, and Lodish (2004), Briesch, Chintagunta, and Fox (2009)) and that customer perceptions of retailers are highly effected by the presence of large assortments (Mogilner, Rudnick, and Iyengar (2008), Hoch, Bradlow, and Wansink (1999)). Retailers positioning strategies are multidimensional, as emphasized by Corstjens and Corstjens (1995), and even relatively small differences in scale can have large effects on profits if they facilitate successful repositioning.

While it is a limitation that the retail chains we study are relatively small, these results still have

[10] A similar type of result is seen in Ilanes and Moshary (2019), who study the deregulation of Washington's retail liquor industry and find that increases in competition lead firms to offer larger assortments.

significant policy implications. Small firms account for 80% of U.S. businesses and are generally seen as especially important for local labor markets and thus are often targeted with subsidies or special treatment by local governments (Jones and Pratap (2020)). We find that clear causal evidence that economies of scale for entrepreneurs operating as mom-and-pop retailers are quite large, which suggests that policies designed to support entrepreneurs, such as by helping to finance their expansion, can be very valuable both for the success of small businesses and for consumers. Our results also suggest that other barriers to expansion, such as zoning restrictions, legal red tape that raises the cost of opening or expanding new businesses, corruption, access to capital, insurance or other services, potentially have very high costs to both retailers and consumers.[11] These implications are likely true for entrepreneurs entering in industries with licensure restrictions or retail zoning restrictions like the one we study. Severe restrictions on securing retail licenses are common in alcohol retail in many states and of course in the newly growing retail cannabis industry, although at some level nearly all retail is subject to licensing requirements (Pozzi and Schivardi (2015)). Most directly, as policymakers develop rules for cannabis retail many states limited the size of retail chains using similar licensure restrictions and our results suggest these limitations are highly costly both for entrepreneurs and consumers.[12] The presence of co-owned stores generated by the lottery is analogous to exogenously imposed mergers, and so our results also have implications for the understanding of retail mergers.[13]

The results also provide clear managerial implications. First, we show that the returns to expansion for small retailers are large, plausibly larger than most entrepreneurs would predict. Second, we show that in this category, and likely in many similar categories, positioning a retailer with a large-assortment, low-price brand early can be a highly valuable use of a first-mover advantage. Indeed, we show that having multiple stores is a sufficient condition for this positioning. Nevertheless, it may not be necessary as we do observe some single-store retailers operating successfully in

[11]Related work by Maican and Orth (2020) uses a dynamic structural model of firm entry and finds that a reduction in entry regulations in the Swedish retail industry lead to productivity improvements and that retailers re-position themselves and offer larger varieties. For an extensive overview of other work on the effects of retail entry restrictions see Pozzi and Schivardi (2015). A related issue is corruption and governance quality, Sudhir and Talukdar (2015) shows that Indian retailers avoid productivity enhancing investments and remain small to reduce transparency and avoid regulatory compliance.

[12]A total of 15 U.S. states and several Canadian provinces currently employ similar license caps. Similar regulations are also used for alcohol or tobacco retail licenses in 17 states. Other states prevent entry altogether in favor of a state monopoly on alcohol retail outlets (Waldfogel and Seim (2013))

[13]For an overview of the literature on retail mergers, see Hosken and Tenn (2016). Recent work includes Argentesi, Buccirossi, Cervone, Duso, and Marrazzo (2021), who show how retail stores adjust their assortments following mergers.

this way. For most retailers, however, the marginal effect of an increase in assortment by adding a new brand or supplier is not very large when taken alone and when focusing on the short run. To the extent that many entrepreneurs who enter the retail sector therefore do not realize (or underestimate) the long-term gains associated with a large-assortment positioning strategy there is a clear managerial implication from our results, although one that is subject to the same caveats about the uniqueness of the setting described above.

The rest of the paper proceeds as follows: Section 1 describes the data and setting with an emphasis on the transaction-level retail data and the retail license lottery, Section 2 provides results on the differences in variable profits and price and assortment decisions between multi-store chains and single-store firms, Section 3 studies consumer demand differences between these types of stores, and Section 4 discusses and concludes.

1 Data and Setting

This section describes the institutional setting and key features of the data. The regulatory setting dates back to a November 2012 popular referendum passed by voters in Washington state. The new law made marijuana products legal for licensed firms to produce and sell and legal to purchase by any person over 21 years of age. The state legislature subsequently created a tax and regulatory regime for the new legal market by passing I-502 which set up the rules for the legal market to begin sales in July 2014. The state created 3 new types of firm licenses, differentiated by their position in the vertical structure of the industry, similar to the three tier system for alcohol regulation.

Firms can be licensed as retailers, processors, or producers. Processors and producers are allowed to hold both licenses and vertically integrate, but retailers are not allowed to vertically integrate. In addition, the total number of retail licenses was strictly capped.[14] This license cap and how licenses were allocated forms the basis of our empirical strategy and we therefore discuss it at length.

License Lottery:

During the creation of the legal marijuana industry, Washington decided to strictly limit the total amount of entry by retailers. This was motivated by concerns about widespread use of marijuana, which is thought to have negative health effects and social externalities.[15] In addition, there was

[14]See also Thomas (2019) who studies the effects on consumption and welfare of this cap and simulates a free entry counterfactual. A total of 15 U.S. states and several Canadian provinces currently employ similar license caps. Similar regulations are also used for alcohol or tobacco retail licenses in 17 states.

[15]For a review of these issues, see Hall, Stjepanovic, Caulkins, Lynskey, Leung, Campbell, and Degenhardt (2019).

a concern about the impact of over-entry by retailers on neighborhood character and property values.[16] Finally, one of the goals of legalization is to remove marijuana sales from the black market so that they can be regulated and monitored, and this goal is more easily achieved with fewer retail shops for regulators to monitor.

The result was the choice to limit entry to an initial total of 334 retailers for the state of Washington.[17] These licenses were allocated at the city level, with the allocation determined by population, population density, and an estimate of past-month marijuana users taken from historical survey data. Expectations by market participants were that this industry would be highly lucrative and demand to enter the industry by entrepreneurs significantly exceeded the number of entrants preferred by the state government, leading to the unusual choice to allocate licenses via a lottery.

Lotteries were held separately at the city level, and 75 cities experienced excess demand for the available retail licenses, resulting in 75 different lotteries being held. In addition, in 47 cities there was not excess demand for licenses.[18] We observe the full list of applicants as well as the ordering determined by the random draw that constituted each lottery.[19] In order to potentially win a retail license in the lottery, firms needed to file a valid application, which included securing a location for the retail store within the regulatory guidelines and paying a $250 non-refundable application fee.[20] Among the regulatory guidelines the proposed location of each store had to be at least one thousand feet from elementary or secondary schools, public parks, libraries, among other locations. These regulations along with reluctance by landlords to permit cannabis shops made securing the store location a major barrier to entry for filing an application for the lottery.

Table 1 shows summary statistics on license applications in lottery markets. On average, there were 4.1 applicants per license in these markets with a wide degree of variation. In the largest market, Seattle, there were 191 applications for 21 licenses. In order to prevent large firms from dominating the retail sector, firms were not allowed to own more than 3 total retail licenses anywhere in the state.[21]

[16]See Tyndall (2019) for a study of the effect of dispensaries on nearby home prices, which finds close to zero but potentially small negative effects in Vancouver, BC.

[17]This number was chosen somewhat arbitrarily to match the number of state-owned liquor stores under Washington's state monopoly on retail alcohol sales that lasted until 2012.

[18]"Lottery Results for Marijuana Retail Stores Available on WSLCB Website," Washington State Liquor and Cannabis Board, available at https://lcb.wa.gov/pressreleases/lottery-results-marijuana-retail-stores-available-wslcb-website.

[19]The lottery results for the market of Longview, WA were not available.

[20]If issued, the store was responsible for paying a $1000 annual fee for issuance and renewal.

[21]According to the regulation, "Any entity and/or principals within any entity are limited to no more than three retail marijuana licenses with no multiple location licensee allowed more than thirty-three percent of the allowed

In July 2015, the state updated its licensing regime. In the first year of the market, Washington had failed to close down formerly unregulated medical marijuana retailers and they were operating in a grey market. In July 2015, Washington increased the total number of retail licenses available from 334 to 556 in order for some of these medical marijuana retailers to enter the market. At the same time, any medical marijuana retailer that did not receive a license was forced to close. The newly available licenses were awarded according to the initial lottery draws and thus these draws were still overwhelmingly the mechanism by which the new licenses were allocated in the second wave.

Table 1 also shows the resulting distribution of stores across markets. The number of stores per thousand people in 2017 was 1.38 but with substantial variation. Table 2 shows the joint distribution of applications filed in the lottery and store licenses won. Conditional on the number of applications filed, the number of licenses won is the result of a random draw. This represents the basis of our identification strategy.

There are two complicating factors. First, licenses can be acquired in both non-lottery markets or through the secondary market where firms that own licenses can be purchased by other firms. The second of these is rare and we observe it when it occurs.[22] Second, we observe loose partnerships between stores that are owned by different firms. This typically takes the form of stores operating under similar names or sharing the same website. We carefully document these practices in our data.

Ultimately, our goal is to compare the outcomes of stores in multi-store chains to those operating in single-store firms using the lottery to provide cleanly exogenous variation. Multi-store chains that acquire their licenses bypassing the original lottery or form partnerships would not make for valid comparisons. Therefore we take a conservative approach and exclude any firm who acquired its stores outside the lottery or other multi-store partnerships from our definition of "multi-store". The result is that some of the firms we designate as "single-store" may benefit from the same economies of scale as the multi-store firms, either on the cost side or on the demand side. Therefore all our results should be taken as lower bounds for the true size of these effects. Finally, we note that other than their chain size, the two types of stores are broadly similar on observable characteristics, with no significant differences in their entry timing or location, and single-store and multi-store firms

licenses in any county or city." Other regulations included: the prohibition of internet sales and delivery of product, the prohibition of sales across state lines and the sale of marijuana products below their acquisition cost.

[22]Only 32 licenses are bought or sold during the sample period.

have 13% and 15% of their locations in Seattle, respectively.

A final concern might be strategic entry into lotteries with better chances of winning a store. Higher quality managers may be strategic about entry, as shown by Goldfarb and Xiao (2011), which could hinder our identification strategy. Strategic entry would specifically require that managers have foresight not about market quality but about which markets have too few lottery entries relative to market quality. However, the number of lottery entries is not observed by firms at the time they file their own application, which mitigates this concern. In addition, we run a series of tests shown in Appendix B that rules out strategic entry as an explanation for our results.

We also collect data from Kantar Analytics on advertising spending for firms in this industry. Summary statistics for this data are shown in the Appendix, as well as robustness tests for our main results when advertising spending is included as a covariate. We find little difference in advertising spending between single-store and multi-store firms and little change in our results when advertising is included.[23]

Transactions Data:

In addition to the awarding of entry rights via lottery, there is a second unique feature of this setting. In order to tightly monitor the marijuana industry, Washington requires all industry participants to enter all transactions into an administrative database. Thus we are able to observe all sales that have ever taken place in the industry, including both retail sales to consumers and sales between retailers and wholesalers, both at the transaction level. These data include both retail price and wholesale price for each transaction. Observing wholesale costs is particularly unusual as this is typically carefully guarded information. Washington regulations only allow for linear prices between processors and retailers, so no vertical arrangements such as fixed payments or slotting allowances take place in this market.[24] The comprehensive and detailed data on firm outcomes and choices provide a unique opportunity to track how a new industry evolves from the beginning.

[23]We also note that these retailers are listed on Yelp and specialty cannabis industry online review sites. While we do not have data on the retailer online reviews, we note that Hollenbeck (2018) finds that online review sites benefit independent firms at the expense of chain firms.

[24]If retailers and processors were allowed to use vertical contracts with fixed payments, it would significantly complicate our analysis for two reasons. First, the fixed payments would be unobserved in the tracking system, although Hristakeva (2020) shows how the details of these contracts can be estimated using product selection decisions. Second, they would effect both wholesale prices and assortments and could be related to retailer size. Hristakeva (2020) shows that firms use these vendor allowances to promote their products and exclude low-cost rivals and that the use of vertical contracts distorts both assortment and pricing decisions. In a related work, Hristakeva (2021) shows that retailers' ability to extract these vertical payments depend in an important way on their ability to threaten to replace a processor's product with a competitor's product and that smaller retailers benefit more from this ability than do larger retailers.

Most notably, we are able to construct profit margins at the transaction level by measuring the wholesale price each retailer paid for each product and link those prices to the final retail sale. In addition, the sum of these margins over all transactions gives a direct measure of variable profits. In total, we observe roughly 80 million transactions worth \$2.5 billion between July 2014 and September 2017.

Table 3 presents summary information on the distribution of monthly revenues and variable profits across firms and time. Retailers in this industry earn large revenues, with a mean of \$180,000 per month or \$2.2 million per year in 2017. This is somewhat right-skewed, as the largest retailers average \$6-10 million per year. To provide a comparison, the average store-level revenue is approximately 3-4 times larger than the average revenue of Washington's liquor stores from 2012-2015, according to Ilanes and Moshary (2019).

There are 4 main product categories. These are: usable marijuana (flower products meant for smoking), liquid products, solid edible products, and extract for vaporizers (similar to e-cigarettes). There are some additional miscellaneous products (topical creams, etc) that do not fit into these and are labelled "other". These categories are defined in the Washington administrative data. In 2017, usable products are a large majority of sales, accounting for 63.4% of revenue (83% of units sold). The second largest category is extract products, accounting for 25.4% of revenue (9.1% of units), followed by edible products (7.4% of revenue and 4.5% of units.) While usable flower products can be differentiated along both vertical and horizontal dimensions, extract and edible products have greater ability to differentiate, including with branding, packaging, flavors, potency, form (in the case of edibles), and the associated device needed for use (in the case of extract).

Table 3 also shows the distribution of average prices and total monthly sales across firms and time. Figure 1 shows visually how average wholesale and retail prices started out much higher in the first year of the industry, were highly volatile for the first 12 months, and eventually settled down to a stable lower price. In 2017, retailers charged an average price of \$15.2 per unit for marijuana products and paid an average price of \$7.5 per unit to their upstream supplier. This leaves an average profit margin of .54, or a markup of roughly 140%. Prices are volatile and falling in the first two years of the data as most firms (manufacturers and retailers) enter the market. We thereby focus most of our analysis on the last year of the data when the market is relatively stable.

Table 1: Summary Statistics for 74 markets

Variable	Mean	Std. Dev.	Min	Max
Initial Cap	3.43	3.72	1	21
Revised Cap	5.82	6.92	1	42
Applicants per Market	15.07	25.62	2	191
Distinct companies per Market	12.52	18.69	2	135
Applicants per License	4.07	2.78	1.25	16
Prob. Win	0.34	0.17	0.06	0.8
Stores per 1k People[1]	0.35	1.65	0.01	29.41

Note: The population count per market is taken from the 2010 Census. The number of stores is from January 2017.

Table 2: Joint Distribution of Applications and Licenses

		Approved		
		1	2	3
Applied	1	117	0	0
	2	60	10	0
	3	76	18	3
	4	26	8	0
	5+	22	10	3

Note: This table shows the joint distribution of applications filed and stores ultimately won in the 2014 retail lottery.

2 Effects of Scale on Profits and Prices

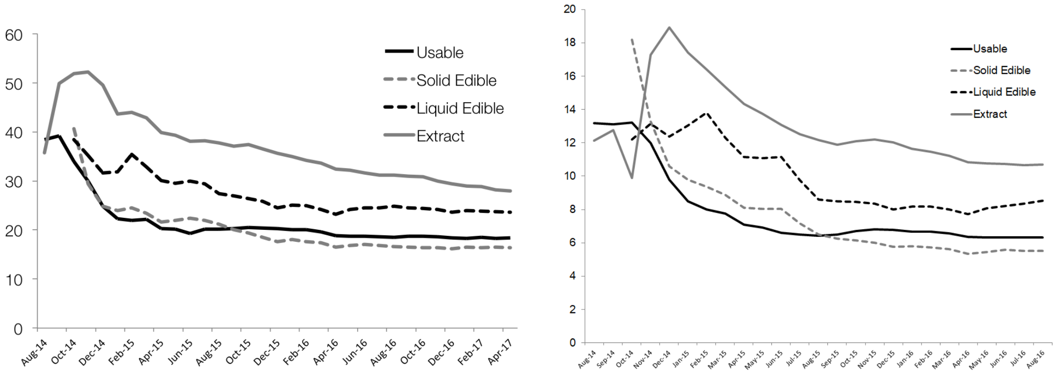
The first question we study is whether there exists a direct causal effect of firm scale on profits in the mom-and-pop retail sector and how large is it. In general, scale is a strategic choice. We

Table 3: Monthly Variable Profits, Revenue, and Total Sales

Subsample:	Mean	Std. Dev.	5th %ile	95th %ile	Mean Seattle	Mean Lottery	Mean Non-Lottery
Variable profit:							
2014	45,508	66,328.6	555.7	179,369.4	112251.7	49,870.6	29,966.2
2015	81,505.8	88,407.5	3,734.2	239,839.5	128,837.8	91,067.3	52,886.7
2016	96,069.7	95,846.3	5,670.3	274,647	109,313.7	116,866	66,536
2017	83,793.1	82,037.6	6,184.9	240,325.5	97,674.2	104,280.7	63,831.4
Revenue:							
2014	81,441	106,468.4	3,274.8	312,072.5	210,699	89,991.1	50,981.5
2015	146,057.4	152,181.1	10,131.5	428,832	233,379.1	162,932.6	95,547.5
2016	184,124.4	180,933.7	13,512.1	540,096.4	204,465.8	222,994.6	128,923.6
2017	170,765	162,839.2	14,538.1	487,896.3	193,003.8	211,094.9	131,470.3
Retail Price:							
2014	17.9	6.4	8.1	29.6	18.9	18.4	16
2015	10.9	2.7	7.3	15.2	11.7	11.1	10.4
2016	8.8	1.7	6.6	11	9.5	8.9	8.8
2017	8.3	1.3	5.8	10.3	8.8	8.3	8.3
Wholesale Cost:							
2014	7.9	1.7	5.4	11.1	8.8	7.9	7.9
2015	4.9	1	3.6	6.6	5.2	4.9	4.8
2016	4.2	0.9	3.4	5.1	4.4	4.2	4.2
2017	4.2	0.5	3.4	5	4.3	4.1	4.2
Total Units Sold:							
2014	4,541	5,468.9	232	15,213.8	12,529.6	5,106.5	2,526.7
2015	13,801.1	14,590.9	893.4	40,924	20,973.8	15,325.5	9,238.6
2016	21,214.5	21,443	1,564.4	59,753	21,875.8	25,547.5	15,060.9
2017	21,029.9	20,838.4	1,618.7	59,033.6	21,969	26,012.5	16,175.3
Assortment:							
2014	8.4	6.1	1	21	13.4	9	6.2
2015	24.8	12.1	7	46	27.1	26.1	21
2016	38.5	17.4	13	71	39.1	41.2	34.6
2017	46.6	20.4	17	86	49.8	49.4	44

Note: This table shows summary data on store-level variable profits, revenues, retail prices, and units sold. Data shown are monthly and do not include the first partial month in which each store opened. Retail price data and total sales are calculated within store each month. Units refer to the quantity sold in terms of weight. Lottery markets refer to markets where excess demand for retail licenses resulted in entry lotteries. Assortment is measured as the number of brands carried.

Figure 1: Average Retail and Wholesale Price By Category Over Time ($/gram)



Note: These figures show category level average retail prices and wholesale prices over time. Retail prices are shown on the left and are tax-inclusive. Wholesale prices are shown on the right.

therefore expect a positive association between firm size and profits, due in part because more efficient entrepreneurs are able to grow larger by expanding and adding more outlets. In this case, it is a challenge to separately identify the effect of scale from entrepreneurial quality in profitability. Our setting removes this aspect of reverse causality and allows us to directly measure the effect of randomly generated size differences on profitability.

An important component of the empirical strategy is that we observe the applications filed that did not win licenses via the lottery. Firms who apply for more entry licenses may have higher quality management, greater commitment to the industry, or be better capitalized than firms applying for fewer licenses. Such selection effects in the applications phase could hinder the assumption of scale being exogenous. Therefore, it is key to our analysis that we are able to control for number of applications filed. Conditional on them, we rely on the retail license lottery to generate random variation in firm size.

2.1 Variable Profits

Specification Our primary dependent variable is the variable profits constructed from the transaction-level sales data. These are defined as total monthly revenues minus total monthly wholesale costs incurred. This differs from profits after other costs such as rents, wages, marketing and other costs. We discuss below how these costs may effect the interpretation of our results but take observed variable profits as the initial benchmark outcome of interest.

We ultimately want to identify the causal effect of retail firm size as measured by whether or not a store is part of a multi-store firm on store-level profits. To measure this effect we regress store profits on an indicator for whether or not the firm won multiple stores in the lottery, conditional on the number of applications filed. Our preferred empirical specification takes the form of the following regression equation:

$$y_{imt} = \alpha + \beta \cdot \text{Multi-Store}_i + \sum_{j=1}^{N} \gamma_j \cdot \mathbb{1}\{\text{Applications}_i = j\} + \sum_{k=1}^{T} \delta_k \cdot \mathbb{1}\{\text{Age}_{it} = k\} + \phi_t + \eta_m + \epsilon_{imt} \quad (1)$$

Here the dependent variable y_{imt} is the store-month variable profits in market m. The right hand side contains a dummy for if the store is a member of a multi-store firm as well as fixed effects for time, market and store age. We control for the number of applications filed in the lottery flexibly, by including fixed effects for each possible number of applications. Our assumption is that conditional on these fixed effects assignment in to the multi-store treatment is a result of random chance.

An exception is the case of firms who only apply for a single store license. In this case, they are by definition ineligible for the "treatment" of becoming a multi-store firm. Because these applicants may also be of lower quality than firms who apply for multiple stores, comparing them could bias upwards the estimated effects associated with owning multiple stores. We therefore exclude single-applicant firms from all our results.[25]

Results Table 4 shows a benchmark set of results with different levels of fixed effects included. In each case we focus on the last year of the data in recognition of the fact that this is an evolving market with entry of new firms (both at the retail level and upstream) taking place throughout 2014-2016 and prices falling rapidly in 2014-2015. By the last year of the data the industry is more mature and the number of firms and their prices and sales levels are relative stable.

First, in column 1 we show the baseline result with no control variables. It shows that stores in multi-store firms earn roughly $28,000 more in variable profits than single-store firms per month. Column 2 includes fixed effects for number of applications filed in order to account for differences in

[25]We thank an anonymous referee for pointing this out. A previous version of this paper included single-applicants and found effect sizes somewhat larger but qualitatively consistent than those shown here.

Table 4: Effect of Multi-Store Firm Membership on Store Profits

	(1)	(2)	(3)	(4)	(5)
Multi-store (lottery)	27618.5***	22488.2**	22046.5**	28295.2***	24188.2***
	(6546.514)	(7012.913)	(6973.287)	(6149.262)	(4687.365)
# Applications FE		Yes	Yes	Yes	Yes
Month-Year FE			Yes		Yes
Market FE				Yes	Yes
Age in Months FE					Yes
Observations	2248	2176	2176	2174	2174
adj-R^2	0.008	0.032	0.039	0.475	0.594

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

Note: This table shows the effects of being in a multi-store firm on store-level variable profits. Only multi-store firms who acquired each of their licenses via the retail lottery are included. Data sample period is April 2016 to April 2017. Standard errors are robust and clustered at the store-time level.

management quality or capitalization that may lead to more applications and thus more stores. The coefficient on the multi-store firm dummy therefore isolates the effect of retail chain membership on profits which, conditional on the number of applications filed, is generated by random chance via the lottery. This reduces the profit difference to just under \$23,000 per month. Columns 3 and 4 show the effects of date and market fixed effects, respectively.[26] These fixed effects control for differences across markets in profitability and time trends. Column 5 shows the results with each of these as well as age fixed effects to account for differences in entry timing and the natural increase in profits during a firm's first year. Accounting for each of these results in shows that after conditioning on number of applications as well as market, time, and age, stores in multi-store firms earn roughly \$24,000 higher monthly profits than single-store firms. The effect is highly significant and its size amounts to $\$290,000$ in higher annual profits. This difference is quite substantial, as median store profits during this period are \$820,000 per year and mean store profits are just under \$1.2 million.

Next, we take our preferred specification with all fixed effects included and show how the effect varies over different sub-samples of the data. The results are in Table 5. For comparison purposes, column 1 repeats the main result from Table 4 that used only the last year of the data. Columns 2 displays this result when we use the full sample from 2014 to 2017. We find a smaller overall effect

[26]We consider alternative definitions of 'market' when constructing market fixed effects. These include city and county fixed effects and markets defined by radii around each retailer of 1 mile, 5 miles, and 10 miles. We find consistent results for each specification. The latter set of results are available in the Appendix.

Table 5: Effect of Multi-Store Firm Membership on Store Profits

	(1) 2016-17	(2) 2014-2017	(3) 2016-17 Stores $\leq$ 1 year old	(4) 2016-17 Stores $>$ 1 year old	(5) 2016-17 ln(profits)
Multi-store (lottery)	24188.2***	13590.3***	22329.4***	55773.3***	0.48***
	(4687.365)	(3887.242)	(5462.176)	(9009.645)	(0.052)
# Applications FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes
Age in Months FE	Yes	Yes	Yes	Yes	Yes
Observations	2174	3617	1069	1172	2174
adj-R^2	0.594	0.512	0.686	0.590	0.599

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

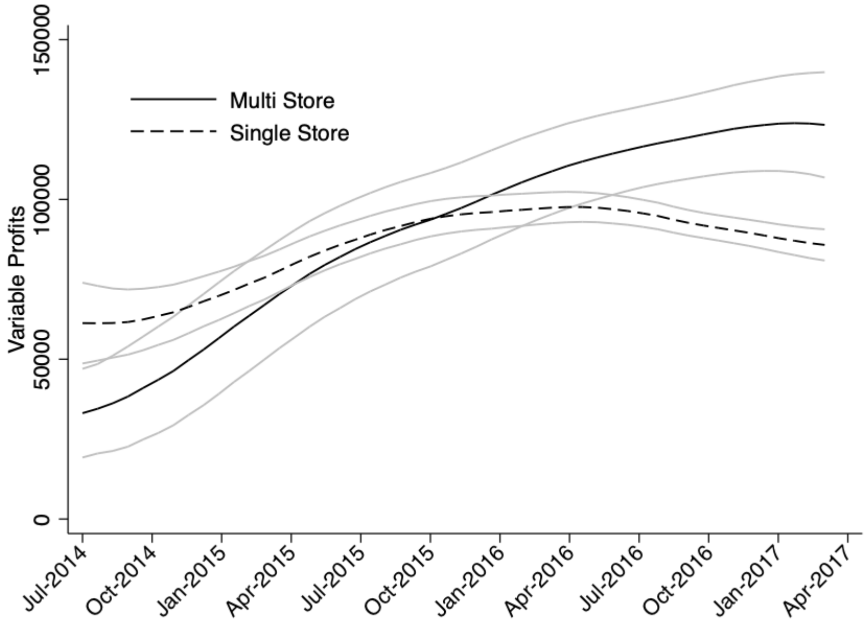
Note: This table shows the effects of being in a multi-store firm on store-level variable profits. The dependent variable is variable profits in columns 1-4 and log of variable profits in column 5. Data sample period is April 2016 to April 2017 in columns 2-5 and 2014-2017 in column 1. Columns 3 and 4 show results only for stores less than one year old greater than 1 year old, respectively. Standard errors are robust and clustered at the store-time level.

when the initial years of data are included. This finding is supported by Figure 2, which illustrates the result visually, showing the average monthly variable profits of multi-store and single-store firms throughout the sample period. They begin the sample roughly equal and multi-store firms slowly gain a profit advantage which becomes significant in 2016 and continues to grow through the end of the sample period. This shows that the profit advantage is not simply a feature of an initial period when the industry was just ramping up. Instead, the advantage associated with being a member of a multi-store firm is growing with time in a manner consistent with learning. This figure also illustrates the magnitude of the effect of firm size on store profits.

Columns 3 and 4 compare the effect size for firms in their first year of operation relative to the period after the first year. The profit advantage associated with being part of a multi-store firm is substantially larger later on in a store's life compared with a smaller advantage in the first year. This finding reinforces that the advantage is not temporary but is something that grows over time. Finally, column 5 shows the result when the dependent variable is log of profits, to account for potentially large variance and skewness in this variable.

Appendix B shows this causal effect of scale on profits is robust to a series of potentially confounding factors. These include robustness tests for strategic entry into markets with less competition for lottery slots, replication of the results with product fixed effects included, tests for the impact of store advertising, and instrumenting for potential non-compliance with the lottery.

Figure 2: Variable Profits Over Time



3 Mechanisms Explaining Higher Profits

Next we explore the mechanism by which larger scale causes higher profits. We proceed in three stages, first breaking the variable profits into their component parts to analyze differences across store types in retail prices, wholesale prices, and units sold. Then we study whether assortment decisions vary across different types of retailers. Finally, we study whether these effects vary based on the relative proximity of stores that are partners in a multi-store firm.

3.1 Retail Prices and Wholesale Costs

In this subsection we analyze differences in pricing between independent stores operating alone and stores that are members of multi-store firms. In particular we are interested if the large profit advantage enjoyed by multi-store firms comes at the expense of consumers through higher retail prices.

This serves as a test of to what extent less local competition leads retailers to increase prices.

Two stores owned by the same firm could internalize the pricing externality and raise prices as a result. In addition, the theoretical literature on retail competition makes ambiguous predictions on whether larger or more prominent retailers will charge higher or lower prices than smaller retailers, all else equal. This makes this setting especially interesting to investigate the effect of scale on pricing decisions as a primary mechanism.

We begin by using transaction level data on sales and prices to construct average retail prices, average wholesale prices, variable profits per unit sold, and total units sold. We use data at the product level to allow for product fixed effects, whereas variables were calculated at the store level in the previous subsection. We define product at the manufacturer-category level, thus if a manufacturer makes multiple products in the same category we aggregate these together.[27]

We estimate the effect of being in a multi-store firm on each of these variables following the specification below: y_{ikmt} refers to the outcome of store i, selling product k, in market m, and time t.

$$y_{ikmt} = \alpha + \beta \cdot \text{Multi-Store}_i + \sum_{j=1}^{N} \gamma_j \cdot \mathbb{1}\{\text{Applications}_i = j\} + \sum_{k=1}^{T} \delta_k \cdot \mathbb{1}\{\text{Age}_{it} = k\} + \phi_t + \eta_m + \psi_k + \epsilon_{ikmt} \tag{2}$$

Table 6 shows the outcomes of this regression for a set of different dependent variables. The effect of membership in a multi-store firm on variable profits is smaller because the unit of observation is now product as opposed to store. While the variable profit at the product level is not statistically significantly higher for multi-store firms, it is higher and when combined with the results on assortment sizes shown in the next subsection creates the overall variable profit advantage previously shown.

We observe that multi-store firms have lower average wholesale prices than single-store firms. This is evidence of countervailing power, a traditional notion of the source of economies of scale in retail, which likely results from volume discounts or greater bargaining power with suppliers. The existence and nature of countervailing power is a central question in the study of retail mergers (Hosken and Tenn (2016)).

We also observe that multi-store firms set significantly lower retail prices than single-store firms for the same products. This difference does not merely result from the multi-store firms passing

[27] The categories are: usable marijuana (leaf) products, solid edible products, liquid products, extract products for vaporizers, and "other" miscellaneous products. Together these account for over 95% of product sales and products are defined by these categories in the regulatory transactions data.

Table 6: Effect of Multi-Store Firm Membership on Primary Outcomes

	(1) Variable Profit	(2) Retail Price	(3) Wholesale Price	(4) Profit/Unit	(5) Units sold
Multi-Store	41.1	-0.36**	-0.22***	-0.13*	18.5
	(35.789)	(0.109)	(0.043)	(0.064)	(10.044)
# Applications	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes
Obs	119479	119479	119479	119479	119479
adj-R^2	0.241	0.733	0.755	0.618	0.198

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

Note: This table shows the effects of membership in a multi-store firm on 5 outcome variables. In each column the dependent variable is described in the column header. Data sample period is April 2016 to April 2017. The observation level is product-store-week. Standard errors are clustered at the product-time level.

along the lower wholesale costs to final retail prices. Wholesale prices are lower by $.22 on average, compared to a $.36 difference in retail prices. Consequently, multi-store firms have significantly lower variable profits per unit sold than single-store firms. They are able to have significantly higher overall variable profits because they sell substantially more more products and more total units per product. Multi-store firms sell 19 more units of each product per month than single-store firms, a roughly 12% higher sales volume.

It is notable that the profit advantage enjoyed by stores that are members of multi-store firms comes through lower prices and lower margins and not the opposite. Several advantages of expansion to form local chains would be expected to result in higher and not lower prices. These include greater reputation or consumer awareness, lower competition since these stores do not compete with one another, and higher quality stores with larger assortments. The effect of a reduction on competition by removing a competitor should be even more valuable in this setting due to the lack of potential entry. We observe that the median number of stores in a market is 4 and stores that are part of multi-store firms tend to be located near each other, with a median distance of 11 miles and 75% of stores are within 25 miles of their chain partners. Therefore these multi-store chains have potentially substantial pricing power in their local areas and yet still charge lower prices than stores operating alone.

We note that removing the product fixed effects from these specifications yields nearly identical

Table 7: Change Over Time in Effects of Multi-Store Firm Membership

	(1) Variable Profit	(2) Retail Price	(3) Wholesale Price	(4) Profit/Unit	(5) Units sold
Multi-Store=1 × year=2015	-590.1***	0.17	-0.31**	0.48**	-115.1***
	(82.866)	(0.179)	(0.097)	(0.153)	(17.682)
Multi-Store=1 × year=2016	9.02	-0.12	-0.25***	0.13	0.51
	(48.231)	(0.100)	(0.054)	(0.088)	(15.355)
Multi-Store=1 × year=2017	85.7*	-0.60***	-0.26***	-0.34***	32.9*
	(36.244)	(0.149)	(0.073)	(0.099)	(16.196)
# Applications	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes
Obs	192330	192330	192330	192330	192330
adj-R^2	0.223	0.722	0.735	0.611	0.200

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

Note: This table shows the effects of membership in a multi-store firm on 5 outcome variables. In each column the dependent variable is described in the column header. The observation level is product-store-week.

results for retail and wholesale prices, and slightly larger effects on units sold and thus variable profit. This suggests that the results are not driven by differences in composition of products offered, where multi-store chains offer more low quality products.

While this set of results focused on the last year of the data when store entry and pricing had stabilized, in Table 7 we show how the results for each of these dependent variables changes over the full 2014 to 2017 sample period.[28] Notably, we see a clear time trend in that the difference in average prices charged by multi-store firms is growing over time. The price difference is negligible in 2015 but grows to \$.60 by 2017. This represents a substantial gap in average prices as the median price of 1 unit is \$6.65 in 2017. We see no clear trend over time in wholesale prices, where there is a clear advantage to multi-store firms in 2015 but no change over time. This suggests the growth in the pricing gap is not caused by simply passing along to customers the wholesale costs savings associated with multi-store firm membership.

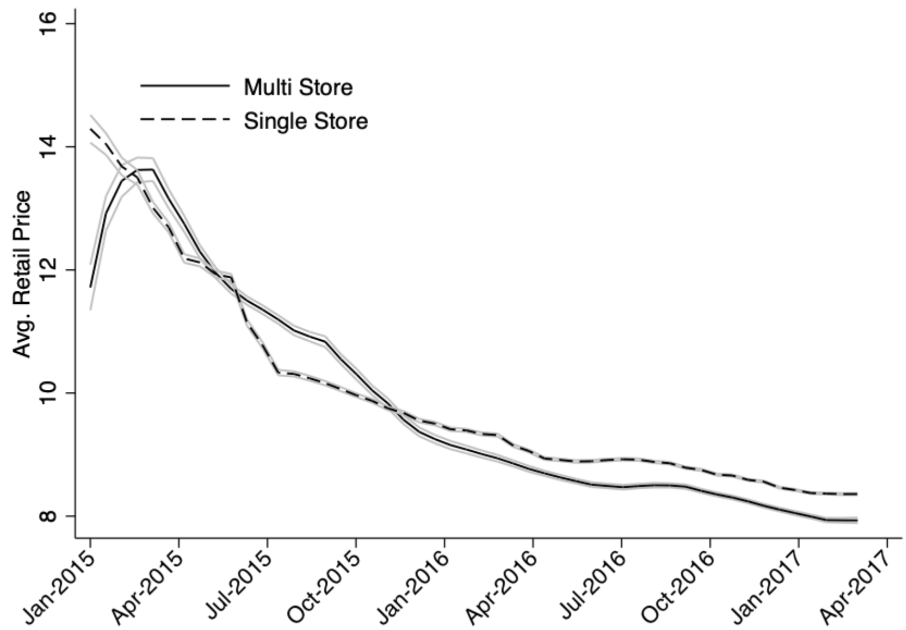
Price margins, as measured by variable profit per unit sold, also fall substantially over time, from a positive \$.48 gap in 2015 to negative \$.34 in 2017. At the same time, there is a large relative

[28]We implement the same specification as in equation 2 with the difference that the Multi-Store dummy is interacted with year indicators.

increase in the number of units sold per product, from 115 fewer units per month in 2015 to 33 more units in 2017.

This growth in the price and profit advantage associated with multi-store chain membership over time are consistent with the overall pattern shown in Figure 2. We visualize the difference in retail prices over time in a similar way in Figure 3, and for wholesale prices in Figure 4.

Figure 3: Retail Price Gap Grows Over Time

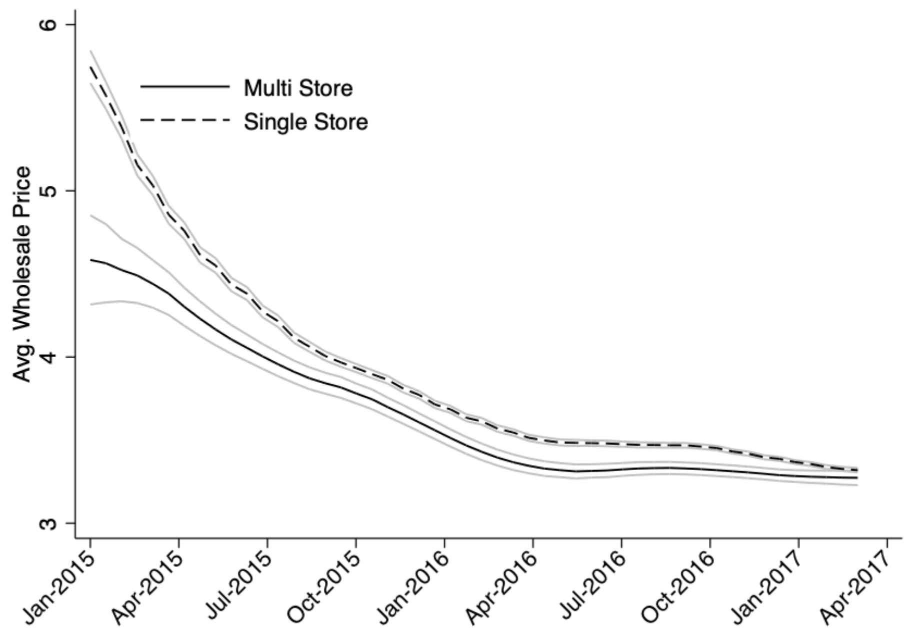


Note: This figure shows average retail prices over time for multi-store firms and single-store firms. The grey area represents 95% confidence intervals.

3.2 Assortment Decisions and Store Variety

This section investigates results for assortment decisions. Choosing how many and which products to stock are key decisions of a retailer. The theoretical literature on retail strategy and customer preferences has grown to emphasize that the number of products sold and consumer search over multiple products have significant interactions (Briesch, Chintagunta, and Fox (2009), Mogilner, Rudnick, and Iyengar (2008), Betancourt and Gautschi (1990), Broniarczyk, Hoyer, and McAlister (1998)).

Figure 4: Wholesale Price Over Time



Note: This figure shows average wholesale prices over time for multi-store firms and single-store firms. The grey area represents 95% confidence intervals.

Retailers in this industry carry products from a set of five main categories, but carry potentially very large numbers of varieties within those categories. Carrying products from a manufacturer incurs a fixed cost, and multi-store firms are able to split that fixed cost over multiple stores such that the benefit of carrying one more product may outweigh the cost for a larger number of products. Multi-store firms have the option of expanding assortment size beyond what single-store firms can offer if it is profitable to do so. We investigate whether this is true following the same empirical strategy as depicted in equation 1.

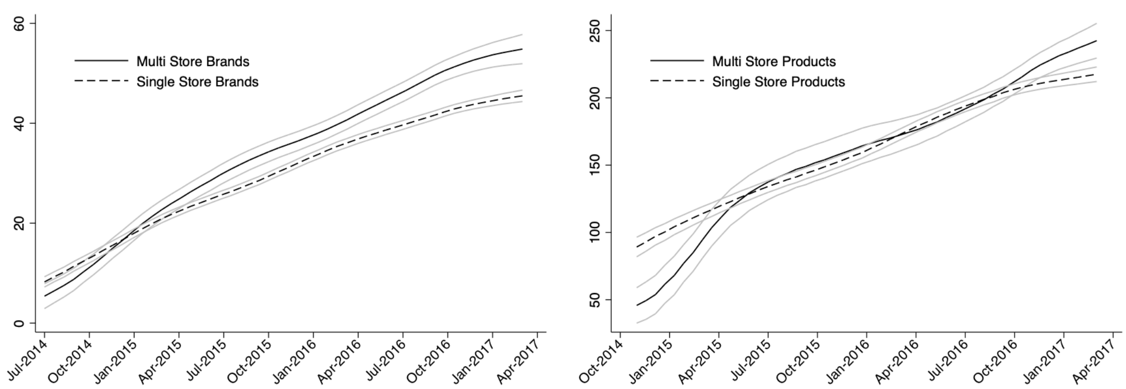
Using transaction level data we construct the number of unique products sold in each store in each month as well as the number of brands or manufacturers purchased from in each month.[29]

[29] A potential issue related to assortment is stockouts caused by supply chain shortages. These have been a persistent feature of the Canadian retail cannabis industry due to a limitation on entry at the manufacturer level. It is possible that multi-store firms are able to avoid stockouts, either by having greater leverage with regard to their suppliers or by having larger assortments in the first place, and that this contributes to their overall advantage relative to single-store firms. The setting we study has no limitation on manufacturer entry and subsequently has hundreds of upstream suppliers. Therefore, we do not believe stockouts to be an important factor here.

Results are shown in Table 8, which shows the effect of being a member of a multi-store firm on assortment size defined these ways. Multi-store firms offer substantially larger assortments defined in both ways compared to single-store firms, on a per-store basis. They offer products from 10.8 more brands, which is roughly 16% more brands than the typical single-store firm.

We also show how this assortment difference varies over time by interacting the main effect with year dummies. We show this result in columns 3 and 4 of Table 8. Figure 5 also demonstrates these results visually using the raw data without fixed effects. At the beginning of the sample single-store and multi-store firms offer similar assortment sizes but over time the multi-store firms increase their per-store assortments. The disparity in number of products and number of brands offered increases consistently over the course of the sample and by 2017 there is a substantial difference in number of brands and products offered.[30] While their cost advantage is fairly stable over time, the assortment and pricing strategy of multi-store firms evolves over time in a manner consistent with learning.

Figure 5: Number of Unique Brands and Products Offered Over Time



These combined results showing multi-store firms offer larger assortments and charge lower prices are consistent with the literature on store choice. Rhodes (2015) shows that when consumers desire multiple products and have search costs, firms that offer more products will attract a larger but more price-sensitive set of consumers. This model makes specific predictions about consumer demand which we explore in the next section.[31]

[30]These results are consistent with Ellickson (2007), showing that firms with the ability to pay the fixed cost to increase assortment use increases in variety to compete with rivals.

[31]An alternative explanation is that larger firms such as multi-store chains have greater name recognition or awareness in a market and thus may be the first choice for consumers searching for a specific product or low price. In

Table 8: Multi-Store Firms Offer Larger Assortments

	(1) Log(# Products)	(2) Log(# Brands)	(3) Log(# Products)	(4) Log(# Brands)
Multi-Store	0.074*	0.15***		
	(0.031)	(0.026)		
Multi-Store=1 × year=2015			-0.018	0.067
			(0.043)	(0.035)
Multi-Store=1 × year=2016			0.044	0.15***
			(0.033)	(0.024)
Multi-Store=1 × year=2017			0.14***	0.16***
			(0.039)	(0.042)
# Applications	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Observations	2174	2174	2984	2984
adj-R^2	0.523	0.541	0.645	0.634

Standard errors in parentheses

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

Note: This table shows the effects of membership in a multi-store firm on assortment size and how this varies over time. In each column the dependent variable is described in the column header. Number of products is the monthly number of unique inventory IDs at the store level. Number of brands is the monthly number of processors purchased from at the store level. Standard errors are robust and clustered at the store-time level.

Table 9: Multi-Store Firms Make More Multi-Product Sales

	(1) Unique Brands per Sale	(2) Categories per Sale	(3) log(# Brands)	(4) log(# Categories)
Multi-store	6.41	2.00*	1.27*	0.96**
	(3.709)	(0.950)	(0.519)	(0.323)
# Applications FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Age in Months FE	Yes	Yes	Yes	Yes
Observations	278	278	286	286
R^2	0.332	0.330	0.224	0.219

Standard errors in parentheses

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

Note: This table shows the effects of membership in a multi-store firm on 2 measures of multi-product sales. In each column the dependent variable is described in the column header. Number of unique brands per sale is the average number of unique brands per transaction at the store level. Categories per sale is the average number of categories per transaction at the store level. These variables are not available for all stores because not all stores enter data into the tracking system at the transaction level and we only include stores and markets where this data is available. Standard errors are robust and clustered at the store-time level.

We also test another prediction of this model by examining whether shoppers at multi-store firms are more likely to purchase multiple items together. Using the retail sales data we are able to observe for a subset of stores which individual items are bought together. Using this data, we construct measures of how many distinct brands and how many categories are purchased together.

We use these measures of multi-product bundling as the dependent variables and repeat the analysis above. Results are shown in Table 9. We find that customers who shop at stores that are part of multi-store firms are more likely to buy from multiple brands and are more likely to buy products in multiple categories during the same shopping trip. This is consistent with models of consumer search and multi-product purchase that predict large assortment retailers to attract a larger but more price sensitive group of customers.[32]

this case, search models like Armstrong, Vickers, and Zhou (2009) or Zhou (2014) predict that this prominence gives these stores an incentive to charge lower prices to deter customers from searching elsewhere. We test one prediction of this model, that firms who have prominence due to being the first entrant into a market also charge lower prices and find no difference in prices between first entrants and later entrants, both overall and in small markets. Results are available upon request.

[32]These models, particularly Rhodes (2015), also make predictions about which prices retailers will advertise, effectively reducing search costs to zero for those items. In our setting, an analogous issue is that retailers can post prices online for some or all of their products. Given that the number of products stocked by retailers in this industry is often in the hundreds, it is unlikely that they are able to post updated prices for a large share of them. Unfortunately we do not have data on whic retailers posted prices or on what products they were posted.

3.3 The Role of Proximity

In this subsection we analyze to what extent proximity between multi-store chain partners is necessary for the profit results to hold and to what extent the results vary for nearby versus distance chain partners. We also study to what extent our results depend on how we define a local geographic market or the degree of competition in a market.

First, we collect data on the geographic distances between all retailers in the state. We use these to define a more granular definition of competition and create a new variable capturing the distance between chain partners. Most chain partners are located within the same market and relatively close to each other, with a mean distance of 19.8 miles and a median distance of 10.8 miles. We use this median to divide our set of multi-store firms into two groups, those nearer to one another than the median distance and those further away from one another than the median. A distance of roughly 10 miles is also a reasonable proxy for the amount of travel time that is realistic in this setting before a retailer is out of reach, given that other options are available.[33]

In Table 10 we present the main set of results from the previous sections but stratified based on whether the multi-store firms are nearby or far away from one another. We find that the effects of multi-store firm membership on store variable profits are substantially higher for stores with nearby chain partners compared to those whose chain partners are further away. We also find a larger difference in assortment sizes, retail prices, and margins. The results for pries and margins are especially noteworthy, given that we would expect nearby competitors who are co-owned to take advantage of this reduction in competition to increase prices (Thomadsen (2005)). Multi-store firms whose partners are farther away actually have slightly higher prices than their market-level single-store competitors but not significantly so, and when combined with a similar advantage on wholesale prices results in higher margins.

It is also noteworthy that multi-store firms whose stores are more than 10 miles away from each other are still more profitable than single-store firms in their markets. They also have larger assortments, although this effect is not significant at the 5% level. In the case of multi-store firms with stores that are far from each other, we expect less consumer awareness that the stores are part of chains and possibly no awareness. The fact that they still earn a substantial profit advantage despite this suggests the advantage does not come purely from consumer perceptions about chains,

[33] Pancras, Sriram, and Kumar (2012) study cannibalization between chain stores and find that once a distance of 10 miles between stores is reached there is virtually no cannibalization between chain partners.

Table 10: Main Effects Based on Store Proximity

	(1) Profits	(2) Log(# Brands)	(3) Retail Price	(4) Profit/Unit
Multi-store × Near	26604.8***	5.57***	-1.46***	-0.92***
	(6441.999)	(1.640)	(0.118)	(0.078)
Multi-store × Far	17894.0***	2.94	0.27	0.62***
	(4468.466)	(1.715)	(0.281)	(0.185)
# Applications FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Age in Months FE	Yes	Yes	Yes	Yes
Observations	2174	2174	183125	183125
adj-R^2	0.594	0.511	0.594	0.486

Standard errors in parentheses

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

for instance that they are higher quality.

4 Consumer Demand

In this section we estimate store-level consumer demand elasticities for each firm type over time. The previous section has shown that multi-store firms eventually charge significantly lower prices and margins than single-store firms, offer larger product varieties, and earn significantly higher profits. This leaves open the question of whether this strategy is replicable by single-store firms. That is, does each firm type face the same consumer demand and or do multi-store firms face a different marginal customer in terms of price sensitivity? Answering this will also further shed light on what mechanism results in the substantially higher profits earned by multi-store chains.

4.1 Specification and Identification

We proceed to separately estimate the store-level elasticity of demand faced by each firm type over time. We follow Hoch, Montgomery, Kim, and Rossi (1995) and Hitsch, Hortacsu, and Lin (2019) in estimating and aggregating demand elasticities using category-level prices and sales volumes. Let $\mathcal{J}_{st}$ consist of the categories sold at store s at week t. We construct these at the weekly level and estimate the following log-log demand equation:

$$log(q_{jst}) = \alpha_s + \sum_{k \in \mathcal{J}_{st}} \beta_{jk} log(p_{jst}) + \tau_t + \epsilon_{jst} \quad (3)$$

We construct sales-weighted average prices p_{jst} at the category level.[34] α_s are store fixed effects and τ_t are county-week fixed effects. These account for local time-varying demand shocks and store-level time-invariant factors such as location or market-level demographics. We estimate this equation separately for each category. The result are estimates of average own-price elasticities β_{jj} and cross-price elasticities β_{jk} for every category and category-pair.

After including category, county-week, and store fixed effects there remains the possibility that there are unobserved demand shocks at the store-week level that are correlated with prices and cause price to be endogenous. This would bias price elasticity estimates towards zero, although we are primarily interested in the difference in elasticity faced between single-store and multi-store firms and this relative comparison is not necessarily biased. We use the availability of product-level wholesale prices to construct cost-shifting instruments. In particular, for each product category, we construct the average (log-unit) wholesale cost of all stores in a market and use these as instruments for retail prices. This assumes that wholesale prices have a direct effect on retail prices but not on final demand. The reason we use market-level averages is that if wholesalers observe the same store-week demand shocks and have sufficient market power to adjust store-specific wholesale prices, those prices would also respond to the same demand shocks. Using market-level wholesale prices avoids this potential issue.

We also collect data from the National Oceanic and Atmospheric Administration (NOAA) on the temperature and average monthly rainfall at the county level in Washington state. In Washington most growers use primarily or partially outdoor farming and so over the course of the year and across the state the weather conditions plausibly have a large impact on the productivity and costs of growing the raw inputs. We link these data to the county locations of each producer, then, using the fact that we observe the full supply chain we link these cost shifters to final retail prices. We calculate these variables first at the manufacturer-category level and then find the average at the retailer-category level based on the set of manufacturers each retailer purchases from and lag them by one month to include as additional cost-shifting instruments to identify the demand system.

[34] To construct average prices we simply divide total revenue at the store-week-type level by the corresponding quantity of sales.

4.2 Results of Demand Estimation

The estimated own-price elasticities are negative and lower than 1 for all categories. We thus focus on the usable (leaf) marijuana product category which accounts for over 84% of sales. We estimate demand separately for different firm type and time periods.

Table 11 shows the estimated store-level elasticities by store type. Elasticities are estimated with the prices of the other categories included in the regression but their coefficients are excluded for space. We see that the OLS results are close to 1 for both firm types. When instruments are included elasticities are substantially more negative, indicating the OLS results are biased towards zero. Our preferred specification uses both the cost-shifting instruments and those constructed from wholesale prices.

Our estimates show that the price coefficient for multi-store firms is significantly more negative than the single-store coefficient, meaning multi-store firms face a significantly more price sensitive marginal customer. Next, we test how these elasticities vary over time. Given that the stores and products are new and there is rapid entry in 2014 and 2015, we expect consumer demand responses may shift over time. We modify the demand model in equation 3 to allow for separate β_{jk} coefficients for each store type each year in the data.

We find that demand is increasingly elastic over time for both store types, presumably due to greater competition as stores who were awarded licenses in the lottery continue to enter the industry during the full sample. We also find that in each time period multi-store firms have significantly more elastic demand than the single-store firms. The pairwise comparison of coefficients for each year is highly significant.

This difference in elasticities is true despite the fact that multi-store firms are also charging significantly lower retail prices than single-store firms. This is of particular interest because it is a priori unclear whether multi-store firms face a different marginal demand than single-store firms. That is, whether they face different residual demand curves or if they are merely pricing at different points along the same demand curve. In the latter case, we would expect to estimate a price coefficient for multi-store firms that is closer to 0 than the coefficient for single-store firms because multi-store firms charge on average lower prices. For this reason, our results suggest that multi-store firms face more price sensitive customers.

Our combined set of results suggest that over time consumer demand shifts outwards for multi-store firms, as evidenced by their higher profits and sales, but also that the marginal consumer

Table 11: Estimated Price Elasticities

	(1) OLS	(2) IV	(3) IV	(4) IV
Single-Store × ln(Price)	-0.92***	-1.37***	-1.50***	
	(0.028)	(0.138)	(0.133)	
Multi-Store × ln(Price)	-1.01***	-3.01***	-2.92***	
	(0.099)	(0.238)	(0.232)	
Single-Store × Year=2015 ×ln(Price)				-1.13***
				(0.178)
Single-Store × Year=2016 ×ln(Price)				-1.51***
				(0.220)
Single-Store × Year=2017 ×ln(Price)				-3.46***
				(0.510)
Multi-Store × Year=2015 × ln(Price)				-2.86***
				(0.490)
Multi-Store × Year=2016 × ln(Price)				-3.05***
				(0.537)
Multi-Store × Year=2017 × ln(Price)				-4.77***
				(0.723)
Store FE	Yes	Yes	Yes	Yes
Market*Time FE	Yes	Yes	Yes	Yes
Wholesale Price IVs		Yes	Yes	Yes
Cost Shifter IVs			Yes	Yes
Observations	23038	23038	23012	23012
R^2	0.904	0.895	0.899	0.893
First-stage F		445.3	155.3	67.0

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

Note: This table shows estimated price elasticities for each store type in different subsamples based on year. In each column the dependent variable is ln(Units sold). Both units sold and price are for the usable marijuana product category. Elasticities are estimated with the prices of the other categories included in the regression but their coefficients are excluded for space. The pairwise comparison of coefficients in column 3 yields a p-value $<$ .0001. For column 4, the pairwise comparison of coefficients between single-store and multi-store are: for 2015 $p <$ .0001, for 2016 $p =$ .004, and for 2017 $p =$ .02.

visiting a multi-store firm is substantially more price sensitive than the marginal consumer faced by a single-store firm.

5 Discussion and Conclusion

Nearly 90% of retail firms are small businesses and retail is one of the most common types of businesses started by entrepreneurs (Hurst and Pugsley (2011)). These small firms are also seen as especially important for local economies and targeted with a wide range of special policies. Therefore, it is especially important to measure and understand the size and nature of economies of scale for retail entrepreneurs. This is particularly true in industries where license regulations mean that local policymakers have direct control over the scale that new firms can achieve.

We use a unique setting where this type of license restriction resulted in the unusual choice to use a lottery to award licenses. By combining this lottery mechanism with extremely rich data on firm actions and profits we are able to provide clear causal evidence on how firm scale effects both entrepreneurial outcomes and consumers. Our setting is also unique in that retail cannabis is a new industry and we are able to document the full evolution of firm strategies and outcomes as they develop over time in what is already a large and rapidly growing market worth $20 billion in the U.S. in 2020.

Our results show that license caps like those used by Washington and other states are highly costly for the entrepreneurs starting new businesses in this industry. The difficulty they face expanding their retail operations result in a huge amount of foregone profits. Our results also imply that customers are also harmed by barriers to expansion by small retailers. Together, these results suggest that policies designed to help entrepreneurs and mom-and-pop retailers expand their firms and grow can be extremely valuable.

The unique nature of the data in this setting also allow it to be informative for retail strategy more broadly. By tracking detailed measures of firm strategies over time from the beginning of the industry, we show how multi-store retailers are able to take a small initial advantage in offering larger assortments and cumulatively build this into a very large advantage in profitability by offering a combination of low prices and large assortments. This finding contributes to a growing literature on the importance of endogenous product positioning in understanding price effects (Draganska, Mazzeo, and Seim (2009), Mazzeo, Seim, and Varela (2018)).

The combination of low prices and large assortments is somewhat counterintuitive. Much of the literature on retail variety argues that larger varieties will result in higher prices (Anderson and De Palma (2006), Kim, Allenby, and Rossi (2002)). In addition, multi-store firms have greater local market power and face less competition, which most models predict will also result in higher consumer prices. An exception is Rhodes (2015), who shows how in the presence of search costs and consumers who value multiple products, firms that carry a larger assortment will attract a more price-sensitive "mass market" set of consumers and respond by lowering prices. Our evidence is consistent with this model. We find a large outward shift in demand associated with stores being members of a multi-store chain, but also a shift towards more price-sensitive consumers who make more multi-product purchases. This model is a general one, it simply requires that consumers have search costs and heterogeneous preferences over products. We would expect the results to replicate in many retail settings, but especially in settings with similar preferences, such as the retail markets for wine, liquor, and tobacco. The results should also hold in the general class of single-category retailers such as bookstores, music stores, pet supplies, tools and hardware, and certain speciality food and apparel categories.

Two important caveats are that this is a new industry and that the license restrictions in this market are unusual in that there are no truly large chains for small firms to contend with. But, while our results are limited to a set of relatively small players unlike truly large retailers like Amazon or Walmart, there is value in focusing on smaller firms not just for the study of entrepreneurs but for studying economies of scale as well. We would expect larger effects as firms vary between 1 and 2 stores vs 100 and 101, and generally if scale effects have decreasing returns it would be hard to replicate this type of study for very large retail chains.

Still, our results provide clearest takeaways on the value of scale to small entrepreneurs. A cross-sectional analysis of the entrepreneurs who entered this industry would find large differences in profits and number of outlets and again might assume that higher quality entrepreneurs were able to run their businesses more successfully and expand as a result, when the true causation in this case runs in the opposite direction. Therefore barriers to scale, such as capital constraints, legal red-tape, etc are likely to be a significant impediment to entrepreneurial success if they keep firms too small.

Ultimately consumers may also benefit from a more concentrated retail sector with fewer but larger firms. This is clear from the lower prices, larger assortments, and higher sales associated with retail expansion. Despite reducing competition, margins decrease rather than increase at these stores. This suggests that barriers to scale such as Washington's cap on the number of licenses a firm can own, ultimately decrease the benefits of the retail sector for firms and consumers alike.

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A Data Appendix

A.1 Application Data

The list of businesses that have applied to licenses is available at the Washington State Liquor and Cannabis Board website.[35]. This list of licenses is not cumulative as we noticed that some licenses are dropped from the file through time. To recover the history of all license applications we use the website wayback machine. It allows us to recover all the listings made available to the public since the market opened. We use this procedure to recover the list of processors, producers, and retailers that have ever applied to a license. In 22 instances, firms receive a new license number but maintain their operation at the same location. We treat these cases as continuously operating firms.

A.2 Transaction Data

We have two distinct data sets that are put together to form the final transactions data.

- Retail dispensing data: contains all transactions between retailers and consumers with timestamp, prices, quantity, product type, strain, and parentid. The parentid variable indicates a 16 digit barcode identifier of the batch or lot the sample was taken from. It displays the company making the sale but it does not have the exact license that was responsible for the sale.

- Inventory transfers data: contains all transactions between the upstream and downstream markets. Importantly, it displays the information at the license level. Other variables that are included in this data are: strain, type, quantity, sale price, and parentid.

The parentid variable indicates a 16 digit barcode identifier of the batch or lot the sample was taken from. This variable is also present in dispensing and allows us to match the datasets above.

A.3 Outliers

As with any administrative data, the data contains a small fraction of errors, misentries, and outliers. We systematically delete observations believed to be mis-entered into the BioTrack system.[36] Namely, cases where the final sales price is below \$3 per gram or above \$80 per gram (0.8% of transactions), wholesale prices below \$1 or above \$30 per gram (.04% of transactions), weight below .5 grams or above 30 grams .07% of transactions) and markups above 3 (.04% of transactions).[37]

A.4 Taxation

We check for whether retailers enter tax-inclusive or pre-tax prices into the dataset. This first requires collecting sales tax rates for every store in every month because sales taxes may vary at the 9-digit zip code level. We find the 9-digit zip code of each store and match each store to the correct sales tax in each month of the data.

[35] https://data.lcb.wa.gov

[36] We follow the same procedure as Hollenbeck and Uetake (2021) for the removal of outliers and treatment of taxes, described below.

[37] Legal purchase limits are one ounce for usable, 16 ounces for solid, 72 ounces for liquid, and 7 grams for concentrates.

Since the majority of final prices use integer units, we check for the share of integers generated by each possible data entry rule. These rules include entering the pre-tax price, the price with excise and sales taxes included, and the prices that include either excise or sales taxes alone. Then at the retailer-month level we choose the rule that generates the highest share of integer prices, in some cases we also compare pricing within a retailer-category from month to month and checking final prices against the market average in each month to insure consistent treatment. We find that prior to the tax change in July 2015, roughly 8% of retailers enter tax-exclusive prices, 60% enter prices that include excise but not sales taxes, and 25% enter fully tax-inclusive prices. After the tax law changes, over 90% of retailers enter tax-exclusive prices. Once we recover the rule at the retailer-month level we construct the correct tax-inclusive and tax-exclusive prices for every transaction.

A.5 Advertising

We acquired data on retailer advertising from Kantar Media, a firm that tracks advertising spending across media. They have tracked advertising spending in the cannabis industry since before legalization through the current time for the Seattle and Spokane markets, including outer suburbs. We observe total spending at the monthly level for each media: outdoor, newspaper, magazines, television, radio, and internet display. Advertising in this industry is heavily regulated and restricted, and consequently there is relatively little of it.[38]

Table 12: Summary Statistics for Kantar Media Advertising Data

	Ad Spending ($)	Share
Media		
Internet Display	2,094,816	11.5%
Local Magazines	52,922	.3%
Local Radio	404,485	2.2%
Newspapers	3,578,534	19.7%
Outdoor	12,028,456	66.2%
Total	18,159,213	
Market		
Seattle	16,996,795	93.5%
Spokane	1,162,418	6.4%

We use Kantar Media's product description, which includes the store name, to match by hand the advertising data to the main data. Table 12 provides summary information on firm advertising. Almost all of it takes place in Seattle, broadly defined. Two thirds of all spending is on outdoor billboards, followed by roughly 20% spent on newspaper ads.

[38]For instance, all advertising is prohibited "in any manner that would be especially appealing to children or other persons under 21 years of age." Advertising within 1000 feet of a school is also prohibited and all advertising must include a variety of cautionary text. Outdoor billboard advertising is limited to providing the name and location of a business.

A.6 Co-branded and Former Medical Stores

The regulation WAC 314-55-155, from May 2016, regulated the advertising in the WA cannabis industry. Among other rules, it allowed firms to have their own website where an "our story" tab is usually found. This feature and the wayback machine digital archive allowed us to map the lottery winners that had experience in the cannabis industry prior to the legalization as collective gardens. We explore whether stores formerly operating as medical dispensaries prior to I-502 have different likelihoods of being present in multi-store firms or whether including this as a covariate changes any of our results. We find that former medical stores have lower sales and profits consistently, even at the very beginning of the sample when they might have an advantage based on awareness and reputation. No other results are effected by including this distinction.

The same data features made it possible to identify sets of stores that operate under the same brand, which might encompass one or more firms. This is because their store locations were listed on their websites. We find several instances of co-branded stores that are part of separate firms, meaning they have separate owners and acquired their licenses through separately filed lottery applications but at some point they chose to align themselves in their marketing. They either share the same name or have a similar name and list all stores on a joint website.

An empirical concern in treating these as multi-store firms is that these arrangements may be more likely to be entered into by higher quality managers or they may be more likely for stores with prime locations. We therefore exclude co-branded but legally distinct sets of stores from our definition of multi-store.

A.7 Non-Compliance with Lottery Outcomes

While the Washington retail license lottery granted entrepreneurs the right to enter if they won a license, it did not require them to enter. If a substantial share of firms did not comply with the lottery it could generate potential bias in our estimates that rely on the lottery for identification. In particular, if low-quality entrepreneurs who won multiple licenses chose to only enter with one store instead of multiple stores because they lacked access to capital, had insufficient motivation, or other reasons, it would decrease the quality of the single-store firm pool and increase the quality of the multi-store pool.

We therefore investigate the extent of non-compliance and describe it here. We ultimately find just 11 examples of non-compliers, or firms that won licenses but did not open stores using those licenses. Details on these firms are shown in Table 13.

Of the 11 retail applications that won licenses, 5 were owned by firms that had filed multiple applications and 6 had only filed 1 application. Out of all 11, none of them entered using the store application in question and none of them were awarded any other licenses. This last fact is reassuring, because it means that no potential multi-store firms we focus our analysis on ultimately entered under any other retail locations (as single-store firms).

We might infer that these entrepreneurs lacked either the motivation or financing to open a retail store and therefore they were likely to be lower quality firms in the counterfactual where they had entered. In this case, the average quality of the set of single-store retailers is higher because of their non-compliance, making our comparison of multi-store to single-store retailers more favorable for multi-store retailers. Of course, given that only 11 stores did not enter the extent to which the results could be affected is limited.

A related issue is that 7 stores who won licenses via the lottery were later rejected by either the state regulator (the Washington State Liquor and Cannabis Board) or by local governments.

Table 13: Overview of non-entering lottery winners

Retailer Name	License	UBI	City	Lottery Jurisdiction	# Apps
Stores Who Opted Out:					
Max Market	413411	603354273	Kennewick	Kennewick	1
The Higher Class	413825	603356943	Yakima	Yakima	1
Josh Locke	415577	603359581	Spanaway	Pierce County at Large	1
Buds Forever	413830	603354821	Prosser	Benton County at Large	3
Blow "N" Smoke & Glass	414352	603347463	Vancouver	Clark County at Large	2
Best Budz	413964	602153506	Marysville	Marysville	1
Jeff Mahan	415582	603359569	Rainier	Thurston County at Large	2
Purple Haze	414979	603293668	Maple Valley	Maple Valley	3
Going Green	415185	603362593	Moxee	Yakima County at Large	1
Green Easy Herbals	414848	603357680	Concrete	Skagit County at Large	3
Medible Mikes	415556	603362604	Walla Walla	Walla Walla	1
Rejected Applications:					
The Pot Shop	413387	603351701	Bremerton	Bremerton	1
RIU420	415045	603357879	Centralia	Centralia	3
The Lid	413671	603353091	Brewster	Douglas County at Large	1
Chronics	415292	603397627	Rock Island	Douglas County at Large	1
Herb Market	413939	603346937	Shoreline	Shoreline	2
Trippy Hippy Company	414943	603361953	Granite Falls	Snohomish County at Large	1
Purple Dank	415018	603290913	Tukwila	Tukwila	3

These firms passed an initial screening in order to enter the lottery but were rejected after further scrutiny. The issues included a part-owner with a criminal record and store locations within 1000 feet of a park or school. Similar to non-compliers, we presume that these 7 stores would have been of lower quality than replacement stores simply because the fact that they were rejected suggests a poor attention to detail as a signal of managerial quality.

Because the results could be effected by this non-compliance, we also consider an empirical specification that uses the number of licenses won in the lottery as an instrument for the number of stores that opened. For the vast majority of firms there is no non-compliance and so these are the same, and therefore this is a strong instrument. Moreover, unlike the number of stores that opened, there is no non-compliance with the number of licenses won which is determined by random draw. This means that this instrument satisfies the exclusion restriction. We therefore estimate a variation on equation 1 using the number of licenses won in the lottery to construct an instrument for the variable "Multi-Store." Table 14 contrast our results from the OLS and IV specifications and shows that accounting for non-compliance in this way does not reduce the estimated effect size, it actually increases although the standard error of the estimate also increases a large amount.

Table 14: Comparison of Main Effects with IV for Non-Compliance

	(1) OLS	(2) IV
Multi-store (lottery)	24188.2***	35028.8*
	(4687.365)	(17333.013)
# Applications FE	Yes	Yes
Month-Year FE	Yes	Yes
Market FE	Yes	Yes
Age in Months FE	Yes	Yes
IV		Yes
Observations	2174	3255
R^2	0.594	0.010
First-stage F-stat		1905.5

Standard errors in parentheses

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

B Robustness Tests

B.1 Robustness on Lottery

In this section we present a set of robustness checks for the primary results on variable profits. First, we show in Table 15 tests regarding the random distribution of licenses via the lottery. Conditional on filing a valid application, the result of the lottery is a uniform draw over all firms. Nevertheless, sophisticated firms might have strategically chosen markets based on their beliefs about the number of participants that would enter in each lottery. In this case, these firms would be more likely to win multiple licenses, albeit in less desirable markets. If this strategic entry were correlated with managerial quality, as in Goldfarb and Xiao (2011) this could cause endogeneity bias in the main results.

In Table 15 we show how our main results on profits across stores change if we include a set of additional variables related to the lottery outcomes. Column 1 shows the baseline result. Column 2 shows results with a dummy indicator for lottery vs non-lottery licenses. Column 3 includes city fixed effects and shows the effect of including the probability of wining as a covariate, where probability of winning is calculated as the number of applications filed divided by the number of licenses available. Column 4 includes the number of applications at the market level directly. In column (3) we observe that effectively expanding the market definition has little effects on store profits. In each case we replicate the size and significance of the effect of multi-store firm membership on store profits.

Next we analyze whether the distribution of licenses allocated in the lottery is significantly different from a random allocation. While the licenses were distributed according to random draws, if firms were able to choose markets strategically there might be a non-random relationship between number of applications and number of licenses won. We therefore test whether the joint distribution of licenses is significantly different than what might occur if all licenses had the same win probability. To do so, we calculate the expected number of licenses won if they were distributed from a poisson

Table 15: Robustness Checks on Lottery

	(1)	(2)	(3)	(4)
Multi-Store	24188.2***	25260.9***	19651.1**	28021.8***
	(4687.365)	(4866.530)	(6686.019)	(6789.293)
All Lottery		-3980.7		
		(3717.558)		
Pr(win)			123316.9***	
			(23902.179)	
# Applications (Lottery)				74.7*
				(29.535)
# Applications	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes		
City FE			Yes	Yes
Obs	2174	2174	1472	1472
adj-R^2	0.594	0.594	0.601	0.596

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

Note: The dependent variable in each column is variable profits. Data sample period is April 2016 to April 2017. Standard errors are robust and clustered at the store-time level.

process where all applications had an equal probability of winning a license. We use a poisson parameter λ equal to the overall probability determined by the total number of applications and licenses.

Table 16 shows the result of row-by-row chi-square goodness-of-fit tests for the joint distribution of applications and licenses under the assumption of independent poisson draws. For 3 out of 4 rows we cannot reject the null of independent draws with p-values between .3 and .4. For the row with 3 applications per firm, we do reject independent draws with $p = .038$. Essentially, among firms that applied for 3 licenses too few won multiple licenses. Combining all rows, for the sample as a whole we cannot reject independent draws, however.

Table 16: Test of Independence: Distribution of Applications and Licenses

		Approved				
		1	2	3	χ^2	p-value
Applied	1	117	0	0		
	2	60	10	0	1.80	.406
	3	76	18	3	6.52	.038
	4	26	8	0	.85	.357
	5+	23	10	3	.83	.362

Note: This table shows the joint distribution of applications filed and stores ultimately won in the 2014 retail lottery. We calculate the expected number of licenses in each bin assuming all applications have an equal probability of winning and calculate a chi-square goodness-of-fit test independently for each row.

B.2 Store Advertising

In this section we test whether the multi-store profit advantage is attributable to higher levels of advertising spending. First, we compute monthly ad spending by each store type and find that multi-store firms do not advertise more basis than single-store firms. Multi-store firms spend \$540 per month on ads on average, with a median spending of \$0 and a standard deviation of \$3238. Single-store firms spend \$734 per month on ads on average, with a median spending of \$0 and a standard deviation of \$2849. The figures for multi-store firms are at the firm level since we cannot separately measure advertising at the store level.

Table 17 shows the primary results for profits when advertising is included as a covariate. For multi-store firms we show firm-level advertising and store-level advertising, calculated by dividing the firm level amount by the number of stores. We also include $log(\text{adspend}_{st} + 1)$ due to the highly skewed nature of the data. In Columns 2-4 of Table 17 we see that advertising is positively correlated with variable profits, but including this covariate does not weaken the main effects.

Table 17: Robustness of Primary Outcomes to Advertising

	(1)	(2)	(3)	(4)
Multi-Store	24188.2***	25098.1***	25927.2***	28864.1***
	(4687.365)	(4733.662)	(4690.744)	(4843.766)
Firm Ad Spending		2.07***		
		(0.568)		
Store Ad Spending			2.36***	
			(0.628)	
log(Ad Spending)				3645.6***
				(553.485)
# Applications	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Observations	2174	2174	2174	2174
adj-R^2	0.594	0.600	0.601	0.606

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

Note: The dependent variable in each column is variable profits. Data sample period is April 2016 to April 2017. Standard errors are robust and clustered at the store-time level.

B.2.1 Entry Timing

Next we explore how the timing of entry by the stores in a multi-store chain effect their partner firms' profits. One possible explanation for the profit advantage caused by being in a multi-store firm is that firms can use the profits generated by their first store to open a larger or higher quality second or third store, thus generating higher average variable profits.

Table 18 shows the result investigating this mechanism. Column 1 of Table 18 shows that, among multi-store firms only, stores that enter second or third are not more profitable compared to the first store opened by that firm. In fact, after conditioning on firm age and time fixed effects, later entrants are less profitable than first entrants but not statistically significantly so. The lower profits experience by these stores may be due to a strategic decision to open in more desirable locations first and less desirable locations later. This rules out a story where the multi-stores are more profitable per store through a larger investment in fixed costs in second or third stores after successfully operating one store for some period of time.

Similarly, we compare the effect of being in a multi-store firm on the first entrants in each firm by using the timing of future store entries. Column 2 of Table 18 uses only first entrant members of multi-store firms and shows that when the number of stores in the firm goes from 1 to 2, the profits of the first entrant are higher conditional on age, time and market fixed effects. Again, the result is not statistically significant due to the small sample size. This is suggestive that the profits of the first entrant may increase after the second entrant opens, although we note that this could also be the result of reverse causality if the firm owner waits to open the second store until when they anticipate the first store becoming more profitable.[39]

[39] A similar result is found in Pancras, Sriram, and Kumar (2012).

Table 18: Timing of Main Effects

	(1) All Multi-Store Firms	(2) First Entrants Only
Entry order=2 or 3	2045.5	
	(32417.701)	
# Stores open>1		18943.1
		(12338.500)
# Applications FE	Yes	Yes
Store Age in Months FE	Yes	Yes
Firm Age in Months FE	Yes	
Month-Year FE	Yes	Yes
Market FE	Yes	Yes
Observations	324	209
R^2	0.805	0.807

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

Note: This table shows results for two subsamples of multi-store firms. The dependent variable in both columns is variable profits. Column 1 shows results for all stores in multi-store firms and shows the effects of being the 2nd or 3rd entrant on variable profits. Column 2 shows results only for stores who were the first entrant in a multi-store firm and shows the effects of the 2nd firm's entry on the focal stores variable profits.

B.2.2 Competition and Market Definition

Next we present two robustness checks related to local competition faced by each retailer. To do so, we collect data on the geographic distances between all retailers in the state. We use these to define a more granular definition of competition. We begin by drawing radii around each retailer of distances 1 mile, 5 miles, and 10 miles. For each firm and each radii we find the identities of all competing retailers falling into the given radius. We then aggregate these lists of firms and calculate their intersections to define local markets around each store each month. Next, we compute the number of competitors active in each radius in each time period. We then include this number as a covariate to control for the local competition faced by each firm each period.[40]

Results are shown in Table 19. We find that having more competitors nearby is typically associated with lower variable profit, as we would expect. When these measures are included the main effect is largely unaffected. This is likely because there is not a clear reason to believe that stores belonging to multi-store firms and stores operating independently would face different local levels of competition given that the treatment in this case is generated randomly.

Similarly, we can test the robustness of our results to different market definitions using these radius-based markets. We show results in Table 20. When we use market fixed effects based on the intersection of local radii around each retailer, we find results that are broadly consistent with the standard market fixed effects. For the 1 mile radius we find larger effects of being a member of a multi-store chain on variable profits. For the 5 and 10 mile radius markets we find smaller effects but still find a substantial profit advantage.

[40] An alternative way to handle competition would be to use data on customer location and define competition based on to what extent each store's customers were located near different competitors, as in Taylor and Hollenbeck (2021), but customer location data is not available in this context.

Table 19: Robustness Checks on Competitors

	(1) Variable Profits	(2) Variable Profits	(3) Variable Profits	(4) Variable Profits
Multi-Store	24188.2***	24517.4***	23638.8***	24079.1***
	(5751.847)	(5755.533)	(5755.459)	(5742.547)
# Firms: 1m Radius		-94.1		
		(68.201)		
# Firms: 5m Radius			43.8	
			(23.030)	
# Firms: 10m Radius				-95.3**
				(34.224)
# Applications	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Observations	2174	2174	2174	2174
adj-R^2	0.594	0.594	0.594	0.595

Standard errors in parentheses

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

Table 20: Robustness Checks on Market Definition

	(1) County Markets	(2) 1 mile Radius	(3) 5 mile Radius	(4) 10 mile Radius
Multi-Store	24188.2***	34844.5***	22402.2***	22898.3***
	(5751.847)	(6176.940)	(6035.534)	(6171.667)
# Applications FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Age in Months FE	Yes	Yes	Yes	Yes
Observations	2174	2247	2248	2248
adj-R^2	0.594	0.233	0.215	0.162

Standard errors in parentheses

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

Note: This table compares the main results using different definitions of market. Column 1 presents results using county-level markets. Columns 2-4 use markets constructed by calculating the set of firms within a certain distance of each other and then taking the intersection of these sets around each retailer to form market definitions. The distance radius used for each is noted in the column header.