

# Rule-of-thumb Pricing: Retail Cannabis in Washington State

Matias Escudero\*

Northwestern University  
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## Abstract

Conventional methods in industrial organization assume that firms are strategically sophisticated and set prices as best responses to their competitive environment. In this paper, I use a detailed dataset of both retail and wholesale prices from the new cannabis industry in Washington state to show that firms are instead widely using fixed markup rules. I show that almost half of all units sold in this market have prices that can be explained by simple rules of thumb, such as setting a 50% markup over price. Moreover, these same markup rules are used for a diverse set of products and in many different competitive environments. I document a robust convergence process across all products toward this 50% markup rule. While this strategy adheres to the conventional wisdom in the retail industry, these findings cast doubt on the idea that firms learn to price to exploit the specific differences across products and markets. Using a discrete choice model of demand for differentiated cannabis products, I find that this rule-of-thumb markup is not consistent with optimal pricing behavior, and firms capture about 75% of the variable profits they would get if they were to maximize profits. These results indicate that the widespread use of uniform pricing rules by multiproduct oligopolists can lead to non-negligible losses in terms of foregone profits.

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\*2211 Campus Drive, Office 3354, Evanston, IL 60208, USA. E-mail: [mescudero@u.northwestern.edu](mailto:mescudero@u.northwestern.edu). I am extremely grateful to Gaston Illanes, Robert Porter, and Vivek Bhattacharya for their continuous support and helpful comments. I am also grateful to Gabriela Cugat, Mariano Irace, and all participants at the IO Workshop and the IO Student Seminar at Northwestern University. All errors are my own.

# 1 Introduction

Most of the literature in Industrial Organization assumes observed prices are firms' optimal responses to their external conditions. Firms are thought to be sophisticated, resourceful, and capable of implementing complex pricing strategies for each of the products they sell, denoting a clear and correct understanding of the competitive environment they live in. However, it seems reasonable to think that in some circumstances these assumptions might not fit well. For example, if markets are relatively new or competition is characterized by relatively small sellers, firms could be inexperienced or simply lack the resources needed to optimize. In these scenarios, sellers may resort to alternative pricing schemes that follow simple rules of thumb. Even though the debate between rules and optimality has received theoretical attention in the past, empirical assessments in the economics literature have been scarce. Using a rich dataset with unit-level information on retailers' prices and acquisition costs for the new retail cannabis industry in Washington state, I contribute to this discussion by showing that (i) a sizable share of products sold in this market had prices that are consistent with a simple rule of thumb in which retailers apply a fixed percentage markup over price to a wide array of products, and (ii) such strategy leads to non-negligible losses in terms of foregone profits.

In this paper I use detailed data on unit-level transactions from the new legal retail cannabis industry in Washington state, a dataset that covers all wholesale and retail operations in the market since its inception in July 2014 until November 2016. To assess the prevalence of pricing rules, I perform an accounting exercise in which I compute the fraction of marijuana units that are sold at prices that are consistent with schedules that mix a fixed percentage markup over price and institutional features of this industry. I am able to perform such exercise because the data I observe includes not only the price received by the retailer for each unit sold, but also the acquisition cost she paid to procure them, a piece of information that is usually unavailable to researchers. I find that for the sample under study, almost half of the units sold in the market were priced consistently with such rules. Additionally, I study the prevalence of rule-of-thumb pricing over sellers, time, products, and markets, finding that rules become more ubiquitous over time regardless of these characteristics. I find that the practice of doubling acquisition costs to set retail prices, a strategy commonly known in the retail industry as "keystone pricing", becomes more prevalent over time across all product types, leading to 50% markups over price being the norm in this industry.<sup>1</sup>

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<sup>1</sup>Even though there is no full agreement regarding the origins of this term, most sources coincide in its roots being on the jewelry trade. In a series of articles to its subscribers in 1896, *The Keystone*, a monthly

Naturally, it could be the case that optimal markups happen to fall in this range too. To evaluate this claim, I estimate a discrete choice model of demand for cannabis products at the retail level in order to recover consumers' underlying preferences and determine optimal firms' responses. I employ the traditional demand estimation approach in industrial organization (Berry (1994), Nevo (2000), Nevo (2001)) allowing for observed and unobserved consumer heterogeneity in preferences. Using these estimates, I simulate two counterfactual scenarios. First, I compute the prices and variable profits a given seller could get if she had access to demand estimates and were to best respond to the status quo in her market. Second, I compute prices and industry-level variable profits under the assumption of firms engaging in Bertrand-Nash competition with full information. My estimates from both counterfactual exercises reveal that while for some products the observed 50% markup over price is consistent with optimal pricing, it turns out to be a fairly poor approximation to optimal schedules for other products in the market. These results indicate that by following similar pricing strategies across all types of products, retailers end up setting prices that are not consistent with those that would be obtained in an equilibrium with price competition and differentiated products. Additionally, since in this counterfactual scenario variable profits would be overall higher than those observed in the data, the possibility of observed data reflecting a cooperative equilibrium seems less likely.

Fixed markup rules are common in the retail industry. A search of the term "retail markup" on *Google.com* reveals that, despite being a frequently overlooked strategy in economics, "keystone pricing" (setting a product's price at two times its acquisition cost) is not just an element of the retail industry's conventional wisdom, but also provides sellers with a generally accepted reference point for their pricing strategies.<sup>2</sup> Because of their simplicity and ease of implementation, pricing rules such as uniform percentage markups over costs are appealing from a practitioner's point of view, and a priori even more so when information about the market is scarce. In the first part of this paper, I argue that fixed markup rules of thumb provide a decent approximation to the way in which sellers in this market price their products. Specifically, I show evidence that supports the idea of sellers' behavior being consistent with rule-of-thumb pricing by means of finding similar pricing patterns across products, time, and retailers.

I focus on Washington state's retail cannabis market for three reasons. First and

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booklet targeted to members of the jewelry industry, encouraged advertisers to stop including manufacturer level ("net") prices in their ads to avoid final consumers finding out retailers' markups on those products. Alternatively, the magazine implemented a new method, "keystone key", by which manufacturer level prices were displayed at two times their true value (see figure 1 in appendix A).

<sup>2</sup>See figure 2 in appendix A.

foremost, regulatory features of the market allow me to put together a comprehensive dataset comprising information about market participants and transactions, both at the upstream and downstream levels of the retail market. Specifically, I am able to build a dataset that covers the first 29 months of the market (from July 2014 until November 2016), more than 300 retailers and 600 manufacturers, and approximately 60 million retail units sold. More importantly, I am able to link downstream and upstream transactions to find the exact acquisition cost of each product sold in the market, which allows me to assess the prevalence of the previously described rules. The second reason why I focus on Washington's cannabis industry is that this is an entirely new market, characterized by sellers that at the beginning had scant information about competitors, products, or consumers' preferences. At least from an intuitive level, it seems natural then to think that such a large degree of uncertainty makes pricing rules attractive. Finally, understanding the actual pricing strategies used by marijuana sellers is relevant in terms of its implications for public policy. Despite still being classified in the U.S. as an illegal substance from a federal point of view, in the last six years Colorado, Washington, Oregon, Alaska, Nevada, and California have legalized and organized active markets for recreational marijuana. Other states (Maine and Massachusetts) have followed closely and are in the process of drafting the rules for their respective recreational markets. If legal possession and medical marijuana are added to the mix, the question regarding how marijuana is priced at the retail level is relevant for thirty-three states and Washington DC. Understanding the way sellers price their products in these markets is then a natural and necessary step towards the assessment of the impact of tax structures and other policy initiatives on prices, profits, and final consumption.

The construction of the aforementioned dataset allows me to quantify and assess the prevalence of pricing rules based on multipliers defined by the ratio between retail prices and acquisition costs. In principle, such exercise simply requires computing and analyzing the distribution of the ratio between the price a retailer receives for a product and the acquisition cost paid when procuring it. Peaks at numbers such as two in the distribution for this ratio would provide evidence that is consistent with the hypothesis of at least some retailers effectively pricing their products with this rule-of-thumb logic. However, an institutional feature of this industry complicates this analysis. Because most banks, credit card companies, and other financial institutions are regulated at the federal level, these entities are reluctant to do business with the still federally-illegal marijuana industry. This constraint forced all early participants in the cannabis market to almost exclusively operate in cash.<sup>3</sup> In order to limit the hassles of dealing with cash, retailers had an incentive to

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<sup>3</sup>Although the constraint has been somewhat mitigated in the last couple of months with more banks

set final consumer prices at integer values, reducing both the need to use coins and the time spent in each transaction. As a consequence, if sellers use a markup rule to determine the price they want to receive for the products they sell and at the same time offer tax-inclusive, round consumer prices, the direct assessment of pricing rules cannot be based on the simple ratio between the prices retailers receive and pay for the units they sell.

I deal with this complication by means of constructing a pricing rule that for each value of the acquisition cost and each potential multiplier (either 2 or 2.5) incorporates both Washington's tax structure and rounding to determine prices that are consistent with the use of these multipliers. I then quantify the share of units sold in the market whose final consumer prices match the prediction for each rule. As a result, I find that approximately 46% of all units sold in the market had prices that were consistent with such multipliers. Importantly, I am able to document not only an increasing role for these rules over time (in the sense of showing a higher matching rate), but also a concentration around keystone pricing (50% markup over price). I then perform several robustness checks by conditioning the analysis on alternative covariates in order to assess whether the prevalence and concentration results are robust. Both findings remain valid even when conditioning on product types, retailer size (as per their sales volume) and competition intensity at the city level. Strikingly, pricing rules show an increasing matching rate even in the case of monopoly markets, for whom the evolution of the share of units explained by rules is similar to highly competitive markets. A priori, as markets get older and more information about products, prices, and players becomes available, it should be expected that profit-maximizer sellers will abandon simple pricing strategies in favor of more complex mechanisms that acknowledge the intrinsic features and competitive environment of each product. On the contrary, markups tend to converge towards 50% despite an observed expansion of the product set and more available information.

A natural question to pose at this point is whether this behavior is consistent with optimal pricing given knowledge of demand. In the second part of this paper, I estimate consumers' preferences for differentiated cannabis products in a discrete-choice environment. I focus on the best selling product type (usable marijuana) and package sizes (1 gram and 3.5 grams) and define an alternative as a retailer-manufacturer pair. I construct markets geographically by means of a hierarchical clustering algorithm on the basis of the actual configuration of retail locations in the state and the distribution of consumers

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willing to take the risk, the first marijuana markets (Colorado, Washington, Oregon) had no option but to operate almost exclusively in cash. See, for example, "*Why marijuana retailers can't use banks*". The Economist. January 22, 2018. <https://www.economist.com/the-economist-explains/2018/01/22/why-marijuana-retailers-cant-use-banks>

across census tracts. To estimate the set of parameters governing demand I follow [Berry \(1994\)](#) and [Berry et al. \(1995\)](#), one of the most popular approaches to recover consumer preferences associated with discrete-choice problems in Industrial Organization. I use these estimates to compute counterfactual scenarios in which firms behave optimally given demand. The comparison between observed and simulated aggregate outcomes indicates a differential performance of rules across product types. While for the case of 1-gram packages of Usable Marijuana a 50% markup rule provides a reasonable approximation to optimal pricing, this is not the case for 3.5-gram packages, which are being largely overpriced. These differences lead to observed variable profits that are about 75% of what they would be in a pricing equilibrium situation.

## Related Literature

Pricing on the basis of rules of thumb has received little to no attention in the modern economic literature. Though some theoretical work has assessed the possibility of firms actively including rules of thumb in their decision process toolkit (see for instance [Baumol and Quandt \(1964\)](#)), the empirical literature on pricing rules is quite limited. In their pioneering work, [Hall and Hitch \(1939\)](#) relied on data obtained from interviews to approximately forty businessmen to conclude that a sizeable share of the sampled firms applied a rule of thumb (“full cost policy”) to price their products. Opposedly, [Earley \(1956\)](#) also relies on data from questionnaires and finds evidence that most firms behave in a manner that is consistent with the optimization hypothesis. In an effort to reconcile marginalist and cost-based arguments for pricing, [Langlois \(1989\)](#) develops a model that accounts for simultaneous inventory and pricing decisions and tests the implications of such model using data from the US automobile industry post World War II. However, the author is not able to find conclusive evidence on the use of marginalist principles in the absence of more precise cost data at the retail level.

One of the reasons that might explain the scarcity of empirical work on pricing rules might be the difficulty to obtain cost data at the individual product level. This is a necessary condition to infer whether a given seller sets prices on the basis of rules of thumb. [Miravete et al. \(2018\)](#) have access to such data for the government-run retail market for liquor in Pennsylvania and study the welfare implications of uniform markups, an extreme form of pricing rules. Since the markup is decided by the state monopolist no competitive forces operate at the retail level, making it possible to interpret the rule as equivalent to a commodity tax over optimally-set manufacturer-level prices. To the best of my knowledge,

mine is the first paper to empirically evaluate the prevalence of non-mandatory pricing rules in the context of a competitive environment.

This paper is also related to a growing literature on learning at the firm level. In particular, two recent papers study the way in which firms learn to price on newly deregulated markets. [Doraszelski et al. \(2018\)](#) find that for the case of the market for frequency response in the UK electricity system, a model that mixes adaptive learning and fictitious play fits the data better than one that assumes equilibrium behavior immediately after the market deregulation. [Huang et al. \(2018\)](#) find that after the liberalization of the liquor market in Washington state sellers do learn about demand over time, but in a costly and asymmetric fashion, foregoing profits in the initial stages with respect those they could obtain if they were fully informed. Unlike the setup in my paper, valuable information was available to sellers in these markets from the very beginning, since most sellers were known and most products were being consumed before liberalization took place. I contribute to this literature by introducing an alternative possibility in which new firms do not actively learn in a sophisticated fashion but settle on a simple rule of action.

This paper further contributes to the literature on the economics of marijuana markets. Much of the research in this area has focused on the implications of marijuana decriminalization on social outcomes such as criminal activity ([Chu and Townsend, 2018](#)), health ([Hansen et al. \(2018\)](#) and [Anderson et al. \(2018\)](#)), and the consumption of other recreational “sin goods” ([Miller and Seo, 2018](#)), among many others. The last couple of years have witnessed an increased interest in the study of marijuana markets from a strictly economic point of view. [Hansen et al. \(2017\)](#) study the impact of a change in the initial tax structure in Washington on vertical integration incentives, profit distributions across the production chain, and consumer prices. Similarly, [Hollenbeck and Uetake \(2018\)](#) take a close look at the relationship between taxation and market power in the cannabis industry in Washington state using a structural model of demand. Finally, [Thomas \(2018\)](#) estimates demand for cannabis in Washington state as a step towards analyzing the effects of license quotas at the retail level on allocative costs and total surplus.

Lastly, this paper is also related to the empirical literature in industrial organization focused on the estimation of discrete choice models of demand. Following [Berry et al. \(1995\)](#) and [Nevo \(2001\)](#), among many others, this literature has taken advantage of the optimality assumption and exclusion restrictions to back out model primitives such as unobserved marginal costs. By comparing estimated marginal costs to acquisition costs, the dominant component of true marginal costs in the retail industry, I am able to assess the accuracy of the implications of these techniques in the specific context of the market

under study in this paper. Although not generally applicable to all markets, my results provide cautionary evidence regarding the inversion strategy: optimality might not be the general principle guiding all firms choices.

The remainder of the paper is organized as follows. Section 2 provides an overview of the retail cannabis industry in Washington state and its institutional setup. Section 3 presents descriptive evidence regarding the prevalence of retail prices that are consistent with the use of simple rules of thumb. Section 4 specifies a static discrete choice model of demand for cannabis. Section 5 details the estimation of such model and reports the corresponding results. Section 6 discusses counterfactual scenarios, emphasizing the differential outcomes that would emerge at the industry level if retailers were to behave in a way that is more consistent with the traditional informational and behavioral assumptions made in the Industrial Organization literature. Section 7 provides concluding remarks.

## 2 Industry Background

In October 1970 President Richard Nixon signed into law the Controlled Substance Act (CSA), a piece of legislation that establishes the legal status of certain drugs at the federal level. Marijuana, as well as other well-known substances such as heroin and LSD, was classified as a Schedule I drug, i.e. as one of several “...drugs with no currently accepted medical use and a high potential for abuse.” (Drug Enforcement Administration, 2017). As a consequence, and given no changes have taken place since then, marijuana is still considered an illegal drug at the Federal level.

Nonetheless, taking advantage of a more tolerant approach by the Justice Department, several states have challenged the federal ban over time by approving medical and recreational marijuana programs in their jurisdictions.<sup>4</sup> Specifically, as of November 2018 ten states and Washington DC have fully legalized medical and recreational marijuana, with six of them already operating fully-functioning markets (AK, CA, CO, NV, OR, & WA). Additionally, a total of thirty-three states and Washington DC have authorized the use of marijuana with medical purposes.<sup>5</sup> It is estimated that, as a whole, legal cannabis in the U.S. is a \$9bn industry that employs more than 120,000 workers and generates more than

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<sup>4</sup>See Ogdén (2009) and Cole (2013) for more details in terms of the Federal stance towards state-regulated marijuana programs.

<sup>5</sup>See table 1 and figure 3 in appendix B for a complete summary of the status of legal cannabis in the US as of November 2018

\$1bn in tax revenues.<sup>6</sup>

## 2.1 The Cannabis Industry in Washington State

The first recreational marijuana shops in Washington State opened their doors on July, 2014. In the eighteen months that passed between the approval of the initiative that legalized recreational marijuana (I-502, 2011) and the the beginning of legal marijuana sales, the State of Washington developed a set of rules under which the new market would function, identifying the Washington State Liquor and Cannabis Board (WSLCB) as the regulator of the new industry.

The main structure of the cannabis industry in Washington mostly resembles the one used by the WSLCB to regulate alcohol sales in the state. Specifically, three differentiated tiers were defined by distinguishing between producers, processors, and retailers: while producers are the ones actually growing the cannabis plant, processors are responsible for packaging and labeling the units that retailers will later sell in the market. Importantly, retailers were constrained to not modify any physical characteristics of the products they sell, acting in this way as intermediaries between processors and consumers. Additionally, retailers were required to set business in new, separate and independent stores, forcing consumers to access cannabis by patronizing a physical location that is only allowed to sell marijuana products and related paraphernalia. Finally, producers and processors were allowed to be vertically integrated among them, but not with retailers.

An important feature of the regulatory scheme in place is the fact that while no limits were imposed to the number of producers and processors, a cap of 334 licenses was levied on retailers. To allocate these licenses across 122 geographic jurisdictions defined by the regulator, a lottery was performed and applicants were selected at random until quotas were filled. A special provision in the regulation allowed cities, towns, and counties to entirely or partially opt out of the marijuana program. By means of zoning restrictions, moratoria, or bans, several jurisdictions imposed either temporary or permanent limitations to the existence of marijuana-related business in their territories.<sup>7</sup> Permanent

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<sup>6</sup>“The U.S. legal marijuana industry is booming”. CNN. January 31, 2018.  
<https://money.cnn.com/2018/01/31/news/marijuana-state-of-the-union/>

<sup>7</sup>Location restrictions and buffer zones were imposed by both the WSLCB and local governments in order to avoid marijuana-related activities in designated areas, such as public and private spaces of high traffic by minors: “The board shall not issue a new marijuana license if the proposed licensed business is within one thousand feet of the perimeter of the grounds of any of the following entities (...) (a) Elementary or secondary school; (b) Playground; (c) Recreation center or facility; (d) Child care center; (e) Public park; (f) Public transit center; (g) Library;

increases to the jurisdiction quotas were discussed by the end of 2015 and implemented in 2016 in order to accommodate the needs of a newly-regulated medical program.

Figure 4 in appendix B describes the evolution of the market in terms of number of participants and the dynamics of entry and exit in the retail sector.<sup>8</sup> The fairly large number of manufacturers (approximately 600) suggests this industry is characterized by a highly competitive and unconcentrated upstream market, while at the retail level there exists a large amount of heterogeneity in terms of competition strength given the quotas and geographical restrictions imposed by the regulator.

The right panel of figure 4 illustrates the entry and exit dynamics of retailers for each month and the entire state. While entry averages about ten retailers per month, retail firms exiting the market is clearly not a feature of this market. Broadly speaking, the entry pattern has two discernible periods. First, during the initial stage of the recreational market, firms entered following their own timing but mostly conditioned by that of the jurisdictions who were gradually allowing cannabis businesses to locate in their geographic space. Transitory bans and regulatory discussions delayed the authorization to operate, inducing the staggered entry noticeable in the plot. The second wave of entry begun in the first quarter of 2016. This is the moment in which newly authorized retail stores began operations in order to accommodate medical marijuana consumers, added to the regulated system by the approval of Washington State's Cannabis Protection Act in July 2015. By providing an additional source of variation that aids in the identification of substitution patterns across retailers and the products they carry in each market, this process of staggered entry will prove useful later on in this paper when estimating preferences for cannabis products in the retail market.

Figure 5 presents the evolution of monthly revenue generated by downstream retailers. Both the increase in the number of stores and a more positive attitude toward marijuana, are the main factors driving the observed 12% average increase in monthly revenues during the first thirty months of operations. The figure also shows the revenue split among different product categories. Although innovation on the supply side and preferences on the demand side have cooperated to make other types of products more ubiquitous, Usable Marijuana (i.e. the dried cannabis flower) has been the dominating product category since the market inception, accounting for at least two thirds of every dollar sold at the state level.

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or (h) Any game arcade (where admission is not restricted to persons age twenty-one or older)." (WAC 314.55.50).

<sup>8</sup>For the purposes of this paper I label as "manufacturers" or "wholesalers" all those processors and producers that sell product directly to retailers, without distinguishing across these categories.

### 2.1.1 Prices, Taxes, and Markups

Figure 6 presents the evolution of the 25th, 50th, and 75th percentiles in the (sales-weighted) distributions of the price per gram of recreational Usable Marijuana charged by retailers (left) and wholesalers (right panel) before any taxes. At the market onset, high prices on both ends of the market are consistent with the expected response to an eager-to-be-satisfied demand and staggered entry. As more participants entered the market both wholesale and retail prices decreased, though while the former stabilized at \$3 per gram, the latter was also negatively affected by the entry of new retail stores at the beginning of 2016, driving the median retail price before taxes to \$6.2 per gram by the end of that year.

One important feature of the evolution of these prices is the response to the unexpected change in the tax structure governing the industry. The State of Washington initially imposed a 25% gross receipts tax collected at every step in the supply chain. However, in July 2015 this scheme was replaced by a single 37% excise tax only applied at the retail level. From June to July of that year, the median wholesale price increased by approximately 22%, a figure that is very close to the 25% intermediate tax that was eliminated in that time frame. This crowding out process (consistent with the findings in Hansen et al. (2017)) left retail costs almost unchanged, a feature that justifies the almost invariable retail price observed before and after the tax change. The combination of unchanged final acquisition costs, a relatively constant markup, and a higher excise taxes at the final transaction level, resulted all in a median consumer price in the market of approximately \$9 per gram by the end of 2016.<sup>9</sup>

The impact of this evolution in prices and the change in the tax structure can be also noticed in figure 7, where I plot the retail gross margin and markup over price in the left and right panels, respectively. While markups fluctuated during the first months, by the end of 2015 they had already stabilized at approximately 50%-55% of the retail price, with an implied gross margin of about \$3 per gram of usable marijuana.

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<sup>9</sup>In addition to the excise tax imposed by the regulator, for each unit of product acquired consumers were levied the usual state and local sales tax rates. In this way, prices paid by consumers ( $P^c$ ) can be computed by means of the following expression linking the price received by the retailer ( $P^r$ ), local- and state-level sales tax rates ( $\tau$ ) and the tax structure on a given month  $t$ :

$$P_t^c = \begin{cases} P_t^r \times \frac{4}{3} \times (1 + \tau) & \text{if } t \leq \text{June 2015} \\ P_t^r \times (1.37 + \tau) & \text{otherwise} \end{cases}$$

## 2.2 Data

In order to avoid product diversion to the black market and facilitate both the collection of and the control over tax obligations, the WSLCB implemented a traceability system capable of recording every single step in the production chain. From the seed to the final sale, every transformation, conversion, transfer, and sale at both the wholesale and the retail level is recorded in the system. The generated data is then roughly compiled by the regulator and made available to the public on what it is seen as a strong effort to increase market transparency.

The main public data I use in this paper includes each participant's location, transfers, and final sales since the market opened in July 2014 until November 2016. In particular, I focus on all transactions involving retail licensees, i.e. intermediate transfers from processors to retailers (upstream level) and final sales from retailers to consumers (downstream level). For each of the transactions at the upstream and downstream levels I am able to learn the identity and location of the retailer and manufacturer involved, the agreed price and quantity and the type of product being transacted. Because prices in this dataset do not include any state or local sales taxes, I complement it with data from Washington's Department of Revenue on quarterly levels of local and state rates for sales taxes in order to recover the final prices paid by consumers.

Finally, although it is possible to know the exact location of each industry member, there does not exist similar information on consumers. In order to incorporate consumers' heterogeneity as a determinant of their product choices in the analysis, I augment regulator-provided datasets with information obtained from different complementary sources. First, I obtain demographic characteristics at different geographic levels from the Census Bureau using both decennial census data and the American Community Survey. I take into account not only geographies across Washington, but also others in both Oregon and Idaho to capture the possibility of consumers from neighboring states traveling to access legal cannabis. Second, I compile data on attitudes toward marijuana at the local level by means of accessing voting results corresponding to marijuana legalization ballots Initiative 502 (WA) and Measure 91 (OR) obtained from the corresponding Secretary of State.<sup>10</sup> I complement this data by means of computing driving distances across locations using Google Maps' Distance Matrix API.

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<sup>10</sup>Since Idaho has not yet held an election regarding marijuana initiatives, I allocate to each relevant county in Idaho the voting results obtained in its closest neighboring county in either WA or OR. I also use the 2016 general election results to check whether there exist major differences between the way counties in ID and their WA/OR counterparts vote, finding no major deviations.

### 3 Rule-of-Thumb Pricing

Rules of thumb are frequently understood as general guidelines for decision making. Constructed and strengthened on the basis of experience and common sense, rules of thumb are simple, easy to learn and to implement. Importantly, decisions based on rules of thumb are usually thought to be correct despite their lack of scientific foundations. The link between this decision strategy and economics is not new. In their discussion on the relationship between rules of thumb and optimal decisions, Baumol and Quandt (1964) argue that the interaction between the costs of the decision process and the relevance of the decision itself may justify situations in which only approximate solutions are needed. They understand that, under some circumstances, rules of thumb are capable of providing those approximate answers, and therefore can be characterized to be “...among the more efficient pieces of equipment of optimal decision-making” (Baumol and Quandt, 1964). On a similar note, Simon (1959) describes the possibility of firms stating their goals in “satisficing” terms, i.e. attainable goals that once reached make it unnecessary to keep looking for even better solutions to the problem under consideration. However, despite their appealing features from a practitioner’s point of view, rules of thumb have not received much attention in the empirical economics literature.

In this section, I quantify the prevalence of this type of rules using data from the retail cannabis market in Washington state. To this aim, I focus on a set of rules in which retailers price their products by applying some fixed percentage markup to their acquisition cost. Maybe the most common example of this type of strategy is the practice known as *keystone pricing*. This strategy, which constitutes an important element in the baggage of conventional wisdom associated to the retail industry, refers to the practice of setting retail prices that generate a 50% markup over price, i.e. prices that double the acquisition cost of the goods being sold. For decades, keystone pricing has been an important element of the retail strategy and the new cannabis industry has not been immune to it. It is common to find booklets in which the first pricing recommendation marijuana retailers get is the 50% markup over price that characterizes the keystone pricing strategy.<sup>11</sup>

Keystone pricing is just an example of pricing on the basis of rules of thumb. For the remaining of this section, I will focus on the empirical behavior of the multiplier  $m^r$  that results from the ratio between the price received by the retailer ( $P^r$ ) and the price she paid

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<sup>11</sup>See, for instance, <https://www.greenbits.com/resources/pricing-guide>

(*AcqCost*) for every unit  $j$  being sold in the market:

$$P_j^r = \text{AcqCost}_j \times m_j^r$$

Since the data observed includes both measures, it is straightforward to compute the observed multipliers that result from every unit sold in the dataset and plot their distribution. The density function associated to the empirical distribution of these multipliers in the 1%-99% range of their values is shown in figure 8 in appendix C, along with vertical lines at different a priori potentially relevant levels for mass concentration such as  $m = 2$  (keystone pricing), or  $m = 2.5$ , among others. The plot reveals that although there seems to be significant mass concentration around some of the highlighted values, a clear-cut coincidence of peaks and vertical lines is not observed. This result, on a first approximation, seems to be at odds with the hypothesis of firms pricing their products by applying a fixed markup (multiplier) to the acquisition cost of the units they sell.

However, a specific feature of this market makes the case for a more refined type of analysis. Despite having been legalized by several states, marijuana is still defined as an illegal substance by the U.S. Federal Justice System. Since most financial institutions such as banks and credit card companies are regulated at the federal level, there are clear incentives for these institutions not to engage into any class of marijuana-related activity. As a consequence, cannabis industry participants have found themselves in a particularly difficult situation regarding the use of alternative means of payments. Specifically, they have been forced to restrict to cash as the almost exclusive payment method for all types of transactions. The implications of this constraint over daily retail operations are non-negligible. In order to partially avoid the hassles of dealing with cash, retailers have a strong incentive to set final consumer prices at integer levels. In particular, round prices help to reduce the time associated to each customer transaction, as well as contribute to attenuate the need for coins. The distribution of final consumer prices is presented in figure 9, which shows very noticeable peaks at integer values. Furthermore, it also highlights the fact that when prices are high (say, above the median value of \$15) retailers seem to not only set integer prices, but also ones that are multiples of \$5. Overall, 75% of the approximately 60 million prices paid by consumers are within one cent of an integer value, as shown in figure 10).<sup>12</sup>

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<sup>12</sup>Given that several cities and counties modified their local tax rate in the sample under observation and the fact that the tax rates dataset lives at the quarterly level, it might even be possible that a higher fraction of units sold actually had an integer price. In fact, the prevalence of consumer-level integer prices in this industry is also noted in Hansen et al. (2017), where they confirm this feature by means of conversations with retailers and an inspection of historical menus advertised by sellers in industry related websites.

Retailers’ preferences for whole-dollar final consumer prices opens the doors to re-assessing the possibility of pricing rules based on fixed multipliers. Table 2 presents the relevant numbers from a simple example that is useful to illustrate the implications of rounding on observed multipliers and their distribution. Consider a retailer that purchases a unit of product for \$6 and assume she follows keystone pricing to determine the price she wants to receive for that unit. Since keystone pricing assumes a 50% markup over price (or, equivalently, a multiplier  $m$  equal to 2), she plans on receiving \$12 for that specific unit. When applying taxes, say at a rate equal to 0.455 cents per dollar, the final price the seller should charge to consumers is equal to \$17.46. However, because of strong preferences for integer prices, the final consumer price is rounded up (or down), generating a final consumer price of \$18 (\$17). When entering this information on the system the researcher observes a recorded final price received by the retailer equal to \$12.37 (\$11.68), implying an observed ratio between received and paid prices equivalent to  $m = 2.06$  ( $m = 1.95$ ). This example illustrates the possibility that some of the observed multipliers might still be consistent with rule-of-thumb pricing behavior, and suggests that in order to account for such possibility it is necessary to allow for a more flexible procedure.

### 3.1 An algorithm to quantify rule-of-thumb pricing

This section describes the algorithm I use to identify observations (units sold) with prices that could be consistent with firms pricing their products by means of applying a fixed multiplier to acquisition costs. To this goal, I first define a discrete set of multipliers  $\mathcal{M}$  based on the observed distribution of multipliers presented in figure 8. This figure shows that multipliers bunch at values that are close to 2 and 2.5, such as 2.05 and 2.25. Consequently, I define  $\mathcal{M}$  as follows:

$$\mathcal{M} = \{2.00, 2.50\}$$

in which every element  $m \in \mathcal{M}$  is regarded as a specific *rule*. Second, using the corresponding values for the acquisition cost and tax structure, for each unit sold and each rule  $m$  I compute lower and upper bound predictions for the final consumer price that result from using  $m$  as a pricing rule and rounding up and down to the closest integer. To capture the idea that higher prices tend to be rounded to multiples of \$5, when the exact price implied by the use of  $m$  is above \$20 I compute floor and ceiling values using the closest multiple of 5 instead of the closest integer. More formally, for a unit purchased at acquisition cost  $w$  and for which the retailer has to apply tax structure  $\tau$  (which, as described before, is a

function of both time and geographical location), the upper and lower bounds for rule  $m$  are given by:

$$LB(m, w, \tau) = \begin{cases} \text{Floor}(w * m * \tau) & \text{if } w * m * \tau \leq 20 \\ 5 * \text{Floor}\left(\frac{w * m * \tau}{5}\right) & \text{otherwise} \end{cases}$$

$$UB(m, w, \tau) = \begin{cases} \text{Ceiling}(w * m * \tau) & \text{if } w * m * \tau \leq 20 \\ 5 * \text{Ceiling}\left(\frac{w * m * \tau}{5}\right) & \text{otherwise} \end{cases}$$

Once these lower and upper bounds are defined for each unit sold in the sample and for each rule  $m \in \mathcal{M}$ , I proceed to define matches between recovered consumer prices and rules. In particular, I say unit  $j$  has a price that is consistent with rule  $m$  if its consumer price is either exactly equal to or a cent away from  $LB(m, w, \tau)$  or  $UB(m, w, \tau)$ . While table 3 in appendix C illustrates this algorithm with an example, figure 11 illustrates the coverage of these rules as a function of the acquisition cost and for the modal tax structure in the sample. As can be noticed, for each acquisition cost only a handful of prices are considered to be a match.

The performance of this algorithm across different product categories is summarized in table 4. Several points are worth emphasizing from this table when analyzing the overall matching rate. First, I find that for the entire sample of 60 million observations the algorithm generates an overall matching rate of 46%, indicating that approximately 28 million units sold had prices that were consistent with the use of at least one of the rules in  $\mathcal{M}$ . Second, although there seems to be heterogeneity across product types, no product category has a matching rate below 36%, which suggests that the aggregate result is not just driven by a specific type of cannabis good. Third, the top product category in terms of units sold and revenue generated, Usable Marijuana, records a matching rate of 47%, a number that suggests consistency with behavior based on rules of thumb strengthens for products that are sold more often. Fourth, it can also be noticed that there seems to exist an almost one-to-one inverse relation between consumer prices and matching rates rankings. Inhalable products depart from this observation by exhibiting a matching rate that is four percentage points higher than that of Liquid Edibles, despite having a median price that is \$4 more expensive. Finally, the comparison across the performance of each individual rule ( $m = 2.0$  and  $m = 2.5$ ) reveals that keystone pricing is able to account on its own for a larger share of units sold across all product categories than the alternative rule of  $m = 2.5$ , and that this difference in coverage tends to increase with the median consumer price. Additionally, the overlapping between rules does not seem to be a concern, at least overall,

given how similar the aggregate matching rate and the sum of the individual ones are.

### 3.2 Rule-of-thumb pricing: retailers and time

In this section I extend the aggregate analysis of the previous paragraphs to focus on the performance of rules across retailers and time. Two reasons motivate this analysis. First, since retailers are the ones actually pricing their products, it is natural to group observations at the retailer level. Second, section 2 described two features of the retail cannabis industry that are worth looking at in terms of their potential impact on the measures analyzed in this section. First, retailers' entry has taken place across all months at a generally stable frequency of approximately ten retailers per month. Second, both wholesale and retail prices exhibit a general downward trend that could potentially affect the distribution of observed multipliers and, as a consequence, the matching rate of the pre-defined rules. These factors underline the relevance of considering a temporal dimension. Since approximately 85% of all products are sold in the thirty days that follow their respective purchase date, whenever a time dimension is added to the analysis I group observations at the monthly level.

Consider first the overall performance of rules in  $\mathcal{M}$  within retailers independently of time. Figure 12 plots the distribution of the share of observations that are consistent with this pricing strategy for each given retailer. Rules in  $\mathcal{M}$  account for at least 50% of all units each retailer sells for half of the more than 300 active sellers in the sample. Additionally, both  $m = 2.0$  and  $m = 2.5$  are responsible for 28% and 23% of all units sold by the median retailer, respectively.

Next, consider the prevalence of rules over time without distinguishing across retailers. Figure 13 describes the evolution of the monthly share of observations that can be explained by the multipliers in  $\mathcal{M}$ . As markets grew older and more information became available, the fraction of observations that were consistent with the use of rules increased in almost every month, from a modest less than 8% to approximately 50% by the end of the data. Such increase appears to have been driven by both rules, with keystone pricing showing a higher performance both at the beginning and the end of the sample. The figure also presents the evolution of the mean observed multiplier in the data, independently of whether the observations are explained by the rules. The behavior of the mean multiplier contrasts with that of the share of observations explained by rules in the sense that no clear pattern is observable. While the prevalence of rules increases continually over time, the mean multiplier goes through at least three very distinguishable phases characterized by a

sharp contraction, a rapid recovery, and a final stage of sustained but smooth decline.<sup>13</sup>

A natural step now is to put together the two previous pieces of evidence in order to assess the role of rule-of-thumb pricing across retailer-month pairs. This is shown in figure 14, where the distribution of the within-retailer fraction of observations that are consistent with rules is presented for three different (equally-spaced) months in the sample. For the case of the 59 active retailers in October 2014, the median explained share was below 5% and almost entirely due to keystone pricing. A year later rules had already become much more prevalent, accounting for at least 48% of all units sold for half of the 184 retailers in the sample. Even though the individual prevalence of both rules increased with respect to the previous year,  $m = 2.5$  seemed to have played a larger role in this stage. Finally, in October 2016 the fraction of overall observations accounted for by these rules increased again, specially for  $m = 2.0$ . According to this distribution, about 235 of the 317 active retailers in this month sold at least 40% of their units at prices that were consistent with the rules in  $\mathcal{M}$ .

Figure 14 also highlights an additional feature. For each month, I compute the mean observed multiplier for both observations that are considered a match to set  $\mathcal{M}$  and those which are not. These numbers are indicated in each subplot as the mean explained/unexplained multipliers, respectively. While the mean explained multiplier is consistent with the relative performance of  $m = 2.0$  *vis a vis*  $m = 2.5$ , the mean observed multiplier for unmatched observations decreases continually, indicating a larger concentration of markups in the neighborhood of the rules defined in  $\mathcal{M}$ . Summarizing, the reduced form evidence so far highlights two main features in the evolution of this market. First, rules become more prevalent with time, accounting for an increasing share of observations. Second, keystone pricing seems to play an important role by explaining at least 30% of observations for half of the retailers in the market.

### 3.2.1 Rules across products

Considering the fact that only two types of products (usable marijuana and inhalables) account for more than 85% of all units sold and revenue generated (see table 4), it is worth exploring whether they are exclusively responsible for the results obtained so far. To this aim, figure 15 shows the distribution of the within-retailer share of observations that are

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<sup>13</sup>As a reminder, notice that while a multiplier of  $m = 2$  is equivalent to a 50% markup over price, a multiplier of  $m = 2.5$  is equivalent to a 60% markup over price. In general, if  $\mu$  is the markup over price and  $m$  is the price-to-cost multiplier then it is possible to write:  $\mu = \frac{p - w}{p} = \frac{m - 1}{m}$ .

consistent with the rules in  $\mathcal{M}$  for each product category in the top-4 of revenue generated, considering both a month at the beginning of the sample (January 2015) and another at its end (November 2016).

Product-level distributions in each plot of figure 15 resemble the general results discussed when looking at the aggregate picture (figure 14). In all cases, rules in  $\mathcal{M}$  substantially increase their participation over time: regardless of the product category, half of the retailers selling these products in November 2016 do so at prices that are consistent with rules in at least 37% of all cases. Importantly, the prevalence of rules increases notably for both “cheap” (Usable Marijuana and Solid Edibles) and “expensive” (Inhalables and Liquid Edibles) products. Moreover, keystone pricing becomes the norm across all products by explaining a larger share of observations than  $m = 2.5$ . Both observations suggest that the concentration of markups around rules in  $\mathcal{M}$  is a common feature across all types of products.

### 3.2.2 Rules across retailer size and competition intensity

In this subsection I explore the possibility that results might vary when looking at retailers that differ in either the amount of revenue they generate or the number of competitors they face at the city level. Figure 16 looks at the first possibility. For its construction, every month I split the sample of active retailers in quartiles according to the distribution of retail revenue generated by each store, and then plot the distribution of the share of units that are consistent with rules across revenue categories for both October 2014 and October 2016. The similarities across all four plots indicate that both the prevalence of pricing rules and their increasing role over time appear to be quite homogeneous across all types of retailers’ sizes.

Figure 17 inspects the possibility of competition intensity being responsible for these results. For the construction of this plot I split retailer-month pairs into six buckets, according to the number of retailers each seller had to compete against at the city level. A quick look at the plot reveals that the prevalence of pricing rules is similar across all types of markets. While duopoly and triopoly markets record a similar performance for rules than markets with more than ten sellers, markets with 6-10 firms behave similarly than monopoly markets, an indication that there is no clear pattern in the relation between rules’ performance and competition intensity.

It is still noticeable the fact that the overall median frequency of observations explained

by rules for a retailer in cities with more than 10 sellers is about ten percentage points higher than the corresponding value for monopoly markets. This result seem to be driven by the prevalence of keystone pricing in the former category of markets, given  $m = 2.0$  explains for the median retailer a share of observations that is twice as high as the one explained by this rule for the median monopolist. However, this observation has to be linked to the patterns governing the evolution over time discussed in figure 13. Given staggered entry by retailers, markets with larger number of sellers are more ubiquitous in the latest months of the sample, where it has been showed that rules that concentrate around keystone pricing are more prevalent. To assess whether retailers in monopoly markets behaved in a significantly different way, figure 18 compares the performance of rules for monopoly and very competitive markets in the last month of the sample (November 2016). As can be seen from the plot, retailers in monopoly markets ( $N = 59$ ) exhibit the same patterns as their counterparts in more competitive markets ( $N = 119$ ) do, both in terms of rules' prevalence and concentration around keystone pricing; in fact, rules explain a slightly larger share of observations in monopoly markets.

### 3.2.3 Rule-of-thumb Pricing: A Summary

In this section I have provided descriptive evidence supporting the idea that a sizable share of prices observed during the first two years of Washington's retail cannabis industry is consistent with the use of rule-of-thumb pricing. In particular, I have introduced the algorithm that I used to match units sold to rules and described its performance. I have shown that despite a slow start, as months go by rules become more prevalent (in the sense of showing a higher matching rate), and tend to concentrate around the pricing strategy commonly known as keystone pricing, which implies a 50% markup rule over price. Additionally, I have analyzed how these results take place across product categories and retailers of all sizes, in both monopoly and oligopoly markets. In the next section I study an additional potential explanation: the possibility that observed prices and markups are indeed optimal given preferences for marijuana products.

## 4 A Demand Model for Cannabis Products

Customers in Washington can consume recreational marijuana by means of different types of products, being solid and liquid edibles, marijuana extracts, and dried marijuana

flowers the most popular ones. Even though other categories have become relatively more ubiquitous with time, Usable Marijuana (UM), legally defined by the State of Washington as “*dried marijuana flowers (...) not includ(ing) either marijuana-infused products or marijuana concentrates*”, accounts for at least two thirds of total retail revenues in every month since the first store doors opened, denoting its extensive popularity among recreational users.<sup>14</sup>

Several features differentiate products within the Usable Marijuana category. Dried marijuana flowers are classified and offered according to their strain, i.e. their variety, which determines the product’s flavor, smell, desired effect, and potency. Most of the marijuana effects on a consumer’s brain and body are the result of the combination of two of the main chemical components produced by the marijuana plant: *tetrahydrocannabinol* (THC) and *cannabidiol* (CBD). All cannabis products sold in Washington must undergo potency tests that certify, among other quality assurance evaluations, both the THC and CBD content.<sup>15</sup> While higher THC (the main psychoactive in marijuana products) concentrations have been normally associated to higher levels of euphoria and stronger effects at the brain level, CBD is believed to be responsible for the medical effects of marijuana consumption.

For the sake of this exercise, I restrict attention to usable marijuana products. The choice of limiting the sample to just UM obeys to two main reasons. First, the fact that this product category accounts for at least two thirds of total revenues on every month; in particular, UM is responsible for 70.9% of all revenue and 75.1% of all units sold in the sample under observation, as seen in the last two columns of table 4. Second, because of data limitations on the original dataset that make it difficult to get appropriate measures of quantity-level shares and prices per unit sold for alternative product categories. While UM is sold in packages with clear and identifiable weight (measured in grams), the information regarding package content and specific weight for other product categories such as liquid and solid edible products is not properly detailed in the dataset (sometimes missing and frequently entered manually by retailers in string-based descriptive fields), preventing the possibility of constructing both market shares based on quantities and unit prices that are comparable across products.<sup>16</sup>

When restricted to UM, individual products can be identified in the dataset by means of their inventory code, which provides an extremely detailed definition that can be

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<sup>14</sup>RCW 69.50.

<sup>15</sup>WAC 314-55-102.

<sup>16</sup>Additionally, how to interpret the equivalence between any solid/liquid product and a gram of usable marijuana is not a trivial problem. In fact, its solution relies on chemical equivalences among products that are beyond the scope of this paper.

interpreted as the equivalent of a batch of product. The first three columns in table 5 in appendix D summarize the distribution of the number of different UM products sold by each retailer using this definition. Though the identification of products as a retailer-inventory code combination provides the finest definition and perfectly pinpoints the specifics of each variety, its use would imply the existence of an extremely large number of products (there are approximately 110,000 of them only in July 2016 for instance), with minuscule shares.

An alternative definition is given by the identification of products by combining the identities of retailers and manufacturers. Under this definition, all varieties produced by a given manufacturer and sold at a given store are pooled together to define a specific product  $j$ . The distribution of products carried by retailers under this definition is summarized in the three middle columns of table 5. Even though this definition generates a number of products that looks more reasonable from a demand-estimation practitioner's point of view, there is still a relevant consideration that is worth mentioning. Given UM is sold in packages of different size, it is important to control for potential non linearities in the pricing schemes of wholesale and retail firms. This introduces a complication in the sense that simply grouping all sizes of product  $j$  is no longer an option. However, the distinction across sizes increases in a substantial way the number of products offered by each retailer, as noticeable per the last three columns of table 5.

It is because of these reasons that I further restrict the product set to the best selling package sizes (1 and 3.5 grams). These packaging options are responsible for 69% of all UM revenue in the sample, as well as for 79% of all UM units sold. Additionally, for each retailer-month-size triplet I compute the inner shares across manufacturers and keep all those that, in decreasing and cumulative fashion, are responsible for 80% of sales at the retailer-month-size level. Summarizing, for the purposes of this exercise a product will be defined as a retailer-manufacturer combination in which all varieties of a given package size  $s$  produced by manufacturer  $m$  and offered by retailer  $r$  in market  $t$  are pooled together. Though it is not possible to know the set of all products each seller had actually in display for consumers to choose from at each moment in time, I assume such set is given by all those UM products that had at least one sale recorded in data and that satisfy the threshold requirement specified before. This choice of product definition generates product-level variation that is induced by the fact that (i) manufacturers are not linked to every possible retailer, and (ii) when linked, a retailer does not necessarily carries every variety produced by the manufacturer.

A product is then described by three sets of observable characteristics. First, features

that are specific to the corresponding retailer on a given month: (i) the total number of UM alternatives offered as per the full count of manufacturers with which she relates in that month, and (ii) the total number of product categories carried by the retailer. Second, features that are specific to each product: (i) a dummy for whether the product has a weight of 3.5 grams, (ii) the median value of THC and CBD concentration across the varieties (conditional on size) that were pulled together to construct the product, as well as their squared values to control for non-linear preferences over these features, and (iii) the median consumer price across the varieties (conditional on size) that were pulled together in the construction of the product. Finally, I include retailer, manufacturer, and year-month dummies to control for unobservable features at those levels.

Finally, I define a market by means of a specific geography and at the monthly level. To determine market size, I follow a similar procedure to the one used in [Miravete et al. \(2018\)](#) for the estimation of consumers preferences for spirits in Pennsylvania. In particular, I define the market size  $M_t$  as the potential consumption of all marijuana products on market  $t$ . To compute this measure I combine survey data on cannabis consumption trends from the National Survey on Drug Use and Health ([SAMHSA \(2015\)](#) and [SAMHSA \(2016\)](#)) with quantity- and size-level estimates of consumption. Though by the very nature of the product it is hard to find estimates regarding average consumption and frequency of use, [Chen et al. \(1997\)](#) estimates a weighted average consumption (conditional on using) of approximately 55 marijuana cigarettes per user per month. Additionally, an average marijuana cigarette (“joint”) is estimated to weight approximately 0.32 grams ([Ridgeway and Kilmer, 2016](#)). Finally, data on marijuana consumption trends from SAMHSA reveals that, for example, approximately 17% of the population in WA consumed marijuana in 2014 while that figure increased to about 20% in 2015 and 2016. Therefore, the market size measure is summarized by the following formula:

$$M_t = [\text{Population} \geq 21 \text{ y.o.}] \times [\text{Prevalence in state}] \times [55 * 0.32]$$

## 4.1 Geographic Markets Definition

In order to capture the dynamics of (mostly) entry and (almost negligible) exit of stores across the entire state, geographic markets are defined taking into account both time and space. In the following subsections I describe how retail stores’ locations determine the spatial configuration to which consumers are allocated across time in order to define markets.

### 4.1.1 Retail Stores

I construct geographic markets for retailers following a similar approach to the ones used by Carranza et al. (2015) and Lemus and Luco (2018) for the retail gasoline industry. The market for gasoline provides an interesting reference point for the definition of markets in the cannabis industry since in both cases location restrictions are the norm.<sup>17</sup> In this approach, markets are defined by means of a clustering algorithm that takes into account geographical locations of stores and driving distances between them.<sup>18</sup>

In order to construct these markets, I use all retail locations that were ever active throughout the sample, identified by their longitude and latitude. Using Google Maps API I then compute both the driving distance and the driving time associated to traveling from one retail store to another, which allows me to construct a matrix of distances among these locations (known as the dissimilarity matrix). A posteriori, I use a hierarchical clustering algorithm to group locations according to their proximity, defined by means of considering the maximum distance between pair of objects, one in one cluster, one in the other (complete linkage method).<sup>19</sup> The procedure begins with as many clusters as stores are in the data ( $N$ ), and proceeds to join the two closest ones in terms of the driving time between them. In the next round, using the newly defined  $N - 1$  clusters, it repeats the first step by joining the next two closest clusters. The procedure can be repeated up to the point in which all observations are on the same cluster, so in order to determine markets a cutoff value is needed. Considering the distribution of driving times across stores, I define a cutoff value of 30 minutes. This cutoff generates a configuration with sixty geographically differentiated markets which can be appreciated in figure 19 from appendix D, which illustrates the location of all 336 ever active retailers in the state of Washington.<sup>20,21</sup> Figure 20 plots the distribution of the number of retail stores per market,

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<sup>17</sup>For example, a sizeable fraction of gas stations and cannabis stores in Washington tend to be located at the side of important avenues, state roads, and interstate highways.

<sup>18</sup>This approach differs from the one adopted in other papers studying the retail cannabis market in Washington state. Thomas (2018) constructs a ball around each consumer address of a given radius that changes across jurisdictions, an approach that acknowledges the role of local competition but that counts retail stores multiple times. Hollenbeck and Uetake (2018) define markets at the city level and while this measure also recognizes the local character of competition, it does not incorporate the fact that because of the geographic constraints imposed by the regulator in terms of the definition of “jurisdictions” to determine store quotas, several retailers located on the border of important cities such as Seattle but outside its limits, just to comply with the regulation.

<sup>19</sup>For more details on this procedure, in particular about the alternatives to cluster observations, see Everitt et al. (2011).

<sup>20</sup>I consider an active retailer as one with at least two months of continuous operations in the downstream market.

<sup>21</sup>The sixty differentiated geographies can be contrasted with the one hundred and twenty-two jurisdictions defined by the WSLCB to issue licenses, which in principle opened the door for stores to open

i.e. across, the 1,354 geography-month pairs in the sample.

#### 4.1.2 Consumers

Consumers are assumed to live at the geographic center of population of their corresponding census tract, letting this point's latitude and longitude define their 'address'. For each address and period of time I compute the driving distances from such point to each active retail location and identify the minimum in the corresponding distribution. Consumers are then allocated, on a monthly basis, to the geographic market to which their closest retailer belongs to. This assumption is introduced in order to capture two ideas: 1) the fact that we have a changing distribution of retail locations across time, and 2) the idea that consumers are not willing to travel extremely long distances when they can find product at a closer reach.

In order to account for potential purchasing spillovers of cannabis product to the neighboring states of Idaho and Oregon, I include all census tracts in WA as well as all those in OR and ID located at no more than 50 miles from an active retail location. This cutoff of 50 miles is chosen based on the maximum distance between a census tract and a retail location in WA state (42.2 miles). Census tracts with no population over 21 years old or no households are excluded. This selection generates a total of 1,957 addresses that every month are matched to their closest retailer's market. Figure 21 presents the allocation of consumers' addresses to retailers' markets at the beginning (left) and end (right) of the sample, in which 11 and 60 retail markets, respectively, are in place.

The relevant population for each market configuration is given by the pool of individuals legally allowed to purchase cannabis products, i.e. all adults over 21 years old living in the census tracts that are matched to each market in each month. For the purposes of the estimation procedure, I simulate individuals in each market based on the distribution of a set of demographic characteristics observed in the data (adult population, population density, income, age, gender, race, and college education). For the case of non-binary covariates (income and age), for each census tract I fit a beta distribution to the corresponding data (using midpoints for each interval defined in the source of information), obtain its parameters, and then simulate values according to such distribution. For the binary covariates (gender (male/female), race (white/no white), and college educated (yes/no)), I use the reported proportions to simulate individuals from a binomial distribution with

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in eighty-four cities and thirty-eight "counties at large" (cities or towns outside the group of eighty-four predefined cities).

mean given by the corresponding value of the proportion. Finally, I use the same binomial procedure to include a simulation of voting actions (voted in favor (yes/no)) for the Marijuana Initiative in order to capture each region’s attitude toward the product.

Summarizing, in order to allocate consumers to markets I use a partition of the state’s geographic space into  $Z$  smaller regions (census tracts) and allow each consumer to live in one of these partitions  $z$ . Each census tract is then entirely described by means of two vectors:  $d_z$  and  $D_z$ . The first vector ( $d_z$ ) provides the distances between region  $z$ ’s center of population and each retail store location, while the second vector ( $D_z$ ) collects socio-demographic information on region  $z$  (adult population, population density, income distribution, racial, gender, college-education and age distributions, as well as attitude towards marijuana markets). Table 6 summarizes these geo-demographic characteristics for the census tracts included in the sample.

## 4.2 The Model

I consider a discrete choice model in which consumers have well-defined preferences over a finite set of products defined by their vector of characteristics. In particular, I follow this ideas in [Berry \(1994\)](#) and [Nevo \(2001\)](#), incorporating a geographic dimension to the decision process by means of adding the distance to a store as one of the several (indirect) utility determinants, as in [Davis \(2006\)](#) and [Aguirregabiria and Vicentini \(2016\)](#), among others. The main role of this geographic component is to serve as a different source of horizontal product differentiation, capturing the idea that accessing the product is costly on a different dimension beyond the price paid for it.

I assume that every month each consumer chooses either one of the usable marijuana alternatives available in the market (summarized by the set  $\mathcal{J}^t$ ) or the outside option. As in [Miravete et al. \(2018\)](#), the definition of potential market discussed in the previous section implies that: (i) the total expected volume of marijuana consumption is accounted for no matter its source, and (ii) the outside option is defined by the consumption of marijuana products outside the selected products included in  $\mathcal{J}^t$ .

In what follows,  $j$  indicates a specific product (A UM package of a given size sold by retailer  $r$  and processed by manufacturer  $m$ ),  $i$  a given consumer,  $z_i$  her address, and  $t$  the market (geography-month pair) in which this consumer makes her choices. Retail stores are identified by  $r$ , and  $z_r$  represents their location in the space. Finally, as per the process described in the previous section, every consumer and every retailer in each month belong

to one geographic market. Conditional on purchasing product  $j$ , consumer  $i$  located at  $z_i$  gets indirect utility as specified in the following expression:

$$u_{i(z)jt} = \beta_{i(z)} \mathbf{X}_{jt} + \zeta_{jt} + \alpha_{i(z)} P_{jt}^c + d(z_i, z_r, D_z; \lambda) + \epsilon_{ijt} \quad (1)$$

In this expression:

- $\mathbf{X}_{jt}$  is a vector of product characteristics that includes: a constant; retailer, manufacturer, and month-year level indicators; a size indicator that takes a value of 1 when the product has a weight of 3.5 grams; total number of product lines and total number of marijuana alternatives offered by the retailer; and median THC and CBD concentration levels across all pooled varieties, as well as their squared values.
- $\zeta_{jt}$  is an unobserved (to the econometrician) product characteristic that is understood to be a vertical utility component in the sense that a larger value implies higher (indirect) utility. In particular, the idea behind  $\zeta$  is to capture special product features outside the dataset that cannot be captured by either the observed characteristics or the included indicators, such as monthly variations in product assortment, in-store display, or manufacturer quality
- $P_{jt}^c$  is the (after-tax) price paid by consumers for each product, where the tax structure is given by that imposed by the regulator in Washington, incorporating state and local sales taxes on the basis of the retailer location.
- $d(z_i, z_r, D_z; \lambda)$  is the (dis)utility generated by the transportation costs associated to traveling from the consumer's to the retail's locations. As in [Thomas \(2018\)](#), I assume this function is additive in two components: a linear one that is directly related to the actual driving distance between these locations ( $dr(z_i, z_r)$ ), and an extra term that intends to capture the difficulties associated to traveling in denser areas, measured as the product between the actual driving distance and the natural logarithm of the population density of census tract  $z$ . Summarizing:

$$d(z_i, z_r, D_z; \lambda) = \lambda_1 dr(z_i, z_r) + \lambda_2 dr(z_i, z_r) \ln(\text{PopDen}(z_i))$$

- The parameters  $(\beta_{i(z)}, \alpha_{i(z)})$  represent the preferences of consumer  $i$  for products' features and the (dis)utility associated to price, respectively. Heterogeneity at the consumer level is introduced by means of unobserved shocks to preferences and the influence of demographic characteristics. As customary in this literature, I assume

the following linear specification:

$$\begin{bmatrix} \beta_{1i} \\ \vdots \\ \beta_{Ki} \\ \alpha_i \end{bmatrix} = \begin{bmatrix} \bar{\beta}_1 \\ \vdots \\ \bar{\beta}_K \\ \bar{\alpha} \end{bmatrix} + \begin{bmatrix} \pi_{\beta_1 1} & \pi_{\beta_1 2} & \cdots & \pi_{\beta_1 D} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{\beta_K 1} & \pi_{\beta_K 2} & \cdots & \pi_{\beta_K D} \\ \pi_{\alpha 1} & \pi_{\alpha 2} & \cdots & \pi_{\alpha D} \end{bmatrix} \begin{bmatrix} d_1 \\ \vdots \\ d_D \end{bmatrix} + \begin{bmatrix} \sigma_{\beta_1} & & & \\ & \sigma_{\beta_2} & & \\ & & \ddots & \\ & & & \sigma_{\alpha} \end{bmatrix} \begin{bmatrix} v_{\beta_1} \\ \vdots \\ v_{\beta_K} \\ v_{\alpha} \end{bmatrix}$$

In which the vector  $(\bar{\beta}, \bar{\alpha})$  measures mean parameter values,  $(d_1, \dots, d_D)$  is a vector of demographic characteristics,  $\Pi$  is a matrix of coefficients that link demographic features to the taste parameters and  $\Sigma$  is a diagonal matrix that contains the random coefficients of the specification. The unobserved preference shocks  $(v_{\beta}, v_{\alpha})$  are constructed by means of obtaining sequences of scrambled Halton draws.

- $\epsilon_{irt}$  is an unobserved shock to consumers preferences for store  $r$  that is assumed to follow a Type-1 Generalized Extreme Value distribution.

In each period, this utility specification can be rewritten based on the linearity of the parameters to be estimated in the following fashion:

$$u_{i(z)jt} = \underbrace{\delta_{jt} \left( \mathbf{X}_{jt}, \bar{\zeta}_{jt}, P_{jt}^c; \bar{\beta}, \bar{\alpha} \right)}_{\text{Mean product utility}} + \underbrace{d(z_i, z_r, D_{zi}; \lambda)}_{\text{Transportation utility}} + \underbrace{\mu_{ijt} \left( \mathbf{X}_{jt}, P_{jt}^c, \mathbf{D}_i, \mathbf{v}_i; \Pi, \Sigma \right)}_{\text{Deviation from mean utility}} + \epsilon_{ijt}$$

Where the mean product utility  $\delta_{jt}$ :

$$\delta_{jt} = \bar{\beta} \mathbf{X}_{jt} + \bar{\zeta}_{jt} + \bar{\alpha} P_{jt}^c \quad (2)$$

refers to the common benefit all consumers get when purchasing product  $j$  in market  $t$ , while  $\mu_{ijt}$ :

$$\mu_{ijt} = \left[ \mathbf{X}_{jt} \quad , \quad P_{jt}^c \right] \times \left[ \Pi \mathbf{d}_i + \Sigma \mathbf{v}_i \right] \quad (3)$$

captures the effect of the random coefficients and demographic features on preferences for product  $j$ . As usual in this literature, I normalize the utility for the outside option in each market to be equal to zero. In this way, product  $j$  will be chosen if and only if  $u_{i(z)j} > u_{i(z)j'}$  for all alternative products in the market ( $j' : j' \in \mathcal{J}^t \ \& \ j' \neq j$ ), including

the outside option ( $j = 0$ ). In this way, the acceptance rate for product  $j$  can be written as:

$$A_j = \left\{ (\boldsymbol{\epsilon}_i, \boldsymbol{v}_i, \boldsymbol{D}_i, \boldsymbol{z}_i) : u_{ij} > u_{ij'}, \forall j' \neq j \in \mathcal{J}^t \right\}$$

Then, by assuming that the distribution of  $\boldsymbol{v}$  and  $\boldsymbol{\epsilon}$  are independent with respect to each other and the demographic characteristics, it is true that for any given market  $t$ :

$$s_j = \int_{A_j} dP(\boldsymbol{\epsilon}, \boldsymbol{v}, \boldsymbol{D}, \boldsymbol{z}) = \int_{A_j} dP_{\boldsymbol{\epsilon}}(\boldsymbol{\epsilon}) dP_{\boldsymbol{v}}(\boldsymbol{v}) dP_{\boldsymbol{D}|\boldsymbol{z}}(\boldsymbol{D}|\boldsymbol{z}) dP_{\boldsymbol{z}}(\boldsymbol{z})$$

Given the assumed distribution for the unobservable taste shock  $\boldsymbol{\epsilon}$ , the market share for product  $j$  in each market can be simulated by drawing  $N$  vectors  $(\boldsymbol{v}_i, \boldsymbol{z}_i, \boldsymbol{D}_i)$  and then computing:

$$\hat{s}_j = \frac{1}{N} \sum_{i=1}^N \frac{\exp\{\delta_j + \mu_{ij} + d_{ij}\}}{1 + \sum_{\forall j' \in \mathcal{J}} \exp\{\delta_{j'} + \mu_{ij'} + d_{ij'}\}} \quad (4)$$

## 5 Estimation

The estimation of the full mixed-logit demand system described in the previous section is performed by adapting the estimation approach in [Nevo \(2000\)](#) to account for the specifics details of the model, such as transportation costs. This approach, originally introduced by [Berry \(1994\)](#), can be summarized as a GMM estimator constructed on the basis of the average behavior across simulated individuals in each market (equation 4). In particular, it defines the objective function of the GMM problem as the weighted “square” of the interaction between a set of instruments and the structural error of the model. In order to compute the latter, the method initializes the search with a starting point for the vector of non-linear parameters  $(\boldsymbol{\lambda}, \boldsymbol{\Pi}, \boldsymbol{\Sigma})$ , computes the value of  $\delta$  such that observed and simulated market shares are equal to each other, and finally obtains the residual or structural error of the model  $\boldsymbol{\xi}$  by means of estimating equation 2 via an instrumental variables procedure. The set of estimated parameters is then given by those that minimize the value of the GMM objective function.

Regarding the simulation of consumers and their corresponding individual choice probabilities, I first randomly draw (with replacement) six hundred consumer addresses (census tracts) from each market (geography-month pair) and compute the corresponding distances to each active store in the market. Finally, I use the conditional distributions that

result from the demographic information of each address described in subsection 4.1.2 to simulate individual covariates at the consumer level. Once idiosyncratic components have been obtained, I follow the steps described in the previous paragraph to obtain the full vector of estimated parameters and their corresponding standard errors, for which I use two steps of the same procedure to improve the weighting matrix in the objective function to account for the possibility of heteroskedastic errors.

## 5.1 Identification, Endogeneity and Instrumental Variables

In order to estimate the demand model described in the previous section I exploit three different sources of variation that contribute to identify the parameters associated to the assumed indirect utility function. First, staggered entry by retailers, demographic differences across census tracts, and the mechanism described to allocate consumers locations to markets provide a source of variation that is potentially helpful to explain parameters associated to preferences for each retail store and the distance cost of traveling to them. Second, the uninterrupted addition of stores, manufacturers, and varieties across the sample generates an additional source of useful variation by means of continuously expanding the product set  $\mathcal{J}^t$ . Finally, relative price variation over time, as described in section 2, also contributes to identify substitution patterns across specific products.

A usually frequent concern when estimating these models is related to the endogenous relation between the unobserved component  $\xi$  and prices. The effects of endogeneity bias arise as a result of retailers making decisions when knowing more about the unobserved characteristics  $\xi$  than the researcher does. In particular, at the time of making pricing decisions retailers not only observe the features included in  $X_{jt}$ , but also those summarized in  $\xi_{jt}$ . To capture most of the unobserved features, I include in the mean utility specification dummies at both the retailer and the manufacturer level, capturing retailer and manufacturer specific average features across the entire sample. Additionally, I include month-year level dummies that capture the evolution of monthly unobserved determinants of demand. In this way, the econometric error that remains in  $\xi_{jt}$  will include idiosyncratic (product-level) deviations from the expected retailer-manufacturer-month average quality. Changes in store structure, retailer customer service, manufacturer quality, in-store product display, promotions, and even unobserved consumer preferences are all examples of terms that the econometrician ignores but the retailer might not.

Given the potential dependence of prices on  $\xi_{jt}$  and the need to estimate the entire vector of parameters in the model, I use three sets of variables while performing the

estimation procedure. First, I construct a set of instruments *a la* [Berry et al. \(1995\)](#) on the basis of the set of characteristics in  $X$  (excluding dummy variables). Second, I add distance- and market size-related measures in order to account for the effect of local competition on prices. For each store and each month I compute the following measures: total population of and average distance to the 1, 2, 5 and 10 closest consumer addresses (census tracts' centers of population), (inverse-distance) weighted population in the closest 2, 5 and 10 consumer addresses, the average distance to the closest 1, 2, 5 and 10 retailers (no matter whether they are on the same geographic market or not), the average distance to competitors in the market, and lastly the average distance between retailers in the market. Finally, as mentioned before, I expand this dataset by means of adding retailer, manufacturer, and month-year fixed on the right hand side of the regression.

## 5.2 OLS and IV Estimates

I first present the results associated to the OLS and IV estimation of the logit demand model defined by the specification of the mean utility  $\delta_{jt}$  in equation 2. Because of the assumption that idiosyncratic shocks  $\{\epsilon_{ijt}\}$  follow Type-1 Generalized Extreme Value distribution,  $\delta_{jt}$  is equivalent to the natural log of the ratio between the market share of product  $j$  and that of the outside option  $j = 0$ . The results of regressing  $\ln(s_{jt}) - \ln(s_{0t})$  on the vector of observable product characteristics and the set of retailer, manufacturer, and month-year dummies are presented in Table 7 from appendix E.

The first column in the table corresponds to the application of the regular OLS procedure. Coefficients for which one has a strong prior are statistically significant and have the expected sign: lower prices, and greater variety at the store level (both in terms of number of UM alternatives and total number of product lines) generate higher chances of patronizing a given store and purchasing a product from there. Additionally, the significance of the linear and quadratic terms for THC and CBD concentration suggests that preferences are non-monotonic over these product level features. Unexpectedly, the coefficient for the size dummy is negative, suggesting larger packages are less attractive even when controlling for prices. These estimates imply that only a 30% of products in the market are priced elastically, with a median own price elasticity of -0.51.

The second column in the table present estimates of the model that controls for the possibility of unobservable (to the econometrician) attributes  $\xi_{jt}$ , the error term of the estimated expression, being correlated with prices. To account for this potential source of endogeneity, I estimate the model following an instrumental variables approach con-

sidering the set of IV variables described in the previous subsection. In this case, albeit signs and magnitudes for most covariates experience little changes with respect to the OLS estimates, the new price coefficient indicates demand is almost three times more sensitive to prices. The increase in the intensity of the price coefficient directly translates into a larger share of products being priced elastically (55%), with a median elasticity value of -1.32. Additionally, the coefficient on the size dummy is positive, suggesting consumers obtain a higher mean utility from bigger packages. The last two rows in the table present the statistics that result from considering both the endogeneity of consumer prices and the relevance of the instruments used. While the value of the Kleibergen-Paap  $rk$ -statistic indicates the set of instruments is not weak, the statistic associated to the null hypothesis of prices being exogenous strongly rejects such possibility.<sup>22</sup>

An important point to notice is that the set of instrumental variables used in the IV regression does not include the acquisition cost of the product. In principle, one might think that since a cost shifter is available it should be used to aid in the identification of the price coefficient. However, I have argued in previous sections of this paper that for a significant share of products the acquisition cost is just a fraction of the retail price. Therefore, if some of the unobserved characteristics summarized by  $\zeta$  are indeed observed and priced by manufacturers, acquisition costs will not help to resolve the endogeneity concern.<sup>23</sup>

### 5.3 Full Model Estimates

Table 8 presents the estimates that result from the full mixed-logit demand system using the same instruments as described above while ignoring the acquisition cost. The upper left panel of this table summarizes the coefficients governing the mean utility specification. The comparison of these estimates to their counterparts in table 7 (specifically, column “IV2”) reveals that while most effects become stronger (larger coefficients in absolute value), some of them remain significant from a statistical point of view and some others do not. In particular, preferences for prices, larger packages, in-store variety and THC are still

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<sup>22</sup>This statistic is constructed as the difference between the Sargan-Hansen J-stats that result from two models: one in which consumer price is treated as endogenous and therefore instrumented with the corresponding set of IVs, and another in which consumer price is treated as exogenous. It is distributed  $\chi^2$  with as many degrees of freedom as suspected endogenous regressors (1 in this case).

<sup>23</sup>In fact, if the acquisition cost is indeed included in the set of instruments two results are worth mentioning. As expected, instruments become extremely strong (the Kleibergen-Paap  $rk$ -statistic is now about eight times larger). However, estimated coefficients are almost identical to those obtained by OLS. In particular, the price coefficient decreases in absolute value to -0.0241, leading to an even smaller share of products being priced in the elastic portion of their corresponding demand schedules (23%).

significant at conventional levels. However, preferences for CBD content are now much noisier than before.

The upper right panel of the table presents the coefficients associated to unobserved heterogeneity in preferences. While most coefficients are associated to large standard errors, the impact of the random coefficient on price is strongly significant and represents about 10% of the mean coefficient. Finally, the lower panel of the table summarizes the impact of demographics on consumer preferences. When estimating the model, I restrict most interactions to just affect the constant term, except for income which has traditionally been interacted with the price variable in order to capture the fact that richer consumers are less sensitive to changes in prices. Finally, the lower panel also presents the results associated to the utility generated by traveling to each store. As in [Thomas \(2018\)](#), which uses the same functional form to capture this utility, the linear parameter is positive and about two times larger in absolute value than the term that is interacted with the population density. According to my estimates, both terms in the transportation function are strongly significant, stressing the relevance of adding this term in the decision process of consumers in this market.

The overall performance of the estimated model is assessed by means of the own-price elasticity and transportation costs distributions, summarized in table 9. Transportation costs in this model are estimated to have a median value of \$1.8 per mile, a figure that is in line with estimates of such costs in retail markets.<sup>24</sup> Additionally, less than 2% of the census tracts derive positive utility from traveling, a feature that mostly obeys to their extremely low population densities.

Regarding own price elasticities, estimates from the full model result in values that are about three times larger than in the model without heterogeneity in preferences (up to the idiosyncratic shock  $\epsilon$ ). As a consequence, almost all products (99.8%) are now priced at the elastic portion of their demand schedules, a result that is in line with what [Hollenbeck and Uetake \(2018\)](#) and [Thomas \(2018\)](#) have obtained for this market. Additionally, larger packages are more elastic than their smaller counterparts, a feature also observed in [Miravete et al. \(2018\)](#) for the case of spirits bottles in Pennsylvania. The month-by-month evolution of the overall median elasticity and that of small and large package sizes is presented in figure 22.

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<sup>24</sup>[Houde \(2012\)](#) estimates a cost of \$0.90 per minute in the case of retail gasoline markets. At an average speed of 15 mph (20 mph) this would imply a cost of about \$3.60 (\$1.80) per mile. [Thomas \(2018\)](#) estimates a cost of \$0.75 per mile, although is worth repeating her markets were defined to be constrained at a given radius around each consumer address, resulting in much shorter trips to stores and therefore dwindling the relevance of distance as a decision driver.

Estimates of the full model also generate the expected results in terms of substitution patterns across products, conditional on either their package size or the retailer who is selling the product. First, as can be noticed in the left panel of table 10, demand for 1-gram (3.5-gram) packages is relatively more responsive to changes in prices of products of the same size than to changes in prices of packages with larger (smaller) content. Second, when looking at substitution across retailers the right panel of table 10 reveals that demand reacts more to changes in prices of other products within the same retailer than to changes in prices of products sold by other sellers in the market.

## 6 Counterfactual Exercises

Based on the demand estimates described in the previous section, I perform two exercises in order to understand how far are observed prices from their optimal counterparts. In both of these exercises, I assume retailer  $r$  chooses prices for all goods she sells (grouped in set  $\mathcal{J}_t^r$ ) in order to maximize their market-level variable profits, so her problem in every market  $t$  can be expressed as follows:

$$\max_{\{P_{jt}^r\}_{j \in \mathcal{J}_t^r}} \sum_{j \in \mathcal{J}_t^r} (P_{jt}^r - w_j^r) s_{jt}(\mathbf{P}_t^c) M_t \quad (5)$$

in which  $P_j^r$  is the price the retailer charges for product  $j$  before any taxes;  $w_j^r$  is the marginal cost associated to such product;  $s_j(\mathbf{P}^c)$  is the market share function for product  $j$ , which depends on the full vector of consumer prices (post-tax prices) for all products in the market; and  $M$  is the corresponding market size.

### 6.1 Best Responses

As mentioned in section 2, industry regulators in Washington established quotas to the number of retailers that could operate on any given geography in the state. In order to deal with situations in which the number of applicants for a license exceeded the number of allowed stores, the regulator implemented a lottery to select which applicants would be licensed to operate, potentially resulting into a considerable degree of heterogeneity across retailers in terms of “business skills”.<sup>25</sup> A possible implication of this potential

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<sup>25</sup>In conversations with industry participants, for example, I was once told that “Because retail was a lottery system, you have used car salesmen, dispensary owners, accountants, anyone and everyone who owns retail businesses.”

heterogeneity can be assessed by means of analyzing each retailer responses to the competitive environments in which they operate. In particular, it could be hypothesized that more experienced or knowledgeable sellers have a better understanding of demand and competitors' behavior, leading to prices being set in such a way that observed profits do not differ much from the ones that those retailers would obtain if they were to react to what every other competitor is doing.

Therefore, in this counterfactual scenario I let each retailer at a time learn the estimated demand for her products, keeping fixed prices for all other competitors in the market. Given this knowledge, every retailer at a time is allowed the possibility to re-optimize her prices in order to potentially increase her variable profits. As an important note, in this exercise I assume marginal costs are equal to the observed acquisition costs in the sample. In fact, acquisition costs only provide a lower bound for the true value of marginal costs, albeit it seems reasonable to argue that the former should represent a sizable share of the latter.<sup>26</sup>

Figure 23 presents the cumulative distribution function for both observed and best-response prices in this counterfactual scenario, distinguishing across package sizes. A remarkable feature of these distributions is given by the fact that while best-response prices for 1-gram packages are very close to observed prices, this is not true for the case of 3.5-gram packages, where the distribution for observed prices first-order stochastically dominates the one that results from pooling together prices generated from unilateral deviations. This can also be appreciated in the scatter plots presented in figure 24. When only looking at 1-gram products, I find that observed prices are higher than those that result from optimal unilateral deviations in 56% of the 32,392 cases, indicating an even split between over- and under-pricing situations. On the contrary, such figure increases to 98% of the 30,266 product-market pairs involving 3.5-gram packages, suggesting that regardless of any possible characteristics, these products are almost always being overpriced by retailers.

These pricing discrepancies across package sizes can also be noticed when adding a temporal dimension to the analysis. To do this, I first compute the median observed price deviation from best-response prices (as a percentage of the latter) using all products in each market. Then, I compute the interquartile range and median value for this variable across markets, and plot them as a function of time, as presented in figure 25. At the

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(...) *(E)stablishing retail relationships can be maddening*".

<sup>26</sup>Additional marginal cost elements could include the cost of storage, the opportunity cost of shelf space, and the cost of the capital invested to build stocks. To the extent these costs do not make up for a sizeable share of marginal costs, the assumption in this exercise does not seem like an unreasonable one.

industry onset, both small and large packages were being overpriced in the median market. However, as months went by trends begun to differ: while observed prices for 1-gram packages started to get closer and closer to their optimal values in unilateral deviations, this was not the case for 3.5-gram packages, which remained about 40% above their best-response value for the entire data span. Surprisingly, the convergence of prices to optimal values in smaller packages did not stop at zero deviation levels, leading to the under-pricing situation that justifies the figures discussed in the previous paragraph.

Summarizing, these figures suggest that while retailers have improved their pricing of small packages over time, this has not necessarily been the case for larger packages, where overpricing is the norm. As a result, most retailers do not get to realize a large fraction of their potential profits. To learn about this possibility, for each retailer-month I compute her effective share of profits, understood as the ratio of realized variable profits to those she would obtain by best-responding to the status quo in her competitive environment. Additionally, for each retailer I then compute the mean and standard deviation across months for the effective share measure. In order to distinguish old from new sellers, I split the sample into those who were active for more than twelve months and those who were not. The scatter plots with the corresponding means and standard deviations across these groups are presented in figure 26. Despite a slight difference in standard deviations, both groups of retailers record a similar average performance regarding their ability to capture potential profits in the market. In both cases, the median retailer is able to obtain, on average, half of the variable profits she would get if she were to best respond to her competitive environment. The heterogeneity across retailers can still be appreciated by means of the ample range that characterizes the distribution of the mean effective share: while some retailers only obtain 30% of what they could get, others manage to get more than twice as much in relative terms.

## 6.2 Bertrand-Nash Competition

In the following exercises I consider the possibility of firms engaging in full information Bertrand-Nash competition. Differently from the best-response scenario described before, in this case firms play a game in which they simultaneously choose prices in order to maximize their profits, under the assumption that all payoff-relevant elements are known not only to them but to every competitor in the market. Therefore, in the Bertrand-Nash equilibrium all firms set prices that solve the first order conditions that derive from the profit maximization problem presented in expression 5 given their competitors' choices,

which are, in turn, also optimal.

In the next subsections I discuss the results associated with two different but related exercises. First, I assume that marginal costs are equal to observed acquisition costs and let firms engage in full information Bertrand-Nash competition. Once equilibrium prices are computed, I calculate the corresponding quantities and tax revenue generated by this model of competition and compare it to the observed measures. Additionally, I also compute the distribution of multipliers (retail price divided by acquisition cost) that results from this model and compare it to the observed distribution in the data. Second, I follow the standard practice in the literature and assume that observed prices in the market are consistent with a Bertrand-Nash equilibrium. Under this assumption, it is customary to invert the first order conditions from the profit maximization problem of each firm in order to back out unobserved marginal costs. Given I observe acquisition costs for each product, I then compare marginal costs estimates to the lower-bound reference value provided by observed per-unit acquisition costs in the data.

### 6.2.1 Bertrand-Nash Equilibrium

In this section I compute the equilibrium outcomes that result from the combination of two assumptions: Bertrand-Nash competition, and the equality between observed acquisition costs and marginal costs. Table 11 summarizes the main departures of this counterfactual scenario with respect to the observed market outcomes in the data. The analysis of profitable unilateral deviations in the first counterfactual scenario discussed in this section revealed that firms had a lot to gain from decreasing prices, specially in the case of 3.5-gram packages. Since when competing *a la* Bertrand choice variables are strategic complements, it is not surprising then that in this alternative scenario equilibrium prices are, on average, 20% lower than their observed counterparts. However, price competition has different effects conditional on package size: while prices for small products fall by 6%, those for large products decrease by 34%. Given demand for 3.5-gram products was highly elastic at observed prices (as presented in figure 22), these price contractions have a significant impact on the total grams of Usable Marijuana consumed, which increases by more than three times. However, such increase is completely driven by large products; in fact, consumption of small products falls despite the described (mild) reduction in their prices, denoting substitution towards larger products.

The impact of these changes in variable profits follows the same pattern as changes in quantities sold. While variable profits generated by 1-gram products are cut in half, those

coming from 3.5-grams double. In this way, variable profits at the industry level increase by 32% though this is not an homogeneous qualitative effect across retailers, since about 30% of all retailer-month pairs record a negative variation in variable profits. Finally, the contraction in prices does not seem to prevent the state from increasing its tax revenue; on the contrary, the expansion in consumption allows the state to collect about 2.5 times more than what it currently obtains under the observed price distribution.

The final step is to concentrate now on the relationship between the results that emerge from this exercise and the use of the pricing rules as described in section 3. The 1-gram and 3.5-gram products of Usable Marijuana selected for the demand estimation exercise are not only the most important ones in terms of quantity shares (39% and 15% of all units sold, respectively) and sales shares (21% and 25% of all sales, respectively), but also exhibit different final consumer prices (see figure 27) in such a way that end up providing an accurate representation of the price spectrum over which the prevalence of rules can be assessed.

The prevalence of rules across these two products in the observed data is presented in figure 28. As documented in section 3 when conditioning on different covariates, it is possible to notice an increase over time in the prevalence of rules for both small and large product sizes. More specifically, in the case of 1-gram packages both  $m = 2.0$  and  $m = 2.5$  have a considerable role in explaining prices (about 30% each, considering all units sold by the median retailer in terms of rules' prevalence), leading to an overall matching rate of almost 60% for the median retailer. When looking at 3.5-grams packages, about 40% of all products sold have prices that are consistent with the use of these rules, being this result mostly driven by keystone pricing ( $m = 2.0$ ). Importantly, these plots show that by the end of the sample (November 2016), the distribution of the within-retailer share of units sold that are explained by  $m = 2.0$  is almost identical for both small and large products. This result points in the direction of retailers using similar rules to price both types of goods, a strategy that is in principle at odds with the idea of firms optimally defining pricing schedules that take into account all relevant differences across products.

The cumulative distribution functions for both observed and counterfactual prices conditional on package size are shown in figure 29. The left panel of the figure focuses on 1-gram packages. Up to their median value of approximately \$10, observed prices seem to be consistent with Bertrand-Nash pricing behavior as per the overlapping between the two CDFs. In the remaining half of the data it is possible to notice some overpricing, although the decreasing price trend observed in figure 27 for these products suggests most of these differences come from earlier months in the sample. The right panel of figure 29

focuses on 3.5-gram packages, for which the story is substantially different. In this case, the distribution of observed prices first-order stochastically dominates the one obtained in the Bertrand-Nash equilibrium scenario, suggesting overpricing is the norm for these products. These results indicate that by following similar pricing strategies across both products, retailers set prices that are not consistent with a Bertrand-Nash equilibrium. Although the 50% markup rule seems to approximate the optimal pricing behavior for small products in a satisfactory manner, this strategy generates prices that are far off from their optimal counterparts when looking at large products. Table 12 summarizes the average price deviation from Bertrand-Nash prices across product sizes and whether observed prices are a match or not to the rules defined in section 3. While the average price deviation for 1-gram products that match the rule (8.5%) is a half of the one observed in prices that did not match the rule (16.9%), this relation reverses in the case of 3.5-gram packages: while conditional on being consistent with rules prices are 62.6% above their optimal value, those products for which the rule was not a match record a slightly lower deviation of 58%.

One might still be concerned about the fact that so far in this exercise I have abstracted away from the institutional constraint defined by the need to resort to cash as the predominant means of payment. Even though it is not possible to know which exact rounding mechanism each retailer uses to price her products, I assess the potential impact of preferences for integer prices by rounding Bertrand-Nash prices with the same formula I used in the algorithm that matched observed prices to rules in section 3. This rounding procedure generates the upper and lower bounds denoted by dashed lines around the Bertrand-Nash optimal prices presented in figure 29. Importantly, the considerations introduced in the previous paragraph regarding the relationship between optimal and observed prices across product types remain all valid, even when allowing for the possibility of rounding. The differences across product types can also be noticed in the density plots for observed multipliers and those that result from rounding up prices in the Bertrand-Nash equilibrium.<sup>27</sup> As can be appreciated in figure 30, while the density plots for 1-gram packages look very much alike both in shape and range, those for 3.5-gram packages are extremely different, being Bertrand-Nash multipliers much more concentrated around  $m = 1.5$  than observed values.

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<sup>27</sup>The density of Bertrand-Nash multipliers when disregarding rounding is smooth, and therefore differs remarkably from that of observed multipliers. To capture the possibility of spikes in the counterfactual distribution of multipliers I choose to round up Bertrand-Nash prices and get the multipliers that would result in this scenario. Rounding down would also generate spikes in this distribution, but it would not account for the fact that retailers seem to be overpricing their products.

## 6.2.2 Using First Order Conditions to Recover Marginal Costs

Suppose now that observed prices in each market are in fact equilibrium prices that result from firms simultaneously choosing their prices to maximize their profits. Given the profit maximization problem presented before (equation 5), the equilibrium assumption implies that all first order conditions for each firm's problem are satisfied and therefore the vector of observed prices  $\mathbf{P}_t^c$  is such that for each product  $j$  and retailer  $r$  in market  $t$  it is true that:

$$0 = s_{jt}(\mathbf{P}_t^c) + \sum_{k \in \mathcal{J}_t^r} (P_{kt}^r(P_{kt}^c) - w_{kt}^r) \frac{\partial s_{kt}(\mathbf{P}_t^c)}{\partial P_{jt}^c}$$

Given marginal costs are frequently unobserved by researchers, the assumptions of competition a la Bertrand and current equilibrium imply that the unique unobservable element in the system of first order conditions in each market is the vector of marginal costs  $w_t$ . Therefore, a simple inversion of the system of first order conditions allows the researcher to recover the vector of marginal costs that is consistent with observed prices in the market.

I follow this idea and use both observed prices and demand estimates to back out the vector of marginal costs that is consistent with a Bertrand-Nash equilibrium being played in each market. Overall this procedure shows a reasonable performance, in the sense that it estimates negative marginal costs for only 0.7% of the products in the sample. More importantly, and given observed acquisition costs should provide a lower bound for the true value of marginal costs, 85.5% of products have estimated marginal costs that are higher than the corresponding observed acquisition cost. As can be noticed in both the cumulative distribution functions and the scatter plots presented in figures 31 and 32, 1-gram packages are responsible for 95% of all cases in which the model underestimates the true marginal cost. For the case of 3.5 grams packages, almost 99% of products are associated to implied marginal costs that are higher than the corresponding acquisition cost.

Figure 33 presents the ratio of acquisition cost to estimated marginal costs for the 85.5% of products in which the latter is larger than observed wholesale prices. While acquisition costs seem to represent a sizable share of the estimated marginal cost for small products (73% on average), their relative importance is diminished once looking at 3.5-gram packages. For these larger products marginal costs are estimated to be, on average, twice as high as the per-unit acquisition cost. These numbers indicate a significant difference between unobservable components of the marginal costs across product sizes,

not only in magnitude but also in relative terms. Although it is possible to think that because larger products are bulkier and more expensive both unobserved storage costs and capital costs, for example, should be higher, these estimates suggest that they have to be more-than-proportionally larger in order to rationalize current prices as the outcome of a Bertrand-Nash equilibrium.

## 7 Concluding Remarks

The fair share of attention paid in the past to the theoretical debate between “satisficing” rules and marginalist principles has not been necessarily paralleled by the development of an empirical counterpart. Likely due to the lack of appropriate data to test alternative hypotheses, empirical assessments of the performance of rules vis a vis optimal decisions are not commonplace in the economics literature. In this paper, I contribute to filling this gap by studying the prevalence of pricing rules and their relative performance in a specific market.

In particular, in this paper I have studied the extent to which multiproduct retailers in the new retail cannabis market in Washington state resort to pricing strategies based on rules of thumb, as well as the corresponding empirical implications of this behavior in terms of market outcomes. To this goal, I put together a comprehensive dataset at the transaction level that covers the universe of retail transactions during the first twenty-nine months of this market’s existence. Using this dataset, I performed two empirical exercises in order to shed light on both the prevalence and the performance of pricing rules in the market.

To quantify and assess the role of pricing rules in the market, I focused on a specific type of behavior in which retailers price their products by means of applying a fixed multiplier to the acquisition cost of the products they sell. To count the share of units sold at prices that are consistent with these types of rules, I constructed an algorithm that embeds an institutional feature from this market (integer prices) into a pricing rule that predicts prices on the basis of two multipliers,  $m = 2.0$  and  $m = 2.5$ , the wholesale cost of each product, and the tax structure in each market. I then computed the share of observations that are matched with these predictions to find that approximately half of all units sold in the market had prices consistent with pricing rules. Importantly, I also find that the prevalence of these rules becomes more important as time goes by and markets get flooded with new products, a result that is in principle at odds with the idea of firms learning to price

by optimally capturing the differences across their products. As a result of this process, markups over price tend to concentrate around 50%, a figure that adheres to an important strategy in the retail industry that is commonly known as “keystone pricing”.

I then evaluated the potential optimality of this behavior by means of simulating a benchmark counterfactual scenario in which fully-informed firms compete a la Bertrand and price optimally. To do so, I estimated a discrete choice model for cannabis products in Washington in order to recover the parameters governing heterogeneous consumers preferences across markets. The simulation of the Bertrand-Nash scenario reveals that although rules perform reasonably well for some type of products, for others they generate prices that are significantly larger than those that would be observed if firms were playing a Bertrand-Nash equilibrium. Moreover, and given the availability of public information, it is reasonable to think that the increasing prevalence of rules could be due to a collusive behavior of retailers in order to obtain higher profits. Since my estimates for the Bertrand-Nash equilibrium imply firms are currently only capturing 75% of the variable profits they would obtain in the counterfactual benchmark, collusion seems a less likely possibility.

Summarizing, these results speak to the difficulties associated with pricing products correctly in competitive environments with multiproduct oligopolists. When firms use rules to price their products, as seems to be the case for a part of this industry, the optimality assumption generally used to back out model primitives such as marginal costs should be scrutinized, inviting researchers to put more thinking into the relative importance of potential divergences that would emerge from assuming optimal behavior.

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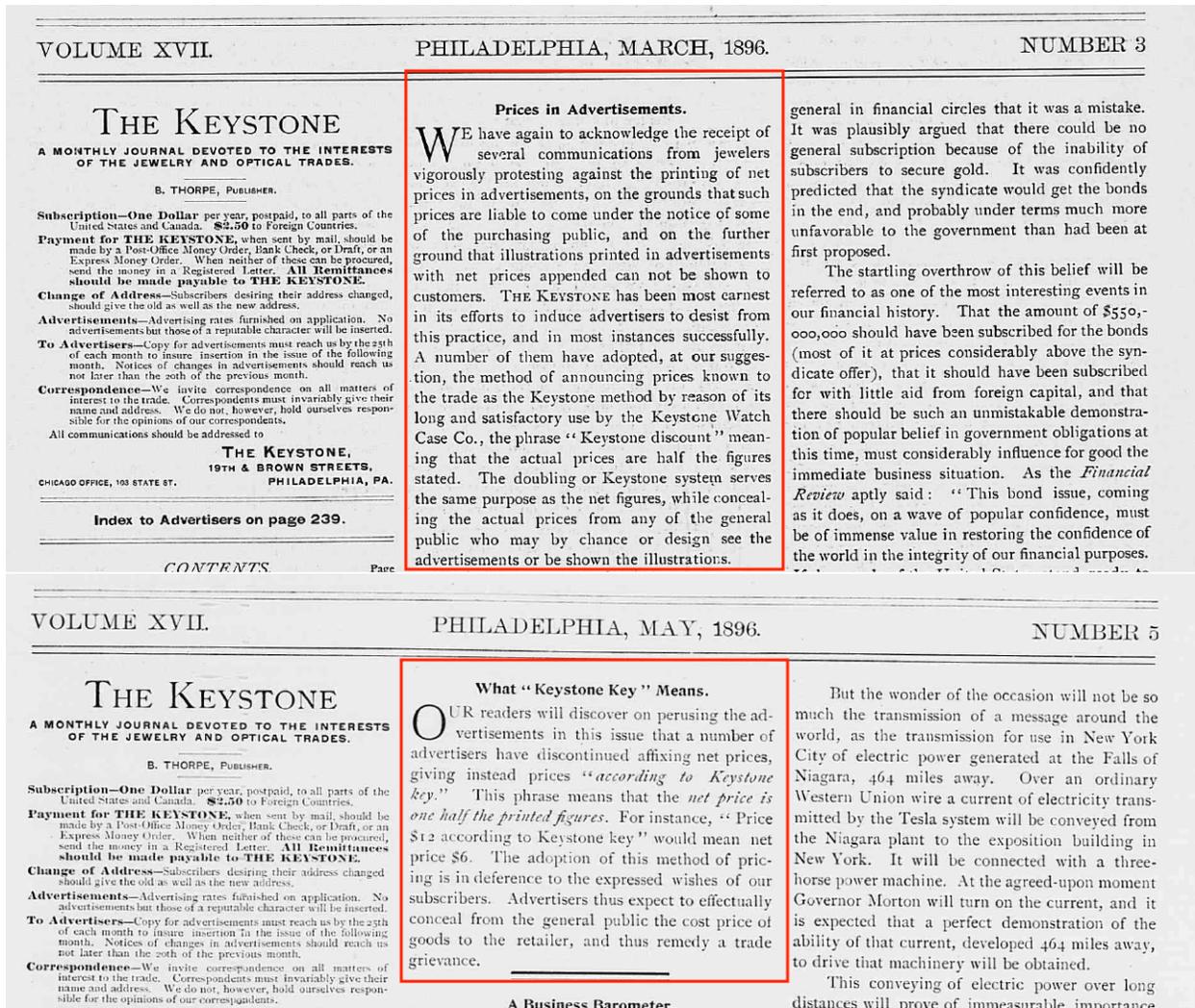
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# A Introduction

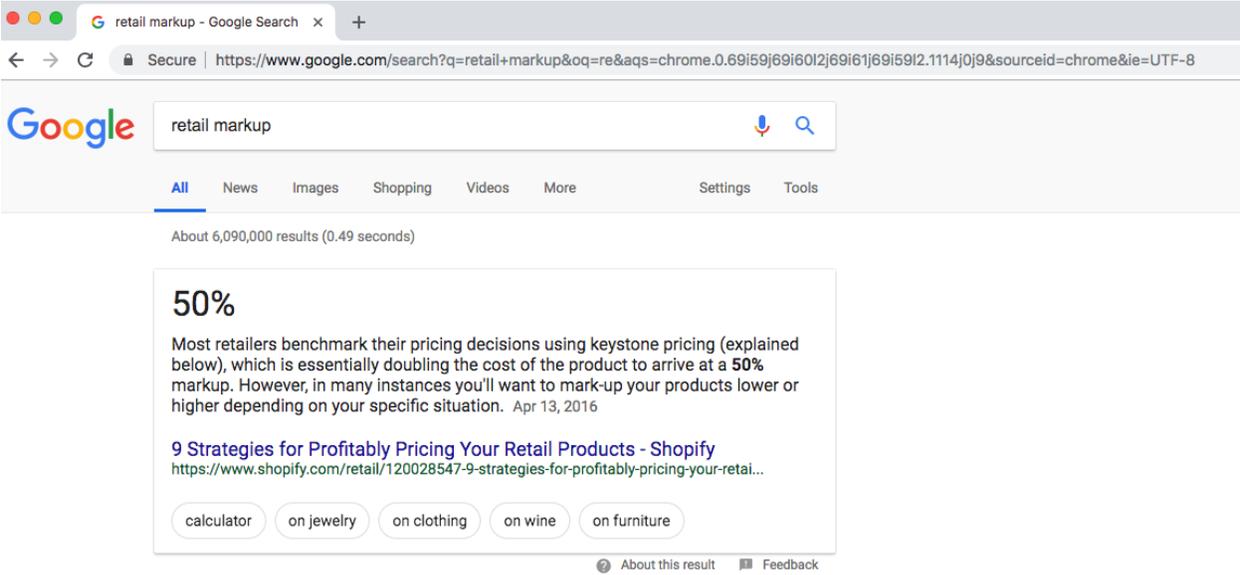
Figure 1: Keystone Pricing



Note: These figures were extracted from the web archives of the National Association of Watch & Clock Collectors on August 2018.

Volumes for "The Keystone" magazine available at <https://nawcc.org/index.php/resources?id=1301>.

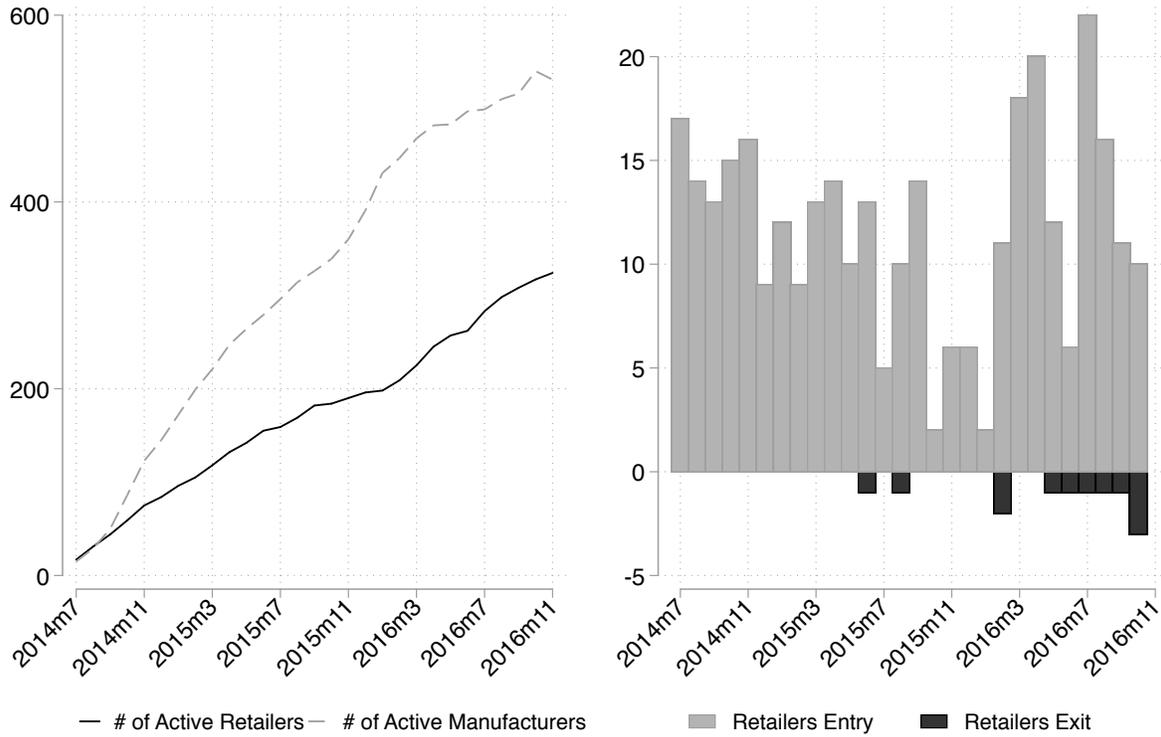
Figure 2: Retail Markup Search



Note: Search performed on www.google.com on September 5, 2018.

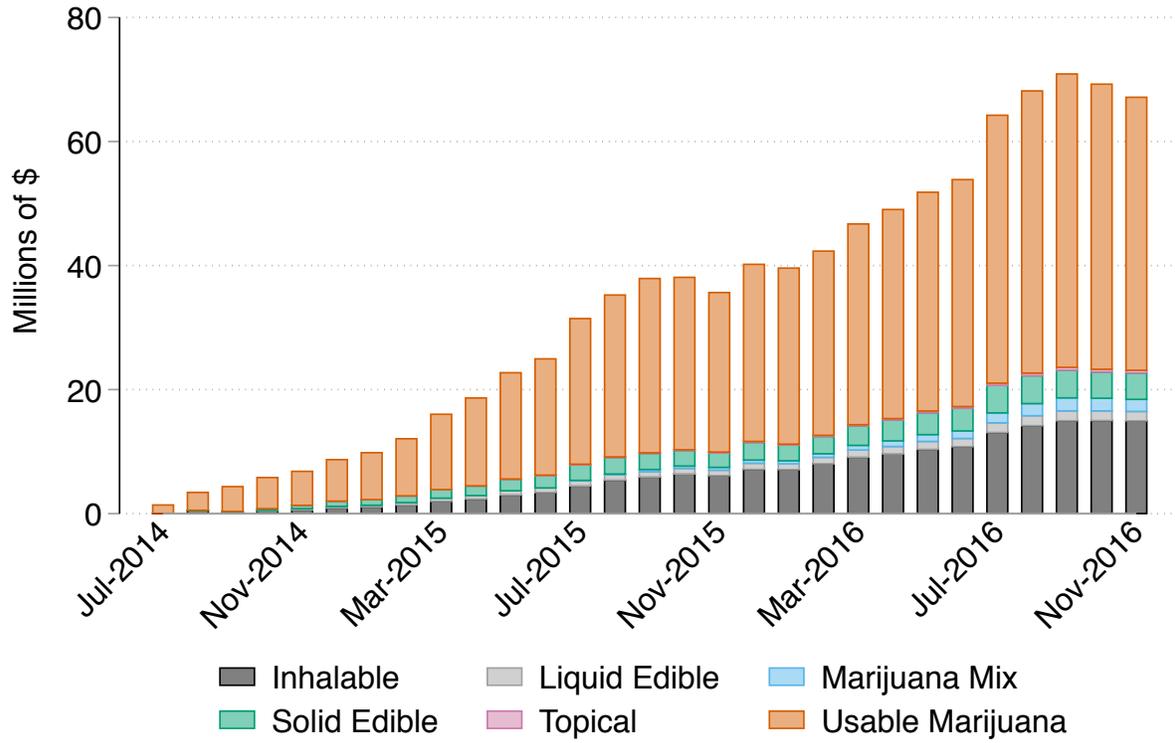


Figure 4: Entry and Exit Dynamics



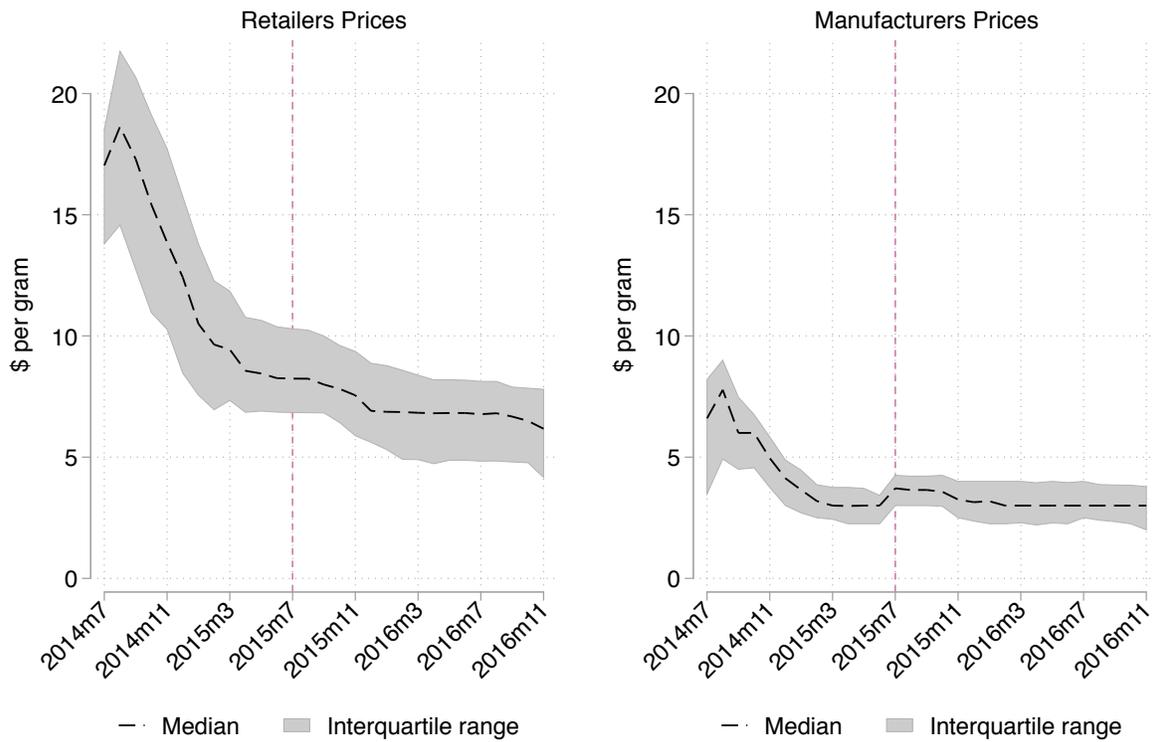
Note: For the purposes of this paper I label as “manufacturers” all those processors and producers that sell product directly to retailers. The left panel in the figure shows the evolution in the number of active manufacturers and retailers in the market. The right panel in the figure shows the pattern of entry and exit by retailers.

Figure 5: Monthly Retail Revenues



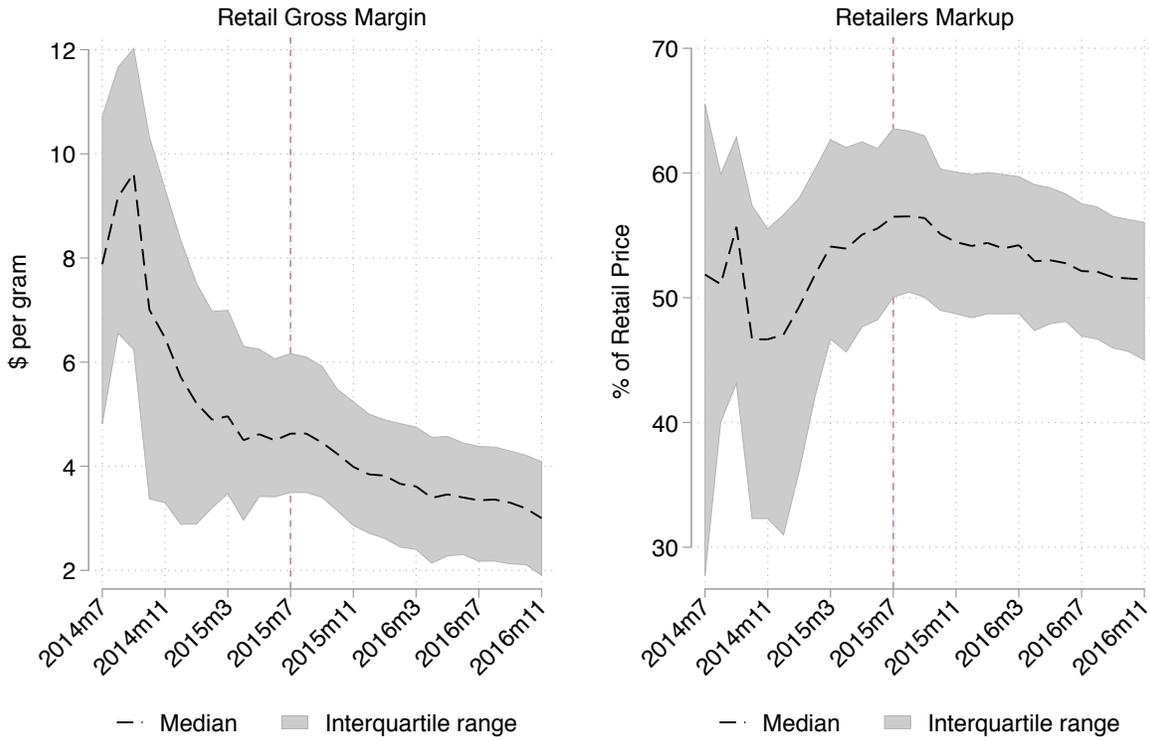
Note: This plot presents the distribution of monthly revenues at the retail level, as well as its decomposition across the product categories.

Figure 6: Retail and Manufacturer (Pre-Tax) Prices per gram of Usable Marijuana



Note: This plot presents the median (horizontal dashed line) and interquartile range (25-75 percentiles, shaded area) for pre-tax retail (left panel) and manufacturer (right panel) level prices for the sample under consideration. The vertical dashed line indicates the month in which the tax structure was changed (July 2015).

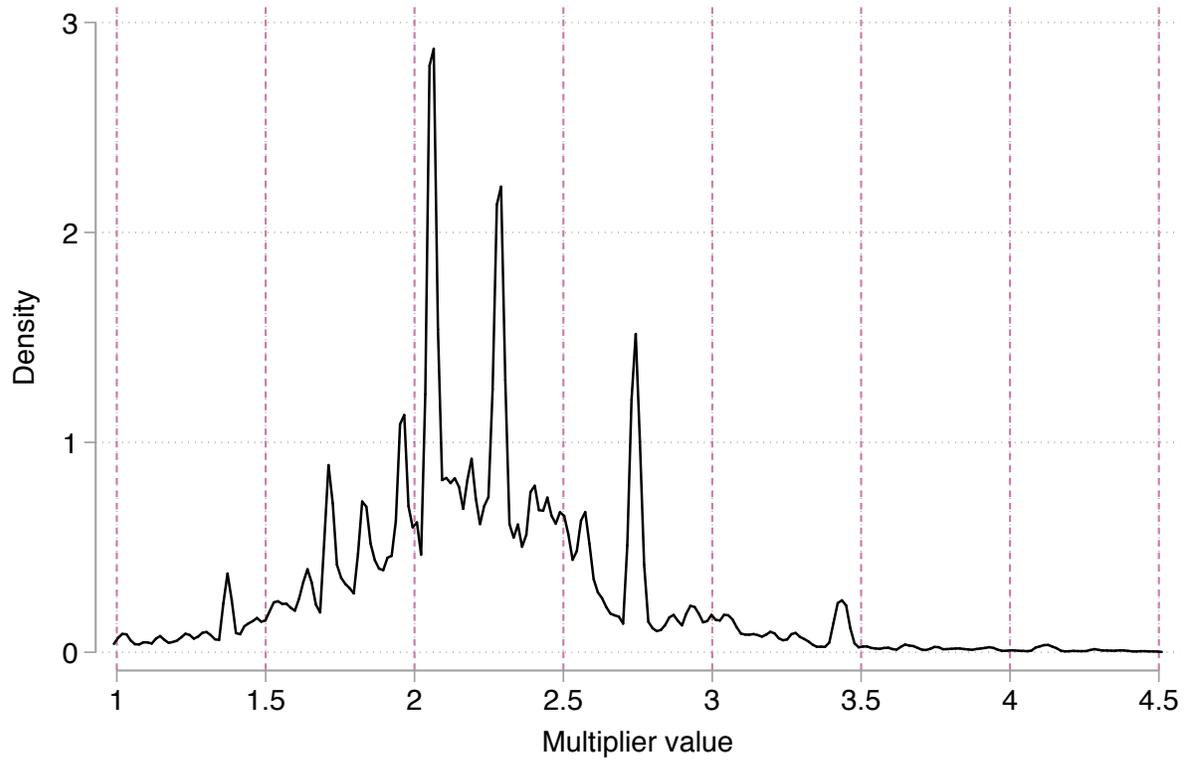
Figure 7: Retail Gross Margins and Markups per gram of Usable Marijuana



Note: This plot presents the median (horizontal dashed line) and interquartile range (25-75 percentiles, shaded area) for the retail gross margin (left panel) and markup over prices (right panel) per gram of Usable Marijuana. The vertical dashed line indicates the month in which the tax structure was changed (July 2015).

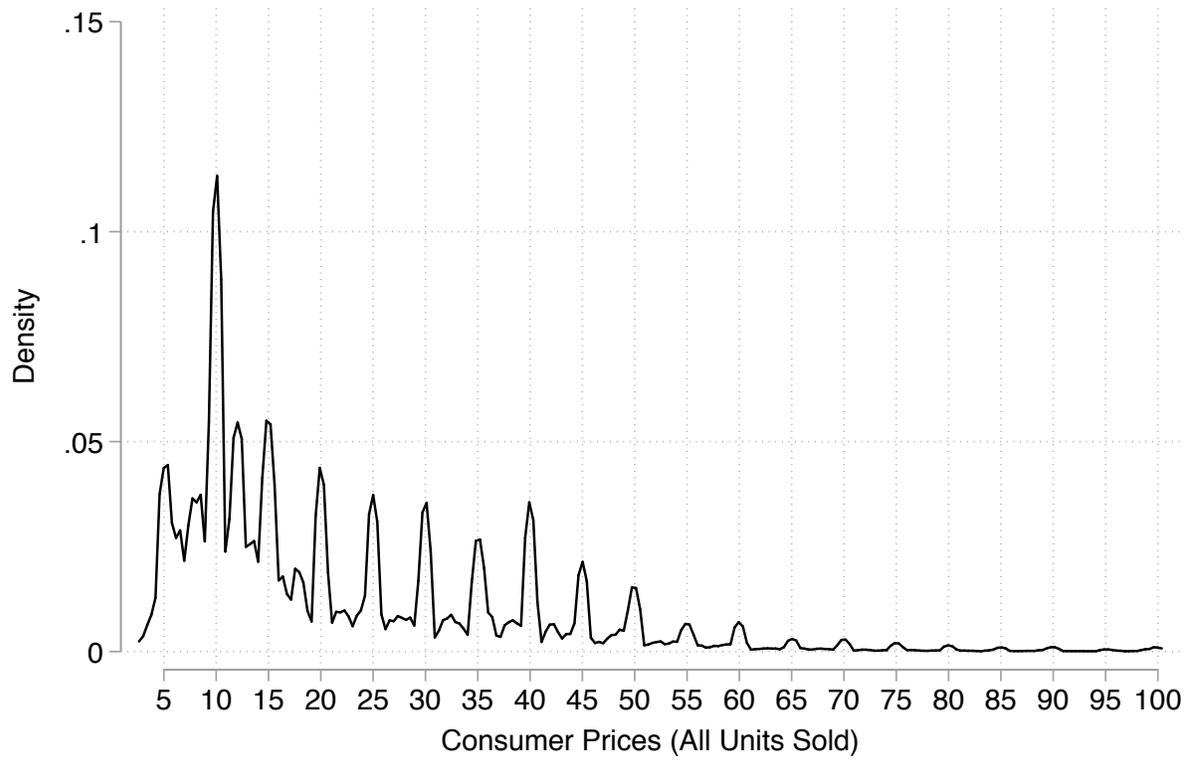
## C Rule-of-thumb Pricing

Figure 8: Empirical Distribution of Observed Multipliers



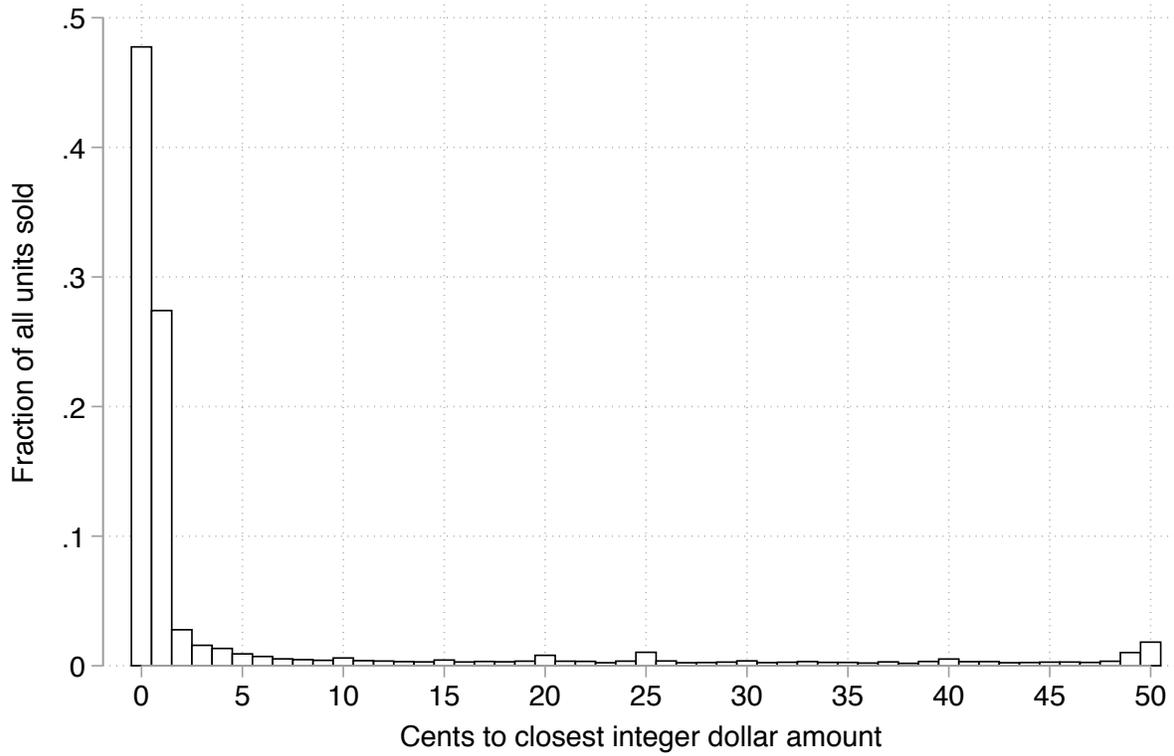
Note: Density plot corresponding to multipliers in the 1%-99% of the entire sample. Vertical lines highlight potentially relevant values for these multipliers in terms of mass concentration. This is an Epanechnikov kernel density plot obtained using 250 points in the estimation.

Figure 9: Empirical Distribution of Consumer Prices



Note: Density plot corresponding to multipliers in the 1%-99% of the entire sample for consumer prices. This is an Epanechnikov kernel density plot obtained using 250 points in the estimation.

Figure 10: Consumer Prices - Cents away from Integer Price



Note: This histogram correspond to the distribution of the number of cents away the price for each unit sold in the market is from its closest integer price.

Table 2: Rounding & Rule-of-thumb Pricing: An Illustration

Acq. Cost	Tax rate	Target Values			Observed Values		
		$m$	$P_j^r$	$P_j^c$	$P_j^c$	$P_j^r$	$m$
6	0.455	2.0	12	17.46	18	12.37	2.06
6	0.455	2.0	12	17.46	17	11.68	1.95

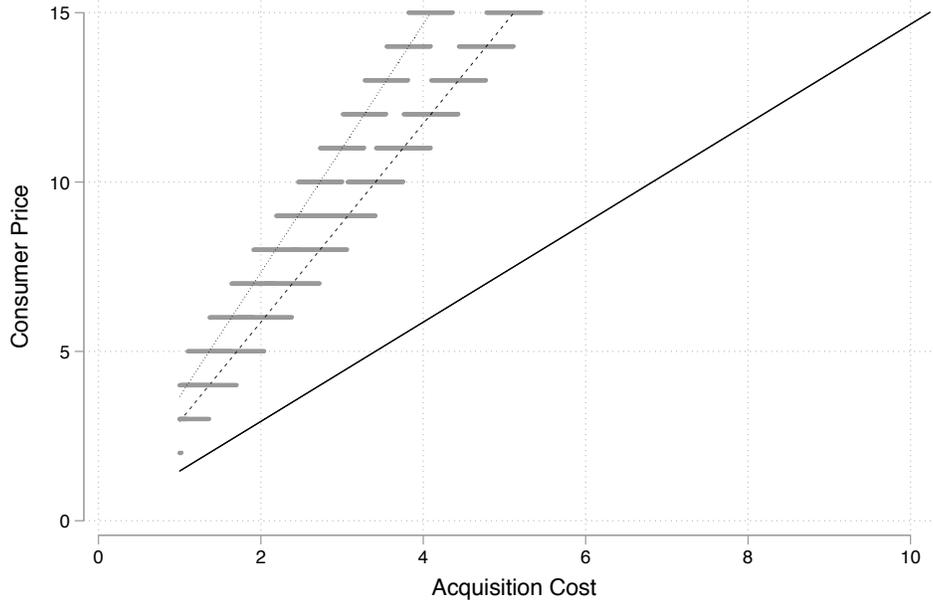
This table presents an example of how rounding behavior might impact on the empirical distribution of multipliers. While in the first row the retailer decides to round up the target value of the consumer price to the closest integer, the second row describes the situation in which rounding happens toward the closest integer from below.

Table 3: Rule-of-thumb Pricing Algorithm: An Illustration

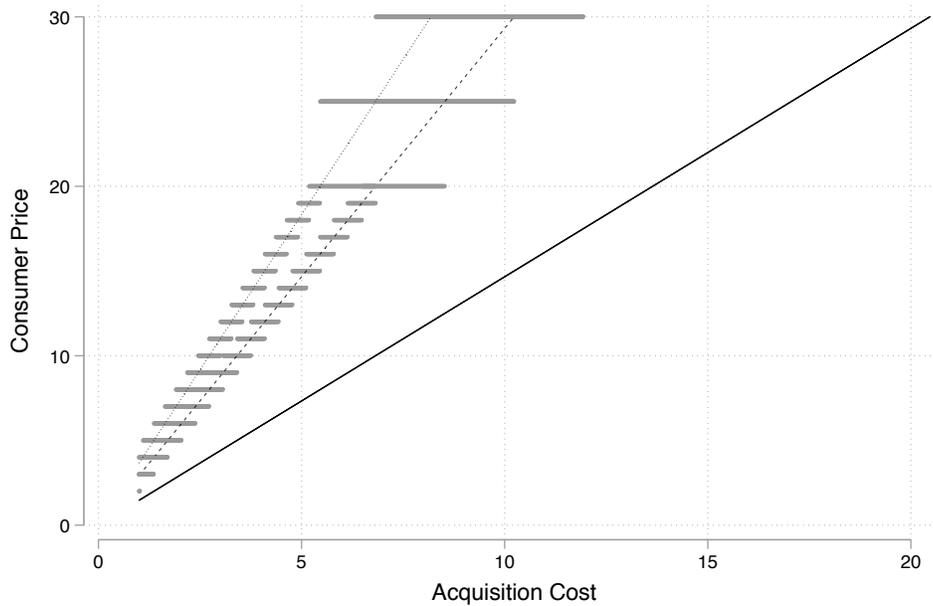
Acq. Cost	Tax rate	$m$	Exact Rule Price	Match with rule $m$ if:
6	1.455	2.0	17.46	$p^{c,obs} \in \{16.99, 17.00, 17.01\} \cup \{17.99, 18.00, 18.01\}$
6	1.455	2.5	21.83	$p^{c,obs} \in \{19.99, 20.00, 20.01\} \cup \{24.99, 25.00, 25.01\}$

This table presents an example of the procedure used to match observed prices with pricing rules, both distinguishing across rules (2.0 and 2.5) and across the two branches defined in terms of the exact value (“exact rule”).

Figure 11: Rule-of-thumb Pricing Algorithm: Matching Rules to Prices



(a) Up to 50th percentile of consumer price



(b) Up to 75th percentile of consumer price

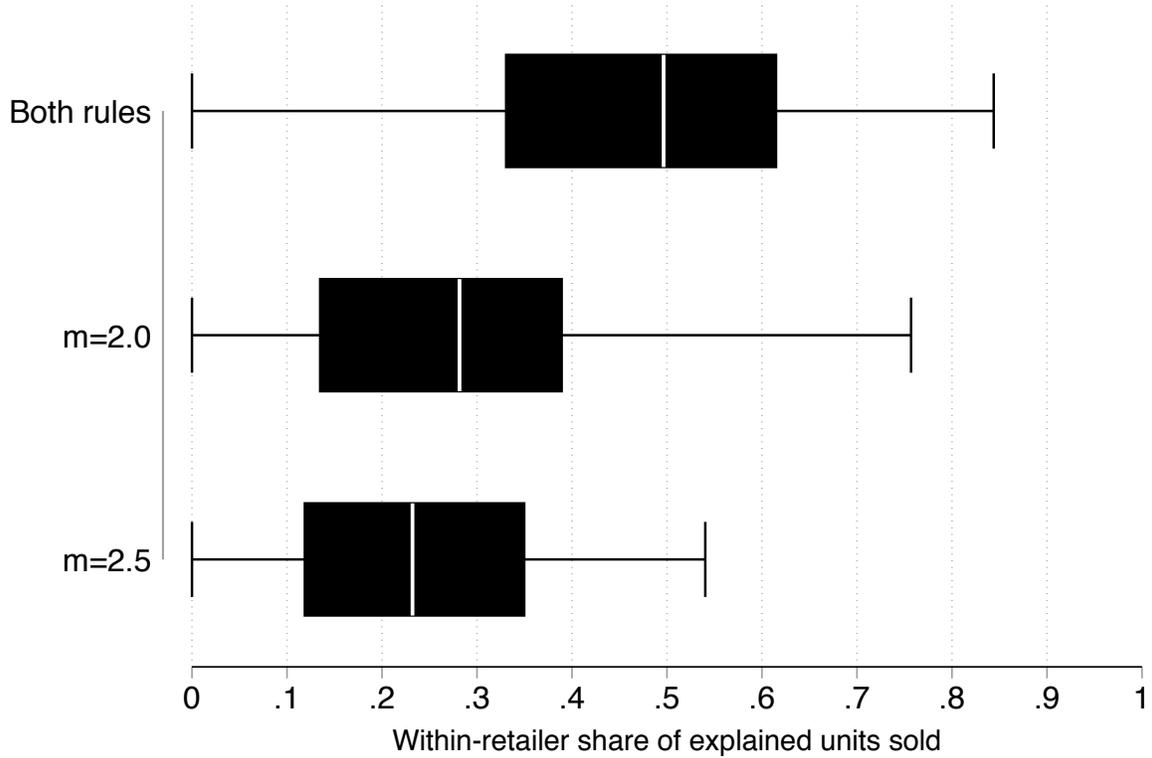
Note: These figures illustrate the coverage of the algorithm as a function of the acquisition cost for the modal tax structure for the sample (which implies a total tax rate of 0.466), considering up to the median consumer price value (panel (a)) and up to the 75th percentile of this variable (panel (b)). The darker solid line measures the break even line. The dashed and dotted lines indicate the exact value of applying a multiplier of 2.00 and 2.50, respectively, to the acquisition cost and the corresponding tax rate. Finally, the grey segments represent the values for the consumer price that are considered as a match for each rule-acquisition cost pair.

Table 4: Rules' Performance Across Product Types

Product Category	Matching Rate ( $m = 2.0$ )	Matching Rate ( $m = 2.5$ )	Matching Rate ( $m \in \{2.0, 2.5\}$ )	Median $P^c$	Quantity Share (units sold)	Revenue Share (dollars sold)
Topicals	25.9%	15.4%	37.7%	\$25	0.4%	0.5%
Liquid Edibles	22.7%	17.2%	36.1%	\$27	2.0%	2.4%
MJ Mix	33.7%	30.5%	55.1%	\$12	2.9%	1.7%
Solid Edibles	30.9%	28.4%	48.2%	\$15	7.8%	6.9%
Inhalables	27.3%	18.5%	40.5%	\$31	11.8%	17.6%
Usable MJ	25.9%	25.1%	46.6%	\$14	75.1%	70.9%
All Products	26.6%	24.5%	46.0%	\$15	100%	100%

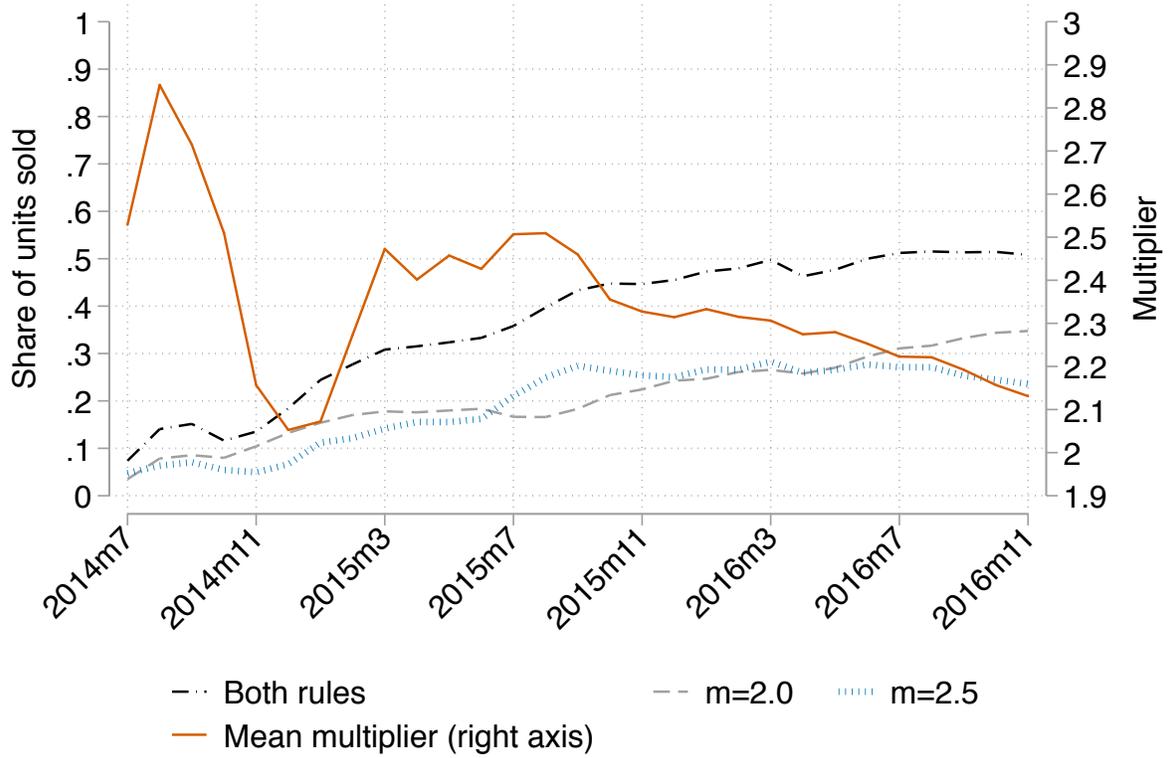
This table summarizes the performance of the procedure described in Section 3 to identify prices that are consistent with the use of a fixed set of multipliers. Columns 2 and 3 summarize the fraction of units sold in each category with prices that are consistent with a rule of  $m = 2.0$  and  $m = 2.5$ , respectively, according to the algorithm described in the aforementioned section. Column 4 presents the share of units sold in the market that can be explained by at least one of the rules in  $\mathcal{M}$ . Column 5 indicates the median consumer price across all categories. Finally, columns 6 and 7 describe the participation of each product category in quantities (units sold) and revenue (dollars sold), respectively.

Figure 12: Rules' Prevalence Across Retailers



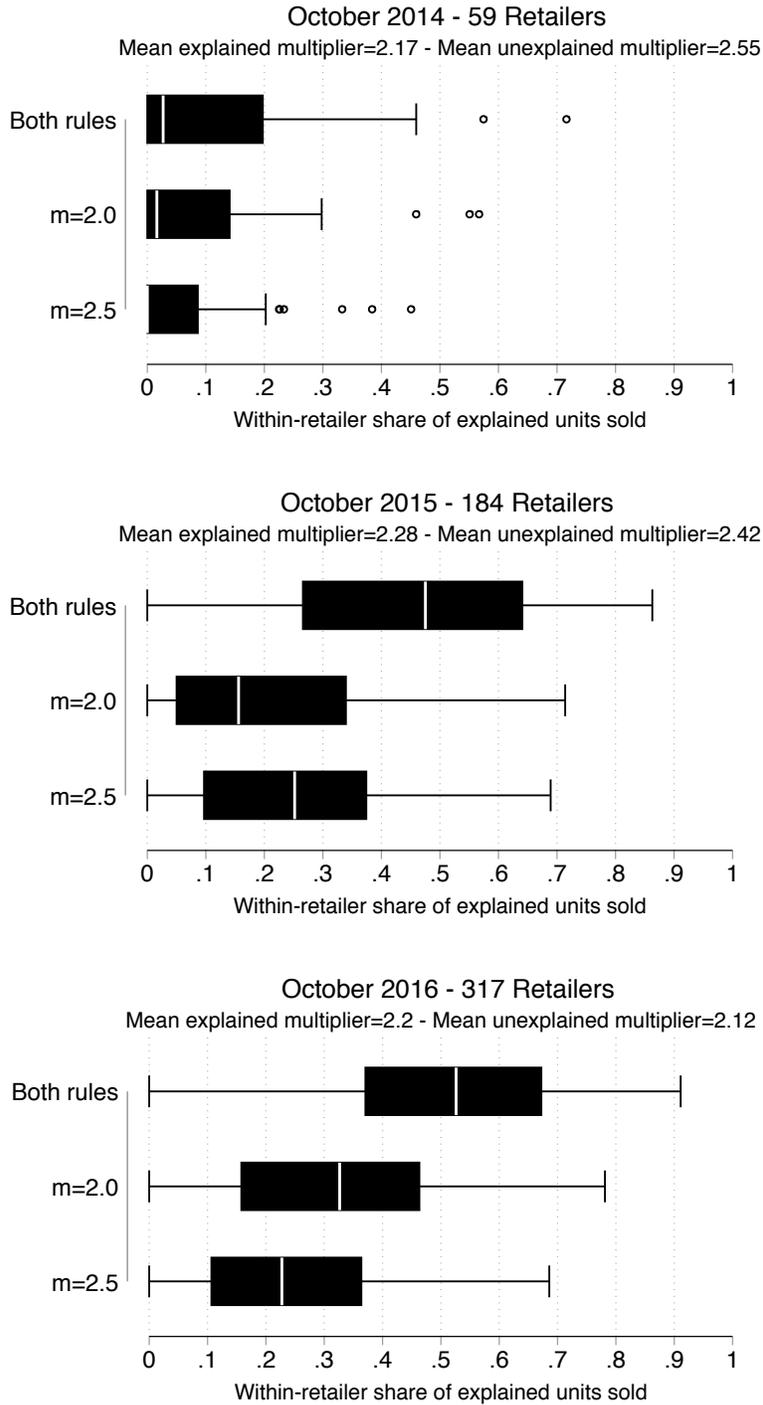
Note: This plot presents the distribution of the share of units sold that are consistent with rules in  $\mathcal{M}$  for each retailer in the market. The horizontal edges of each black box represent the 25th and 75th percentile of the corresponding distribution, while the white line inside the box indicates the median value. The thin lines and their respective extremes indicate the lower and upper adjacent values, respectively, defined as the smallest (largest) observation above (below) the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. Outlier values are denoted by dots. In this plot a retailer is a unit of observation. 336 active retailers are considered.

Figure 13: Rules' Prevalence Across Months



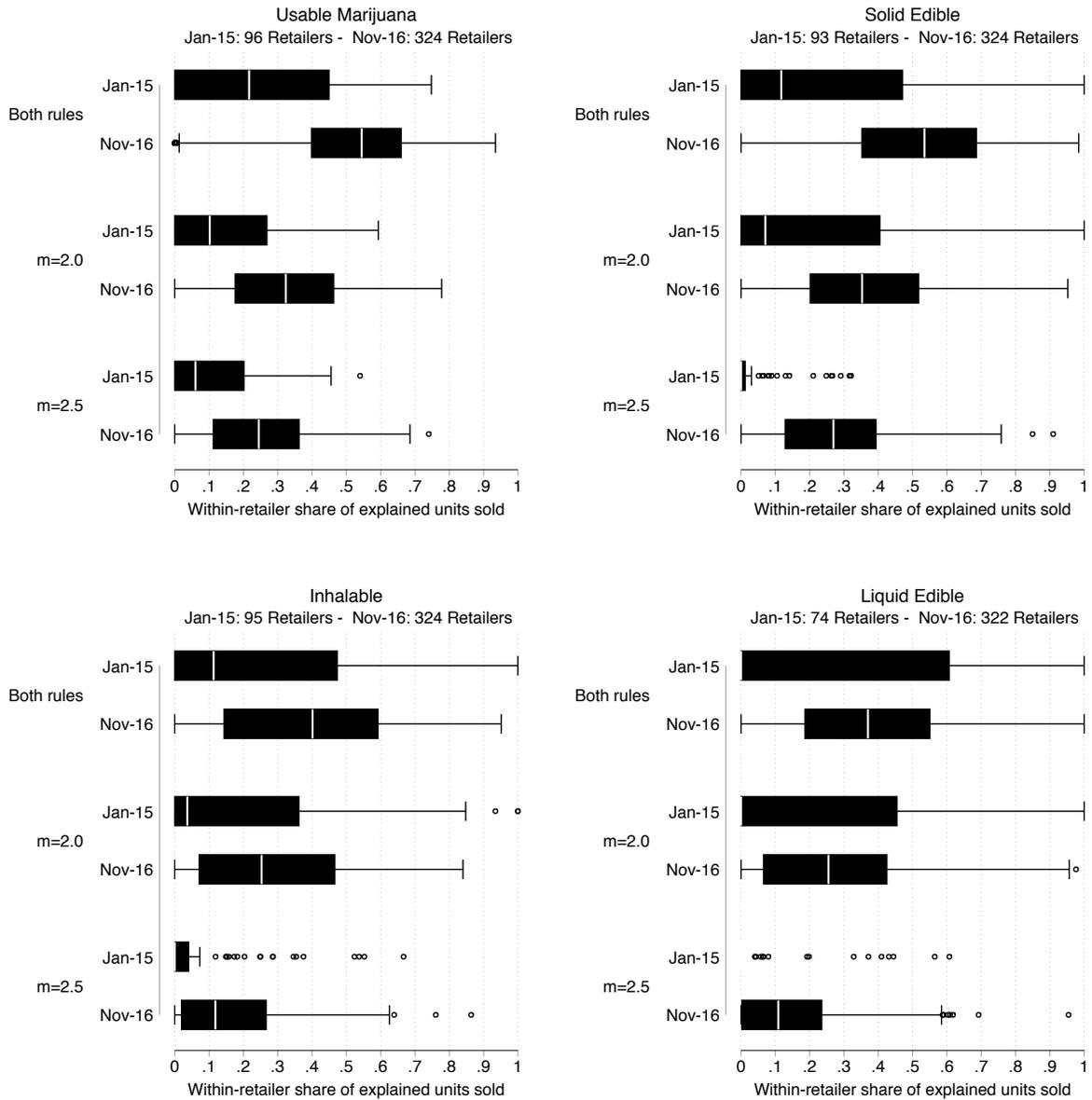
Note: This plot presents the distribution of the share of units sold that are consistent with rules in  $\mathcal{M}$  in each month. Additionally, the solid line measures the mean empirical multiplier observed in each month, independently of observations being explained by the rules in  $\mathcal{M}$ .

Figure 14: Rules' Prevalence Over Time



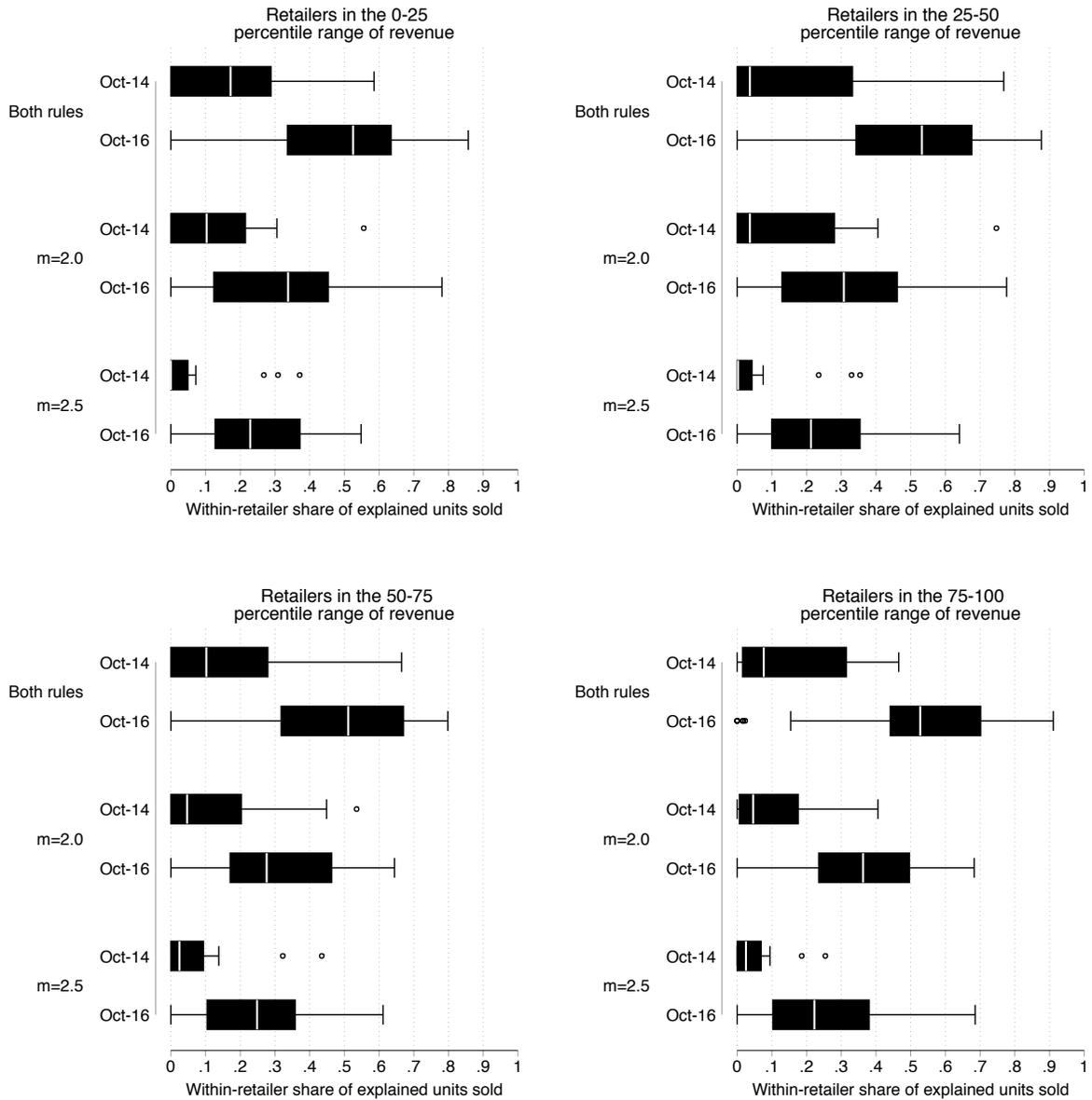
Note: This plot presents the distribution of the share of units sold that are consistent with rules in  $\mathcal{M}$  for each retailer in the market. The horizontal edges of each black box represent the 25th and 75th percentile of the corresponding distribution, while the white line inside the box indicates the median value. The thin lines and their respective extremes indicate the lower and upper adjacent values, respectively, defined as the smallest (largest) observation above (below) the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. In this plot a retailer in the indicated month is a unit of observation.

Figure 15: Rules' Prevalence Over Product Categories and Time



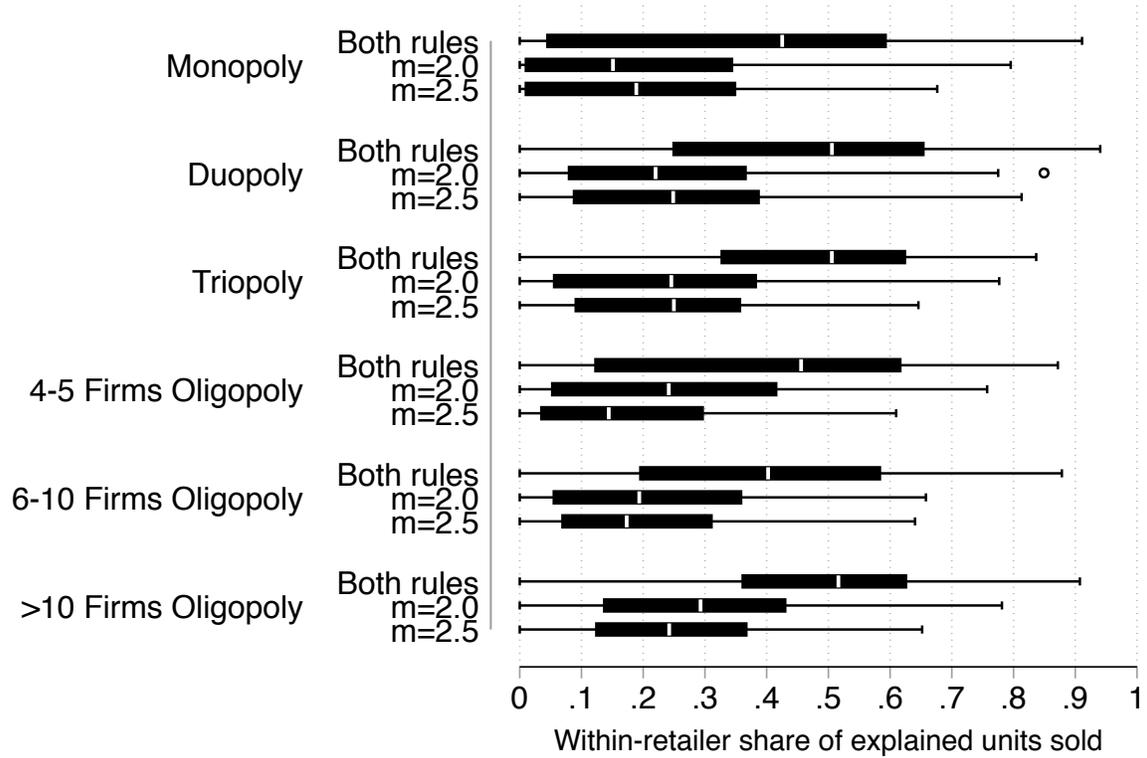
Note: These figures illustrate the prevalence of rules across product categories for a month in the beginning of the sample (January 2015) and one at its end (November 2016). Specifically, the plot presents the distribution of the share of units sold that are consistent with rules in  $\mathcal{M}$  for each retailer in the market, fixing the product type and selected months. The horizontal edges of each black box represent the 25th and 75th percentile of the corresponding distribution, while the white line inside the box indicates the median value. The thin lines and their respective extremes indicate the lower and upper adjacent values, respectively, defined as the smallest (largest) observation above (below) the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. In each box plot a retailer selling the corresponding product category in the indicated month is a unit of observation.

Figure 16: Rules' Prevalence across Revenue Quartiles and Time



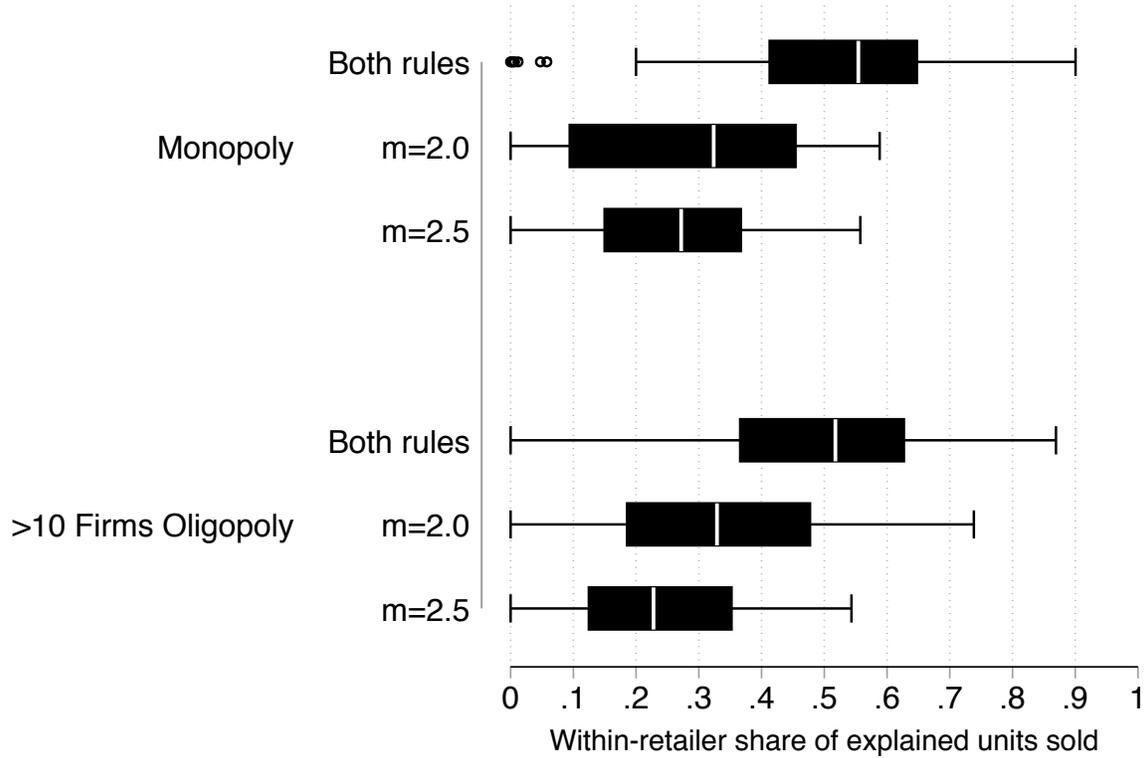
Note: These figures illustrate the prevalence of rules across retailers quartiles defined in terms of their revenues. Specifically, the plot presents the distribution of the share of units sold that are consistent with rules in  $\mathcal{M}$  for each retailer in the market, fixing the revenue quartile to which the retailer belongs and the selected months. The horizontal edges of each black box represent the 25th and 75th percentile of the corresponding distribution, while the white line inside the box indicates the median value. The thin lines and their respective extremes indicate the lower and upper adjacent values, respectively, defined as the smallest (largest) observation above (below) the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. In each box plot a retailer that belongs to the corresponding quartile in the revenue distribution in the indicated month constitutes a unit of observation.

Figure 17: Rules' Prevalence across Competition Intensity at the City Level



Note: This figure describes the prevalence of rules across retailer-month pairs split according to the number of competitors at the city level for each month. The horizontal edges of each black box represent the 25th and 75th percentile of the corresponding distribution, while the white line inside the box indicates the median value. The thin lines and their respective extremes indicate the lower and upper adjacent values, respectively, defined as the smallest (largest) observation above (below) the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. In each box plot a retailer that belongs to the market definition (monopoly, etc.) on any given month is the unit of observation.

Figure 18: Rules' Prevalence: Monopolists vs Competitive Markets - November 2016



Note: This figure describes the prevalence of rules across retailer-month pairs for the case of monopoly markets and markets with more than ten competitors for the last month in the sample. The horizontal edges of each black box represent the 25th and 75th percentile of the corresponding distribution, while the white line inside the box indicates the median value. The thin lines and their respective extremes indicate the lower and upper adjacent values, respectively, defined as the smallest (largest) observation above (below) the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. In this plot an observation is given by a retailer in November 2016, either in monopoly markets ( $N = 59$ ) or in markets with more than ten firms ( $N = 119$ ).

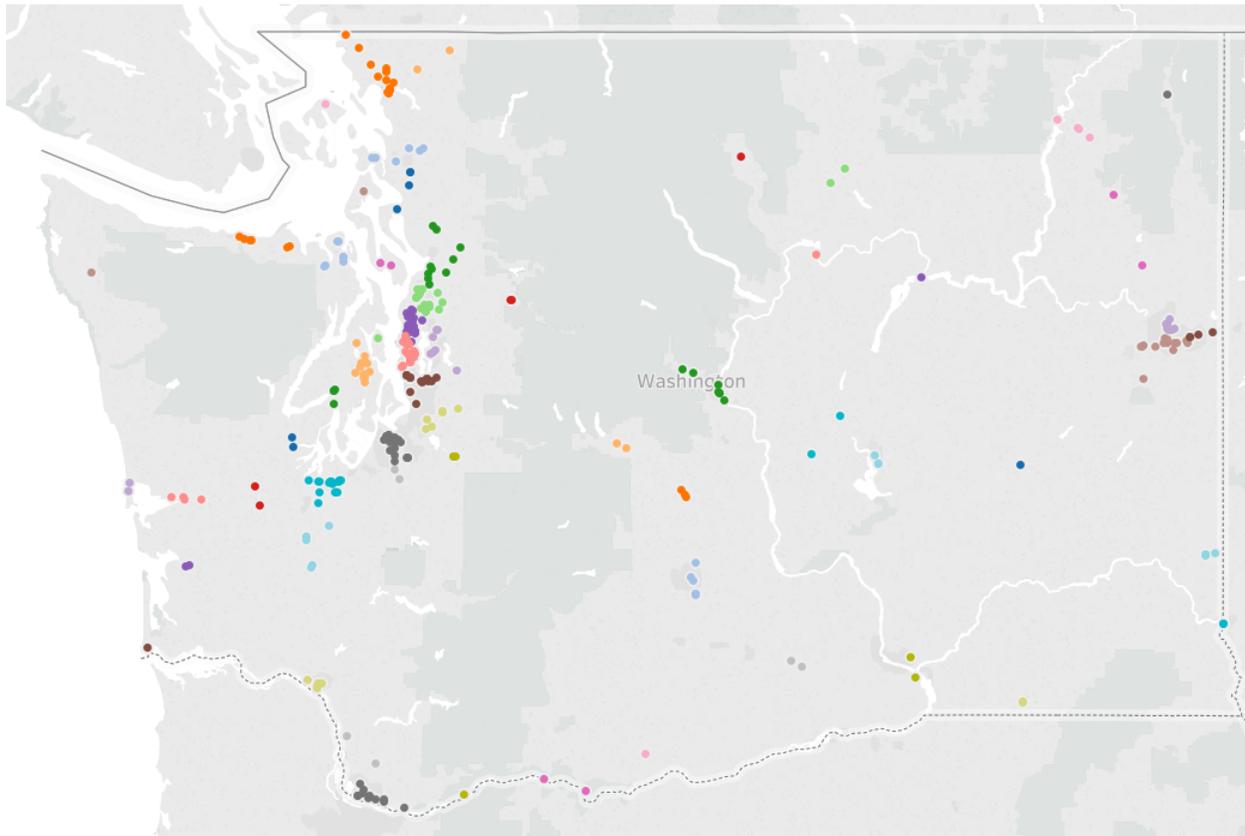
## D A Demand Model for Cannabis Products

Table 5: Number of UM products offered by retailers

	By Inventory Code			By Manufacturer			By Manufacturer-Size		
	Jul-14	Jul-15	Jul-16	Jul-14	Jul-15	Jul-16	Jul-14	Jul-15	Jul-16
# of retailers	17	159	283	17	159	283	17	159	283
Min	3	18	16	1	1	2	1	3	7
25th percentile	9	152	223	1	11	14	2	25	37
50th percentile	29	245	354	2	15	21	4	35	54
75th percentile	51	337	502	4	21	29	6	52	74
Max	206	845	1577	5	37	67	8	96	189
Average	40	264	388	2	16	23	4	39	57
St. Dev	49	145	234	1	7	11	2	19	30

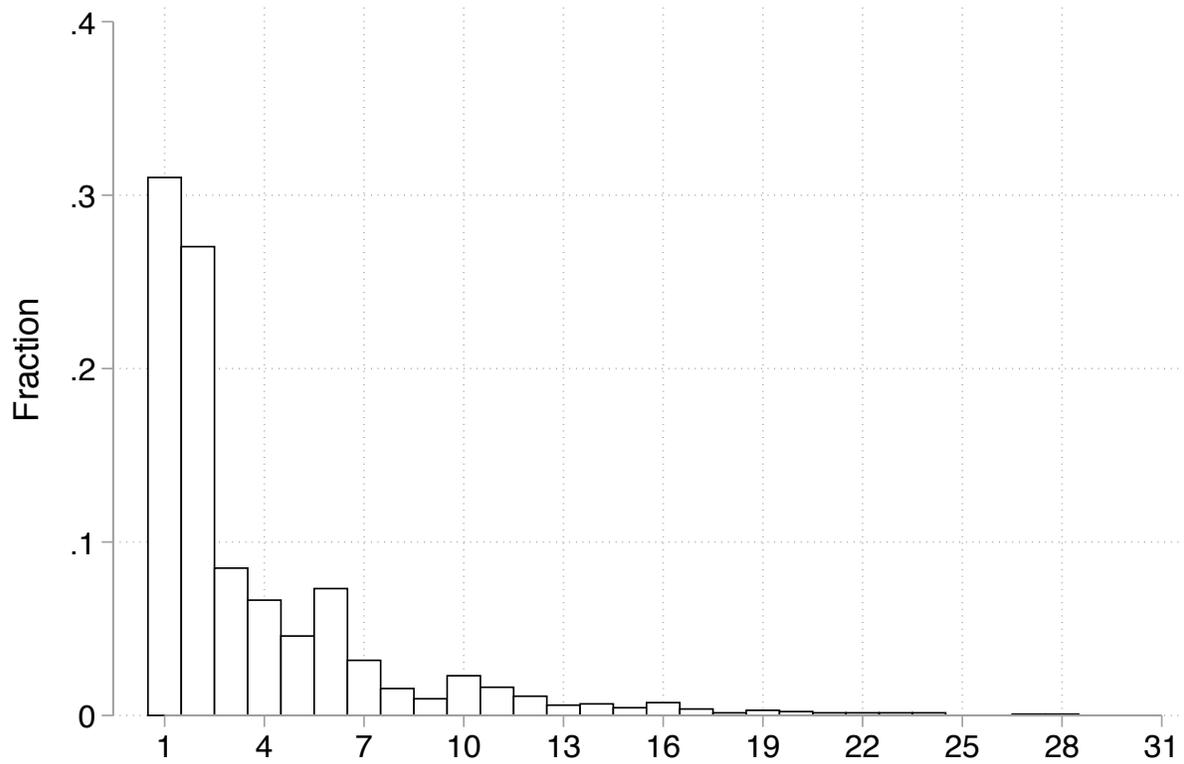
Note: This table describes the number of UM products carried by retailers according to different product definitions. In the case of the last definition, I restrict attention to the top-7 sold sizes (0.5, 1, 2, 3.5, 7, 14, and 28 grams), which account for approximately 93% of revenue and 91% of all UM units sold.

Figure 19: Distribution of Retail Locations and Markets



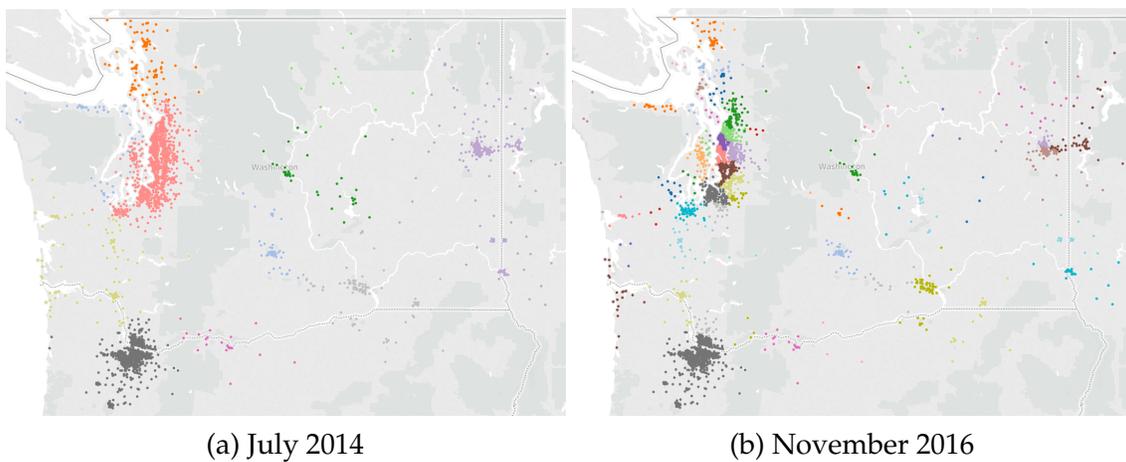
Note: This figure shows the distribution of all 336 ever active retailers in Washington's territory. Colors define membership to a specific geographic market.

Figure 20: Number of Retailers across Markets



Note: This figure shows the distribution for the number of retailers across the 1,354 geography-month (markets) pairs in the dataset.

Figure 21: Consumers allocation to retail markets



Note: This figure shows the distribution of census tracts across markets for the beginning and the end of the sample. In each month, each color represents a specific market and each dot a specific census tract.

Table 6: Consumers Demographics

	Adult Pop.	Pop. Density	Income	Age	Male Share	White Share	Yes Vote	College Educ.	Distance to retailers
Min	16	0.05	5.9	20	35	9	34	1	0.0
25th percentile	2,634	470	45.4	34	48	77	52	16	8.2
50th percentile	3,380	2,838	57.6	38	50	88	55	24	14.7
75th percentile	4,299	5,140	75.4	43	52	94	63	39	22.5
Max	11,477	53,573	188.1	65	89	100	71	82	42.2
Average	3,497	3,512	62.2	39	50	84	56	29	16.0
St. Dev	1,285	4,051	24.3	7	3	13	8	17	9.7

\*For all columns in this table, the summary refers to the distribution of the median value of each of these variables across all 1,957 selected census tracts in WA, OR, and ID with at least one household. Income refers to household income. Distance data uses information for the last month of the sample, in which the maximum number of active retailers is achieved. Adult population is measured in thousands; Population density in terms of people per square mile; Income in thousands of dollars; Male Share, White Share, Vote, and College Education in percentages; and Distance to retailers in driving miles.

## E Estimation

Table 7: OLS & IV Demand Estimates

	OLS	IV
# UM Alternatives	0.0017*** (0.0006)	0.0024*** (0.0007)
# Product Lines	0.1979*** (0.0107)	0.1986*** (0.0113)
Size=3.5 grams	-0.3000*** (0.0187)	0.8950*** (0.1280)
THC	0.0990*** (0.0082)	0.1253*** (0.0097)
THC <sup>2</sup>	-0.0022*** (0.0002)	-0.0024*** (0.0002)
CBD	-0.1203*** (0.0138)	-0.0958*** (0.0158)
CBD <sup>2</sup>	0.0083*** (0.0010)	0.0012*** (0.0079)
Consumer Price	-0.0256*** (0.0006)	-0.0665*** (0.0044)
Own-Price Implied Elasticities		
p25	-0.28	-0.74
p50	-0.51	-1.32
p75	-1.03	-2.67
Mean Value	-0.63	-1.74
% Elastic	30.2	55.3
Price Exogeneity Test ("C-Stat")		109.7
Weak Instruments Test (F-Stat)		32.1

In both specifications the left-hand-side variable is the log of the ratio between the market share for each product and that of the outside option. Both specifications include retailer, manufacturer, and month fixed effects, for the N=62,658 market shares in the sample. Heteroskedasticity-consistent standard errors reported in parenthesis. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . IV instruments the consumer price with the set of variables described in subsection 5.1.

Table 8: Mixed-Logit Demand Estimates

Mean Coefficients		Random Coefficients	
Constant	-8.6095 (6.1119)	Constant	1.2740 (1.4408)
# UM Alternatives	0.0073* (0.0041)	# UM Alternatives	0.0024 (0.0578)
# Product Lines	0.2221** (0.0997)	# Product Lines	0.1287 (0.1857)
Size=3.5 grams	4.4164** (1.8761)	Size=3.5 grams	-0.3382 (3.4030)
THC	0.5857* (0.3222)	THC	0.1044* (0.0581)
THC <sup>2</sup>	-0.0168* (0.0094)	THC <sup>2</sup>	-0.0034 (0.0021)
CBD	-3.1124 (3.5846)	CBD	-2.3921 (1.7021)
CBD <sup>2</sup>	-0.2780 (0.2536)	CBD <sup>2</sup>	0.0665 (0.1171)
Consumer Price	-0.4601*** (0.1141)	Consumer Price	0.0553*** (0.0179)

Interactions

Constant*Age	0.0477 (0.7827)
Constant*Gender	0.8236 (1.7912)
Constant*Race	-1.5242 (1.7378)
Constant*Attitude	-1.0087 (2.1295)
Constant*College	-0.1065 (1.3688)
Price*Income	0.0202** (0.0084)

Utility from Traveling

Driving Miles	0.1327*** (0.0152)
Driving Miles*ln(PopDensity)	-0.0762*** (0.0190)

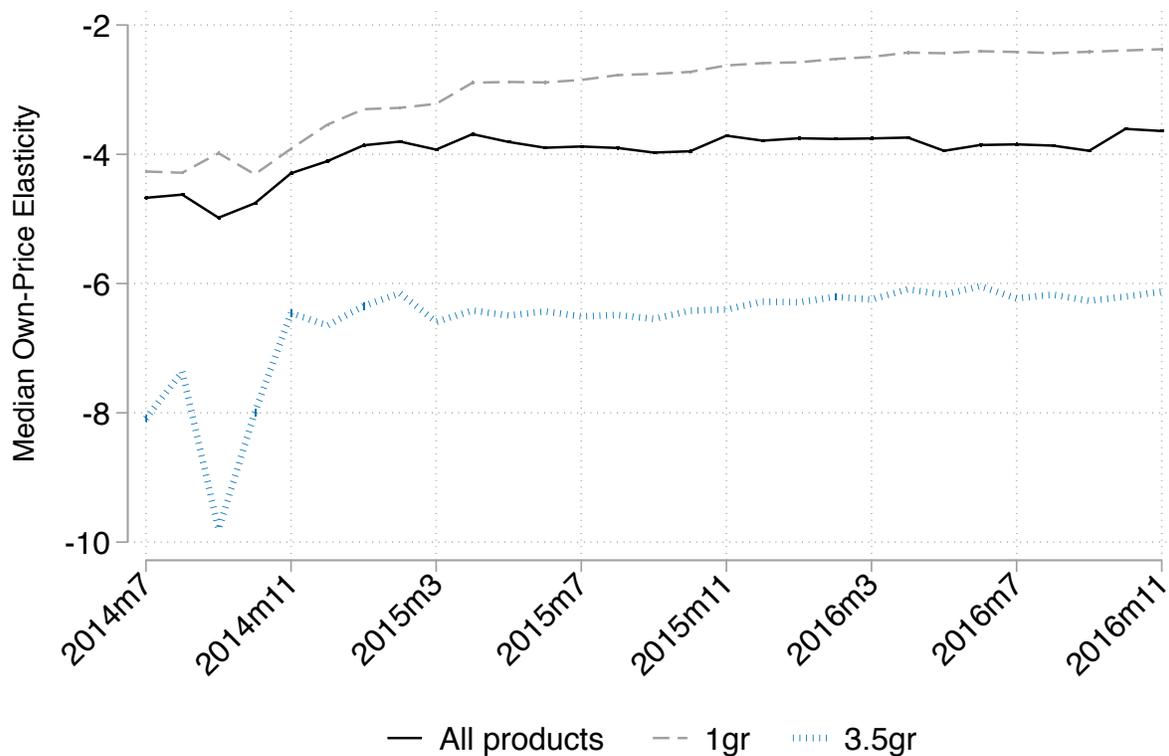
Note: The estimation includes retailer, manufacturer, and year-month fixed effects for the  $N = 62,658$  products in the sample. Standard errors robust to heteroskedasticity in parenthesis. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table 9: Mixed-Logit Demand Estimates: Own-Price Elasticities and Transportation Costs

	Transportation Cost (\$ per mile)	Own-Price Elasticities
10th pctlile	0.67	-2.17
25th pctlile	1.25	-2.51
50th pctlile	1.77	-3.86
75th pctlile	2.27	-6.21
90th pctlile	2.83	-7.04
Mean Value	2.47	-4.38
% Elastic Products:		99.78
% Positive Utility from Traveling:	1.75	

Note: This table shows the distribution of the own-price elasticities and transportation costs (in dollars per mile) that result from estimating the full mixed-logit model.

Figure 22: Median Own-Price Elasticities



Note: This figure shows the month-by-month evolution of the median own-price elasticity across products in all markets. It also plots the same trend but restricting the sample to small (1 gram) and large (3.5 grams) package sizes.

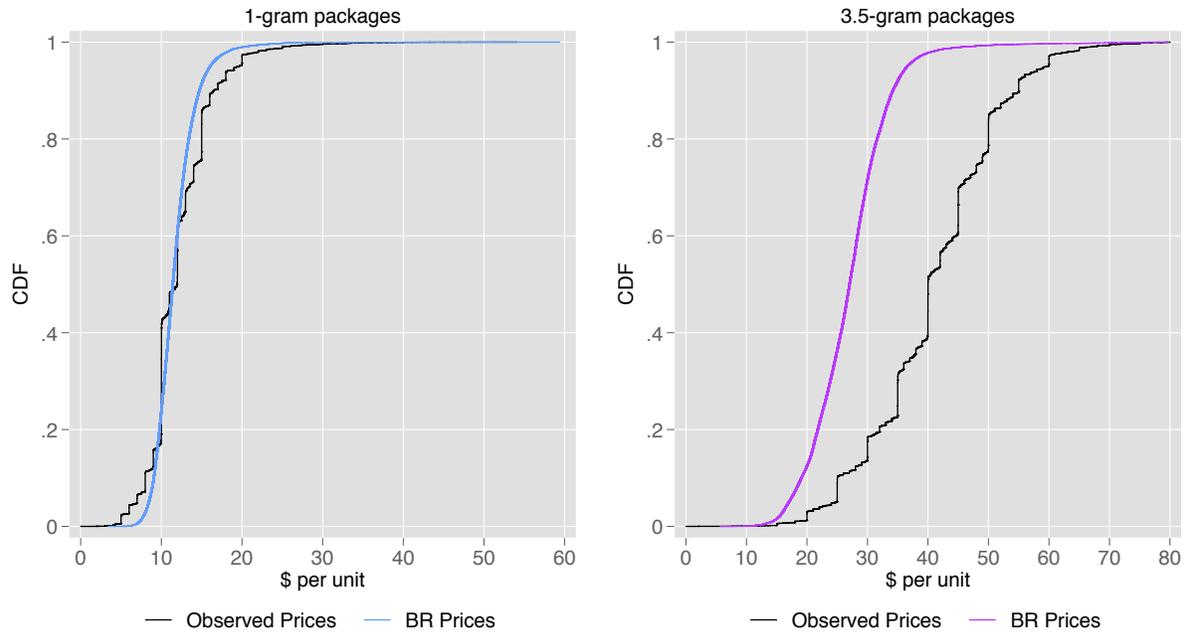
Table 10: Cross-Price Elasticities

	(a) By Package Size		(b) By Retailer	
	1gr pks	3.5gr pks	Same Retailer	Different Retailer
1gr pks	0.0141	0.0103	0.0373	0.0103
3.5gr pks	0.0077	0.0212		

Note: The left panel of this table shows the average cross price elasticities for packages with size given by rows, with respect to changes in prices of other packages with size given by columns. The right panel summarizes the average cross-price elasticity for changes in prices of other products sold by the same retailer (first column) or other retailers in the market (second column).

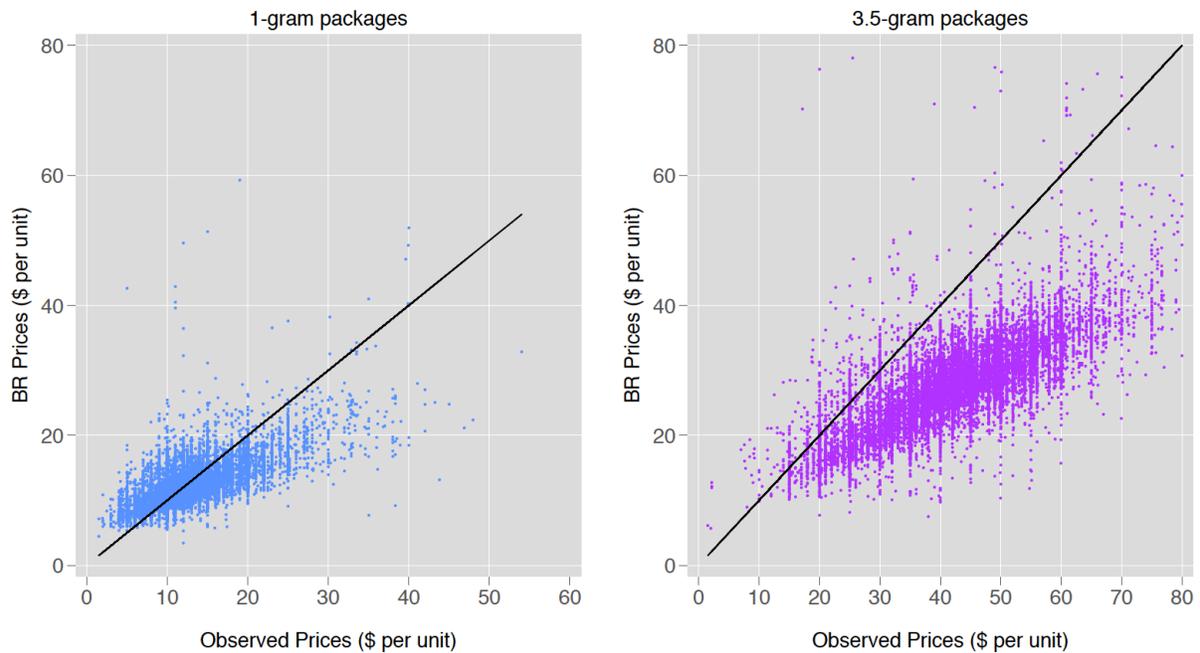
## F Counterfactual Results

Figure 23: Best-Response Scenario - CDF for Consumer Prices



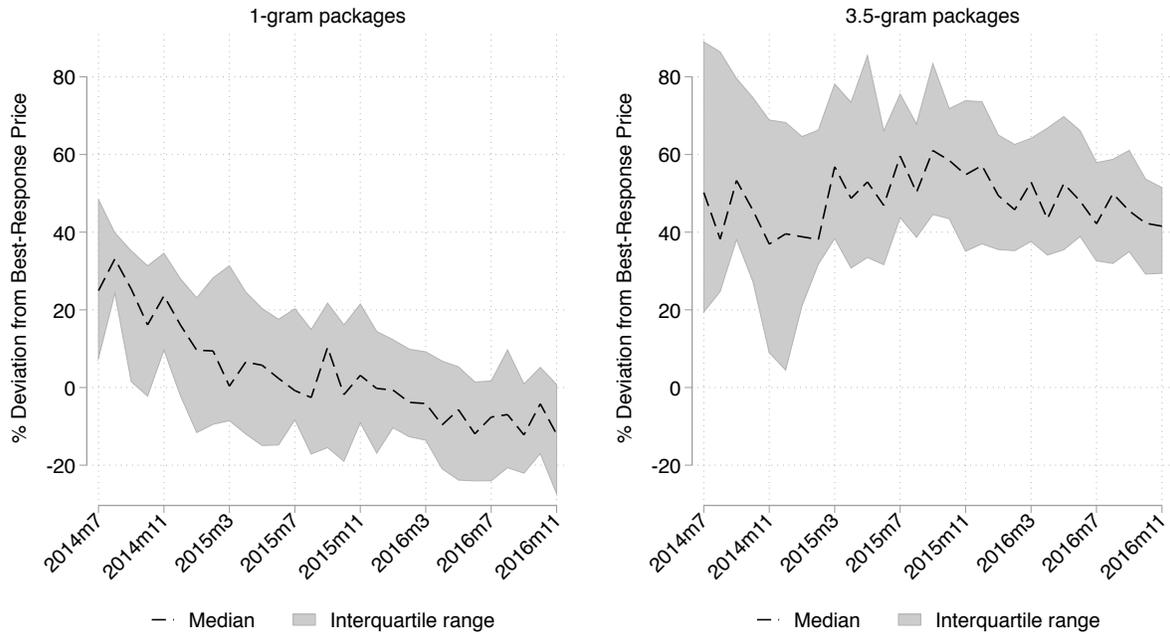
These plots describe the cumulative distribution function associated to observed prices (black line) and those that are obtained from pooling together profitable unilateral deviations for each retailer (color line).

Figure 24: Best-Response Scenario - Observed vs BR Prices



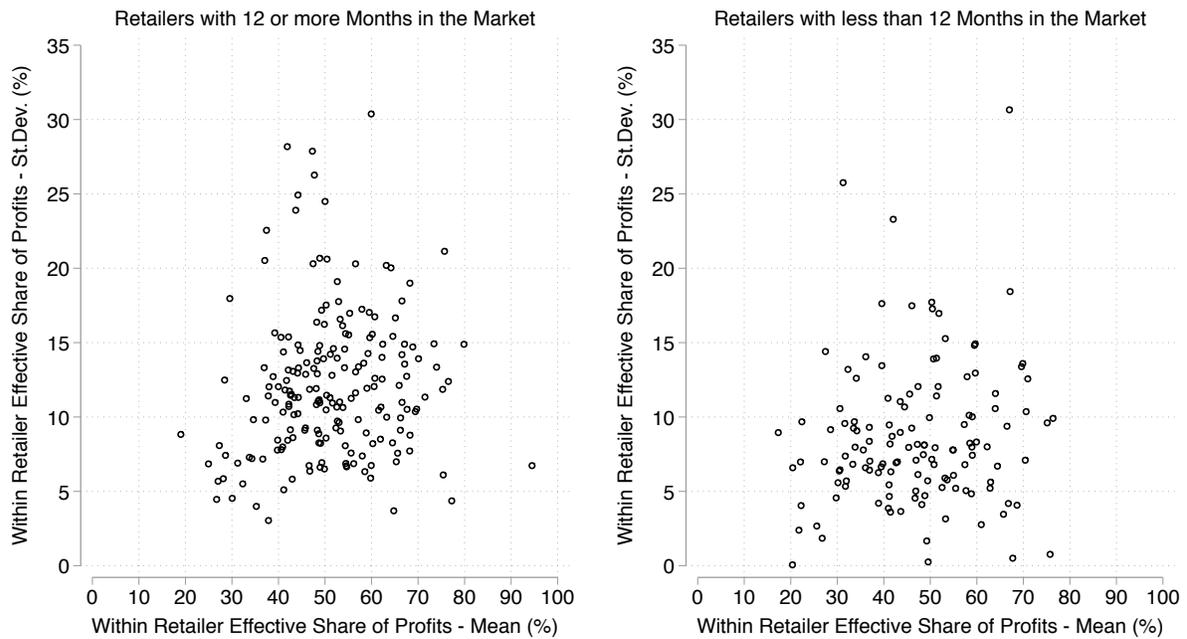
These scatter plots show the association between observed prices (horizontal axis) and those that are obtained when considering profitable unilateral deviations for each retailer (vertical axis).

Figure 25: Best-Response Scenario - Observed Prices Deviation from Optimal Prices



These plots show the median (dashed line) and interquartile range (shaded area) across markets for the median percentage deviation of prices with respect to their optimal value (in profitable unilateral deviations) over time and across package sizes.

Figure 26: Best-Response Scenario - Variable Profits Deviation from Optimal Profits



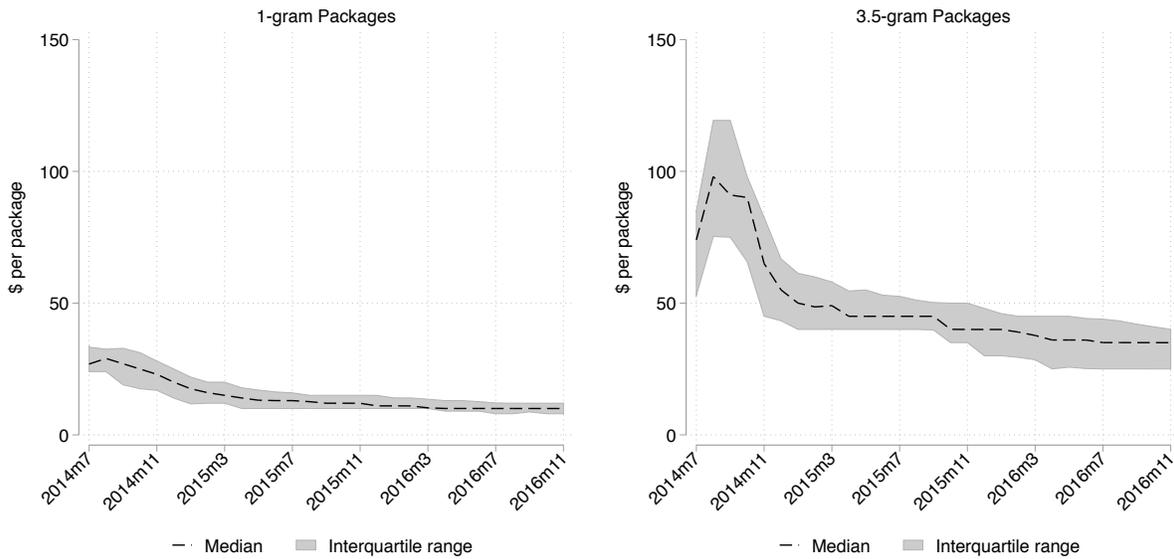
Note: These plots summarize the distribution of the mean and standard deviation for the effective share of profits obtained by each of the 336 ever active retailers in the sample. Every month, for each retailer I compute the effective share of profits as the ratio between observed variables profits and those that the retailer would obtain if allowed the chance to best respond to what competitors are doing. Then, I compute the mean and standard deviation of the monthly shares and plot them distinguishing between those retailers with more (left panel) and (strictly) less (right panel) than a year of presence in the market. Each mark in these plots represents a specific retailer.

Table 11: Bertrand-Nash Scenario - % Variation in Main Outcomes

	All Products	1-gram Packages	3.5-gram Packages
Mean Prices	-20%	-6%	-34%
Median Prices	-26%	-11%	-38%
Grams of UM	+252%	-35%	+470%
Industry-level Variable Profits	+32%	-44%	+99%
Tax Revenues	+151%	-36%	+302%

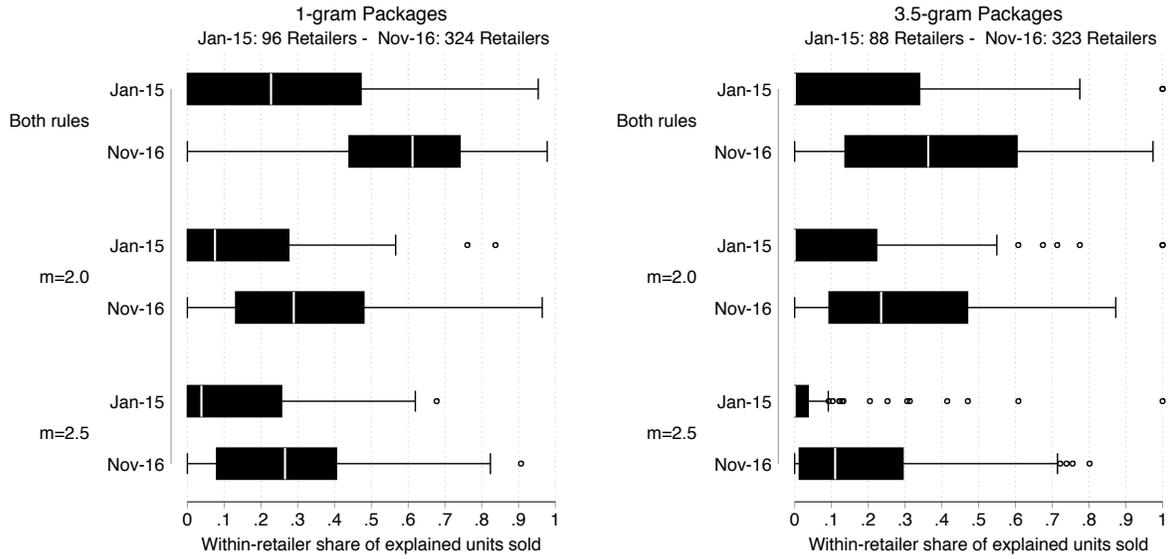
This table presents the percentage variation that results in each aggregate outcome from assuming retailers engage in full-information Bertrand-Nash competition, with respect to observed values in the data.

Figure 27: Prices across UM Package Sizes



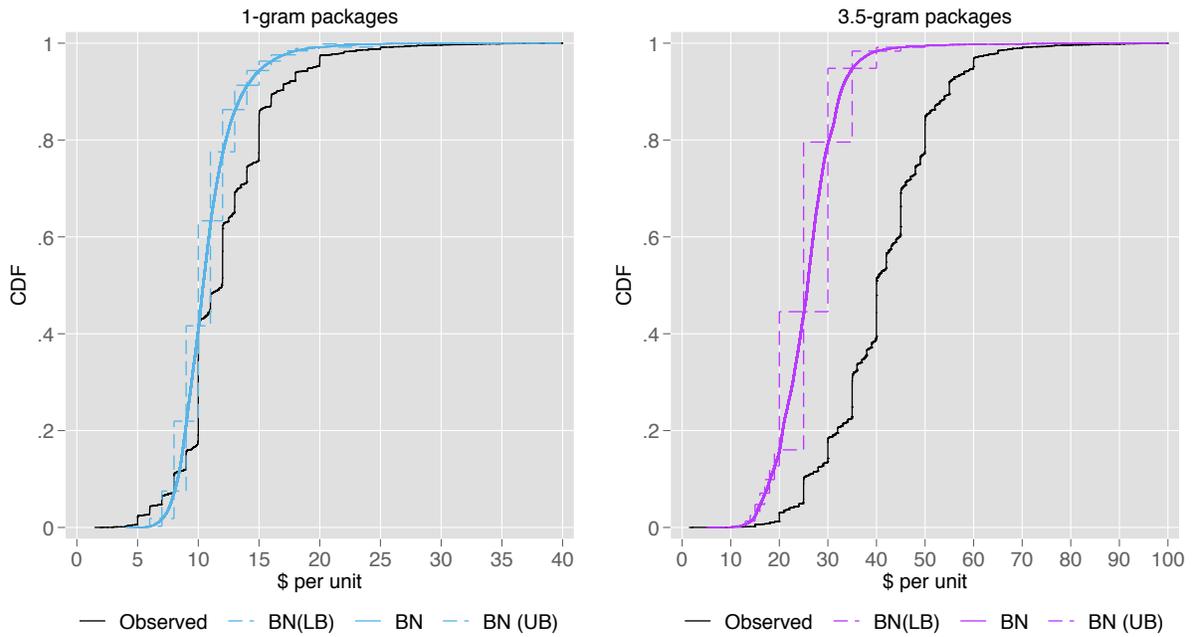
Note: This plot presents the median (horizontal dashed line) and interquartile range (25-75 percentiles, shaded area) for the final consumer prices of 1-gram products (left panel) and 3.5-gram products (right panel).

Figure 28: Rules' Prevalence across UM Package Sizes



Note: This figure describes the prevalence of rules across retailer-month pairs for the case of 1-gram and 3.5-gram usable marijuana packages. The horizontal edges of each black box represent the 25th and 75th percentile of the corresponding distribution, while the white line inside the box indicates the median value. The thin lines and their respective extremes indicate the lower and upper adjacent values, respectively, defined as the smallest (largest) observation above (below) the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. In this plot an observation is given by a retailer-month pair, for the selected months in the corresponding plots.

Figure 29: Bertrand-Nash Scenario - CDF for Consumer Prices



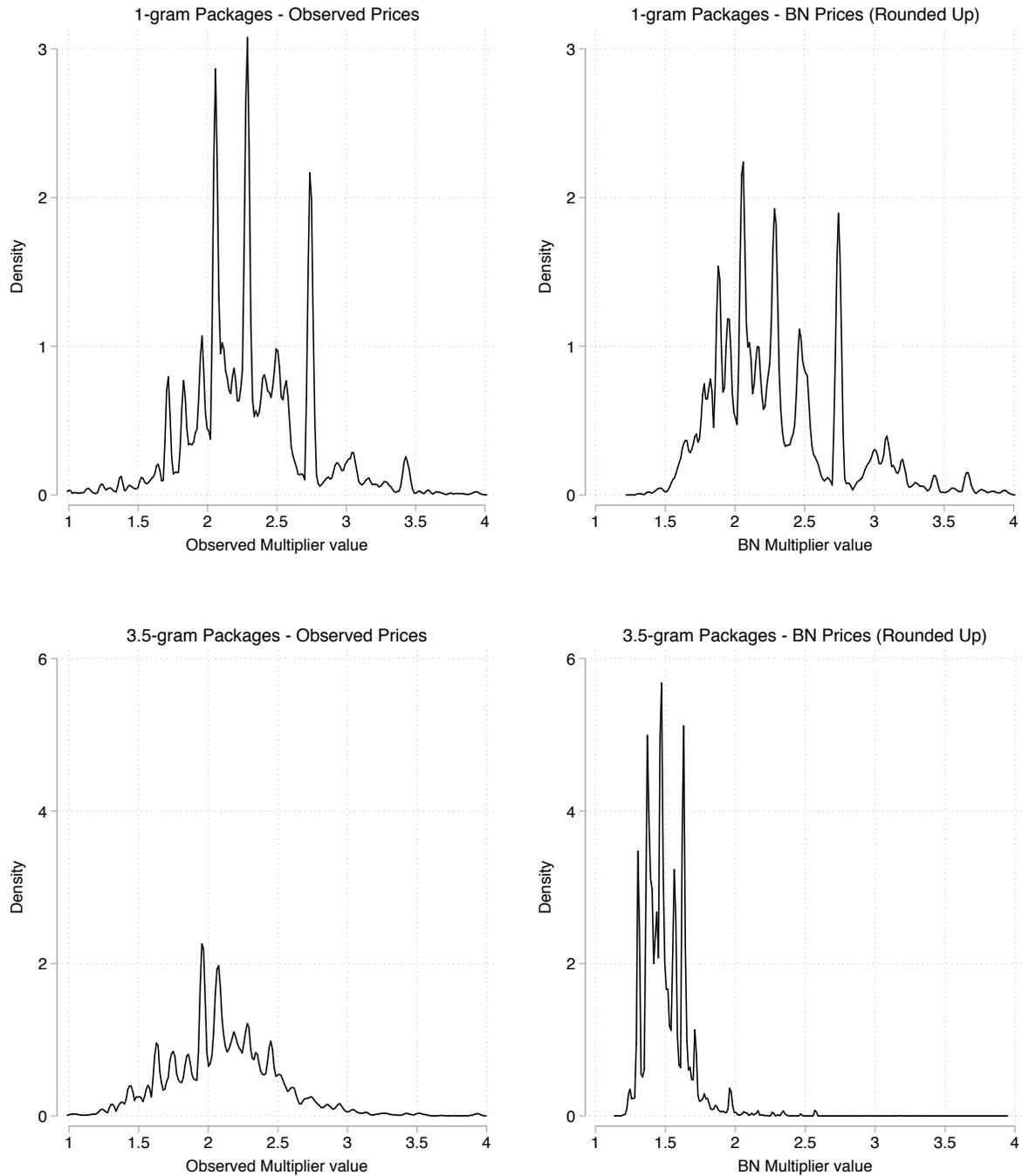
These plots describe the cumulative distribution function associated to observed prices (black line) and those that result from assuming that observed acquisition costs are equal to true marginal costs and firms engage in full-information Bertrand-Nash competition in each market (color line).

Table 12: Average Price Deviation from Bertrand-Nash Prices

	Rule	No Rule
1gr pks	8.5%	16.9%
3.5gr pks	62.6%	58.0%

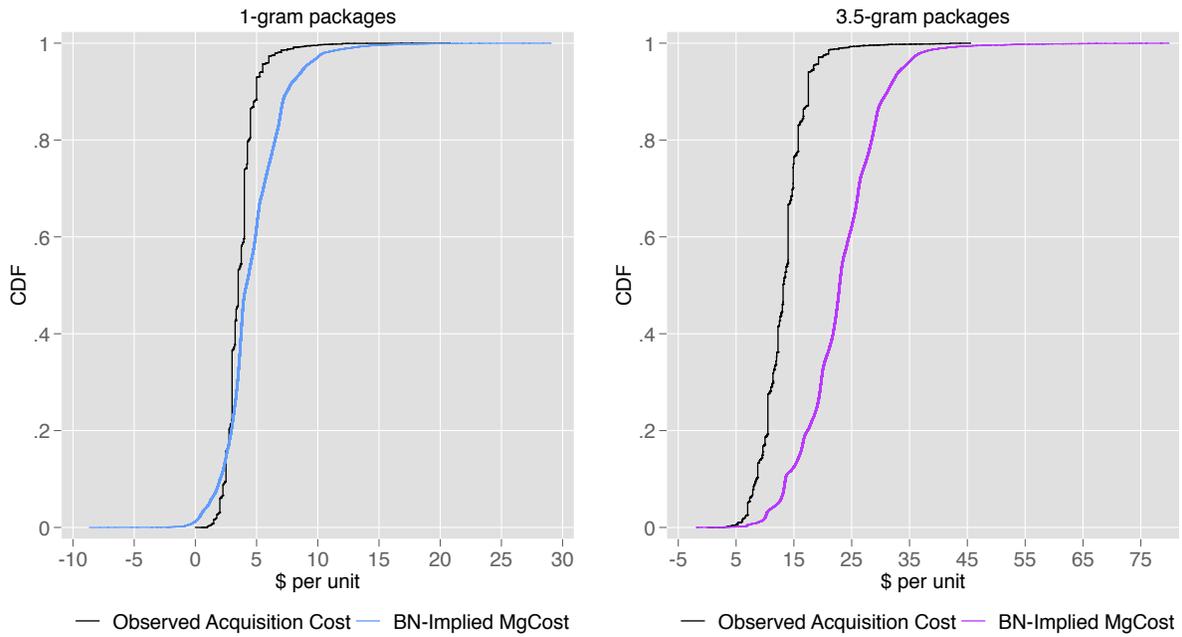
Note: This table presents the average price deviation of observed prices with respect to those obtained under the Bertrand-Nash competition assumption. For each product I compute such deviation and an indicator of whether the observed price is consistent with the rules defined in section 3. Then, I compute the average across both product size and whether the product is a match to those rules. These averages are provided in each cell of this table.

Figure 30: Multipliers across UM Package Sizes



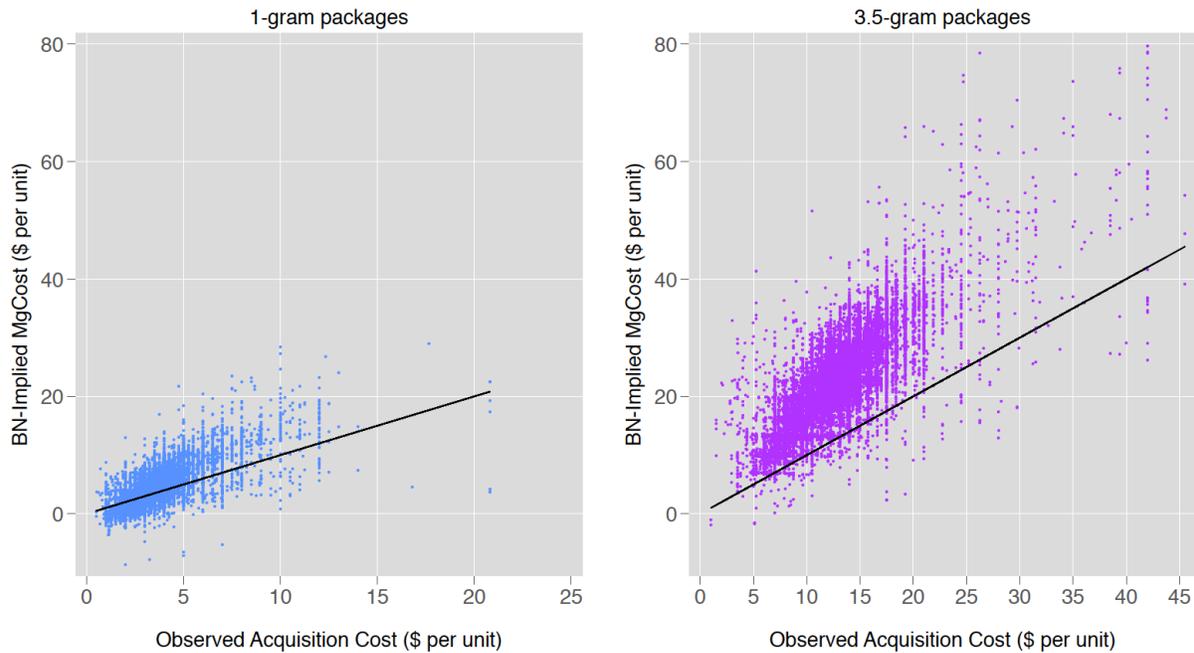
Note: Density plots corresponding to multipliers in the 1%-99% of the corresponding sample for 1-gram (upper panels) and 3.5-gram (lower panels) products. The distinction between left and right panels is given by distributions corresponding to observed multipliers (left panels) and those that result from rounding up the equilibrium Bertrand-Nash prices (right). These are Epanechnikov kernel density plots obtained using 250 points in the estimation.

Figure 31: Bertrand-Nash Scenario - CDF for Marginal Costs



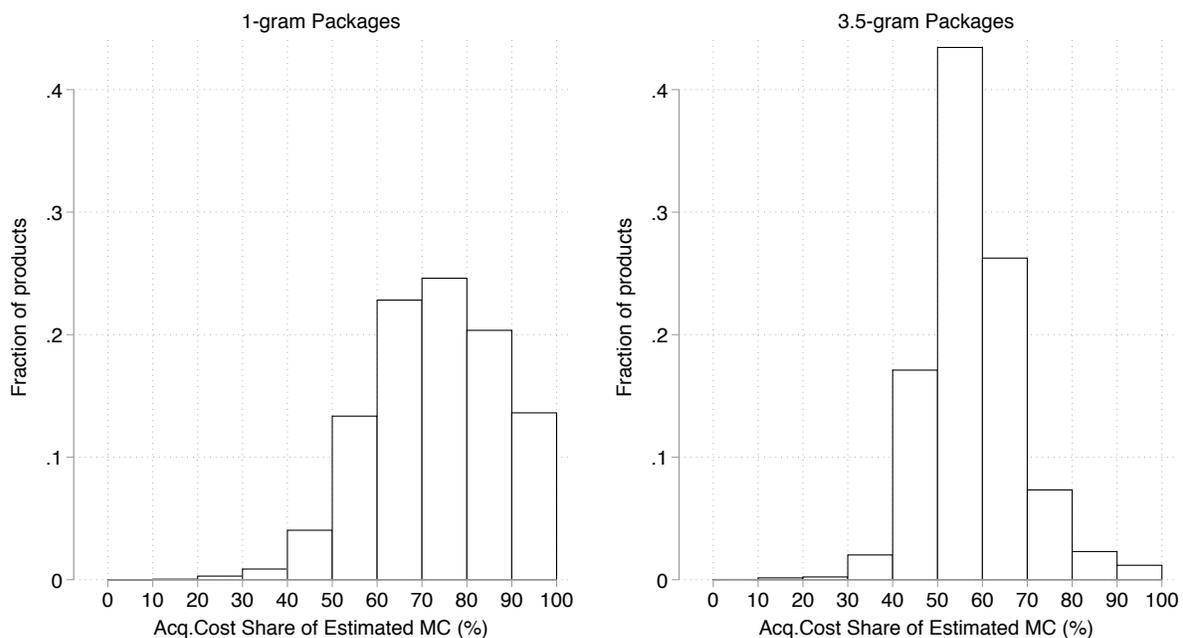
These plots describe the cumulative distribution function associated to observed acquisition costs (black line) and the estimated marginal costs that rationalize observed prices as a Bertrand-Nash equilibrium in all markets (color line).

Figure 32: Bertrand-Nash Scenario - Observed Acquisition Costs vs BN Marginal Costs



These scatter plots show the association between observed acquisition costs (horizontal axis) and the estimated marginal costs that rationalize observed prices as a Bertrand-Nash equilibrium in all markets (vertical axis).

Figure 33: Bertrand-Nash Scenario - Observed Acquisition Costs as a Share of BN Marginal Costs



These plots show the distribution of the ratio between observed acquisition costs and estimated marginal costs across all products for which this ratio is between 0 and 1 (85.5% of the products in the model), conditional on package size.