An Experimental Evaluation of a Portion Cap Rule with a Two-Product Seller

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Abstract

Portion cap rules have been proposed to regulate the consumption of foods and ingredients deemed unhealthy. Theoretical work suggests that, when bundling is used to price-discriminate, consumers are not necessarily affected by these measures, and some may even benefit. The claim assumes that the seller strictly adheres to perfect profit-maximizing strategies. I relax this premise in a controlled experiment where two-product sellers serve buyers with private preferences. Subjects can design and price their menus as they wish. The data largely corroborate the predicted theoretical impacts on consumer surplus, speaking to their robustness: one consumer segment prefers the capped environment.

PRELIMINARY VERSION. PLEASE DO NOT CITE.

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1 Introduction

Portion cap rules limit the default maximum quantity at which products can be offered. These have been proposed to regulate the consumption of foods and ingredients deemed unhealthy when consumed liberally. Perhaps the most prominent example is the 2012 New York City (NYC) "soda ban." According to the proposed plan, establishments regulated by NYC would not be allowed to sell sugar-sweetened beverages in containers larger than 16 ounces.[1] At the time, most public discussions around the proposed rule implied that it would hurt consumers. Recent work questions this intuition indicating that, when the retailer uses bundling as a means to separate buyers by their preferences, some consumers may be better off after the cap; particularly, those who highly appreciate the unregulated item but do not value the restricted product (Nuno-Ledesma, 2021). This claim is derived from a theoretical analysis assuming that the seller only implements profit-maximizing strategies. Here, I empirically evaluate the finding with data from an experiment where participants are free to design their menus and thus can adopt imperfect pricing schedules. I manipulate the regulatory environment across treatments. Compared to the baseline, I find that consumer surplus does increase for buyers characterized by low valuation for the limited component and high appreciation for the unregulated item. Thus, the pattern is robust, on average, to different segmentation and pricing schemes.

In the experiment, sellers offer menus with up to four "packages". Each package is priced independently and is composed of two products. Because the experiment is designed to test predictions from a stylized model, the laboratory conditions abstract away from institutional

[1] This is about 473 milliliters, the size of most "small cup" options in popular American quick-service restaurants.

details. Even though this is detrimental to the study's external validity, at the same time the experiment furthers our understanding of a general phenomenon: the effect on consumer surplus given an interaction between quantity limits and price-discriminating practices. This topic is relevant to address because price discrimination is rampant in the food retail industry (Holton 1957; McManus 2007; Sharpe and Staelin 2010; Hendel and Nevo 2013), and calls to regulate foods and ingredients are frequent.

To discern parallelisms between the laboratory and naturally occurring market conditions, the experimental structure can be given two interpretations. In the first one, sellers can be seen as operating in quick-service restaurants where products are always sold in combos or "value meals." In an alternative reading, sellers decide the formula of a product offered in different presentations. Under this light, each component is an ingredient and sellers aim to segment demand based on the buyers' preferences for each of the two items.[2] To make the interpretation tangible, imagine a sugary beverage producer deciding different presentations of its main product. Each presentation features a particular sugar-"other ingredients" ratio. The component "other ingredients" serves as an umbrella term to include ingredients such as fruit extracts, carbon dioxide, flavoring agents and items other than sugar. Thus, the seller offers products with two items: sugar and "other ingredients." A product reformulation proposal could target sugar content within portions, to which the seller can respond by adjusting all variables to her disposal including other ingredients and the good's final price. Other stand-alone products can be seen as bundles of traits and ingredients,

[2] The idea of considering single products as collections of traits and ingredients is already present in the seminal work on bundling (Adams and Yellen, 1976). Moreover, this interpretation is close to the rationale behind random utility theory, which happens to be widely used by agricultural and food economists that conduct discrete choice experiments (Louviere and Woodworth 1983; Lancaster 1966). According to this theory, total utility derived from consuming a good equals the sum of the individual utilities provided by each of the attributes existing within the product.

including breakfast cereals (containing cereal, nuts, sugar, and other add ons), flavored milks (composed of milk and flavoring agents), energy drinks (incorporating caffeine, sugar, and flavoring ingredients), and organic vegetables (the bundle of the vegetables themselves plus their "organic" status), to name a few.

By embracing this last reading of the experimental environment, this paper can inform possible outcomes of product reformulation policies. An example of such a measure is the United Kingdom's sugar reduction programme (Public Health England, 2017). Officially adopted in 2016, the ambition of the plan is to reduce overall sugar content in a set of foods popular among children by 20% taking 2015 levels as a benchmark. The means to achieve the objective include reduced portions and reformulation to reduce the sugar levels within a given portion. Although the programme commenced as essentially self-enforced, my analysis can help to identify the outcomes of these types of plans if firms leverage their product composition as a means to price-discriminate and they either strictly abide by their self-imposed goals or are forced to do so by a binding public ordinance.

The argument that caps necessarily hurt buyers is intuitively appealing: a reduction in quantity implies less consumption and, all else equal, the consequence is lower consumer surplus. However, there are more factors at play. Once a cap rule is enacted, sophisticated sellers can revise their pricing strategies to accommodate the mandate while minimizing its impact on profit. The outcomes affecting consumers following these adjustments are not easy to anticipate *ex ante*. This is particularly true when sellers leverage bundling. Bundling is a marketing strategy that gives consumers the product they want tied to another good they may not value as much. If the cap affects one of the goods, the move could benefit the type of consumers who highly value the unregulated product but have a low appreciation for the capped item (Nuno-Ledesma, 2021). I set out to evaluate this claim with help from a controlled experiment.

Subjects are granted the freedom to decide critical characteristics of the menus: number of alternatives, quantities, and prices. This effectively relaxes the perfect-pricing premise allowing sellers to deviate from perfect screening strategies. This characteristic of the experimental design is important to better understand the effects of caps when sellers behave as observed in the field. Research points out that sellers often implement sub-optimal schemes because they are simpler to design and do not require a large sacrifice in expected profit (Chu et al., 2011). Moreover, even when playing stripped-down versions of the principal-agent model with adverse selection (the framework behind price-discrimination models), a non-negligible fraction of sellers deploy simple non-optimal screening strategies (Hoppe and Schmitz, 2015). Thus, whether the effects of caps on consumer surplus in multi-product markets predicted by Nuno-Ledesma (2021) would hold if the sellers implement sub-optimal pricing schedules remains an open question.

To equip the experiment to tackle the question at hand, I incorporate three stylized observations. First, buyers have private taste. It is fair to assume that food preferences can be considered as exogenous by retailers. Second, the seller offers more than one product. In this way, the design incorporates the fact that virtually all food retailers are either multi-product vendors or sell products that themselves are constituted by more than one component. Lastly, instead of fixing the number of alternatives sellers can offer, I allow for flexible menu design. In other words, number of options, quantities, and prices are all under control of the seller. This is consistent with how sellers are assumed to behave in standard screening models. Following a restriction in quantities, it is reasonable to assume that seller will modify prices, quantities, and demand segmentation to accommodate the intervention.

2 Relevant literature

Food firms' behaviour under regulation remains understudied compared to the attention received by the demand side of the market (Duvaleix-Treguer et al., 2012). My work expands the corpus of research projects investigating how firms react to food and nutritional policies.

I directly contribute to an expanding set of studies examining responses from price-discriminating sellers to cap rules and how, as a result, consumer surplus is impacted. Work in this area rests on theoretical analyses, but the findings are enticing. They suggest that if one-product sellers practice second-degree price discrimination, cap rules may not impact consumer surplus (Bourquard and Wu, 2019). In the multidimensional case, they can even benefit some consumer types (Nuno-Ledesma, 2021). An implicit assumption in this last paper is that the seller will strictly adhere to profit-maximizing segmentation and pricing across policy environments. However, as discussed in the introduction, empirical work reports that sellers aiming to screen demand are likely not to design perfectly-priced menus (Chu et al. 2011; Hoppe and Schmitz 2015). To the degree that subjects and professional retailers fail to perfectly execute profit-maximizing strategies, it is not clear whether the theoretical hypotheses would extrapolate to environments where actual human behaviour takes place.[3] I tackle the issue with help from a controlled economic experiment.

[3] Chu et al. (2011) concentrate on how sellers move away from mixed bundling (the scheme whereby sellers price every discrete combination of products possible) as it gets more and more difficult. Even though in Nuno-Ledesma (2021) the seller does not adopt mixed but pure bundling (i.e. the products are always sold together), the essence of the question remains because the seller needs to compare the expected profit associated with every single {price, quantities, number of segments} triplet and choose whichever produces the largest benefit for her, making the pricing decision computationally difficult for sellers facing cognitive, computational, and other types of limitations.

My study is related to works analyzing how buyers respond to quantity limits (Ahn and Lusk 2020; John et al. 2017; Wilson et al. 2013). These concentrate on the identification of framework effects and other non-pecuniary aspects of quantity limits from the point of view of customers. My investigation focuses on the seller's answer to the regulatory move. A comprehensive account of the consequences of cap rules must include studies of both buyers and sellers accommodating the policy.

If retailers leverage traits intrinsic to their products to price discriminate, and stand-alone products can be thought of as collections of ingredients and traits, Nuno-Ledesma (2021) points out that the tools from multidimensional screening can be used study policies affecting the formula of food products. In this paper, I rely on a screening model to design an experiment that can inform these class of interventions. The need to conduct analyses of these type of policies from varied perspectives is salient because their potential health benefits are noticeable (Leroy et al., 2015).

Ingredients that have been impacted by (mostly voluntary) measures akin to product reformulation include caffeine in energy drinks (Chen et al., 2019), salt (Wyness et al., 2011), and trans-fatty acids (Unnevehr and Jagmanaite 2008, LAbbé et al. 2009), among others. As pointed out by Requillart and Soler (2014), when the target ingredient happens to be what makes the product flavorful, public regulation can substitute market incentives and voluntary approaches. In this paper, I look at a hypothetical perfectly-enforced cap limiting one component in a product composed by two items. Thus, I provide some evidence about the possible outcomes of such a measure and illuminate the possible mechanisms at play. However, because the nature of product composition measures is extremely variable and depends on the specific characteristics of the target products, the contribution of this paper remains necessarily limited. Nonetheless, I provide a starting point for future projects better tailored to specific circumstances.

More broadly, my study is linked to the experimental literature addressing issues related to screening, and multi-commodity markets in general (Hoppe and Schmitz 2015; Hinloopen et al. 2014; Caliskan et al. 2007).

3 Theory

The experimental design relies on the bi-dimensional nonlinear pricing model used by Nuno-Ledesma (2021), in turn an adaptation from Armstrong and Rochet (1999). It is not my objective to provide a contribution to the economic theory behind the consequences of cap rules. I provide a brief description of the model and its predictions to offer the reader an opportunity to become familiar with the theoretical framework I rely on to shape the experiment.

The ij-type buyer (he) has private preferences i and j for products A and B, correspondingly. Preferences are either high (H) or low (L). Therefore, there are four types: HH, HL, LH, and LL. A given consumer is of an ij-type with probability β_{ij}. If a buyer pays price p_{ij} for a package containing quantities q^A_{ij} and q^B_{ij} of the corresponding good, he earns the following consumer rents:

$$R_{ij} = \theta^A_i u(q^A_{ij}) + \theta^B_j u(q^B_{ij}) - p_{ij} \tag{1}$$

Where the taste parameters θ^A_i and θ^B_j for i, j = H, L satisfy $\theta_H > \theta_L$. Possible health benefits are absent from this definition of consumer surplus. This is because to argue a precise measure of consumer welfare improvement due to the cap would be difficult. Attempting to model a health benefit would require arbitrary assumptions regarding how reduce consumption translates into health improvements. These assumptions could be selected to produce any desired outcome. However, the model likely underestimates the benefits to consumers. The more salient effect derived from the model is that the cap will benefit a segment of consumers, even if there are no additional benefits associated with lower intake of the alleged unhealthy ingredient or food.

The seller (she) offers the goods in packages $[q^A, q^B]$ and charges a single price. The cost of production $c(\cdot)$ is the same for both products. Her expected profit is defined as follows:

$$\mathbb{E}[\pi] = \sum_{ij} \beta_{ij} \Big[p_{ij} - c(q^A_{ij}) - c(q^B_{ij}) \Big] \tag{2}$$

The monopolist assumption is not the main force behind the results. Nonlinear pricing is mainly motivated by the desire to separate buyer types with private information. Thus, outcomes are determined less by competitive stress and more by the profit-enhancing opportunities emerging from the presence of different submarkets with particular preferences (Wilson, 1993). This incomplete information problem is independent of the strength of the market competitive pressures. Moreover, most cases where sellers adopt price-discriminating techniques, such as nonlinear pricing, occur in monopolistic markets (Tirole, 1988). Therefore, the use of these type of sorting schemes by the seller does not imply the absence or prevalence of competition. Even patterns perceived during casual observation of the food retail industry expose the relative independence between competition and market segmentation. Most food retailers implement segmentation strategies such as quantity discounts and bundling, even though their markets are competitive.

Assuming that the buyer's reservation value is $\bar{u}$, the seller maximizes her expected profit subject to the following participation (PC) and incentive-compatibility (IC) constraints:

$$\text{PC:} \;\; R_{ij} \geq \bar{u} \; \forall \; ij \tag{3}$$

$$\text{IC:} \;\; R_{ij} \geq R_{kl} + u(q_{kl}^{A})(\theta_i^A - \theta_k^A) + u(q_{kl}^{B})(\theta_j^B - \theta_l^B) + \bar{u} \; \forall \; ij \text{ and } kl; i \neq k \text{ and } j \neq l \tag{4}$$

Because the products are always sold together (the scheme known as "pure bundling"), the seller is said to bundle the products if, for a given set of alternatives, the quantity of good i increases with the preference for component j. With bundling, the following allocation pattern arises: compared to the LL-type, i) the LH buyer receives more product A, and ii) the HL consumer gets more good B. These allocations are said to be distorted. The LH (HL) buyer's first-best quantity of product A (B) equals the quantity offered to the LL-type buyer; however the LH (HL) type receives a larger quantity of A (B) as an enticement to get him to reveal his type and buy the combo intended for him by the seller. The reason why these types purchase a distorted quantity of the product they value lowly, is that it comes tied with the first-best portion of the product they appreciate most. The seller leverages their high willingness to pay for one product to persuade them into buying a larger portion of the component they do not appreciate as much.

If a portion cap rule is enacted to limit the quantity of product A, the LH-type sees his consumer surplus increase. The outcome emerges regardless of whether the products are independent, complements, or substitutes. Intuitively, this is because the cap moves the portion of good A closer to his firs-best without distorting the quantity of product B he receives. This is the main hypothesis to evaluate with help from the experimental data.

Main hypothesis: *Limiting the portion of product A to a level below the largest unregulated portion suggested by the model, causes an increase of the LH-type buyer's consumer surplus.*

The seller's prefect strategy would sort buyers into ideal (from the point of view of the retailer) market segments, requiring precise quantity-price combinations. To maximize expected profit, she needs to keep this level of surgical precision across all policy environments. Whether the outcome will hold with imperfect pricing is important to clarify because with two products, four types, and no cap there are 25 possible segmentation strategies, each of them possibly achieved with different price-quantity combinations.[4] To this end, I design an experiment where human subjects play the role of sellers.

4 Experimental design

An economic experiment is better suited to address the goals of this paper compared to alternative methodologies. These include i) a complete theoretical analysis looking at all possible pricing possibilities, and ii) numerical exercises with parameterized versions of the model. A theoretical study using a multidimensional screening model would be onerously

[4]For example, one possible segmentation strategy would be to serve all types with a single one-size-fits-all option; another would be to offer one package to serve the HH, HL, and LH types while excluding the LL-type; yet another would be to offer one package to serve the HH and HL-types, a second package to serve the LH-type, and a third to the LL-type. Each segmentation strategy can be either perfectly (given a separation pattern, choose the prices-quantities combination that would maximize profit), or imperfectly achieved.

long, convoluted, and the outcomes would likely be inscrutable. Regarding a potential numerical approach where the researcher manually solves for all possible pricing possibilities and compares all combinations and their outcomes across scenarios, there are three main reasons why an experiment is to be preferred. First, the complexity of the segmentation problem (which buyer types to exclude, which to serve separately with tailored alternatives, and which types to serve as a group with a single option) increases exponentially with the number of dimensions along which the seller screens. Second, in a numerical exercise, the difficulty of listing all possible screening alternatives further increases if, for a giving segmentation strategy (say, one alternative for each buyer type), the seller can set sub-optimal prices and quantities. Lastly, to make meaningful comparisons across treatments, the researcher must adopt arbitrary assumptions to make the case about which segmentation-pricing combinations are more likely to occur in the field. None of these issues arise if we let human sellers to decide their own marketing strategies.

In table 1, I show the parameters I chose to use during the experimental sessions. With these parameter values, I provide subjects operating under no restrictions with incentives to exclude the LL-type from participation and finely sort the remaining types into their own market segment. Table 2 shows the treatments. For completeness, I briefly describe the theoretically optimal pricing schedule resulting from this parametrization.

The expected-profit maximizing seller offers the following set of alternatives $\{[q^A_{LL}, q^B_{LL}, p_{LL}]$, $[q^A_{LH}, q^B_{LH}, p_{LH}], [q^A_{HL}, q^B_{HL}, p_{HL}], [q^A_{HH}, q^B_{HH}, p_{HH}]\}$ (rounded to the closest integer). *Baselie*: {[0,0,0], [111, 152, 290], [152, 111, 290], [152, 152, 317]}, *Cap*: {[0,0,0], [75, 152, 272], [75, 106, 233] [75, 152, 272]}. Note that with a cap, the alternative [75, 152, 272] is to be consumed by both, the HH and the LH buyer types. These menus would result in the following consumer surplus distributions $\{R_{LL}, R_{LH}, R_{HL}, R_{HH},\}$ (rounded to the fifth decimal): *Baseline*: {0.0000, 0.00000, 0.00000, 52.71475}, *Cap*: {0.00000, 0.00042, 0.0000, 51.51569}.[5]

Table 1: Parameter values used in this study

Parameter	Value	Description
β_{HH}	0.1	Probability of the buyer being an HH-type
β	0.4	Probability of the buyer being an HL or LH-type
β_{LL}	0.1	Probability of the buyer being an LL-type
θ_H	15	Taste parameter when preference is high
θ_L	10	Taste parameter when preference is low
$\theta_i u(q)$	$\theta_i \sqrt{q}$	Buyer's gross utility
$c(q)$	$q^2/500$	Seller's cost of producing q units of a given good
$\bar{q_A}$	75	Maximum-quantity cap on good A in the cap treatment

Other than to have been chosen to provide incentives to bundle, the selected distribution of buyer types is fairly generic, its properties are not particular and can be considered to be fairly representative of other probability-combinations with negative correlation.[6] Because it is symmetric (the probability of the buyer being a LL is the same as the probability of being an HH, and similarly for the HL and LH types) and it can be expressed with probabilities with only one decimal, this distribution simplifies the experimental instructions.

Each subject dealt exclusively with buyers simulated by his/her own computer. No action taken by any subject affected the outcomes or the decisions made by the buyers facing other participants. The situation where each subject holds a monopoly but each of them face the same regulatory environment can be interpreted as follows. All sellers offer the same product

[5]To notice the changes in surplus, I need to round to the fifth decimal. This fact highlights how sensitive to any changes in variables and parameters the behaviour of agents in a multidimensional screening model is. This is precisely the reason why we need to evaluate theoretical predictions against actual human decision making.

[6] With this framework, a given distribution of types is said to be "negatively correlated" when the proportion of HL and LH types is high enough that separating them from the HH and LL would increase profits. In distributions of types with "positive" correlation, the proportion of LH and HL types is small and not worth the effort to separate from the rest of buyer types.

A, but component B is particular to each of them. In a first (not modeled) stage, buyers sort themselves into a particular seller according to good B and then choose from the menus presented to them by the retailer. Much as when deliberating whether to eat at Chipotle or McDonalds, a consumer decides between burritos and burgers (good B) knowing that soda pop (product A) will be available in both places.

The role of the buyer is played by a computer program. This is for two reasons. First, this eliminates uncertainty about the consumer's purchasing behaviour. Human participants can be certain that the customer chooses the alternative maximizing his surplus, has no memory, does not commit mistakes, and does not engage in strategic behaviour beyond surplus maximization. Second, I can be confident that subjects did not adopt level-k strategies. Particularly, inequity aversion (preoccupation about perceived fairness of the outcomes), will not explain the patterns (Fehr and Schmidt, 1999). In sum, by automating the role of the buyer, I can isolate the role that the interaction between the seller's pricing strategy and the policy environment has on surplus distribution.

4.1 Procedures and experimental task

I randomly assigned subjects to one of two experimental treatments: *Baseline* or *Cap* named after their policy environment. In total, 82 subjects participated in the experiment. They were recruited via ORSEE (Greiner, 2015) and the sample was randomly drawn from the student population of a large public American university. There were three sessions per treatment with 12 to 14 subjects each. No subject participated in more than one session. In table 2, the reader can see the payoff functions and the ranges of choice per treatment. I designed the experimental interface with oTree (Chen et al., 2016).

Table 2: Treatments

	Payoffs		Choice variables: ranges		
Treatment	Seller	ij-type buyer	Product A	Product B	Price
Baseline	$p - \frac{(q_A)^2+(q_B)^2}{500}$	$\theta_i\sqrt{q_A} + \theta_j\sqrt{q_B} - p$	$[0,\ldots,250]$	$[0,\ldots,250]$	$[0,\ldots,500]$
Cap	$p - \frac{(q_A)^2+(q_B)^2}{500}$	$\theta_i\sqrt{q_A} + \theta_j\sqrt{q_B} - p$	$[0,\ldots,75]$	$[0,\ldots,250]$	$[0,\ldots,500]$

In all sessions, subjects played "trading periods" where the seller submits a menu of choices and the buyer makes consumption decisions. There are 6 training periods with no financial consequences to familiarize subjects with the interface and game structure. Following the training phase, each subject played 11 paying-effective periods. Every menu of choices submitted and the corresponding purchase decision constitute an observation in my database. Excluding training periods, the final database contains 902 observations, 440 from the *Baseline* group and 462 from the *Cap* treatment. All subjects were assigned to the role of a seller and did not interact with any other human subject in the room. A computer program mimicked the choices of a rational consumer whose type was randomly and independently assigned before each trading period. Throughout the experiment, earnings are denominated in points. Final earnings were converted into cash at the exchange rate of 31 points per US Dollar following a protocol I describe later. All sessions had the same structure: first, subjects answered a pre-experimental quiz; second, there were six "training" non-paying trading periods; then, eleven "effective" trading rounds were played; lastly, subjects answered a post-experimental survey. [7]

The game in each trading period closely mirrors the screening problem I described in the

[7] Examples of the experimental materials, including instructions, are available from the author upon reasonable requests.

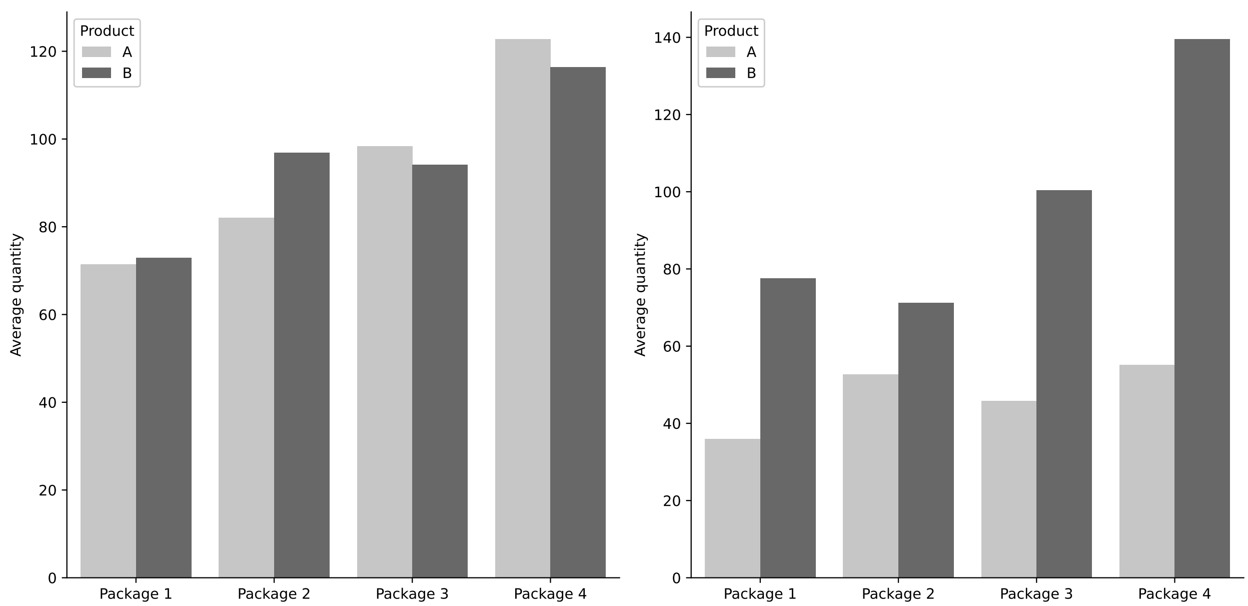
theory section. At the beginning of each trading round, the seller chooses to offer a number of packages from one to four, or not to offer any package at all. Next, the seller specifies quantities and prices. Thus, the seller is designing a menu consisting of up to four packages, each with three arguments: quantity of good A, quantity of component B, and a price for the combo. Following the design of the menu, the offer is submitted to the computerized buyer for consideration. The buyer is assigned a type according to the probabilities I show in table 1. The buyer can purchase only one package per period. The buyer chooses the package that maximizes his payoff, but rejects the entire menu if all packages result in earnings lower than the reservation value of zero. If more than one packages generate in the same non-negative earnings for him, then the first of these packages (in the order they were submitted by the seller) is chosen. The seller and buyer payoffs in points are determined using the purchased package, if any. If no menu is submitted or if the buyer rejects the entire menu, both parties receive zero points. At the end of each trading period, the seller is shown the terms of the menu she offered, the choice made my the consumer and her period earnings in points. They can take notes in a physical earnings-tracking sheet provided by the experimenter. Subjects also have access to a calculator during the menu-design phase. With it, the seller can experiment with different quantities-price combinations and learn how these would translate into profit, cost of production, and consumer surplus per buyer type.

The sum of points earned in four out of the eleven effective trading periods determined the final experimental earnings for the subjects. These were randomly chosen via the following protocol. Labeled from 1 to 330, the experimenter had a list with all possible combinations of four periods. A computer application, programmed by the experimenter, that randomly chooses numbers between 1 to 330 -all equally likely- was activated before the experiment started. The application was activated three times, so that subjects could witness the randomness of its operation. The number that appeared the third time represented the label of the selected combination of paying periods. The selected paying combination was kept secret during the session. After subjects finished their tasks, the experimenter showed all the possible combinations and their corresponding labels to them, and reminded them about the selected combination of paying periods. If, for a given participant, the sum earnings of the four randomly selected periods was negative, the earnings of the subject was set to zero. This protocol was detailed in the experimental instructions.

5 Results

I first offer an overview of the the data. If these follow general patterns consistent with some aspects of price-discriminating behaviour, I can be reasonably assured that my experimental design appropriately captures the essence of the theory, that subjects understood the instructions, and that their decisions were not aimless.

According to the theory, I should expect to observe evidence of bundling in the control treatment. With the framework I have been using, bundling manifests itself as increments in product i given an increase in preference for product j. If I take all of the submitted menus featuring at least one package, order the packages within a menu by the sum of their quantities (from the package containing more units of bot products to the option with less units of the goods), and average across all menus, the result is figure 1. Let us suppose that the smaller, and second smaller (average) packages target LL and LH types, and the largest and the second largest target HH and HL types, respectively. Visually, the reader can confirm that, in the baseline group, product A (B) increases with preferences for B (A). This is a crude approximation to the sellers' pricing scheme because it is not immediately obvious which of the two "medium" packages (options between the smallest and the largest) would be selected by either the HL or the LH type. Moreover, it ignores that some sellers engaged in bunching (serving more than one type with a single package), and exclusion. However, it is not one of my objectives to formally test the theory of multidimensional screening as such. Therefore, I consider the pattern of offered quantities shown in the figure to be sufficient evidence of sellers behaving as expected to a reasonable degree.



(a) Baseline (b) Cap Rule

Figure 1: Packages by sum of offered quantities

I now turn to the the characteristics of the menus. Evidence of learning during the experiment would add and additional layer of confidence on the data. This is because it would indicate that subjects not only understood the instructions, but that they took non-arbitrary decisions and increased their pricing accuracy as the session progressed. To elicit price discrimination, subjects were informed that they were going to be matched with a single buyer each trading round but the type of the buyer would change across periods according to a known vector of probabilities. From the submitted menus, I can infer which package all type of buyers would have purchased had they been presented with the submitted menu. These packages and their associated payoffs are the data I use to test hypotheses throughout the rest of this document.

In table 3, I show average price and quantities of the packages purchased by each buyer type. In both treatments, price and quantities are larger in later periods. The evolution of both prices and quantities would be evidence of a greater degree of pricing sophistication if buyers' rents are lower and seller's per-period payoffs are larger in later trading periods. This would hint at a progressively better ability of sellers to extract surplus from customers. Table 4 shows that this is generally the case. As the experiment progresses, subjects seem to learn to more precisely price their packages and extract more surplus from the buyers as a consequence.

Table 4 classifies the set of submitted offers by the number of segments into which they divide the demand. If a submitted menu serves one or more buyer types with a single package, and no other package could be purchased by a consumer, then the offer creates one market segment.[8] Equivalently, if two packages from an offer serve one or more buyer types each, and no other package would be purchased by a consumer, then the offer creates two market segments. The logic extends to larger number of segments.

[8]Some examples of menu offers that create one segment are: i) one package to serve the HH-type only; ii) one package to serve the HH and HL types only, and iii) one package to serve all types at the same time.

Table 3: Average characteristics of the purchased packages per buyer type

	Baseline				Cap			
	LL	LH	HL	HH	LL	LH	HL	HH
All periods:								
Mean price	160.14	209.66	211.35	218.80	128.97	180.04	170.19	184.22
Mean q^A	93.27	98.32	117.15	115.87	41.43	48.71	56.59	55.32
Mean q^B	90.58	112.93	97.11	107.98	95.21	120.12	97.03	117.19
First 5 periods:								
Mean price	145.49	197.63	200.18	204.39	121.30	171.55	162.18	177.25
Mean q^A	84.82	92.07	112.38	108.53	37.50	45.76	54.05	52.97
Mean q^B	83.80	107.98	91.26	101.30	88.67	114.05	92.13	112.22
Last 6 periods:								
Mean price	173.66	219.69	220.75	230.57	136.26	187.14	176.79	190.03
Mean q^A	101.06	103.53	121.16	121.87	45.16	51.19	58.67	57.28
Mean q^B	96.83	117.05	102.03	113.45	101.43	125.19	101.07	121.33

Table 4: Average per-period earnings

	Number of segments (Baseline)				Number of segments (Cap)			
	0	1	2	3	0	1	2	3
All periods:								
#Obs/Total (Share)	4/440 (0.9)	251/440 (57.0)	170/440 (38.6)	15/440 (3.4)	2/462 (0.4)	300/462 (64.9)	121/462 (26.2)	39/462 (8.4)
Mean R_{LL}	0	10.96	8.51	8.01	0	15.69	9.85	5.10
Mean R_{LH}	0	40.25	33.81	36.51	0	52.18	36.68	34.75
Mean R_{HL}	0	41.48	34.04	36.60	0	35.29	27.93	25.47
Mean R_{HH}	0	90.44	79.59	74.73	0	87.13	72.34	62.26
Mean payoff seller	0	142.33	144.51	140.93	0	126.00	135.33	134.41
Mean $\mathbb{E}[\pi]$	0	107.15	110.39	117.62	0	95.93	102.04	117.38
First 5 periods:								
#Obs/Total (Share)	4/200 (2.0)	111/200 (55.5)	76/200 (38.0)	9/200 (4.5)	1/210 (0.5)	133/210 (63.3)	58/210 (27.6)	18/210 (8.6)
Mean R_{LL}	0	16.70	8.10	8.95	0	17.75	12.17	3.24
Mean R_{LH}	0	48.44	33.76	39.25	0	53.60	41.71	34.66
Mean R_{HL}	0	49.52	33.53	39.84	0	36.50	33.22	25.02
Mean R_{HH}	0	96.49	78.13	77.96	0	87.31	76.13	62.23
Mean payoff seller	0	136.68	142.38	134.61	0	117.70	127.62	144.21
Mean $\mathbb{E}[\pi]$	0	102.34	109.46	121.51	0	92.17	105.36	120.87
Last 6 periods:								
#Obs/Total (Share)	0/240 (0.0)	140/240 (58.3)	94/240 (39.1)	6/240 (2.5)	1/252 (0.4)	167/252 (66.3)	63/252 (25.0)	21/252 (8.3)
Mean R_{LL}	0	6.41	8.84	6.61	0	14.05	7.71	6.70
Mean R_{LH}	0	33.76	33.85	32.40	0	51.05	32.04	34.83
Mean R_{HL}	0	35.10	34.45	31.74	0	34.32	23.05	25.85
Mean R_{HH}	0	85.65	80.77	69.88	0	86.99	68.85	62.29
Mean payoff seller	0	146.81	146.23	150.41	0	132.61	142.43	126.01
Mean $\mathbb{E}[\pi]$	0	110.96	111.14	111.78	0	98.92	99.00	114.39

There are commonalities across treatments regarding the number of segments into which demand was separated by sellers. Three is the maximum number of demand partitions in both conditions. Most offers created a single market bin. The second most common number of demand sections in both groups was two, leaving the type of offers creating three segments in the minority. However, the exact proportion figures of the offers creating one, two and three market partitions are different across treatments. A natural question is whether the cap changed the likelihood of sellers segmenting the demand into a given number of bins. Table 5 shows logit models estimated to address this question and their associated estimated marginal effects. The cap does not seem to have induced a significant change in the number of segments into which the sellers separate the demand.

Table 5: Probabilities that sellers separated demand into one, two or three segments

Dependent	One package		Two packages		Three packages	
variable:	Logit Model	Marginal effect	Logit Model	Marginal effect	Logit Model	Marginal effect
Cap	0.504	0.060	-0.872	-0.104	0.657*	0.022
	(0.552)	(0.066)	(0.600)	(0.071)	(0.390)	(0.014)
Period	0.014	0.001	-0.003	0.000	-0.016	0.000
	(0.039)	(0.004)	(0.029)	(0.003)	(0.042)	(0.001)
Constant	0.448***		-0.837***		-5.592***	
	(0.166)		(0.180)		(0.539)	
N	902	902	902	902	902	902

$*$ Pr $<$ 0.1, $**$ Pr $<$ 0.05, $***$ Pr $<$ 0.01. Robust standard errors clustered at the session level in parentheses. Marginal effects: standard errors estimated with delta method in parentheses.

The motivation to experimentally evaluate main hypotheses put forward by recent theory-based work is that, given the large number of pricing and segmentation possibilities, it is unclear whether human sellers would closely adhere to the theoretically best segmentation and pricing schedule across regulatory situations. In the early parts of the document, I posited that one could expect a sizable fraction of human players to adopt sub-optimal strategies. Summary figures from both tables 3 and 4 give justification to this expectation.

Submissions varied in the number of packages offered. Indeed, most menus in both treatments contained only one package, which suggests that participants did tend to seek simple pricing strategies. In addition, the specific pricing of the menus changed across periods, implying adaptation from the part of the sellers.

5.1 Main result: Effect of the cap rule on consumer surplus

I begin by testing the cardinal hypothesis of this study. Namely, that buyers that highly value the unregulated component and not so much the restricted product are better off with a cap rule, in the sense of receiving a larger surplus after the move. Within the framework under study, a cap on A should benefit the LH type customer. Table 6 shows econometric estimates of the impact of the cap on earnings by consumer type and expected profit. The column under R_{LH} displays the estimated effect on surplus earned by the LH type. I find the impact on this consumer to be positive. Given the large number of strategies subjects could adopt, this outcome is notable because it suggests that this market segment is expected to benefit from the quantity restriction even if sellers are not implementing the theoretically optimal pricing scheme. In other words, the evidence suggests that this result is robust to the segmentation strategy adopted by the seller,on average.

Main finding: *As expected, limiting the quantity of product A, results in larger consumer surplus for the LH-type buyer.*

To see what this outcome implies, consider the two interpretations I have suggested: subjects can be seen as either retailers designing a menu of "value meals," or food manufacturers deciding the ingredient composition of a product they offer under several presentations (each

Table 6: Estimates: impact of the quantity cap on per-period earnings

	Seller	Buyers			
	$\mathbb{E}[\pi]$	R_{HH}	R_{HL}	R_{LH}	R_{LL}
Cap	-8.975	-4.109	-5.683	9.151**	3.388
	(8.765)	(3.903)	(4.946)	(4.227)	(3.548)
Period	0.992**	-0.509	-0.966***	-1.071***	-0.796***
	(0.387)	(0.406)	(0.357)	(0.344)	(0.214)
Constant	101.952***	87.950***	43.866***	43.703***	14.592***
	(8.437)	(5.338)	(6.214)	(5.534)	(4.275)
Observations	902	902	902	902	902

* P < 0.10, ** P < 0.05, *** P < 0.01. Regressions estimated using multi-level random effects at the session and subject levels. Robust standard errors clustered at the session level in parentheses. Cap takes a value of 1 if the observation belongs to the cap treatment, 0 otherwise. Period is a time trend.

presentation characterized by a unique A to B ingredient ratio). In the first reading, participants tie two products together, e.g. potato chips and burgers, to be offered in combo meals. Recall that with this framework, bundling refers to the practice of giving some consumers the product they want (for example, a burger) tied to other good they may not value as much (a large portion of potato chips, for instance). Under this interpretation, when the cap is applied to the portion of chips, the move benefits buyers who highly value burgers but do not appreciate fries as much. Before the enactment of the measure, this type of buyer was purchasing a portion of chips larger than his ideal, for the sake of getting his preferred portion of burger.

An equivalent interpretation can be constructed if we interpret participants to play as food vendors deciding the mix of two ingredients needed to produce the single good they offer (e.g. sugar and flavoring agents within a portion of sugary drink). Limiting the amount of sugar per serving of the beverage benefits the type of buyer who enjoys the drink because of its flavor (or any other of its traits), but found it to be a little too sweet before the cap caused the reformulation.

The estimated impacts on the remaining payoffs, including expected profit, are not statistically significant. However, this cannot be interpreted as evidence implying that a cap would result in null impacts on these surpluses. This is because participants were adopting a large number of the possible segmentation and pricing possibilities. Thus, unlike the main finding just discussed, these estimations are not robust to the separation scheme adopted by the seller.

Having addressed the primary objective of this document, I proceed to analyze prominent outcomes regarding submitted quantities and prices for completeness sake. I start by looking at the impacts on purchased quantities. In table 7, I show econometric estimates of the cap's impact on quantities purchased by each buyer type. I find significant reductions in consumption of A by all buyer types. I do not find statistically significant evidence of a change in consumption of product B by any of the consumer types.

Table 7: Estimates: impact of the quantity cap on per-period quantities purchased per buyer type

	q^A_{HH}	q^B_{HH}	q^A_{HL}	q^B_{HL}	q^A_{LH}	q^B_{LH}	q^A_{LL}	q^B_{LL}
Cap	-60.065***	9.504	-61.061***	0.609	-49.066***	7.587	-44.567***	9.480
	(8.635)	(11.694)	(9.803)	(9.616)	(8.761)	(12.153)	(5.779)	(9.374)
Period	1.593***	1.647***	1.269***	1.670***	1.512***	1.485***	1.940***	1.984***
	(0.341)	(0.494)	(0.228)	(0.355)	(0.464)	(0.427)	(0.444)	(0.656)
Constant	105.752***	97.726***	109.174***	86.587***	88.623***	103.507***	71.523***	70.542***
	(7.841)	(6.929)	(8.510)	(6.474)	(5.725)	(10.393)	(3.824)	(7.203)
Observations	896	896	872	872	890	890	467	467

* P < 0.10, ** P < 0.05, *** P < 0.01. Regressions estimated using multi-level random effects at the session and subject levels. Robust standard errors clustered at the session level in parentheses. Cap takes a value of 1 if the observation belongs to the cap treatment, 0 otherwise. Period is a time trend.

The reduction in consumption of product A is not surprising if we take into consideration that, in the baseline, average portions of this product are all above the cap level of 75 units. Similarly, I cannot draw solid conclusions from the apparent null effect of the cap on portions of component B, again because of the wide set of possible pricing strategies participants could implement.

Moving to describe changes in package prices, table 8 shows the corresponding econometric estimates. The relevant pattern to notice is that prices paid by buyers with high preference for the regulated component decreased following the cap rule. Changes in the rest of prices are not statistically relevant.

Table 8: Estimates: impact of the quantity cap on per-period prices

	p_{HH}	p_{HL}	p_{LH}	p_{LL}
Cap	-34.163*	-41.644**	-28.745	-18.345
	(19.122)	(19.860)	(18.661)	(15.219)
Period	3.355***	3.200***	3.180***	3.596***
	(0.680)	(0.524)	(0.568)	(0.792)
Constant	198.185***	191.572***	189.616***	118.163***
	(16.693)	(16.872)	(16.421)	(13.467)
Observations	896	872	890	467

* $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$. Regressions estimated using multi-level random effects at the session and subject levels. Robust standard errors clustered at the session level in parentheses. Cap takes a value of 1 if the observation belongs to the cap treatment, 0 otherwise. Period is a time trend.

6 Conclusion

I report an experiment on bi-dimensional screening with and without an upper quantity limit. My intention is to empirically assess the main finding put forward by recent theoretical work: that one market segment is better-off when a cap rule is enacted. The experimental data supports this conclusion. The benefited buyer type highly values the unregulated product but does not appreciate the limited good as much. In the experiment, human subjects enjoyed the flexibility to submit up to four packages containing their chosen quantities and price levels. Thus, the result is robust to different pricing schemes. The demand segmentation profiles are similar across treatments, suggesting that sellers do not radically change their separation strategies following the cap.

The synthetic market from which the data is gathered admits comparisons with two naturally occurring market situations. In one, subjects can be seen as sellers that offer combo meals featuring two items (e.g. soda and hamburgers). In a second interpretation, sellers manufacture a product composed of two ingredients (say, a sugary drink composed of sugar and other ingredients). Thus, this study can be informative about outcomes from portion cap rules similar to the 2012 NYC "soda ban" or product reformulation interventions such as the 2016 UK's sugar reduction programme. Albeit the external validity of the experiment is not strong, it illuminates potential mechanisms at play difficult to observe otherwise. This study is one of the first to provide an empirical foundation for understanding the economics of cap rules and product reformulations in markets characterized by private preferences.

My analysis excludes potential market failures and general equilibrium considerations. Thus, its capacity to address normative questions about whether the government ought to intervene on grounds of welfare and public health is limited. However, as one of the first empirical studies on the impacts of quantity limits in multi-product markets, I provide a staring point to empirically evaluate judgements that seem plausible, but that nonetheless lack supporting evidence. Here, I am concerned by the claim that cap rules unavoidably hurt consumers. This type of studies are important because both, the approval for initial implementation and the public judgment of the relative success of the measure hinge on proponents and opponents normative arguments and their ability to straightforwardly delineate benefits and costs. In this spirit, my analysis offers a basic foundation, on top of which evaluations of the merits of political claims beyond consumer protection can be conducted by other researchers.

Future research can expand this work in multiple forms. To delineate the role of behavioural aspects not addressed by screening models, the buyer end of the transaction can be played by humans. The role of repeat trading remains understudied. Competition can be added, to evaluate the robustness of the outcome to this pressure. Studies allowing for the possibility of mixed bundling are natural extensions. Formal comparisons between cap rules and other popular forms of regulation would be relevant. Health economists could modify this paper's definition of surplus to better account for possible benefits and costs of the policy given the nutritional aspects of specific food products.

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