All Units Discount: Experimental Evidence from the Vending Industry *

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Abstract

Many vertically-separated markets are characterized by common agency, in which competing upstream firms sell products through a common downstream agent. The downstream agent may provide ancillary services or exert effort in order to sell products, and non-exclusive agency may result in an under-provision of these services from the point of view of an upstream firm. If so, an upstream firm may try to align the downstream firm's incentives to provide increased effort through contractual arrangements such as quantity discounts, rebate contracts, or exclusive dealing. These arrangements may also have anti-competitive effects by crowding out the products of competing manufacturers. We examine a particular vertical rebate, an all-units-discount. Under this contract, the downstream firm pays a linear wholesale price until a target quantity is met. Once that target quantity is met, a discount applies not only to all future units purchased, but also to all previous units. This has the effect that the marginal cost to the agent is effectively negative over parts of the curve, which might appear hard to justify in the absence of anti-competitive reasons. The tension between the efficiency-enhancing and anti-competitive effects provides the motivation for empirical work.

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1 Introduction

This paper considers whether or not a dominant manufacturer can use vertical contracts, such as a lump-sum rebate, to foreclose competitors, and whether or not that foreclosure is necessarily inefficient. It offers as an alternative hypothesis that vertical contracts may be used to better align incentives of upstream and downstream firms, especially as those incentives relate to providing costly service or maintaining product availability.

These sorts of vertical arrangements have attracted scrutiny from antitrust authorities. Recently, several cases were brought against the computer chip manufacturer Intel. Central in these cases was the use of an all-units-discount (AUD) form of rebate contract, where if a sales target was attained, a linear discount applied retroactively to previous sales. Much of the controversy involved whether or not these rebates constituted a "bribe" to downstream firms. In 2009, *AMD vs. Intel* was finally settled for $1.25 billion, and the same year the European Commission levied a record fine of €1.06 billion against the chipmaker. In a 2010 *FTC vs. Intel* settlement, Intel agreed to cease the practice of conditioning rebates on exclusivity or on sales of other manufacturer's products. Similar issues were raised in the European Commission's 2001 case against Michelin and *LePage's v. 3M.*

In another recent case *Z.F. Meritor v. Eaton* (2012), Eaton allegedly used rebates to obtain exclusivity in the downstream heavy-duty truck transmission market. The 3rd Circuit ruled that the contracts in question were a violation of the Sherman and Clayton Acts as they were *de facto* (and partial) exclusive dealing contracts. This was despite Eaton's defense that they had not engaged in predatory pricing behavior under *Brooke Group*, because the post-discount average price was still above cost. The court ruled that because the contracts contained considerable non-price measures, *Brooke Group* did not apply. This was significant for two reasons. The first was that Meritor only claimed partial rather than full exclusion from the market. The second was that as an exclusion case, it meant that it was evaluated on its economic impact and both pro- and anti-competitive arguments applied.

There is a long tradition of theoretically analyzing potential foreclosure effects of vertical contracts. One of the important developments in the theory of vertical restraints is the so-called *Chicago Critique* of Bork (1978) or Posner (1976), which makes the point that because the downstream firm must be compensated for any exclusive arrangement, we should only observe exclusion when it maximizes industry profits. Much of the subsequent literature has focused on demonstrating that the *Chicago Critique's* predictions are a bit special. For example, Aghion and Bolton (1987) show that long-term contracts that require a liquidated damages payment from the downstream firm to the incumbent can result in inefficient exclusion; while Bernheim and Whinston (1998) show that the *Chicago Critique* ignores externalities across buyers, and that once externalities are accounted for, inefficient exclusion is again possible. Later work by Fumagalli and Motta (2006) links exclusion to the degree of competition in the downstream market. While extremely influential with economists, these arguments have (thus far) been less persuasive with the courts than Bork (1978).

We also consider pro-competitive justifications for vertical restraints. In many markets, retailers must expend effort to maintain product availability. This is especially true when firms face capacity constraints, high storage costs, or have limited shelf space. In vertically-separated markets, optimal stocking choices for downstream firms may differ substantially from those of upstream manufacturers, resulting in the under-provision of costly effort relative to the social optimum. This is an example of the well-known downstream moral hazard problem described by Telser (1960) or in Chapter 4 of Tirole (1988). These effects are often exacerbated when the products of competing firms are close substitutes. In such settings, manufacturers may use vertical arrangements to better align the stocking decisions of the downstream firms with their own interests.

While the role of potentially exclusionary vertical contracts has proved fertile ground for theoretical work, empirical work has been limited. One of the major challenges has been that most contractual arrangements between upstream and downstream firms are treated as trade secrets and are not readily observable. Another is that, even if contracts are observable, downstream effort by the agent is often hard to measure (both by the upstream firm and by researchers). The final challenge is that in order to evaluate the effects of exclusivity, we must often consider profits in counterfactual worlds that we do not observe.

Our paper examines the use of an AUD rebate contract by a dominant chocolate candy manufacturer, Mars Inc.. With revenues in excess of $50 billion, Mars is the third largest privately-held company in the United States (after Cargill and Koch Industries). Our objective is to measure both the efficiency-enhancing results of the rebate contract, as well as the extent to which the rebate is capable of foreclosing competition by Mars' top competitor, The Hershey Company (about $5 billion in revenues). We examine the effect of the rebate contract through the lens of a single retail vending operator, MarkVend Inc., by observing 60 vending machines located in five office buildings in downtown Chicago. By working with a single retailer, we are able to collect extremely detailed information on demand, as well as on wholesale costs, and contractual terms. Additionally, the retailer was able to run some field experiments on our behalf, which provide us with some insights regarding how contracts might influence the retailer's decisions.

We consider two exercises to measure the effect of Mars' AUD contracts. The first exercise is to understand the impact that retailer effort has on profits, in order to understand potential efficiency gains from vertical restraints. In our case, we interpret effort as being represented by the frequency with which the retailer restocks. One approach to measuring the impact of effort on profits might be to persuade the retailer to directly manipulate the restocking frequency, but this has some disadvantages. For example, the effects of effort (through decreased stock-out events) are only observed towards the end of each service period, and measuring these effects might prove difficult. Instead, we focus on manipulating the likely results of a reduced restocking frequency – by experimentally removing the best selling Mars products. We find that in the absence of the rebate contracts, Mars bears almost 90% of the cost of stock-out events, as many consumers substitute to competing brands, which often have higher retail margins. The lower wholesale price of the rebate reduces this to roughly 50% of the cost of stock-out events, and the quantity-target aspect of the rebate provides additional motivation for the retailer to set a high service level.

The goal of the second exercise is to understand the potential that rebate contracts have to foreclose competitors. We ask whether or not the downstream firm could increase profits by replacing a Mars product with a competitor's product. We choose not to design a second field experiment, because the marginal product stocked has relatively low sales and we would need to run our experiment for an exceptionally long period of time. Instead we use observational data on product rotations, and a discrete choice demand model, to compare sales under alternative product assortments. In some sense, this exercise represents "in-sample" variation for the demand model. We find some evidence that rebates foreclose competition, that is the retailer could increase profits by substituting a Hershey product for a Mars product, but that the threat of losing the rebate discourages him from doing so. In some cases, we find that the foreclosure maximizes industry profits consistent with the predictions in Bork (1978), but in other cases we find that the rebate contract acts as an inefficient barrier to entry to Hershey as predicted in the game-theoretic literature on vertical exclusion.

1.1 Relationship to Literature

This paper connects several different literatures. The first is a growing literature in economics, marketing, and operations research that focuses on firms' stocking decisions and the importance of product availability for vertical arrangements. In more recent empirical work, Anupindi, Dada, and Gupta (1998) study product availability, also in the context of vending machines. Several examples in this literature focus on scanner data and availability at supermarkets and convenience stores, such as Bruno and Vilcassim (2008), and Musalem, Olivares, Bradlow, Terwiesch, and Corsten (2010), and Matsa (2010). Aguirregabiria (1999) uses scanner data to examine the strategic implications of dynamic inventory decisions in the context of vertically-separated markets. There is a small related literature that uses experiments to study the effects of stockouts. Fitzsimons (2000) studies psychological effects of stockouts on consumers in the laboratory, and Anderson, Fitzsimons, and Simester (2006) examine psychological framing effects of how stockouts are presented to consumers in the context of a mail-order company.

The second is the larger, mostly theoretical literature on the role of vertical restraints in industrial organization. There is a literature which explores the efficiency enhancing aspects of vertical restraints, such as resale price maintenance (RPM), rebates, and exclusive contracts going back to Telser (1960) and the *Downstream Moral Hazard* problem (Ch 4 Tirole (1988)). Klein and Murphy (1988) show that without vertical restraints retailers "will have the incentive to use their promotional efforts to switch marginal customers to relatively known brands...which possess higher retail margins". More directly, Deneckere, Marvel, and Peck (1996), Deneckere, Marvel, and Peck (1997) examine markets with uncertain demand and stockouts and show that vertical restraints can induce higher stocking levels that are good for both consumers and manufacturers.

Vertical restraints can also be anti-competitive, and a separate theoretical literature has explored this issue in the context of upfront payments or slotting fees paid by manufacturers to retailers in exchange for limited shelf space (primarily in supermarkets). This literature includes Shaffer (1991b), Shaffer (1991a) which analyze slotting allowances, RPM, and aggregate rebates to see whether or not they help to facilitate collusion at the retail level. Bernheim and Whinston (1998) examine when exclusion is efficiency enhancing, has no effect, or is harmful. Sudhir and Rao (2006) analyze anti-competitive and efficiency arguments for slotting fees in the supermarket industry.

2 The Vending Industry and Experimental Data

2.1 Vertical Arrangements in the Vending Industry

Vertical arrangements are widely used in the vending industry and apply to several of the upstream relationships of the firm with whom we worked. The most commonly-used vertical arrangement in the industry is referred to as a "rebate program." Under a rebate program, a manufacturer refunds a portion of a vending operator's wholesale cost at the end of a fiscal quarter if the vending operator meets a quarterly sales goal, typically expressed as a percentage of year-over-year sales. The sales goal for an operator is typically set for the combined sales of a manufacturer's products, rather than for individual products. Some manufacturers also require a minimum number of product "facings" in an operator's machines. The amount of the rebate and the precise threshold of the sales goal or facing requirement is specific to an individual vending operator, and these terms are closely guarded by participants in the industry.

We are fortunate in that we observe the specific terms of the Mars Gold Rebate program; we include some promotional materials in Figure 1. The program employs the slogan *The Only Candy You Need to Stock in Your Machine!*, and provides a list of 'must-stock' items (Snickers, M&M Peanut, M&M Plain, Twix, a choice of 3 Musketeers or Milkyway, and a choice of Skittles or Starburst), as well as a sales target (90% of quarterly year-over-year sales) that applies to the total cases of Mars products sold. We also observe, but are not allowed to directly report, the amount of the rebate. Unlike the Intel rebate program, these rebates do not explicitly condition on marketshare or the sales of competitors. However, they do mandate 6 'must-stock' items, and most vending machines typically carry only 6 or 7 candy bars. While there is some ability for the vending operator to adjust the overall number of candy bars in a vending machine, it is often technologically difficult to do without upgrading capital equipment because candy bars and potato chips do not use the same size 'slots.')

An important benefit of rebate programs for manufacturers is the ability to more closely align the downstream operator's incentive to carry and re-stock the manufacturer's products with the manufacturer's own incentives. Specifically, at any wholesale cost greater than the cost of production, the downstream firm chooses to stock fewer units of inventory than the upstream manufacturer would choose. This inventory stocking problem is well understood, and is referred to as the "newsvendor" problem in the case when prices are fixed and demand is stochastic.[1] Rebates lower the wholesale cost for downstream operators, leaving them with a higher expected return from stocking an additional unit of inventory.

By structuring payments as a rebate, rather than directly reducing wholesale price, manufacturers are able to tailor the amount of the cost reduction to each individual operator,

[1]The "newsvendor" problem dates back to Edgeworth (1888), Spengler (1950), and Arrow, Harris, and Marschak (1951), and describes the potential for mis-aligned inventory incentives between upstream and downstream firms. More recent theoretical work formalizes and extends the solution to this problem (e.g., Kraiselburd, Narayanan, and Raman (2004), Schweitzer and Cachon (2000), and many others).

and to match it to targets that are retailer specific (e.g., 90 percent of his previous year's sales).[2] Kolay, Shaffer, and Ordover (2004) demonstrate that AUD contracts may be more effective for the upstream firm when discriminating across retailers than a menu of two-part tariffs. Rebates may also have an anti-competitive effect, because one way of increasing sales of a manufacturer's product is to stock fewer competing products.

2.2 Data Description

All of our price and quantity data are provided by Mark Vend Company. Data on the quantity and price of all products vended are recorded internally at each vending machine used in our experiment. The data track vends and revenues since the last service visit (but do not include time-stamps for each sale). Any given machine can carry roughly 35 products at one time, depending on configuration. We observe prices and variable costs for each product at each service visit during our 38-month panel. There is relatively little price variation within a site, and almost no price variation within a category (e.g., chocolate candy) at a site. Very few "natural" stock-outs occur at our set of machines.[3] Over all sites and months, we observe 185 unique products. We consolidate some products with very low levels of sales using similar products within a category produced by the same manufacturer, until we are left with the 73 'products' that form the basis of the rest of our exercise.[4]

All of these data are recorded at the level of a service visit to a vending machine. Because machines are serviced on different schedules it is sometimes more convenient to organize observations by machine-week, rather than by visit. When we do this, we assume that sales are distributed uniformly among the business days in a service interval, and assign those to weeks. Because different experimental treatments start on different days of the week, we allow our definition of when weeks start and end to depend on the client site and experiment.[5]

In addition to the data from Mark Vend, we also collect data on the characteristics of each product online and through industry trade sources.[6] For each product, we note its manufacturer, as well as the following set of product characteristics: package size, number

[2] Robinson-Patman prevents manufacturers from directly price discriminating across competing downstream firms when selling 'inputs.'

[3] Mark Vend commits to a low level of stock-out events in its service contracts.

[4] For example, we combine Milky Way Midnight with Milky Way, and Ruffles Original with Ruffles Sour Cream and Cheddar.

[5] At some site-experiment pairs, weeks run Tuesday to Monday, while others run Thursday to Wednesday.

[6] For consolidated products, we collect data on product characteristics at the disaggregated level. The characteristics of the consolidated product are computed as the weighted average of the characteristics of the component products, using vends to weight. In many cases, the observable characteristics are identical.

of servings, and nutritional information.[7]

In Table 2 we report the national sales ranks as reported from the industry association, as well as the aggregate shares within the candy category from the Mark Vend data. We also report the percentage of machine-weeks in which the product is stocked by Mark Vend. There are some patterns that emerge. The first is that Mark Vend stocks some of the most popular products sold by Mars Inc. (Snickers, M&M Peanut, Twix, and Skittles) in most of the machines in our sample. However, Mark Vend only stocks Hershey's best-selling product Reese's Peanut Butter Cups in 29% of machine-weeks, and it constitutes less than 4% of candy sales, even though nationally it is the fourth most popular product. Likewise, Nestle's best-selling product, Butterfinger, represents 2.7% of Mark Vend's sales and is only stocked about one-third of the time. Hershey's with Almonds is the tenth most popular candy product nationally, and isn't stocked at all by our retailer. Milky Way, another Mars product, is somewhat overrepresented in our sample, as are Rasinets, a Nestle product, which is stocked in 78% of machine weeks and constitutes almost 9% of overall sales, despite being ranked 17th nationally.

There are two possible explanations for Mark Vend's departures from the national best-sellers. One is that Mark Vend has better information on the tastes of its specific consumers, and that the product mix is geared towards those tastes. These are mostly high-income, professional office workers in Chicago, and they may have drastically different tastes than consumers from other demographic groups.[8] The alternative is that the rebate contracts may induce the retailer to substitute from Nestle and Hershey brands to Mars Inc. brands when making stocking decisions. Similarly, it might be the case that when the retailer does stock brands from competing manufacturers (e.g., Raisinets), they choose brands that do not steal business from key Mars Inc. brands.

3 Model

3.1 Toy Model

The specific rebate contract we examine is known as the All-Units-Discount (AUD). In most conventional nonlinear discount contracts, the retailer pays some price w for the first $\overline{q}$ units of a good, and then pays $w-\Delta$ (for $\Delta > 0$) thereafter. Both contracts are shown in Figure 3. Under AUD, the discount applies retroactively to all previous units, as well as to additional

[7]Nutritional information includes weight, calories, fat calories, sodium, fiber, sugars, protein, carbohydrates, and cholesterol.

[8]For example, Skittles, a fruit flavored candy sold by Mars is primarily marketed to younger consumers.

units. Thus, retailer cost is $C(q) = wq - \mathbf{1}[q > \overline{q}] \cdot \Delta \cdot q$. This has the effect that the marginal cost $C'(q)$ is negative for values of q that approach the threshold. This has led some to believe that AUD is de facto evidence of anticompetitive behavior, but Kolay, Shaffer, and Ordover (2004) show that AUD is similar to a two-part tariff, as it avoids double marginalization and may be somewhat more flexible in allocating surplus between upstream and downstream firms.

We consider a simple example in which two upstream firms (A and B) sell to a single downstream retailer. Firm A sells two products (products 1 and 3) and offers an AUD, and Firm B sells a single product (product 2) under a simple linear price schedule. We assume both upstream firms face production costs of zero, and sell their products to the downstream firm at wholesale prices of (w_A, w_B) (i.e., the two-product firm sells products 1 and 3 at the same wholesale price).[9] We also assume that the downstream firm chooses two products to stock (i.e., [1,2], [2,3], or [1,3]), sets a single price p for all products, and faces a per-product capacity constraint r, which is equal for all products. We examine this simple setting because it captures the important trade-offs of the AUD contract that we observe, and also because it mimics the arrangements within the chocolate confections vending market. However, it is worth noting that many other markets may be similarly characterized.[10]

Consumers choose a single product from the pair of products stocked by the downstream firm, or the outside good (product 0). Each consumer has a preference ranking over two of the four possible products (e.g., a consumer's preference ranking might be [1,3], or [2,0], etc.). No consumer in the market ranks the outside good first. If a consumer's first-choice product is not available, he chooses his second-choice product. If neither the first- or second-choice product is available, the consumer exits the market. We choose the distribution of consumer types so that demand is strongest for product 1 and weakest for product 3, and we allow for random consumer arrivals. When consumer arrivals are selected for the whole population without replacement, demand is deterministic (although realized sales may vary based on arrival order and capacity). Random selection of consumers with replacement implies stochastic demand.

The choice variables are: w_A, $\overline{q}$ (the threshold for the AUD), and Δ (for firm A), w_B (for firm B), and a (for the downstream firm). We are interested in the conditions under which the AUD prompts the downstream firm to drop product 2 in favor of product 3 (i.e., to

[9] We explore the results of a model in which firm A sets different wholesale prices for products 1 and 2 in appendix XXX.

[10] For example, many digital markets such as iTunes display limited price variation, both at the retail and wholesale levels, and do not carry all possible products.

contract exclusively with firm A), and the welfare implications of this decision. We generate random arrivals of 100 consumers with replacement, setting p equal to \$1, w_A equal to \$0.40, w_B equal to \$0.20, Δ equal to \$0.15, and the AUD threshold equal to 65. We simulate the model 10,000 times to account for differences in outcomes based on the random ordering of consumers and the stochasticity of demand.

The results of the model for two different capacities is shown in Table 1. Under either capacity, the rebate is paid if and only if the retailer exclusively sells A's products $[1, 3]$, thus even in the presence of stochastic demand, the AUD can be used to obtain exclusivity. Under either capacity, the profits of the retail firm and firm A are higher under the exclusive arrangement 74% and 99.4% of the time for the retailer, and 99.5% and 85.4% of the time for firm A for the low and high capacities respectively. Less than 1% of the time the retailer would prefer the exclusive arrangement in the absence of the AUD. Given these demands, and the expected profits of the retailer and Firm A, we might expect both firm A and the retailer to agree to an AUD contract that led to de-facto exclusivity.

However, the two capacities yield different predictions for overall sales. In the low capacity case (first column), total sales under the non-exclusive stocking arrangement $[1, 2]$ exceed sales under the exclusive [1.3] about 66% of the time and are lower about 26% of the time. In the higher capacity case, the results are nearly flipped with higher sales under the exclusive arrangement $[1, 3]$ about 66% of the time. Because prices and costs are the same across products (and the marginal cost of production is zero) total sales are equivalent to overall industry profits. Thus we can see that in the low capacity case, the non-exclusive arrangement maximizes industry profits about two-thirds of the time, while in the high capacity case the exclusive arrangement maximizes industry profits about two-thirds of the time. This is an important point, because all else being equal, the AUD should achieve exclusion, but whether or not that exclusion is efficient (from the industry perspective) depends on retail capacity.

We can see some clear effects of the AUD. The first effect is that through the lower marginal cost, the rebate increases the equilibrium level of service, r. The other two effects come through the threshold. Near the threshold, there is an additional incentive to increase r from the IC constraint of D. At the same time, there is an exclusionary motive, because sales of q_1 can be increased by switching $a : \{1, 1\} \rightarrow \{1, 0\}$. This effect is reinforced by the fact that service provision incentives are better aligned under exclusion, strengthening the incentive to increase service level, r.

3.2 Experimental Design

We ran three experimental treatments with the help of Mark Vend Company. Mark Vend is a medium-sized independent vending operator in the Chicago area. We identified 60 snack machines located in office buildings, for which demand was historically quite stable.[11] Most of the customers at these sites are 'white-collar' employees of law firms and insurance companies. Our goal in selecting the machines was to choose machines that could be analyzed together, in order to be able to run each experiment over a shorter period of time across more machines.[12] Finally, we selected machines on routes that were staffed by experienced drivers, so that the implementation of the experiments would be successful. The 60 machines used for each experiment were distributed across five of Mark Vend's clients, which had between 3 and 21 machines each. The largest client had two sets of floors serviced on different days, and we divided this client into two sites. Generally, each site is spread across multiple floors in a single high-rise office building, with machines located on each floor.

Implementation of each product removal was fairly straightforward; we removed either one or both of the two top-selling Mars, Inc. products from all machines for a period of roughly 2.5 to 3 weeks. The focal products were Snickers and Peanut M&Ms. Whenever a product was experimentally stocked-out, poster-card announcements were placed at the front of the empty product column. The announcements read "This product is temporarily unavailable. We apologize for any inconvenience." The purpose of the card was two-fold: first, we wanted to avoid dynamic effects on sales as much as possible, and second, the firm wanted to minimize the number of phone calls received in response to the stock-out events.

The dates of the interventions range from June 2007 to September 2008, with all removals run during the months of May - October. We collected data for all machines for just over three years, from January of 2006 until February of 2009. During each 2-3 week experimental period, most machines receive service visits about three times. However, the length of service visits varies across machines, with some machines visited more frequently than others.

The cost of the experiment consisted primarily of driver costs. Drivers had to spend extra time removing and reintroducing products to machines, and the driver dispatcher had to spend time instructing the drivers, tracking the dates of each experiment, and reviewing the data as they were collected. Drivers are generally paid a small commission on the

[11]More precisely, demand at these sites is "relatively" stable compared to the population of sites serviced by the vending operator.

[12]Many high-volume machines are located in public areas (e.g., museums or hospitals), and have demand that varies enormously from one day to the next, so we did not use machines of this nature. In contrast, the work-force populations at our experimental sites are relatively homogenous.

sales on their routes, so if sales levels fell dramatically as a result of the experiments, their commissions could be affected. Tracking commissions and extra minutes on each route for each driver would have been prohibitively expensive to do, and so drivers were provided with \$25 gift cards for gasoline during each week in which a product was removed on their route to compensate them for the extra time and the potential for lower commissions. With the exception of an individual site in one treatment, implementation was successful.[13]

4 Analyses of the Experimental Outcomes

4.1 Computing Treatment Effects

One goal of our experiment is to determine how product-level sales respond to changes in availability. Here it is helpful to define some basic quantities. We let q_{jt} denote the sales of product j in machine-week t, and we use a superscript 1 to denote sales when a focal product(s) is removed, and a superscript 0 to denote sales when a focal product(s) is available. We denote the set of available products as A, and F as the set of products we remove for our experiment. Then $Q_t^1 = \sum_{j \in A \setminus F} q_{jt}^1$ and $Q_s^0 = \sum_{j \in A} q_{js}^0$ are the overall sales during a treatment week, and control week respectively. It is also convenient to write the sales of the removed products $q_{fs}^0 = \sum_{j \in F} q_{js}^0$. Our goal is to compute $\Delta q_{jt} = q_{jt}^1 - E[q_{jt}^0]$, the treatment effect on the sales of product j of the experiment.

In principle, this calculation is straightforward. In practice, however, there are two challenges in implementing the experiments and interpreting the data generated by them. The first challenge is that there is a large amount of variation in overall sales at the weekly level independent of our experiments. This can be seen in Figure 6 which plots the overall sales of all machines in our sample on a weekly basis. For example, a law firm may have a large case going to trial in a given month, and vend levels will increase at the firm during that period. In our particular setting, many of the experiments were run during the summer of 2007, which was a high-point in demand at these sites, most likely due to macroeconomic conditions. In this case, using a simple measure like previous weeks' sales, or overall average sales for $E[q_{jt}^0]$ could result in unreasonable treatment effects, such as sales increasing due to stock-out events, or sales decreasing by more than the sales of the focal products.

In order to deal with this challenge, we impose two simple restrictions based on consumer theory. Our first restriction is that our experimental product removals should not increase

[13] In the unsuccessful run, the driver at one site forgot to remove the focal product, so no intervention took place.

overall demand, so that $Q^0_t - Q^1_s \geq 0$. Our second restriction is that our experiments should not reduce overall demand by more than the sales of the products we removed, or $Q^0_t - Q^1_s \leq q^0_{fs}$. This means we choose control weeks s that correspond to treatment week t as follows:

$$\{s : s \neq t, Q^0_t - Q^1_s \in [0, q^0_{fs}]\} \tag{1}$$

While this has the nice property that it imposes the restriction on our selection of control weeks that all products are weak-substitutes, it has the disadvantage that it introduces the potential for selection bias. The bias results from the fact that weeks with unusually high sales of the focal product q^0_{fs} are more likely to be included in our control. This bias would likely overstate the costs of product removal, which would be problematic for our study.

We propose a slight modification of (1) which removes the bias. That is, we can replace q^0_{fs} with $\widehat{q^0_{fs}} = E[q^0_{fs}|Q^0_s]$. An easy way to obtain the expectation is to run an OLS regression of q^0_{fs} on Q^0_s, at the machine level and use the predicted value. This has the nice property that the error is orthogonal to Q^0_s, which ensures that our choice of weeks is now unbiased.

The second challenge is that, although the experimental design is relatively clean, the product mix presented in a machine is not necessarily fixed across machines, or within a machine over long periods of time because we rely on observational data for the control weeks. For example, manufacturers may change their product lines, or Mark Vend may change its stocking decisions over time). Thus while our experiments intend to isolate the treatment effect of removing Snickers, we might instead compute the treatment effect of removing Snickers jointly with changing pretzel suppliers.

To mitigate this issue, we restrict our set of potential control weeks to those at the same machine with similar product availability within the category of our experiment. In practice, two of our three treatments took place during weeks where 3 Musketeers and Reese's Peanut Butter Cups were unavailable, so we restrict our set of potential control weeks for those experiments to weeks where those products were also unavailable. We denote this condition as $A_s \approx A_t$.

We use our definition of control weeks s to compute the expected control sales that correspond to treatment week t as:

$$S_t = \{s : s \neq t, A_t \approx A_s, Q^0_t - Q^1_s \in [0, \hat{b_0} + \hat{b_1} Q^0_s]\} \tag{2}$$

And for each treatment week t we can compute the treatment effect as

$$\Delta q_{jt} = q_{jt}^1 - \frac{1}{\#S_t} \sum_{s \in S_t} q_{js}^0 \tag{3}$$

While this approach has the advantage that it generates substitution patterns consistent with consumer theory, it may be that for some treatment weeks t the set of possible control weeks $S_t = \{\emptyset\}$. Under this definition of the control, some treatment weeks constitute 'outliers' and are excluded from the analysis. Of the 1470 machine-experiment-week combinations, 991 of them have at least one corresponding control week, and at the machine-experiment level, 528 out of 634 have at least one corresponding control. Each included treatment week has an average of 24 corresponding control weeks, though this can vary considerably from treatment week to treatment week.[14]

Once we have constructed our restricted set of treatment weeks and the set of control weeks that corresponds to each, inference is fairly straightforward. We use (3) to construct a set of pseudo-observations for the difference, and employ a paired t-test.

4.2 Parametric Specifications

In addition to computing treatment effects, we also specify two parametric models of demand: nested logit and random-coefficients logit, which are estimated from the full dataset (including weeks of observational data that do not meet any of our control criteria).

We consider a model of utility where consumer i receives utility from choosing product j in market t of:

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt}. \tag{4}$$

The parameter δ_{jt} is a product-specific intercept that captures the mean utility of product j in market t, and μ_{ijt} captures individual-specific correlation in tastes for products.

In the case where $(\mu_{ijt} + \varepsilon_{ijt})$ is distributed generalized extreme value, the error terms allow for correlation among products within a pre-specified group, but otherwise assume no correlation. This produces the well-known nested-logit model of McFadden (1978) and Train (2003). In this model consumers first choose a product category l composed of products g_l,

[14] We ran a few other treatments during other weeks of the data, including some removals of products in the salty snack and cookie categories. These data are not relevant to our analysis here, and are excluded from the data for the purpose of selecting control weeks.

and then choose a specific product j within that group. The resulting choice probability for product j in market t is given by the closed-form expression:

$$p_{jt}(\delta, \lambda, a_t) \quad = \quad \frac{e^{\delta_{jt}/\lambda_l} (\sum_{k \in g_l \cap a_t} e^{\delta_{kt}/\lambda_l})^{\lambda_l - 1}}{\sum_{\forall l} (\sum_{k \in g_l \cap a_t} e^{\delta_{kt}/\lambda_l})^{\lambda_l}} \tag{5}$$

where the parameter λ_l governs within-group correlation, and a_t is the set of available products in market t.[15] The random-coefficients logit allows for correlation in tastes across observed product characteristics. This correlation in tastes is captured by allowing the term μ_{ijt} to be distributed according to $f(\mu_{ijt}|\theta)$. A common specification is to allow consumers to have independent normally distributed tastes for product characteristics, so that $\mu_{ijt} = \sum_l \sigma_l \nu_{ilt} x_{jl}$ where $\nu_{ilt} \sim N(0,1)$ and σ_l represents the standard deviation of the heterogeneous taste for product characteristic x_{jl}. The resulting choice probabilities are a mixture over the logit choice probabilities for many different values of μ_{ijt}, shown here:

$$p_{jt}(\delta, \theta, a_t) = \int \frac{e^{\delta_{jt} + \sum_l \sigma_l \nu_{ilt} x_{jl}}}{1 + \sum_{k \in a_t} e^{\delta_{kt} + \sum_l \sigma_l \nu_{ilt} x_{kl}}} f(v_{ilt}|\theta) \tag{6}$$

In both the nested-logit and random-coefficient models we let $\delta_{jt} = d_j + \xi_t$, that is we break it into a product intercept and a market specific demand shifter. We include an additional ξ_t for each of our 15,256 machine-visits. For the nested-logit model, we allow for heterogeneous tastes across five major product categories or nests: chocolate candy,non-chocolate candy, cookie, salty snack, and other.[16] For the random-coefficients specification, we allow for three random coefficients, corresponding to consumer tastes for salt, sugar, and nut content.[17]

[15] Note that this is not the IV regression/'within-group share' presentation of the nested-logit model in Berry (1994), in which σ provides a measure of the correlation of choices within a nest. Roughly speaking, in the notation used here, $\lambda = 1$ corresponds to the plain logit, and $(1 - \lambda)$ provides a measure of the 'correlation' of choices within a nest (as in McFadden (1978)). The parameter λ is sometimes referred to as the 'dissimiliarity parameter.'

[16] The vending operator defines categories in the same way. "Other" includes products such as peanuts, fruit snacks, crackers, and granola bars.

[17] We do not allow for a random coefficient on price because of the relative lack of price variation in the vending machines. We also do not include random coefficients on any discrete variables (such as whether or not a product contains chocolate). As we discuss in Conlon and Mortimer (Forthcoming), the lack of variation in a continuous variable (e.g., price) implies that random coefficients on categorical variables may not be identified when product dummies are included in estimation. We did estimate a number of alternative specifications in which we include random coefficients on other continuous variables, such as carbohydrates, fat, or calories. In general, the additional parameters were not significantly different from zero, and they had no appreciable effect on the results of any prediction exercises.

5 Results

We begin by discussing the results of our three experimental treatments. In the first treatment we removed Snickers, in the second we removed Peanut M&Ms, and in the third we removed both products. These products correspond to the top two sellers in the chocolate candy category, both at Mark Vend and nationwide. They are also the two best-selling brands for Mars Inc. as a whole. We can think of these as the *dominant* brands within the category.

We report the results of the product removals in tables 3, 4, 5, and summarize substitution from the focal (stocked-out) product to the top five substitutes in table 5. In general, the substitution patterns we recover are reasonable; the top substitutes generally include Snickers or Peanut M&Ms if only one of the products is available. Twix, the third-best selling Mars Inc. brand both nationally and in our sample, is also a top substitute. Consumers also substitute to products outside the chocolate candy category, such as Planters Peanuts or Rold Gold Pretzels. In the double stock-out treatment, 93 consumers substitute to Reese's Peanut Butter Cups, which represents an 85.6% increase in sales for the Hershey product. Note that Reese's Peanut Butter Cups were not available in any of the other experimental treatments. In that same experiment, nearly 123 consumers substitute to other Assorted Chocolate products within the same product category, representing an increase of 117%, this includes mostly products from Mars such as Milky Way or Three Musketeers, but also some products from other manufacturers, such as Nestle's Butterfinger. Meanwhile, Raisinets (Nestle), a product that Mark Vend stocks very frequently compared to national averages, sees an increase in sales of only 17% when both products are removed, and only 3.3% when only Snickers is removed. This gives some indication that Raisinets are not a close competitor to Snickers, and compete less closely with Mars Inc. products than other products within the chocolate candy category.

5.1 Efficiency

One of the results of the product removal is that many consumers find another product in the vending machine. While many of the alternative brands are owned by Mars Inc., several of them are not. If those other brands have similar (or higher) margins for Mark Vend, substitution may cause the costs of the product removal to be distributed unevenly across the supply chain. Table 7 summarizes the impact of the experiments on Mark Vend, our retailer. In the absence of any rebate agreements, we see the following results. Though the experiment where we remove Peanut M&Ms reduces the overall number of vends by almost 200 units, the average margin on all items sold in the machine rises by 0.78 cents, and retailer revenue declines only by \$10.74. Likewise, in the double product removal, overall vends decline by 282.66 units, but the average margin rises by 1.67 cents per unit, and the cost to the retailer is $\$ - 4.54$.[18]

Now we examine the impact of our experiments on the upstream firms (manufacturers). The first is that a removal of Peanut M&Ms costs Mars about \$68.38 but only costs the retailer \$10.74, thus nearly 86.4% of the cost of stocking out is born by Mars. In the double removal, because M&M Peanut customers can no longer buy Snickers, and Snickers customers can no longer buy Peanut M&Ms, Mars bears 96.7% of the cost of the stockout. In the Snickers experiment, most of the cost appears to be born by the downstream firm, one potential explanation is sampling error, but the other is that of consumers who choose another product, many of them select another Mars Product (Twix or M&M Peanut) for this experiment. We also see the impact of the removal on other manufacturers. Hershey (Reese's Peanut Butter Cups and Hershey's Chocolate Bars) enjoyed relatively little substitution in the Snickers experiment, in part because Reese's Peanut Butter cups were not available as a substitute. In the double experiment, when Peanut Butter Cups were available, Hershey profits rose by nearly \$61.43, capturing about half of Mars' losses. Likewise we see slightly more substitution to the two Nestle products in the Snickers Experiment, about \$19.32 (as consumers substitute to Butterfinger and Raisinets), but a smaller percentage in the other two experiments.

Finally, we examine the potential efficiency impact of the rebate. There are two ways to understand this. The first is that, similar to a two-part tariff, the rebate lowers the marginal cost to the retailer (and reduces the margin of the manufacturer). This helps to better align the incentives to maintain a high level of availability. The rebate reallocates approximately (\$17, \$30, \$50) for the Snickers, Peanut M&Ms, and Double product removals from the upstream to the downstream firm. Under the rebate contract the retailer now bears about 50% of the cost of the Peanut M&Ms removal, 40.5% of the cost of the double removal, and the majority of the cost of the Snickers stockout. As this more evenly allocates the costs of stocking out, this should better align the incentives of the upstream and downstream firms, and lead the retailer to increase the overall service level.

[We plan on providing a more detailed discussion of how the retailer increases the service

[18] One reason that total losses appear smaller in the double product removal is the smaller sample size of viable treatment weeks (89) as compared to 115 for the Peanut M&Ms removal.

level here, including a discussion that involves why the quantity target $\overline{q}$ provides additional incentives.]

5.2 Foreclosure

Our second set of results consider whether or not AUD rebates can be used by Mars to foreclose their competition. For this scenario we choose a representative product mix that corresponds to the most frequently stocked set of products outside the candy category. We report those products in Table 12. We then consider the retailer's choice of candy products in Tables (13-16). Throughout this exercise, we assume that all candy manufacturers have the same manufacturing costs of $c = 0$.[19]

In Table 13, we fix the five most commonly-stocked candy products, four Mars products (Peanut M&Ms, Snickers, Twix, and Skittles) and one Nestle product (Raisinets), and consider the retailer's choice of a sixth product. Here, if the retailer knows they are going to receive the rebate, (Column RetailR), then they increase their profit by 14 units by switching from Plain M&Ms (Mars) to Reese's Peanut Butter Cups (Hershey). In the case where the retailer is not being paid the rebate (RetailerNR) the retailer can increase profits by 32 units. However, if the retailer faces the choice of stocking the Mars product and receiving the rebate vs. stocking the Hershey product and not receiving the rebate, the retailer prefers to stock the Mars product ($3062 - 2996 = 66$). Obviously Mars' profit is always lower when paying the rebate, but Mars prefers that the retailer stock Plain M&Ms and pay the rebate, rather than have the retailer stock Reese's Peanut Butter Cups and not pay the rebate ($512 - 500 = 12$). Thus in this scenario, we would expect to see Mars use the rebate to foreclose Hershey. The remaining question is whether or not foreclosure would be efficient. In the final column we consider the joint profits of Hershey, Mars, Nestle and the Retailer together and we find that industry profits are maximized under the choice of the Mars product (either Plain M&Ms or 3 Musketeers). Another way to see this, is to recognize that moving from Reese's Peanut Butter Cups with no rebates to Plain M&Ms with the rebate increases the retailer's profit by 66 and Mars profit by 12, while Hershey has at most 64 units of profit to prevent this from happening. Even if Hershey set a wholesale price of zero, they could not prevent exclusion. Thus the exclusion is efficient for the industry, in line with the predictions of the *Chicago Critique* of Bork (1978).

In Tables 14-16, we fix different sets of six candy products, and consider the choice of

[19] As long as the cost is constant across manufacturers this does not affect the results. If Mars had substantially higher marginal costs than Hershey, then it might.

a seventh product. In each of these cases, the baseline scenario of six Mars products plus Raisinets is identical, but we consider substituting different Mars products for competitor's products. Table 14, and 15 yield similar results, so let's examine Table 15. Taking the rebate status as fixed, the retailer increases his profits by replacing the Mars product with the Reese's Peanut Butter Cups. The retailer increases his profit by $(3218 - 3111 = 107)$ by choosing the Mars product and the rebate over the Hershey product. However, now Mars overpays for exclusivity as profits go from $702 - 708 = -6$. Again Hershey only has 65 units of profit, so cannot prevent exclusion from happening. And exclusion of Hershey from the vending machine is efficient for the industry $(3992 - 3956 = 36)$, in line with the *Chicago Critique*. However, now there is evidence that if Mars is using the rebate solely to keep Hershey off of the shelves, it is paying too much for exclusion, though only 0.9% too much. As described in the previous section, there are other (product availability) benefits to Mars from the rebate. Alternatively, under a slightly smaller rebate, it would still be rational for the retailer to exclude Hershey, as well as rational for Mars. Part of the issue is that most of Hershey's profits come at the expense of Mars, rather than through expansion of the market. Hershey appears attractive to the retailer through a lower wholesale cost (even after factoring in rebate arrangements).

In the final table, Table 16 we present evidence of inefficient exclusion. Rather than removing a Mars chocolate product, we consider replacing a non-chocolate Mars product (Skittles) with a Hershey chocolate product Reese's Peanut Butter Cups in the seventh candy slot in our vending machine. Again, all things being equal, the retailer increases his profit by switching to the Hershey product. Also, the retailer would prefer to receive the rebate and stock the Mars product, rather than not receive the rebate and stock the Hershey product. However now, exclusion costs Mars $(702 - 745 = -43)$ units of profit, and only benefits the retailer by $(3218 - 3131 = 87)$. Thus the rebate only generates 44 units of bilateral surplus, while Hershey has the potential to earn 65 units of profit if it is not excluded. In this case, industry profits are maximized when the retailer carries the Hershey product $(4014 - 3992)$, thus if we observe exclusion it is no longer efficient for the industry. We could imagine Hershey trying to write a contract, perhaps a 'sell-out' contract or two-part tariff (charging a fixed fee and then selling at cost) that prevents exclusion. We should also point out that by replacing Skittles with Reese's Peanut Butter Cups, the retailer obtains the highest profit among any set of 7 candy products.

There are a few explanations for the inefficiency we find in the last scenario. One is that the Mars rebate contract is not a pure AUD contract, but also includes a list of 'must stock items' that includes Skittles, similar to a tying arrangement. Thus Mars is able to use profits from Peanut M&Ms, Snickers, and Twix (products nearly all retailers stock) and the rebate arrangement to foreclose Hershey and force Skittles onto the shelf. The difficulty is that in many scenarios, it appears that without some other benefits coming from increased service, Mars is possibly overpaying for this privilege. The other potential explanation is that we examine only a subset of the retailer's business, in which Skittles may be a particularly bad fit for the segment of the market that we examine. There is some support for this idea, because Skittles are primarily marketed towards a younger market, and our study involves mostly older professional workers (lawyers and accountants). Thus, when considering the entirety of MarkVend's business, the rebate may still be rational for Mars. The other possibility is that because the Robinson-Patman Act has been interpreted to mean that Mars must offer the same form of contract to all retailers, it may be that Mars overpays some retailers in order to maximize profits across the entire vending industry.

6 Conclusion

We examine candy sales in the vending machine industry and conduct a simple field experiment that simulates out-of-stock events. We find that in the absence of rebate contracts, the upstream firm bears approximately 80-90% of the costs associated with stock-out events, and that rebates more evenly allocate the cost of these events across upstream and downstream firms. We also find that the rebate contracts can be used by Mars, the dominant manufacturer, to prevent the retailer from stocking competing brands. In some cases, the exclusion is rational for both Mars and for the retailer, and maximizes industry profits in line with the *Chicago Critique*. However, in other circumstances, the rebate contract induces inefficient exclusion of Hershey by the retailer.

On one hand our results provide evidence that the *Chicago Critique* might not be as 'special' as one may have thought; they provide evidence that contracts may be used for efficient exclusion under common product assortments in 'the wild.' On the other hand, we find that rebate contracts can be used for inefficient exclusion under the potentially most important case, that of the industry optimal product assortment.

This is potentially important for several reasons, one of which is that product assortment has been the subject of many recent debates about obesity and the appropriate public policy response to the mix of products offered in vending machines, particularly in school settings.[20]

[20] Forty states now tax junk food or soda products, and cities, school districts, and other local jurisdictions have proposed or implemented restrictions on the set of products that may be offered in vending machines.

These rebate contracts may serve not just as barriers for existing competitors such as Hershey, but also for potential entrants producing healthier products.

As vertical contracts transition from a world of *per se* violations to *rule of reason* considerations, we show that it is possible to consider evaluating some of the efficiency and foreclosure effects not only via structural empirical work, but through reasonably-sized field experiments as well. In a world where antitrust litigation costs range in the hundreds of millions of dollars (such as the *Intel* case), well-conceived field experiments may provide a reasonable alternative when weighing the effects of vertical restraints.

See Engber (2009) for a recent press article summarizing many policy responses in this area. More recent examples include rules requiring that the mix of beverages in city vending machines favor water in New York City, a ban on sales of sugary drinks in city buildings in San Francisco, and a similar proposed ban in Boston (Smith 2010). The medical literature has also weighed in on the issue of taxing sugary drinks (e.g., see Brownell and Frieden (2009) and Brownell, Farley, Willett, Popkin, Chaloupka, Thompson, and Ludwig (2009)).

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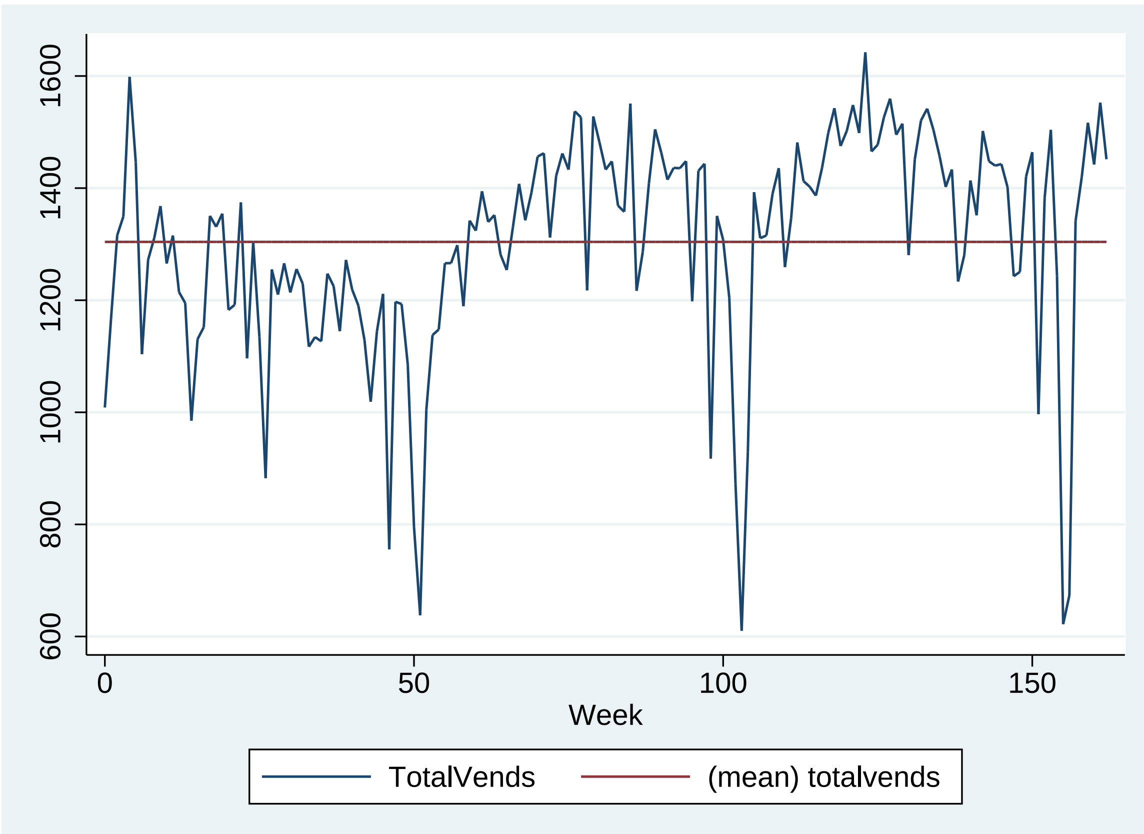
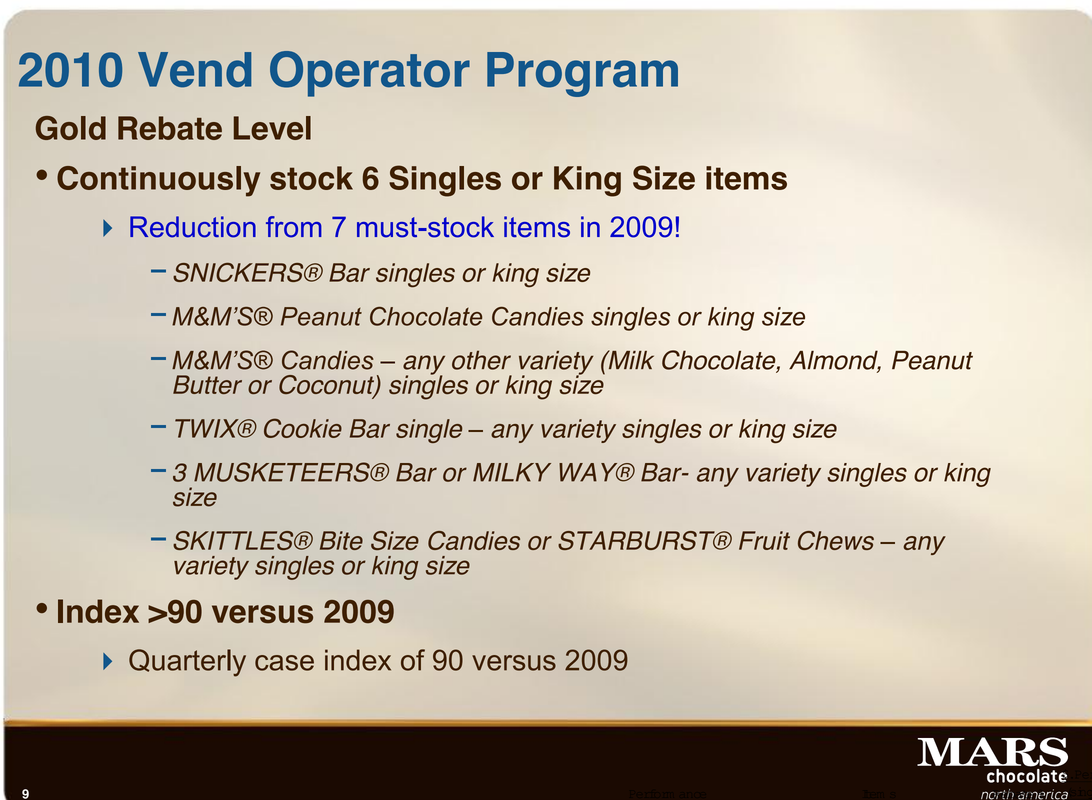


Figure 1: Overall Weekly Sales at Site 93



Performance	Items		$ Per Bar (singles)
GOLD Rebate	SNICKERS® and M&M's® Peanut	3%	$ 0.015
Index 90	All other MARS vend items	8%	$ 0.040

Figure 2: Mars Vend Operator Rebate Program

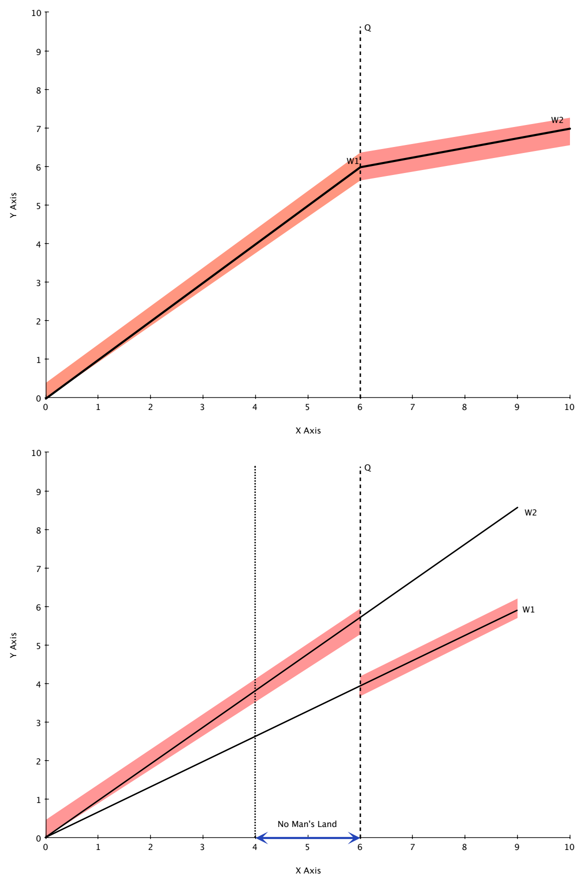


Figure 3: Conventional Quantity Discount and All Units Discount

Threshold $\overline{q} = 65$	Capacity = 45	Capacity = 65
Market:		
Total Sales([1,2]) > Total Sales([1,3])	66.72%	24.16%
Total Sales([1,2]) < Total Sales([1,3])	26.49%	66.59%
Total Sales([1,2]) = Total Sales([1,3])	6.79%	9.25%
Mean(Sales([1,2])-Sales([1,3]))	2.92	-2.00
as percent of sales	3.36%	-2.17%
Retailer:		
Retailer prefers [1,2]	25.80%	0.61%
Retailer prefers [1,3], No Rebate	0.33%	0.69%
Retailer prefers [1,3]	74.20%	99.39%
Mean Retailer profit([1,2])	60.41	63.21
Mean Retailer profit([1,3]), No Rebate	50.36	56.68
Mean Retailer profit([1,3])	62.88	70.85
Firm A:		
Firm A prefers [1,2]	0.19%	13.78%
Firm A prefers [1,3]	99.55%	85.43%
Mean Firm A profit under [1,2]	17.98	21.52
Mean Firm A profit under [1,3]	20.96	23.62
Firm A pays rebate under [1,2]	0%	0%
Firm A pays rebate under [1,3]	100%	100%
Firm B:		
Mean Firm B profits under [1,2]	8.36	7.73

Under the assumed demand patterns, retailer always stocks product 1.

Table 1: Results from varying capacity in toy model

Natl Rank	Manuf	Product	Avail	Share
1	Mars	M&M Peanut*	96	23
2	Mars	Snickers*	96	22
3	Mars	Twix Bar*	79	13
4	Hershey	Reeses Peanut Butter Cups	29	3.7
5	Mars	Three Musketeers*	34	4.3
6	Mars	Skittles*	77	6.5
7	Mars	M&M Milk Chocolate*	47	6.4
8	Mars	Starburst	16	1.0
9	Nestle	Butterfinger	33	2.7
10	Hershey	w/Almond	0	0
11	Mars	Milky Way/Other	33	2.6
17	Nestle	Raisinets*	78	8.9

National Shares: Mars 64%, Hershey 24%

MarkVend Shares: Mars 80%, Hershey 8.5%

MarkVend averages 6.86 confection facings per machine

Table 2: Comparison of National Marketshares with Experimental Firm

Table 3: Results for Snickers Experiment

Product	Control	Treatment	Change	% Change	Difference	T-Stat	Obs
M&M Peanut	608.5	800.5	192.1	31.6	1.76	4.68	109
Twix Caramel	247.3	373.2	125.9	50.9	1.61	4.92	78
Assorted Pretzel/Popcorn	1201.1	1291.7	90.5	7.5	0.83	1.93	109
Assorted Nuts	441.9	518.3	76.4	17.3	0.76	2.50	100
Assorted Fruit Snack	189.5	244.5	55.0	29.0	0.60	2.01	92
Assorted Chocolate	124.3	175.7	51.4	41.4	0.58	2.72	89
Assorted Cookie	445.6	490.1	44.5	10.0	0.41	1.22	109
Sun Chip LSS	272.2	313.6	41.4	15.2	0.44	1.92	94
M&M Milk Chocolate	223.8	261.5	37.6	16.8	0.53	1.73	71
Zoo Animal Cracker Austin	350.5	374.4	23.9	6.8	0.23	0.94	106
Baked Chips (Con)	343.7	355.1	11.3	3.3	0.10	0.48	109
Rasbry Knotts	63.5	71.8	8.4	13.2	0.09	0.64	89
Raisinets	184.2	190.2	6.1	3.3	0.08	0.33	74
Assorted Cracker	87.7	89.1	1.5	1.7	0.02	0.13	79
Assorted Salty Snack	875.2	873.5	-1.8	-0.2	-0.02	-0.04	109
Choc Chip Famous Amos	277.4	275.4	-2.0	-0.7	-0.02	-0.07	109
Assorted Pastry	330.7	293.1	-37.6	-11.4	-0.37	-1.74	103
Cheeto LSS	473.2	423.3	-49.9	-10.5	-0.46	-1.60	109
Assorted Nonchcolate Candy	318.4	262.6	-55.7	-17.5	-0.54	-1.79	103
Dorito Nacho LSS	409.8	346.3	-63.4	-15.5	-0.58	-3.12	109
Assorted Chips	699.7	598.3	-101.3	-14.5	-0.93	-2.62	109
Assorted Energy	261.3	125.4	-135.9	-52.0	-1.66	-4.40	82
Snickers	540.0	5.0	-535.0	-99.1	-4.91	-17.61	109
Total	8,969.6	8752.7	-216.8	-2.4	-1.99	-12.86	109

Table 4: Results for M&M Peanut Experiment

Product	Control	Treatment	Change	% Change	Difference	T-Stat	Obs
Snickers	551.1	721.7	170.6	31.0	1.48	4.74	115
Assorted Pretzel/Popcorn	1206.9	1338.0	131.1	10.9	1.14	2.73	115
Assorted Nuts	519.7	602.6	82.9	16.0	0.75	2.80	110
Twix Caramel	284.4	345.8	61.4	21.6	0.69	3.05	89
M&M Milk Chocolate	181.0	229.2	48.2	26.7	0.77	2.56	63
Reeses Peanut Butter Cups	75.9	105.4	29.5	38.8	0.41	2.13	72
Raisinets	188.3	214.5	26.2	13.9	0.29	1.24	91
Assorted Nonchcolate Candy	370.7	396.2	25.4	6.9	0.23	0.81	112
Rasbry Knotts	80.0	104.3	24.3	30.4	0.24	1.71	101
Assorted Fruit Snack	158.1	181.6	23.5	14.9	0.25	1.01	94
Assorted Cookie	453.8	466.5	12.7	2.8	0.11	0.41	115
Assorted Chocolate	156.8	169.2	12.4	7.9	0.13	0.56	92
Zoo Animal Cracker Austin	346.5	353.6	7.0	2.0	0.06	0.30	115
Choc Chip Famous Amos	283.0	287.0	3.9	1.4	0.03	0.25	114
Assorted Salty Snack	920.6	919.5	-1.1	-0.1	-0.01	-0.03	115
Assorted Cracker	90.4	83.8	-6.6	-7.3	-0.07	-0.60	90
Sun Chip LSS	289.3	276.1	-13.2	-4.6	-0.13	-0.67	105
Assorted Energy	293.3	262.1	-31.1	-10.6	-0.36	-1.19	86
Cheeto LSS	478.0	443.9	-34.0	-7.1	-0.30	-1.13	115
Baked Chips (Con)	355.7	318.1	-37.6	-10.6	-0.33	-1.63	114
Dorito Nacho LSS	382.0	343.8	-38.2	-10.0	-0.33	-1.64	115
Assorted Chips	727.9	688.7	-39.2	-5.4	-0.34	-1.08	114
Assorted Pastry	373.3	323.0	-50.2	-13.5	-0.47	-1.68	106
M&M Peanut	617.8	12.2	-605.5	-98.0	-5.27	-18.03	115
Total	9,384.4	9186.9	-197.6	-2.1	-1.72	-11.21	115

Table 5: Results from Snickers and M&M Peanut Joint Experiment

Product	Control	Treatment	Change	% Change	Difference	T-Stat	Obs
Assorted Chocolate	104.5	227.8	123.2	117.9	1.79	6.12	69
Twix Caramel	213.0	313.3	100.3	47.1	1.43	5.64	70
Reeses Peanut Butter Cups	109.0	202.2	93.3	85.6	1.23	4.30	76
Assorted Pastry	287.4	374.2	86.9	30.2	1.16	3.60	75
M&M Milk Chocolate	132.0	196.9	64.9	49.2	1.18	3.59	55
Assorted Nuts	359.3	415.8	56.6	15.7	0.73	2.28	78
Assorted Cookie	314.7	359.3	44.6	14.2	0.51	1.75	88
Assorted Nonchcolate Candy	263.4	301.1	37.7	14.3	0.45	1.80	83
Assorted Chips	548.2	585.6	37.4	6.8	0.43	1.35	87
Raisinets	184.0	215.9	31.9	17.3	0.44	1.99	73
Choc Chip Famous Amos	227.0	241.2	14.1	6.2	0.16	0.73	89
Rasbry Knotts	70.7	79.7	8.9	12.6	0.11	0.82	79
Assorted Pretzel/Popcorn	962.0	969.8	7.8	0.8	0.09	0.24	89
Assorted Fruit Snack	103.6	107.7	4.1	4.0	0.06	0.31	71
Dorito Nacho LSS	284.5	282.6	-1.9	-0.7	-0.02	-0.10	89
Baked Chips (Con)	262.8	255.8	-7.0	-2.7	-0.08	-0.35	88
Assorted Cracker	114.4	93.3	-21.1	-18.5	-0.28	-1.18	75
Sun Chip LSS	198.1	174.6	-23.5	-11.9	-0.29	-1.34	80
Cheeto LSS	349.8	325.7	-24.1	-6.9	-0.27	-1.38	89
Assorted Salty Snack	711.9	678.1	-33.9	-4.8	-0.38	-1.16	89
Assorted Energy	272.1	229.0	-43.1	-15.8	-0.61	-1.90	71
Zoo Animal Cracker Austin	292.1	235.0	-57.1	-19.6	-0.64	-3.18	89
Snickers	379.4	13.2	-366.2	-96.5	-4.11	-16.00	89
M&M Peanut	425.9	9.4	-416.5	-97.8	-4.68	-18.19	89
Total	7,170.0	6887.3	-282.7	-3.9	-3.18	-12.07	89

Table 6: Top 5 Substitutes (Vends)

Snickers	Peanut M&M	Both
M&M Peanut*	Snickers*	Assorted Chocolate*
Twix Caramel*	Assorted Pretzel/Popcorn*	Twix Caramel*
Assorted Pretzel/Popcorn	Assorted Nuts*	Reeses Peanut Butter Cups*
Assorted Nuts*	Twix Caramel*	Assorted Pastry*
Assorted Fruit Snack*	M&M Milk Chocolate*	M&M Milk Chocolate*
Focal (-535.0)	Focal (-605.5)	Focal (-782.7)
Top 5 (539.9)	Top 5 (494.3)	Top 5 (468.6)
Total (-216.8)	Total (-197.6)	Total (-282.7)

Table 7: Downstream Profit Impact

			Before Rebate			After Rebate		
			Difference In:		T-Stat	Difference In:		T-Stat
Experiment	Vends	Obs	Margin	Profit	of Diff	Margin	Profit	of Diff
Snickers	-216.82	109	0.39	-56.75	-2.87	0.24	-73.26	-4.33
Peanut M&Ms	-197.58	115	0.78	-10.74	-0.58	0.51	-39.37	-2.48
Double	-282.66	89	1.67	-4.54	-0.27	1.01	-54.87	-3.72

Table 8: Upstream (Manufacturer) Profits

Experiment	Mars	Hershey	Nestle	Other	% Before	% After
Snickers	-26.37	5.89	19.32	-20.26	31.7%	11.9%
Peanut M&Ms	-68.38	32.76	11.78	-9.36	86.4%	50.2%
Snickers + Peanut M&Ms	-130.81	61.43	20.22	37.10	96.7%	59.5%

Table 9: (Retail) Profit Impacts M&M Peanut Experiment

Product	Δ Vends	Margin	Treatment	Control	ΔΠ
Snickers	170.63	0.21	153.51	117.22	36.29
Assorted Pretzel/Popcorn	131.10	0.46	608.43	553.35	55.07
Assorted Nuts	82.94	0.46	283.72	241.11	42.61
Twix Caramel	61.41	0.21	73.56	60.50	13.06
M&M Milk Chocolate	48.25	0.21	48.75	38.49	10.26
Reeses Peanut Butter Cups	29.48	0.32	34.00	24.49	9.51
Raisinets	26.20	0.31	66.49	58.37	8.12
Assorted Nonchcolate Candy	25.42	0.26	106.14	95.16	10.98
Rasbry Knotts	24.35	0.58	60.90	46.69	14.22
Assorted Fruit Snack	23.51	0.48	91.20	76.59	14.61
Assorted Cookie	12.73	0.53	244.26	241.99	2.27
Assorted Chocolate	12.39	0.28	45.78	43.70	2.07
Zoo Animal Cracker Austin	7.04	0.61	216.92	212.61	4.32
Choc Chip Famous Amos	3.95	0.58	167.08	164.78	2.30
Assorted Salty Snack	-1.11	0.40	366.51	371.25	-4.74
Assorted Cracker	-6.63	0.49	40.62	44.45	-3.84
Sun Chip LSS	-13.21	0.41	113.18	118.60	-5.42
Assorted Energy	-31.14	0.47	127.89	137.47	-9.58
Cheeto LSS	-34.04	0.41	182.02	195.98	-13.96
Baked Chips (Con)	-37.62	0.41	130.41	145.84	-15.43
Dorito Nacho LSS	-38.24	0.41	140.94	156.62	-15.68
Assorted Chips	-39.22	0.37	257.55	272.45	-14.90
Assorted Pastry	-50.23	0.50	159.52	186.19	-26.67
M&M Peanut	-605.53	0.21	2.61	131.40	-128.80
Total	-197.58	0.40	3,721.99	3,735.29	-13.30

Table 10: Retail Profit Impacts of Snickers and M&M Peanut Experiment

Product	Δ Vends	Margin	Treatment	Control	$\Delta\Pi$
Assorted Chocolate	123.23	0.28	58.70	29.25	29.45
Twix Caramel	100.28	0.21	66.64	45.31	21.33
Reeses Peanut Butter Cups	93.28	0.32	65.22	35.14	30.08
Assorted Pastry	86.85	0.51	198.41	146.58	51.83
M&M Milk Chocolate	64.92	0.21	41.89	28.08	13.81
Assorted Nuts	56.58	0.46	192.77	165.88	26.89
Assorted Cookie	44.61	0.52	187.06	163.96	23.10
Assorted Nonchcolate Candy	37.69	0.25	77.82	65.52	12.30
Assorted Chips	37.41	0.37	219.16	205.43	13.73
Raisinets	31.90	0.31	66.94	57.05	9.89
Choc Chip Famous Amos	14.13	0.58	140.40	132.17	8.23
Rasbry Knotts	8.94	0.58	46.50	41.28	5.22
Assorted Pretzel/Popcorn	7.78	0.47	453.79	452.46	1.34
Assorted Fruit Snack	4.13	0.49	55.35	50.64	4.71
Dorito Nacho LSS	-1.88	0.41	115.89	116.66	-0.77
Baked Chips (Con)	-7.05	0.41	104.87	107.76	-2.89
Assorted Cracker	-21.12	0.46	41.63	53.06	-11.43
Sun Chip LSS	-23.48	0.41	71.57	81.20	-9.63
Cheeto LSS	-24.09	0.41	133.55	143.43	-9.88
Assorted Salty Snack	-33.86	0.40	274.50	287.33	-12.83
Assorted Energy	-43.09	0.47	107.26	127.91	-20.65
Zoo Animal Cracker Austin	-57.10	0.61	144.15	179.18	-35.03
Snickers	-366.21	0.21	2.81	80.70	-77.89
M&M Peanut	-416.50	0.21	2.00	90.59	-88.59
Total	-282.66	0.40	2,868.87	2,886.57	-17.69

Table 11: Parametric Model Estimates

	Random Coefficients		Nested Logit	
σ_{Salt}	0.506	0.458		
	[.006]	[.010]		
σ_{Sugar}	0.673	0.645		
	[.005]	[.012]		
σ_{Peanut}	1.263	1.640		
	[.037]	[.028]		
$\lambda_{Chocolate}$			0.828	0.810
			[.003]	[.005]
$\lambda_{CandyNon-Choc}$			0.908	0.909
			[.007]	[.009]
$\lambda_{Cookie/Pastry}$			0.845	0.866
			[.004]	[.006]
λ_{Other}			0.883	0.894
			[.005]	[.006]
$\lambda_{SaltySnack}$			0.720	0.696
			[.003]	[.004]
# Nonlinear Params	3	3	5	5
Product FE	73	73	73	73
# Fixed Effects ξ_t	15256	2710	15256	2710
Total Parameters	15332	2786	15334	2788
LL	-4372750	-4411184	-4372147	-4410649
Total Sales	2960315	2960315	2960315	2960315
BIC	8973960	8863881	8972783	8862840
AIC	8776165	8827939	8774962	8826873

Table 12: Products used in Counterfactual Analyses

Strwbry Pop-Tarts
Oat n Honey Granola Bar
Grandmas Choc Chip
Choc Chip Famous Amos
Rasbry Knotts
Ritz Bits Chs Vend
Ruger Vanilla Wafer
Kar Sweet & Salty Mix
Farleys Mixed Fruit Snacks
Planters Salted Peanuts 2 oz LSS
Zoo Animal Cracker Austin
Rold Gold Pretzels LSS
Snyders Nibblers F/F
Ruffles Ched/SC LSS
Cheez-It Original SS
Frito LSS
Dorito Nacho LSS
Cheeto LSS
Smartfood LSS
Sun Chip LSS
Lays Potato Chips 1oz SS
Baked Lays LSS
Munchos Potato Chips
Hot Stuff Jays

Table 13: Foreclosure: Choice of Sixth Product

Product	RetailerR	RetailerNR	Rebate	MarsR	MarsNR	Hershey	Nestle	Industry
M&M Plain (M)	3062	2964	98	512	610	0	70	3645
Reeses PB (H)	3076	2996	80	420	500	64	70	3630
Payday(H)	3042	2962	80	418	498	41	69	3570
Crunch(N)	3012	2933	79	417	497	0	95	3524
Butterfinger(N)	3030	2950	80	419	499	0	121	3569
Milkyway(M)	3037	2945	92	484	576	0	70	3591
3Musketeers(M)	3065	2966	98	516	615	0	70	3651

Five Base Candy Products: M&M Peanut, Snickers, Twix, Skittles, Raisinets (N)

Table 14: Foreclosure: Choice of Seventh Product

Product	RetailerR	RetailerNR	Rebate	MarsR	MarsNR	Hershey	Nestle	Industry
M&M Plain	3218	3084	134	702	835	0	73	3992
Reeses	3229	3114	115	602	717	65	72	3968
Payday	3193	3079	114	600	714	42	72	3907
Crunch	3164	3050	114	598	712	0	98	3860
Butterfinger	3182	3068	115	601	716	0	126	3909
Milkyway	3192	3065	128	671	799	0	72	3936

Six Base Candy Products: M&M Peanut, Snickers, Twix, Skittles, 3 Musketeers, Raisinets (N)

Table 15: Foreclosure: Choice of Seventh Product

Product	RetailerR	RetailerNR	Rebate	MarsR	MarsNR	Hershey	Nestle	Industry
3 Musketeers	3218	3084	134	702	835	0	73	3992
Reeses	3224	3111	113	595	708	65	72	3956
Payday	3189	3076	113	593	705	42	72	3895
Crunch	3159	3047	113	591	704	0	98	3849
Butterfinger	3177	3064	113	594	707	0	125	3897
Milkyway	3187	3061	126	663	789	0	72	3923

Six Base Candy Products: M&M Peanut, Snickers, Twix, Skittles, M&M Plain, Raisinets (N)

Table 16: Tying: Getting Rid of Skittles

Product	RetailerR	RetailerNR	Rebate	MarsR	MarsNR	Hershey	Nestle	Industry
Skittles	3218	3084	134	702	835	0	73	3992
Reeses	3250	3131	119	625	745	65	72	4014
Butterfinger	3203	3085	119	624	743	0	126	3953
Milkyway	3213	3081	132	694	826	0	72	3979

Six Base Candy Products: M&M Peanut, Snickers, Twix, M&M Plain, 3 Musketeers, Raisinets (N)