Efficiency and Foreclosure Effects of Vertical Rebates: Empirical Evidence*

Christopher T. Conlon†
Julie Holland Mortimer‡

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Abstract

In many industries, upstream manufacturers pay downstream retailers for achieving quantity or marketshare targets. These 'vertical rebates' may mitigate downstream moral hazard by inducing greater retail effort, but may also incentivize retailers to drop competing products. We study these offsetting effects empirically for a rebate paid to one retailer. Using a field experiment, we exogenously vary the outcome of retailer effort. We estimate models of consumer choice and retailer behavior to quantify the rebate's effect on retail assortment and effort. We find that the rebate is designed to exclude a competing product and fails to maximize social surplus.

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†Department of Economics, NYU Stern, 44 W 4th St, New York City, NY 10012. email: cconlon@stern.nyu.edu

‡Department of Economics, Boston College, 140 Commonwealth Ave., Chestnut Hill, MA 02467, and NBER. email: julie.mortimer.2@bc.edu

1. Introduction

Conditional payments from manufacturers to retailers, often referred to as 'vertical' arrangements, are widely used in the economy and have important implications for how markets function. On one hand, a payment from a manufacturer to a retailer may align the retailer's incentives with those of the manufacturer and induce the retailer to provide costly but demand-enhancing effort, making the market more efficient. On the other hand, a retailer may choose not to carry the products of rival manufacturers, an act known as foreclosure, in order to more easily meet the conditions for payment. This may limit consumers' product choices and discourage competition. Many types of vertical arrangements can induce these offsetting efficiency and foreclosure effects, including 'vertical rebates,' in which a manufacturer pays a retailer a rebate for meeting pre-specified quantity or marketshare targets. Indeed, vertical rebates are prominently used across many industries, including pharmaceuticals, hospital services, microprocessors, snack foods, and heavy industry, and have been the focus of several recent antitrust cases.[1]

Although vertical rebates are important in the economy and have the potential to induce both pro- and anti-competitive effects, understanding their economic impacts can be challenging. Tension between the potential for both efficiency gains and foreclosure of upstream rivals implies that vertical rebates must be studied empirically in order to gain insight into the relative importance of the two effects. Unfortunately, the existence and terms of these arrangements are usually considered to be proprietary information by their participating firms, frustrating most efforts to study them empirically. Three additional challenges for empirically analyzing the effect of vertical rebates are: the difficulty in measuring downstream effort (for both the upstream firm and the researcher); the fact that rebates are determined endogenously by the participating parties; and the fact that empirical evidence has primarily been available only through the selection mechanism of litigation.

We address these challenges by examining a vertical rebate known as an All-Units Dis-

[1]The use of rebate payments to 'loyal' customers was central to several recent antitrust cases involving Intel. In 2009, *AMD vs. Intel* was 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. In 2014, *Eisai v. Sanofi-Aventis* applied the *Meritor* reasoning to loyalty contracts between Sanofi and hospitals for the purchase of a blood-clotting drug, ruling in favor of the drug manufacturer on the basis of a predatory pricing standard.

count (AUD). An AUD is a volume-based rebate paid to a retailer by a manufacturer once the retailer's sales of that manufacturer's products exceed a pre-specified volume threshold. Once activated, the discount applies retroactively to all units sold of the manufacturer's products. Although almost every vertical arrangement employed by firms is unique to its parties, AUDs are a common and important form of vertical rebate.[2]

By empirically studying an actual AUD, we shed light on two important effects of these arrangements. First, we gain insight into principal-agent settings in which downstream moral hazard plays an important role. Downstream moral hazard arises whenever a downstream agent takes a costly action that is beneficial to an upstream principal but is not fully contractible. It is an important feature of many vertically-separated markets, and is thought to drive a variety of vertical arrangements such as franchising and resale price maintenance (RPM).[3] Second, we gain insight into the potential anti-competitive incentives created by the AUD. Despite the potential for vertical rebates to incentivize retail effort, they may also induce a retailer to replace high-performing products produced by rival manufacturers with products of the rebating firm in order to qualify for payment.[4] Of course, in reality, vertical rebates may generate both efficiency gains by mitigating downstream moral hazard, and induce exclusion or foreclosure of rivals' products. Our goal is to analyze both effects empirically, identifying them through a combination of exogenous variation from a field experiment and models of consumer and retailer behavior.

The specific AUD we study is used by the dominant chocolate candy manufacturer in the United States: Mars, Inc.[5] The AUD implemented by Mars consists of three main features: a retailer-specific per-unit discount, a retailer-specific quantity target or threshold, and a 'facing' requirement that the retailer carry at least six Mars products. Mars' AUD stipulates that if a retailer meets the facing requirement and its total purchases exceed the quantity target, then Mars will pay the retailer an amount equal to the per-unit discount multiplied

[2]AUDs are related to 'loyalty contracts,' which we define as a vertical rebate that is calculated based on a retailer's sales volumes of both the rebating, and competing, manufacturers. Genchev and Mortimer (2017) provides a review of empirical evidence, including many of the relevant court cases, on 'Conditional Pricing Practices,' which is a term used by the Department of Justice and the Federal Trade Commission to describe the class of vertical arrangements that includes AUDs, loyalty and 'full-line forcing' contracts, and other contractual arrangements between retailers and manufacturers that use market-based conditions to determine payment.

[3]See, among others, Shepard (1993) for an early empirical study of principal-agent problems in the context of gasoline retailing, and Hubbard (1998) for an empirical study of a consumer-facing principal-agent problem.

[4]This differs from the types of settings more often studied in the theoretical literature, which typically concern the possibility that a single-product monopolistic incumbent can use exclusive contracts to deter entry of competing manufacturers.

[5]With revenues in excess of $35 billion, Mars is one of the largest closely held firms in the United States.

by the retailer's total quantity purchased. We examine the effect of Mars' AUD through the lens of a retail vending operator, MarkVend Company, for whom we are able to collect detailed information on sales, wholesale costs, and rebate terms. On our behalf, MarkVend also ran a large-scale field experiment, in which we exogenously remove two of Mars' best-selling products from a set of 66 machines. We observe subsequent substitution patterns, as well as the profit impacts for the retailer and all manufacturers. This provides important insight into the effect of the retailer's actions on manufacturer profitability, as well as the potential impact of the AUD on the retailer's decisions. To the best of our knowledge, no previous study has had the benefit of examining a vertical rebate contract using such rich data and exogenous variation.

Several features of the vending industry motivate its use for studying vertical rebates. Vending machines are a ubiquitous retail format with fixed capacities for a discrete number of unique products. This makes them well-suited to studying the impacts of the AUD contracts, because the retailer's decisions are discrete and relatively straightforward. Furthermore, an absence of price variation means that assortment is the primary focus, for both the retailer and the upstream manufacturer.[6] Vending machines are also experimentally friendly relative to many other retail markets, where inventory can spoil, get lost, or ride around in consumers' carts while other sales are recorded. Finally, Mars' AUD has not been litigated, which allows us to examine a contract in use without imposing the selection mechanism of litigation.

In order to analyze the effect of Mars' AUD contract, we specify a model of consumer choice and a model of retailer behavior, in which the retailer chooses two actions: a set of products to stock, and an effort level. The number of units the retailer can stock for each product is constrained by the capacity of its vending machines, and we interpret retailer effort as the frequency with which the retailer restocks its machines. We hold retail prices fixed throughout the analysis, consistent with the data and common practice in this industry.[7] In order to calculate the retailer's optimal effort level, we compute a dynamic restocking model à la Rust (1987), in which the retailer chooses how long to wait between restocking visits.[8] The restocking decision is important for many retail environments that have scarce

[6]These features also characterize other industries, such as brick-and-mortar retail and live entertainment.

[7]A number of other retail settings feature the same lack of price variation as vending machines (e.g., markets for recorded music, and movies – both theatrical and digital). In other settings, retail price reductions would serve as an analogous form of costly retail effort.

[8]Rather than assuming retailer wait times are optimal and using the dynamic model to estimate the cost of re-stocking, as in Rust (1987), we do the reverse: we use an outside estimate of the cost of re-stocking based on wage data from the vending operator, and use the model to compute the optimal wait time until the next restocking visit.

shelf space and little storage room. Due to the capacity constraints of a vending machine, the number of unique products the retailer can stock is relatively small. Thus, we compute the dynamic restocking model for several discrete sets of products, and we assume that the retailer chooses to stock the set of products that maximizes its profits.

Identification of our consumer choice and supply-side models benefits from two sources of variation. First, industry sources indicate that Mars reduced its quantity target during our sample period and that was a national change implemented in response to macroeconomic conditions. We provide evidence that the retailer's re-stocking frequency falls significantly in the period when Mars reportedly reduced its quantity target, and that the retailer changes its product offerings at around the same time to include fewer Mars products and more Hershey products.

Second, MarkVend Company implemented a field experiment on our behalf. The experiment enables us to manipulate the likely outcome of reduced retailer restocking frequency by exogenously removing the best-selling Mars products.[9] The experimental data indicate that in the absence of the rebate contracts, Mars bears almost 90% of the cost of stock-out events. The reason for this is that many consumers substitute to competing brands, which often have higher margins for the retailer. The rebate, which effectively lowers the retailer's wholesale price for Mars products conditional on meeting the rebate's criteria, increases the retailer's share of the cost of stock-out events from around 10% to nearly 50%.

After estimating the models of consumer choice and retailer behavior, we explore the welfare implications of MarkVend's effort and assortment decisions. Most vending machines for snack food have seven slots that can hold candy bars (or 'confection' products) across a single row. The 'first' several slots in each row, on the left hand side of the machine, are filled with top-selling products, and the 'last' few slots, on the right hand side, are typically stocked with less popular products. We define a 'typical' machine as one with fixed assortment except for the 'last' two candy products, and we examine three possible assortments for those two slots: two Mars products, two Hershey products, or one of each. We estimate the effect of the AUD by analyzing the profit impacts for MarkVend and Mars for each of the three assortments in this 'typical' machine under (i) MarkVend's actual (observed) effort levels, and (ii) optimal retailer effort levels at the observed driver wages and time costs of restocking. Compared to Mark Vend's observed effort level, an optimizing retailer services machines less

[9] 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.

frequently, which increases the scope of potential efficiency gains from the AUD.

Whether we use observed or optimal retailer effort, we find that, in the absence of the rebate, MarkVend would be better off carrying Hershey products in the last two slots of the 'typical' machine. However, under the observed 2007 rebate terms, MarkVend instead chooses to carry two Mars products in those slots instead, and is better off. Under the observed terms, Mars prefers paying the rebate in order to avoid an outcome in which MarkVend carries two additional Hershey products, and Hershey lacks a profitable deviation to avoid this foreclosure. In 2008, when industry sources indicate that Mars reduces the quantity target, we observe that MarkVend replaces the worst-performing Mars product (3 Musketeers) with the best-performing Hershey product (Reese's Peanut Butter Cup), and also reduces the frequency of its service visits.

Under our model's predicted optimal choice of effort, we can also quantify the effect of MarkVend's effort and product assortment on consumer and producer surplus. Despite the fact that the AUD has the potential to induce efficient increases in retailer effort (i.e., more frequent restocking visits), the fact that it induces foreclosure of Hershey Peanut Butter Cups results in lower consumer surplus and aggregate producer surplus. Mars benefits with higher profit, suggesting that, on balance, the AUD rebate allows Mars to leverage market power from dominant brands (Snickers, Twix, and Peanut M&M's) to secure shelf space for under-performing brands (3 Musketeers) at the expense of the rival (Hershey's Reeses Peanut Butter Cups). Mars is able to accomplish this by using the rebate contract to effectively tie the products together.

1.1. Relationship to Literature

There is a long tradition of theoretically analyzing the potential efficiency and anti-competitive effects of vertical contracts. The literature that explores the efficiency-enhancing aspects of vertical restraints goes back at least to Telser (1960) and the *Downstream Moral Hazard* problem discussed in Chapter 4 of Tirole (1988).[10] An important theoretical development on the potential anti-competitive effects of vertical contracts is the so-called *Chicago Critique* of Bork (1978) and Posner (1976), which makes the point that because the downstream firm must be compensated for any exclusive arrangement, one should only observe exclusion

[10] In addition, Deneckere et al. (1996), and Deneckere et al. (1997) examine markets with uncertain demand and stock-out events, and show that vertical restraints can induce higher stocking levels that are good for both consumers and manufacturers. For situations in which retailers have the ability to set prices, 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."

of rivals in cases for which a narrow product assortment is economically efficient. Subsequent theoretical literature demonstrates that exclusion may not maximize industry profits but rather, bilateral profits, which need not maximize economic efficiency in settings with market power.[11]

We depart from the basic theoretical framework of the *Chicago Critique* of Bork (1978) and Posner (1976) in some key ways. First, we allow for downstream moral hazard and potential efficiency gains, similar to much of the later theoretical work on vertical arrangements. Second, we study an environment in which the degree of competition across upstream firms may vary across the potential sets of products carried by the retailer, because upstream firms own multiple, differentiated products. Finally, we restrict the retailer to carrying a fixed number of these differentiated products.[12]

Outside of the theoretical literature on vertical rebates, our work also connects to the empirical literature on the impacts of other vertical arrangements. The most closely-related empirical work is work on vertical bundling in the movie industry, and on vertical integration in the cable television industry. The case of vertical bundling, known as full-line forcing, is studied by Ho et al. (2012a) and Ho et al. (2012b), which examine the decisions of upstream firms to offer bundles to downstream retailers, the decisions of retailers to accept these 'full-line forces,' and the welfare effects induced by the accepted contracts. The case of vertical integration is studied by Crawford et al. (2018), which examines efficiency and foreclosure effects of vertical integration between regional sports networks and cable distributors. A distinction between our work and Crawford et al. (2018) is that we examine the potential for upstream foreclosure (i.e., manufacturers being denied access to retail distribution), while that study examines the potential for downstream foreclosure (i.e., distributors not having access to inputs).[13]

The rest of the paper proceeds as follows. Section 2 describes the vending industry, data,

[11]Bernheim and Whinston (1998) show that the *Chicago Critique* ignores externalities across buyers, and that once externalities are accounted for, it is possible to generate exclusion that is not efficient. Later work by Fumagalli and Motta (2006) links exclusion to the degree of competition in the downstream market. See Whinston (2008) and Rey and Tirole (2007) for additional discussion. While influential with economists, these arguments have (thus far) been less persuasive with the courts than Bork (1978).

[12]This contrasts with the 'naked exclusion' of Rasmusen et al. (1991), in which there is a single good.

[13]From a methodological perspective, Crawford et al. (2018) differ from us in their use of a bargaining model to describe the equilibrium carriage decisions of cable channels and downstream distributors. These carriage decisions are equivalent to a retailer's choice of product assortment. Both papers model a downstream firm's carriage/stocking decision, given a fixed supply contract, unilaterally as an unobservable (moral hazard) choice. Crawford et al. (2018) employ the bargaining model to help determine supply terms, which we do not model. The biggest difference is that Crawford et al. (2018) examine whether an integrated firm responds to foreclosure incentives in its supply decisions, while we simulate the effects of particular contracts.

and the design and results of the field experiment, and Section 4 provides the details for the empirical implementation of the model. Section 6 provides results, and Section 7 concludes.

2. Background

We observe data from one retailer, MarkVend Company. MarkVend is located in a northern suburb of Chicago. During the period we study, which is January 2006 through February 2009, MarkVend services 728 snack machines throughout the greater Chicago metropolitan area.[14] We observe the quantities, prices, and wholesale cost of all products, along with the size of the discount associated with MarkVend's rebate from Mars. Data on quantity and price are recorded internally at each of MarkVend's machines, and include total vends and revenues for each product since the last service visit to the machine. A typical snack machine carries roughly 34 standard products, including three rows that hold a total of 15 salty snacks, two rows that hold 12 baked goods like cookies, and one row of seven confection products (i.e., chocolate and non-chocolate candy products).[15] MarkVend bids to provide service to client locations on an exclusive basis for periods of about three to five years. Locations include office buildings, schools, hospitals, museums, and other venues, and some of MarkVend's contracts with locations also commit it to maintain a pricing structure over the period of the contract. We observe retail and wholesale prices for each product at each service visit, but there is almost no pricing variation over time or across products within a category (i.e., all candy bars are priced the same as each other, and this price holds throughout the period of analysis). The two most important decisions that MarkVend makes with respect to its client locations is the assortment to stock in each machine and the frequency of service visits.

2.1. The Mars AUD and Evidence on MarkVend's Assortment and Service

Mars' AUD rebate program is the most commonly-used vertical arrangement in the vending industry.[16] Under the program, Mars refunds a portion of a vending operator's wholesale

[14] MarkVend services an additional 800+ machines that vend beverages, frozen food, or coffee.

[15] Candy bars and salty snacks do not fit in the same size 'slots.' (Candy bars will fall out of salty-snack slots, and salty snacks do not fit in candy bar slots.) Many machines have a few additional slots at the bottom for gum and mints. We focus primarily on a set of (nearly identical) snack machines in offices. Public areas such as schools, parks, and hospitals often have larger, higher-capacity machines.

[16] For confections products, Mars is the dominant manufacturer in vending, and is the only manufacturer to offer a true AUD contract. The AUD is the only program offered to vendors by Mars. Hershey and Nestle offer wholesale 'discounts,' but these have a quantity threshold of zero (i.e., their wholesale pricing is equivalent to uniform pricing). The salty snack category is dominated by Frito-Lay (a division of PepsiCo) which does not offer a rebate contract. We do not examine beverage sales, because many beverage machines

expenditure at the end of a fiscal quarter if the vending operator meets a quarterly sales goal. The sales goal for an operator is set on the basis of its combined sales of Mars products, rather than for individual Mars products. Mars' rebate contract stipulates a minimum number of product 'facings' that must be present in an operator's machines, although in practice, this provision is difficult to enforce because Mars cannot observe the assortments in individual vending machines. The per-unit amount of the rebate and the precise threshold of the sales goal are specific to each individual vending operator, and these terms are closely guarded by participants in the industry, although we know that our retailer qualifies for the rebate in every period of our dataset.

Figure 1 shows some promotional materials from Mars' rebate program in 2010; just after the period we analyze.[17] These promotional materials represent the same type of rebate in which MarkVend participated, but may differ from the terms available to MarkVend during our period of study. The program employs the slogan *The Only Candy You Need to Stock in Your Machine!*, and specifies a facing requirement of six products and a quarterly sales target. The second page of the document shown in Figure 1 refers to discontinuing a growth requirement, which we understand to be 5% (i.e., a target of 105% of year-over-year sales) for 2007 and around 90-95% of year-over-year sales for 2008. According to industry sources, Mars modified its rebate program and reduced the sales threshold in the first half of 2008, in response to changes in macro-economic conditions. The rebate does not explicitly condition on market share or the sales of competitors.

In the seven slots sized to hold candy bars, MarkVend typically carries five core products plus two additional products.[18] We report the overall number of product facings in Figure 2. The top pane reports the total number of product facings averaged over a balanced panel of 364 machines, which are present in at least 90% of months. The total number of facings per manufacturer is relatively stable over time, with the exception that in 2008 the number of Mars facings decreases and the number of Hershey facings increases. In the bottom pane of Figure 2, we report the average number of product facings (across machine-visits) for a set of individual products. The main takeaway is that in 2008 the retailer switches from stocking

at the locations we observe are serviced directly by Coke or Pepsi.

[17] A full slide deck, titled '2010 Vend Program,' and dated December 21, 2009, is available at http://vistar.com/KansasCity/Documents/Mars%202010%20Operatopr%20rebate%20program.pdf. (Last accessed on April 19, 2015; available from the authors upon request.)

[18] Snickers, Peanut M&M, Plain M&M, and Twix most often belong to this core set of products across all machines in the MarkVend enterprise. The other core products differ based on location. Skittles are frequently stocked in schools; Raisinets are commonly stocked in office settings. Core product facings are documented in Figure A3.

3 Musketeers (Mars) to Reese's Peanut Butter Cups (Hershey). Examining these 'marginal' products anticipates our model of MarkVend's assortment decision, which takes a set of core products as given and focuses on the 'last' two candy bar slots in each machine.[19]

In Table 1 we report the national sales ranks, availability, and shares in the vending industry for the top-ranked products nationally, as well as the shares for the same products at MarkVend's machines. We report MarkVend's sales separately for the pre- and post-2008 periods. There are some patterns that emerge. The first is that the most popular confection products sold by Mars (Snickers, Peanut M&Ms, Twix, Plain M&M's, and Skittles) tend to have higher shares at MarkVend than they do nationally. The second is that during 2007 MarkVend sells virtually no Hershey products despite the fact that Reese's Peanut Butter Cups are the #4 brand in the national sample, and Hershey's with Almond and Payday are numbers #10 and #11 respectively. Starting in 2008 MarkVend sells substantially more Reese's Peanut Butter Cups (6.5% – greater than the national average of 5.5%) and substantially fewer 3 Musketeers (0.5%; compared to a national average of 4.3%). This is consistent with the change in product facings shown in Figure 2.

We investigate MarkVend's behavior more closely in Table 2. For confidentiality reasons we report all sales as an index relative to 2006Q1. Overall sales vary by as much as 12% and are slightly higher in 2008 than in 2006 and 2007, suggesting that MarkVend was not hit particularly hard by the 2008 macroeconomic downturn. We also report the sales and share of Mars products quarter-by-quarter. The rebate terms in Figure 1 suggest that the rebate threshold is determined by a quarterly year-over-year sales target. We report the year-over-year sales index for Mars products and find that it averages 105% prior to 2008 and 93% afterwards.[20] This evidence is consistent with MarkVend narrowly achieving rebate targets of 105% in 2007 and 90% in 2008.[21]

Table 2 also reports how the retailer adjusts his effort over time as the terms of the rebate are reportedly adjusted. We measure the retailer's effort in two ways: how frequently he visits machines to restock them, and how many products are sold between restocking

[19]This pattern is even more pronounced for the set of (white-collar/office-setting) machines used to estimate our model and conduct our experiments. (See Figure A4.) We provide a more complete comparison of the overall MarkVend enterprise and the subsample we use to run our experiments and estimate demand in Appendix B.1.

[20]We don't have point-of-sale data for 2005, which prevents us from computing year-over-year sales changes for 2006.

[21]We are cautious about interpreting individual quarterly sales. Our numbers reflect the time period when sales take place in vending machines, while the rebate is paid based on quarterly orders MarkVend places with the wholesaler. In correspondence with MarkVend, the owner assures us that these differences are small and do not change over time.

visits for the top quartile of machines in the overall sales distribution.[22] In 2008, after the rebate threshold is reportedly reduced, the retailer visits machines every 4.89 days on average instead of every 4.16 days, a difference that is statistically significant. We also observe that the average machine experiences 144 sales between service visits for the post-2008 period, compared to 137 in the pre-2008 period, suggesting that machines are more empty when they are restocked (as opposed to visiting machines less often because overall sales are slower). In Table 3, we confirm similar results in regressions that control for both machine and week-of-year fixed effects, with Mark Vend restocking the machine about 0.83 days and 8.7 vends later on average in the post-2008 period.[23] Together, these imply that MarkVend is reducing effort, rather than responding to a slower rates of sales.

While one must be cautious about causally interpreting the retailer's post-2008 behavior, it appears that there is both a substantial reduction in its 'effort,' as measured by service frequency and sales between visits, and a substantial change in assortment, based on the information in Figure 2. The timing of these responses corresponds to the period identified by the owner of MarkVend as having reduced AUD quantity target requirements. In subsequent sections, we construct a model of consumer demand and optimal retailer restocking to evaluate the welfare implications of retailer changes in effort and assortment.

3. Experimental Design and Reduced-Form Evidence

When we run our experiment and estimate our consumer choice model, we focus on a set of 66 vending machines that are located in six locations consisting of office environments in Chicago. The field experiment was implemented by MarkVend drivers, who exogenously removed either one or two top-selling Mars confection products from this set of 66 'experimental' machines. The product removals are recorded during each service visit.[24] Implementation of each product removal was fairly straightforward; the driver removed either one or both of the two top-selling Mars products from all machines at a location for a period of roughly 2.5 to 3 weeks. The focal (i.e., removed) products were Snickers and Peanut

[22] We focus on these high volume machines because our conversations with the retailer suggest they determine his scheduling decisions. Less busy machines are often restocked because the driver is already on site to restock a high volume machine.

[23] The differences between the means and the regression results are largely the consequence of the fixed effects and the fact that the retailer reduces the restocking frequency relatively more at slower machines.

[24] The machines have substitution patterns that are very stable over time. In addition to the three treatments described here, we also ran five other treatment arms, for salty-snack and cookie products, which are described in Conlon and Mortimer (2010).

M&Ms.[25] The dates of the product removal interventions range from June 2007 to September 2008, with all removals run during the months of May - October. Over all sites and months, we observe 185 unique products. We consolidate products that had very low levels of sales with similar products within a category that are produced by the same manufacturer, until we are left with the 73 'products' that form the basis of the rest of our exercise.[26]

During each 2-3 week product removal period, most machines receive about three service visits. However, the length of service visits varies across machines, with some machines visited more frequently than others. Machines are serviced on different schedules, and as a result, it is convenient to organize observations by machine-week, rather than by visit, when analyzing the results of the experiment. When we do this, we assume that sales are distributed uniformly among the business days in a service interval, and assign those business days to weeks. Different experimental treatments start on different days of the week, and we allow our definition of when weeks start and end to depend on the client site and focal product.[27]

Two features of consumer choice are important for determining the welfare implications of the AUD contract. These are, first, the degree to which MarkVend's consumers prefer the marginal Mars products (Milky Way and Three Musketeers) to the marginal Hershey products (Reese's Peanut Butter Cup and Payday), and second, the degree to which any of these products compete with the dominant Mars products (Peanut M&Ms, Snickers,

[25]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, MarkVend wanted to minimize the number of phone calls received in response to the stock-out events. 'Natural,' or non-experimental, stock-outs are extremely rare for our set of machines and nearly all of the variation in product assortment comes either from product rotations, or our own exogenous product removals. Product rotations primarily affect 'marginal' products, so in the absence of exogenous variation in availability, the substitution patterns between marginal products is often much better identified than substitution patterns between continually-stocked best-selling products. Conlon and Mortimer (2010) provides evidence on the role of the experimental variation for identification of substitution patterns.

[26]For example, we combine Milky Way Midnight with Milky Way, and Ruffles Original with Ruffles Sour Cream and Cheddar. In addition to the data from MarkVend, we also collect data on product characteristics online and through industry trade sources. For each product, we note its manufacturer, as well as the following set of product characteristics: package size, number of servings, and nutritional information. Nutritional information includes weight, calories, fat calories, sodium, fiber, sugars, protein, carbohydrates, and cholesterol. 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.

[27]For example, at some site-experiment pairs, we define weeks as Tuesday to Monday, while for others we use Thursday to Wednesday.

and Twix). Our experiment mimics the impact of a reduction in restocking frequency by simulating the stock-out of the best-selling Mars confections products. This provides direct evidence about which products are close substitutes, and how the costs of stock-outs are distributed throughout the supply chain. It also provides exogenous variation in the choice sets of consumers, which helps to identify the discrete-choice model of consumer choice.

In principle, calculating the effect of product removals is straightforward. In practice, there are two challenges in implementing the removals and interpreting the data generated by them. First, there is variation in overall sales at the weekly level, independent of our exogenous removals. Second, 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, and we rely on observational data for the control weeks. To mitigate these issues, we report treatment effects of the product removals after selecting control weeks to address these issues. We provide the details of this procedure in Appendix B.2.

3.1. Results of Product Removals

Our first exogenous product removal eliminated Mars' Snickers product from all 66 vending machines involved in the experiment; the second removal eliminated Mars' Peanut M&Ms product, and the third eliminated both products. These products correspond to the top two sellers in the confections category, both at MarkVend and nationwide.

One of the results of the product removals is that many consumers purchase another product in the vending machine. While many of the alternative brands are owned by Mars, several of them are not. If those other brands have similar (or higher) margins for MarkVend, substitution may cause the cost of each product removal to be distributed unevenly across the supply chain. Table 4 summarizes the impact of the product removals for MarkVend. When Snickers is removed, average weekly vends decrease by 1.99 units per machine and, in the absence of any rebate payment, MarkVend's weekly profits decline by $0.52 per machine.[28] When Peanut M&Ms is removed, vends go down by 1.72 units per machine, but MarkVend's average margin on all items sold in the machine rises by 0.78 cents, and weekly retailer profit declines by only $0.09 per machine (a statistically insignificant decline). Similarly, in the joint product removal, weekly vends decline by 3.18 units per machine, but MarkVend's average margin rises by 1.67 cents per unit, so that its weekly profit declines by only $0.05 per machine (again statistically insignificant).

[28]Throughout Table 4, we use MarkVend's observed wholesale cost (absent the rebate payment) for each product.

Table 5 examines the impact of the product removals on the upstream firms.[29] Removing Peanut M&Ms decreases Mars' weekly profit by \$0.59 per machine, compared to MarkVend's loss of \$0.09; thus roughly 86.4% of the cost of stocking out is born by Mars (reported in the fifth column). In the double removal, because Peanut M&M 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 removal, most of the cost appears to be born by the downstream firm; one potential explanation is that among consumers who choose another product, many select another Mars Product (Twix or Peanut M&Ms). We also see the impact of each product removal on the profits of other manufacturers. Hershey (which owns Reese's Peanut Butter Cups and Hershey's Chocolate Bars) enjoys relatively little substitution in the Snickers removal, in part because Reese's Peanut Butter cups are not available as a substitute. In the double removal, when Peanut Butter Cups are available, Hershey's weekly profits rise by nearly \$0.69 per machine, capturing about half of Mars' losses. We see substitution to the two Nestle products in the Snickers removal, so that Nestle gains \$0.18 per machine-week as consumers substitute to Butterfinger and Raisinets; Nestle's gains are a smaller percentage of Mars' losses in the other two removals. a Returning to Table 4, the right-hand panel reports the retailer's profit loss from the product removals after accounting for its rebate payments, assuming it qualifies. We see that the rebate reallocates part of the cost of the Snickers, Peanut M&Ms, and joint product removals from the upstream to the downstream firm. Taking the rebate into account, the retailer loses \$0.67, \$0.34, and \$0.62 in weekly profit per machine (instead of \$0.52, \$0.09, and \$0.05 without accounting for the rebate payment), which is statistically significant. The last column of Table 5 shows that after accounting for the rebate payment, the manufacturer now bears about 50% of the cost of the Peanut M&Ms removal, 60% of the cost of the joint removal, and 12% of the cost of the Snickers removal.

Directly analyzing the effects of the exogenous product removals tells us how the rebate reallocates revenues between the manufacturer and the retailer when a product is not available, but it doesn't offer any direct insight into how the retailer might change its assortment or restocking effort in response to the rebate. By more evenly allocating the costs of stocking out, the rebate should better align the incentives of the upstream and downstream firms, potentially leading the retailer to increase its overall service level and/or favor the products of the rebating manufacturer. In the remaining sections, we describe and estimate a model of

[29] Throughout Table 5, we assume a production cost of \$0.15 for all manufacturers and we use each manufacturer's observed wholesale price.

those retail decisions, along with a flexible demand system, to shed light on these important questions.

4. Consumer Choice: Model and Estimation

In order to consider the optimal product assortment, we need a parametric model of consumer choice that predicts sales for a variety of different product assortments. We estimate a mixed (random-coefficients) logit model on our sample of 66 machines, including both experimental and non-experimental periods.

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

$$u_{ijt} = d_j + \sum_l \sigma_l \nu_{ilt} x_{jl} + \xi_t + \varepsilon_{ijt}. \tag{1}$$

The parameter d_j is a product-specific intercept that captures the mean utility for product j. Consumers have heterogeneous preferences for product characteristics x_{jl} (sugar, fat or peanut content in our case). We assume that the heterogeneity is normally distributed so that $\nu_{ilt} \sim N(0,1)$ with unknown standard deviation σ_l. We also incorporate ξ_t which is a parameter common to all products in market t and captures variation in demand for the outside good across markets; the error term ε_{ijt} follows a Type-I extreme value distribution. Each consumer has an outside option $u_{ijt} = \varepsilon_{i0t}$ of 'no-purchase,' which includes the possibility of not having a snack, bringing a snack from home, or purchasing a snack from somewhere other than a vending machine.

We define a_t as the set of products stocked in market t, and a market as a machine-visit pair (i.e., a_t is the product assortment stocked in a machine between two service visits). Consumers purchase the single product in the set a_t which gives them the highest utility $u_{ijt} > u_{ij't}$ for all $j' \neq j$. The resulting choice probabilities are a mixture over the logit choice probabilities for many different values of ν_{ilt}, shown here where $\theta = [d, \xi, \sigma]$:

$$s_{jt}(a_t;\theta) = \int \frac{e^{d_j + \xi_t + \sum_l \sigma_l \nu_{ilt} x_{jl}}}{1 + \sum_{k \in a_t} e^{d_k + \xi_t + \sum_l \sigma_l \nu_{ilt} x_{kl}}} f(v_{it}). \tag{2}$$

We estimate the potential daily market size for each machine, $\hat{M}_t$, as twice the maximum daily sales rate observed at the machine across our panel and calculate the sales of the outside good as $q_{0t} = M_t - \sum_j q_{jt}$. We estimate the parameters of the choice probabilities via maximum simulated likelihood (MSL) McFadden and Train (2000); Train (2003). The log-likelihood is:

$$\ell(\mathbf{q}|a_t;\theta) \quad \propto \quad \sum_t \sum_{j \in a_t} q_{jt} \log s_{jt}(a_t;\theta). \tag{3}$$

where q_{jt} are sales of product j in market t.

Parametric identification of $\theta = [d_j, \sigma_l, \xi_t]$ is straightforward. The d_j parameters are identified from average sales levels in a single market after we normalize the utility of the outside good to zero. The ξ_t parameters are identified from cross-market variation in the outside good share. Across machines and time, we observe 2,710 different product assortments a_t. The σ parameters are identified by the covariance of the changes in the observed sales across product assortments with the characteristics of the products that are added or removed from the choice set. For example, when we exogenously remove Peanut M&Ms during our experiment, we observe whether more consumers appear to switch to products with a similarly high peanut content (such as Planter's Peanuts) or to products with a similar sugar content (such as Plain M&Ms). A common challenge in the literature is the identification of an (endogenous) price effect (Berry et al., 1995). In our application, price effects are subsumed into d_j because we do not observe any within-product price variation (the entire confections category is priced at 75 cents in our sample). This limits our ability to measure consumer surplus but not to predict substitution patterns for changes in product assortment.

Unlike in our previous work, Conlon and Mortimer (2013), there are virtually no 'natural' stock-outs in the data; thus, changes to product assortment happen for two reasons: (i) MarkVend changes the assortment when re-stocking, or (ii) our field experiment exogenously removes one or two products. While MarkVend's assortment decisions are chosen endogenously, they are often temporary and due to changes in manufacturer product lines.[30] There is considerable product churn created by non-experimental changes in assortment, which helps to identify substitution between non-experimentally removed products. Non-experimental churn creates 262 unique choice sets for confection products; our exogenous product removals increase the number of unique choice sets to 427.[31]

Implicitly, our estimation of the consumer choice model assumes away dynamic effects of stock-outs (i.e., we assume no change in consumer preferences after the temporary removal

[30]Implicitly, we assume that changes to manufacturer product lines are taken with the national market in mind, rather than to induce a behavioral change by MarkVend.

[31]Further discussion and analyses of choice-set variation in this dataset are contained in Conlon and Mortimer (2010).

of a product).[32] Nevertheless, one should view our consumer choice model as capturing substitution patterns that are stable in the short run. Other factors, including manufacturer advertising, may impact substitution patterns in the long run.

We report the parameter estimates in Table 6. We estimate 73 product intercepts. We report two levels of aggregation for ξ_t. The first allows for 15,256 fixed effects, at the level of a machine-service visit, while the second allows for 2,710 fixed effects, at the level of a machine-choice set (i.e., we combine machine-service visit 'markets' for which the choice set does not change). We allow for three random coefficients, corresponding to consumer tastes for salt, sugar, and nut content.[33] We report the log-likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for each specification. We use BIC to select the specification with 2,710 ξ_t fixed effects. Our simulated ML parameters tend to be very precisely estimated, because we observe 2.96 million sales.[34]

5. Retailer Behavior: Model and Estimation

On the supply side, we begin with the retailer's problem, taking the manufacturer's choice of contract terms in the AUD as given. Appendix A provides a model that motivates a manufacturer's decision to offer an AUD, but our primary goal is to understand the effects of the contract as we observe it. We model the retailer's optimal choices of assortment, a, and effort, e. We hold retail prices fixed, consistent with the data from MarkVend.[35]

Later, when we describe the predicted effects of the Mars' AUD contract, we focus on a single 'base' assortment (and capacity), in which all but the last two confection products are fixed. This focus allows us to avoid solving separate dynamic programming problems on hundreds of heterogeneous machines, each with its own demand conditions, which we could not expect to accurately estimate on a machine-by-machine basis. Allowing for a more

[32] Using the same data, Kapor (2008) examines this assumption and finds no evidence that temporary stock-outs affect future demand patterns.

[33] Nut content is a continuous measure of the fraction of product weight that is attributed to nuts. 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 (2013), 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 estimated a number of alternative specifications in which we included 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.

[34] When we construct standard errors on counterfactuals, we sample from the asymptotic distribution $\theta^s \sim N(\hat{\theta}, V^{-1}(\hat{\theta}))$ (see Appendix B.3 Algorithm 4).

[35] We do not require an equilibrium model of downstream pricing responses to the AUD contract because we hold retail prices fixed. Retail price reductions would serve as an analogous form of costly retail effort.

flexible approach (i.e., with heterogeneous assortments or capacities across machines) would be computationally difficult – and also difficult to understand, as it would require presenting a distribution of potential effort policies that vary across machines. In practice, there is not a lot of variation across machines in assortment or capacity.

Assuming that Mars offers the same wholesale price across all goods w_m and has a constant marginal cost for all goods c_m, one can re-write a quantity-based AUD contract in terms of the profit of the rebating firm, π^M. Denoting the per-unit discount payment as τ, we define the payment from Mars (M) to the retailer MarkVend (R) as:

$$\tau \cdot q_m = \underbrace{\left(\frac{\tau}{w_m - c_m}\right)}_{\lambda} \cdot \pi^M \tag{4}$$

And we define MarkVend's problem as:

$$\begin{aligned} \max_{(a,e)} \pi(a,e) &= \begin{cases} \pi^R(a,e) + \tau \cdot q^M(a,e) & \text{if } q^M(a,e) \geq \overline{q}^M \\ \pi^R(a,e) & \text{if } q^M(a,e) < \overline{q}^M \end{cases} \\ &= \begin{cases} \pi^R(a,e) + \lambda \cdot \pi^M(a,e) & \text{if } \pi^M(a,e) \geq \overline{\pi}^M \\ \pi^R(a,e) & \text{if } \pi^M(a,e) < \overline{\pi}^M \end{cases} \end{aligned} \tag{5}$$

where $\pi^R(a,e)$ is the retailer's variable profit including the cost of effort e but absent any rebate payment, $\pi^M(a,e)$ is the variable profit of Mars, given by $\pi^M(a,e) = (w_m - c_m) \cdot q_m(a,e)$, and λ is the share of Mars' profit paid to the retailer, if it qualifies for payment. We define the threshold $\overline{\pi}^M$ as the minimum level of Mars' profit required for the retailer to qualify for payment. Equation (5) demonstrates that knowledge of $\pi^M(a,e)$ and $\pi^R(a,e)$ are sufficient to evaluate rebate contracts at any level of generosity λ and threshold $\overline{\pi}^M$. This means that the retailer's assortment (and effort) decision involves simple discrete comparisons across a finite number of choices. For each potential choice of assortment, we enumerate the profits at all relevant effort levels, including the observed effort level(s). We explain the set of potential assortments that we analyze at the end of the next section.

5.1. Computing Long-run Profits

Based on conversations with the owner, we understand MarkVend's effort decision to be operationalized as follows. At the beginning of each quarter, MarkVend decides on a policy to restock after e 'likely consumers' have arrived to each of its vending machines.[36] It then translates this policy into a restocking schedule for each individual vending machine (e.g., every Tuesday, every 10 days, every other day, etc.) based on knowledge of a machine-specific consumer arrival rate. Once the schedule for the quarter is set, the schedule is distributed across individual service routes, and routes are assigned to drivers and trucks. In order to reduce the number of consumer arrivals between service visits, MarkVend must hire additional trucks and drivers, which increases its costs. An implication of this setup is that MarkVend commits to a restocking policy for an entire quarter. This means that if sales are below expectations (i.e., if it repeatedly draws from the left-tail of the consumer arrival distribution), MarkVend does not adjust its stocking policy until the next quarter.[37]

MarkVend solves the following dynamic stocking problem, where $u(x)$ denotes the cumulative variable retailer profits after x likely consumers have arrived. Profits are not collected by MarkVend until it restocks. Its value function is:

$$V(x) = \max\{u(x) - FC + \beta E_{x'}[V(x'|x = 0)], \beta E_{x'}[V(x'|x)]\}. \tag{6}$$

The problem posed in (6) is similar to the 'Tree Cutting Problem' of Stokey et al. (1989), which for concave $u(x)$ and increasing $x' \geq x$, admits a monotone policy such that the firm re-stocks if $x \geq e$. For a given policy e, we can compute the post-decision transition-probability-matrix $\tilde{P}(e)$ and the post-decision pay-off $\tilde{u}$, defined as:

$$\tilde{u}(x, e) = \begin{cases} 0 & \text{if } x < e \\ u(x) - FC & \text{if } x \geq e. \end{cases} \tag{7}$$

For a given effort level e, we can solve the value function and compute long-run profits:

$$V(x, e) = (I - \beta\tilde{P}(e))^{-1}\tilde{u}(x, e) \tag{8}$$

$$\pi(a, e) = \Gamma(e)V(x, e) \quad \text{and} \quad \Gamma\tilde{P}(e) = \Gamma \tag{9}$$

[36] Mars' AUD rebate contract is evaluated quarterly on the basis of MarkVend's entire enterprise, which includes 728 snack vending machines.

[37] Within a quarter, it appears that machines are on an extremely predictable fixed schedule, and there is no evidence that the schedule is adjusted in either direction towards the end of each quarter. This is consistent with a model of effort in which the frequency of service is set in response to the payoff function, but the schedule is not set dynamically within a quarter as a function of the distance from the threshold. As MarkVend does not observe sales, except at the time of a service visit, this makes a lot of sense (i.e., it doesn't receive new information by which to dynamically adjust a service schedule across days).

where Γ represents the long-run stationary distribution corresponding to the post-decision transition matrix $\tilde{P}(e)$.[38]

Rather than recover the optimal effort and assortment under a particular contract, we compute the long-run profits $\pi(a, e)$ under all relevant effort levels e and assortment choices, a. Later, these long-run profits enable us to evaluate conditional transfers, such as the rebate contract, under a variety of terms and thresholds $(\lambda, \overline{\pi}^M)$. We are able to compute the long-run profits $\pi^i(a, e)$ not only of the retailers, but of the upstream manufacturers (Hershey, Mars, Nestle) as well.[39] We provide pseudo-code for the entire procedure in Appendix B.3. Below, we define the state space for the dynamic model, describe relevant features of the data and the empirical implementation of the dynamic model, and discuss the process of determining retailer assortment.

Defining the State Space and Transition Rule

In order to compute long-run profits in (9), we need to construct estimates of (i) the payoffs $u(x)$, by simulating consumer purchases and (ii) the transition rule or arrival rate $P(x'|x)$. The state variable x measures how many consumers have arrived at the vending machine since the most recent restocking event. For small values of x the machine should be nearly full with complete availability of the product assortment, while for larger values of x products will increasingly stock-out. For the retailer, if all products had similar margins, we would expect $u(x)$ to be (weakly) decreasing in x.

A naive approach to estimating the static payoffs $u(x)$ is to simulate the purchase of a single consumer by drawing from the multinomial distribution implied by the demand system (2), which depends on the current inventory of the machine, denoted A. The distribution of consumers is given by:

$$y \sim \text{Multinomial}\left(s_0(A), s_1(A), \ldots, s_J(A)\right)$$

Equivalently, we could separate this into two steps. For step 1, draw a Bernoulli variable with probability $\overline{s_0}$ that denotes 'likely' vs. 'unlikely' consumers, and which is independent of the demand system or current inventory A. For step 2, draw from a multinomial distribution

[38] The post-decision transition matrix is simply the transition rule for incremental mileage under a particular policy e:

$$\tilde{P}(e) = \begin{cases} x + \Delta x & \text{if } x < e \\ \Delta x & \text{if } x \geq e. \end{cases}$$

[39] It is important to note that manufacturers do not pay the restocking cost $FC = 0$ only the retailer does.

conditional on being a 'likely' consumer.[40] This two-step procedure defines a distribution of 'likely consumers' y^* as follows:

$$y \sim \begin{cases} 0 & \text{w.p. } \overline{s_0} \\ y^* & \text{w.p. } 1 - \overline{s_0} \end{cases} \qquad y^* \sim \text{Multinomial}\left(s_0(A) - \overline{s_0}, \frac{s_j(A)}{1 - \overline{s_0}}\right). \tag{10}$$

The second procedure does not appear to possess any immediate advantage over the first. However, in many discrete-choice settings, the outside good or 'no purchase' option is large (i.e., around 80-90% of potential customers don't make a purchase). Moreover, consumers who never make a purchase impact neither the payoffs of the firms nor the inventory of the vending machines. This means that if $\overline{s_0} = 0.9$, the first procedure requires simulating $10\times$ as many consumers from the distribution of y as the second procedure, which draws from the distribution of y^*.

Another important advantage of the second procedure is that we can redefine the dynamic programming problem in terms of the distribution of y^* instead of the distribution of y. This affects our transition rule. Our state variable x denotes the cumulative arrivals since the previous restocking of 'likely consumers' (from y^*) rather than 'all consumers' (from y). We estimate the incremental rate of 'likely consumer arrivals' non-parametrically from the data: $\hat{P}(\Delta x)$ where $\Delta x_t = x_t - x_{t-1}$. For each visit across MarkVend's entire enterprise, we observe the total number of products sold between visits and we compute the number of 'likely consumer arrivals' under y^* needed to match these. We can then compute the required number of "likely consumer arrivals" per day.[41]

We report the distribution of average daily sales for the top 25% of machines in MarkVend's enterprise in the left pane of Figure 4.[42] The distribution of average daily sales has a mean of 38.35 and a standard deviation of 25.6 across 35,172 visits. The right pane of Figure 4 reports cumulative sales at the time of restocking (which we match to calculate arrival rates). Our policies, which correspond to "Restocking after e 'likely customers,'" may imply that some machines are visited every two weeks and other machines every two days, because the arrival rate of consumers differs across machines. This allows for a standardized policy that

[40] We require that $s_0(A) > \overline{s_0}$ for any relevant A in order for both procedures to be equivalent. We must choose $\overline{s_0} < s_0(A)$ for the full-machine under all possible assortments because the no-purchase option is (weakly) increasing in the number of consumer arrivals due to the fact that products stock-out.

[41] This has obvious parallels to Rust (1987), who estimates a discrete distribution of weekly incremental mileage rather than working with cumulative mileage $P(x_{t+1}|x_t)$. Our full procedure is described in Appendix B.3 Algorithm 2. As we show in Appendix C.1, our qualitative results are not sensitive to changes in the arrival rate, as this tends to scale all profits up or down proportionally.

[42] In Appendix C.1 we consider alternate assumptions to estimate the arrival process.

can be applied to all machines, even though individual machines may have substantially different daily arrival rates.

On average, we observe that MarkVend restocks after 136 sales in the pre-2008 period, and 142 sales in the post-2008 period.[43] This pane also reports the policies calculated under our model (for retailer optimal and vertically-integrated levels of effort) as vertical lines (appropriately adjusted for stockouts).[44]

Simulating Consumer Purchases

We estimate the empirical counterpart of the per-consumer flow payoffs $u(x)$ from (7) as follows:

1. We define a 'typical full machine' as one that contains a set of the 29 most commonly-stocked products, listed in Table 7, with observed machine capacities for each product.[45] We generate 100,000 such full machines.

2. We simulate the arrival of 'likely consumers' by taking a draw s from the distribution of y^* one-at-a-time in accordance with an assortment a and the corresponding inventory A_s and mixed-logit choice probabilities, which are governed by a single set of demand parameters $(\hat{d}_j, \hat{\sigma_l})$ estimated from the set of 66 experimental vending machines. We set ξ to its median value of 0.75.

3. After each consumer s chooses, we update the inventories of each product, denoted A_s, as well as the choice probabilities $s_j(A_s)$ if the consumer's choice causes a product to stock out. We continue to simulate consumer arrivals until each of the 100,000 vending machines is empty (this takes $S \approx 800$ 'likely consumers').

4. We compute the flow profits $u^i(x)$ for every agent i (the retailer, Mars, Hershey, Nestle, and consumers) and every machine as a function of the cumulative number of consumer arrivals. We average these profits over the 100,000 machines and smooth them with a smoothing spline to generate a single estimate of flow profits, $\hat{u}^i(x)$.[46]

[43] The number of likely consumers is only $1-2$ more than the number of sales because MarkVend restocks before most product stockouts occur.

[44] Note that our policies are calculated terms of the cumulative number of likely consumers x in the model, while the plot concerns the number of realized sales when the driver restocks the machine. These numbers are very similar, but differ because in the adjusted state-space a small number of consumers still select the outside option (particularly as products stock out). That is $s_0(A) - \overline{s_0} > 0$.

[45] These capacities are nearly uniform across the 66 machines in our experimental sample, and are: 15 units for each confection product, 12 units for each salty snack product, and 15 units for each cookie/other product.

[46] We use the MATLAB package `slmengine`. After checking for monotonicity, we impose that

Costs and Prices Used to Estimate Per-Consumer Flow Payoffs

Two more inputs are required for calculating the per-consumer flow payoffs: the manufacturer variable cost of production, and prices/wholesale costs at the retail level. We observe and use MarkVend's wholesale costs for all manufacturers. We do not observe manufacturer costs of production. We use industry estimates of production costs to calibrate manufacturers' cost of production to \$0.15 per unit. All results report manufacturers' variable profit under this assumption.[47] We observe that MarkVend's retail prices are fixed at 75 cents for all confection products.[48] In order to convert consumer surplus into dollars, our estimates of consumer surplus calibrate the median own-price elasticity to -2 and assume the social planner puts equal weight on producer and consumer surplus ($\gamma = 1$). We view this as a relatively inelastic estimate of elasticity, implying that our consumer surplus calculations are likely to capture an upper bound on the potential efficiency effects of the AUD.[49]

Figure 3 provides a visual depiction of the (smoothed) per-consumer flow payoffs that result from our procedure for the (H, M) assortment. Both Mars' and the retailer's per-consumer variable profits are decreasing in the number of consumer arrivals. Mars' profit is roughly ten times the profit of each rival. Rival profits peak at around $e = 350$ likely consumers, because the rival products initially benefit from forced substitution as Mars products stock out; beyond $e = 350$, rival profits fall as the rival products begin to stock-out themselves.

Solving the Dynamic Problem

The last two inputs necessary for solving the dynamic problem are a daily discount factor β, and the fixed cost of a restocking visit, FC. We choose $\beta = 0.999863$, corresponding to a 5% annual interest rate.[50] We assume a fixed cost of a restocking visit, $FC = \$10$, approximating the per-machine restocking cost using MarkVend's wage data for drivers and the average number of machines serviced per day. Appendix C.3 reports robustness tests at

$\hat{u}^R(x), \hat{u}^M(x), \hat{u}^C(x)$ are all decreasing functions. We do not impose monotonicity on $\hat{u}^H(x), \hat{u}^N(x)$. In general the fit is good except in the tails, which are far from optimal policies. $R^2 > 0.98$.

[47] If upstream firms have constant marginal costs (fixed markups) then this is without loss of generality for the ordering of various assortment options. We report results at a manufacturer cost of zero in Appendix C.2. The zero-cost estimate provides an upper bound on the gap between the retailer optimal effort level e^R and the vertically-integrated optimal level e^{VI}.

[48] Correspondingly, our consumer-choice model does not estimate a price coefficient. Thus, although our consumer-choice model identifies an ordinal ranking of product assortments for consumers, it does not identify a monetary measure of consumer welfare.

[49] We provide additional details on the calibration exercise, as well as robustness to elasticities of -1 and -4 and alternative values for γ in Appendix B.4.

[50] Restocking behavior does not respond substantially to interest rates as high as 10% or as low as 1%.

$FC = \{5, 15\}$, which generate qualitatively similar predictions.

Given values of the discount factor β, the fixed cost FC, the prices and costs of manufacturers and the retailer, and estimates of $\hat{u}(x)$ and $\hat{P}(\Delta x)$, we solve the dynamic problem in (7)-(9) and compute $\pi(a, e)$ at under all relevant effort choices (rather than just the "optimum").[51] We provide additional details in Algorithm 3 of Appendix B.3.

Retailer Assortment Choice and Estimated Long-Run Average Profits

There are many possible choices of product assortment, even after we restrict our attention to the confections category. However, a large number of these potential assortments are dominated under a wide range of wholesale prices and rebate payments (e.g., replacing Peanut M&M's with the worst-selling product). For reporting purposes, we fix the five main products in the confections category as four Mars products: Snickers, Peanut M&M's, Regular M&M's, Twix Caramel; and one Nestle product: Raisinets (reported in Table 7). We treat the final two slots as 'up for grabs' and consider an assortment that places two Hershey products in the final spots (H, H): Reese's Peanut Butter Cups and Payday; one Hershey and one Mars product (H, M): Reese's Peanut Butter Cups and 3 Musketeers; and two Mars products (M, M): 3 Musketeers and Milky Way. We compute, but do not report, a wide variety of alternative assortments that are dominated by these three options.

Table 8 reports the simulated long-run average profits for the retailer and the combined retailer-Mars pair, and total producer and consumer surplus (PS and CS) for each of the three potential assortments. Each outcome is reported for several retail effort levels. This sets up the two main conflicts in our empirical exercise: in the absence of the rebate contract, the (H, H) assortment maximizes retailer profits; the (H, M) assortment maximizes producer and consumer surplus (and thus overall welfare); and the (M, M) assortment maximizes the bilateral surplus between Mars and the retailer (and is the assortment most commonly observed in the data).[52] The driving force behind the better welfare effects of the (H, M) assortment is that Reese's Peanut Butter Cups are more popular than 3 Musketeers, which results in an overall sales increase.

[51] Both our model of restocking and our estimation strategy are similar to the dynamic inventory management model in Aguirregabiria (1999). Our setting is simpler, because we don't need to incorporate menu costs or monopolistic competition.

[52] Algorithms (1)-(3) in Appendix B.3 provide further detail on how profits are simulated, and Table A7 provides a complete version of Table 8, including the profits of individual rivals.

5.2. Discussion of Limitations and Robustness

In order to evaluate a wide range of contract terms, product assortments, and effort decisions, our model deviates from MarkVend's actual problem in a few key ways.

First, we assume that the demand model reported in Table 6 is representative of MarkVend's overall business. We do not estimate machine-specific demand parameters, arrival rates, or assortments/capacities. One drawback of this assumption is that our demand estimates, which are based on the 66 machines in our experimental sample, may not appropriately capture the preferences of consumers in other locations. We are limited in how much we can do on this front because we lack experimental variation in choice sets outside of our experimental sample; we also lack within-product price variation, which limits the usual identification strategies. Two features of the estimation strategy mitigate this concern: (i) the fact that the main outputs of the demand model are the relative purchase probabilities of inside goods and their substitution patterns (and not the outside good share), due to the presence of the ξ_t fixed effects, and (ii) our modeling of the state-space as 'likely consumer' purchases. Our belief is that the relative substitution patterns for the products we analyze (e.g., Reese's Peanut Butter Cups, Snickers, Milky Way) are similar across locations.

Second, we assume that the arrival process we estimate, which uses the top quartile of Mark Vend's machines based on overall sales volume, is the key margin on which restocking decisions are made. In general, we find that modifying the consumer arrival rate has little bearing on the qualitative results, but rather tends to scale all the numbers up or down proportionally. We estimate the model using the arrival rate for the middle 50% of machines in Appendix C.1 as a robustness test.

Third, we implicitly assume that when the retailer chooses an assortment, the assortment applies to the entire enterprise. Strictly speaking, there is some cross-sectional variation in assortment across machines, although the confections category is relatively stable.[53] We ignore the possibility of a 'mixed' strategy, in which the retailer varies assortment with the time of year or stocks the 3 Musketeers product in some machines and MilkyWay in others.[54]

Finally, although retailer effort is modeled as the solution to a dynamic restocking problem, we assume that the retailer commits to a choice of (a, e) each quarter, and cannot respond to individual demand conditions within that period of time (i.e., it can't change assortment or effort if sales are slower/faster than expected within the quarter). Further-

[53] One key exception is that in locations with many children, non-chocolate confections such as Starburst and Skittles are more popular than they are in office settings.

[54] Such strategies would lead to a convex combination of the profits we report, and would be dominated by one alternative or the other.

more, we assume this decision is made absent any uncertainty about aggregate demand, so that when the retailer chooses (a, e), it receives its expected payment with certainty. This eliminates the risk that the retailer chooses (a, e) under the belief it will reach the threshold and receive the rebate payment, but a negative aggregate shock causes it to miss its target. It also allows us to plug in the average of $\hat{u}(x)$ from 100,000 simulated chains rather than considering the full distribution of outcomes. With a large enough set of machines (more than 700), our hope is that the law of large numbers applies and idiosyncratic shocks at the individual machine level wash out, particularly because MarkVend does not observe sales until after restocking.

6. Effects of Mars' AUD Contract

The remaining discussion focuses on differences in the long-run average profits of various agents across different contracts, assortments, and effort levels. We define this difference as $\Delta\pi = \pi(a, e) - \pi(a', e')$, using the estimated profits from the supply-side model. Our strategy is as follows. We use the same 'typical' machine as listed in Table 7 and used in the dynamic restocking model, in which all but two products are fixed. We allow the retailer to choose among the remaining two products: two Mars products (M, M), two Hershey products (H, H), or one product from each manufacturer (H, M).

We observe the wholesale price w and generosity of the rebate λ, and can evaluate any potential transfer $\lambda\pi^M(a, e)$ under these terms. We do not observe the quantity threshold $\overline{\pi}^M$. However, we can use the calculated values of $\pi^R(a, e)$ and $\pi^M(a, e)$ from (5) to evaluate which assortment the retailer prefers under any particular threshold $\overline{\pi}^M$ set by Mars. This allows us to determine whether a threshold exists at which Mars could foreclose Hershey, and whether or not that would constitute an equilibrium from which neither Mars, Hershey, nor the retailer could profitably deviate.

As is typical of the literature, our analyses provide insights into the potential effects of the contractual form we observe in a stylized environment. It does not provide an exact estimated effect of the contract on MarkVend's set of (heterogeneous) machines at a point in time *per se*. For the purpose of policy guidance, the stylized approach taken here is likely to be more relevant than an exact calculation of the contract's impact on MarkVend's machines in 2007 or 2008.

We calculate $\pi(a, e)$ at all relevant effort levels. We focus on a subset of effort levels when reporting profits and results. The first two effort levels of interest correspond to the effort level chosen by a maximizing retailer in (5) without the rebate $e^{NR}(a)$, and with the rebate

$e^R(a)$, respectively. The next two effort levels are those that maximize the bilateral surplus between Mars and the retailer, $e^{VI}(a)$, and the overall industry surplus, $e^{IND}(a)$ (which also includes the profits of Hershey and Nestle). Finally, we report the 'socially optimal' effort level e^{SOC}, which maximizes the surplus of all industry firms plus a weighted measure of consumer surplus. We use weight $\frac{\gamma}{\alpha}$, which depends on how the social planner weights consumer surplus (in utils) relative to producer surplus (in dollars) and is isomorphic to a (calibrated) price elasticity of demand.[55]

6.1. Results at MarkVend's Observed Effort Levels

As noted earlier, MarkVend restocks his machines more often than our dynamic model estimates to be optimal. On one hand, this is helpful: our experimental product removals are uncontaminated by non-experimental stock-outs. Furthermore, the owner of MarkVend was interested in running the experiment in large part because he suspected he was over-servicing.[56] On the other hand, one might want to know whether the effect of the AUD differs when it is evaluated at MarkVend's observed effort level. Thus, we begin by analyzing payoffs under different assortments at Mark Vend's observed effort levels.

We report the level of simulated profits for each agent in Table 8 and comparisons of profits in Table 9. The row labeled $e^{Pre2008}$ ($e^{Post2008}$) refers to simulated outcomes at MarkVend's observed pre-2008 (post-2008) effort level of restocking after 137 (144) sales.[57] The pattern that emerges from Table 8 is that if we ignore the rebate, our simulated retail profits are maximized under the (H, H) assortment. This assortment is worse for consumer surplus and overall producer surplus than the (M, M) assortment that the retailer actually chooses in the pre-2008 period. The first column of Table 9 reveals that Mars gains $\pi^M =$ \$5,519 when the retailer chooses (M, M) instead of (H, H) and pays a rebate to the retailer of $\lambda\pi^M =$ \$4,483 in return. The retailer gains more from the rebate than they lose from choosing the (M, M) assortment (i.e., gaining the \$4,483 rebate payment but realizing retail profit under (M, M) that is lower by $\Delta\pi^R =$ \$1,665), and it is rational for Mars to pay the rebate.

Mark Vend's year-over-year sales of Mars products reveal a discrete change before and after 2008, with average year-over-year sales growth of 105% in the pre-2008 period and 92%

[55]For a more complete description on how we calibrate α please consult Appendix B.4.

[56]Indeed, MarkVend reduced service levels after learning from the experiment.

[57]We use sales instead of 'likely consumers' for calculations that depend on MarkVend's observed restocking schedule. At these observed levels of effort, stockouts are rare, so that sales and 'likely consumers' are usually within one or two units of each other.

in the post-2008 period. In conversations with Mark Vend, we learned that Mars reduced MarkVend's target threshold at that time. As shown in Figure 2 and Table 2, there were two main effects: Mark Vend replaced 3 Musketeers with Reese's Peanut Butter Cups in many machines (a switch from the (M, M) assortment to the (H, M) assortment), and reduced its effort level from 137 sales between service visits to 144 sales. We analyze the net impact of this change in the last column of Table 9. Consumer surplus, retailer profits, and Hershey profits all increase at the (H, M) assortment. This comes at the expense of Mars, whose profit falls because Mark Vend no longer stocks 3 Musketeers. Mars no longer forecloses Hershey, and it no longer makes sense for Mars to pay the rebate at the given discount λ.[58] There are efficiency losses associated with the retailer's effort level in the post-2008 period. These are highlighted by comparing outcomes for each agent under the (H, M) or (M, M) assortments at the higher ($e = 137$) vs. lower ($e = 144$) effort level. The primary beneficiary of the additional retailer effort in the pre-2008 period is consumers, who gain ancillary benefits from reduced stockouts in other product categories such as salty snacks. For example, the third column illustrates that consumer surplus under an (M, M) assortment at the lower post-2008 effort level is lower than consumer surplus under the pre-2008 effort by the (calibrated) equivalent of \$113.[59] The retailer benefits from exerting lower effort in the post-2008 period because servicing the machines is costly. Around 40% of the gains to consumers from having the preferred (H, M) assortment are lost as a result of the reduced effort (i.e., a consumer surplus gain of 165 under (H, M) at $e = 144$ vs. a gain of 277 under (H, M) at $e = 137$). Nevertheless, on net, consumers (and producers as a whole) benefit more from the preferred (H, M) assortment that is observed after 2008 than they lose from the reduced effort in that period.

On balance, this suggests that, at the observed retailer effort levels, the negative effects of foreclosing Reese's Peanut Butter Cups dominate the efficiency gains from the additional effort.[60] This result comes with some caveats, the most important of which is that we take as given the observed effort levels of $e = 137$ (pre-2008) and $e = 144$ (post-2008). There are two important caveats to this analysis. First, we don't think Mars would be willing to pay the rebate at these effort levels over the long term. Indeed, industry sources indicate

[58] At the observed (H, M) assortment and post-2008 effort level, the rebate produces a gain for Mars of \$5,570 - \$2,551 = \$3,319 (assuming the retailer reverts to (H, H) without the rebate) but costs Mars \$5,142 in rebate payments.

[59] In the second and fifth columns, we see higher consumer surplus numbers, which reveals consumers' preference for the (H, M) assortment relative to the baseline (M, M) assortment.

[60] If we are willing to consider partial equilibrium checks, it may also suggest that the more lenient terms of the post-2008 AUD contract do not constitute a long-run equilibrium outcome for Mars.

that Mars ratchets up its rebate requirements the following year. Second, we don't know whether the retailer's effort choice of $e = 144$ is constrained by a binding rebate threshold or not. If the rebate is binding at $e = 144$, then eliminating the rebate might lead to a further reduction in effort.[61]

6.2. Results for an Optimizing Retailer

Next we consider a retailer who chooses effort to optimally solve the dynamic restocking problem in (6), and sets a lower level of effort for all contract types (by about 80 'likely consumers' as shown in Figure 4). One can rationalize MarkVend's high effort level by placing some weight on consumer surplus in its objective function, which provides a reduced-form value of the long-run relationships between MarkVend and its customers. (i.e., if the machine is always empty, the client terminates the contract and selects a different vending operator). We calibrate such a model to match the observed pattern of MarkVend's effort and report the results in Appendix C.4. The overall patterns look much like Table 9 except that the scope of potential efficiency gains is smaller at the higher effort level. The reason for this is that if consumer surplus constrains MarkVend's effort, the effect of the contract terms is reduced, and changes to the contract will have less of an impact. Thus, the approach below can be viewed as an upper bound on potential efficiencies.

Role of the Threshold

The rebate threshold can be used by the dominant firm to affect the retailer's effort and assortment decisions. As the threshold $\overline{\pi}^M$ increases, the retailer responds either by increasing costly effort (restocking more frequently) or by replacing a competitor's product with a product of the rebating firm. By varying the threshold, Mars changes the retailer's incentive compatibility (IC) constraint and is able to indirectly select (a, e) among a set of feasible options. We characterize those options below.[62]

Holding fixed the generosity of the rebate, λ, at the observed value, we vary the threshold and measure the response of an optimizing retailer in (5). Table 10 documents the assortment and effort decisions of the retailer (a, e) in response to different thresholds $\overline{\pi}^M$. For any threshold below $19,418$, the retailer will stock (H, H) and set the e^R effort level, knowing that it will receive the rebate. When the threshold increases to $19,686$, the retailer responds by increasing its effort. When the threshold increases beyond $19,686$, the retailer responds

[61]In contrast, if the threshold is not binding at $e = 144$, then the observed effort levels give a complete measure of the efficiency gain of the rebate program.

[62]Appendix A.2 provides more detail on the retailer's IC constraint.

by switching the assortment to (H, M). The retailer stays at the e^R effort level for values of the threshold up to $22,464$, and increases effort further for a threshold up to $\overline{\pi}^M = 22,747$. When the threshold exceeds $22,747$, the retailer responds by dropping the last Hershey product and changing the assortment to (M, M). Further increases in the threshold lead to increases in retailer effort up to $\overline{\pi}^M = 25,815$, at which point the rebate is unobtainable and R reverts to (H, H).

We provide a graphical illustration of the threshold in Figure 5. We plot the post-rebate profits of the retailer $(\pi^R + \lambda\pi^M)$ against the profits of Mars π^M (and hence the threshold). Movement along the curve from left to right corresponds to an increase in retail effort (and Mars' profit). We plot two curves. The curve on the left corresponds to retailer profit under a (H, M) assortment; the curve on the right corresponds to a (M, M) assortment. The peak of each curve corresponds to the e^R profit level. We denote the 'foreclosure threshold,' $22,747$, with a vertical dotted line. For any threshold to the right of this point, the retailer's payoff is higher when it switches from the (H, M) assortment to the (M, M) assortment than it would be under an even higher effort level with the (H, M) assortment. This illustrates that the rebate cannot be used to implement the (H, M) assortment and e^{SOC} effort level (to the right of the vertical dotted line), because an optimizing retailer would instead switch to an (M, M) assortment with e^R.

Note that it may be in the interest of the rebating firm to set a threshold high enough to induce effort in excess of e^{VI}, because $\pi^M(e)$ is increasing everywhere (i.e., Mars bears none of the retailer's restocking cost). This can be accomplished by choosing a threshold $\overline{\pi}^M > \pi^M(e^{VI})$.[63] Indeed, in equilibrium, it may be possible for Mars to design an AUD that results in socially inefficient excess effort.

Effort, Efficiency and Welfare

The left-hand panel of Table 11 reports the effort policies of an optimizing retailer for all three assortments, under each effort level $e^{NR}, e^R, e^{VI}, e^{IND}$, and e^{SOC}.[64] The right-hand panel reports the percentage change from the effort policy e^{NR} that an optimizing retailer would choose in the absence of the rebate for any given assortment.

[63] When an optimizing retailer exerts greater effort than e^{VI} (i.e., $e < e^{VI}$), the bilateral surplus is increasing in effort, just as for $e > e^{VI}$ the bilateral surplus is decreasing in effort; however, at all levels of e, effort (weakly) functions as a transfer from R to M.

[64] Effort of an optimizing retailer is measured in units of 'likely consumers,' so a lower number implies a greater frequency of restocking and more effort. Consumer surplus is scaled by the price elasticity, which we normalize to $\epsilon = -2$ for the base case e^{SOC}; alternative policies check robustness to elasticities of -1 (e^{SOC1}) and -4 (e^{SOC4}). As consumers become less elastic, they receive more weight in the social planner's objective and the socially-optimal policy calls for the retailer to restock more often.

The AUD can affect effort in two ways. First, the lower effective wholesale price (due to λ) directly addresses the downstream moral hazard problem and better aligns the interests of the manufacturer and the retailer. This effect increases the frequency of restocking by 5-6 likely consumers or around 2-3%, and is reported in the second row of Table 11, which corresponds to the retailer's optimal effort level under the rebate terms for each of the three assortments (e^R). The second effect of the AUD on retailer effort derives from the retailer's attempt to meet the threshold requirement in the case that the threshold is set above the level that would be obtained by e^R. This illustrates that the AUD can be used to induce effort beyond what the retailer would optimally choose under the discounted wholesale price. The combined effect is reported in subsequent rows, which correspond to different effort levels, e^{VI}, e^{IND}, etc. For example, under an (M, M) assortment and a threshold that maximizes the profits of a vertically-integrated Mars-retailer pair (e^{VI}), the retailer restocks after 195 consumers, rather than after 214 consumers, or almost 9% more often. With around 36 consumers arriving each day to our experimental machines, this implies restocking every 5.3 days instead of every 5.8 days on average. The socially-optimal restocking policy calls for restocking after 171 likely consumers or around 4.67 days on average.

In Table 12, we compare the profit and welfare consequences of the AUD contract to several benchmarks. Under our baseline, we assume that the AUD contract results in an optimizing retailer choosing the (M, M) assortment and the e^R effort level. The e^R effort level is the optimal level of effort for the retailer at the post-rebate per-unit price predicted by the dynamic model, assuming that the quantity threshold is not binding. We choose the e^R effort level as our baseline because it represents a lower bound on the rebate's potential efficiency gains.[65] We then analyze how an optimizing retailer's choice of effort and assortment varies under different alternatives: (i) the elimination of the rebate holding everything else fixed, (ii) a rebate with the threshold set to induce the vertically-integrated optimum for the Mars-retailer pair, (iii) an industry optimum, and (iv) the social optimum.

The first column reports the results of eliminating the AUD contract while holding everything else fixed. The retailer chooses assortment (H, H) and effort e^{NR}, which results in higher profit for Hershey $\Delta\pi^H = 3644$ (whose two products are now stocked), lower profits for Mars $\Delta\pi^M = -5671$, and lower producer $\Delta PS = -425$ and consumer surplus

[65] The results in Table 10 report effort levels that satisfy the IC constraint of the retailer. The e^R effort level is easy for Mars to achieve vis-a-vis the retailer's IC constraint. If Mars sets a high enough threshold $\overline{\pi}^M$, then many higher effort levels $e < e^R$ are also possible, including those exceeding the vertically-integrated level $e < e^{VI}$ or social optimum $e < e^{SOC}$.

$\Delta CS = -534$ overall.[66] The second column reports the results of increasing the threshold to the level of e^{VI}. An optimizing retailer continues the (M, M) assortment, and the e^{VI} threshold leads to lower retailer profits $\pi^R = -109$, higher Mars profits $\Delta\pi^M = 191$, and slightly higher producer surplus $\Delta PS = 78$. Most of the gains from the retailer's additional effort are captured by consumers $\Delta CS = 423$.

While the vertically-integrated outcome maximizes the bilateral surplus between Mars and the retailer, it does not maximize producer surplus because the (M, M) assortment is inferior to (H, M). The third column reports outcomes under the industry optimum, which is an (H, M) assortment and e^{IND} effort level. The profits of both the optimizing retailer and Hershey both increase ($\Delta\pi^R = 612$ and $\Delta\pi^H = 2173$), and Mars earns a lower profit ($\Delta\pi^M = -2339$). Overall, producer and consumer surplus both increase ($\Delta PS = 451$ and $\Delta CS = 670$). The socially optimal outcome, in the last column, also uses an (H, M) assortment, but with a higher e^{SOC} effort level. This further increases effort to the benefit of consumers (and Mars) at the expense of the retailer.

Net Effects and Rival Countermeasures

In this section we address two remaining questions: Does the additional effort induced by the AUD for an optimizing retailer compensate for the non-optimal (M, M) assortment (measured in terms of overall producer and consumer surplus)? And, at the observed generosity λ, does the AUD rebate represent an equilibrium from which no party (the retailer, Mars, or Hershey) wishes to deviate?[67]

In Table 13 we compare welfare calculations under the (M, M) assortment with each of three (e^R, e^{VI}, and e^{SOC}) effort levels, to two potential alternatives. The first alternative is the (H, H) assortment under the e^{NR} effort level. This mimics what an optimizing retailer would choose if the AUD contract were banned but wholesale prices remained unchanged. The second alternative is the (H, M) assortment with the e^{NR} effort level. This is the assortment that would be chosen by the social planner, but without efficiency gains from lower wholesale prices or the need to achieve a higher threshold through effort provision.

The right-hand panel of Table 13 shows that the likely outcome of the rebate with an (M, M) assortment (for any of the three effort levels) is unambiguously better than the (H, H) assortment with an effort level of e^{NR} for both consumers and producers. Consumer and producer surplus are both increasing functions of the threshold, so that a higher threshold

[66] This does not constitute an equilibrium outcome (e.g., it precludes the possibility that prices adjust).

[67] This approach provides only a partial check of optimality, as we hold many other variables fixed, such as the observed size of λ and the wholesale prices of rival firms.

improves welfare.

Perhaps the more important comparison is the left-hand panel of Table 13, which compares the outcome under the rebate to the industry (and socially) optimal assortment (H, M). Relative to the socially optimal assortment, the AUD that induces an (M, M) assortment unambiguously reduces total producer surplus $(-300, -222, -480)$ for (e^R, e^{VI}, e^{SOC}) respectively. The results for consumer surplus are more ambiguous. If the rebate threshold under an (M, M) assortment is set at the e^R effort level, then consumer surplus is reduced $(\Delta CS = -55)$. While consumers benefit from more effort (the optimizing retailer restocks after 209 instead of 217 customers), these benefits are dominated by having access to a less-preferred assortment: MilkyWay instead of Reese's Peanut Butter Cups in the final slot. However, if the AUD sets the threshold high enough to induce at least the vertically-integrated effort level e^{VI}, then the net effect on consumer surplus becomes positive $(\Delta CS = 367.)$[68] At this level of effort (restocking after 195 consumers instead of 217), the avoidance of other stockouts compensates consumers for the less desirable assortment. This effect is even more pronounced at the socially-optimal effort level $(\Delta CS = 980.)$[69]

In order to analyze the potential for rival countermeasures, we ask whether or not the observed rebate constitutes an equilibrium under our simulated (counterfactual) profits. We verify the following three conditions, derived in Appendix A.1.

$$\Delta\pi^R + \lambda\pi^M \geq 0 \qquad \text{(Retailer IR constraint)}$$
$$\Delta\pi^M - \lambda\pi^M \geq 0 \qquad \text{(Mars IR constraint)}$$
$$\Delta\pi^R + \Delta\pi^M + \Delta\pi^H \geq 0 \qquad \text{(Three-party surplus)}$$

The first is the Individual Rationality (IR) constraint of the retailer: whether it prefers to choose (a, e) and receive the rebate, or choose (a', e') without the rebate. This is easily verified in Table 13, as the rebate (labeled $\lambda\pi^M$) is always at least $5,500$, and the minimum value of $\Delta\pi^R$ in Table 13 is $-2,182$. The next condition is the IR constraint of Mars (i.e., whether Mars prefer to pay the rebate if it induces the retailer to switch from (a', e') to (a, e)). We see clearly that the rebate is only rational from the perspective of Mars if it induces a switch from (H, H) to (M, M). Even under the lowest rebate-optimal effort e^R, Mars' gain from changing to (M, M) from (H, H) is $5,671$, which exceeds its payment of

[68] This particular comparison tends to be sensitive to assumptions about fixed costs. See Appendix C.

[69] As always, interpreting social surplus measures requires care, because the assumed elasticity of demand is proportional to the weight that the social planner places on consumers. See Appendix B.4.

$5,547$.[70] In contrast, the rebate would be too generous (and thus violate Mars' IR constraint) if it only induced a switch from $(H, M) \rightarrow (M, M)$, as Mars' gain in this case is between $2,625$ and $3,085$, whereas its payment is between $5,547$ and $5,649$.[71]

The three-party surplus constraint, $\Delta\pi^R + \Delta\pi^M + \Delta\pi^H \geq 0$, is determined by whether or not Hershey can deviate in order to avoid being foreclosed. As Hershey earns no profit under (M, M), one can ask whether Hershey can give up all of its profit under (H, H) as a lump-sum transfer to the retailer to avoid foreclosure. Under an assortment choice of (H, H), the retailer receives $(\pi^R((H, H), e^{NR}) + \pi^H((H, H), e^{NR}))$, while under (M, M) the retailer receives the rebate payment as before. Thus, the retailer will choose (M, M), and Hershey will fail to avoid foreclosure in equilibrium if:

$$\pi^R((M, M), e) + \lambda\pi^M((M, M), e) \geq \pi^R((H, H), e^{NR}) + \pi^H((H, H), e^{NR}). \tag{11}$$

Substituting Mars' IR constraint into (11) produces the three-party surplus condition.[72]

We express this condition by calculating the Hershey wholesale price that leaves the retailer indifferent between the two assortments in (11), and comparing that price to the manufacturer's 15-cent marginal cost.[73] We find, in the fourth and fifth columns of Table 13, that Hershey would have to set a wholesale price below 13 cents in order to avoid foreclosure. In the final column, for a threshold set to induce the socially-optimal effort level e^{SOC}, we find that Hershey might be able to avoid foreclosure by deviating to a wholesale price of $w_h = 16.35$ cents. Alternatively, one can perform a similar exercise and ask: what value of λ equates both sides of (11)? Table 13 suggests that under e^R or e^{VI}, Mars can only reduce the generosity of the rebate by 5-6% (see the last row, columns 4 and 5) before Hershey is able to deviate and avoid foreclosure. From the perspective of Mars, this evidence suggests that the AUD is well-designed. Were it 6% less generous, it would allow for a profitable deviation by Hershey. Were it 6% more generous, it would violate the IR constraint of Mars, unless the threshold induced a high amount of additional effort.

Equation (11) also sheds light on the way in which the AUD fails to lead to the industry-

[70] This condition was not violated in any of our bootstrapped simulations.

[71] In unreported results, we verify that this is also true for any rebate that induces a switch from $(H, H) \rightarrow (H, M)$.

[72] Equation (11) is related to the game in Bernheim and Whinston (1998), in which manufacturers bid for representation by a retailer. Appendix A.1 provides additional detail.

[73] Technically there is a small difference between a lump-sum transfer and setting $w_h = 0.15$. If retail prices were to respond only to wholesale prices, this difference might be substantial. In our setting, retail prices are fixed, so the only difference arises from additional incentives for effort that result when the retailer faces a lower wholesale price. The additional effort effect is small $\Delta e \leq 2$ likely consumers.

optimal assortment, (H, M), because it depends on a comparison of only two alternatives: the assortment preferred by Mars and induced by the rebate threshold, (M, M); and the assortment chosen by the retailer absent the rebate, (H, H). It does not depend on the assortment that maximizes three-party surplus (H, M). By conditioning the rebate threshold on the sales of all of its products through $\overline{\pi}^M$, Mars effectively ties its products together.[74]

In Appendix C, we reproduce Table 13 under a variety of alternative assumptions: higher or lower fixed costs $FC = \{5, 15\}$, zero marginal cost, and an arrival rate matched to the middle 50% of machines. In all of our robustness tests, the net effects maintain the same signs as those in Table 13. Nearly all of these alternatives suggest that two IR conditions and the three-party surplus condition are satisfied for the same scenarios as above. The only exception is ΔCS, when compared to (H, M) under e^{VI}. In some cases, the AUD is able to induce sufficient efficiencies to justify the inferior assortment (slower arrival, and zero marginal cost) and in others it is not (alternative fixed costs).[75]

7. Conclusion

Using a new proprietary dataset that includes exogenous variation in product availability, we provide empirical evidence regarding the potential efficiency and foreclosure aspects of an AUD contract. Similar vertical rebate arrangements have been at the center of several recent major antitrust settlements, and have attracted the attention of competition authorities in many jurisdictions.

In order to understand the relative size of the potential efficiency and foreclosure effects of the contract, our framework incorporates endogenous retailer effort and product assortment decisions. A model of consumer choice allows us to characterize the downstream substitutability of competing products, and combining this with a model of retailer effort allows us to estimate the impact of downstream effort across upstream and downstream firms. Identification of both the consumer choice and retailer-effort models benefits from exogenous variation in product availability made possible through a field experiment. We show that the vertical rebate we observe has the potential to increase effort provision, and that the benefit of this additional effort is mostly captured by consumers. The rebate also enables the rebating firm, Mars, to foreclose Hershey by leveraging its profits from dominant

[74]This is similar but not identical to the tying argument in Whinston (1990). See Appendix A.1.

[75]In Appendix C.4, we also calibrate a model in which MarkVend places an additional weight on consumer surplus in its objective function. One can consider this specification as providing a reduced-form value of the long-run relationships between MarkVend and its customers. We calibrate this model to match the observed policies of MarkVend ($e \approx 130$). At this high level of effort, one essentially eliminates the scope for any efficiencies, and the welfare losses from the inferior assortment dominate.

products (such as Snickers and Peanut M&Ms), to obtain shelf-space for products such as Milky Way.

We find that at the prevailing wholesale prices, the rebate falls short of implementing the product assortment that maximizes industry profits. The differential impact on social welfare is small, and depends on how the rebating firm sets the quantity threshold in the AUD. We also show that the use of the AUD by Mars to foreclose Hershey represents an equilibrium outcome, and that no player possesses a profitable deviation.

In addition to providing a road-map for empirical analyses of vertical rebates, and results on one specific vertical rebate, our detailed data and exogenous variation allow us to contribute to the broader literature on the role of vertical arrangements for mitigating downstream moral hazard and inducing downstream effort provision. Empirical analyses of downstream moral hazard are often limited not only by data availability, but also by the ability to measure effort, and our setting provides a relatively clean laboratory for measuring the effects of downstream effort.

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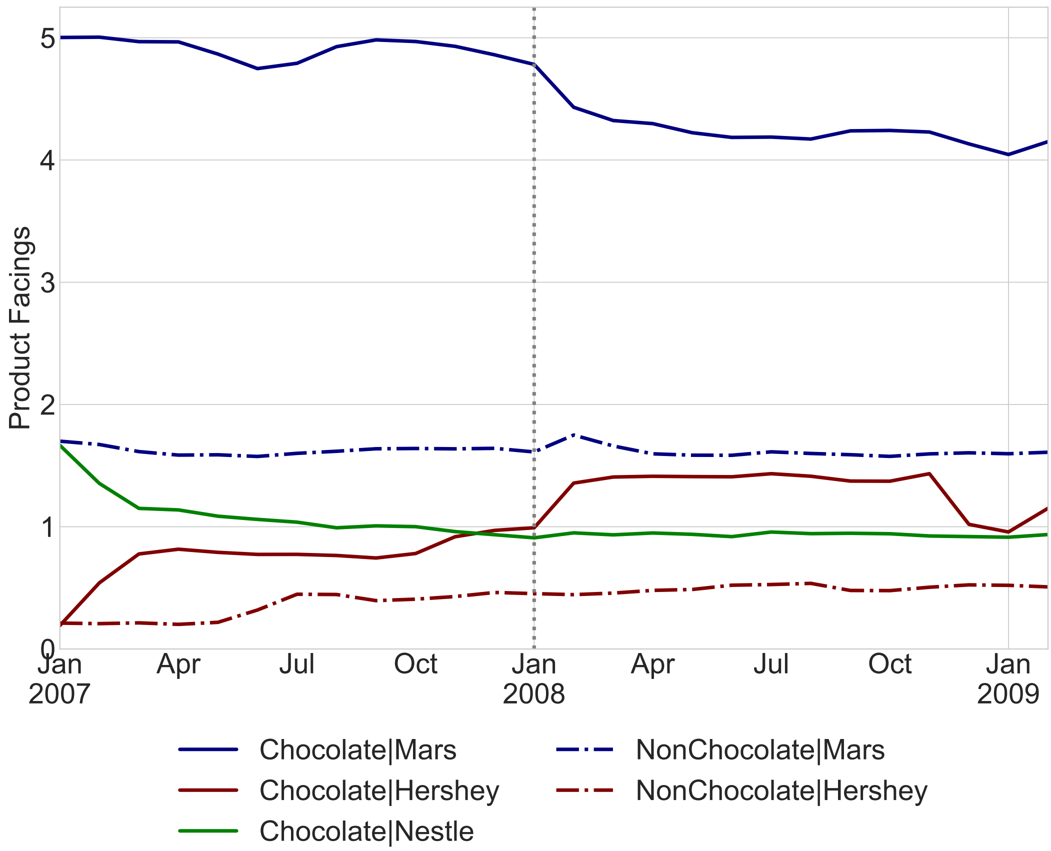
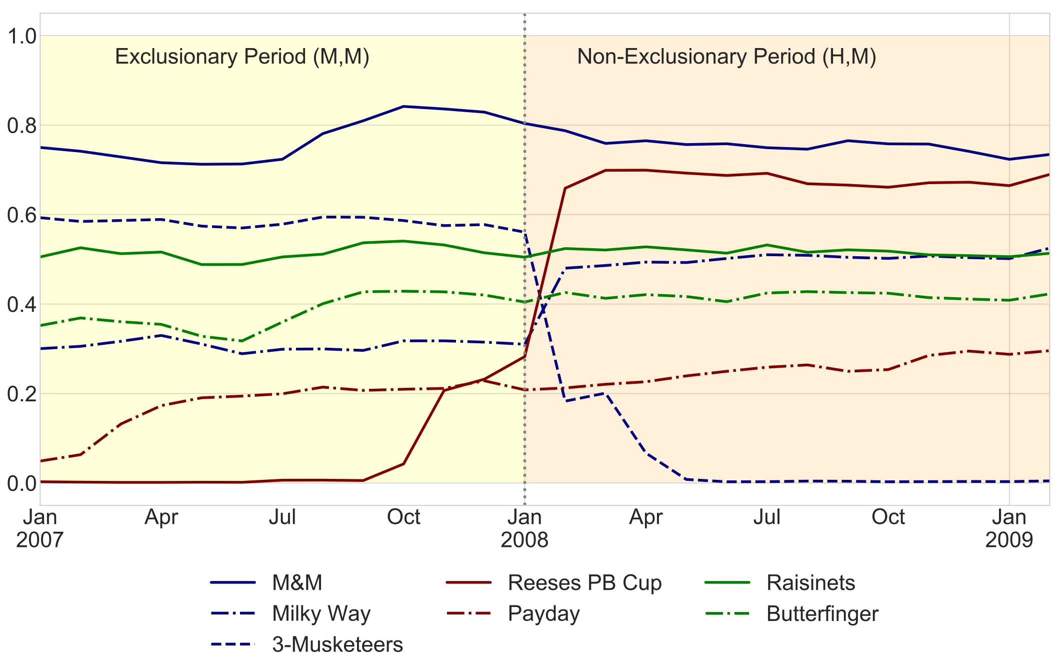
Figure 1: Mars Vend Operator Rebate Program

Notes: From '2010 Vend Program' materials, dated December 21, 2009; last accessed on February 2, 2015 at `http://vistar.com/KansasCity/Documents/Mars%202010%20Operatopr%20rebate%20program.pdf`.

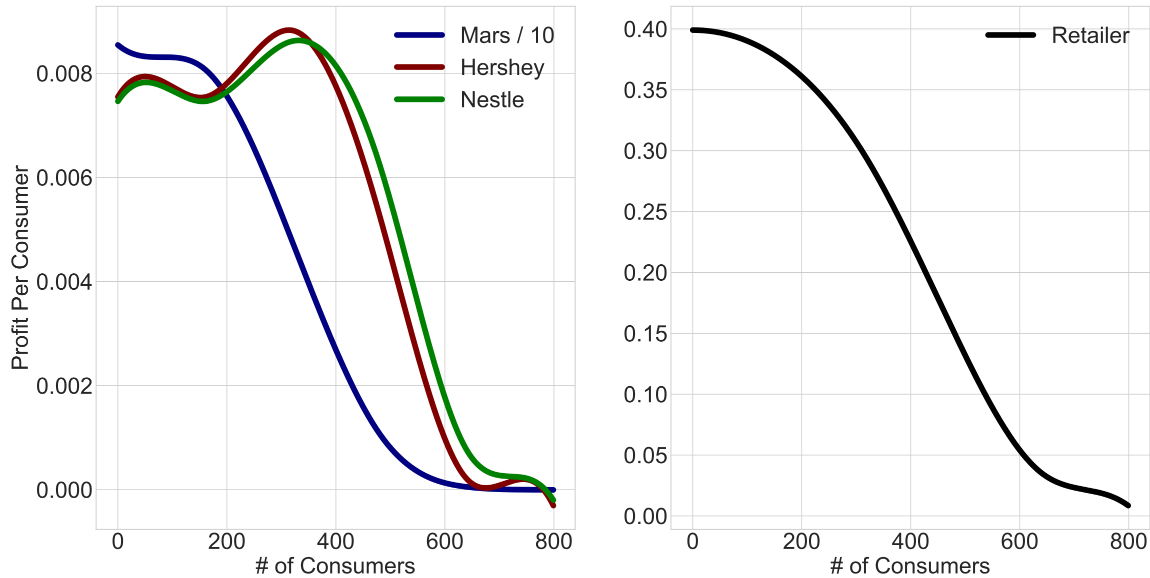
Figure 2: Variation in Product Facings Over Time





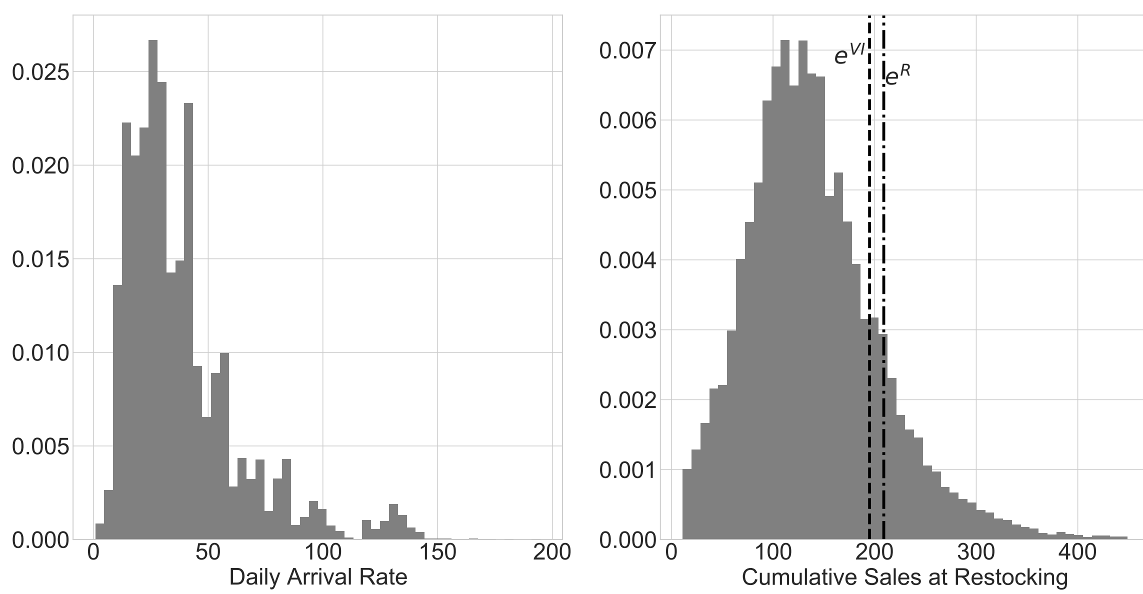
Notes: Both panes report average number of product facings per machine-visit for a balanced panel of 364 machines (reporting visits for at least 90% of months displayed). Top pane reports manufacturer facings at the category level. Bottom pane reports facings at the individual product level for *marginal* products. Data aggregate over different machine models and capacities.

Figure 3: Profits Per Consumer as a Function of the Restocking Policy



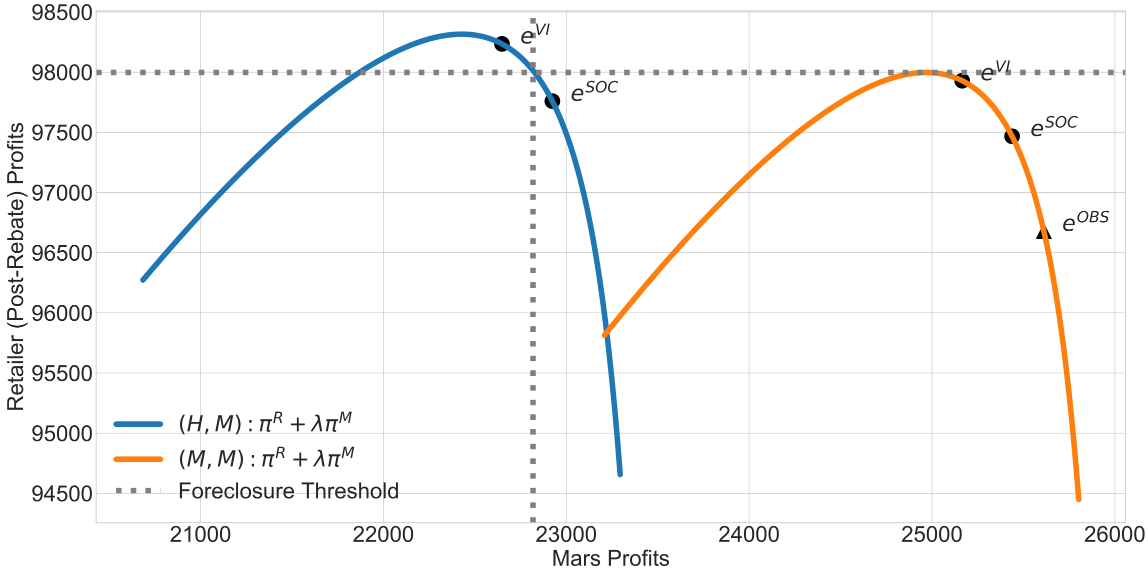
Notes: Each curve reports the per-consumer variable profits $u(x)$ of the retailer, Mars, Hershey and Nestle as a function of the retailer's restocking policy, using the product assortment in which the retailer stocks 3 Musketeers (Mars) and Reese's Peanut Butter Cups (Hershey) in the final two slots. Specifically, the vertical axes report variable profit per consumer for each of the four firms, and the horizontal axes report the number of expected sales between restocking visits. Mars' profit is normalized to be $\frac{1}{10}$th the amount of its competitors' profits.

Figure 4: Observed Policies and Arrival Rates



Notes: Left pane reports average daily arrival rate for top 25% of machines at MarkVend's overall enterprise. These are used to estimate $f(\Delta x_t)$. The mean is 38.4 vends per day. Right pane reports cumulative sales at restocking. The mean is to restock after 139 sales. Right pane also reports policies calculated under the dynamic restocking model as vertical lines (i.e., e^{VI} for optimal effort under vertical integration and e^R for optimal retailer effort). Policies and cumulative sales are in the same units, except for 'sales' of the outside good. Histograms are from 35,172 machine-visits.

Figure 5: Impact of AUD Quantity Threshold on Retail Assortment Choice



Notes: Figure reports retailer variable profit under two assortment choices, (H,M) on the left and (M,M) on the right, against Mars' revenues. Two points are marked on each curve representing the e^{VI} effort policy and the e^{SOC} effort policy. The e^R policy is the maximum of each curve. The dotted line denotes the threshold value above which Mars forecloses the rival. Once π^R falls below $\pi^R((H,H), e^{NR}) = 95,532$, and optimizing retailer reverts to the (H,H) assortment (omitted to preserve the scale of the figure).

Table 1: Comparison of National Availability and Shares with Mark Vend

Product	Rank	National Sample Availability %	Share	MarkVend Share Pre 2008	Post 2008
Snickers (Mars)	1	89	12.0	16.9	17.1
M&M Peanut (Mars)	2	88	10.7	16.0	16.1
Twix (Mars)	3	67	7.7	11.9	13.7
Reeses PB Cup (Hershey)	4	72	5.5	0.7	6.5
3-Musketeers (Mars)	5	57	4.3	4.6	0.5
M&M (Mars)	6	65	4.2	6.9	6.2
Starburst (Mars)	7	38	3.9	3.2	3.0
Skittles (Mars)	8	43	3.9	5.3	6.0
Butterfinger (Nestle)	9	52	3.2	2.2	2.1
Hershey w/ Almond (Hershey)	10	39	3.0	0.1	0.1
Payday (Hershey)	11	47	2.9	0.9	1.8
Milky Way (Mars)	13	39	1.7	2.2	3.6
Raisinets (Nestle)	45	N/R	N/R	4.5	3.2

Notes: National Rank, Availability and Share refers to total US sales for the 12 weeks ending May 14, 2000, reported by Management Science Associates, Inc., at http://www.allaboutvending.com/studies/study2.htm, accessed on June 18, 2014. National figures are not reported for Raisinets because they are outside of the 45 top-ranked products. By manufacturer, the national shares of the top 45 products (from the same source) are: Mars 52.0%, and Hershey 20.5%. For MarkVend's total enterprise, shares are: Mars 73.6%, and Hershey 15.0%; for our experimental sample: Mars 78.3% and Hershey 13.1% (calculations by authors).

Table 2: Changes in Retailer Behavior Over Time

	Overall Sales	Mars Sales	Mars Share	Mars YoY Sales	Retailer Effort Vends/Visit	Retailer Effort Days/Visit
2006Q1	100.00	19.80	19.89		143.10	4.20
2006Q2	100.79	20.73	20.66		135.17	4.16
2006Q3	102.75	21.96	21.47		138.49	4.22
2006Q4	100.32	19.94	19.97		135.86	4.17
2007Q1	106.92	21.58	20.27	1.09	139.14	4.09
2007Q2	112.36	22.20	19.84	1.07	133.87	4.01
2007Q3	104.39	21.73	20.91	0.99	134.22	4.27
2007Q4	106.57	21.04	19.83	1.05	135.77	4.14
2008Q1	110.19	21.40	19.50	0.99	142.34	4.53
2008Q2	108.55	21.36	19.76	0.96	145.70	4.65
2008Q3	106.30	20.24	19.13	0.93	141.56	4.99
2008Q4	106.62	19.12	18.01	0.91	144.66	5.03
2009Q1	105.55	18.58	17.68	0.87	146.17	5.26
Pre 2008 Avg	104.26	21.12	20.35	1.05	136.95	4.16
Post 2008 Avg	107.44	20.14	18.82	0.93	144.09	4.89

Notes: 'YoY Sales' reports the ratio of total Mars sales relative to Mars sales in the same quarter one year prior. For quarters prior to 2008q1 we believe the quantity target to be 105%. For quarters after 2008q3 we believe the target was reduced to 90%, with an intermediate adjustment in 2008q1 and 2008q2. Retailer effort measures are computed for machines at the 75th percentile of the sales distribution. Retailer effort is expressed in units of accumulated vends between visits, with lower numbers constituting greater frequency and higher effort; and elapsed days between visits.

Table 3: Changes in Retailer Effort

	Elapsed Days Per Visit	Vends Per Visit
Post-2008 Period	0.837***	8.733***
	(0.0528)	(0.3301)
Observations	122734	122734
R-squared	0.1085	0.3579
Machine FE	✓	✓
Week of Year FE	✓	✓

Standard errors in parentheses: *** p<0.01

Notes: Table reports linear regression analysis of 'Vends Per Visit' and 'Elapsed Days Per Visit' on an indicator for the period beginning in 2008, when industry sources identify a switch by Mars to a lower AUD quantity target. Results use MarkVend's entire population of snack vending machines, and include fixed effects for machines and week-of-year. An observation is a service visit at a snack vending machine.

Table 4: Downstream Profit Impact

			Without Rebate			With Rebate		
Exogenously Removed Product	Diff in Vends	Obs	Difference In: Margin	Difference In: Profit	T-Stat of Diff	Difference In: Margin	Difference In: Profit	T-Stat of Diff
Snickers	-1.99	109	0.39	-0.52	-2.87	0.24	-0.67	-4.33
Peanut M&Ms	-1.72	115	0.78	-0.09	-0.58	0.51	-0.34	-2.48
Snickers + Peanut M&Ms	-3.18	89	1.67	-0.05	-0.27	1.01	-0.62	-3.72

Notes: Calculations by authors, using exogenous product removals from the field experiment. An observation is a treated machine-week. 'Diff in Vends' reports change in total number of all products sold per machine-week. 'Difference in margin' is reported as cents per unit, averaged over machine-weeks using MarkVend's observed wholesale cost. 'Difference in profit' is reported in dollars per machine-week.

Table 5: Upstream (Manufacturer) Profits

Exogenously Removed Product	Mars	Hershey	Nestle	Other	% Borne by Mars Without Rebate	% Borne by Mars With Rebate
Snickers	-0.24	0.05	0.18	-0.19	31.7%	11.9%
Peanut M&Ms	-0.59	0.28	0.10	-0.08	86.4%	50.2%
Snickers + Peanut M&Ms	-1.47	0.69	0.23	0.23	96.7%	59.5%

Notes: An observation is a treated machine-week. All variables report the average difference in dollars of profit per machine-week assuming a production cost of $0.15 per unit for all manufacturers. The variable '% Borne by Mars Without Rebate' reports the percentage of the total cost of a product removal that is borne by Mars, without accounting for the rebate payment to the retailer. '% Borne by Mars With Rebate' is equivalently defined.

Table 6: Random Coefficients Choice Model

	Parameter Estimates	
σ_{Salt}	0.506	0.458
	[.006]	[.010]
σ_{Sugar}	0.673	0.645
	[.005]	[.012]
σ_{Peanut}	1.263	1.640
	[.037]	[.028]
# Fixed Effects ξ_t	15,256	2,710
LL	-4,372,750	-4,411,184
BIC	8,973,960	8,863,881
AIC	8,776,165	8,827,939

Notes: Estimates correspond to the choice probabilities described in Section 4. Both specifications include 73 product fixed effects but different numbers of market fixed effects, ξ_t. Total sales are 2,960,315.

Table 7: Products Used in Counterfactual Analyses

Confections:	Salty Snacks:
Peanut M&Ms	Rold Gold Pretzels
Plain M&Ms	Snyders Nibblers
Snickers	Ruffles Cheddar
Twix Caramel	Cheez-It Original
Raisinets	Frito
Cookie:	Dorito Nacho
Strawberry Pop-Tarts	Cheeto
Oat 'n Honey Granola Bar	Smartfood
Grandma's Chocolate Chip Cookie	Sun Chip
Chocolate Chip Famous Amos	Lays Potato Chips
Raspberry Knotts	Baked Lays
Other:	Munchos Potato Chips
Ritz Bits	Hot Stuff Jays
Ruger Vanilla Wafer	Potential Products:
Kar Sweet & Salty Mix	Milky Way
Farley's Mixed Fruit Snacks	3 Musketeers
Planter's Salted Peanuts	Reese's Peanut Butter Cup
Zoo Animal Cracker Austin	Payday

Notes: These products form the base set of products for the 'typical machine' used in the counterfactual exercises. For each counterfactual exercise, two additional products are added to the confections category, which vary with the product assortment selected for analysis.

Table 8: Simulated Profits $\pi(a, e)$

Policy	π^R	$\pi^R + \pi^M$	PS	CS
(H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers				
$e^{NR}(217)$	94,733	117,095	121,425	65,491
$e^{R}(211)$	94,723	117,177	121,502	65,685
$e^{VI}(197)$	94,612	117,260	121,576	66,105
$e^{IND}(197)$	94,612	117,260	121,576	66,105
$e^{SOC}(172)$	94,060	116,994	121,303	66,738
$e^{Pre2008}(137)$	92,296	115,503	119,824	67,387
$e^{Post2008}(144)$	92,768	115,931	120,247	67,276
(H,H) Assortment: Reeses Peanut Butter Cup and Payday				
$e^{NR}(212)$	95,548	114,864	120,700	64,902
$e^{R}(206)$	95,537	114,952	120,783	65,095
$e^{VI}(191)$	95,407	115,048	120,869	65,539
$e^{IND}(191)$	95,407	115,048	120,869	65,539
$e^{SOC}(168)$	94,876	114,802	120,619	66,111
$e^{Pre2008}(137)$	93,339	113,533	119,364	66,688
$e^{Post2008}(144)$	93,791	113,934	119,761	66,574
(M,M) Assortment: Three Musketeers and Milkyway				
$e^{NR}(217)$	94,005	118,872	121,013	65,173
$e^{R}(211)$	94,005	118,962	121,101	65,371
$e^{VI}(197)$	93,915	119,067	121,201	65,801
$e^{IND}(197)$	93,915	119,067	121,201	65,801
$e^{SOC}(172)$	93,397	118,835	120,967	66,448
$e^{Pre2008}(137)$	91,673	117,387	119,523	67,111
$e^{Post2008}(144)$	92,139	117,807	119,942	66,998

Notes: Profit numbers represent the long-run expected profit from a top quartile machine. Retailer profits do not include rebate payments. Policy types are; retailer-optimal without rebate e^{NR}; retailer-optimal with rebate e^{R}; optimal for the bilateral retailer-Mars pair e^{VI}; industry-optimal e^{IND}; and socially-optimal, assuming a median own-price elasticity of -2 and weight relative to producer surplus of $\gamma = 1$, for consumer surplus e^{SOC}. Calibration of consumer surplus only affects the scale of consumer surplus calculations, not the ranking of various options. For more details see Appendix B.4. The number of likely consumers between restocking events for each policy type is reported in parentheses. Policies labeled $e^{Pre2008}$ and $e^{Pre2008}$ report actual values of MarkVend's effort prior to, and after, January 1, 2008 respectively. Shaded cells indicate the pay-off maximizing assortment for the relevant column and row. Assumes $FC = 10, MC = 0.15$.

Table 9: Welfare Comparisons at Observed Stocking Policies: Baseline is (M, M) and $e = 137$

Assortment	Effort = 137 (H,H)	Effort = 137 (H,M)	Effort = 144 (M,M)	Effort = 144 (H,H)	Effort = 144 (H,M)
$\Delta\pi^R$	1665	623	465	2117	1095
	[19.43]	[5.94]	[1.83]	[18.36]	[5.38]
$\Delta\pi^M$	-5519	-2506	-45	-5570	-2551
	[48.99]	[7.93]	[0.39]	[49.2]	[8.09]
$\Delta\pi^H$	3637	2174	0	3635	2172
	[35.35]	[23.0]	[0.0]	[35.3]	[22.95]
$\Delta\pi^N$	57	10	-2	55	8
	[3.69]	[1.4]	[0.08]	[3.68]	[1.38]
ΔPS	-159	300	418	237	724
	[48.18]	[18.31]	[1.95]	[49.21]	[18.39]
$\Delta CS(\epsilon = -2)$	-423	277	-113	-536	165
	[117.37]	[41.6]	[1.43]	[119.07]	[42.74]
ΔSS	-582	577	305	-299	889
	[165.52]	[59.73]	[2.93]	[168.24]	[61.02]
$\lambda\pi^M$	4483	5152	5698	4472	5142
	[6.42]	[14.98]	[16.52]	[6.36]	[14.97]

Notes: A rebate that induces the retailer to switch from $(H, M) \to (M, M)$ violates the IR constraint of Mars because it would pay $5,152 to gain $2,506 in profit. Consumer Surplus calibrates α to a median own-price elasticity of $\epsilon = -2$ and assumes a weight relative to producer surplus of $\gamma = 1$. Calibration only affects the scale of consumer surplus calculations, not the ranking of various options. For more details see Appendix B.4.

Table 10: Critical Thresholds and Retailer-Optimal Assortment at Observed λ

$\bar{\pi}_M^{MIN}$	$\bar{\pi}_M^{MAX}$	Assortment	Effort
0	19,383	(H,H)	$e^R(H, H)$
19,383	19,812	(H,H)	$e\left(\bar{\pi}_M(H, H)\right)$
19,812	22,424	(H,M)	$e^R(H, M)$
22,424	22,818	(H,M)	$e\left(\bar{\pi}_M(H, M)\right)$
22,818	24,973	(M,M)	$e^R(M, M)$
24,973	25,732	(M,M)	$e\left(\bar{\pi}_M(M, M)\right)$
25,732	0	(H,H)	$e^{NR}(H, H)$

Notes: Calculations report the retailer's optimal assortment and effort policy ($e^R(a)$) at the observed λ for different values of Mars' profit threshold. In the absence of a rebate payment, the retailer's optimal effort policy is denoted $e^{NR}(a)$. The values associated with an optimizing retailer's choice of effort with and without the rebate are reported in Table 11 (e.g., $e^R(H, H)$ takes value 206). In other cases, effort that is constrained to exactly meet the threshold is denoted $e(\bar{\pi}_M(a))$. This range may include vertically-integrated or industry-optimal effort levels. This is illustrated in Figure 5.

Table 11: Optimal Effort Policies: Restock after how many customers?

	(H,M)	(H,H)	(M,M)	(H,M)	(H,H)	(M,M)
	Effort Policy			% Change from e^{NR}		
e^{NR}	217	212	214	0.00	0.00	0.00
e^{R}	211	206	209	2.76	2.83	2.34
e^{VI}	197	191	195	9.22	9.91	8.88
e^{IND}	197	191	195	9.22	9.91	8.88
e^{SOC}	172	168	171	20.74	20.75	20.09
e^{SOC1}	157	154	156	27.65	27.36	27.10
e^{SOC4}	183	178	181	15.67	16.04	15.42

Notes: Policy types are: retailer-optimal without rebate e^{NR}; retailer-optimal with rebate e^{R}; optimal for the bilateral retailer-Mars pair e^{VI}; industry-optimal e^{IND}; and socially-optimal, assuming a median own-price elasticity of -2 and weight relative to producer surplus of $\gamma = 1$, for consumer surplus e^{SOC}. Policy types e^{SOC} and e^{SOC} report values when the socially-optimal effort policy is calibrated to elasticities of $\alpha = -1$ and $\alpha = -4$ respectively. Calibration of consumer surplus only affects the scale of consumer surplus calculations, not the ranking of various options. For more details see Appendix B.4. The width of the 95% CI is at most one unit.

Table 12: Welfare Comparisons: Baseline Case is (M, M) and e^R : 209

	No Rebate	Vertical Integration	Industry Optimal	Social Optimum ($\epsilon = -2$)
Assortment	(H,H)	(M,M)	(H,M)	(H,M)
Effort	e^{NR} : 212	e^{VI} : 195	e^{IND} : 197	e^{SOC} : 172
$\Delta\pi^R$	1548	-109	612	60
	[9.45]	[5.89]	[5.89]	[14.29]
$\Delta\pi^M$	-5671	191	-2339	-2053
	[51.8]	[10.33]	[10.33]	[13.31]
$\Delta\pi^H$	3644	0	2173	2168
	[35.36]	[0.0]	[0.0]	[22.87]
$\Delta\pi^N$	54	-4	5	3
	[3.68]	[0.24]	[0.24]	[1.42]
ΔPS	-425	78	451	178
	[62.37]	[5.72]	[5.72]	[26.75]
$\Delta CS(\epsilon = -2)$	-534	423	670	1303
	[112.78]	[42.43]	[42.43]	[50.11]
ΔSS	-958	501	1121	1481
	[174.42]	[47.26]	[47.26]	[64.97]

Notes: Values report how welfare under the baseline scenario ((M, M) and e^R) compares to several benchmarks. The e^R effort level corresponds to the case where the threshold is set high enough so that the retailer chooses the (M, M) assortment at a retailer-optimizing effort level, but not so high as to generate any additional effort. For the 'No Rebate' case, we assume that all wholesale prices are held fixed at current levels and the rebate is eliminated. (This is not an equilibrium.) The vertically-integrated scenario can be obtained with a higher threshold. The socially-optimal effort level depends on a calibrated median own-price elasticity of demand. For further details, see Appendix B.4.

Table 13: Net Effect of Efficiency and Foreclosure

from: to (M,M) and:	(H,M) and e^{NR} e^{R}	e^{VI}	e^{SOC}	(H,H) and e^{NR} e^{R}	e^{VI}	e^{SOC}
$\Delta\pi^R$	-733	-842	-1367	-1548	-1657	-2182
	[2.63]	[5.68]	[12.59]	[9.45]	[10.74]	[16.56]
$\Delta\pi^M$	2625	2815	3085	5671	5862	6132
	[13.5]	[15.43]	[17.73]	[51.8]	[53.67]	[55.2]
$\Delta\pi^H$	-2181	-2181	-2181	-3644	-3644	-3644
	[23.05]	[23.05]	[23.05]	[35.36]	[35.36]	[35.36]
$\Delta\pi^N$	-10	-14	-17	-54	-58	-60
	[1.52]	[1.54]	[1.53]	[3.68]	[3.75]	[3.8]
ΔPS	-300	-222	-480	425	503	246
	[24.9]	[23.74]	[22.19]	[62.37]	[62.27]	[60.22]
$\Delta CS(\epsilon = -2)$	-55	367	980	534	956	1569
	[56.29]	[61.23]	[76.45]	[112.78]	[125.27]	[140.08]
ΔSS	-356	145	500	958	1459	1815
	[79.3]	[82.73]	[94.53]	[174.42]	[186.09]	[198.11]
$\lambda\pi^M$	5547	5590	5649	5547	5590	5649
	[17.1]	[16.92]	[16.88]	[17.1]	[16.92]	[16.88]
w_h to avoid foreclosure	-18.49	-17.64	-11.73	12.3	12.81	16.35
	[0.47]	[0.47]	[0.44]	[0.21]	[0.21]	[0.2]
Reduced λ (Percent)	47.46	45.91	37.2	6.39	5.16	-3.13
	[0.36]	[0.37]	[0.38]	[0.5]	[0.51]	[0.51]

Notes: Consumer Surplus calibrates α to median own-price elasticity of $\epsilon = -2$ and assumes a weight relative to producer surplus of $\gamma = 1$. Calibration only affects the scale of consumer surplus calculations, not the ranking of various options. For more details see Appendix B.4. Bootstrapped standard errors of differences are reported in brackets. Only one of our 1000 bootstrap iterations (ΔSS for the $e^{SOC}(H, M)$ case) yields a different sign than those reported in the table.

A. Theoretical Motivation for Offering an AUD

A.1. Foreclosure and Optimal Assortments: A Motivating Example

We define the difference in payoffs between two assortments as $\Delta\pi(a, a') = \pi(a) - \pi(a')$. We introduce the possibility that the dominant firm M offers the retailer a lump sum transfer T in exchange for switching from assortment a' to assortment a. For this to be an equilibrium the following necessary conditions must be met:

$$\Delta\pi^R + T \geq 0 \qquad \text{(Retailer IR)}$$

$$\Delta\pi^M - T \geq 0 \qquad \text{(Mars IR)}$$

The retailer must prefer to receive the rebate under assortment a than to not receive the rebate under assortment a'. Meanwhile the dominant firm must prefer to pay the rebate under assortment a over not paying the rebate under assortment a'. For a to represent an equilibrium assortment, it must also be the case that no player has an incentive to deviate, including the rival firm H. Were H to offer its own transfer T_h in exchange for the retailer choosing assortment a' instead of a this becomes the opposite of the Mars IR constraint:

$$\Delta\pi^H + T_h \leq 0 \qquad \text{(Hershey Deviation)}$$

We can consider the 'bidding for representation' argument of Bernheim and Whinston (1998), where each transfer is set at the maximum amount so that $T_h = -\Delta\pi^H$ and $T = \Delta\pi^M$ in order to see whose transfer persuades the retailer:

$$\pi^R(a) + T \geq \pi^R(a') + T_h$$

$$\Delta\pi^R + \Delta\pi^M \geq -\Delta\pi^H$$

$$\Delta\pi^R + \Delta\pi^M + \Delta\pi^H \geq 0 \qquad \text{(Three-Party Surplus)}$$

This tells us if the three conditions are satisfied (Retailer IR, Mars IR, and Three-Party Surplus) then some transfer T (conditioned on assortment a) makes a an equilibrium when the no-transfer equilibrium is a'. In the subsequent section we show how the AUD contract allows the dominant firm to design the rebate threshold $\overline{\pi}^M$ to pay the transfer conditional on particular assortments a.[76]

[76] We also show how it can be used to select effort levels e in accordance with the (IC) constraint of the retailer.

We show how to adapt this setup to our empirical example. There are three potential assortments for the last two products on the shelf, two Mars products (M, M), two Hershey's products (H, H), or the best of each (H, M). Each manufacturer earns higher profits when more of their own products are stocked. Absent transfers, the retailer prefers to stock more Hershey's products and fewer Mars products. We assume that the profits of each agent can be ordered as follows (this mimics the actual payoffs in our empirical example):

$$\begin{aligned} \pi^R(H,H) > &\pi^R(H,M) > \pi^R(M,M) \\ \pi^H(H,H) > &\pi^H(H,M) > \pi^H(M,M) \\ \pi^M(M,M) > &\pi^M(H,M) > \pi^M(H,H) \end{aligned} \tag{12}$$

Given the ordering of profits above, absent the rebate the retailer prefers the assortment (H, H). Now we can consider decomposing profit differences into two steps. The first is the difference between (H, H) and (H, M) which we call Δ_H and the second is the difference between (H, M) and (M, M) which we call Δ_M so that $\Delta = \Delta_H + \Delta_M$ represents the difference between (H, H) and (H, M).

Conditions A $a = (M, M)$ and $a' = (H, H)$. $\Delta\pi^R + T \geq 0$ (IRR), $\Delta\pi^M - T \geq 0$ (IRM) and $\Delta\pi^R + \Delta\pi^M + \Delta\pi^H \geq 0$ (3 Party).

Conditions B $a = (M, H)$ and $a' = (H, H)$. $\Delta_H\pi^R + T \geq 0$ (IRR), $\Delta_H\pi^M - T \geq 0$ (IRM) and $\Delta_H\pi^R + \Delta_H\pi^M + \Delta_H\pi^H \geq 0$ (3 Party).

Conditions C $a = (M, M)$ and $a' = (M, H)$. $\Delta_M\pi^R + T \geq 0$ (IRR), $\Delta_M\pi^M - T \geq 0$ (IRM) but not necessarily the three-party surplus condition.

If conditions A hold then we have shown that there exists a transfer T such that (M, M) is an equilibrium as no player possesses a profitable deviation. It is also the case that the three-party surplus or industry profits $\pi^I = \pi^M + \pi^H + \pi^R$ are higher under (M, M) than (H, H) as $\Delta\pi^I \geq 0$.

From conditions B we know that that $\Delta_H\pi^I \geq 0$ or that the three-party surplus under (H, M) is higher than that under (H, H).

It could be that $\Delta_M\pi^I < 0$ or that the (H, M) assortment rather than the (M, M) assortment maximizes the three-party surplus. This does not contradict any of the other conditions.

The main takeaway is that M can set the transfer payments in order to obtain full (M, M) or partial (H, M) foreclosure. We show that under (A), full foreclosure is feasible. However, if (B), (C), and $\Delta_M \pi^I < 0$ also hold, full foreclosure does not lead to the assortment that maximizes overall industry surplus. In this case, partial foreclosure maximizes industry surplus, but full foreclosure leads to higher bilateral surplus among the retailer and dominant firm. As long as the dominant firm chooses the transfers and conditions, full foreclosure will be the equilibrium outcome.

The intuition behind this result relates to that of the *Chicago Critique* of Bork (1978) and Posner (1976), which we interpret as asking "When foreclosure is obtained in equilibrium, must the assortment necessarily be optimal?" Our answer is related to the work by Whinston (1990) on tying. When the dominant firm is able to condition the transfer payment on the (M, M) outcome, he can commit to tying the products together, and thus the equilibrium assortment need not maximize the surplus of the entire industry.

A.2. Effort Derivation

Consider the effort choice of the retailer faced with an AUD contract from (5):

$$\max_{(a,e)} \pi(a,e) = \begin{cases} \pi^R(a,e) + \lambda \cdot \pi^M(a,e) & \text{if } \pi^M(a,e) \geq \overline{\pi}^M \\ \pi^R(a,e) & \text{if } \pi^M(a,e) < \overline{\pi}^M. \end{cases}$$

It is helpful to temporarily ignore the assortment choice a and focus on effort only. In the case where the rebate is paid, we can express the retailer's problem as:

$$e_1 = \arg\max_e \pi^R(e) + \lambda \pi^M(e) \quad \text{s.t.} \quad \pi^M(e) \geq \overline{\pi}^M$$

The solution to the constrained problem is given by:

$$e_1 = \max\{e^R, \overline{e}\} \quad \text{where} \quad \overline{e} \text{ solves} \quad \pi^M(\overline{e}) = \overline{\pi}^M$$

If the rebate is not paid then:

$$e_0 = e^{NR} = \arg\max_e \pi^R(e)$$

The retailer's IC constraint:

$$\pi^R(e_1) + \lambda\pi^M(e_1) \geq \pi^R(e_0) \tag{IC}$$

and the dominant firm M's IR constraint:

$$(1-\lambda)\pi^M(e_1) \geq \pi^M(e_0) \tag{IRM}$$

When we consider the sum of (IC) and (IRM) it is clear that a rebate which induces effort level e_1 must increase bilateral surplus relative to e_0:

$$\pi^R(e_1) + \pi^M(e_1) \geq \pi^R(e_0) + \pi^M(e_0)$$

This provides an upper bound on the effort that can be induced by the rebate contract.

Thus, for $\overline{e} \geq e^R$, M can set the effort level of the retailer via the threshold $\overline{\pi}^M$, subject to satisfying the retailer's IR constraint. That is, the retailer must prefer to collect the rebate to their next best no rebate alternative (generally the (H, H) assortment).

A.3. Alternative Contracts

This section compares the AUD contract to other contractual forms; it is meant to be expositional and does not present new theoretical results.

Quantity Discount

A discount τ, can be mapped into λ (a share of M's variable profit margin). However the discount no longer applies to all q_m, only those units in excess of the threshold, so that $\rho(\overline{\pi}^M) = \max\left\{0, \frac{\pi^M - \overline{\pi}^M}{\pi^M}\right\}$. This implies $T \equiv \rho(\overline{\pi}^M) \cdot \lambda \cdot \pi^M$, so that as the threshold increases, M is limited in how much surplus it can transfer to R, assuming that the post-discount wholesale price is non-negative. In the limiting case, the threshold binds exactly and M cannot offer R any surplus. This makes the discount, rather than the threshold, the primary tool for incentivizing effort. (Recall that for the AUD, $\overline{e} \geq e^R$ implies that M can directly set the retailer's effort). This means that high effort levels, $e > e^R$, will be more expensive to the dominant firm under the quantity discount than under the AUD. In fact, the vertically-integrated level of effort is only achievable through the 'sell out' discount, where $\tau = w_m - c_m$ such that M earns no profit on the marginal unit, and some $\overline{q}_m$ significantly less than the vertically-integrated quantity.

Quantity Forcing Contract

The quantity forcing (QF) contract is similar to a special case of the AUD contract. Specify a conventional AUD $(w_m, \tau, \overline{q}_m)$ as:

$$\begin{cases} (p_m - w_m + \tau) \cdot q_m & \text{if } q_m \geq \overline{q}_m \\ (p_m - w_m) \cdot q_m & \text{if } q_m < \overline{q}_m \end{cases}$$

One can increase the wholesale price w_m by one unit, and the generosity of the rebate (τ) by one unit. Continuing with this procedure, the retailer profits when the threshold is met. For any $q_m \geq \overline{q}_m$, the retailer's profit remains unchanged, while its profit for any $q_m < \overline{q}_m$, tends to zero as $w_m \to p_m$. This has the effect of 'forcing' the retailer to accept a quantity at least as large as $\overline{q}_m$. By choosing the threshold, the QF contract can achieve the vertically-integrated level of effort, just like the AUD. For quantities $q_m > \overline{q}_m$, the AUD works like a QF contract plus a uniform wholesale price on 'extra' units.[77]. Without some outside constraint on τ or w_m, and absent uncertainty about demand, the dominant firm has an incentive to increase τ and w_m together to replicate the QF contract.

Two-Part Tariff

One can also construct a two-part tariff (2PT), described by two terms: a share of M's revenue λ and a fixed transfer T from $R \to M$. The retailer chooses between the 2PT contract and the standard wholesale price contract.

$$\begin{cases} \pi^R(a,e) + \lambda \cdot \pi^M(a,e) - T & \text{if } 2PT \\ \pi^R(a,e) & \text{o.w.} \end{cases}$$

We define $\underline{\pi}^R = \max_{a,e} \pi^R(a,e)$ (the retailer's optimum under the standard wholesale price contract). For the retailer to choose the 2PT contract it must be that $\max_{a,e}\{\pi^R(a,e) + \lambda \cdot \pi^M(a,e) - T\} \geq \underline{\pi}^R$. An important case of the 2PT contract is the so-called 'sellout' contract where $\lambda = 1$. In this case, the retailer maximizes the joint surplus of $\pi^R + \pi^M$ and achieves the vertically-integrated assortment and stocking level. Just like in the AUD, this may lead to foreclosure of the rival H, even when that foreclosure is not optimal from an industry perspective. The dominant firm can choose T so that $\max_{a,e}\{\pi^R(a,e) + \pi^M(a,e)\} - T = \underline{\pi}_M$ and 'fully extract' the surplus from R. Likewise, the dominant firm can choose $T = (1 -$

[77] For a more complete discussion of the connection between the AUD and the QF contract in the presence of a capacity constrained rival see Chao et al. (2018)

$\lambda_{AUD}) \cdot \overline{\pi}^M$ (the dominant firm's profits under the AUD) so long as the retailer is willing to choose the 2PT contract.

This indicates that it is also possible for a 2PT contract to implement the assortment and effort level that maximizes the bilateral profit between $M + R$, even if that assortment does not maximize overall industry profits. An important question is: how do the AUD and the 2PT differ? One possibility is that the AUD can be used to implement an effort level in excess of the vertically-integrated optimal effort, e^{VI}, which results in higher profits for M at the expense of the retailer. A major challenge of devising a 2PT in practice is arriving at the fixed fee T, especially when there are multiple retail firms of different sizes, and the 2PT contract (or menu of contracts) is required to be non-discriminatory.[78] It may be easier in practice to tailor sales thresholds to the size of individual retailers (as opposed to setting individual fixed-fee transfer payments).[79]

[78]Kolay et al. (2004) shows that a menu of AUD contracts may be a more effective tool in price discriminating across retailers than a menu of 2PTs. In the absence of uncertainty, an individually-tailored 2PT enables full extraction by M, but is a likely violation of the Robinson-Patman Act.

[79]Another possibility as shown by O'Brien (2013) is that the AUD contract can enhance efficiency under the double moral-hazard problem (when the upstream firm also needs to provide costly effort such as advertising).

B. Econometric Appendix

B.1. Additional Descriptive Figures

We provide alternative version of the descriptive figures in the text to illustrate how our experimental sample of machines that we use to estimate demand is similar (and different) from the overall enterprise of MarkVend. In all of these figures the unit observation is a machine-visit, and we average across machine-visits both by month. Thus machines that are visited more frequently are given more weight. We've also computed each of these figures re-weighted based on monthly machine sales and we obtain nearly identical results.

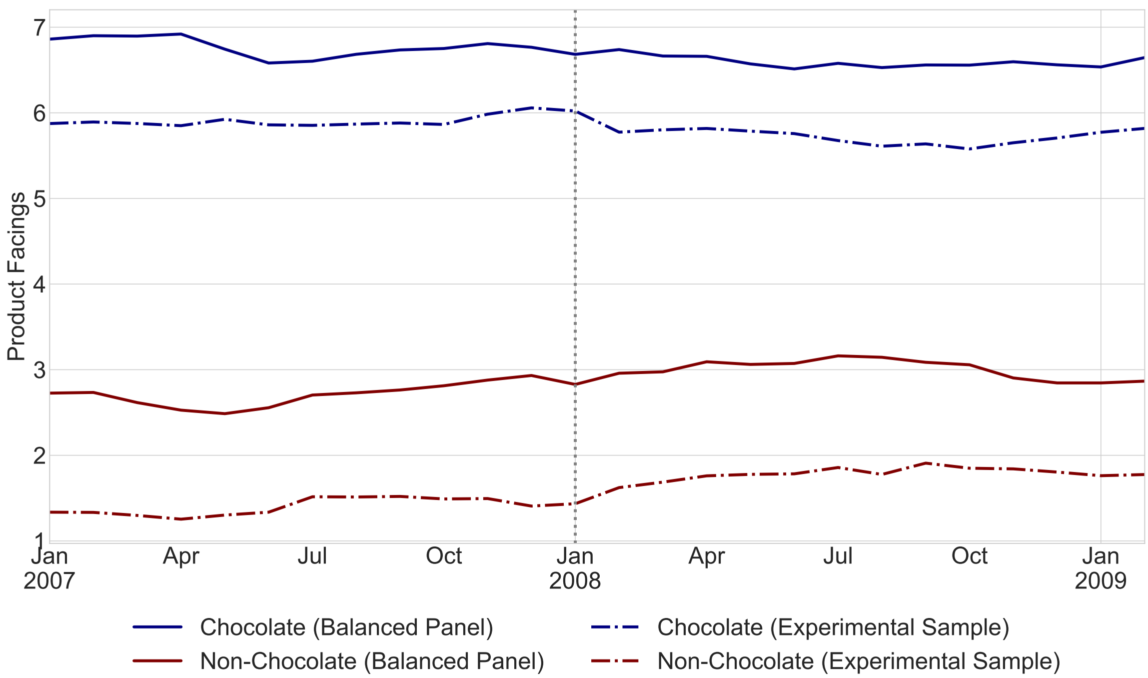
In Figure A1, we show the overall number of product facings in confections is relatively stable over time, but differs between our experimental sample of machines in white-collar office locations and MarkVend's wider enterprise which also includes some larger machines with more product facings in schools, museums, parks, etc. We should also note that if one considered an 'unbalanced' panel of MarkVend's entire enterprise, the number of product facings would appear to decline over time as the relative share of smaller office located machines grew relative to the share of larger machines.

In Figure A2, we reproduce Figure 2 from both the 'balanced' panel of 364 machines and our smaller experimental sample in office locations. In both cases, there is a pronounced shift around the beginning of 2008 when we believe that Mars changes the rebate threshold. Around the time the threshold changes, MarkVend replaces Chocolate Mars products with Chocolate Hershey products. This change takes place in both samples.

To further illuminate which product facings change over time we then produce Figure A3. Here we show that there are a set of base Mars products which are highly available in both samples, and don't vary much over time (Snickers, Peanut M&M's, Twix). We aggregate the two non-chocolate confections (Skittles and Starburst) as MarkVend tends to alternate machines (each machine stocks either Skittles or Starburst). A small number of machines (mostly in schools) stock both Skittles and Starburst, which explains why more than once facing is reported for the combined product.

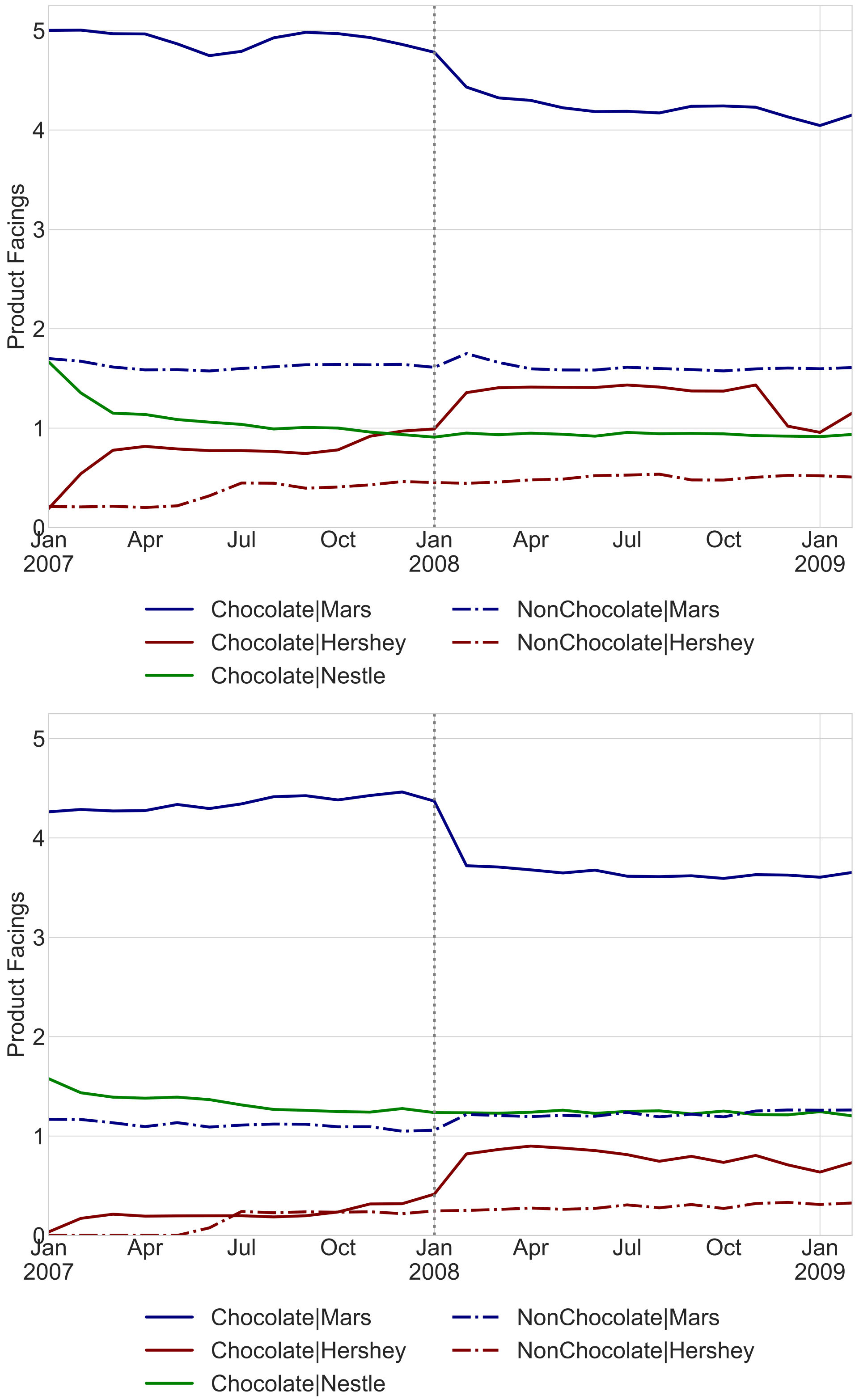
Finally we reproduce Figure 2 from the main text in Figure A4. Again, the top pane is for a 'balanced' panel of 364 machines, while the bottom panel is for the 66 machines we use to conduct our experiments and estimate our demand model. Here we show the set of 'non base' product for each manufacturer. These are the products we generally view as competing for the final slots in the vending machine. The main takeaway is that when Mars reduces the threshold in 2008, MarkVend substitutes the worst performing Mars chocolate product (3 Musketeers) for the best performing Hershey product (Reese's Peanut Butter Cup). There are some other important differences between the two samples, the broader sample tends to include M&M Plain in roughly 80% of machines while our experimental sample includes it only 40%. The broader sample includes Sour Patch Kids (Hershey) in around half of machines, though they are almost never available in our office sample. Meanwhile the experimental sample stocks Raisinets (Nestle) in around 80% of machines as compared with 50% of the broader sample. We think these can largely be explained by differences in demand patterns between white collar office workers (Raisinets) and school-aged children (Sour Patch Kids), as well as the larger overall machines in the schools and museums.

Figure A1: Product Facings by Category



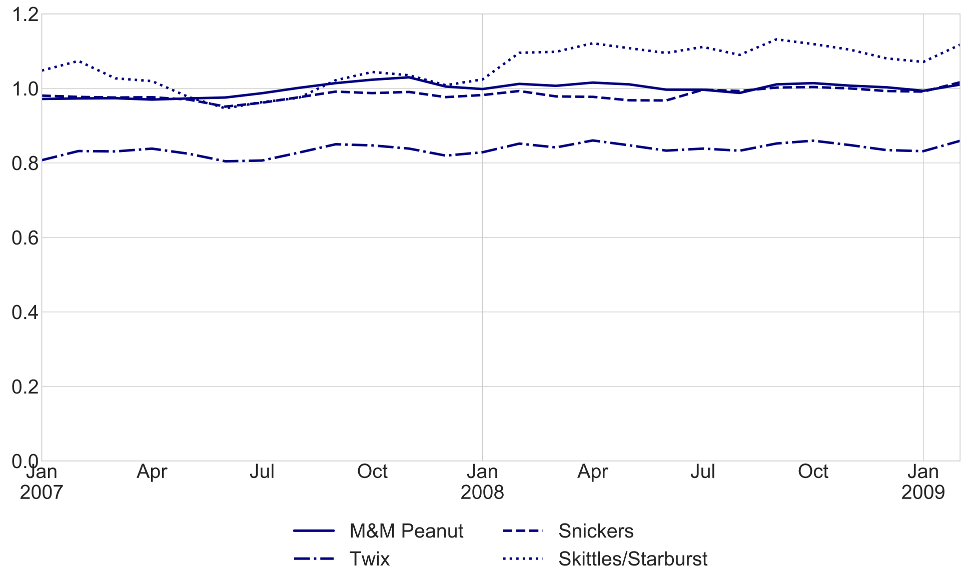
Notes: An observation is a machine-visit pair. Figure reports average product facings of confection products across machine-visits by month and product category for two sets of machines: a balanced panel of 364 MarkVend vending machines, as the set of 66 vending machines used in for our experimental product removals. Blue lines report chocolate confection products; red lines report non-chocolate confection products.

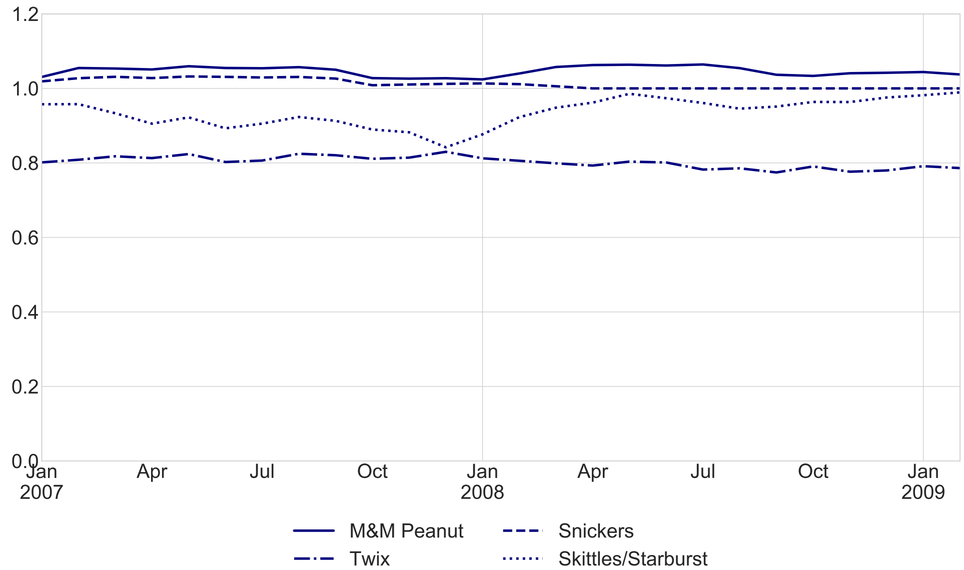
Figure A2: Product Facings by Manufacturer and Category



Notes: An observation is a machine-visit pair. Figure reports average product facings of confection products across machine-visits by month, product category, and manufacturer for two sets of machines: a balanced panel of 364 MarkVend machines (top pane), and the set of 66 machines used in for our experimental product removals (bottom pane).

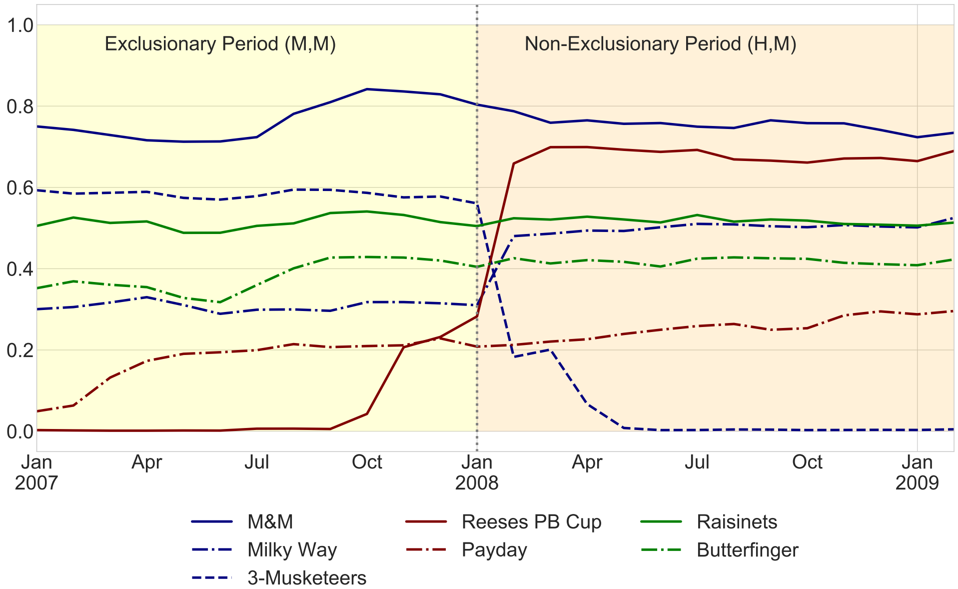
Figure A3: Product Facings for Commonly Stocked (Base) Assortment

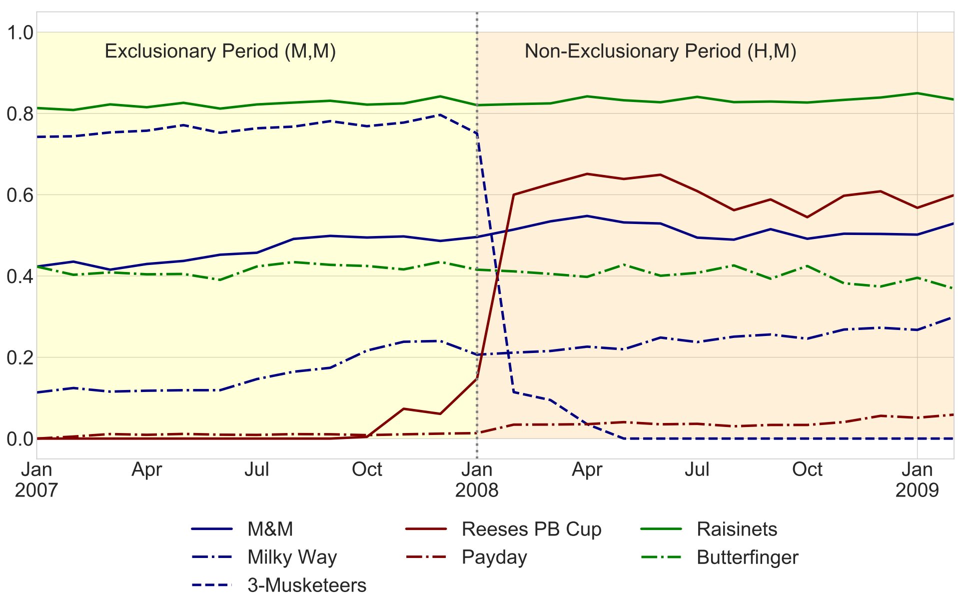




Notes: An observation is a machine-visit pair. Figure reports average product facings of products commonly included in MarkVend's base assortment across machine-visits by month for two sets of machines: a balanced panel of 364 MarkVend vending machines, as the set of 66 vending machines used in for our experimental product removals.

Figure A4: Product Facings for Marginal Products





Notes: An observation is a machine-visit pair. Figure reports average product facings of *marginal* products in MarkVend's base assortment across machine-visits by month for two sets of machines: a balanced panel of 364 MarkVend vending machines, as the set of 66 vending machines used in for our experimental product removals.

B.2. Computing Treatment Effects

One goal of the exogenous product removals is to determine how product-level sales respond to changes in availability. Let q_{jt} denote the sales of product j in machine-week t, superscript 1 denote sales when a focal product(s) is removed, and superscript 0 denote sales when a focal product(s) is available. Let the set of available products be A, and let F be the set of products we remove. Thus, $Q_t^1 = \sum_{j \in A \setminus F} q_{jt}^1$ and $Q_s^0 = \sum_{j \in A} q_{js}^0$ are the overall sales during treatment week t, and control week s respectively, and $q_{fs}^0 = \sum_{j \in F} q_{js}^0$ is the sales of the removed products during control week s. Our goal is to compute $\Delta q_{jt} = q_{jt}^1 - E[q_{jt}^0]$, the treatment effect of removing products(s) F on the sales of product j.

There are two challenges in implementing the removals 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 exogenous removals. 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 product removals were done 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 product removals, 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 overall demand, so that $Q_t^0 - Q_s^1 \geq 0$ for treatment week t and control week s. Our second restriction is that the product removal(s) should not reduce overall demand by more than the sales of the products we removed, or $Q_t^0 - Q_s^1 \leq q_{fs}^0$. This means we choose control weeks s that correspond to treatment week t as follows:

$$\{s : s \neq t, Q_t^0 - Q_s^1 \in [0, q_{fs}^0]\}. \tag{13}$$

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_{fs}^0 are more likely to be included in our control. This bias would likely overstate the costs of the product removal, which would be problematic for our study.

We propose a slight modification of ((13)) which removes the bias. That is, we 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 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 field experiment intends to isolate the treatment effect of removing Snickers, we might instead compute the treatment effect of removing Snickers jointly with Mark Vend 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:

$$S_t = \{s : s \neq t, A_t \approx A_s, Q^0_t - Q^1_s \in [0, \hat{b_0} + \hat{b_1} Q^0_s]\}. \tag{14}$$

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

$$\Delta q_{jt} = q^1_{jt} - \frac{1}{\# S_t} \sum_{s \in S_t} q^0_{js}. \tag{15}$$

While this approach has the advantage that it generates substitution patterns consistent with consumer theory, it may be the case 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.[80]

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 ((15)) to construct a set of pseudo-observations for the difference, and employ a paired t-test.

B.3. Estimation Algorithm

Here we provide pseudocode of our entire procedure for calculating $\pi(a, e)$. The first and third algorithm need to be repeated for each bootstrapped draw from the asymptotic distribution of $(\hat{d}_j, \hat{\sigma})$.

The computational 'trick' is to re-normalize the choice probabilities in Algorithm 1 steps 1(c-e). The normalization implicitly conditions on the set of customers who would have made a purchase at some hypothetical machine containing a superset of products $A_0 = A_t \cup \{(H, H), (H, M), (M, M)\}$. This can be justified in stages: the first stage is a draw from a binomial distribution where a consumer arrives and either selects the outside good or is labeled a 'likely consumer.' Likely consumers then face a second stage described by our re-normalized multinomial distribution where they choose either an available product or choose the outside good with a much smaller probability than the overall demand model $s_0(A_t) - \widetilde{s_0}(A_0)$. This saves time because we don't need to simulate the arrivals of consumers who never make a purchase. If the outside good share were 90% this would represent an order of magnitude reduction in the state space we ultimately need to keep track of as well as the number of consumer arrivals we need to simulate. This also makes the choice of ξ_t largely irrelevant as it governs the market share of the outside good and that gets normalized away. A larger ξ_t still increases the substitution probability to the outside option after products stock out. We calibrate this to $\xi = \text{med}(\xi_t) \approx 0.75$.[81]

If we were to increase ξ_t, this would decrease the share of the outside good and increase sales for any fixed number of consumers. However, because in Algorithm 2 we also estimate the arrival rate of consumers $P(x + \Delta x_k | x)$ in the normalized state-space, what happens instead is that as ξ_t increases we estimate a slower arrival process so that P is chosen to match the average daily sales observed in the top quartile of all machines across the entire MarkVend enterprise. We could have worked with the entire distribution of all machines, but

[80]Weeks in which the other five treatments were run (for the salty-snack and cookie categories) are excluded from the set of potential control weeks.

[81]We use the median because the distribution is highly skewed. We have also tried $\xi = E[\xi_t] = 0$, which gives nearly identical results. The optimal policies change by at most one unit.

we focus on this top quartile because we believe those machines drive restocking decisions – many of the slower machines are restocked because the driver is already nearby. A separate question is: "What is the point of ξ_t in the model?" and the answer is that we incorporate ξ_t in order to get unbiased estimates of $\hat{d}_j$ and $\widehat{\sigma}$.

Algorithm 1 Simulate Payoffs

1. Simulate consumer purchases from a full vending machine under assortment a.
   (a) Set $\xi = \text{med}[\widehat{\xi_t}] \approx 0.75$.
   (b) Initialize inventory of 15 confections products per slot for $a \in \{(H,H),(H,M),(M,M)\}$ plus products listed in table 8 (at modal max inventory). Label this inventory/assortment $A_0(a)$.
   (c) Use observed random coefficients demand parameters $(\widehat{d_j}, \widehat{\sigma})$ and quadrature nodes (w_i, ν_i) to calculate outside good purchase probability at an unobserved machine containing a superset of all possible products: $\tilde{A} = A_0 \cup \{(H,H),(H,M),(M,M)\}$.

$$\overline{s_0} = \sum_{i=1}^{NS} w_i \frac{e^{-\xi}}{\exp^{-\xi} + \sum_{k\in\tilde{A}} e^{\hat{d}_k + \sum_l \widehat{\sigma}_l \nu_{il} x_{kl}}}$$

   (d) Use observed random coefficients demand parameters $(\widehat{d_j}, \widehat{\sigma})$ and quadrature nodes (w_i, ν_i) to calculate purchase probabilities of a single consumer for current inventory/assortment A_t:

$$s_j(A_s) = \sum_{i=1}^{NS} w_i \frac{e^{\hat{d}_j + \sum_l \widehat{\sigma}_l \nu_{il} x_{jl}}}{\exp^{-\xi} + \sum_{k\in A_s} e^{\hat{d}_k + \sum_l \widehat{\sigma}_l \nu_{il} x_{kl}}}$$

   (e) Draw a single consumer purchase as y_t^*, a $(J+1)$ vector with re-normalized outside good probability.

$$y_s^* \sim Multinom\left(\frac{s_j(A_s)}{1-\overline{s_0}}, s_0(A_s) - \overline{s_0}\right)$$

   (f) Update $A_{s+1} = A_s - y_s^*$ or $A_{s+1} = A_s$ if outside good is chosen.
   (g) Continue for $s = 1, \ldots, 800$ consumers or (until machine is empty $A_s = \emptyset$).
   (h) Repeat for $n = 1, \ldots N = 100\,000$ machines to construct $y_{n,s}$: a $(J+1)$ vector.
2. Smooth Expected Flow Payoffs
   (a) Load retail and wholesale prices for all products. Assume $mc = 0.15$ for all confections.
   (b) Compute the expected flow payoffs for each agent as a function of cumulative arrivals x:

$$\begin{aligned}
u^R(x,a) &= \frac{1}{N}\sum_{n=1}^{N}\sum_{s=1}^{x} y_{n,s}^* \cdot (p_r - w)\\
u^M(x,a) &= \frac{1}{N}\sum_{n=1}^{N}\sum_{s=1}^{x} y_{n,s}^* \cdot I_{nt}[\text{Mars}] \cdot (w_m - mc)\\
u^H(x,a) &= \frac{1}{N}\sum_{n=1}^{N}\sum_{s=1}^{x} y_{n,s}^* \cdot I_{nt}[\text{Hershey}] \cdot (w_m - mc)\\
u^C(x,a) &= \frac{1}{N}\sum_{n=1}^{N}\sum_{s=1}^{x} \log\left(1 + \sum_{j\in A_s} \exp\left[\hat{\delta}_k + \widehat{\xi} + \sum_l \widehat{\sigma}_l \nu_{il} x_{kl}\right]\right)
\end{aligned}$$

   (c) Smooth the expected profits $\left(u^R(x,a), u^M(x,a), u^H(x,a), u^C(x,a)\right) \rightarrow \left(\hat{u}^R(x,a), \hat{u}^M(x,a), \hat{u}^H(x,a), \hat{u}^C(x,a)\right)$ using MATLAB `slmegine`. Verify/require monotonicity for (R,M,C) but not (H,N).

Algorithm 2 Estimate the Arrival Rate

1. As in Algorithm 1 (Part 2) construct an estimate of total sales as a function of 'likely consumers'

$$u^{\text{sales}}(x, a) = \frac{1}{N} \sum_{n=1}^{N} \sum_{s=1}^{x} \sum_{j=1}^{J} y^*_{n,s}$$

2. For each visit in the data, measure the total sales Q_t since the previous service visit and calculate the fewest number of elapsed consumers x required to realize Q_t sales:

$$\hat{x}_t = \{\min x : u^{\text{sales}}(x, a) > Q_t\}$$

3. Denote the number of elapsed (business) days since the previous service visit as $days_t$ and define $\Delta x_t = \left(\frac{\hat{x}_t}{days_t}\right)$ as the average number of consumer arrivals per day for each visit t.

4. Construct a nonparametric frequency estimator for Δx_t:

$$P(\Delta x_t) = \frac{1}{T} \sum_{t=1}^{T} \mathbf{1}\left[b_k < \Delta x_t \le b_{k+1}\right]$$

Algorithm 3 Solve the Dynamic Programming Problem

There exists a monotone policy such that the agent re-stocks if $x \geq e$:

1. Assume a known discount factor β and a fixed cost $FC = 10$.
2. Given a guess of the optimal policy, we can compute the post-decision pay-off $\tilde{u}$:
$$\tilde{u}(x,a,e) = \begin{cases} 0 & \text{if } x < e \\ \hat{u}(x,a) - FC & \text{if } x \geq e. \end{cases}$$
3. Compute the post-decision transition matrix $\tilde{P}$ by replacing columns of P.
$$\tilde{P}(x,e) = \begin{cases} x + \Delta x & \text{if } x < e \\ \Delta x & \text{if } x \geq e. \end{cases}$$
4. This allows us to solve the value function at all states in a single step:
$$V(x,a,e) = (I - \beta \tilde{P}(e))^{-1} \tilde{u}(x,a,e).$$
5. Find the ergodic/stationary distribution of x under policy e as the vector $\Gamma(e)$ that solves:
$$\Gamma(e) = \Gamma(e)\tilde{P}(x,e) \quad \text{with } \sum \Gamma(e) = 1.$$
6. Compute long-run expected profits under the Markov Chain using the stationary distribution:
$$\pi(a,e) = \Gamma(e) V(x,a,e)$$
7. Repeat this exercise for all possible choices of (a,e) and all agents R, M, H, N, C. Enumerate over e to find the optimal policy for each agent(s) (NR, R, VI, IND, SOC).

Algorithm 4 Compute the Standard Errors

1. Draw $\hat{\theta}^b \sim N\left(\hat{\theta}^{MLE}, \sqrt{diag(V(\hat{\theta}^{MLE})}\right)$. We only need: $(\hat{d}_j, \hat{\sigma})$. Assume $\xi = 0.75$ as before.
2. Simulate consumer arrivals and payoffs using Algorithm 1 $\hat{u}(x, a, \hat{\theta}^b)$ for each agent.
3. Use the same estimated consumer arrival process/ transition matrix $\hat{P}$ from Algorithm 2.
4. Use same calibrated discount factor β and same calibrated restocking cost $FC = 10$ and solve the dynamic programming problem using Algorithm 3.
5. Use $\pi^*(a, e|\hat{\theta}^b)$ to calculate the optimal policies for different groups of agents $(e^{NR}, e^R, e^{VI}, e^{SOC})$ for every (a, e) pair.
6. Compute all of the profit differences $\Delta\pi^R, \Delta\pi^M, \Delta\pi^H$.
7. Repeat 1000 times and report the standard deviations.

In this procedure there are two sources of variation. The first is the variation introduced by the uncertainty in the simulated ML estimates of the demand parameters (as reported in table 6). The second is the simulation variance introduced from our simulation procedure, because we use the average over 100,000 chains this is designed to be at most ±\$2.

B.4. Consumer Surplus and Welfare Calculations

Our calculation of the expected consumer surplus of a particular assortment and effort policy (a, e) parallels our calculation of retailer profits. We simulate consumer arrivals over many chains, and compute the set of available products as a function of the initial assortment a and the number of consumers to arrive since the previous restocking visit x which we write $a(x)$. For each assortment $a(x)$ that a consumer faces, we can compute the logit inclusive value and average over our simulations, to obtain an estimate at each x:

$$CS^*(a, x|\theta) = \frac{1}{I_t} \sum_{i=1}^{I_t} \log \left(\sum_{j \in a(x^s)} \exp[\delta_j + \mu_{ij}(\theta)] \right)$$

The exogenous arrival rate, $P(x'|x)$, denotes the expected daily number of consumer arrivals (from x cumulative likely consumers today to x' cumulative likely consumers tomorrow). Using this arrival rate and a policy e, we obtain the post-decision transition rule $\tilde{P}(x, e)$ and evaluate the ergodic distribution of consumer surplus under policy e:

$$CS^*(a, e) = [I - \beta \tilde{P}(x, e)]^{-1} CS^*(a, x|\theta)$$

The remaining challenge is that $CS^*(a,e)$ relates to arbitrary units of consumer utility, rather than dollars. Recall our utility specification from Section 4, with $\theta = [\delta, \alpha, \sigma]$:

$$u_{ijt}(\theta) = \delta_j + \alpha p_{jt} + \xi_t + \sum_l \sigma_l \nu_{ilt} x_{jl} + \varepsilon_{ijt}$$

Without observable, within-product variation in price, $p_{jt} = p_j$, and α is not separately identified from the product fixed-effect δ_j. If α were identified, then we could simply write $CS(a,e) = \frac{1}{\alpha} CS^*(a,e)$. Instead, we can calibrate α given an own price elasticity:

$$\epsilon_{j,t} = \frac{p_{jt}}{s_{jt}} \cdot \frac{\partial s_{jt}}{\partial p_{jt}} = \frac{p_{jt}}{s_{jt}} \cdot \int \frac{\partial s_{ijt}}{\partial p_{jt}} f(\beta_i|\theta) d\,\beta_i = \alpha \cdot \underbrace{\frac{p_{jt}}{s_{jt}} \cdot \int (1 - s_{ij}(\delta, \beta_i)) \cdot s_{ij}(\delta, \beta_i) f(\beta_i|\theta) d\,\beta_i}_{\epsilon^*_{j,t}(\theta)}$$

The term $\epsilon^*_{j,t}$ does not depend directly on α once we have controlled for the fixed effect d_j. Thus, we can calibrate own-price elasticities. As is conventional in the literature, we work with the median own-price elasticity, $\overline{\epsilon}(\theta) = \text{median}_j(\epsilon^*_{j,t}(\theta))$, and recover α as $\alpha = |\frac{\epsilon}{\overline{\epsilon}(\theta)}|$. We then calculate α at three different values of ϵ: $\epsilon \in \{-1, -2, -4\}$.

As is well known, α has an alternative interpretation in the social planner's problem as the planner's weight on consumer surplus:

$$SS(a,e) = PS(a,e) + \frac{\gamma}{|\alpha|} CS^*(a,e)$$

The social planner's problem is equivalent in the following cases: (1) the median own-price elasticity is $\epsilon = -2$ and $\gamma = 1$; (2) the median own-price elasticity is $\epsilon = -4$ and the planner puts twice as much weight on consumer surplus $\gamma = 2$; (3) the median own-price elasticity is $\epsilon = -1$ and the planner puts half as much weight on consumer surplus $\gamma = \frac{1}{2}$.

C. Robustness Checks

For each of our robustness checks we change the parameters of the dynamic decision problem and see if it changes the welfare implications of the AUD contract. To summarize these results, we compare our alternative specifications to Table 13 from the main text. This allows us to compare both foreclosure and efficiency effects at the same time. We focus on some key outcomes, the first is the sign of the change in producer and consumer surplus for transitions between $(H, H) \to (M, M)$ under different effort levels and from $(H, M) \to (M, M)$. In nearly all of the robustness test we find results qualitatively similar to those in the main text. First, both consumers and producers are better off under the (H, M) assortment than the (M, M) assortment. Second, the overall impact on consumers is sometimes ambiguous as they can be compensated for an inferior assortment with a higher effort level under e^{VI}. As in the main text this depends on the retailer setting a lower effort level e^{NR} under the (H, M) assortment. Third, Hershey would have to set a very low wholesale price (often below our assumed 15 cent marginal cost) in order to avoid being foreclosed. Similarly, this implies that Mars could only modestly reduce the generosity of the rebate (by 4-6%) without Hershey being able to respond and avoid foreclosure.

We consider a broad array of alternatives: changing the arrival rate of consumers; setting the marginal cost to zero and maximizing potential efficiencies; increasing or decreasing the fixed cost of restocking; and having the retailer place some weight on consumer surplus when making decisions.

C.1. Arrival Rate: Details and Robustness

We estimate the arrival rate $P(\Delta x_t)$ by grouping machines across the entire MarkVend enterprise into quartiles based on average daily sales for the entire sample. Our main specification focuses on the top quartile of machines by this metric. As a robustness test, we also consider the next 50% (25th to 75th percentile machines). For each machine-visit we calculate the average daily sales and the total sales when the machine was restocked. The first metric can be used to estimate $P(\Delta x_t)$ while the second metric can be thought of as an empirical estimate of the policy function $e(\cdot)$. Neither of these are strictly correct because some consumers arrive at the machine and elect to purchase the outside option. However, in our normalized state space x_t represents the cumulative number of consumer arrivals since our last restocking event, *who would have purchased at a full machine.* Thus the only gap arises from consumers who would have purchased at a full machine but do not purchase because of stockouts. For $x_t \leq 300$ consumer arrivals this implies an adjustment of $\leq 10\%$ between the policy in the space of realized sales and consumer arrivals in the model.

In Figure A5 we replicate Figure 4 from the main text above and below include the middle 50% of machines. We see that the arrival rate is substantially lower for the middle 50% of machines (15.4 per day) than for the top 25% of machines (37.6 per day) as we might expect. We also see that the empirical distribution of restocking policies for these machines is lower (mean of $e \approx 130$ versus mean of $e \approx 80$). This does not imply that MarkVend services less popular machines *more frequently* but rather they service less popular machines *after fewer consumer arrivals*; the confound is the lower arrival rate at these machines. A likely story is that these machines have lower fixed costs to service (perhaps because the driver is already on-site servicing a nearby machine, or because it takes less time to restock fewer products). This is part of the reason we chose to focus on machines with above average consumer arrival rates, because we believe those are more likely to drive MarkVend's stocking decisions.

An important question is whether or results are sensitive to the arrival rate of consumers. We reproduce the 'net effects' table (Table 13) from the text as Table A1 below. We find that all of the qualitative results are the same: the rebate can be used to foreclose the rival even though (H, M) generates more producer surplus than (M, M). Overall welfare impacts are the same as in the main text. The (H, M) assortment maximizes producer surplus and consumer surplus. It is possible that consumers receive sufficient benefits in moving from e^{NR} to e^{VI} to compensate them for the inferior assortment (M, M), though e^{R} does not provide sufficient compensation.

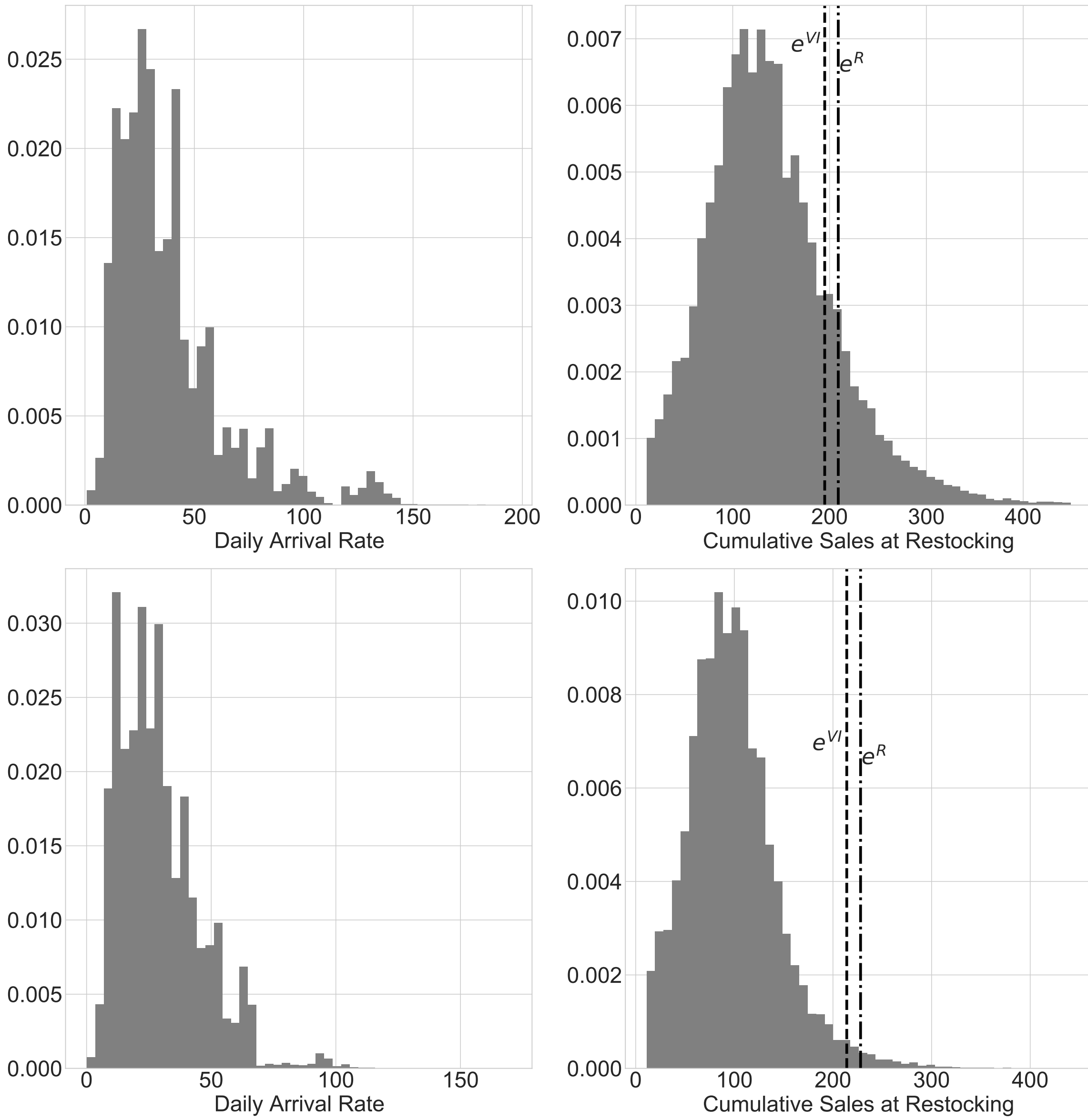
Table A1: Net Effect of Efficiency and Foreclosure (Middle 50% of Machines)

from	(H,H) and e^{NR}			(H,M) and e^{NR}		
	e^R	e^{VI}	e^{SOC}	e^R	e^{VI}	e^{SOC}
$\Delta\pi^R$	-304	-350	-570	-646	-692	-912
$\Delta\pi^M$	1094	1174	1285	2362	2442	2553
$\Delta\pi^H$	-908	-908	-908	-1518	-1518	-1518
$\Delta\pi^N$	-4	-6	-7	-22	-24	-25
ΔPS	-123	-91	-201	176	207	97
$\Delta CS(\epsilon = -2)$	-22	153	406	222	398	650
ΔSS	-145	62	204	398	605	747
$\lambda\pi^M$	2321	2339	2364	2321	2339	2364
w_h to avoid foreclosure	-18.87	-18	-12.03	12.12	12.64	16.22
Reduced λ (Percent)	47.76	46.18	37.44	6.78	5.51	-2.81

Notes: Consumer Surplus calibrates α to median own price elasticity of $\epsilon = -2$. Calibration only affects the scale of consumer surplus calculations, not the ranking of various options. For more details see Appendix B.4.

We tried alternative assumptions on the arrival rate by either doubling or halving the

Figure A5: Observed Policies and Arrival Rates



Notes: Top row reports daily arrival rate for top 25% of machines at MarkVend's overall enterprise. Bottom row reports daily arrival rate for middle 50% of MarkVend's machines. These are used to estimate $f(\Delta x_t)$. Right column reports cumulative sales at restocking as well as calculated optimal policies from the model. Policies and cumulative sales are in the same units except for 'sales' of the outside good.

rate at which customers arrive. Though we don't report those results here, we didn't find a substantial effect on anything other than the absolute magnitude of profits.

C.2. Robustness to Alternative Marginal Costs

We reproduce the 'net effects' as Table A2 where we set the marginal cost of production equal to zero. The main difference is that manufacturer profits are larger in all scenarios. The gap between the retailer optimal policy e^R and the vertically integrated e^{VI} or socially optimal e^{SOC} policy becomes larger. This can be viewed as a way to obtain an 'upper bound' on potential efficiencies as now production is costless. We find that all of the qualitative results and signs of point estimates are the same: the rebate can be used to foreclose the rival even though (H, M) generates more producer surplus than (M, M). Hershey's countermeasures are similar to those we calculated in the main text. It would have to cut its wholesale price below 15 cents to avoid foreclosure under both e^R and e^{VI}. Likewise, Mars could not reduce the rebate by much and still foreclose Hershey: only 4% at the vertically-integrated effort level and 6.6% at e^R.

Overall, welfare impacts are the same as in the main text. The (H, M) assortment maximizes producer surplus and consumer surplus. It is possible that consumers receive sufficient benefit in moving from e^{NR} to e^{VI} to compensate them for the inferior assortment (M, M), though e^R, and does not provide sufficient compensation.

Table A2: Net Effect of Efficiency and Foreclosure ($MC = 0$)

from	(H,H) and e^{NR}			(H,M) and e^{NR}		
	e^R	e^{VI}	e^{SOC}	e^R	e^{VI}	e^{SOC}
$\Delta\pi^R$	-733	-930	-1467	-1548	-1746	-2282
$\Delta\pi^M$	3641	4009	4320	7868	8236	8547
$\Delta\pi^H$	-3361	-3361	-3361	-5614	-5614	-5614
$\Delta\pi^N$	-16	-23	-25	-82	-89	-91
ΔPS	-469	-306	-533	624	787	560
$\Delta CS(\epsilon = -2)$	-55	534	1047	534	1122	1636
ΔSS	-524	228	514	1157	1909	2195
$\lambda\pi^M$	5546	5605	5655	5546	5605	5655
w_h to avoid foreclosure	-18.48	-16.72	-10.53	12.31	13.36	17.06
Reduced λ (Percent)	47.45	44.48	35.49	6.38	3.84	-4.79

Notes: Consumer Surplus calibrates α to median own price elasticity of $\epsilon = -2$. Calibration only affects the scale of consumer surplus calculations, not the ranking of various options. For more details see Appendix B.4.

C.3. Robustness to Alternative Fixed Costs

We reproduce the 'net effects' from the text as Tables A3 and A4 below. The main response to the fixed cost is that potential efficiency effects are smaller when the fixed costs are smaller and larger when the fixed costs are greater. Higher fixed costs reduce both the profits and the effort level of the retailer.

We find that all of the qualitative results are the same: the rebate can be used to foreclose the rival even though (H, M) generates more producer surplus than (M, M). The point estimates all have the same sign as those in 13, though for $FC = 15$ the sign flips on ΔCS when moving from (H, M) and e^{NR} to e^{R} and (H, H). Thus even at the vertically integrated effort level, it is impossible to compensate consumers for the inferior assortment.

The effect on rival countermeasures are similar: at the lower fixed cost Hershey would need to reduce prices even more than in the main text to avoid foreclosure; while Mars could reduce the generosity of the rebate slightly more (around 7%); at the higher fixed cost Hershey would need to reduce prices less than in the main text to avoid foreclosure; while Mars could reduce the generosity of the rebate slightly less (around 5%).

Table A3: Net Effect of Efficiency and Foreclosure ($FC = 5$)

from	(H,H) and e^{NR}			(H,M) and e^{NR}		
	e^{R}	e^{VI}	e^{SOC}	e^{R}	e^{VI}	e^{SOC}
$\Delta\pi^{R}$	-656	-698	-950	-1622	-1664	-1915
$\Delta\pi^{M}$	2549	2621	2741	5542	5614	5734
$\Delta\pi^{H}$	-2168	-2168	-2168	-3631	-3631	-3631
$\Delta\pi^{N}$	-9	-8	-3	-55	-54	-50
ΔPS	-285	-253	-381	234	266	138
$\Delta CS(\epsilon = -2)$	-183	-9	289	426	600	897
ΔSS	-468	-262	-92	660	865	1035
$\lambda\pi^{M}$	5670	5686	5712	5670	5686	5712
w_h to avoid foreclosure	-21.41	-21.08	-18.2	11.81	12.01	13.73
Reduced λ (Percent)	50.18	49.59	45.41	7.36	6.89	2.92

Notes: Consumer Surplus calibrates α to median own price elasticity of $\epsilon = -2$. Calibration only affects the scale of consumer surplus calculations, not the ranking of various options. For more details see Appendix B.4.

Table A4: Net Effect of Efficiency and Foreclosure ($FC = 15$)

from	(H,H) and e^{NR}			(H,M) and e^{NR}		
	e^R	e^{VI}	e^{SOC}	e^R	e^{VI}	e^{SOC}
$\Delta\pi^R$	-792	-971	-1788	-1509	-1688	-2505
$\Delta\pi^M$	2679	2992	3414	5777	6090	6512
$\Delta\pi^H$	-2202	-2202	-2202	-3673	-3673	-3673
$\Delta\pi^N$	-12	-21	-30	-54	-63	-73
ΔPS	-328	-203	-607	541	666	261
$\Delta CS(\epsilon = -2)$	24	702	1630	606	1284	2212
ΔSS	-303	500	1023	1147	1950	2474
$\lambda\pi^M$	5426	5496	5590	5426	5496	5590
w_h to avoid foreclosure	-15.64	-14.26	-5.15	13.15	13.98	19.45
Reduced λ (Percent)	44.82	42.25	28.61	4.5	2.45	-10.53

Notes: Consumer Surplus calibrates α to median own price elasticity of $\epsilon = -2$. Calibration only affects the scale of consumer surplus calculations, not the ranking of various options. For more details see Appendix B.4.

C.4. Joint Retailer-Consumer Surplus

We also allow the retailer to optimize the joint surplus of the retailer and the consumer. This may be an important consideration if providing good service to the consumer is an important aspect of how our retail operator competes with other vending operators for contracts with retail locations. It may also help explain why our retailer provides an extremely high frequency of service visits (beyond what we can justify with an optimal stocking model). We find that for $\epsilon = -1$ and $\gamma = 3$ so that $\frac{\gamma}{\alpha} = 6$, we are able to produce an effort policy which matches the mean of the observed distribution of retailer effort in Figure 4 of $e \approx 130$.

Table A5 reports the optimal effort policies of a joint Retailer-Consumer entity. By placing a large weight on consumer surplus, the retailer substantially increases its effort under all assortments. Also, because the resulting effort level is so high the potential efficiency effects of the rebate are highly limited and the gap between the effort set by the retailer and e^{VI} is quite small.

Table A5: Optimal Effort Policies: Restock after how many customers?

	(M,H)	(H,H)	(M,M)	(M,H)	(H,H)	(M,M)
	Effort Policy			% Change from e^{NR}		
e^{NR}	130	130	130	0.00	0.00	0.00
e^{R}	130	130	130	0.00	0.00	0.00
e^{VI}	130	130	130	0.00	0.00	0.00
e^{IND}	130	130	130	0.00	0.00	0.00
e^{SOC}	172	168	171	164.62	167.69	165.38
e^{SOC1}	157	154	156	176.15	178.46	176.92
e^{SOC4}	183	178	181	156.15	160.00	157.69

Notes: Reported for retailer who places weight $\frac{\gamma}{\alpha} = 6$ on consumer surplus. For further details, see Appendix B.4. The width of the 95% CI is at most one unit.

The potential gains are much smaller than they are in the case where the retailer does not take consumer surplus into account. For all elasticities, the potential change in the restocking frequency is now less than 5%. Likewise, the maximum change in social surplus is less than \$75 for all elasticities and assortments. Once the retailer internalizes the effect of effort on consumers, there is little to be gained from internalizing the same effort effect on the upstream manufacturer. The retailer-consumer pair exerts more effort than the vertically integrated retailer-Mars pair in our base scenario.

Though it is likely in practice that MarkVend at least partially considers consumer surplus when choosing its effort level, our base scenario ignores this possibility. Incorporating consumer surplus in the retailer's effort decision drastically reduces potential efficiency effects of the rebate contract. Ultimately, we are interested in whether an efficiency effect might outweigh potential foreclosure effects, and we design our baseline estimates to be an 'upper bound' on such effects.

Table A6: Net Effect of Efficiency and Foreclosure

from	(H,H) and e^{NR}			(H,M) and e^{NR}		
	e^R	e^{VI}	e^{SOC}	e^R	e^{VI}	e^{SOC}
$\Delta\pi^R$	-616	-616	1624	-1679	-1679	561
$\Delta\pi^M$	2507	2507	2199	5514	5514	5207
$\Delta\pi^H$	-2176	-2176	-2176	-3641	-3641	-3641
$\Delta\pi^N$	-11	-11	-18	-58	-58	-65
ΔPS	-296	-296	1630	137	137	2062
$\Delta CS(\epsilon=-2)$	-275	-275	-1021	422	422	-324
ΔSS	-571	-571	609	559	559	1738
$\lambda\pi^M$	5718	5718	5649	5718	5718	5649
w_h to avoid foreclosure	-22.31	-22.31	-50.01	11.97	11.97	-4.59
Reduced λ (Percent)	51.17	51.17	90.23	6.96	6.96	45.49

Notes: Reported for retailer who places weight $\frac{\gamma}{\alpha}=6$ on consumer surplus. For more details see Appendix B.4.

D. Full $\pi(a,e)$ Tables

We compute $\pi(a,e)$ for every agent and 15 assortments. We report only the most relevant assortments and effort levels below. Note that $\pi(a,e)$ denotes the present discounted value of profits from a single machine in the top quartile of the MarkVend enterprise. We cannot report exact profits at the enterprise level but it is safe to assume they are orders of magnitude larger. First column reports policy type and value in parentheses.

Policy	π^R	$\lambda\pi^M$	π^M	π^H	π^N	$\pi^R + \pi^M$	PS	CS
(H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers								
e^{NR}(217)	94,733	4,964	22,363	2,181	2,149	117,095	121,425	65,491
e^{R}(211)	94,723	4,985	22,454	2,179	2,146	117,177	121,502	65,685
e^{VI}(197)	94,612	5,028	22,648	2,173	2,143	117,260	121,576	66,105
e^{IND}(197)	94,612	5,028	22,648	2,173	2,143	117,260	121,576	66,105
e^{SOC}(172)	94,060	5,091	22,934	2,168	2,141	116,994	121,303	66,738
e^{SOC1}(157)	93,469	5,121	23,068	2,169	2,142	116,536	120,848	67,048
e^{SOC4}(183)	94,363	5,066	22,818	2,170	2,141	117,181	121,492	66,478
(H,H) Assortment: Reeses Peanut Butter Cup and Payday								
$e^{Pre2008}$(137)	92,296	5,152	23,207	2,174	2,147	115,503	119,824	67,387
$e^{Post2008}$(144)	92,768	5,142	23,162	2,172	2,145	115,931	120,247	67,276
e^{NR}(212)	95,548	4,288	19,316	3,644	2,192	114,864	120,700	64,902
e^{R}(206)	95,537	4,310	19,415	3,641	2,190	114,952	120,783	65,095
e^{VI}(191)	95,407	4,360	19,642	3,634	2,187	115,048	120,869	65,539
e^{IND}(191)	95,407	4,360	19,642	3,634	2,187	115,048	120,869	65,539
e^{SOC}(168)	94,876	4,424	19,926	3,630	2,187	114,802	120,619	66,111
(M,M) Assortment: Three Musketeers and Milkyway								
e^{SOC1}(154)	94,316	4,454	20,063	3,632	2,189	114,379	120,200	66,398
e^{SOC4}(178)	95,161	4,398	19,812	3,631	2,186	114,972	120,789	65,878
$e^{Pre2008}$(137)	93,339	4,483	20,194	3,637	2,194	113,533	119,364	66,688
$e^{Post2008}$(144)	93,791	4,472	20,144	3,635	2,192	113,934	119,761	66,574
e^{NR}(217)	94,005	5,521	24,867	0	2,141	118,872	121,013	65,173
e^{R}(211)	94,005	5,541	24,958	0	2,139	118,962	121,101	65,371
e^{VI}(197)	93,915	5,584	25,152	0	2,135	119,067	121,201	65,801
e^{IND}(197)	93,915	5,584	25,152	0	2,135	119,067	121,201	65,801
e^{SOC}(172)	93,397	5,647	25,438	0	2,132	118,835	120,967	66,448
e^{SOC1}(157)	92,825	5,677	25,572	0	2,133	118,397	120,530	66,765
e^{SOC4}(183)	93,686	5,621	25,322	0	2,132	119,008	121,141	66,182
$e^{Pre2008}$(137)	91,673	5,708	25,713	0	2,137	117,387	119,523	67,111
$e^{Post2008}$(144)	92,139	5,698	25,668	0	2,135	117,807	119,942	66,998

Table A7: Simulated Profits for Main Specification

Notes: Profit numbers represent the long-run expected profit from a top quartile machine. Rebate payments are assumed to only be paid under an (M, M) assortment; rebate payments are assumed to not be paid to the retailer. The socially-optimal assortment is (H, M). First column reports policy type and value in parenthesis. $FC = 10, MC = 0.15$.

Policy	π^R	$\lambda\pi^M$	π^M	π^H	π^N	$\pi^R + \pi^M$	PS	CS
(H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers								
$e^{NR}(217)$	94,733	4,964	31,024	3,361	3,260	125,756	132,377	65,491
$e^{R}(211)$	94,723	4,984	31,150	3,356	3,257	125,873	132,486	65,685
$e^{VI}(191)$	94,523	5,044	31,525	3,345	3,250	126,048	132,643	66,271
$e^{IND}(192)$	94,539	5,041	31,508	3,345	3,250	126,048	132,643	66,244
$e^{SOC}(169)$	93,959	5,097	31,856	3,340	3,248	125,815	132,403	66,804
$e^{SOC1}(155)$	93,372	5,124	32,024	3,342	3,251	125,396	131,989	67,086
$e^{SOC4}(179)$	94,265	5,075	31,716	3,341	3,248	125,981	132,570	66,576
(H,H) Assortment: Reeses Peanut Butter Cup and Payday								
$e^{Pre2008}(137)$	92,296	5,151	32,195	3,348	3,258	124,491	131,098	67,387
$e^{Post2008}(144)$	92,768	5,141	32,133	3,345	3,255	124,901	131,501	67,276
$e^{NR}(212)$	95,548	4,287	26,797	5,614	3,326	122,344	131,284	64,902
$e^{R}(206)$	95,537	4,310	26,935	5,609	3,323	122,472	131,403	65,095
$e^{VI}(185)$	95,310	4,378	27,362	5,595	3,317	122,672	131,584	65,700
$e^{IND}(186)$	95,328	4,375	27,343	5,596	3,317	122,671	131,585	65,674
$e^{SOC}(165)$	94,772	4,430	27,687	5,593	3,318	122,459	131,370	66,176
(M,M) Assortment: Three Musketeers and Milkyway								
$e^{SOC1}(152)$	94,219	4,457	27,857	5,596	3,322	122,076	130,994	66,435
$e^{SOC4}(174)$	95,058	4,408	27,550	5,593	3,317	122,608	131,518	65,974
$e^{Pre2008}(137)$	93,339	4,482	28,016	5,604	3,329	121,354	130,287	66,688
$e^{Post2008}(144)$	93,791	4,471	27,945	5,599	3,325	121,736	130,660	66,574
$e^{NR}(217)$	94,005	5,520	34,498	0	3,248	128,503	131,751	65,173
$e^{R}(211)$	94,005	5,540	34,624	0	3,245	128,629	131,873	65,371
$e^{VI}(191)$	93,835	5,600	34,999	0	3,237	128,833	132,070	65,970
$e^{IND}(192)$	93,850	5,597	34,982	0	3,237	128,831	132,069	65,943
$e^{SOC}(169)$	93,300	5,653	35,330	0	3,234	128,631	131,865	66,516
$e^{SOC1}(155)$	92,731	5,680	35,499	0	3,236	128,230	131,466	66,804
$e^{SOC4}(179)$	93,593	5,630	35,190	0	3,235	128,783	132,018	66,282
$e^{Pre2008}(137)$	91,673	5,708	35,672	0	3,242	127,345	130,587	67,111
$e^{Post2008}(144)$	92,139	5,697	35,609	0	3,239	127,748	130,987	66,998

Table A8: Simulated Profits for $MC = 0$ Specification

Notes: Profit numbers represent the long-run expected profit from a top quartile machine. Rebate payments are assumed to only be paid under an (M, M) assortment; rebate payments are assumed to not be paid to the retailer. The socially-optimal assortment is (H, M). First column reports policy type and value in parenthesis. $FC = 10, MC = 0$.

Policy	π^R	$\lambda\pi^M$	π^M	π^H	π^N	$\pi^R + \pi^M$	PS	CS
(H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers								
$e^{NR}(236)$	39,596	2,078	9,362	908	895	48,958	50,761	27,388
$e^{R}(231)$	39,593	2,086	9,394	907	894	48,987	50,788	27,456
$e^{VI}(216)$	39,544	2,105	9,481	905	892	49,025	50,822	27,643
$e^{IND}(217)$	39,549	2,104	9,476	905	892	49,025	50,822	27,631
$e^{SOC}(192)$	39,325	2,130	9,595	903	891	48,920	50,714	27,894
$e^{SOC1}(177)$	39,084	2,142	9,650	903	892	48,733	50,528	28,022
$e^{SOC4}(202)$	39,439	2,120	9,552	903	891	48,991	50,785	27,797
(H,H) Assortment: Reeses Peanut Butter Cup and Payday								
$e^{Pre2008}(137)$	37,885	2,163	9,743	909	898	47,629	49,436	28,265
$e^{Post2008}(144)$	38,168	2,160	9,731	908	897	47,900	49,704	28,231
$e^{NR}(231)$	39,938	1,797	8,095	1,518	913	48,032	50,463	27,143
$e^{R}(225)$	39,933	1,806	8,136	1,516	912	48,069	50,498	27,224
$e^{VI}(210)$	39,878	1,827	8,231	1,513	911	48,109	50,533	27,408
$e^{IND}(211)$	39,884	1,826	8,225	1,513	911	48,109	50,533	27,396
$e^{SOC}(188)$	39,670	1,852	8,344	1,512	910	48,014	50,436	27,634
(M,M) Assortment: Three Musketeers and Milkyway								
$e^{SOC1}(174)$	39,442	1,865	8,400	1,513	912	47,842	50,266	27,752
$e^{SOC4}(197)$	39,775	1,843	8,302	1,512	910	48,077	50,499	27,548
$e^{Pre2008}(137)$	38,348	1,886	8,496	1,521	918	46,844	49,283	27,977
$e^{Post2008}(144)$	38,623	1,883	8,482	1,519	917	47,105	49,541	27,943
$e^{NR}(236)$	39,294	2,310	10,406	0	892	49,701	50,592	27,256
$e^{R}(231)$	39,295	2,317	10,438	0	891	49,733	50,624	27,325
$e^{VI}(216)$	39,255	2,337	10,525	0	889	49,781	50,670	27,517
$e^{IND}(217)$	39,260	2,335	10,520	0	889	49,780	50,669	27,505
$e^{SOC}(192)$	39,051	2,362	10,639	0	888	49,690	50,578	27,775
$e^{SOC1}(177)$	38,818	2,374	10,694	0	888	49,512	50,400	27,905
$e^{SOC4}(202)$	39,160	2,352	10,596	0	888	49,755	50,643	27,675
$e^{Pre2008}(137)$	37,635	2,395	10,790	0	894	48,425	49,319	28,152
$e^{Post2008}(144)$	37,916	2,393	10,777	0	892	48,694	49,586	28,118

Table A9: Simulated Profits for Middle 50% machines

Notes: Profit numbers represent the long-run expected profit from a 25-75 percentile machine. Rebate payments are assumed to only be paid under an (M, M) assortment; rebate payments are assumed to not be paid to the retailer. The socially-optimal assortment is (H, M). First column reports policy type and value in parenthesis. $FC = 10, MC = 0.15$.

Policy	π^R	$\lambda\pi^M$	π^M	π^H	π^N	$\pi^R + \pi^M$	PS	CS
(H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers								
$e^{NR}(166)$	101,096	5,104	22,991	2,168	2,141	124,087	128,396	66,869
$e^{R}(163)$	101,093	5,110	23,017	2,168	2,141	124,111	128,420	66,931
$e^{VI}(154)$	101,052	5,126	23,091	2,169	2,143	124,144	128,456	67,105
$e^{IND}(153)$	101,045	5,128	23,099	2,170	2,143	124,144	128,456	67,123
$e^{SOC}(135)$	100,787	5,155	23,219	2,174	2,148	124,007	128,329	67,418
$e^{SOC1}(130)$	100,669	5,161	23,248	2,176	2,150	123,917	128,243	67,492
$e^{SOC4}(143)$	100,932	5,144	23,169	2,172	2,145	124,101	128,419	67,293
(H,H) Assortment: Reeses Peanut Butter Cup and Payday								
$e^{Pre2008}(137)$	100,829	5,152	23,207	2,174	2,147	124,036	128,357	67,387
$e^{Post2008}(144)$	100,947	5,142	23,162	2,172	2,145	124,109	128,426	67,276
$e^{NR}(161)$	102,062	4,439	19,998	3,631	2,188	122,059	127,877	66,260
$e^{R}(158)$	102,059	4,446	20,026	3,631	2,188	122,085	127,904	66,320
$e^{VI}(148)$	102,008	4,465	20,113	3,633	2,190	122,121	127,945	66,507
$e^{IND}(148)$	102,008	4,465	20,113	3,633	2,190	122,121	127,945	66,507
$e^{SOC}(131)$	101,755	4,492	20,234	3,640	2,196	121,989	127,826	66,780
(M,M) Assortment: Three Musketeers and Milkyway								
$e^{SOC1}(130)$	101,732	4,493	20,241	3,641	2,197	121,973	127,810	66,795
$e^{SOC4}(138)$	101,888	4,482	20,187	3,637	2,194	122,075	127,906	66,673
$e^{Pre2008}(137)$	101,872	4,483	20,194	3,637	2,194	122,066	127,897	66,688
$e^{Post2008}(144)$	101,969	4,472	20,144	3,635	2,192	122,113	127,939	66,574
$e^{NR}(166)$	100,442	5,660	25,495	0	2,132	125,937	128,068	66,581
$e^{R}(163)$	100,442	5,666	25,522	0	2,132	125,964	128,096	66,645
$e^{VI}(154)$	100,412	5,682	25,596	0	2,133	126,008	128,141	66,822
$e^{IND}(153)$	100,405	5,684	25,604	0	2,133	126,009	128,143	66,841
$e^{SOC}(135)$	100,167	5,711	25,726	0	2,137	125,893	128,030	67,142
$e^{SOC1}(130)$	100,053	5,718	25,755	0	2,139	125,808	127,947	67,217
$e^{SOC4}(143)$	100,304	5,700	25,675	0	2,135	125,978	128,114	67,015
$e^{Pre2008}(137)$	100,206	5,708	25,713	0	2,137	125,920	128,057	67,111
$e^{Post2008}(144)$	100,317	5,698	25,668	0	2,135	125,985	128,120	66,998

Table A10: Simulated Profits for $FC = 5$

Notes: Profit numbers represent the long-run expected profit from a top quartile machine with $FC = 5$. Rebate payments are assumed to only be paid under an (M, M) assortment; rebate payments are assumed to not be paid to the retailer. The socially-optimal assortment is (H, M). First column reports policy type and value in parenthesis. $FC = 5, MC = 0.15$.

Policy	π^R	$\lambda\pi^M$	π^M	π^H	π^N	$\pi^R+\pi^M$	PS	CS
(H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers								
$e^{NR}(251)$	89,383	4,832	21,764	2,202	2,165	111,147	115,514	64,228
$e^{R}(244)$	89,369	4,861	21,898	2,198	2,161	111,267	115,626	64,510
$e^{VI}(226)$	89,185	4,932	22,218	2,186	2,152	111,403	115,741	65,183
$e^{IND}(227)$	89,201	4,929	22,201	2,187	2,153	111,402	115,742	65,148
$e^{SOC}(197)$	88,372	5,028	22,648	2,173	2,143	111,020	115,336	66,105
$e^{SOC1}(179)$	87,477	5,075	22,862	2,169	2,141	110,339	114,649	66,576
$e^{SOC4}(209)$	88,794	4,991	22,483	2,178	2,146	111,277	115,600	65,748
(H,H) Assortment: Reeses Peanut Butter Cup and Payday								
$e^{Pre2008}(137)$	83,763	5,152	23,207	2,174	2,147	106,970	111,291	67,387
$e^{Post2008}(144)$	84,590	5,142	23,162	2,172	2,145	107,752	112,069	67,276
$e^{NR}(246)$	90,100	4,144	18,666	3,673	2,207	108,766	114,646	63,646
$e^{R}(239)$	90,084	4,176	18,811	3,666	2,203	108,894	114,764	63,927
$e^{VI}(220)$	89,871	4,257	19,176	3,650	2,195	109,047	114,891	64,632
$e^{IND}(221)$	89,889	4,253	19,158	3,651	2,195	109,046	114,892	64,597
$e^{SOC}(193)$	89,080	4,354	19,613	3,635	2,187	108,693	114,515	65,483
(M,M) Assortment: Three Musketeers and Milkyway								
$e^{SOC1}(176)$	88,223	4,404	19,836	3,631	2,186	108,059	113,875	65,926
$e^{SOC4}(205)$	89,510	4,314	19,431	3,640	2,190	108,941	114,771	65,126
$e^{Pre2008}(137)$	84,805	4,483	20,194	3,637	2,194	105,000	110,831	66,688
$e^{Post2008}(144)$	85,612	4,472	20,144	3,635	2,192	105,756	111,582	66,574
$e^{NR}(251)$	88,599	5,389	24,273	0	2,157	112,872	115,030	63,885
$e^{R}(244)$	88,597	5,418	24,406	0	2,154	113,003	115,157	64,172
$e^{VI}(226)$	88,443	5,488	24,723	0	2,145	113,166	115,310	64,859
$e^{IND}(227)$	88,457	5,485	24,706	0	2,145	113,164	115,309	64,823
$e^{SOC}(197)$	87,675	5,584	25,152	0	2,135	112,827	114,962	65,801
$e^{SOC1}(179)$	86,806	5,631	25,366	0	2,132	112,172	114,304	66,282
$e^{SOC4}(209)$	88,078	5,547	24,987	0	2,138	113,066	115,204	65,436
$e^{Pre2008}(137)$	83,140	5,708	25,713	0	2,137	108,854	110,990	67,111
$e^{Post2008}(144)$	83,960	5,698	25,668	0	2,135	109,628	111,763	66,998

Table A11: Simulated Profits for $FC = 15$

Notes: Profit numbers represent the long-run expected profit from a top quartile machine with $FC = 15$. Rebate payments are assumed to only be paid under an (M, M) assortment; rebate payments are assumed to not be paid to the retailer. The socially-optimal assortment is (H, M). First column reports policy type and value in parenthesis. $FC = 15, MC = 0.15$.

Policy	π^R	$\lambda\pi^M$	π^M	π^H	π^N	$\pi^R + \pi^M$	PS	CS
(H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers								
$e^{NR}(130)$	91,742	5,161	23,248	2,176	2,150	114,990	119,316	67,492
$e^{R}(130)$	91,742	5,161	23,248	2,176	2,150	114,990	119,316	67,492
$e^{VI}(130)$	91,742	5,161	23,248	2,176	2,150	114,990	119,316	67,492
$e^{IND}(130)$	91,742	5,161	23,248	2,176	2,150	114,990	119,316	67,492
$e^{SOC}(172)$	94,060	5,091	22,934	2,168	2,141	116,994	121,303	66,738
$e^{SOC1}(157)$	93,469	5,121	23,068	2,169	2,142	116,536	120,848	67,048
$e^{SOC4}(183)$	94,363	5,066	22,818	2,170	2,141	117,181	121,492	66,478
(H,H) Assortment: Reeses Peanut Butter Cup and Payday								
$e^{Pre2008}(137)$	92,296	5,152	23,207	2,174	2,147	115,503	119,824	67,387
$e^{Post2008}(144)$	92,768	5,142	23,162	2,172	2,145	115,931	120,247	67,276
$e^{NR}(130)$	92,805	4,493	20,241	3,641	2,197	113,045	118,883	66,795
$e^{R}(130)$	92,805	4,493	20,241	3,641	2,197	113,045	118,883	66,795
$e^{VI}(130)$	92,805	4,493	20,241	3,641	2,197	113,045	118,883	66,795
$e^{IND}(130)$	92,805	4,493	20,241	3,641	2,197	113,045	118,883	66,795
$e^{SOC}(168)$	94,876	4,424	19,926	3,630	2,187	114,802	120,619	66,111
(M,M) Assortment: Three Musketeers and Milkyway								
$e^{SOC1}(154)$	94,316	4,454	20,063	3,632	2,189	114,379	120,200	66,398
$e^{SOC4}(178)$	95,161	4,398	19,812	3,631	2,186	114,972	120,789	65,878
$e^{Pre2008}(137)$	93,339	4,483	20,194	3,637	2,194	113,533	119,364	66,688
$e^{Post2008}(144)$	93,791	4,472	20,144	3,635	2,192	113,934	119,761	66,574
$e^{NR}(130)$	91,126	5,718	25,755	0	2,139	116,881	119,020	67,217
$e^{R}(130)$	91,126	5,718	25,755	0	2,139	116,881	119,020	67,217
$e^{VI}(130)$	91,126	5,718	25,755	0	2,139	116,881	119,020	67,217
$e^{IND}(130)$	91,126	5,718	25,755	0	2,139	116,881	119,020	67,217
$e^{SOC}(172)$	93,397	5,647	25,438	0	2,132	118,835	120,967	66,448
$e^{SOC1}(157)$	92,825	5,677	25,572	0	2,133	118,397	120,530	66,765
$e^{SOC4}(183)$	93,686	5,621	25,322	0	2,132	119,008	121,141	66,182
$e^{Pre2008}(137)$	91,673	5,708	25,713	0	2,137	117,387	119,523	67,111
$e^{Post2008}(144)$	92,139	5,698	25,668	0	2,135	117,807	119,942	66,998

Table A12: Simulated Profits with Weight on Consumer Surplus

Notes: Profit numbers represent the long-run expected profit from a top quartile machine with $MC = 0.15$ and $FC = 10$ but with weight of $\gamma = 3$ on consumer surplus ($\epsilon = -1$) in retailer's objective function. Retail profits do not include rebate payments. The socially-optimal assortment is (H, M). First column reports policy type and value in parenthesis. $FC = 10, MC = 0.15$.