# Efficiency and Foreclosure Effects of Vertical Rebates: Empirical Evidence*

Christopher T. Conlon†
Julie Holland Mortimer‡

August 21, 2019

**Abstract**

Upstream manufacturers pay downstream retailers for achieving quantity or marketshare targets in many industries. 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 increases industry profitability and consumer surplus, but also induces the retailer to drop competing products.

*We thank Mark Stein, Bill Hannon, and the drivers at MarkVend Company for implementing the experiment used in this paper, providing data, and generally educating us about the vending industry. We thank Susanto Basu, Michaela Draganska, Scott Hemphill, Wills Hickman, J. F. Houde, Sylvia Hristakeva, Robin Lee, Joe Quinn, Michael Riordan, Maher Said, Greg Shaffer, Mike Whinston, and seminar participants at Boston College, Boston University, Georgetown University, Harvard University (Harvard Business School, and the Department of Economics), MIT, Notre Dame University, Ohio State University, Pennsylvania State University, Rochester University, Stanford University (Graduate School of Business and the Department of Economics), SUNY Stony Brook, Texas A & M University, Toulouse School of Economics, Tufts University, Universitat Autonoma de Barcelona, Universitat Pompeu Fabra, University College London, University of Southern California, University of Texas at Austin, University of Toronto, University of Western Ontario, University of Virginia, Washington University in St. Louis, Yale University, and participants at the Bates White and Quantitative Marketing and Economics conferences and the Workshop on Conditional Pricing Practices (held jointly by the Department of Justice and the Federal Trade Commission), for helpful comments. We thank Adam Kapor and Sharon Traiberman for excellent research assistance in running and analyzing the field experiment utilized in this research. Financial support for this research was generously provided through NSF grant number SES-0617896. Any remaining errors are our own.

†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 is the difficulty in measuring downstream effort, both for the upstream firm and the researcher; the fact that they 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, through the lens of one retailer.

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

[2] AUDs are closely 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 $50 billion, Mars is the third-largest privately-held company in the United States (after Cargill and Koch Industries).

target, then Mars will pay the retailer an amount equal to the per-unit discount multiplied 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.[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, the Mars' contract 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, we observe a discrete change in the quantity target of Mars' AUD during our sample period. We believe this change was a national change implemented in response to macroeconomic conditions, rather than a response to conditions at MarkVend Company. Although re-stocking schedules remain fixed within rebate periods (which are fiscal quarters), we provide evidence that the retailer's re-stocking frequency falls significantly when the quantity target is reduced.

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 the retailer's optimal effort and assortment decisions. A typical vending machine for snack foods has seven slots that can hold candy bars (or 'confection' products) across the top row. The 'first' several slots in the 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 show that, in the absence of a rebate, the retailer prefers to carry Hershey products in both of the 'last' two slots, but that under the observed rebate terms, it prefers to carry two Mars products in those slots instead. We also show that Mars prefers to pay the rebate rather than allow the retailer to carry two additional Hershey products, and that Hershey lacks a profitable deviation that prevents the retailer from dropping their products at the observed wholesale prices and contractual terms. Thus, we conclude that the AUD induces the retailer to drop two of Hershey's products in

[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.

favor of carrying two additional Mars products.

We also find evidence that the AUD induces greater retailer effort, and that consumers capture most of the gains from the higher effort level. Overall, we find that social surplus increases, but that the market fails to achieve the socially-optimal assortment and effort policies. In further results, we find that Mars cannot significantly reduce the generosity of its rebate while still inducing the retailer to stock both of the last two slots with Mars products. Finally, we examine the implications of the AUD under various potential upstream mergers. We find, paradoxically, that an AUD can achieve the socially-optimal assortment after a merger between Mars and Hershey. However, we document incentives for the merged firm to reduce the generosity of the AUD post-merger, to the detriment of the retailer.

## 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 of rivals in cases for which a narrow product assortment is economically efficient. Subsequent theoretical literature demonstrates that exclusion may instead maximize industry (or even bilateral) profit, which need not coincide with maximizing 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.

[10]In addition, Deneckere, Marvel, and Peck (1996), and Deneckere, Marvel, and Peck (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."

[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).

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, Ho, and Mortimer (2012a) and Ho, Ho, and Mortimer (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, Lee, Whinston, and Yurukoglu (2018), which examines efficiency and foreclosure effects of vertical integration between regional sports networks and cable distributors. A distinction between our work and Crawford, Lee, Whinston, and Yurukoglu (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, 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

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

[13]From a methodological perspective, Crawford, Lee, Whinston, and Yurukoglu (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, Lee, Whinston, and Yurukoglu (2018) employ the bargaining model to help determine supply terms, which we do not model. The biggest difference is that Crawford, Lee, Whinston, and Yurukoglu (2018) examine whether an integrated firm responds to foreclosure incentives in its supply decisions, while we simulate the effects of particular contracts.

area.[14] We observe the quantities, prices, and wholesale costs of all products, along with all of MarkVend's rebate terms. 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 cost 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.

Figure 1 shows some promotional materials from Mars' rebate program in 2010; just after

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

[15] Many machines have a few additional slots at the bottom for gum and mints.

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

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). The rebate does not explicitly condition on market share or the sales of competitors. However, most vending machines typically carry seven candy bar varieties, so the facing requirement may effectively limit shelf space for competing brands.[18]

In the seven slots sized to hold candy bars, MarkVend typically carries five core products plus two additional products.[19] The focus of our empirical exercise is the two additional products the retailer stocks in the last two slots. We consider MarkVend's choice between stocking two additional Mars products (Milkyway and 3 Musketeers) or two Hershey products (Reese's Peanut Butter Cups and Payday), or one product from each manufacturer. 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 availability and shares for the same products at MarkVend's machines. There are some patterns that emerge. The first is that MarkVend stocks some of the most popular products sold by Mars (Snickers, Peanut M&Ms, Twix, Plain M&M's, and Skittles) in most of its machines, and these products tend to have higher shares at MarkVend than they do nationally. Among the machines used in our experiment, the patterns are even more stark. For example, MarkVend only stocks Hershey's best-selling product (Reese's Peanut Butter Cups) in 45% of weeks for these machines, even though nationally Reese's Peanut Butter Cups is the fourth most popular product. Overall MarkVend tends to sell more Mars products (around 73% of all confections sales) than the national average (around 52% of all confections sales). The non-Mars product most frequently stocked by MarkVend is Nestle's Raisinets (at 47% of machine-weeks), which does not rank in the top 45 products nationally in confections sales.

There are two possible explanations for MarkVend's departures from the national best-

[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] While there is some ability for a vending operator to adjust the overall number of candy bars in a machine, it is often difficult to do without upgrading capital equipment, because candy bars and salty snacks do not fit in the same size 'slots.'

[19] 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.

sellers. One is that MarkVend has better information on the tastes of its specific consumers, and its product mix is geared towards those tastes. A second explanation is that the Mars AUD induces MarkVend to substitute from Nestle/Hershey brands to Mars brands when making stocking decisions, and that when MarkVend does stock products from competing manufacturers (e.g., Nestle Raisinets), it chooses products that do not steal business from key Mars products.

Table 2 compares year-over-year quarterly sales across MarkVend's entire enterprise for all but the first four quarters of our data for all products. We see that from the first quarter of 2007 through the third quarter of 2008, MarkVend generally hits a threshold of 105% of year-over-year sales. (The exceptions are the third quarter of 2007 and the second quarter of 2008, when it sells about 100% of year-over-year sales.) In the wake of the 2008 macroeconomic downturn, Mars modified its rebate program and reduced the threshold in the third quarter of 2008. We can see clearly in table 2 that MarkVend's sales of Mars products appear to respond to the lower threshold, and indeed track a 90% threshold quite closely.[20] This response comes primarily through a lower share of Mars products (declining from 20-21% in the third quarter of 2007 down to 17.6% in the first quarter of 2009). At the same time, we see that MarkVend's enterprise-level sales were not hit particularly badly by the macroeconomic downturn, as (normalized) total vends across all products remained largely flat between 2007 and 2009.

Under the assumption that the reduction in Mars' rebate threshold is an exogenous event (rather than a direct response to behavior by MarkVend), we can examine its impact on MarkVend's assortment and effort decisions. To examine the impact on assortment, we count the average number of product facings per machine dedicated to each manufacturer's products. In table 3, we see that when Mars reduced the threshold, between the second and third quarters of 2008, MarkVend reduced the number of Mars product facings in an average vending machine from around 6.6 to around 5.3. Over the same time period, the number of Hershey facings increased from around 1 facing per machine to around 2 facings per machine. The right-hand-side panel of the table shows that the major switch was to swap Mars' Three Musketeers (stocked in around half of machines at the beginning of the

[20] Our data reflect retail sales in vending machines, while the sales targets are derived from wholesale cases ordered. In later analyses, we implicitly assume that retail sales track wholesale orders perfectly. Some products may spoil or melt, or be damaged in delivery or stolen. Likewise, the retailer can place its wholesale orders in order to meet the threshold, while holding extra inventory in its warehouse (or even disposing of products). This implies there is a small margin of error between our threshold calculation and the calculation Mars uses to establish whether the conditions of the rebate have been met. In correspondence with MarkVend, the owner assures us that these effects are small and do not change over time.

sample) for Hershey's Reese's Peanut Butter Cups and Payday (stocked in 62% and 23% of machines respectively at the end of the sample period). Although it is difficult to attribute causality, it is worth pointing out that prior to the reduction in the threshold, both Reese's Peanut Butter Cups and Payday are effectively foreclosed, as they are stocked in very few of MarkVend's machines.

We can also measure how MarkVend adjusts its effort when the sales threshold changes. In table 4, we report regression results at the machine-visit level for two effort variables: the number of vends between visits and the elapsed number of days between visits. We include machine and week-of-year fixed effects. Thus, the regressions examine variation in these effort variables within a particular vending machine over time, while trying to control for overall seasonality in how often machines are serviced (if, for example, employees in office buildings take more vacation in summer). We find that after the threshold is reduced (at the beginning of the third quarter of 2008), MarkVend waits an average of 0.85 days longer before servicing machines, and that machines have sold 8.26 more products on average since the last service visit. Together, these imply that MarkVend is reducing effort, rather than merely responding to a slower rates of sales. While one must be cautious about causally interpreting the retailer's response to changes in the threshold by Mars, 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 table 3.

## 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.[21] 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

[21] 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) and Conlon and Mortimer (2013b).

M&Ms.[22] 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.[23]

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 experiment.[24]

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, Three Musketeers, Plain M&Ms) to the marginal Hershey products (Reese's Peanut Butter Cup, Payday), and second, the degree to which any of these products compete with the dominant Mars products (Peanut M&Ms, Snickers,

[22]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.

[23]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.

[24]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, however, 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 A.4.

## 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 5 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. 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).

Table 6 examines the impact of the product removals on the upstream firms. 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 profits rise by nearly $61.43, capturing about half of Mars' losses. We see substitution to the two Nestle products in the Snickers removal, so that Nestle gains $19.32 as consumers substitute to Butterfinger and Raisinets; Nestle's gains are a smaller percentage of Mars' losses in the other two removals.

Direct analysis of the product removals can only account for the marginal cost aspect of the rebate; one requires a model of restocking in order to account for the impact of the quantity threshold. By more evenly allocating the costs of stocking out, the rebate should better align the incentives of the upstream and downstream firms, and lead the retailer to increase its overall service level. Returning to table 5, 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 approximately ($17, $30, $50) of the cost of the Snickers, Peanut M&Ms, and joint product removals from the upstream to the downstream firm. The last column of table 6 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.

# 4 Consumer Choice: Model and Estimation

## 4.1 Consumer Choice

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).[25]

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 $\sigma_l$. We also incorporate $\xi_t$ which is a parameter common to all products in market $t$ and captures variation in demand for the outside good across markets. 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 $\nu_{ilt}$, shown here:

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

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:

$$\ell(\mathbf{q} | d, \xi, \sigma, a_t) \propto \sum_t \sum_{j \in a_t} q_{jt} \log s_{jt}(d, \xi, \sigma | a_t). \tag{3}$$

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 even a single market after we normalize the utility

[25] Results from an alternative nested-logit specification are available from the authors upon request.

of the outside good to zero. The $\xi_t$ 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 $\sigma$ 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, Levinsohn, and Pakes 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).

Unlike in our previous work (Conlon and Mortimer 2013a), there are virtually no 'natural' stock-outs in the data; thus, changes to product assortment happen for two reasons: (1) MarkVend changes the assortment when re-stocking, or (2) 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.[26] 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.[27]

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 of a product).[28] 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 7. We estimate 73 product intercepts. We report two levels of aggregation for $\xi_t$. 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

[26] 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.

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

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

for salt, sugar, and nut content.[29] 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 $\xi_t$ fixed effects. Our simulated ML parameters tend to be very precisely estimated, because we observe 2.96 million sales.[30]

# 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.[31]

Assuming that Mars offers the same wholesale price across all goods $w_m$ (which is true in the data) and has a constant marginal cost for all goods $c_m$ (which industry estimates put at approximately \$0.15), one can re-write a quantity-based AUD contract in terms of the profit of the dominant firm, $\pi^M$. Denoting the per-unit discount payment as $d$, we define the payment from Mars ($M$) to the retailer MarkVend ($R$) as:

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

[29]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 (2013a), 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.

[30]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.2 Algorithm 4).

[31]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.

And we define MarkVend's problem as:

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

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

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 $\lambda$ is the share of Mars' profit paid to the retailer, assuming 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. The retailer's assortment decision involves simple discrete comparisons across a finite number of choices. We explain the set of potential assortments that we analyze in section 5.2. For each potential choice of assortment, we calculate the retailer's optimal choice of effort.

## 5.1 Retail Effort Choice: Dynamic Model of Re-stocking

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 an (enterprise-wide) policy to restock after $e$ 'likely consumers' have arrived to each of its vending machines.[32] 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 draw from the left-tail of the consumer arrival distribution), MarkVend does not adjust its stocking policy until the next quarter.[33]

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

[33] Within a quarter, it appears as the most 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,

In our application, we model the retailer's choice of effort, $e$, as setting a restocking frequency, using an approach similar to Rust (1987), but 'in reverse.' Rather than assuming that observed retailer wait times are optimal and using Rust's model to estimate the cost of re-stocking, 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. In order to model the choice of effort, we consider a multi-product ($\mathbf{s}$,$\mathbf{S}$) policy, in which the retailer pays a fixed cost $FC$ and fully restocks (all products) to target inventory $\mathbf{S}$. The challenge is to characterize the critical re-stocking inventory level, $\mathbf{s}$. In our application, it is more convenient to work with the number of 'likely consumer arrivals' (a scalar, which we denote $x$), rather than working with the vector $\mathbf{s}$.[34] This implies an informational restriction on the retailer when it makes a restocking decision: it observes the expected number of 'likely consumers,' but not necessarily the actual inventory levels of each individual product.[35]

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 equation (6) is similar to the 'Tree Cutting Problem' of Stokey, Lucas, and Prescott (1989), which for concave $u(x)$ and increasing $x' \geq x$, admits a monotone policy such that the firm re-stocks if $x \geq e$. Given a guess of the optimal policy, we can compute the post-decision transition-probability-matrix $\tilde{P}(e)$ and the post-decision pay-off $\tilde{u}$, defined as:

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

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. It doesn't have new information by which to dynamically adjust a service schedule across days.

[34] In the multi-product setting, $\mathbf{s}$ is multi-dimensional (and may not define a convex set).

[35] This closely parallels the problem of MarkVend. MarkVend may have information on whether particular days are likely to be busy or not, but does not observe the actual inventory levels of individual products until visiting the machine to restock it. In other retail contexts this assumption might be less realistic and could be relaxed; its role is primarily to reduce the computational burden in solving the re-stocking problem.

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

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

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

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

In the typical model with only a retail agent, analogous to (Rust 1987), the long-run profits in equation (9) correspond to the retailer profit in equation (5). Assuming the retailer anticipates the outcome of the rebate payment for any given effort level, it chooses either a 'rebate' level of effort, denoted $e^R$, when its effort and assortment decisions qualify it for the rebate payment, or a 'non-rebate' level of effort, denoted $e^{NR}$, when its effort and assortment choices do not qualify it for payment.

In the case of a vertically-separated market structure, however, one can also evaluate profits under alternative stocking policies, or policies that arise under counterfactual market structures. For example, in order to understand the incentives of a vertically-integrated firm, $M+R$, one defines $u(x)$ as $(u^R(x)+u^M(x))$, which incorporates the profits of both the retailer and the dominant upstream manufacturer. This is a useful benchmark, because the joint profit of Mars and the retailer may be the relevant constraint for the terms of the AUD. We denote the effort policy that maximizes this bilateral payoff as $e^{VI}$. Similarly, we define effort levels that maximize payoffs for the industry as a whole (i.e., also including profits of the rivals), which we denote $e^{IND}$, or social surplus (i.e., also including consumer surplus), which we denote $e^{SOC}$. We enumerate these possibilities below:

$$\begin{aligned}
e^{NR} &= \arg\max_e \pi^R(e) \\
e^{R} &= \arg\max_e \pi^R(e) + \lambda \cdot \pi^M(e) \\
e^{VI} &= \arg\max_e \pi^R(e) + \pi^M(e) \\
e^{IND} &= \arg\max_e \pi^R(e) + \pi^M(e) + \pi^H(e) \\
e^{SOC} &= \arg\max_e \pi^R(e) + \pi^M(e) + \pi^H(e) + \frac{\gamma}{\alpha}\pi^C(e)
\end{aligned} \tag{10}$$

In the above equation, consumer surplus is multiplied by two constants: $\gamma$, the social planner's Pareto weight on consumers, and $\alpha$, a parameter that scales the elasticity of demand. See Appendix B.3 for more detail.

## 5.2 Retailer Choice: Empirical Implementation

Our goal is to estimate the long run profits $\pi(a,e)$ under various assortments and effort levels. We provide pseudo-code for the entire procedure in Appendix B.2. In this subsection, we define the state space for the dynamic model, describe relevant features of the data and the empirical implementation used for the dynamic model, and discuss the process of determining retailer assortment.

### Simulating Consumer Purchases

The first step is to estimate the empirical counterpart of the per-consumer flow payoffs $u(x)$ from equation (7).

1. We define a 'hypothetical full machine' as one that contains a set of the 29 most commonly-stocked products, listed in table 8, with observed machine capacities for each product.[36] We generate 100,000 such full machines.

2. We simulate the arrival of 'likely consumers' one at a time in accordance with the observed assortment $A_t$ 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 $\xi$ to its median value of 0.75.

3. After each consumer choice, we update the inventories of each product and adjust the inventory for each product, as well as the set of available products 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.

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, $\hat{u}^i(x)$.[37]

[36] 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.

[37] We use the MATLAB package `slmengine`. After checking for monotonicity, we impose that $\hat{u}^R(x)$,$\hat{u}^M(x)$,$\hat{u}^C(x)$ are all decreasing functions. We do not impose monotonicity on $\hat{u}^H(x)$,$\hat{u}^N(x)$. In general fit is good (except in the tails which are far from optimal policies). $R^2 > 0.98$.

### Consumer Arrivals

Both the simulation procedure above and the dynamic model define the state space in terms of 'likely consumer arrivals.' When we simulate the arrival of consumers in Step (2) above, we simulate them from a conditional distribution of 'likely consumers.' We label the full availability set $\tilde{A}$, and the corresponding outside good share as $\widetilde{s_0} = s_0(\tilde{A}, \widehat{\theta})$. We simulate the decisions of consumers facing inventory $A_t$ from the normalized distribution:[38]

$$y_t \sim Multinom\left(\frac{s_{jt}(A_t)}{1-\widetilde{s_0}}, s_0(A_t) - \widetilde{s_0}\right)$$

When the outside good share $\widetilde{s_0}$ is large, this substantially speeds up the simulation of consumer choices.

We also estimate the arrival process $P(x'|x)$ using the same 'likely consumer' definition. Similar to Rust (1987), we estimate a discrete distribution of daily consumer arrivals $P(\Delta x)$ non-parametrically using the top quartile of the distribution of average daily sales for the MarkVend enterprise.[39] The difference between the distribution of 'likely consumer arrivals' and average daily sales arises because as products stock out, not all likely consumers makes a purchase. This requires an adjustment factor which we discuss in detail in Appendix B.2 Algorithm 2. In practice the adjustment factor is $< 3\%$. We report the distribution of average daily sales for the top 25% of machines in MarkVend's enterprise in the left panel of figure 3.[40] This distribution has a mean of 37.6 daily sales with a standard deviation of 25.6 sales. The right panel of figure 3 reports cumulative sales at the time of restocking. On average, MarkVend restocks after 129 sales or 130-131 likely consumers. This panel also reports the policies calculated under our model (for retailer and vertical-integrated levels of effort) as vertical lines.

### Costs and Prices Used to Estimate Per-Consumer Flow Payoffs

Two more inputs are required for calculating the per-consumer flow payoffs: manufacturer variable costs of production, and prices/wholesale costs at the retail level. We observe and

[38] We can first draw a consumer from a binomial distribution where they are either assigned the outside good or labeled a 'likely consumer' and then a second stage where we draw from the conditional distribution. The trick is that we don't care about the first set of consumers who never make purchases, and that probability doesn't change with inventory.

[39] Rust (1987) estimates a discrete distribution of weekly incremental mileage rather than working with cumulative mileage $P(x_{+1}|x_t)$.

[40] There are 32,680 machine-visits in this upper quartile. In Appendix C.1 we consider alternate assumptions to estimate the arrival process.

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.[41] We observe that MarkVend's retail prices are fixed at 75 cents for all confection products.[42] 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.[43]

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 can be applied to all machines, even though individual machines may have substantially different daily arrival rates. Figure 2 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' profits are roughly ten times the profits of the rivals. 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 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 $\beta$, and the fixed cost of a restocking visit, $FC$. We choose $\beta = 0.999863$, corresponding to a 5% annual interest rate.[44] 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

[41] 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 $e^{VI}$.

[42] 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.

[43] We provide additional details on the calibration exercise, as well as robustness to elasticities of -1 and -4 and alternative values for $\gamma$ in Appendix B.3.

[44] 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 $\beta$, 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 $\pi(a,e)$. We provide additional details in Algorithm 3 of Appendix B.2.

#### 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 reported in table 8) as four Mars products: Snickers, Peanut M&M's, Regular M&M's, Twix Caramel and one Nestle product: Raisinets. We treat the final two slots as 'up for grabs' and consider an assortment which 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 9 reports the simulated long-run average profits for the retailer and Mars, as well as total producer surplus (PS) and consumer surplus (CS) for each of the three potential assortments. Each outcome is reported for five 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 both producer and consumer surplus; while the $(M,M)$ assortment maximizes the bilateral surplus between Mars and the retailer (and is the assortment most commonly observed in the data).[45]

### 5.3 Discussion of Limitations and Robustness

In order to evaluate a wide range of contracts, product assortments, and effort decisions our model deviates from the actual problem that MarkVend solves in a few key ways.

First, we assume that the demand model estimated in table 7 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,

[45] Algorithms (1)-(3) in Appendix B.2 provide further detail on how profits are simulated, and table A8 provides a complete version of table 9, including rivals' profits.

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. Mitigating this concern somewhat is the fact that the main outputs of the demand model are the relative purchase probabilities and substitution probabilities (and not the outside good share), due to the presence of the $\xi_t$ fixed effects, and the way we model the state-space as likely consumer purchases. Our hope 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 using the 25% of the most popular machines across MarkVend's entire enterprise 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 consider the arrival rate for the middle 50% of machines in Appendix C.1, and we have experimented with faster (and slower) arrival rates.

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.[46] We ignore the possibility of a 'mixed' strategy, in which the retailer stocks the 3 Musketeers product in some machines and Reese's Peanut Butter Cups in others; or it varies assortments with the time of year.

Finally, although retailer effort is modeled as an optimal dynamic restocking problem, we assume that the retailer commits to a choice of $(a,e)$ each quarter, and cannot respond to individual demand conditions with that period of time (i.e., it can't change assortment or effort if sales are slower/faster than expected within the quarter). Furthermore, 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 consider the full distribution of outcomes. Here our justification is that with a large enough set of machines (more than

[46] 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.

700), 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.

The benefit of our approach is that we avoid solving separate dynamic programming problems on hundreds of heterogeneous machines, each with their own demand conditions and arrival rates, neither of which we could expect to accurately estimate on a machine-by-machine basis.

# 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. There are four analyses of interest: (i) the role the threshold plays to induce greater retail effort and/or changes to retailer assortment; (ii) the effect of the AUD on retailer effort and welfare, relative to several relevant alternatives; (iii) net effects of the AUD and potential rival countermeasures; (iv) changes to outcomes after potential mergers.

## 6.1 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 competing product with an additional product by the dominant firm. By varying the threshold, Mars affects the retailer's incentive compatibility (IC) constraint and enables Mars to indirectly select $(a,e)$ among a set of feasible options. We characterize those options below.[47]

We hold fixed the generosity of the rebate, $\lambda$, at the observed value, and vary the threshold and measure the optimal response of the 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, as the rebate is paid. When the threshold increases to 19,686, the retailer responds by increasing its effort. When the threshold increases beyond 19,686, the retailer responds 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

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

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 4. We plot the post-rebate profits of the retailer $\pi^R + \lambda\pi^M$ against the profits of Mars $\pi^M$ (and hence the threshold). Movement along the curve to the right corresponds to an increase in the retailer's effort (and Mars's profits). The peak of each curve corresponds to the $e^R$ profit level. We denote the foreclosure threshold, 22,747, with a vertical dotted line. This helps illustrate that the rebate cannot be used to implement the ($H$,$M$) assortment and $e^{VI}$ effort level, because the retailer would simply switch to ($M$,$M$) and $e^R$.

Note that it may be in the interest of the dominant firm to set a threshold in excess of $e^{VI}$, because $\pi^M(e)$ is increasing everywhere. This can be accomplished by choosing a threshold $\overline{\pi}^M > \pi^M(e^{VI})$. For $e < e^{VI}$ the bilateral surplus is increasing in effort, and 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 $M$. Thus, in equilibrium, it may be possible for Mars to design an AUD that results in socially inefficient excess effort. This is the case for the mean of the empirical distribution, ($e^{OBS} = 130$) under ($M$,$M$).

### 6.2 Effort, Efficiency and Welfare

The left-hand panel of table 11 reports the effort policies for all three assortments, under each effort level.[48] The right-hand panel reports the percentage change from the effort policy $e^{NR}$ that results (for any given assortment) in the absence of a rebate.

The AUD can affect effort in two ways. First, the lower effective wholesale price (due to $\lambda$) 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 the right-hand panel of table 11 for each of the three assortments. The second effect on effort derives from the retailer's attempt to meet the threshold requirement. This is the source of the effect on effort reported in the right-hand panel in all subsequent rows, $e^{VI}$, $e^{IND}$, etc. For example, under an ($M$,$M$) assortment and a threshold set to maximize the profits of a vertically-integrated

[48] Effort 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.

Mars-retailer pair, 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 the 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 efficiency gains.[49] We then analyze how the retailer's choice of effort and assortment vary 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, (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 $\Delta\pi^H = 3650$ (whose two products are now stocked), lower profits for Mars $\Delta\pi^M = -5660$, and lower producer $\Delta PS = -438$ and consumer surplus $\Delta CS = -539$ overall.[50] The second column reports the results of increasing the threshold to the level of $e^{VI}$. Compared to $e^R$, the $e^{VI}$ threshold leads to lower retailer profits $\pi^R = -109$ but higher Mars profits $\Delta\pi^M = 190$, and thus slightly higher producer surplus $\Delta PS = 78$. Most of the gains from additional effort are captured by consumers $\Delta CS = 422$.

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 fourth column reports the industry optimum, which is an $(H,M)$ assortment and $e^{IND}$ effort level. Not accounting for the rebate, increases the retailer's and Hershey's profit ($\Delta\pi^R = 612$ and $\Delta\pi^H = 2177$), which are partially offset by lower profits for Mars ($\Delta\pi^M = -2320$). Overall, producer and consumer surplus both increase ($\Delta PS = 465$ and $\Delta CS = 674$). The social optimum also uses an $(H,M)$ assortment, but with a higher

[49] 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 $e < e^{SOC}$.

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

$e^{SOC}$ effort level. This further increases effort to the benefit of consumers (and Mars) at the expense of the retailer.

### 6.3 Net Effects and Rival Countermeasures

The rebate contract leads to an inferior assortment relative to an industry optimum: $(M,M)$ instead of $(H,M)$, but potentially higher effort levels. In this section we address two remaining questions: Does the additional effort compensate for the inferior assortment in terms of producer and consumer surplus? And, at the observed generosity $\lambda$, does the AUD rebate represent an equilibrium from which no party (the retailer, Mars, or Hershey) wishes to deviate?

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 baselines. The first baseline is the $(H,H)$ assortment under the $e^{NR}$ effort level. This mimics what the retailer would choose if the AUD contract were banned, but wholesale prices remained unchanged. The second baseline 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 rebate threshold.

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 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 social) optimal assortment $(H,M)$. Relative to the social optimal assortment, the AUD that induces an $(M,M)$ assortment unambiguously reduces producer surplus $(-313, -235, -493)$ 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 ($\Delta CS = -61$). While consumers benefit from more effort (restocking after 209 instead of 217 customers), these benefits are dominated by the 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 the vertically-integrated effort level $e^{VI}$, then the net effect on consumer surplus becomes positive ($\Delta CS = 361$.)[51] Now the additional effort (restocking after 195 consumers

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

instead of 217) compensates for the less desirable assortment. This effect is even more pronounced at the socially optimal effort level.[52]

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 $-2{,}161$. 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 effort $e^R$ Mars' gain of 5,660 exceeds its payment of 5,545.[53] 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 2,606 and 3,065, whereas its payment is between 5,545 and 5,647.[54]

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:

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

Substituting Mars' IR constraint into equation 11 produces the three-party surplus condi-

[52] 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.3.

[53] Although this difference is small, in none of our bootstrapped simulations was this condition violated.

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

tion.[55]

We express this condition by calculating the Hershey wholesale price that leaves the retailer indifferent between the two assortments in equation (11), and comparing that price to our 15-cent marginal cost.[56] 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 at $e^{SOC}$, we find that Hershey might be able to avoid foreclosure by deviating to a wholesale price of $w_h = 16.24$ cents. Alternatively, one can perform a similar exercise and ask: what value of $\lambda$ equates both sides of equation (11)? Table 13 suggests that under $e^R$ or $e^{VI}$, Mars can only reduce the generosity of the rebate by 5-6% 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-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 $(H,M)$, which maximizes three-party surplus. By conditioning the rebate threshold on the sales of all of its products through $\overline{\pi}^M$, Mars effectively ties its products together.[57]

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 $\Delta CS$, 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).[58] We also analyze

[55]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.

[56]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.

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

[58]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

what happens when Mars is restricted to uniform prices in Appendix C.5. Those results are difficult to interpret because the resulting game lacks a pure-strategy Nash equilibrium, although in some scenarios, it is no longer worthwhile for Mars to foreclose Hershey.

### 6.4 Implications for Mergers

Vending is one of many industries for which retail prices are often fixed across similar products and under different vertical arrangements. Indeed, there are many industries for which the primary strategic variable is not retail price, but rather a slotting fee or other transfer payment between vertically-separated firms. Thus, our ability to evaluate the impact of a potential upstream merger may turn on how the merger affects payments between firms in the vertical channel. We consider the impact of three potential mergers (Mars-Hershey, Mars-Nestle, and Hershey-Nestle) on the AUD terms offered to the retailer by Mars. Given the degree of concentration in the confections industry, antitrust authorities would likely investigate proposed mergers, especially mergers involving Mars.[59]

Table 14 measures how competing manufacturers might respond to an upstream merger. The first column duplicates the fifth column of table 13 as a baseline. In the second column, we examine a potential Mars-Hershey merger. We assume that after the merger, the Hershey product (Reeses Peanut Butter Cup) is priced at the Mars wholesale price and included in Mars' rebate contract. The merged (Mars-Hershey) firm is now happy for consumers to substitute to Reese's Peanut Butter Cups, and the AUD is able to achieve the industry-optimal (and socially-optimal) product assortment of (H,M).[60] The merged firm faces competition from Nestle (Nestle Crunch and Butterfinger), which charges lower wholesale prices but sells less-popular products.[61] In the absence of an AUD, the retailer maximizes its profit by stocking the two Nestle products, but the AUD induces the retailer to choose an (H,M) assortment and an $e^{VI}$ effort policy (evaluated at the observed discount $\lambda$ and wholesale prices).[62] Post-merger, the welfare effects of the AUD are unambiguously positive $\Delta CS = 416$ and $\Delta PS = 796$, because Mars no longer has an incentive to foreclose Reese's Peanut Butter Cups. The potential negative impact of the merger is that Mars has an incentive to reduce

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.

[59]For a related analysis of diversion ratios in this market, see Conlon and Mortimer (2013b).

[60]We assume that the AUD retains $\lambda$ at the pre-existing level, and sets $\overline{\pi}^M = \pi^M(e^{VI}(H,M))$ to induce the vertically-integrated optimal level of effort.

[61]We use Nestle's observed wholesale price when computing changes in profits and producer surplus.

[62]Table 14 reports changes in variable profit for each agent, but not levels. For the full details of post-merger profits at all $\pi(a,e)$, please see Appendix D.

the generosity of the rebate by 40% and still foreclose the rival because Nestle is a weaker rival than Hershey.[63]

We perform a similar exercise in the third column, in which we allow Mars and Nestle to merge. The main difference now is that the merged firm internalizes the profits of Nestle's Raisinets, and is able to include the profit from Raisinets in the rebate. This again provides incentives for the merged firm to reduce the generosity of the rebate (by 11.6%). Finally, we examine a Hershey-Nestle merger in the final column. Giving Hershey access to the profits of Raisinets does very little, because Raisinets is not in danger of being foreclosed. This exercise closely resembles our baseline (No Merger) scenario.

Throughout the paper, we report the variable profits for the retailer; it is likely that its overall operating profits, after accounting for administrative and overhead costs, are substantially lower. Based on communication with industry participants, we think that the Mars rebate may account for a substantial fraction of operating profits in the vending industry, so that a 40% rebate reduction (implied by the hypothetical Mars-Hershey merger) would have a major impact on retailers.

# 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 large 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 dominant firm, Mars, to foreclose Hershey by leveraging its profits from dominant products

[63] There is no positive price Nestle could set to avoid foreclosure; and in this case, foreclosing Nestle leads to the socially-optimal product assortment.

(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, this foreclosure enhances the profitability of the overall industry and improves social surplus, but falls short of a implementing the product assortment that maximizes industry profits. The differential impact on social welfare is small, and depends on how the dominant 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. Finally, we explore the potential impact of three hypothetical upstream mergers on the likely terms of the AUD contract, holding retail prices fixed. We find that a merger between the two largest upstream firms has the potential to induce the socially-optimal product assortment, but may also lead to a reduction in the rebate payments made to retailers.

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 proves a relatively clean laboratory for measuring the effects of downstream effort.

## References

Bernheim, B. D., and M. Whinston (1998): "Exclusive Dealing," *Journal of Political Economy*, 106(1), 64–103.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4), 841–890.

Bork, R. (1978): *The Antitrust Paradox*. New York: Free Press.

Chao, Y., and G. Tan (2014): "All-Units Discounts as a Partial Foreclosure Device," Working Paper.

Conlon, C., and J. H. Mortimer (2013a): "Demand Estimation Under Incomplete Product Availability," *American Economic Journal: Microeconomics*, 5(4), 1–30.

Conlon, C. T., and J. H. Mortimer (2010): "Effects of Product Availability: Experimental Evidence," NBER Working Paper No. 16506.

——— (2013b): "An Experimental Approach to Merger Evaluation," NBER Working Paper No. 19703.

Crawford, G., R. Lee, M. Whinston, and A. Yurukoglu (2018): "The Welfare Effects of Vertical Integration in Multichannel Television Markets," *Econometrica*, 86(3), 891–954.

Deneckere, R., H. Marvel, and J. Peck (1996): "Demand Uncertainty Inventories and Resale Price Maintenance," *Quarterly Journal of Economics*, 111(3), 885–913.

——— (1997): "Demand Uncertainty and Price Maintenance: Markdowns as Destructive Competition," *American Economic Review*, 87(4), 619–641.

Fumagalli, C., and M. Motta (2006): "Exclusive Dealing and Entry, when Buyers Compete," *American Economic Review*, 96(3), 785–795.

Genchev, B., and J. H. Mortimer (2017): "Empirical Evidence on Conditional Pricing Practices," *Anti-trust Law Journal*, 81(2), 343–370.

Ho, J., K. Ho, and J. H. Mortimer (2012a): "Analyzing the Welfare Impacts of Full-line Forcing Contracts," *Journal of Industrial Economics*, 60(3), 468–498.

——— (2012b): "The Use of Full-line Forcing Contracts in the Video Rental Industry," *American Economic Review*, 102(2), 686–719.

Hubbard, T. N. (1998): "An empirical examination of moral hazard in the vehicle inspection market," *Rand Journal of Economics*, 29(2), 406–426.

Kapor, A. (2008): "Queueing and Novelty Effects in Consumer Demand," Harvard Archives.

Klein, B., and K. M. Murphy (1988): "Vertical Restraints as Contract Enforcement Mechanisms," *Journal of Law and Economics*, 31(2), 265–297.

Kolay, S., G. Shaffer, and J. A. Ordover (2004): "All-Units Discounts in Retail Contracts," *Journal of Economics and Managment Strategy*, 13(3), 429–459.

McFadden, D., and K. Train (2000): "Mixed MNL Models for Discrete Response," *Journal of Applied Econometrics*, 15, 447–470.

O'Brien, D. P. (2013): "All-Units Discounts and Double Moral Hazard," FTC Working Paper No. 316.

Posner, R. (1976): *Antitrust Law: An Economic Perspective*. University of Chicago Press.

Rasmusen, E. B., J. M. Ramseyer, and J. Wiley, John S. (1991): "Naked Exclusion," *The American Economic Review*, 81(5), 1137–1145.

Rey, P., and J. Tirole (2007): "A Primer on Foreclosure," in *Handbook of Industrial Organization, Volume 3*, ed. by M. Armstrong, and R. Porter, pp. 2145–2220. North Holland, Amsterdam, The Netherlands.

Rust, J. (1987): "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, 55(5), 999–1033.

Shepard, A. (1993): "Contractual Form, Retail Price, and Asset Characteristics in Gasoline Retailing," *RAND Journal of Economics*, 24(1), 58–77.

Stokey, N. L., R. Lucas, and E. Prescott (1989): *Recursive Methods for Economic Dynamics*. Harvard University Press.

Telser, L. (1960): "Why Should Manufacturers Want Fair Trade?," *Journal of Law and Economics*, 3, 86–105.

Tirole, J. (1988): *The Theory of Industrial Organization*. MIT Press.

Train, K. (2003): *Discrete Choice Methods with Simulation*. Cambridge University Press.

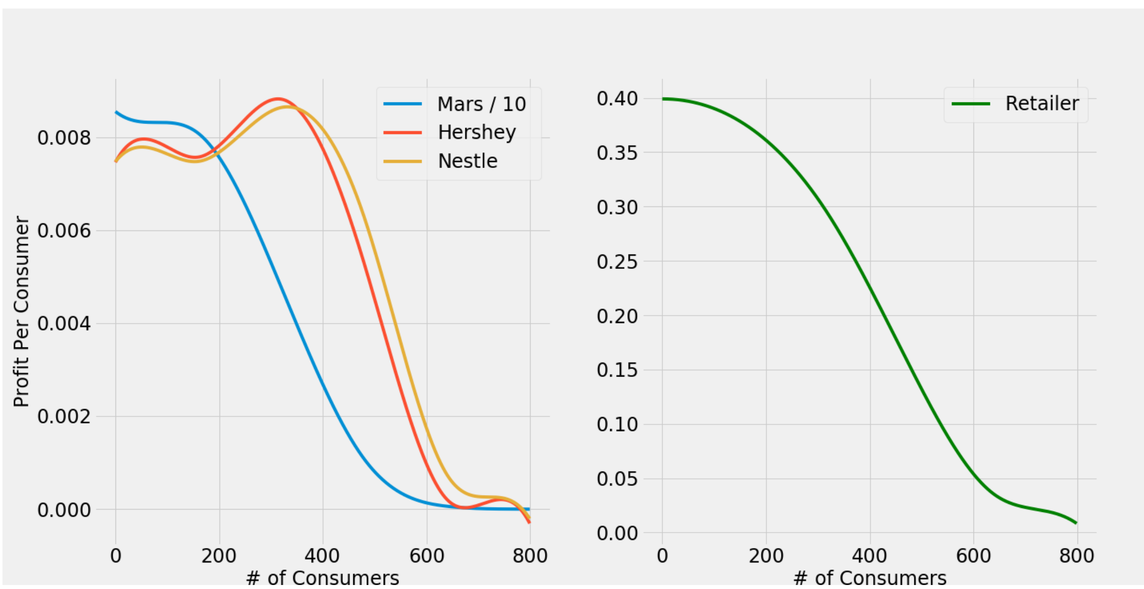
Whinston, M. (1990): "Tying, Foreclosure, and Exclusion," *American Economic Review*, 80(4), 837–59.

——— (2008): *Lectures on Antitrust Economics*. The MIT Press.

Figure 1: Mars Vend Operator Rebate Program

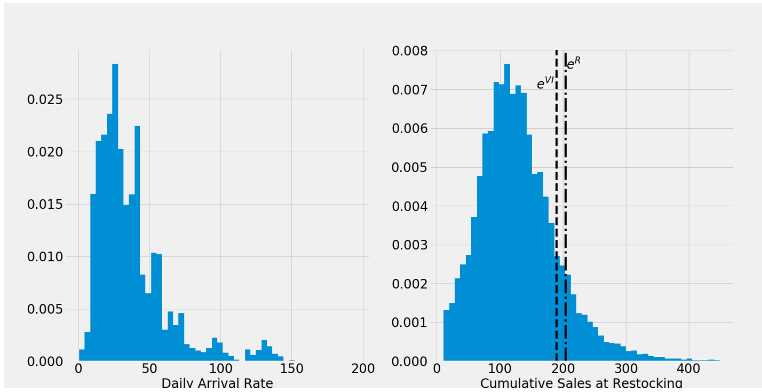

Notes: From '2010 Vend Program' materials, dated December 21, 2009; last accessed on February 2, 2015 at http://vistar.com/KansasCity/Documents/Mars%202010%20Operatopr%20rebate%20program.pdf.

Figure 2: Profits Per Consumer as a Function of the Restocking Policy



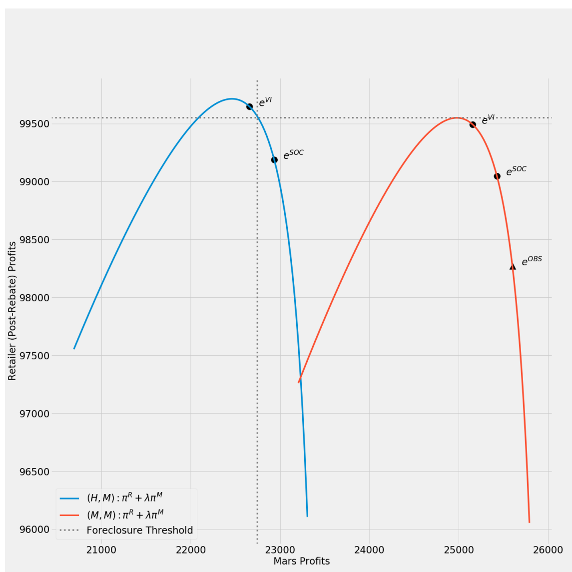

Notes: Each curve reports the per-consumer variable profits $u(x)$ of the retailer, Mars, Hershey and Nestle as a function of the retailer's restocking policy, using the product assortment in which the retailer stocks 3 Musketeers (Mars) and Reese's Peanut Butter Cups (Hershey) in the final two slots. 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 3: Observed Policies and Arrival Rates




Notes: Left pane reports 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 37.6 vends per day. Right pane reports cumulative sales at restocking. The mean is to restock after 129 sales. Right pane also reports policies calculated under the dynamic restocking model as vertical lines. Policies and cumulative sales are in the same units, except for 'sales' of the outside good. Histograms are from 32,680 machine-visits.

Figure 4: 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 $\pi^R$ falls below $\pi^R((H,H), e^{NR}) = 95{,}532$, the retailer reverts to $(H,H)$ (omitted to preserve the scale of the figure).

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

| Manu-facturer | Product | National: Rank | National: Avail-ability | National: Share | Mark Vend: Avail-ability | Mark Vend: Share | Experimental: Avail-ability | Experimental: Share |
|---|---|---|---|---|---|---|---|---|
| Mars | Snickers | 1 | 89 | 12.0 | 87 | 16.9 | 97 | 21.3 |
| Mars | Peanut M&Ms | 2 | 88 | 10.7 | 89 | 16.0 | 97 | 22.1 |
| Mars | Twix Bar | 3 | 67 | 7.7 | 80 | 12.6 | 79 | 13.0 |
| Hershey | Reeses Peanut Butter Cups | 4 | 72 | 5.5 | 71 | 6.6 | 45 | 6.2 |
| Mars | Three Musketeers | 5 | 57 | 4.3 | 35 | 3.1 | 41 | 5.2 |
| Mars | Plain M&Ms | 6 | 65 | 4.2 | 71 | 6.6 | 45 | 6.2 |
| Mars | Starburst | 7 | 38 | 3.9 | 41 | 3.2 | 16 | 1.0 |
| Mars | Skittles | 8 | 43 | 3.9 | 65 | 5.6 | 79 | 6.3 |
| Nestle | Butterfinger | 9 | 52 | 3.2 | 32 | 2.1 | 32 | 2.6 |
| Hershey | Hershey with Almond | 10 | 39 | 3.0 | 1 | 0.1 | 0 | 0.0 |
| Hershey | PayDay | 11 | 47 | 2.9 | 13 | 1.2 | 1 | 0.1 |
| Mars | Milky Way | 13 | 39 | 1.7 | 33 | 2.8 | 18 | 1.5 |
| Nestle | Raisinets | >45 | N/R | N/R | 45 | 4.0 | 81 | 8.7 |

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 Mark Vend, shares are: Mars 73.6%, and Hershey 15.0% and for our experimental sample Mars 78.3% and Hershey 13.1% (calculations by authors).

Table 2: Assortment Response to Changes in the Threshold

| | Achieved Threshold % | Total Vends | Mars Share |
|---|---|---|---|
| 2007q1 | 109.16 | 1000.00 | 20.20 |
| 2007q2 | 106.29 | 1087.45 | 19.77 |
| 2007q3 | 100.81 | 1008.57 | 20.94 |
| 2007q4 | 105.23 | 1092.49 | 19.97 |
| 2008q1 | 106.27 | 1103.42 | 19.45 |
| 2008q2 | 97.20 | 1057.32 | 19.77 |
| 2008q3 | 91.88 | 1014.13 | 19.14 |
| 2008q4 | 87.02 | 1048.26 | 18.11 |
| 2009q1 | 87.03 | 1058.54 | 17.65 |

Notes: Achieved threshold % reports the ratio of total Mars sales relative to Mars sales in the same quarter one year prior. For quarters 2007q1-2008q2 we believe the target to be 100% with a bonus payment at 105%. For quarters 2008q3-2009q1 we believe the threshold was reduced to 90%.

Table 3: Average Number of Confections Facings Per Machine-Visit

| | Mars | Hershey | Nestle | Mars Milkyway | Mars 3 Musketeer | Hershey PB Cup | Hershey Payday |
|---|---|---|---|---|---|---|---|
| 2006q1 | 6.64 | 1.32 | 2.05 | 0.26 | 0.50 | 0.19 | 0.08 |
| 2006q2 | 6.70 | 1.06 | 2.02 | 0.26 | 0.49 | 0.15 | 0.03 |
| 2006q3 | 6.76 | 0.81 | 2.02 | 0.29 | 0.56 | 0.03 | 0.01 |
| 2006q4 | 6.74 | 0.85 | 2.00 | 0.31 | 0.55 | 0.01 | 0.04 |
| 2007q1 | 6.61 | 1.13 | 1.58 | 0.32 | 0.56 | 0.00 | 0.08 |
| 2007q2 | 6.24 | 1.44 | 1.17 | 0.31 | 0.53 | 0.00 | 0.18 |
| 2007q3 | 6.21 | 1.63 | 1.08 | 0.29 | 0.54 | 0.01 | 0.21 |
| 2007q4 | 6.26 | 1.73 | 1.03 | 0.30 | 0.51 | 0.15 | 0.20 |
| 2008q1 | 5.98 | 2.08 | 0.97 | 0.38 | 0.29 | 0.51 | 0.19 |
| 2008q2 | 5.57 | 2.29 | 0.93 | 0.43 | 0.03 | 0.66 | 0.21 |
| 2008q3 | 5.37 | 2.29 | 0.91 | 0.41 | 0.00 | 0.63 | 0.23 |
| 2008q4 | 5.48 | 2.19 | 0.89 | 0.40 | 0.01 | 0.62 | 0.24 |
| 2009q1 | 5.32 | 1.99 | 0.83 | 0.37 | 0.01 | 0.62 | 0.23 |

Notes: Figures represent the weighted average number of product facings per machine-visit for the entire MarkVend enterprise (117,428 visits). Each machine visit is weighted by overall machine-visit sales to confer more weight on higher-volume machines. This is not a balanced panel, and composition of machine-visits may vary over time for reasons unrelated to assortment decisions. Changes in total facings may be due to: facings by other confections producers, substitution between confections and non-confections products, or changes in visit frequency across different machines.

Table 4: Effort Response to Changes in the Threshold

| | Vends Per Visit | Elapsed Days Per Visit |
|---|---|---|
| Lower Threshold | 8.262*** | 0.857*** |
| | (0.410) | (0.0690) |
| Observations | 117,428 | 117,428 |
| R-squared | 0.361 | 0.154 |
| Machine FE | ✓ | ✓ |
| Week of Year FE | ✓ | ✓ |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table reports linear regression analysis of 'Vends Per Visit' and 'Elapsed Days Per Visit' on an indicator for the use of a lower AUD threshold by Mars, which occurs beginning in the third quarter of 2008. Results use Mark Vend'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 5: Downstream Profit Impact

| | | | Without Rebate | | | With Rebate | | |
|---|---|---|---|---|---|---|---|---|
| Exogenous Removal | 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. All variables report the average effect per machine-week.

Table 6: Upstream (Manufacturer) Profits

| | | | | | % Borne by Mars | |
|---|---|---|---|---|---|---|
| Exogenous Removal | Mars | Hershey | Nestle | Other | Without Rebate | 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: Calculations by authors, using exogenous product removals from the field experiment. An observation is a treated machine-week. All variables report the average effect per machine-week. 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 7: Random Coefficients Choice Model

| | Parameter Estimates | |
|---|---|---|
| $\sigma_{Salt}$ | 0.506 | 0.458 |
| | [.006] | [.010] |
| $\sigma_{Sugar}$ | 0.673 | 0.645 |
| | [.005] | [.012] |
| $\sigma_{Peanut}$ | 1.263 | 1.640 |
| | [.037] | [.028] |
| # Fixed Effects $\xi_t$ | 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: The random coefficients estimates correspond to the choice probabilities described in section 4, equation 2. Both specifications include 73 product fixed effects. Total sales are 2,960,315.

Table 8: 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 9: Simulated Profits $\pi(a,e)$

| Policy | $\pi^R$ | $\pi^R + \pi^M$ | PS | CS |
|---|---|---|---|---|
| (H,M): Reeses Peanut Butter Cup and 3 Musketeers | | | | |
| $e^{NR}(217)$ | 94,735 | 117,108 | 121,440 | 65,499 |
| $e^{R}(211)$ | 94,726 | 117,190 | 121,517 | 65,693 |
| $e^{VI}(196)$ | 94,603 | 117,274 | 121,592 | 66,140 |
| $e^{IND}(197)$ | 94,615 | 117,274 | 121,592 | 66,112 |
| $e^{SOC}(172)$ | 94,064 | 117,009 | 121,319 | 66,744 |
| (H,H): Reeses Peanut Butter Cup and Payday | | | | |
| $e^{NR}(212)$ | 95,532 | 114,850 | 120,689 | 64,899 |
| $e^{R}(206)$ | 95,521 | 114,939 | 120,772 | 65,092 |
| $e^{VI}(191)$ | 95,390 | 115,035 | 120,858 | 65,536 |
| $e^{IND}(192)$ | 95,404 | 115,034 | 120,858 | 65,508 |
| $e^{SOC}(168)$ | 94,858 | 114,788 | 120,606 | 66,109 |
| (M,M): 3 Musketeers and Milkyway | | | | |
| $e^{NR}(214)$ | 94,012 | 118,917 | 121,063 | 65,275 |
| $e^{R}(209)$ | 94,004 | 118,982 | 121,127 | 65,438 |
| $e^{VI}(195)$ | 93,895 | 119,064 | 121,205 | 65,860 |
| $e^{IND}(195)$ | 93,895 | 119,064 | 121,205 | 65,860 |
| $e^{SOC}(171)$ | 93,371 | 118,808 | 120,947 | 66,473 |

Notes: Profit numbers represent the long-run expected profit from a top quartile machine. Retailer profits do not include rebate payments. Rebate value is reported independent of whether it is paid at that assortment and effort level. First column reports policy type and value in parenthesis. $FC = 10, MC = 0.15$.

Table 10: Critical Thresholds and Foreclosure at Observed $\lambda$

| $\overline{\pi}_M^{MIN}$ | $\overline{\pi}_M^{MAX}$ | Assortment | Effort |
|---|---|---|---|
| 0 | 19,418 | (H,H) | $e^R(H,H)$ |
| 19,418 | 19,686 | (H,H) | $e(\overline{\pi}_M(H,H))$ |
| 19,686 | 22,464 | (H,M) | $e^R(H,M)$ |
| 22,464 | 22,747 | (H,M) | $e(\overline{\pi}_M(H,M))$ |
| 22,747 | 24,979 | (M,M) | $e^R(M,M)$ |
| 24,979 | 25,815 | (M,M) | $e(\overline{\pi}_M(M,M))$ |
| 25,815 | $\infty$ | (H,H) | $e^{NR}(H,H)$ |

Notes: Calculations report the retailer's optimal assortment and effort policy at the observed $\lambda$ for different values of the threshold.

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

| | (M,H) | (H,H) | (M,M) | (M,H) | (H,H) | (M,M) |
|---|---|---|---|---|---|---|
| | Effort Policy | | | % Change from $e^{NR}$ | | |
| $e^{NR}$ | 217 | 212 | 214 | 0.00 | 0.00 | 0.00 |
| $e^{R}$ | 211 | 206 | 209 | 2.76 | 2.83 | 2.34 |
| $e^{VI}$ | 196 | 191 | 195 | 9.68 | 9.91 | 8.88 |
| $e^{IND}$ | 197 | 192 | 195 | 9.22 | 9.43 | 8.88 |
| $e^{SOC}$ | 172 | 168 | 171 | 20.74 | 20.75 | 20.09 |
| $e^{SOC1}$ | 158 | 154 | 156 | 27.19 | 27.36 | 27.10 |
| $e^{SOC4}$ | 183 | 178 | 181 | 15.67 | 16.04 | 15.42 |

Notes: Socially-optimal effort levels reported for different calibrated median own-price elasticities of demand. For further details, see Appendix A.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 | $e^{NR} : 212$ | $e^{VI} : 195$ | $e^{IND} : 197$ | $e^{SOC} : 172$ |
| $\Delta\pi^R$ | 1528 | -109 | 612 | 60 |
| | [9.45] | [4.02] | [4.02] | [13.17] |
| $\Delta\pi^M$ | -5660 | 190 | -2320 | -2034 |
| | [37.39] | [5.81] | [5.81] | [9.45] |
| $\Delta\pi^H$ | 3650 | 0 | 2177 | 2173 |
| | [22.95] | [0.0] | [0.0] | [14.85] |
| $\Delta\pi^N$ | 45 | -4 | -4 | -8 |
| | [2.43] | [0.12] | [0.12] | [0.94] |
| $\Delta PS$ | -438 | 78 | 465 | 192 |
| | [41.02] | [3.59] | [3.59] | [18.59] |
| $\Delta CS(\epsilon = -2)$ | -539 | 422 | 674 | 1306 |
| | [41.71] | [12.25] | [12.25] | [18.28] |
| $\Delta SS$ | -977 | 500 | 1139 | 1498 |
| | [82.39] | [14.93] | [14.93] | [28.96] |

Notes: Reports 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 $(M,M)$, 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. (Note: 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 A.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 $e^{NR}$ $e^{R}$ | $e^{VI}$ | $e^{SOC}$ |
|---|---|---|---|---|---|---|
| $\Delta\pi^{R}$ | -731 | -840 | -1365 | -1528 | -1637 | -2161 |
| | [2.64] | [4.33] | [11.12] | [9.45] | [9.83] | [15.89] |
| $\Delta\pi^{M}$ | 2606 | 2796 | 3065 | 5660 | 5851 | 6120 |
| | [9.74] | [10.63] | [12.17] | [37.39] | [38.31] | [39.67] |
| $\Delta\pi^{H}$ | -2185 | -2185 | -2185 | -3650 | -3650 | -3650 |
| | [14.96] | [14.96] | [14.96] | [22.95] | [22.95] | [22.95] |
| $\Delta\pi^{N}$ | -2 | -6 | -8 | -45 | -49 | -51 |
| | [1.00] | [1.02] | [1.01] | [2.43] | [2.46] | [2.5] |
| $\Delta PS$ | -313 | -235 | -493 | 438 | 516 | 258 |
| | [16.24] | [15.56] | [15.22] | [41.02] | [41.02] | [39.47] |
| $\Delta CS(\epsilon = -2)$ | -61 | 361 | 973 | 539 | 961 | 1573 |
| | [20.82] | [22.05] | [26.97] | [41.71] | [45.0] | [51.02] |
| $\Delta SS$ | -374 | 126 | 480 | 977 | 1477 | 1831 |
| | [36.16] | [36.35] | [39.03] | [82.39] | [85.45] | [89.06] |
| $\lambda\pi^{M}$ | 5545 | 5588 | 5647 | 5545 | 5588 | 5647 |
| | [12.33] | [12.20] | [12.23] | [12.33] | [12.20] | [12.23] |
| $w_h$ to avoid foreclosure | -18.38 | -17.53 | -11.63 | 12.20 | 12.71 | 16.24 |
| | [0.23] | [0.22] | [0.18] | [0.02] | [0.01] | [0.01] |
| Reduced $\lambda$ (Percent) | 47.40 | 45.85 | 37.13 | 6.63 | 5.39 | -2.90 |
| | [0.32] | [0.34] | [0.36] | [0.43] | [0.44] | [0.46] |

Notes: Consumer Surplus calibrates $\alpha$ to median own-price elasticity of $\epsilon = -2$ and $\gamma = 1$. Calibration only affects the scale of consumer surplus calculations, not the ranking of various options. For more details see Appendix A.4. Only one of our 1000 bootstrap iterations ($\Delta SS$ for the $e^{SOC}(H,M)$ case) yields a different sign than those reported in the table.

Table 14: Comparison under Alternate Ownership Structures

| Merger | None | $M\&H$ | $M\&N$ | $H\&N$ |
|---|---|---|---|---|
| Alternative (from) | $e^{NR}(H,H)$ | $e^{NR}(N,N)$ | $e^{NR}(H,H)$ | $e^{NR}(H,H)$ |
| AUD Assortment (to) | $e^{VI}(M,M)$ | $e^{VI}(H,M)$ | $e^{VI}(M,M)$ | $e^{VI}(M,M)$ |
| $\Delta\pi^R$ | -1725 | -722 | -1725 | -1725 |
| | [13.70] | [16.43] | [13.70] | [13.70] |
| $\Delta\pi^M$ | 5925 | 5284 | 5875 | 5925 |
| | [39.09] | [28.15] | [37.00] | [39.09] |
| $\Delta\pi^{Rival}$ | -3650 | -2619 | -3650 | -3699 |
| | [22.90] | [3.87] | [22.90] | [21.39] |
| Rebate | 5604 | 5530 | 6079 | 5604 |
| | [12.10] | [9.27] | [11.39] | [12.10] |
| $\Delta PS$ | 500 | 1944 | 500 | 500 |
| | [41.38] | [20.39] | [41.38] | [41.38] |
| $\Delta CS(\epsilon = -2)$ | 1127 | 2099 | 1127 | 1127 |
| | [48.67] | [24.38] | [48.67] | [48.67] |
| Price to Avoid Foreclosure | 12.32 | -21.80 | 6.75 | 12.93 |
| | [0.30] | [0.17] | [0.34] | [0.28] |
| % Reduction in Rebate $c = 0.15$ | 4.09 | 39.60 | 11.58 | 3.20 |
| | [0.43] | [0.23] | [0.40] | [0.41] |

Notes: Table compares the welfare impacts of an exclusive Mars stocking policy under alternative ownership structures. This assumes threshold is set at the vertically-integrated effort level.

# 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:

$$\Delta\pi^R + T \geq 0 \tag{Retailer IR}$$
$$\Delta\pi^M - T \geq 0 \tag{Mars IR}$$

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:

$$\Delta\pi^H + T_h \leq 0 \tag{Hershey Deviation}$$

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:

$$\pi^R(a) + T \geq \pi^R(a') + T_h$$
$$\Delta\pi^R + \Delta\pi^M \geq -\Delta\pi^H$$
$$\Delta\pi^R + \Delta\pi^M + \Delta\pi^H \geq 0 \tag{Three-Party Surplus}$$

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 $a$.[64]

[64] 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):

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

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 $\Delta_H$ and the second is the difference between $(H,M)$ and $(M,M)$ which we call $\Delta_M$ 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):

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

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 $\tau$, can be mapped into $\lambda$ (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 $(\tau)$ 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.[65]. Without some outside constraint on $\tau$ or $w_m$, and absent uncertainty about demand, the dominant firm has an incentive to increase $\tau$ 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 $\lambda$ 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 $T = (1 -$

[65] 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 and Tan (2014)

$\lambda_{AUD}) \cdot \overline{\pi}^M$ (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.[66] 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).[67]

# B Econometric Appendix

## B.1 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

[66] Kolay, Shaffer, and Ordover (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.

[67] 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).

due to macroeconomic conditions. In this case, using a simple measure like previous weeks' sales, or overall average sales for $E[q^0_{jt}]$ 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 $Q^0_t - Q^1_s \geq 0$ 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 $Q^0_t - Q^1_s \leq q^0_{fs}$. This means we choose control weeks $s$ that correspond to treatment week $t$ as follows:

$$\{s : s \neq t, Q^0_t - Q^1_s \in [0, q^0_{fs}]\}. \tag{13}$$

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 $q^0_{fs}$ 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:

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

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

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

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.[68]

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.2 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

[68] 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.

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 $\xi_t$ largely irrelevant as it governs the market share of the outside good and that gets normalized away. A larger $\xi_t$ still increases the substitution probability to the outside option after products stock out. We calibrate this to $\xi = \text{med}(\xi_t) \approx 0.75$.[69]

If we were to increase $\xi_t$, 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 $\xi_t$ 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 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 $\xi_t$ in the model?" and the answer is that we incorporate $\xi_t$ in order to get unbiased estimates of $\hat{d}_j$ and $\widehat{\sigma}$.

[69] 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.

**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 $(w_i, \nu_i)$ to calculate outside good purchase probability at an unobserved machine containing a superset of all possible products: $\tilde{A} = A_0 \cup \{(H,H),(H,M),(M,M)\}$.
   $$\widetilde{s_0} = \sum_{i=1}^{NS} w_i \frac{e^{-\xi}}{\exp^{-\xi} + \sum_{k \in \tilde{A}} e^{\hat{d_k} + \sum_l \widehat{\sigma}_l \nu_{il} x_{kl}}}$$
   (d) Use observed random coefficients demand parameters $(\widehat{d_j}, \widehat{\sigma})$ and quadrature nodes $(w_i, \nu_i)$ to calculate purchase probabilities of a single consumer for current inventory/assortment $A_t$:
   $$s_{jt}(A_t) = \sum_{i=1}^{NS} w_i \frac{e^{\hat{d_j} + \sum_l \widehat{\sigma}_l \nu_{il} x_{jl}}}{\exp^{-\xi} + \sum_{k \in A_t} e^{\hat{d_k} + \sum_l \widehat{\sigma}_l \nu_{il} x_{kl}}}$$
   (e) Draw a single consumer purchase as $y_t$, a $(J+1)$ vector with re-normalized outside good probability.
   $$y_t \sim Multinom\left(\frac{s_{jt}(A_t)}{1 - \widetilde{s_0}}, s_0(A_t) - \widetilde{s_0}\right)$$
   (f) Update $A_{t+1} = A_t - y_t$ or $A_{t+1} = A_t$ if outside good is chosen.
   (g) Continue for $t = 1, \ldots, 800$ consumers or (until machine is empty $A_t = \emptyset$).
   (h) Repeat for $N = 1, \ldots N = 100\,000$ machines to construct $y_{nt}$: 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 $x$:
   $$u^R(x,a) = \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{x} y_{nt} \cdot (p_r - w)$$
   $$u^M(x,a) = \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{x} y_{nt} \cdot I_{nt}[\text{Mars}] \cdot (w_m - mc)$$
   $$u^H(x,a) = \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{x} y_{nt} \cdot I_{nt}[\text{Hershey}] \cdot (w_m - mc)$$
   $$u^C(x,a) = \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{x} \log\left(1 + \sum_{j \in A_t} \exp\left[\hat{y_k} + \xi + \sum_l \widehat{\sigma}_l \nu_{il} x_{kl}\right]\right)$$
   (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 Transition Probability Matrix

1. For each machine-visit in the top quartile of all snack machines in the MarkVend enterprise, construct a sample of:
   (a) Average Daily Sales $b_i$.
   (b) Elapsed Sales at Restocking $\overline{x}_i$.
2. Estimate the transition matrix using the empirical distribution $\hat{g}(b)$

$$\hat{g}(b_k) = \frac{1}{I}\sum_{i=1}^{I} \mathbf{1}[b_i = b_k]$$

   at points $k \in \mathcal{K}$ of the support.

   (a) Optional: adjust $\hat{g}(b_k)$ above to incorporate outside good share:

$$c = \int_{t=0}^{t=\overline{x}_i} \frac{1}{1-(s_0(A_t)-\tilde{s}_0)} h(A_t)dt$$

   (b) Choose weights $w_k$ to solve:

$$\min \sum_{k\in\mathcal{K}} (w_k - \hat{g}(b_k))^2 \quad \text{s.t} \quad c \cdot \sum_{k\in\mathcal{K}} b_k \cdot \hat{g}(b_k) = \sum_{k\in\mathcal{K}} b_k \cdot w_k \quad \sum_{k\in\mathcal{K}} w_k = 1 \quad w_k \geq 0.$$

   (c) In practice $c \in [1.00, 1.02]$ and the adjusted weights $w_k$ are imperceptibly different from $\hat{g}(b_k)$
3. Use $w_k$ to construct the transition matrix $P(x + \Delta x_k|x) = w_k$.

**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 $\beta$ 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 $\beta$ 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 7). 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.3 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 (1), 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 $\alpha$ is not separately identified from the product fixed-effect $\delta_j$. If $\alpha$ were identified, then we could simply write $CS(a,e) = \frac{1}{\alpha} CS^*(a,e)$. Instead, we can calibrate $\alpha$ 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 $\alpha$ 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 $\alpha$ as $\alpha = |\frac{\epsilon}{\overline{\epsilon}(\theta)}|$. We then calculate $\alpha$ at three different values of $\epsilon$: $\epsilon \in \{-1, -2, -4\}$.

As is well known, $\alpha$ 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.

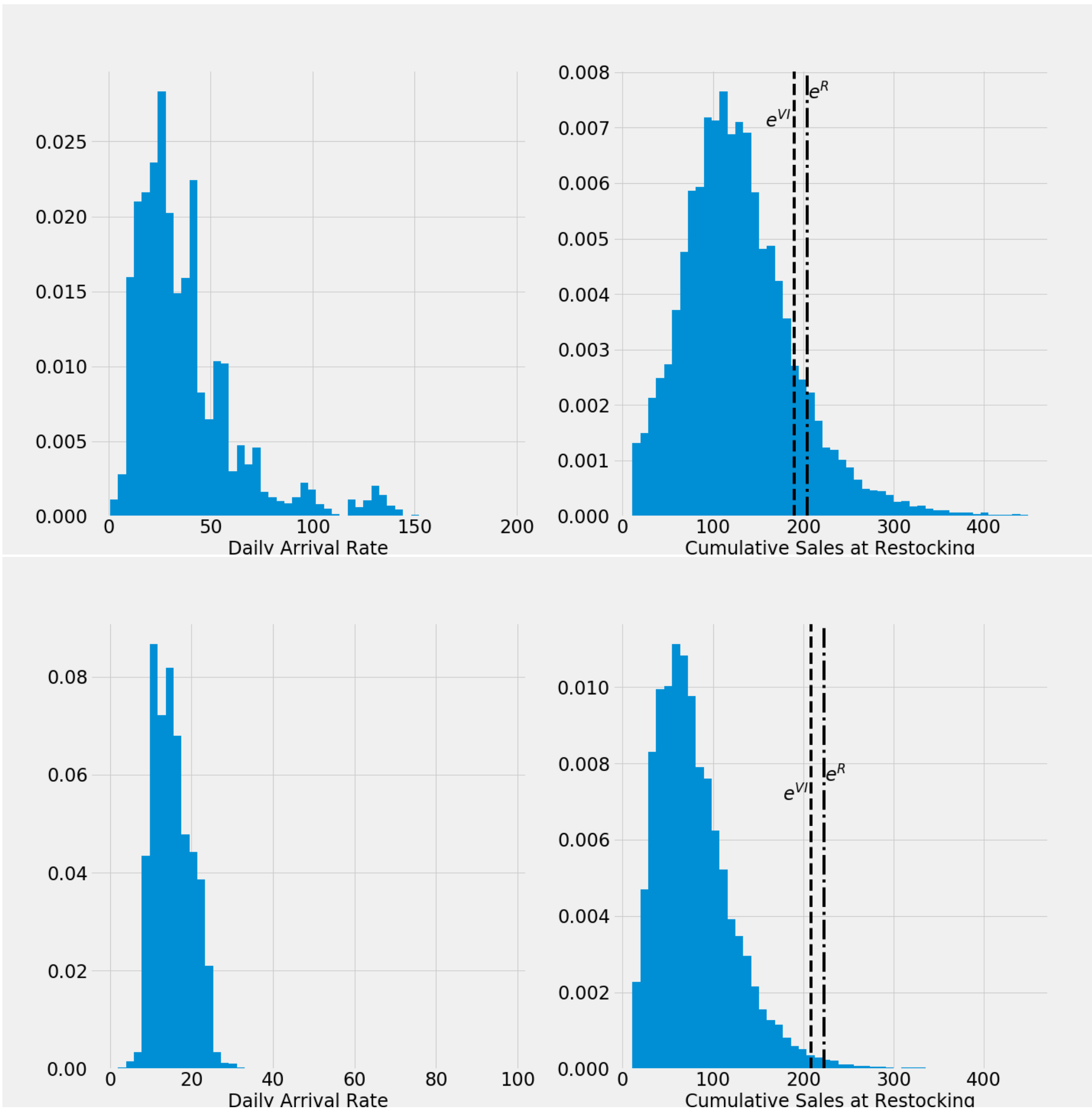
We consider a broad array of alternatives: changing the arrival rate of consumers; setting the marginal cost to zero and maximizing potential efficiencies; increasing or decreasing the fixed cost of restocking; and having the retailer place some weight on consumer surplus when making decisions.

## 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 A2 we replicate figure 3 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.

Figure A2: 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.

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 A2 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 A2: Net Effect of Efficiency and Foreclosure (Middle 50% of Machines)

| from | (H,M) and $e^{NR}$ | | | (H,H) and $e^{NR}$ | | |
|---|---|---|---|---|---|---|
| | $e^{R}$ | $e^{VI}$ | $e^{SOC}$ | $e^{R}$ | $e^{VI}$ | $e^{SOC}$ |
| $\Delta\pi^{R}$ | -299 | -346 | -566 | -638 | -684 | -904 |
| $\Delta\pi^{M}$ | 1048 | 1127 | 1238 | 2350 | 2430 | 2540 |
| $\Delta\pi^{H}$ | -909 | -909 | -909 | -1520 | -1520 | -1520 |
| $\Delta\pi^{N}$ | 0 | -2 | -3 | -19 | -20 | -21 |
| $\Delta PS$ | -160 | -129 | -239 | 175 | 206 | 96 |
| $\Delta CS(\epsilon=-2)$ | -106 | 70 | 322 | 211 | 386 | 638 |
| $\Delta SS$ | -266 | -59 | 83 | 385 | 592 | 734 |
| $\lambda\pi^{M}$ | 2321 | 2338 | 2363 | 2321 | 2338 | 2363 |
| $w_h$ to avoid foreclosure | -18.96 | -18.09 | -12.12 | 12.02 | 12.54 | 16.11 |
| Reduced $\lambda$ (Percent) | 47.93 | 46.35 | 37.60 | 7.04 | 5.76 | -2.57 |

Notes: Consumer Surplus calibrates $\alpha$ 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 A.4.

We tried alternative assumptions on the arrival rate by either doubling or halving the 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 A3 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 A3: Net Effect of Efficiency and Foreclosure ($MC = 0$)

| from | (H,M) and $e^{NR}$ | | | (H,H) and $e^{NR}$ | | |
|---|---|---|---|---|---|---|
| | $e^R$ | $e^{VI}$ | $e^{SOC}$ | $e^R$ | $e^{VI}$ | $e^{SOC}$ |
| $\Delta\pi^R$ | -731 | -929 | -1465 | -1528 | -1725 | -2261 |
| $\Delta\pi^M$ | 3615 | 3982 | 4292 | 7853 | 8220 | 8530 |
| $\Delta\pi^H$ | -3367 | -3367 | -3367 | -5622 | -5622 | -5622 |
| $\Delta\pi^N$ | -4 | -11 | -13 | -68 | -76 | -77 |
| $\Delta PS$ | -486 | -324 | -552 | 634 | 796 | 569 |
| $\Delta CS(\epsilon = -2)$ | -23 | 195 | 384 | 199 | 416 | 606 |
| $\Delta SS$ | -509 | -130 | -167 | 833 | 1213 | 1175 |
| $\lambda\pi^M$ | 5544 | 5603 | 5653 | 5544 | 5603 | 5653 |
| $w_h$ to avoid foreclosure | -18.37 | -16.60 | -10.43 | 12.21 | 13.27 | 16.96 |
| Reduced $\lambda$ (Percent) | 47.39 | 44.42 | 35.43 | 6.62 | 4.07 | -4.56 |

Notes: Consumer Surplus calibrates $\alpha$ 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 A.4.

## C.3 Robustness to Alternative Fixed Costs

We reproduce the 'net effects' from the text as tables A4 and table A5 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 table 13, though for $FC = 15$ the sign flips on $\Delta CS$ 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 A4: Net Effect of Efficiency and Foreclosure ($FC = 5$)

| from | (H,M) and $e^{NR}$ | | | (H,H) and $e^{NR}$ | | |
|---|---|---|---|---|---|---|
| | $e^{R}$ | $e^{VI}$ | $e^{SOC}$ | $e^{R}$ | $e^{VI}$ | $e^{SOC}$ |
| $\Delta\pi^{R}$ | -656 | -698 | -948 | -1599 | -1640 | -1891 |
| $\Delta\pi^{M}$ | 2527 | 2600 | 2719 | 5527 | 5600 | 5719 |
| $\Delta\pi^{H}$ | -2173 | -2173 | -2173 | -3635 | -3635 | -3635 |
| $\Delta\pi^{N}$ | 2 | 3 | 8 | -44 | -43 | -38 |
| $\Delta PS$ | -299 | -267 | -394 | 249 | 281 | 155 |
| $\Delta CS(\epsilon = -2)$ | -186 | -12 | 285 | 429 | 602 | 900 |
| $\Delta SS$ | -486 | -280 | -109 | 678 | 884 | 1055 |
| $\lambda\pi^{M}$ | 5667 | 5684 | 5710 | 5667 | 5684 | 5710 |
| $w_h$ to avoid foreclosure | -21.25 | -20.93 | -18.07 | 11.69 | 11.89 | 13.60 |
| Reduced $\lambda$ (Percent) | 50.08 | 49.50 | 45.35 | 7.64 | 7.18 | 3.22 |

Notes: Consumer Surplus calibrates $\alpha$ 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 A.4.

Table A5: Net Effect of Efficiency and Foreclosure ($FC = 15$)

| from | (H,M) and $e^{NR}$ | | | (H,H) and $e^{NR}$ | | |
|---|---|---|---|---|---|---|
| | $e^R$ | $e^{VI}$ | $e^{SOC}$ | $e^R$ | $e^{VI}$ | $e^{SOC}$ |
| $\Delta\pi^R$ | -746 | -831 | -1648 | -1498 | -1584 | -2401 |
| $\Delta\pi^M$ | 2488 | 2588 | 3009 | 5657 | 5757 | 6178 |
| $\Delta\pi^H$ | -2192 | -2192 | -2192 | -3663 | -3663 | -3663 |
| $\Delta\pi^N$ | 0 | -3 | -12 | -44 | -47 | -56 |
| $\Delta PS$ | -449 | -437 | -843 | 451 | 463 | 58 |
| $\Delta CS(\epsilon = -2)$ | -334 | -116 | 811 | 447 | 665 | 1592 |
| $\Delta SS$ | -783 | -554 | -32 | 898 | 1128 | 1650 |
| $\lambda\pi^M$ | 5472 | 5494 | 5588 | 5472 | 5494 | 5588 |
| $w_h$ to avoid foreclosure | -17.07 | -16.27 | -7.11 | 12.65 | 13.13 | 18.61 |
| Reduced $\lambda$ (Percent) | 46.31 | 44.97 | 31.26 | 5.67 | 4.50 | -8.53 |

Notes: Consumer Surplus calibrates $\alpha$ 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 A.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 3 of $e \approx 130$.

Table A6 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 A6: 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 | 128 | 129 | 0.00 | 0.00 | 0.00 |
| $e^{R}$ | 129 | 127 | 128 | 0.77 | 0.78 | 0.78 |
| $e^{VI}$ | 128 | 126 | 127 | 1.54 | 1.56 | 1.55 |
| $e^{IND}$ | 127 | 125 | 126 | 2.31 | 2.34 | 2.33 |
| $e^{SOC}$ | 172 | 168 | 171 | 164.62 | 168.75 | 165.89 |
| $e^{SOC1}$ | 158 | 154 | 156 | 175.38 | 179.69 | 177.52 |
| $e^{SOC4}$ | 183 | 178 | 181 | 156.15 | 160.94 | 158.14 |

Notes: Reported for retailer who places weight $\frac{\gamma}{\alpha} = 6$ on consumer surplus. For further details, see Appendix A.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 sets 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 A7: Net Effect of Efficiency and Foreclosure

| from | (H,M) and $e^{NR}$ | | | (H,H) and $e^{NR}$ | | |
|---|---|---|---|---|---|---|
| | $e^R$ | $e^{VI}$ | $e^{SOC}$ | $e^R$ | $e^{VI}$ | $e^{SOC}$ |
| $\Delta\pi^R$ | -780 | -866 | 1625 | -1658 | -1743 | 748 |
| $\Delta\pi^M$ | 2496 | 2501 | 2178 | 5498 | 5503 | 5180 |
| $\Delta\pi^H$ | -2180 | -2180 | -2180 | -3646 | -3646 | -3646 |
| $\Delta\pi^N$ | 3 | 3 | -5 | -45 | -45 | -53 |
| $\Delta PS$ | -461 | -541 | 1618 | 149 | 69 | 2228 |
| $\Delta CS(\epsilon = -2)$ | -247 | -234 | -1021 | 424 | 437 | -350 |
| $\Delta SS$ | -709 | -775 | 597 | 572 | 506 | 1878 |
| $\lambda\pi^M$ | 5718 | 5719 | 5647 | 5718 | 5719 | 5647 |
| $w_h$ to avoid foreclosure | -20.1 | -19.02 | -49.81 | 11.85 | 12.49 | -5.92 |
| Reduced $\lambda$ (Percent) | 48.23 | 46.74 | 90.18 | 7.24 | 5.76 | 48.68 |

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

## C.5 Restricting to Uniform Prices

Our baseline analysis has been that, absent the rebate contract, wholesale prices would remain fixed at pre-rebate levels. However, one might want to understand what might happen if manufacturers were restricted to uniform prices, but could respond optimally, absent the AUD contract. This is more difficult than it looks because the retailer makes a discrete decision to switch assortments, and this means that manufacturer best responses are discontinuous. It turns out that these discontinuities imply that best response curves never cross. Thus, there is no pure strategy Nash Equilibria in uniform prices. In fact, we plot the full payoffs in figure A3 and best responses in figure A4 and show they don't cross.

We analyze the game two ways: one in which Mars is restricted to a uniform price on all products (similar to its observed behavior) and another where Mars' prices are fixed at the observed level on its main products, but are allowed to set a uniform price on its two 'marginal' products (3 Musketeers and Milky Way). When Hershey is allowed to best respond, both cases involve best response curves which do not cross. We restrict the set of wholesale prices to lie between the pre-rebate prices observed in the data and the 15 cent marginal cost. We report the strategies of Mars and Hershey below on a discrete grid of one cent price increments.[70] We demonstrate in the following figures. In figure A3, we plot the payoffs of both Mars and Hershey under various uniform wholesale prices under both of our two scenarios. In all four plots, there are three distinct regions corresponding to the retailer's choice of assortment: the upper left where the retailer chooses $(M,M)$, the bottom right where the retailer chooses $(H,H)$ and the middle where the retailer chooses $(H,M)$.

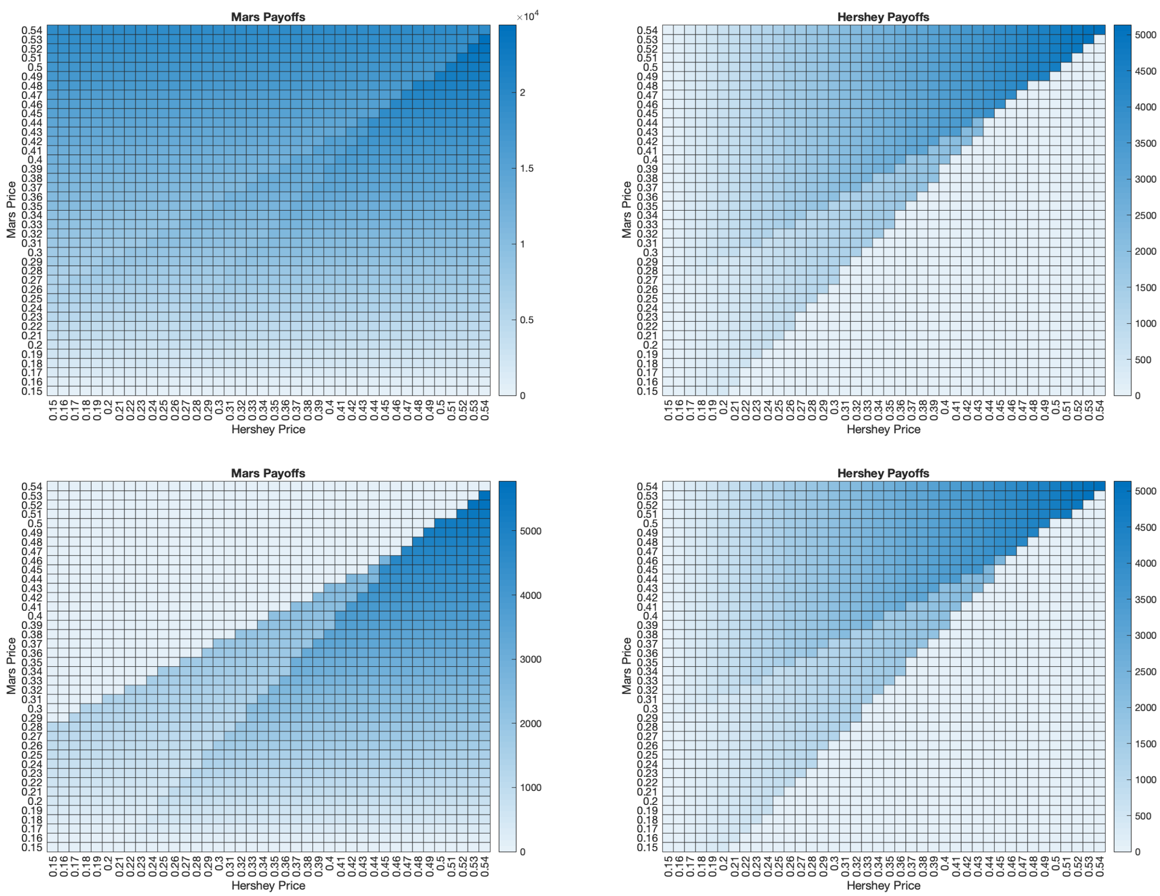
We examine best responses more carefully in the left panel of figure A4. In the first case, where Mars sets a single wholesale price for all products, but the retailer selects among $(H,H)$,$(H,M)$,$(M,M)$ as in the rest of the paper, the best response curves do not cross. They run in parallel from the top right, mirroring the Bertrand result where each manufacturer undercuts the other by a small amount. However, when Hershey reaches the wholesale price of 0.45, Mars finds it better to increase its wholesale price (back to the pre-rebate level) rather than continue to undercut and allow the retailer to adopt the $(H,H)$ assortment. If Hershey could commit to not pricing above 45 cents this would constitute an equilibrium at $(H,H)$ and $e^{NR}$, absent that commitment, there is a 'cycle' in best responses.

In right panel of figure A4, Mars keeps the wholesale price of its main products fixed at the pre-rebate level and adjusts only the prices of MilkyWay and 3 Musketeers. Again towards

[70] We have solved these on finer grids, and continuously, and have obtained similar results. We use the discrete grid for presentation purposes only.

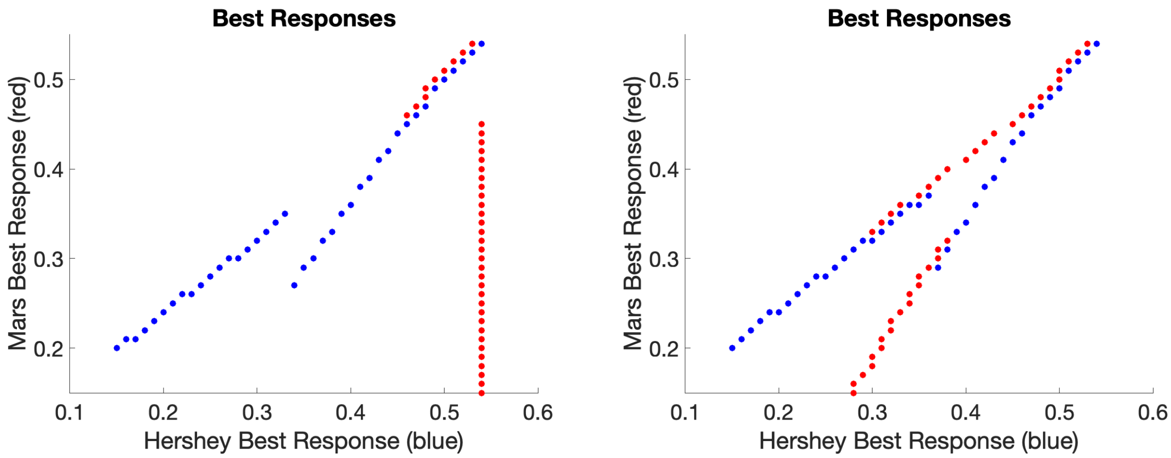
the top right, we see Bertrand-like behavior, where one firm undercuts its rival and induces the retailer to switch back and forth between ($M$,$M$) and ($H$,$H$). However, around 45 cents, the best responses diverge. Now Hershey tries to keep the retailer indifferent between ($H$,$M$) and ($H$,$H$) while Mars tries to keep the retailer indifferent between ($H$,$M$) and ($M$,$M$). As wholesale prices decline further, this relationship inverts, with Mars keeping the retailer indifferent between ($H$,$H$) and ($H$,$M$) and Hershey keeping the retailer indifferent between ($H$,$M$) and ($M$,$M$). Again, following best-responses leads to a cycle. Here the range of prices in the cycle are $\max(w_m, w_h) = (0.38, 0.37)$ and $\min(w_m, w_h) = (0.30, 0.29)$ all of which are much lower than the post-rebate prices charged by Mars, though they apply on the least popular products.

Figure A3: Payoffs under Uniform Wholesale Prices




Notes: Payoffs under uniform wholesale prices. Top row: Mars sets a uniform price on all products; Mars profits reported for all products. Bottom row: Mars sets a uniform price only on marginal products (3 Musketeers and Milky Way); Mars profits reported only for marginal products.

Figure A4: Best Responses under Uniform Wholesale Prices




Notes: Best Responses under uniform wholesale prices. Left: Mars sets a uniform price on all products. Right: Mars sets a uniform price only on marginal products (3 Musketeers and Milky Way). In neither case do best responses cross.

# 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 | $\pi^R$ | $\lambda\pi^M$ | $\pi^M$ | $\pi^H$ | $\pi^N$ | $\pi^R + \pi^M$ | PS | CS |
|---|---|---|---|---|---|---|---|---|
| (H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers | | | | | | | | |
| $e^{NR}$(217) | 94,735 | 4,967 | 22,373 | 2,185 | 2,147 | 117,108 | 121,440 | 65,499 |
| $e^{R}$(211) | 94,726 | 4,987 | 22,464 | 2,183 | 2,145 | 117,190 | 121,517 | 65,693 |
| $e^{VI}$(196) | 94,603 | 5,033 | 22,672 | 2,177 | 2,140 | 117,274 | 121,592 | 66,140 |
| $e^{IND}$(197) | 94,615 | 5,030 | 22,659 | 2,177 | 2,141 | 117,274 | 121,592 | 66,112 |
| $e^{SOC}$(172) | 94,064 | 5,094 | 22,945 | 2,173 | 2,137 | 117,009 | 121,319 | 66,744 |
| $e^{SOC1}$(158) | 93,520 | 5,122 | 23,071 | 2,173 | 2,138 | 116,591 | 120,902 | 67,033 |
| $e^{SOC4}$(183) | 94,368 | 5,068 | 22,829 | 2,174 | 2,138 | 117,197 | 121,509 | 66,484 |
| (H,H) Assortment: Reeses Peanut Butter Cup and Payday | | | | | | | | |
| $e^{NR}$(212) | 95,532 | 4,289 | 19,318 | 3,650 | 2,190 | 114,850 | 120,689 | 64,899 |
| $e^{R}$(206) | 95,521 | 4,311 | 19,418 | 3,646 | 2,188 | 114,939 | 120,772 | 65,092 |
| $e^{VI}$(191) | 95,390 | 4,361 | 19,645 | 3,639 | 2,184 | 115,035 | 120,858 | 65,536 |
| $e^{IND}$(192) | 95,404 | 4,358 | 19,631 | 3,639 | 2,184 | 115,034 | 120,858 | 65,508 |
| $e^{SOC}$(168) | 94,858 | 4,424 | 19,930 | 3,635 | 2,183 | 114,788 | 120,606 | 66,109 |
| $e^{SOC1}$(154) | 94,298 | 4,455 | 20,067 | 3,636 | 2,184 | 114,365 | 120,186 | 66,396 |
| $e^{SOC4}$(178) | 95,143 | 4,399 | 19,815 | 3,636 | 2,183 | 114,959 | 120,777 | 65,876 |
| (M,M) Assortment: Three Musketeers and Milkyway | | | | | | | | |
| $e^{NR}$(214) | 94,012 | 5,529 | 24,905 | 0 | 2,147 | 118,917 | 121,063 | 65,275 |
| $e^{R}$(209) | 94,004 | 5,545 | 24,979 | 0 | 2,145 | 118,982 | 121,127 | 65,438 |
| $e^{VI}$(195) | 93,895 | 5,588 | 25,169 | 0 | 2,141 | 119,064 | 121,205 | 65,860 |
| $e^{IND}$(195) | 93,895 | 5,588 | 25,169 | 0 | 2,141 | 119,064 | 121,205 | 65,860 |
| $e^{SOC}$(171) | 93,371 | 5,647 | 25,438 | 0 | 2,139 | 118,808 | 120,947 | 66,473 |
| $e^{SOC1}$(156) | 92,783 | 5,677 | 25,570 | 0 | 2,140 | 118,354 | 120,494 | 66,786 |
| $e^{SOC4}$(181) | 93,646 | 5,624 | 25,335 | 0 | 2,139 | 118,980 | 121,120 | 66,234 |

Table A8: 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 | $\pi^R$ | $\lambda\pi^M$ | $\pi^M$ | $\pi^H$ | $\pi^N$ | $\pi^R + \pi^M$ | PS | CS |
|---|---|---|---|---|---|---|---|---|
| (H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers | | | | | | | | |
| $e^{NR}$(217) | 94,735 | 4,966 | 31,037 | 3,367 | 3,258 | 125,773 | 132,397 | 65,499 |
| $e^{R}$(211) | 94,726 | 4,986 | 31,164 | 3,362 | 3,254 | 125,890 | 132,507 | 65,693 |
| $e^{VI}$(191) | 94,527 | 5,046 | 31,540 | 3,352 | 3,246 | 126,067 | 132,665 | 66,277 |
| $e^{IND}$(192) | 94,544 | 5,044 | 31,523 | 3,352 | 3,246 | 126,066 | 132,665 | 66,251 |
| $e^{SOC}$(169) | 93,963 | 5,099 | 31,872 | 3,347 | 3,243 | 125,835 | 132,425 | 66,809 |
| $e^{SOC1}$(156) | 93,426 | 5,125 | 32,028 | 3,349 | 3,244 | 125,454 | 132,047 | 67,071 |
| $e^{SOC4}$(179) | 94,269 | 5,077 | 31,731 | 3,348 | 3,243 | 126,001 | 132,592 | 66,582 |
| (H,H) Assortment: Reeses Peanut Butter Cup and Payday | | | | | | | | |
| $e^{NR}$(212) | 95,532 | 4,288 | 26,800 | 5,622 | 3,323 | 122,332 | 131,277 | 64,899 |
| $e^{R}$(206) | 95,521 | 4,310 | 26,938 | 5,617 | 3,320 | 122,459 | 131,395 | 65,092 |
| $e^{VI}$(185) | 95,293 | 4,379 | 27,367 | 5,603 | 3,312 | 122,659 | 131,575 | 65,698 |
| $e^{IND}$(186) | 95,311 | 4,376 | 27,348 | 5,604 | 3,313 | 122,659 | 131,575 | 65,672 |
| $e^{SOC}$(165) | 94,755 | 4,431 | 27,693 | 5,600 | 3,312 | 122,447 | 131,359 | 66,175 |
| $e^{SOC1}$(152) | 94,201 | 4,458 | 27,863 | 5,603 | 3,315 | 122,064 | 130,982 | 66,434 |
| $e^{SOC4}$(174) | 95,040 | 4,409 | 27,556 | 5,600 | 3,311 | 122,596 | 131,507 | 65,972 |
| (M,M) Assortment: Three Musketeers and Milkyway | | | | | | | | |
| $e^{NR}$(214) | 94,012 | 5,528 | 34,550 | 0 | 3,257 | 128,562 | 131,819 | 65,275 |
| $e^{R}$(209) | 94,004 | 5,544 | 34,653 | 0 | 3,254 | 128,657 | 131,911 | 65,438 |
| $e^{VI}$(189) | 93,806 | 5,603 | 35,019 | 0 | 3,247 | 128,826 | 132,073 | 66,026 |
| $e^{IND}$(190) | 93,823 | 5,600 | 35,003 | 0 | 3,247 | 128,826 | 132,073 | 65,999 |
| $e^{SOC}$(168) | 93,271 | 5,653 | 35,330 | 0 | 3,245 | 128,600 | 131,846 | 66,539 |
| $e^{SOC1}$(154) | 92,687 | 5,679 | 35,496 | 0 | 3,248 | 128,183 | 131,430 | 66,824 |
| $e^{SOC4}$(177) | 93,546 | 5,633 | 35,206 | 0 | 3,245 | 128,752 | 131,997 | 66,332 |

Table A9: 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 | $\pi^R$ | $\lambda\pi^M$ | $\pi^M$ | $\pi^H$ | $\pi^N$ | $\pi^R + \pi^M$ | PS | CS |
|---|---|---|---|---|---|---|---|---|
| (H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers | | | | | | | | |
| $e^{NR}$(230) | 39,593 | 2,088 | 9,405 | 909 | 893 | 48,997 | 50,800 | 27,472 |
| $e^{R}$(230) | 39,593 | 2,088 | 9,405 | 909 | 893 | 48,997 | 50,800 | 27,472 |
| $e^{VI}$(216) | 39,546 | 2,106 | 9,486 | 906 | 891 | 49,031 | 50,829 | 27,646 |
| $e^{IND}$(216) | 39,546 | 2,106 | 9,486 | 906 | 891 | 49,031 | 50,829 | 27,646 |
| $e^{SOC}$(192) | 39,327 | 2,131 | 9,599 | 904 | 890 | 48,927 | 50,721 | 27,897 |
| $e^{SOC1}$(178) | 39,105 | 2,143 | 9,651 | 905 | 890 | 48,756 | 50,551 | 28,016 |
| $e^{SOC4}$(202) | 39,441 | 2,121 | 9,556 | 905 | 890 | 48,997 | 50,793 | 27,799 |
| (H,H) Assortment: Reeses Peanut Butter Cup and Payday | | | | | | | | |
| $e^{NR}$(230) | 39,931 | 1,799 | 8,103 | 1,520 | 912 | 48,034 | 50,465 | 27,156 |
| $e^{R}$(225) | 39,926 | 1,806 | 8,137 | 1,518 | 911 | 48,064 | 50,493 | 27,223 |
| $e^{VI}$(210) | 39,871 | 1,828 | 8,232 | 1,515 | 909 | 48,103 | 50,528 | 27,407 |
| $e^{IND}$(211) | 39,877 | 1,826 | 8,226 | 1,515 | 910 | 48,103 | 50,528 | 27,395 |
| $e^{SOC}$(188) | 39,662 | 1,853 | 8,346 | 1,514 | 909 | 48,008 | 50,430 | 27,634 |
| $e^{SOC1}$(174) | 39,434 | 1,865 | 8,402 | 1,514 | 910 | 47,836 | 50,260 | 27,752 |
| $e^{SOC4}$(197) | 39,768 | 1,843 | 8,303 | 1,514 | 909 | 48,071 | 50,494 | 27,547 |
| (M,M) Assortment: Three Musketeers and Milkyway | | | | | | | | |
| $e^{NR}$(230) | 39,296 | 2,318 | 10,441 | 0 | 894 | 49,736 | 50,630 | 27,340 |
| $e^{R}$(228) | 39,293 | 2,321 | 10,453 | 0 | 893 | 49,746 | 50,640 | 27,367 |
| $e^{VI}$(214) | 39,247 | 2,338 | 10,532 | 0 | 892 | 49,779 | 50,671 | 27,542 |
| $e^{IND}$(214) | 39,247 | 2,338 | 10,532 | 0 | 892 | 49,779 | 50,671 | 27,542 |
| $e^{SOC}$(190) | 39,027 | 2,363 | 10,643 | 0 | 891 | 49,670 | 50,561 | 27,794 |
| $e^{SOC1}$(176) | 38,801 | 2,374 | 10,693 | 0 | 891 | 49,494 | 50,385 | 27,914 |
| $e^{SOC4}$(200) | 39,142 | 2,353 | 10,601 | 0 | 891 | 49,743 | 50,634 | 27,696 |

Table A10: 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 | $\pi^R$ | $\lambda\pi^M$ | $\pi^M$ | $\pi^H$ | $\pi^N$ | $\pi^R + \pi^M$ | PS | CS |
|---|---|---|---|---|---|---|---|---|
| (H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers | | | | | | | | |
| $e^{NR}(166)$ | 101,101 | 5,106 | 23,002 | 2,173 | 2,137 | 124,103 | 128,413 | 66,873 |
| $e^{R}(163)$ | 101,098 | 5,112 | 23,029 | 2,173 | 2,138 | 124,126 | 128,437 | 66,935 |
| $e^{VI}(154)$ | 101,057 | 5,129 | 23,103 | 2,174 | 2,139 | 124,159 | 128,472 | 67,108 |
| $e^{IND}(153)$ | 101,049 | 5,130 | 23,110 | 2,174 | 2,139 | 124,159 | 128,472 | 67,127 |
| $e^{SOC}(135)$ | 100,791 | 5,157 | 23,231 | 2,179 | 2,143 | 124,022 | 128,343 | 67,421 |
| $e^{SOC1}(123)$ | 100,474 | 5,172 | 23,296 | 2,183 | 2,146 | 123,770 | 128,099 | 67,587 |
| $e^{SOC4}(143)$ | 100,936 | 5,146 | 23,180 | 2,176 | 2,141 | 124,117 | 128,434 | 67,296 |
| (H,H) Assortment: Reeses Peanut Butter Cup and Payday | | | | | | | | |
| $e^{NR}(161)$ | 102,044 | 4,440 | 20,002 | 3,635 | 2,183 | 122,046 | 127,864 | 66,259 |
| $e^{R}(158)$ | 102,041 | 4,447 | 20,031 | 3,636 | 2,184 | 122,071 | 127,891 | 66,319 |
| $e^{VI}(148)$ | 101,990 | 4,466 | 20,117 | 3,638 | 2,186 | 122,107 | 127,931 | 66,506 |
| $e^{IND}(148)$ | 101,990 | 4,466 | 20,117 | 3,638 | 2,186 | 122,107 | 127,931 | 66,506 |
| $e^{SOC}(131)$ | 101,737 | 4,493 | 20,239 | 3,645 | 2,191 | 121,976 | 127,812 | 66,779 |
| $e^{SOC1}(120)$ | 101,443 | 4,507 | 20,303 | 3,651 | 2,196 | 121,746 | 127,592 | 66,930 |
| $e^{SOC4}(138)$ | 101,870 | 4,483 | 20,192 | 3,641 | 2,189 | 122,062 | 127,892 | 66,672 |
| (M,M) Assortment: Three Musketeers and Milkyway | | | | | | | | |
| $e^{NR}(164)$ | 100,447 | 5,662 | 25,503 | 0 | 2,139 | 125,950 | 128,090 | 66,625 |
| $e^{R}(161)$ | 100,445 | 5,667 | 25,529 | 0 | 2,139 | 125,974 | 128,113 | 66,687 |
| $e^{VI}(152)$ | 100,403 | 5,684 | 25,601 | 0 | 2,141 | 126,005 | 128,146 | 66,861 |
| $e^{IND}(152)$ | 100,403 | 5,684 | 25,601 | 0 | 2,141 | 126,005 | 128,146 | 66,861 |
| $e^{SOC}(134)$ | 100,153 | 5,710 | 25,721 | 0 | 2,145 | 125,874 | 128,019 | 67,158 |
| $e^{SOC1}(122)$ | 99,835 | 5,725 | 25,787 | 0 | 2,149 | 125,622 | 127,772 | 67,327 |
| $e^{SOC4}(142)$ | 100,295 | 5,699 | 25,671 | 0 | 2,143 | 125,966 | 128,109 | 67,032 |

Table A11: 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 | $\pi^R$ | $\lambda\pi^M$ | $\pi^M$ | $\pi^H$ | $\pi^N$ | $\pi^R + \pi^M$ | PS | CS |
|---|---|---|---|---|---|---|---|---|
| (H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers | | | | | | | | |
| $e^{NR}(230)$ | 89,247 | 4,919 | 22,159 | 2,192 | 2,153 | 111,407 | 115,752 | 65,049 |
| $e^{R}(230)$ | 89,247 | 4,919 | 22,159 | 2,192 | 2,153 | 111,407 | 115,752 | 65,049 |
| $e^{VI}(226)$ | 89,187 | 4,934 | 22,227 | 2,190 | 2,151 | 111,414 | 115,756 | 65,192 |
| $e^{IND}(227)$ | 89,203 | 4,931 | 22,211 | 2,191 | 2,152 | 111,414 | 115,756 | 65,157 |
| $e^{SOC}(197)$ | 88,376 | 5,030 | 22,659 | 2,177 | 2,141 | 111,035 | 115,353 | 66,112 |
| $e^{SOC1}(180)$ | 87,541 | 5,075 | 22,862 | 2,173 | 2,138 | 110,403 | 114,714 | 66,558 |
| $e^{SOC4}(209)$ | 88,797 | 4,993 | 22,493 | 2,182 | 2,144 | 111,290 | 115,616 | 65,756 |
| (H,H) Assortment: Reeses Peanut Butter Cup and Payday | | | | | | | | |
| $e^{NR}(230)$ | 90,000 | 4,216 | 18,991 | 3,663 | 2,198 | 108,991 | 114,851 | 64,268 |
| $e^{R}(230)$ | 90,000 | 4,216 | 18,991 | 3,663 | 2,198 | 108,991 | 114,851 | 64,268 |
| $e^{VI}(220)$ | 89,855 | 4,257 | 19,178 | 3,655 | 2,193 | 109,033 | 114,881 | 64,629 |
| $e^{IND}(221)$ | 89,873 | 4,253 | 19,160 | 3,656 | 2,194 | 109,033 | 114,882 | 64,594 |
| $e^{SOC}(193)$ | 89,063 | 4,355 | 19,616 | 3,640 | 2,184 | 108,679 | 114,503 | 65,480 |
| $e^{SOC1}(176)$ | 88,206 | 4,404 | 19,839 | 3,635 | 2,183 | 108,045 | 113,863 | 65,924 |
| $e^{SOC4}(205)$ | 89,493 | 4,314 | 19,434 | 3,645 | 2,188 | 108,927 | 114,760 | 65,124 |
| (M,M) Assortment: Three Musketeers and Milkyway | | | | | | | | |
| $e^{NR}(230)$ | 88,502 | 5,472 | 24,648 | 0 | 2,153 | 113,150 | 115,303 | 64,715 |
| $e^{R}(230)$ | 88,502 | 5,472 | 24,648 | 0 | 2,153 | 113,150 | 115,303 | 64,715 |
| $e^{VI}(224)$ | 88,416 | 5,494 | 24,748 | 0 | 2,151 | 113,164 | 115,315 | 64,933 |
| $e^{IND}(225)$ | 88,432 | 5,490 | 24,732 | 0 | 2,151 | 113,164 | 115,315 | 64,897 |
| $e^{SOC}(195)$ | 87,599 | 5,588 | 25,169 | 0 | 2,141 | 112,768 | 114,909 | 65,860 |
| $e^{SOC1}(178)$ | 86,752 | 5,631 | 25,367 | 0 | 2,139 | 112,119 | 114,258 | 66,308 |
| $e^{SOC4}(207)$ | 88,024 | 5,552 | 25,007 | 0 | 2,144 | 113,032 | 115,176 | 65,501 |

Table A12: 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 | $\pi^R$ | $\lambda\pi^M$ | $\pi^M$ | $\pi^H$ | $\pi^N$ | $\pi^R + \pi^M$ | PS | CS |
|---|---|---|---|---|---|---|---|---|
| (H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers | | | | | | | | |
| $e^{NR}$(130) | 91,745 | 5,164 | 23,260 | 2,180 | 2,144 | 115,005 | 119,329 | 67,494 |
| $e^{R}$(129) | 91,660 | 5,165 | 23,265 | 2,181 | 2,144 | 114,926 | 119,251 | 67,508 |
| $e^{VI}$(128) | 91,575 | 5,166 | 23,271 | 2,181 | 2,145 | 114,846 | 119,172 | 67,522 |
| $e^{IND}$(127) | 91,489 | 5,167 | 23,276 | 2,181 | 2,145 | 114,765 | 119,091 | 67,535 |
| $e^{SOC}$(172) | 94,064 | 5,094 | 22,945 | 2,173 | 2,137 | 117,009 | 121,319 | 66,744 |
| $e^{SOC1}$(158) | 93,520 | 5,122 | 23,071 | 2,173 | 2,138 | 116,591 | 120,902 | 67,033 |
| $e^{SOC4}$(183) | 94,368 | 5,068 | 22,829 | 2,174 | 2,138 | 117,197 | 121,509 | 66,484 |
| (H,H) Assortment: Reeses Peanut Butter Cup and Payday | | | | | | | | |
| $e^{NR}$(128) | 92,623 | 4,497 | 20,258 | 3,646 | 2,192 | 112,881 | 118,719 | 66,823 |
| $e^{R}$(127) | 92,539 | 4,499 | 20,264 | 3,647 | 2,193 | 112,803 | 118,642 | 66,837 |
| $e^{VI}$(126) | 92,453 | 4,500 | 20,270 | 3,647 | 2,193 | 112,723 | 118,563 | 66,851 |
| $e^{IND}$(125) | 92,366 | 4,501 | 20,276 | 3,648 | 2,193 | 112,642 | 118,483 | 66,864 |
| $e^{SOC}$(168) | 94,858 | 4,424 | 19,930 | 3,635 | 2,183 | 114,788 | 120,606 | 66,109 |
| $e^{SOC1}$(154) | 94,298 | 4,455 | 20,067 | 3,636 | 2,184 | 114,365 | 120,186 | 66,396 |
| $e^{SOC4}$(178) | 95,143 | 4,399 | 19,815 | 3,636 | 2,183 | 114,959 | 120,777 | 65,876 |
| (M,M) Assortment: Three Musketeers and Milkyway | | | | | | | | |
| $e^{NR}$(129) | 91,049 | 5,717 | 25,750 | 0 | 2,147 | 116,799 | 118,946 | 67,233 |
| $e^{R}$(128) | 90,965 | 5,718 | 25,756 | 0 | 2,147 | 116,721 | 118,868 | 67,246 |
| $e^{VI}$(127) | 90,879 | 5,719 | 25,761 | 0 | 2,148 | 116,640 | 118,788 | 67,260 |
| $e^{IND}$(126) | 90,792 | 5,720 | 25,766 | 0 | 2,148 | 116,558 | 118,706 | 67,274 |
| $e^{SOC}$(171) | 93,371 | 5,647 | 25,438 | 0 | 2,139 | 118,808 | 120,947 | 66,473 |
| $e^{SOC1}$(156) | 92,783 | 5,677 | 25,570 | 0 | 2,140 | 118,354 | 120,494 | 66,786 |
| $e^{SOC4}$(181) | 93,646 | 5,624 | 25,335 | 0 | 2,139 | 118,980 | 121,120 | 66,234 |

Table A13: 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. $FC = 10, MC = 0.15$.