

Efficiency and Foreclosure Effects of Vertical Rebates: Empirical Evidence ^{*}

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Abstract

Vertical rebates are prominently used across a wide range of industries. These contracts may induce greater retail effort, but may also prompt retailers to drop competing products. We study these offsetting efficiency and foreclosure effects empirically, using data from one retailer. Using a field experiment, we show how the rebate allocates the cost of effort between manufacturer and retailer. We estimate structural models of demand and retailer behavior to quantify the rebate's effect on assortment and retailer effort. We find that the rebate increases industry profitability and consumer utility, but fails to maximize social surplus and leads to upstream foreclosure.

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1 Introduction

Vertical arrangements between manufacturers and retailers have important implications for how markets function. These arrangements may align retailers' incentives with those of manufacturers, and induce retailers to provide demand-enhancing effort. However, they may also result in exclusion of competitors, restricting competition and limiting product choice for consumers. Many types of vertical arrangements can induce these offsetting efficiency and foreclosure effects, including vertical integration, bundling, and rebates, among other contractual forms. Accordingly, these arrangements are a primary focus of antitrust authorities in many countries. Vertical rebates in particular are prominently used across a wide range of industries, including pharmaceuticals, hospital services, microprocessors, snack foods, and heavy industry, and have been the focus of several recent Supreme Court cases and antitrust settlements.¹

Although vertical rebate contracts 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 efficiency gains from mitigating downstream moral hazard on one hand, and exclusion of upstream rivals on the other hand, implies that the contracts must be studied empirically in order to gain insight into the relative importance of the two effects. Unfortunately, the existence and terms of these contracts are usually considered to be proprietary information by their participating firms, frustrating most efforts to study them empirically. An additional challenge for analyzing the effect of

¹Different forms of vertical rebates include volume-based discounts and 'loyalty contracts.' Volume-based discounts tie payments to a retailer's total purchases from the rebating manufacturer, but do not reference the sales of competing manufacturers. An all-units discount is a particular type of volume-based discount in which the discount is activated once sales exceed a volume threshold. Once activated, the discount applies retroactively to all units sold. We refer to payments based on a retailer's sales volume of both the rebating, and competing, manufacturers as 'loyalty contracts.' 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. Genchev and Mortimer (forthcoming) provides a review of empirical evidence on this class of contracts, including many of the relevant court cases. The DOJ and the FTC, in June 2014, held a joint workshop exploring the implications of this class of contracts for antitrust policy.

vertical contracts is the difficulty in measuring downstream effort, both for the upstream firm and the researcher.

We address these challenges by examining a vertical rebate known as an All-Units Discount (AUD). The specific AUD we study is used by the dominant chocolate candy manufacturer in the United States: Mars, Inc.² 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 his total purchases exceed the quantity target, Mars pays the retailer an amount that is equal to the per-unit discount multiplied by the retailer’s total quantity purchased. We examine the effect of the rebate contract through the lens of a retail vending operator, Mark Vend Company, for whom we are able to collect extremely detailed information on sales, wholesale costs, and contractual terms. The retailer also agreed to run a large-scale field experiment on our behalf, which provides us with additional insight into how the AUD might influence 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.

The insights that we gain from studying Mars’ rebate contract allow us to contribute to understanding principal-agent models in which downstream moral hazard plays an important role. Downstream moral hazard arises whenever a downstream firm takes a costly action that is beneficial to the upstream firm but 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 However, empirically measuring the effects of downstream moral hazard is difficult. Downstream effort may be impossible to measure directly, and vertical arrangements are endogenously determined, making it difficult to identify the effects of downstream moral hazard on upstream firms. Our ability to exogenously vary the result of downstream effort (in this case, retail product availability), combined with detailed data on wholesale prices, allows us to directly document the effects of downstream moral hazard on the revenues of upstream firms.

In order to analyze the effect of Mars’ AUD contract, we specify a discrete-choice model of consumer demand and a model of retailer behavior, in which the retailer chooses two actions: a set of products to stock, and an effort level. We hold retail prices fixed throughout the

²With revenues in excess of \$50 billion, Mars is the third-largest privately-held company in the United States (after Cargill and Koch Industries).

³See, 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.

analysis, consistent with the data and common practice in this industry.⁴ The number of units the retailer can stock for each product is constrained by the capacity of his vending machines, and we interpret retailer effort as the frequency with which the retailer restocks his machines. 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.⁵ 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 his profits. These features of the market (i.e., fixed capacities for a discrete number of unique products) make it well-suited to studying the impacts of the AUD contracts, because the retailer’s decisions are discrete and relatively straightforward.⁶

Identification of our demand and supply-side models benefits from the presence of exogenous variation in retailer stocking decisions that were implemented for us by the retailer in a field experiment. One approach to measuring the impact of effort on profits might be to persuade the retailer to directly manipulate the restocking frequency, but this has some disadvantages. For example, the effects of effort (through decreased stock-out events) are only observed towards the end of each service period, and measuring these effects might prove difficult. Instead, we focus on manipulating the likely outcome of reduced restocking frequency – by exogenously removing the best-selling Mars products. 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 retail margins. The rebate, which effectively lowers the retailer’s wholesale price for Mars products, increases the retailer’s share of the cost of stock-out events from around 10% to nearly 50%, and the quantity-target aspect of the rebate provides additional motivation for the retailer to set a high service level.

After estimating the models of demand and retailer behavior, we explore the welfare

⁴By holding retail prices fixed, we do not require an equilibrium model of downstream pricing responses to the AUD contract. In practice, we see 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). Over a short-run horizon of about three to five years, the retailer has exclusive contractual rights to service a location, and these terms may also commit him to a pricing structure during that time.

⁵Rather than assuming retailer wait times are optimal and using the dynamic model to estimate the cost of re-stocking, 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.

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

implications of the retailer’s optimal effort and assortment decisions. When the retailer increases his re-stocking effort, he re-stocks all products, regardless of manufacturer. Demand externalities across products of different upstream firms imply that the retailer’s optimal stocking decision might lead to either over- or under-supply of retailer effort from a welfare perspective. Over the relevant range of the retailer’s re-stocking policy, more frequent re-stocking *reduces* sales of Hershey and Nestle products, because these products no longer benefit from forced substitution when the dominant Mars products sell out. Thus, downstream effort imposes negative externalities across upstream firms and implies that Hershey and Nestle do not have an incentive to offer a rebate of the same form.⁷ We provide evidence that the rebate induces greater retailer effort, and that the level of retailer effort that is optimal from the perspective of a hypothetical vertically-integrated Mars-retailer entity is slightly higher than the effort level preferred by the industry as a whole.

Once we have characterized the retailer’s optimal re-stocking policy, we ask whether or not the downstream firm could increase profits by replacing a Mars product with a competitor’s product in the absence of the AUD contract. The ability to do this is an indication of possible foreclosure. We find evidence that the retailer can increase profits by substituting a Hershey product for a Mars product, but that the threat of losing the rebate discourages him from doing so. Thus, the AUD does result in foreclosure.

In spite of the evidence of foreclosure and the failure of the AUD to implement the industry-optimal level of downstream effort, the overall welfare effects of the AUD depend on what Mars would do in the absence of the AUD. We consider three counterfactual scenarios. First, we measure the effect of dropping the AUD, holding wholesale prices fixed. Under this scenario, the retailer drops some Mars products and reduces his restocking effort. As a result, Mars and the retailer are both worse off, and consumer surplus falls. Hershey and Nestle both benefit from the reduced retailer effort and alternative product assortment, but these effects are small, and overall, social welfare goes down when the AUD is removed. Second, we drop the AUD but allow Mars to re-optimize its wholesale price against the wholesale prices of its competitors, which we hold fixed. In this scenario, Mars is worse off (compared to the current outcome with the AUD), but the retailer benefits. The change to consumer surplus is quite small, and whether the change is positive or negative depends on the level of the quantity threshold under the AUD.

⁷If the retailer reduces his effort below this range, all products stock out, so that more frequent re-stocking increases sales of all products, including those of Hershey and Nestle. Downstream effort would impose positive demand externalities across upstream firms in this range, but it is not profitable for the retailer.

In our third and final exercise, we note that the impacts of upstream mergers are often felt not through the price in the final-goods market, but rather in the wholesale market. Thus, we simulate the impact of various upstream mergers on the willingness of the dominant firm to offer rebate contracts, and the impact that this has on social welfare. Interestingly, we find conditions under which an upstream merger of a dominant firm (Mars) with a close competitor (Hershey) can lead to socially-efficient downstream effort and product assortment. This happens because the merger addresses the demand externalities that lead to the substitutability of retail effort across Mars and Hershey products. We also find that an upstream merger of two smaller rivals (Hershey and Nestle) can bid up the price of a downstream firm’s shelf space, even though it cannot necessarily prevent exclusion.

Having estimated the demand and supply-side models, one can, in principle, conduct a wider range of counterfactual exercises. For example, one can examine alternative contracts, such as two-part tariffs or conventional quantity discounts. Rather than pursue a list of these alternative contractual forms, we consider whether or not there is any action that Hershey could take to avoid exclusion when facing the Mars AUD contract. We find that the answer is, in many cases, “no.”

1.1 Relationship to Literature

There is a long tradition of theoretically analyzing the potential efficiency and foreclosure 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).⁸ An important theoretical development on the potential foreclosure 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 in cases for which it maximizes the profits of the entire industry. Subsequent theoretical literature demonstrates that exclusion may instead maximize industry (or even bilateral) profit, which need not coincide with maximizing efficiency in settings with market power.⁹ A separate, but

⁸In 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.”

⁹For example, Aghion and Bolton (1987) show that long-term contracts that require a liquidated damages payment from the downstream firm to the incumbent can result in exclusion for which industry profits are

related, theoretical literature has explored the potential anti-competitive effects of vertical arrangements in the context of upfront payments or slotting fees paid by manufacturers to retailers in exchange for limited shelf space (primarily in supermarkets).¹⁰ A broader literature has also examined the conditions under which bilateral contracting might lead to (perhaps partial) exclusion.¹¹

Recent theoretical work related to AUDs specifically includes Kolay, Shaffer, and Ordover (2004), which shows that a menu of AUD contracts can more effectively price discriminate than a menu of two-part tariffs when the retailer has private information about demand.¹² More recently, Chao and Tan (2014) show that AUD and quantity-forcing contracts can be used to exclude a capacity-constrained rival, and O’Brien (2013) shows that an AUD may be efficiency enhancing if both upstream and downstream firms face a moral-hazard problem.

We depart from the basic theoretical framework of the *Chicago Critique* of Bork (1978) and Posner (1976) in some key ways. First, we allow for downstream moral hazard and potential efficiency gains, similar to much of the later theoretical work on vertical arrangements. Second, we study an environment in which the degree of competition across upstream firms may vary across the potential sets of products carried by the retailer, because upstream firms own multiple, differentiated products. Finally, we restrict the retailer to carrying a fixed number of these differentiated products.¹³

The theoretical literature following the *Chicago Critique* focuses on a wide range of settings when considering the potential effects of vertical contracts. Specifically, this literature has studied contracts used by dominant vs. non-dominant firms, contracts that do or do not reference rivals, contracts for which downstream price competition is a major concern for upstream firms (or not), and contracts that apply to single products vs. multiple products. Our setting provides empirical evidence on a vertical rebate used by a dominant firm cover-

not maximized; while Bernheim and Whinston (1998) show that the *Chicago Critique* ignores externalities across buyers, and that once externalities are accounted for, it is again possible to generate exclusion that fails to maximize industry profits. Later work by Fumagalli and Motta (2006) links exclusion to the degree of competition in the downstream market. While extremely influential with economists, these arguments have (thus far) been less persuasive with the courts than Bork (1978).

¹⁰This literature includes Shaffer (1991a) and Shaffer (1991b), which analyze slotting allowances, RPM, and aggregate rebates to see whether or not they help to facilitate collusion at the retail level. Sudhir and Rao (2006) analyze anti-competitive and efficiency arguments for slotting fees in the supermarket industry.

¹¹Some key examples include Rasmusen, Ramseyer, and Wiley (1991), Segal and Whinston (2000), and more recently Asker and Bar-Isaac (2014) and Chen and Shaffer (2014).

¹²In addition, Elhauge and Wickelgren (2012) and Elhauge and Wickelgren (2014) explore the potential of loyalty contracts to soften price competition, and Figueroa, Ide, and Montero (2016) examines the role that rebates can play as a barrier to inefficient entry.

¹³This contrasts with the “naked exclusion” of Rasmusen, Ramseyer, and Wiley (1991), in which there is a single good.

ing multiple products, for which excessive downstream price competition is not a concern. Although the contract does not explicitly reference rivals, the facing requirement, combined with the typical capacity constraints of most vending machines, effectively limits the presence of competing brands.

One challenge for understanding the effects of vertical arrangements across this wide range of settings is that empirical evidence has primarily been available only through the course of litigation. This has the potential effect that debates about these contracts may be based on a selected sample. An important distinction of our setting is that we study a contract that has not been litigated, and for which we have detailed information on contract terms and exogenous variation in the results of the retailer’s effort. Although the welfare effects of vertical rebate contracts in other situations may differ from the impacts we estimate in our setting, we hope that our work provides a road-map for how to model the impacts of these contracts empirically.

Outside of the theoretical literature on vertical rebate contracts, our work also connects to the empirical literature on the impacts of vertical arrangements. One strand of this literature examines issues of downstream moral hazard in the context of vertical integration and the boundaries of the firm, rather than through vertical contracts per se.¹⁴ More recently, another strand of this literature examines exclusive contracts, without necessarily focusing on downstream moral hazard or effort decisions.¹⁵ 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 (2015), 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 (2015) is that we examine the potential for upstream foreclosure

¹⁴A few key examples that address downstream (and in some cases upstream) issues of moral hazard include Lafontaine (1992) and Brickley and Dark (1987), which study franchise arrangements, and Baker and Hubbard (2003) and Gil (2007), which study trucking and movies respectively; many other contributions are reviewed in Lafontaine and Slade (2007).

¹⁵Examples of this literature include Asker (2016), Sass (2005), and Chen (2014), which each examine the efficiency and foreclosure effects of exclusive dealing in the beer industry, and Chipty (2001) and Sinkinson (2014), which study the cable television and mobile phone markets respectively. Lee (2013) focuses on the interaction of exclusive contracts and network effects and competition between downstream firms. Lafontaine and Slade (2008) surveys this literature.

(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).¹⁶

In practice, AUDs belong to a class of contractual arrangements that the Department of Justice and the Federal Trade Commission refer to as “Conditional Pricing Practices,” or CPPs. CPPs are understood to cover any arrangement that allows the terms of sale between a producer and a downstream firm to vary based on whether the downstream firm meets a set of conditions specified by the producer. CPPs cover a wide variety of arrangements and are in widespread use throughout many industries. Many of these industries face more complicated decisions than our setting – for example, retailers may be able to restock item by item, choose retail prices, or more perfectly monitor consumer behavior and inventory levels. An outstanding question regarding the use of CPPs is whether or not there are conditions under which one can expect a CPP to be primarily anti-competitive or efficiency inducing. Genchev and Mortimer (forthcoming) provides a recent survey of empirical evidence on this class of contracts. They find that, “CPPs are more likely to be anticompetitive when dominant firms employ them, when market features force firms to drop competitors’ products to comply with the arrangement, and when substitute products or alternative distributors are not widely available.” While the wide variety of arrangements and the diversity of market structures makes generalization difficult with any observed CPP (including the one we study here), the potential for both anti-competitive and efficiency effects makes it important to build on the empirical body of knowledge about these arrangements. As Genchev and Mortimer (forthcoming) point out, it is especially important to empirically analyze the impacts of CPPs that have not been selected through a process of litigation, to avoid selection bias in the set of contracts examined in the literature.

The rest of the paper proceeds as follows. Section 2 provides the theoretical framework for the model of retail behavior. Section 3 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 5 provides results, and section 6 concludes.

¹⁶From a methodological perspective, Crawford, Lee, Whinston, and Yurukoglu (2015) 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 (2015) employ the bargaining model to help determine supply terms, which we do not model. The biggest difference is that Crawford, Lee, Whinston, and Yurukoglu (2015) examine whether an integrated firm responds to foreclosure incentives in its supply decisions, while we simulate the effects of particular contracts.

2 Theoretical Framework

2.1 Foreclosure and Optimal Assortments: A Motivating Example

We begin by providing a working definition, as well as some examples of the measures of *foreclosure* and *optimal assortment* to be used throughout the rest of our paper. To begin, we focus exclusively on the assortment decision (ignoring effort provision) of the downstream retailer (R) in response to a contract offered by a dominant upstream firm (M). In order to match our empirical application, let us suppose that there are two remaining spaces on the retailer's shelf and the retailer selects from among four potential products (two offered by the dominant firm M , and two offered by the rival H). Let us further assume that both retail prices and wholesale prices are fixed, so that the retailer's sole choice is which products to stock.

We denote the profit of the retailer from stocking the two M products as $\pi^R(M, M)$, from stocking one product from each manufacturer as $\pi^R(H, M)$ and from stocking both products from the rival as $\pi^R(H, H)$. We likewise define the profits of M as $\pi^M(\cdot)$, of the rival H as $\pi^H(\cdot)$, consumer surplus $\pi^C(\cdot)$, and the profits of the industry as $\pi^I(\cdot) = \pi^R(\cdot) + \pi^M(\cdot) + \pi^H(\cdot)$. We define the operator Δ as $\Delta\pi^* = \pi^*(M, M) - \pi^*(H, H)$ for any agent R, M , or H .

Base Case: Two Assortments

In the base case, we assume that the only two possible assortment choices are (M, M) and (H, H) . The dominant firm M offers the retailer R a transfer T in exchange for switching from $(H, H) \rightarrow (M, M)$. In order to make the retailer's decision non-trivial, we assume that $\pi^R(M, M) < \pi^R(H, H)$ (i.e., the retailer earns higher profits when stocking the rival's products).¹⁷ The following conditions (A1)-(A3) ensure that such a transfer is sufficient for M to foreclose its rival H .

$$(A1) \quad \Delta\pi^R + T \geq 0$$

$$(A2) \quad \Delta\pi^M - T \geq 0$$

$$(A3) \quad -\Delta\pi^H \leq \Delta\pi^M + \Delta\pi^R$$

(A1) specifies that the retailer would rather switch from $(H, H) \rightarrow (M, M)$ after receiving a transfer of size T ; (A2), that the dominant firm would be willing to pay T to switch from $(H, H) \rightarrow (M, M)$. The third assumption (A3) says that the profits lost by the rival H

¹⁷Under an AUD, the transfer would be conditional on meeting a facing requirement, or a quantity threshold that is only satisfied under an (M, M) assortment.

are smaller than those gained by M and R combined. Thus, (A3) guarantees that even if H offered its own transfer equal to its entire lost profits $\Delta\pi^H(H, H)$, it could not prevent foreclosure.¹⁸

That foreclosure is a feasible equilibrium outcome is guaranteed by (A3) $\Delta\pi^I \equiv \Delta\pi^R + \Delta\pi^H + \Delta\pi^M \geq 0$. This is the main insight of the *Chicago Critique*. H would be willing to give up all of her profits in order to avoid foreclosure, thus when foreclosure is observed it must be that H 's losses are smaller than the gains of R and M combined. From the perspective of industry profits $\Delta\pi^I > 0$ we call this foreclosure *industry optimal*. A separate question is whether or not this change in assortment increases consumer surplus $\Delta\pi^C > 0$ or overall social surplus, $\Delta\pi^C + \Delta\pi^I$.

Adding a Third Assortment

Now we introduce a new assortment (H, M) which yields intermediate profits for all players:

$$\begin{aligned}\pi^R(H, H) &> \pi^R(H, M) > \pi^R(M, M) \\ \pi^H(H, H) &> \pi^H(H, M) > \pi^H(M, M) \\ \pi^M(H, H) &< \pi^M(H, M) < \pi^M(M, M)\end{aligned}\tag{1}$$

For this case, we ignore the possibility of (M, M) , and introduce a new operator $\Delta_H\pi^* = \pi^*(H, M) - \pi^*(H, H)$, with the same set of assumptions:

$$(B1) \quad \Delta_H\pi^R + T_h \geq 0$$

$$(B2) \quad \Delta_H\pi^M - T_h \geq 0$$

$$(B3) \quad -\Delta_H\pi^H \leq \Delta_H\pi^M + \Delta_H\pi^R$$

As above, it is now possible to design a transfer T_h by which M *partially forecloses* the rival H . Again, under (B3) the profits lost by H are less than those gained by the combination of M and R . The resulting (partial) foreclosure is considered *feasible* in the sense that $\Delta_H\pi^I \equiv \Delta_H\pi^H + \Delta_H\pi^M + \Delta_H\pi^R \geq 0$.

Equilibrium Assortment

If we temporarily ignore the possibility of (H, H) , we can consider the effect that the dominant firm's choice of transfer has on the margin of full vs. partial foreclosure and analyze

¹⁸If H is fully excluded from the retailer shelf then $\pi^H(M, M) = 0$ and $\Delta\pi^H = \pi^H(H, H)$.

the equilibrium assortment that is obtained when the dominant firm chooses transfers. For this, we introduce a third operator $\Delta_M \pi^* = \pi^*(M, M) - \pi^*(H, M)$ under slightly different assumptions:

$$(C1) \quad \Delta_M \pi^R + T_m \geq 0$$

$$(C2) \quad \Delta_M \pi^M - T_m \geq 0$$

$$(C3) \quad -\Delta_M \pi^H \leq \Delta_M \pi^M + \Delta_M \pi^R$$

$$(C4) \quad -\Delta_M \pi^H > \Delta_M \pi^M + \Delta_M \pi^R \geq 0$$

(C1) and (C2) are the same as before, but (C3) and (C4) are designed to be mutually exclusive. Either the increase in bilateral surplus among M and R is greater than the losses to H (under (C3)), or it is not (under (C4)). We propose two related results:

Theorem 1. *Under (A1)-(A3), (B1)-(B3) and (C1)-(C3), then there exists a transfer $T \geq 0$ such that (M, M) is an equilibrium assortment that maximizes industry profits: $\pi^I(M, M) > \pi^I(H, H)$ and $\pi^I(M, M) > \pi^I(H, M)$.*

Theorem 2. *Under (A1)-(A3), (B1)-(B3), (C1)-(C2) and (C4), if $\Delta_M \pi^M + \Delta_M \pi^R \geq 0$, then there exists a transfer $T \geq 0$ such that (M, M) is an equilibrium assortment even though $\pi^I(H, M) > \pi^I(M, M) > \pi^I(H, H)$.*

Proofs in Appendix.

The main takeaway is that a transfer payment that is conditioned on assortment can be used to obtain full (M, M) or partial (H, M) foreclosure. We show that under (A1)-(A3), full foreclosure is feasible and increases overall industry surplus. However, it may also be the case that full foreclosure does not lead to the assortment that maximizes overall industry surplus (i.e., if (B1)-(B3) and (C1), (C2), and (C4) also hold). In that case, partial foreclosure maximizes industry surplus, but so long as full foreclosure leads to higher bilateral surplus among the retailer and dominant firm and the dominant firm chooses the vector of transfers T , T_h and T_m , full foreclosure can 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 we see foreclosure in equilibrium, is the assortment necessarily 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 (either by choosing a high threshold or by enforcing a facing requirement), he can commit to tying the products together, and thus the equilibrium assortment need not maximize the surplus of the entire industry.

2.2 All Units Discount Rebates

We are interested in an All Units Discount (AUD) rebate, in which the transfer T to the retailer is calculated on the basis of all units sold to the retailer, conditional on obtaining a level of sales at or above a required threshold.

If we assume that the dominant manufacturer offers the same wholesale price across all goods w_m and has a constant marginal cost for all goods c_m then we can re-write the AUD contract in terms of π^M , the profit of the dominant firm. This one-to-one correspondence means that under these conditions, the contract can be written in terms of quantity for the dominant firm, but interpreted as relating to profits for the dominant firm. Denoting the per unit discount payment as d , we define the transfer from M to R as:

$$d \cdot q_M = \underbrace{\left(\frac{d}{w_M - c_M} \right)}_{\lambda} \cdot \pi^M$$

This allows us to re-write the payoffs governing the retailer's choice of product assortment:

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

This allows us to define an AUD contract as a tuple $(\lambda, \overline{\pi^M})$, such that conditional on the dominant firm M receiving a minimum level of profit $\overline{\pi^M}$, the dominant firm shares a fraction λ of this profit with the retailer.¹⁹ In the notation of the previous section, the transfer is set at $T \equiv \lambda \cdot \pi^M(a)$.

Expressing the contract in terms of $\pi^M(a)$ has some immediate advantages. If conditions such as (1) hold with strict inequality, it is easy to see how M can tailor the threshold to foreclose the rival by setting $\pi^M(H, M) < \overline{\pi^M} \leq \pi^M(M, M)$. Furthermore, for $\lambda \in [0, 1]$, M can transfer between none and all of his profit to R , which means he has access to the full set of transfers that would satisfy conditions such as (A2). This is not necessarily true for the

¹⁹We can also define the threshold in terms of M 's remaining profit after the transfer $(1 - \lambda) \cdot \pi^M(a) \geq (1 - \lambda) \overline{\pi^M}$.

conventional quantity discount.²⁰ In other words, M can write a *de facto* foreclosure contract with an (effectively) unrestricted transfer T . Finally, we can easily verify the conditions such as (A1)-(A3) at different levels of $(\lambda, \overline{\pi^M})$ to see if the AUD contract can be used to foreclose a rival, whether the rival could give up her surplus to avoid foreclosure, and whether the resulting assortment maximizes industry profits.

2.3 Efficiency and Retailer Choice of Effort

A defense of AUD contracts is that they have the potential to be efficiency enhancing if the retailer is encouraged to exert costly effort required to sell the good.²¹ This effort can take any number of forms, so long as the effort is costly for the retailer to provide and increases the profits of the dominant firm. When R and M cannot directly contract on the retailer's choice of effort this is known as a *downstream moral hazard* problem (see Tirole (1988) Chapter 4).²²

In our empirical application, we treat effort as a single scalar variable e which measures the frequency with which the retailer restocks the vending machine. We assume that the cost of providing effort $c(e)$ is increasing in e . If we temporarily hold the assortment fixed, our retailer's payoffs under the AUD look like:

$$\begin{cases} \pi^R(e) - c(e) + \lambda \cdot \pi^M(e) & \text{if } \pi^M(e) \geq \overline{\pi^M} \\ \pi^R(e) - c(e) & \text{if } \pi^M(e) < \overline{\pi^M} \end{cases} \quad (2)$$

Effort can be increased via both features of the contract: (1) a larger per unit discount increases λ and makes R consider the profits of M ; (2) Because $\pi^M(e)$ is increasing in effort, a larger choice of $\overline{\pi^M}$ can be used to increase the retailer's effort. In our empirical example, we quantify both of these channels.

We provide a detailed solution to the effort problem in Appendix A.2. To summarize, when effort is non-contractible, R chooses one of three solutions to equation (2): either the interior solution to the effort problem with the rebate (the first line), which we denote e^R , the interior solution to the effort problem absent the rebate (the second line), which we denote e^{NR} , or the solution that makes the constraint bind $\bar{e} : \pi^M(\bar{e}) = \overline{\pi^M}$. Thus for

²⁰See a comparison to alternative contracts in Appendix A.3.

²¹This defense was employed by Intel in its recent antitrust cases, for example.

²²Perhaps the best known example is the double marginalization problem. A lower retail price reduces the profits of the retailer, but increases the profits of the wholesale firm (under uniform wholesale pricing and constant marginal cost).

$\bar{e} \geq e^R$, M can set the effort level of the retailer via the threshold $\bar{\pi}^M$, subject to satisfying the retailer's IR constraint. The set of effort levels that the threshold can target potentially includes the vertically integrated, and the socially optimal effort levels. Later, we characterize the critical values of $\bar{\pi}^M$ in our empirical exercise.

An important consideration is whether the potential efficiency gains from increased retailer effort can offset the potential surplus lost from foreclosure. In order to analyze this question, we focus primarily on effort levels that maximize efficiency gains. In addition to examining the effort choice that is optimal for the bilateral/vertically-integrated $M + R$, which we denote e^{VI} , or the industry (including the rival), which we denote e^{IND} , one can also examine the effort level that maximizes social surplus, denoted e^{SOC} .²³

We enumerate these possibilities below:

$$\begin{aligned}
e^{NR} &= \arg \max_e \pi^R(e) - c(e) \\
e^R &= \arg \max_e \pi^R(e) - c(e) + \lambda \cdot \pi^M(e) \\
e^{VI} &= \arg \max_e \pi^R(e) - c(e) + \pi^M(e) \\
e^{IND} &= \arg \max_e \pi^R(e) - c(e) + \pi^M(e) + \pi^H(e) \\
e^{SOC} &= \arg \max_e \pi^R(e) - c(e) + \pi^M(e) + \pi^H(e) + \pi^C(e)
\end{aligned} \tag{3}$$

We should also point out that because $\pi^M(e)$ is increasing everywhere, it may be in the interest of the dominant firm to set a threshold in excess of e^{VI} . This can be accomplished by choosing a threshold $\bar{\pi}^M > \pi^M(e^{VI})$. 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 to design a transfer that results in socially inefficient excess effort.

3 The Vending Industry and Experimental Data

3.1 Data Description and Product Assortment

We observe data on the quantity and price of all products sold by one retailer, Mark Vend Company. Mark Vend is located in a northern suburb of Chicago, and services roughly 1600 snack, beverage, and other machines throughout the greater Chicago metropolitan area. [CHECK TOTAL NUMBER.] Data are recorded internally at each of Mark Vend's machines,

23

and include total vends and revenues since the last service visit to the machine. Any given snack machine can carry roughly 31 standard products at one time. These include salty snacks, cookies, and other products, in addition to 6-8 confection products.²⁴ We observe retail and wholesale prices for each product at each service visit during a 38-month panel for all machines in Mark Vend’s enterprise, which runs from January of 2006 until February of 2009. There is relatively little price variation over time for any given machine, and almost no price variation within a product category (e.g., confections) for a machine.

A focus in our empirical exercise is the set of products the retailer stocks in the last two slots in the confections category. Mark Vend chooses between stocking either additional Mars products (Milkyway and 3 Musketeers) or Hershey Products (Reese’s Peanut Butter Cups and Payday). 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 Mark Vend’s machines. There are some patterns that emerge. The first is that Mark Vend stocks some of the most popular products sold by Mars (Snickers, Peanut M&Ms, Twix, Plain M&M’s, and Skittles) in most of his machines. However, Mark Vend only stocks Hershey’s best-selling product (Reese’s Peanut Butter Cups) in 27% of machine-weeks, even though nationally Reese’s Peanut Butter Cups is the fourth most popular product. Overall Mark Vend 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 Mark Vend 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 Mark Vend’s departures from the national best-sellers. One is that Mark Vend has better information on the tastes of its specific consumers, and its product mix is geared towards those tastes. The alternative explanation is that the rebate induces Mark Vend to substitute from Nestle/Hershey brands to Mars brands when making stocking decisions, and that when Mark Vend does stock products from competing manufacturers (e.g., Nestle Raisinets), he chooses products that do not steal business from key Mars products.

²⁴Most machines have another 4-5 slots for smaller items, such as gum and mints.

3.2 Vertical Arrangements in the Vending Industry

Mars’ AUD rebate program is the most commonly-used vertical arrangement in the vending industry.²⁵ 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 typically set on the basis of its combined sales of Mars’ products, rather than for individual products. Mars’ rebate contract also 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 amount of the rebate and the precise threshold of the sales goal are specific to an individual vending operator, and these terms are closely guarded by participants in the industry.

We include some promotional materials from Mars’ rebate program in figure 1.²⁶ 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 believe to be 5% (i.e., a target of 105% of year-over-year sales). On another page, not shown in figure 1, the document describes the sales target for a “Gold” rebate level as 90% of year-over-year quarterly sales. The rebate does not explicitly condition on market share or the sales of competitors. However, most vending machines typically carry between six and eight candy bar varieties, so the facing requirement may effectively limit shelf space for competing brands.²⁷

We observe, but cannot report, the amount of the rebate received by Mark Vend Company. However, we can construct quarterly sales of Mars products at Mark Vend, and compare the year-over-year sales across Mark Vend’s entire enterprise. We present those

²⁵For confections products, Mars is the dominant manufacturer in vending, and is the only manufacturer to offer a true AUD contract. 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.

²⁶A 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.) These promotional materials represent the same type of rebate in which Mark Vend participated, but may differ from the terms available to Mark Vend during the period we study.

²⁷While 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 use the same size ‘slots.’

calculations in table 2. We see that from the first quarter of 2007 through the first quarter of 2008 Mark Vend generally hits a threshold of 105% of year-over-year sales. (The exception is the third quarter of 2007, when he sells 100% of year-over-year sales).

In the wake of the 2008 macroeconomic downturn, Mars modified its rebate program and reduced the threshold. We can see clearly in table 2 that Mark Vend’s sales of Mars products appear to respond to the lower threshold, and indeed track a 90% threshold quite closely.²⁸ 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 Mark Vend was not hit particularly badly by the macroeconomic downturn, as (normalized) total vends across all products remained largely flat between 2007 and 2009.

If we believe that the reduction in Mars’ rebate threshold is an exogenous event (rather than a direct response to behavior by Mark Vend), we can examine its impact on Mark Vend’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, when Mars reduced the threshold around the second or third quarter of 2008, Mark Vend 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 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 Mark Vend’s machines.

We can also measure how Mark Vend adjusts his 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

²⁸Our 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 orders in order to meet the threshold and hold extra inventory in his warehouse (or even dispose of the 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 Mark Vend, they assure us that these effects are small and do not change over time.

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 (in the third quarter of 2008), Mark Vend 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 Mark Vend 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 his “effort,” as measured by service frequency and sales between visits, and a substantial change in assortment, based on the figures in table 3.

3.3 Experimental Design

When we run experiments and estimate our demand model we focus on a set of 66 vending machines which are located in high-income, professional office environments in Chicago, where consumers may have very different tastes than consumers from other demographic groups.²⁹

In addition to sharing the terms of his rebate contact with us, the owner of Mark Vend implemented a field experiment for us in which his drivers exogenously removed either one or two top-selling Mars confection products from a set of 66 vending machines. The product removals are recorded during each service visit to individual vending machines.³⁰ Implementation of each product removal was fairly straightforward; we removed either one or both of the two top-selling Mars products from all machines for a period of roughly 2.5 to 3 weeks. The focal products were Snickers and Peanut M&Ms.³¹ The dates of the product removal

²⁹For example, Skittles, a fruit flavored candy sold by Mars, is primarily marketed to younger consumers. It is stocked far more often across Mark Vend’s entire enterprise (around 66% of the time) when compared to our

³⁰The machines are located in office buildings, and 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). The reader may refer to our other papers for more details.

³¹Whenever a product was experimentally stocked-out, poster-card announcements were placed at the front of the empty product column. The announcements read “This product is temporarily unavailable. We apologize for any inconvenience.” The purpose of the card was two-fold: first, we wanted to avoid dynamic effects on sales as much as possible, and second, the firm wanted to minimize the number of phone calls received in response to the stock-out events. ‘Natural,’ or non-experimental, stock-outs are extremely rare for our set of machines. This implies that much 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

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 some products with very low levels of sales using similar products within a category produced by the same manufacturer, until we are left with the 73 ‘products’ that form the basis of the rest of our exercise.³²

During each 2-3 week experimental 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.³³

Two features of demand are important for determining the welfare implications of the AUD contract. These are, first, the degree to which Mark Vend’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, and Twix). Our experiment mimics the impact of a reduction in retailer effort (i.e., 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 demand.

In principle, calculating the effect of product removals is straightforward. In practice,

products. Conlon and Mortimer (2010) provides evidence on the role of the experimental variation for identification of substitution patterns.

³²For example, we combine Milky Way Midnight with Milky Way, and Ruffles Original with Ruffles Sour Cream and Cheddar. In addition to the data from Mark Vend, 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.

³³For example, at some site-experiment pairs, we define weeks as Tuesday to Monday, while for others we use Thursday to Wednesday.

however, there are two challenges in implementing the removals and interpreting the data generated by them. First, there is considerable 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, because 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 section A.4 of the appendix.

3.4 Results of Product Removals

Our first exogenous product removal eliminated Snickers from all 66 vending machines involved in the experiment; the second removal eliminated Peanut M&Ms, and the third eliminated both products.³⁴ These products correspond to the top two sellers in the confections category, both at Mark Vend and nationwide.

One of the results of the product removal 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 Mark Vend, 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 Mark Vend. In the absence of any rebate payments, we see the following results. Total vends decrease by 217 units and retailer profits decline by \$56.75 when Snickers is removed. When Peanut M&Ms is removed, vends go down by 198 units, but Mark Vend’s average margin on all items sold in the machine rises by 0.78 cents, and retailer revenue declines only by \$10.74 (a statistically insignificant decline). Similarly, in the joint product removal, overall vends decline by roughly 283 units, but Mark Vend’s average margin rises by 1.67 cents per unit, so that revenue declines by only \$4.54 (again statistically insignificant).³⁵

Table 6 examines the impact of the product removals on the upstream firms. Removing Peanut M&Ms costs Mars about \$68.38, compared to Mark Vend’s loss of \$10.74; 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

³⁴As noted in table 1, both Snickers and Peanut M&Ms are owned by Mars.

³⁵Total losses appear smaller in the double-product removal in part because we sum over a smaller sample size of viable machine-treatment weeks (89) for this experiment, compared to the Peanut M&Ms removal (with 115 machine-treatment weeks).

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 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 (i.e., the price reduction given by Δ); one requires a model of restocking in order to account for the threshold aspect, $\overline{q_M}$. 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 the overall service level. Similar to a two-part tariff, the rebate lowers the marginal cost to the retailer and reduces the margin of the manufacturer. Returning to table 5, the right-hand panel reports the retailer’s profit loss from the product removals after accounting for his rebate payments, assuming he 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 contract, the manufacturer 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 Estimation

4.1 Consumer Choice

The intuition provided in our theoretical framework is that the welfare effects of the vertical rebate depends on a few critical inputs. Those are: the substitutability of products in the downstream market, how the costs of reduced effort are distributed across the supply chain, and whether or not effort acts as a substitute or a complement in the profit function of upstream manufacturers. 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).³⁶

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

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt}. \quad (4)$$

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

A random-coefficients logit specification allows for correlation in tastes across observed product characteristics.³⁷ This correlation in tastes is captured by allowing the term μ_{ijt} to be distributed according to $f(\mu_{ijt}|\theta)$. A common specification is to allow consumers to have independent normally distributed tastes for product characteristics, so that $\mu_{ijt} = \sum_l \sigma_l \nu_{ilt} x_{jl}$ where $\nu_{ilt} \sim N(0, 1)$ and σ_l represents the standard deviation of the heterogeneous taste for product characteristic x_{jl} . The resulting choice probabilities are a mixture over the logit choice probabilities for many different values of μ_{ijt} , shown here:

$$s_{jt}(\delta, \theta, a_t) = \int \frac{e^{\delta_{jt} + \sum_l \sigma_l \nu_{ilt} x_{jl}}}{1 + \sum_{k \in a_t} e^{\delta_{kt} + \sum_l \sigma_l \nu_{ilt} x_{kl}}} f(\nu_{ilt}|\theta). \quad (5)$$

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). There are virtually no ‘natural’ stock-outs in the data; thus, changes to product assortment happen for two reasons: (1) Mark Vend changes the assortment when re-stocking, or (2) our field experiment exogenously removes one or two products. While Mark Vend’s assortment decisions are chosen endogenously, they are often temporary and due to changes in manufacturer product lines.³⁸ There is considerable product churn created by non-experimental changes in assortment, which helps to identify substitution between non-focal products. Non-experimental churn creates 262 unique choice sets for confection products; our exogenous product removals increase the number of unique choice sets to 427.³⁹

Implicitly, our demand estimation assumes away dynamic effects of stock-outs (i.e., we assume no change in consumer preferences after the temporary removal of a product). Using

³⁶Results from an alternative nested-logit specification are contained in section A.6 of the appendix.

³⁷See Berry, Levinsohn, and Pakes (1995).

³⁸Implicitly, we assume that changes to manufacturer product lines are taken with the national market in mind, rather than to induce changes by Mark Vend.

³⁹Further discussion and analyses of choice-set variation in this dataset are contained in Conlon and Mortimer (2010).

the same data, Kapor (2008) examines this assumption and finds no evidence that temporary stock-outs affect future demand patterns. Nevertheless, one should consider our demand system to capture substitution patterns that are stable in the short run. Other factors (including manufacturer advertising) may impact substitution patterns in the long run.

We specify $\delta_{jt} = d_j + \xi_t$; that is, we allow for 73 product intercepts as well as market-specific demand shifters. We allow for three random coefficients, corresponding to consumer tastes for salt, sugar, and nut content.⁴⁰ We estimate the parameters of the choice probabilities via maximum simulated likelihood (MSL). The log-likelihood is:

$$l_t(\mathbf{y}_t | \delta, \theta, a_t) \propto \sum_j y_{jt} \log s_j(\delta, \theta, a_t). \quad (6)$$

where y_{jt} are sales of product j in market t .⁴¹

We report the parameter estimates in table 7. We report two levels of aggregation for ξ_t . The first allows for 15,256 fixed effects, at the level of a machine-service visit, while the second allows for 2,710 fixed effects, at the level of a machine-choice set (i.e., we combine machine-service visit ‘markets’ for which the choice set does not change). We report the log-likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for each specification. We use BIC to select the specification with 2,710 ξ_t fixed effects. Because we observe 2.96 million sales, our simulated MLE estimates tend to be very precise.

Parametric identification of d_j and σ parameters is straightforward. The d_j parameters would be identified from average sales levels in even a single market after we normalize the utility of the outside good to zero. Across machines and time, we observe 2,710 different product assortments a_t . The σ parameters are identified by the covariance of the changes in the observed sales across product assortments with the characteristics of the products that are added or removed from the choice set. For example, when we exogenously remove M&M Peanut during our experiments we can observe whether more consumers appear to switch

⁴⁰Nut 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 did estimate a number of alternative specifications in which we include random coefficients on other continuous variables, such as carbohydrates, fat, or calories. In general, the additional parameters were not significantly different from zero, and they had no appreciable effect on the results of any prediction exercises.

⁴¹As in previous work, we do not estimate a price coefficient because there is no price variation in our data to identify the parameter. See Conlon and Mortimer (2013a) for a discussion of this issue.

to products with a similarly high peanut content (such as Planter’s Peanuts) or to products with a similar sugar content (such as M&M Plain). A common identification challenge in the literature is the identification of an (endogenous) price effect. Because we do not observe any within product price variation (the entire confections category is priced at 75 cents in our sample) any price effect is subsumed into d_j .

4.2 Supply

On the supply side, we begin with the retailer’s problem, taking the manufacturer’s choice of contract terms as given. We model the retailer’s optimal choices of assortment, a , and effort, e . Once we characterize the optimal retail choices at the existing contract terms, $(\lambda, \overline{\pi^M})$, we can re-solve the retailer’s problem at different values for $(\lambda, \overline{\pi^M})$. This allows us to explore the space of contract terms, and to analyze what values of the contract terms lead to foreclosure, and what the welfare effects of different contract terms are for various agents in the industry.

The retailer’s problem is:

$$\max_{a,e} \begin{cases} \pi^R(a,e) - c(e) + \lambda \cdot \pi^M(a,e) & \text{if } \pi^M(a,e) \geq \overline{\pi^M} \\ \pi^R(a,e) - c(e) & \text{if } \pi^M(a,e) < \overline{\pi^M} \end{cases} \quad (7)$$

where $\pi^R(a,e)$ is the variable profit of the retailer, $\pi^M(a,e)$ is the variable profit of the dominant manufacturer M , and $c(e)$ represents the cost of retailer effort.

In most empirical contexts, the econometrician has very little data on the cost of effort. In our application, we consider the specific case in which the retailer chooses the restocking frequency. We model the retailer’s choice of effort, e , 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 compute the optimal wait time until the next restocking visit from the model. This approach is motivated by the evidence presented in section 3.2, which documents Mark Vend’s responsiveness to the level of the threshold, as it varies across quarters.⁴²

⁴²In contrast to the variation across quarters described in tables 2 - 4, we also explored variation of service visits within quarter. Although not reported, we found that Mark Vend follows a remarkably consistent service schedule within a quarter. Thus, his response is in line with the stationary solution that is characterized by Rust’s model, in which the frequency of service is set in response to the payoff function, but the schedule is not set dynamically within a quarter as a function of the distance from the threshold. As Mark Vend does not observe sales, except at the time of a service visit, this makes a lot of sense. He doesn’t have

As the assortment decision involves simple discrete comparisons across a finite number of choices, there is no need to provide further detail on that choice. We calculate $\pi^R(a, e), \pi^M(a, e), \pi^H(a, e)$ for each possible choice of a and e . The retailer's choice of optimal effort, however, requires a more detailed explanation.

4.2.1 Retail Effort Choice: Dynamic Model of Re-stocking

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} . For modeling the retailer's decision, it is more convenient to work with the number of potential consumer arrivals, which we denote x , rather than \mathbf{s} , because in a multi-product setting, \mathbf{s} is multi-dimensional (and may not define a convex set), while x is a scalar. This implies an informational restriction on the retailer: namely, that he observes the number of potential consumers (for example, the number of consumers who walk through the door) but not necessarily the actual inventory levels of each individual product when making restocking decisions. This closely parallels the problem of Mark Vend.⁴³

Mark Vend solves the following dynamic stocking problem, where $u(x)$ denotes the cumulative variable retailer profits after x potential consumers have arrived. Profits are not collected by Mark Vend until he restocks. His value function is:

$$V(x) = \max\{u(x) - FC + \beta V(0), \beta E_{x'}[V(x'|x)]\}. \quad (8)$$

The problem posed in (8) 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 $x \geq x^*$. Given a guess of the optimal policy, we can compute the post-decision transition-probability-matrix \tilde{P} and the post-decision pay-off \tilde{u} , defined as:

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

new information by which to dynamically adjust a service schedule across days.

⁴³That is, Mark Vend has 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.

This allows us to solve the value function at all states in a single step:

$$V(x, x^*) = (I - \beta \tilde{P}(x^*))^{-1} \tilde{u}(x, x^*). \quad (9)$$

This also enables us to evaluate profits under alternative stocking policies x' , or policies that arise under counterfactual market structures. For example, in order to understand the incentives of a vertically-integrated firm, M-R, we can replace $u(x)$ with $(u^R(x) + u^M(x))$, which incorporates the profits of the dominant upstream manufacturer. Likewise, we can consider the industry-optimal policy by replacing $u(x)$ with $(u^R(x) + u^M(x) + u^H(x) + u^N(x))$.

To find the optimal policy we iterate between (9) and the policy improvement step:

$$x^* = \min x : u(x) - FC + \beta V(0, x^*) \geq \beta P(x'|x) V(x', x^*). \quad (10)$$

The fixed point $(x^*, V(x, x^*))$ maximizes the long-run average profit of the agent $\Gamma(x^*)V(x, x^*)$ where $\Gamma \tilde{P} = \Gamma$ is the ergodic distribution corresponding to the post-decision transition matrix. These long-run profits will become the basis on which we compare contracts and product assortment choices.

4.2.2 Retail Effort Choice: Empirical Implementation

In order to compute the dynamic restocking model, we construct a “representative vending machine” via the following procedure. We define a ‘full machine’ as one that contains a set of the 29 most commonly stocked products, which we report in table 8, and we use actual machine capacities for each product.⁴⁴ Beginning with a full machine, we simulate consumer arrivals one at a time and allow consumers to choose products in accordance with the mixed logit choice probabilities $s_{jt}(\delta, \theta, a_t)$ (including an outside option of no-purchase). After each consumer choice, we update the inventories of each product and adjust the set of available products a_t if a product has stocked out. We continue to simulate consumer arrivals until the vending machine is empty. We average over 100,000 simulated chains to construct the expected profits after x consumers have arrived, and fit a smooth Chebyshev polynomial to the profits of each agent $\hat{u}^R(x), \hat{u}^M(x), \hat{u}^H(x), \hat{u}^C(x)$.⁴⁵

The state variable of our dynamic programming problem is the number of consumers to have arrived since the vending machine was last restocked. Each day, Mark Vend decides

⁴⁴These capacities are nearly uniform across machines, and are: 15-18 units for each confection product, 11-12 units for each salty snack product, and around 15 units for each cookie/other product.

⁴⁵The fit of the 10th order Chebyshev polynomial is in excess of $R^2 \geq 0.99$. It is generally well behaved except at the very edges of the state space, but these are far from our optimal policies.

whether to restock the machine or whether to wait until the next business day. The exogenous state transition matrix $P(x'|x) \approx P(\Delta x)$ is simply the incremental number of consumers to arrive at the vending machine each business day. We assume that the arrival rate has a discrete distribution and (in a separate stage) form a non-parametric estimate of $P(\Delta x)$ based on a sample of 26 vending machines from our experimental dataset.⁴⁶ These machines have an average daily sales volume of 15.1 units and a standard deviation of 2.0 units. Because policies are defined in terms of the cumulative number of consumer arrivals x (rather than days, etc.), even doubling or tripling the rate at which consumers arrive has very little effect on the optimal policies.⁴⁷

We choose a daily discount factor $\beta = 0.999863$, which corresponds to a 5% annual interest rate. We assume a fixed cost of a restocking visit, $FC = \$10$, which approximates the per-machine restocking cost using the driver’s wage and average number of machines serviced per day. As a robustness test, we also consider $FC = \{5, 15\}$, which generate qualitatively similar predictions. In theory, one should be able to estimate FC directly off the data using the technique of Hotz and Miller (1993). However, our retailer sets a level of service that is too high to rationalize with any optimal stocking behavior, often refilling a day before any products have stocked-out.⁴⁸ This is helpful as an experimental control, but makes identifying FC from data impossible.⁴⁹

In order to speed up computation, we normalize our state space when solving the dynamic programming problem. Instead of working with the number of consumers to arrive at the vending machine, we work with the number of consumers who would have likely made a

⁴⁶This mimics Rust (1987) who estimates a discrete distribution of weekly incremental mileage. To be more precise, for each machine-visit, we observe the product assortment a_t and use our demand system to estimate the size of the market as $\hat{M}_t = \frac{Q_t}{1 - \sum_{j \in a_t} s_j(a_t, \theta)}$ where Q_t are the total sales for that machine-visit. After recovering \hat{M}_t we simply divide by the number of elapsed business days since the previous visit which becomes an observation on the number of daily consumer arrivals: Δx_t .

⁴⁷As a robustness test we have assumed the firm can make decisions consumer by consumer, or can make decisions only every four “days”. Once we appropriately scale the discount factor β , the optimal policies change by only 2-3 units. Policies are not particularly sensitive to the specification of the arrival process.

⁴⁸In conversations with the retailer about his service schedule, he mentioned two points. First, he suspected that he was over-servicing, and reduced service levels after our field experiment. Second, he explained that high service levels are important to obtaining long-term (3-5 year) exclusive service contracts with locations. These specific locations almost certainly do not reflect a company-wide servicing policy. Specifically, these are high-end office buildings with high service expectations. Public locations, such as museums and hospitals, have much higher levels of demand and higher rates of stock-out events. These public locations affect company-wide servicing policies, but are not good candidates for running a successful field experiment.

⁴⁹We do not consider possible dynamic considerations, in which a lower service level leads to a lower arrival rate of consumers (i.e., as consumers facing stock-outs grow discouraged and stop visiting the machine, or the client location terminates Mark Vend’s service contract). In other work, we find very little evidence that the subsequent consumer arrival rate is affected by the history of stock-outs.

purchase at a hypothetical “full” vending machine. This saves us from simulating large numbers of consumers who always choose the outside good, independent of product assortment. We thus label our state-space as “likely” consumer arrivals instead of “potential” consumer arrivals from this point forward.⁵⁰

5 Results

By simulating from our consumer choice model in the previous section, we can compute the payoffs to each agent from any assortment a and any effort level e using equation (9). For the retailer, with a policy e :

$$\pi^R(a, e) = (I - \beta \tilde{P}(e))^{-1} \cdot \hat{u}^R(x, a). \quad (11)$$

The matrix inverse from eqn (11), $(I - \beta \tilde{P}(e))^{-1}$ gives us the ergodic distribution of x (the number of *likely* consumers to have arrived since the vending machine was last restocked) as a function of the restocking policy (restock after $x \geq e$ *likely* consumer arrivals), and does not depend directly on the assortment. The second piece, $\hat{u}^R(x, a)$, is our simulated cumulative payoff function from Section 4.2.2. To evaluate profits for different agents, we can simply replace $\hat{u}^R(x, a)$ with $\hat{u}^M(x, a)$ of the dominant retailer Mars and evaluate at the same policy e .

What $\pi^R(a, e)$ represents, is the net present value of the long-run average (infinite horizon) profits of a single representative vending machine under assortment a and restocking policy e . The AUD rebate contract is evaluated quarterly, and is evaluated on the basis of MarkVend’s entire enterprise of more than 700 vending machines (rather than a single vending machine).

We think the effort decision is operationalized as follows: At the beginning of the quarter, MarkVend decides on an (enterprise-wide) policy to restock after e *likely* consumers have arrived at every vending machine. He then translates this policy into a restocking schedule for each vending machine (every Tuesday, every 10 days, every other day, etc.) based on knowledge of a machine specific arrival rate. Once the schedule for the quarter is set, he breaks up the schedule into individual routes, and assigns routes to drivers and trucks.

⁵⁰The key is that the assortment of our hypothetical machine is a strict superset of any possible observed assortment $a_t \subset a^*$, and that our normalization is the same for all a_t . Also, under the hypothetical ‘full machine’ with outside good share $s_0(\delta, \theta, a^*)$, the relationship between the number of arrivals (marketsize) M_t and the state space Δx is well defined, because $\Delta x_t \sim \text{Bin}(M_t, 1 - s_0(\delta, \theta, a^*))$ by construction. In practice this merely requires inflating all of the ‘inside good’ probabilities by $\frac{1}{1 - s_0(a^*)}$. It is also much easier to match the observed arrival rate in the normalized state space than the original state space.

By reducing the number of consumer arrivals between service visits, MarkVend must hire additional trucks and drivers which increases his costs. An implication of this setup is that MarkVend commits to a restocking policy for the entire period. This means that if sales are below expectations (if we repeatedly draw from the left-tail of the consumer arrival distribution) MarkVend does not adjust his stocking policy until the next quarter.⁵¹

Because our assortment decision is discrete (either a product is on the shelf of the vending machine or it isn't), and our effort decision is discrete (we are restricted to restocking after an integer number of *likely* consumer arrivals), we can and do enumerate the payoffs of all of the agents R, M, H, N, C at all of the possible assortments a and effort levels e . We assume that the retailer chooses an assortment a and effort level e to maximize profits net of any rebate transfers $\pi^R(a, e)$ where wholesale prices and rebate contracts are taken as given. Because we evaluate $\pi(a, e)$ using ergodic distribution of the post-decision transition matrix, there is no randomness in $\pi(a, e)$. This makes it easy to compare across assortments and effort levels.

There are many possible choices of product assortment, even after we restrict our attention to the confections category where there are seven potential product slots. For the case in which the retailer chooses seven products to stock from a set of 12, or $\binom{12}{7}$, there are 792 possible combinations that must be considered. From the retailer's perspective, a large number of these assortment decisions are dominated (replacing the best-selling product: Peanut M&M's with the worst-selling product, etc). After some heuristics, we compute the full payoffs at (a, e) of each agent for 15 assortments.

In the results that we report, we fix Mark Vend's five most commonly-stocked chocolate confections products: four Mars products (Snickers, Peanut M&Ms, Twix, and Plain M&Ms), and Nestle's Raisinets. The retailer is always worse off by replacing any of these five products with some other product. We allow the retailer to choose any combination of six different products for the final two slots in the confections category: two Mars products (Milky Way and Three Musketeers), two Hershey products (Reese's Peanut Butter Cup and PayDay), and two Nestle products (Butterfinger and Crunch).⁵² Though we consider many

⁵¹Within 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 the quarter. (The lone exception is that in the last quarter of the year, the frequency of visits is substantially reduced during the period between Christmas and New Year's. When there are departures from the schedule, they are often correlated with extremely low sales which indicate a mechanical problem with the vending machine.)

⁵²In practice, we consider a larger set of potential products including Mars's Skittles and Mars's Starburst, but those are always dominated by Three Musketeers and MilkyWay. (Skittles and Starburst tend to be more popular with younger customers and less popular with our white-collar professional workers). For some other products, we do not have sufficient information to consider them in our counterfactual analysis. For

possible assortments, only three end up being relevant: (M, M) 3 Musketeers and MilkyWay, (H, M) 3 Musketeers and Reese’s Peanut Butter Cups, and (H, H) Reese’s Peanut Butter Cup and PayDay.

There are some other assumptions and caveats that we should establish. When we present results on the level of effort, we express effort as a measure of service frequency. That is, “restock after how many likely consumers?”. Thus if MarkVend restocks a vending machine after 240 consumers instead of 260 consumers, he is restocking more often and exerting more effort. Another assumption is that while we observe retail prices (fixed at 75 cents for confection products) and wholesale prices which vary across manufacturer (w_m, w_h, w_n) , we do not observe manufacturer costs of production, nor do we try and recover them from first order conditions. In most of the results we report, we assume that the marginal cost of production is zero. Thus Mars *profits* are actually Mars *revenue*. When we consider deviations from observed wholesale prices, we allow for different manufacturer marginal costs. Finally, we should also mention that because we do not estimate a price coefficient in our model of consumer choice, only ordinal ranking of product assortments is identified. In order to convert consumer surplus into dollars, we perform a calibration exercise where we assume that the median own price elasticity is equal to $\epsilon = -2$. We view this as a relatively inelastic estimate of consumer surplus, and view our consumer surplus calculations on the higher end of the reasonable range. We provide details on the calibration exercise as well as robustness in Appendix A.5.

5.1 Foreclosure with Fixed Effort

In this subsection, we parallel our theoretical model from section 2.1. Our objective is to determine whether foreclosure is possible, and whether such foreclosure leads to an assortment which maximizes industry profits. Later, we will see if efficiency gains from additional retailer effort are sufficient to offset any losses from foreclosure. We begin by considering observed wholesale prices (w_m, w_h, w_n) and the observed rebate discount λ . Later, we will explore what happens when we modify these conditions.

We assume that the retailer sets his effort level assuming that he receives the rebate payment $(e^R(a))$ from equation (3)) for each assortment and compute the profits $\pi^R(a, e)$, $\pi^M(a, e)$, $\pi^H(a, e)$ for the (R)etailer, the dominant firm (M)ars, and the competitor (H)ershey under three assortments $\{(H, H), (H, M), (M, M)\}$ which we report in Table 9.⁵³ The optimal (inclusive

example, Hershey’s with Almonds is popular nationally, but is never available in our data.

⁵³We obtain qualitatively similar results if we assume that the retailer chooses some other effort level

of the rebate) effort levels are similar across product assortments and imply the retailer restocks after 257 – 261 likely consumers have visited the vending machine. As in eqn (1): $\pi^R(H, H) > \pi^R(H, M) > \pi^R(M, M)$ or (36656 > 36394 > 36086) thus absent any transfers the retailer would prefer to stock (H, H) in the final two slots.

The first column of the second pane considers a transfer payment conditioned on moving from $(H, H) \rightarrow (H, M)$ (partial foreclosure of the rival H). This change in assortment would reduce retailer profits $\Delta\pi^R = -262$ but increase the profits of the dominant firm $\Delta\pi^M = 1657$ by replacing Reese's Peanut Butter Cups with 3 Musketeers. The bilateral gains to R and M are $\Delta\pi^R + \Delta\pi^M = 1395$ which exceed the losses to the rival $\Delta\pi^H = -868$. Thus, even if H gave up all of her lost profit, she could not avoid being (partially) foreclosed and condition (B3) is satisfied. A feasible transfer (by conditions (B1) and (B2)) would require $T \in [262, 1657]$. Therefore, all three conditions (B1), (B2), (B3) conditions are satisfied; there exists feasible transfer which increases producer surplus (by \$501 units after including Nestle) and consumer surplus by \$262 (assuming $\epsilon = -2$). Thus partial foreclosure (H, M) is possible, and would increase producer (and consumer) surplus relative to (H, H) . However, the value of the rebate evaluated at the observed λ : $\lambda\pi^M(H, M) = 1882$ would exceed the gains to Mars $\Delta\pi^M = 1657$. Thus Mars would be paying more to partially foreclose Hershey than Mars would expect to gain from partial foreclosure.

The second column of the second pane of Table 9 starts from (H, M) and considers a move to (M, M) , now Reese's Peanut Butter Cup is replaced by MilkyWay and H is fully foreclosed. Here we see a different story. Again the retailer gives up some profit $\Delta\pi^R = -308$, the dominant firm gains $\Delta\pi^M = 1338$, for a gain in bilateral surplus of $\Delta\pi^M + \Delta\pi^R = 1030$. However, the gain in bilateral surplus is smaller than the losses to the rival $\Delta\pi^H = -1299$. This means that (C3) is violated, and (C4) holds instead. Moving from partial foreclosure (H, M) to full foreclosure (M, M) reduces producer surplus $\Delta PS = -272$ and consumer surplus (again assuming $\epsilon = -2$) $\Delta CS = -110$ and overall social surplus $\Delta SS = -383$. If we consider a feasible transfer payment (so that (C1) and (C2) hold) this limits us to $T \in [308, 1338]$, while at the observed λ the value of the rebate would be 2096, which implies the rebate would be too generous for Mars to want to offer in order to change the assortment from (H, M) to (M, M) .

The final column of the second pane of Table 9 starts from (H, H) and considers a move to (M, M) (full foreclosure of both Hershey's products). The relationship that $\Delta = \Delta_H + \Delta_M$ implies that we could consider the change in profits as simply the sum of the change in

across assortments such as $e^{NR}(a)$ (no-rebate) or $e^{VI}(a)$ (the vertically integrated level).

profits from moving from $(H, H) \rightarrow (H, M)$ and then from $(H, M) \rightarrow (M, M)$. Again we see that the retailer's profit decreases $\Delta\pi^R = -570$ and Mars's profit increases $\Delta\pi^M = 2995$ so that bilateral surplus rises by $\Delta\pi^M + \Delta\pi^R = 2425$. Meanwhile the losses to Hershey are $\Delta\pi^H = -2167$, which implies that (A3) holds. This implies a net gain in producer surplus $\Delta PS = 229$ and consumer surplus $\Delta CS = 150$ when comparing (M, M) and (H, H) . Meanwhile, the set of feasible transfers (as defined by (A1) and (A2)) are $T \in [570, 2995]$ which includes our observed rebate $\lambda\pi^M(M, M) = 2167$.

There are a few implications of our empirical findings. The first is that (A1)-(A3), (B1)-(B3), and (C4) hold. Therefore Theorem 1 tells us that (M, M) is an equilibrium assortment even though industry profits $\pi^I = \pi^M + \pi^H + \pi^R$ and producer surplus are higher at (H, M) under partial foreclosure than they are at (M, M) under full foreclosure. The second is that given the observed size of the rebate λ , the rebate is only individually rational for Mars to offer if Mars believes it will cause the retailer to switch from $(H, H) \rightarrow (M, M)$. If Mars believes that it would induce a switch only from $(H, H) \rightarrow (H, M)$, then the rebate would be too generous. Likewise, if Mars believes that absent the rebate the retailer might have stocked (H, M) then the rebate would also have been too generous to induce a switch only from $(H, M) \rightarrow (M, M)$. Later, we will add in effort and see if and how these results change.

5.2 Role of the Threshold

These results are meant to parallel those in Section 2.3. In this subsection, we explore how the rebate threshold $\bar{\pi}^M$ affects both retailer assortment and effort decisions. One key idea is that we can express the threshold in terms of the profits of the dominant firm $\bar{\pi}^M$ instead of quantity \bar{q}_m . The results we report below assume that wholesale prices (w_m, w_h, w_n) and the rebate discount λ are fixed at their observed values.

Starting with equation (7):

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

From Section 2.3, we know that there are three solutions to the retailer choice of effort: (1) the interior solution to the first line (where the rebate is paid) which we call $e^R(a)$, (2) the interior solution to the second line (where the rebate is not paid) which we call $e^{NR}(a)$ and (3) the constraint binds so that e is chosen to satisfy: $\pi^M(a, e) = \bar{\pi}^M$.

We explore the role of the threshold in Figure 2. Here we have plotted two curves, each curve represents the profits of the retailer after receiving the rebate $\pi^R(a, e) + \lambda\pi^M(a, e)$. The units of the x-axis are profits of the dominant firm: π^M . The left curve represents the profits at (H, M) and the right curve represents the profits at (M, M) . As we move across each curve from left to right, the effort level is increasing (the policy e is declining). At the peak of each curve is a black dot which represents the $e^R(a)$ level of effort which maximizes the post-rebate retailer profits. For reference we have also plotted the vertically integrated optimal effort level $e^{VI}(a)$ and socially optimal effort level $e^{SOC}(a)$. For any value of $\bar{\pi}^M$ to the left of the maximum (black dot) the retailer chooses the interior (including the rebate) solution $e^R(a)$. As $\bar{\pi}^M$ increases beyond $\pi^M(e^R(H, M))$, the retailer exerts additional effort in order to meet the rebate threshold. Eventually, as the threshold increases, the retailer finds it preferable to foreclose the competitor rather than exerting additional effort and jumps to $e^R(M, M)$. We denote this critical threshold with the dashed lines. A similar pattern happens with the (M, M) assortment. Mars can induce effort beyond $e^R(M, M)$, however, at some point (Mars products are never out of stock) effort no longer increases π^M , no amount of additional effort makes it possible for the retailer to obtain the rebate and he reverts to (H, H) and $e^{NR}(H, H)$.

We solve the problem given by (7) for all possible threshold values $\bar{\pi}^M$ and report those in Table 10. The intuition follows exactly the intuition from Figure 2. We find that given no threshold at all and just the discount λ , the retailer immediately switches to (H, M) from (H, H) . The retailer stays at his interior optimum effort point $e^R(H, M)$ until $\bar{\pi}^M \geq 11,763$. For $\bar{\pi}^M \in [11763, 11912]$ the retailer's choice of effort is dictated by the threshold constraint (including the vertically integrated level of effort but not the social optimum). For $\bar{\pi}^M \in [11912, 13101]$, the retailer switches to the interior optimum effort level $e^R(M, M)$ and fully forecloses Hershey. As the threshold grows, the retailer increases his effort in order to satisfy the threshold (including the vertically integrated e^{VI} and social optimum e^{SOC} effort levels) until he reaches $\bar{\pi}^M = 13320$. From this point forward, no amount of additional effort makes the rebate achievable, and the retailer reverts to $e^{NR}(H, H)$.

5.3 Effort and Potential Efficiency Gains

In this subsection we will measure the potential efficiency gains of the AUD contract that come from incentivizing additional effort. In Table 11, we report the optimal effort policies for different groups of agents which solve the optimization problems from 3. We report the retailer's optimal choice of effort with and without the rebate (ignoring the threshold) e^R

and e^{NR} respectively. We also report the optimal effort level that would be set by a vertically integrated combination of Mars and the retailer e^{VI} , as well as an effort level that would be set to maximize producer/industry surplus e^{IND} . Finally we report three levels of socially optimal effort under different assumptions about consumers' median own price elasticity of demand ranging from inelastic $\epsilon = -1$ to more elastic $\epsilon = -4$.

In general, the effort levels are relatively similar across product assortments, we discuss results for the case where Hershey is fully foreclosed $a = (M, M)$. Absent the rebate, the retailer would choose an effort level of $e^{NR} = 264$, restocking after every 264 consumers. The discount aspect of the rebate λ reduces the effective wholesale price to the retailer, and leads him to increase his effort to restocking after $e^R = 259$ consumers, a relatively small improvement. Accounting for the profits of the dominant upstream firm and maximizing bilateral surplus leads to an effort choice of $e^{VI} = 243$. Maximizing surplus of the entire industry (the retailer plus the three confections manufacturers) actually reduces the effort (though only slightly) relative to e^{VI} so that $e^{IND} = 244$. We demonstrate why this happens in Figure 3 which we report for the optimal assortment (H, M) .⁵⁴ For choices of effort $e \in [200, 400]$, decreasing effort monotonically decreases the profits of Mars and the retailer (ignoring restocking costs), but increases the profits of the rivals Hershey and Nestle. As best-selling Mars products such as M&M Peanut and Snickers stock out, demand for Hershey and Nestle products increases from forced substitution. We previously documented this phenomenon with our experiment in Table 6. Thus additional effort is in part “business-stealing” on the part of Mars. Finally, we consider optimal effort policies which also take into account consumer surplus. These vary with the assumed median own price elasticity of demand $e^{SOC} = \{235, 229, 222\}$ for $\epsilon = \{-4, -2, -1\}$ respectively. In Appendix A.5 we show that as consumers become more inelastic, this is akin to the social planner placing more weight on consumer surplus.

An important question asks: “Which effort levels can be implemented via the AUD rebate contract?”. We have already addressed this in Table 10 where we varied the threshold (assuming that the discount is fixed at the observed value of λ). For the (M, M) assortment, the e^R effort level can be implemented by choosing $\bar{\pi}^M \in [11912, 13101]$. From, $\bar{\pi}^M = 13101$ to $\bar{\pi}^M = 13320$ any desired effort level can be implemented through the threshold, including the vertically integrated level $\pi^M(e^{VI} = 235) = 13195$ and the most extreme socially optimal level $\pi^M(e^{SOC} = 222) = 13280$. For the (H, M) assortment we can implement the e^R effort

⁵⁴Figure 3 can be considered a plot $u'(x)$ (the incremental per consumer profit) for the retailer. Because it is always (weakly) positive (bounded by the case where all products stock out) and is (weakly) decreasing (as more products stock-out), this guarantees the concavity of $u(x)$.

level by choosing $\bar{\pi}^M \in [0, 11763]$. From $\bar{\pi}^M \in [11763, 11912]$ the choice of $\bar{\pi}^M$ directly determines the choice of effort from $e \in [261, 236]$ (which includes e^{VI} but does not include e^{SOC} if $\epsilon \geq -2$). Effort levels beyond 236 cannot be implemented, because the retailer prefers to switch to the full foreclosure (M, M) assortment rather than continue to increase effort.

In Table 12 we consider the potential efficiency gains induced by the AUD rebate. Because we are interested in whether or not potential efficiency gains might outweigh potential losses from foreclosure, we focus on cases where the rebate threshold is set to achieve the vertically integrated e^{VI} or socially optimal e^{SOC} effort levels.⁵⁵ If we focus on the full foreclosure (M, M) policy, we see that switching from the no-rebate retailer effort to the vertically integrated optimum leads to an increase in restocking frequency of 7.95%. We chose the e^{NR} effort level rather than the e^R effort level as our baseline to maximize potential efficiency gains.⁵⁶ Increasing effort is costly to the retailer $\Delta\pi^M = -55$ and beneficial to Mars $\Delta\pi^M = 128$ leading to a net gain of $\Delta PS = 63$ once we include the competing manufacturers. Most of the gains to effort accrue to consumers who gain $\Delta CS = 192$ for a net gain in $\Delta SS = 255$. The socially optimal effort policy leads to an even larger increase in the frequency of restocking (13.26%) but much smaller gains in producer surplus $\Delta PS = 17$ and larger gains in consumer surplus $\Delta CS = 284$ for a net gain of $\Delta SS = 301$. This is designed to represent an upper bound on the potential efficiency gains of the AUD contract.

In Table 13 we provide direct comparisons between the full foreclosure assortment (M, M) under the e^R , e^{VI} , and e^{SOC} effort levels against two potential baselines. The first is the optimal (H, M) assortment with the e^{NR} effort level. This is meant to represent the assortment that would be chosen by the social planner, but without any efficiency gains either from lower wholesale prices or the rebate threshold. The second is the (H, H) assortment under the e^{NR} effort level. This is meant to mimic what the retailer would choose if the AUD contract were to disappear but wholesale prices were to remain fixed.

Starting from a base assortment of (H, H) the AUD contract which leads to full exclusion of the rival Hershey (M, M) , appears to unambiguously increase both consumer and producer surplus. Even when the threshold does not induce additional effort beyond the assortment decision e^R social surplus increases by $\Delta SS = 477$. Producer and consumer surplus improve under the vertically integrated level leading to $\Delta SS = 654$ and increasing effort to the social

⁵⁵For the social optimum, we use $\epsilon = -2$ when calibrating our consumer surplus. We view this as an upper bound on the potential consumer effects.

⁵⁶We see that most of the additional effort comes through the choice of the threshold, because when we start with the e^R optimal (which includes the lower wholesale price) the increase in frequency is still 6.18%.

optimum would increase consumer surplus at the expense of producer surplus for a net gain of $\Delta SS = 700$. When we compare the full exclusion of Hershey (M, M) assortment to the socially optimal assortment (H, M) the welfare effects are more ambiguous. If the AUD threshold $\bar{\pi}^M$ is set large enough to obtain exclusion, but not large enough to incentivize enough additional effort then both producers $\Delta PS = -239$ and consumers $\Delta CS = -49$ are worse off than they would be absent the rebate under the (H, M) assortment. If the threshold is set to obtain the vertically integrated effort level e^{VI} the producer surplus still declines relative to (H, M) $\Delta PS = -203$ but consumers benefit from the additional effort $\Delta CS = 92$. At our assumed median own price elasticity of $\epsilon = -2$ this implies that the net effect $\Delta SS = -111$ is still negative. Even at the socially optimal effort level e^{SOC} the losses to firms (mostly the rival H) imply $\Delta PS = 250$ while the gains to consumers from the higher effort are positive $\Delta CS = 185$.

From a consumer surplus perspective, as is commonly employed by US antitrust authorities, the welfare impact of the AUD contract hinges on whether the threshold is set high enough to induce sufficient effort to compensate the consumer for the less preferred product assortment. From a social surplus perspective, which takes into account foreclosed rivals profits, the AUD contract does not appear improve welfare as the additional effort does not fully compensate for the inferior product assortment. We also reiterate that many of our assumptions were designed to maximize potential efficiency gains from effort (including placing a relatively large amount of weight on consumer surplus). Also, as we point out in Appendix A.5, if the retailer places some weight on consumer surplus when making effort/restocking decisions (perhaps as part of signing up potential locations for vending machines) then the potential gains to effort are drastically reduced, and the foreclosure effect always dominates.

5.4 Role of the Discount and Competitive Response

Thus far, we have sidestepped the possibility that Hershey could cut its wholesale price and avoid foreclosure by simply comparing the bilateral gains of Mars and the retailer to the losses of Hershey using conditions like (A3). The idea is that were a bidding war to break out, Hershey would not have enough surplus to transfer to the retailer to avoid foreclosure, and thus any attempts at wholesale price cuts would be futile. We now explore the mechanics of how this might play out.

We start by holding the wholesale prices of the other firms (w_m, w_n) fixed, as well as the rebate discount λ . We let Hershey adjust its price from $w_h \rightarrow w'_h$, where we calculate w'_h as the price which makes the retailer indifferent among: accepting the rebate payment and

foreclosing Hershey; and purchasing the Hershey products at the reduced wholesale price:

$$w'_h = w_h \cdot \frac{\Delta\pi^R + \lambda\pi^M + \Delta\pi^H}{\Delta\pi^H} \quad (12)$$

We compute the critical values of w'_h and report them in Table 14 which parallels the design of Table 13. If the alternative to the rebate and full foreclosure (M, M) is a baseline assortment of (H, H) and effort level of e^{NR} , then we find that Hershey would have to cut its price to 12.83 – 15.35 cents depending on how much additional effort was induced by the rebate threshold. This is remarkably close to our best estimate of the marginal cost of production which we believe to be around 15 cents per candy bar. Thus at the existing level of the rebate λ , Hershey would likely need to sell at a loss in order to avoid foreclosure.⁵⁷ These results suggest that Hershey would not be able to avoid foreclosure by outbidding Mars for placement in the retail assortment (even before a potential Mars response to increase λ).⁵⁸

Conversely, we consider whether Mars could reduce its discount and still foreclose its rival. We assume that each manufacturer's production cost is \$0.15 per unit, so that Hershey's best offer to the retailer is a wholesale price of $w'_h = c_h = \$0.15$ and re-solve (12) for λ in order to see how much Mars could reduce its rebate payment. Again, the precise estimates depend on the effort level induced by the rebate threshold. At the retailer optimal (inclusive of the rebate) effort level the rebate could be reduced by 5.27%, while at the higher vertically integrated level of effort the rebate could be reduced by only 3.53%.⁵⁹ Assuming that the \$0.15 production cost estimate is reasonable, this gives some indication that the terms of Mars's current rebate program are well designed.

The left panel of Table 13 conducts the same exercise, but assumes that absent the rebate the retailer would choose the (H, M) assortment. Under this scenario, the rebate is much too generous and could be reduced between 38.18% and 44.79% while still foreclosing Hershey. Likewise, holding fixed the terms of the rebate λ , Hershey would need to set a negative wholesale price or pay the retailer to sell its products. This is meant to highlight the fact that the rebate terms are only sensible as a device to make the retailer switch from $(H, H) \rightarrow (M, M)$.⁶⁰

⁵⁷If the rebate was set with a sufficiently high threshold as to induce the socially optimal effort level, then Hershey could avoid foreclosure by setting $w_h = \$0.1535$.

⁵⁸Formally, (A2) provides Mars's IR constraint for a potential λ .

⁵⁹At the socially optimal effort, the rebate is not generous enough were Hershey to set $w_h = c_h = \$0.15$.

⁶⁰It should also be clear that adjusting the baseline from (H, H) to (H, M) means that the current rebate violates Mars's IR constraint (B2) as noted in Table 9.

5.5 Comparison to Uniform Wholesale Pricing

Another important comparison that is helpful in understanding the AUD is to compare it with a uniform wholesale price. In this world, the dominant firm no longer is able to condition a discount on a threshold $\bar{\pi}^M$. We hold fixed the wholesale prices of the competing firms (w_h, w_n) , and compute the optimal wholesale price for M , w'_m . Unlike under the AUD, the resulting set of wholesale prices (w'_m, w_h, w_n) does not constitute an equilibrium (because (w_h, w_n) are not allowed to adjust). This is not meant to represent what would happen to equilibrium prices in the absence of an AUD, rather it is meant as tool to understand how the AUD reduces the price of foreclosure to the dominant firm.

We present results for a uniform wholesale price in Table 15. The main result is that Mars is able to foreclose Hershey (when Hershey cannot respond), but the resulting price is lower than the price under the AUD after we have included the discount. Effectively, Mars pays more for foreclosure without the threshold. We quantify exactly how much more by comparing the linear pricing contract to the AUD which forecloses at two effort levels: the post-rebate optimal effort level $e^R(M, M)$ and the vertically integrated optimum $e^{VI}(M, M)$. Mars profits (after rebates), $(1 - \lambda)\pi^M$, fall from \$11,005 to \$10,094 for a change of \$911. The retailer's profits (after rebates), $\pi^R + \lambda\pi^M$, increase by a similar amount (\$921). The gains to the retailer are slightly larger if the AUD had been used to implement the vertically integrated effort level.

What we explicitly do not consider is an equilibrium where the upstream firms simultaneously set (w_m, w_h) . The challenge is that because the retailer's assortment decision is discrete, no Nash equilibrium exists in pure strategies. Instead, only a mixed strategy Nash equilibrium exists. The non-existence of pure strategy equilibria is well documented in the theoretical literature, see recent work by Jeon and Menicucci (2012). The challenge is that best-response functions are discontinuous, and need not cross. We plot the best response of Mars to the observed (w_h, w_n) prices in Figure 4. We do not characterize the mixed strategy Nash equilibrium of the uniform wholesale pricing game, which is not easily interpretable in our context, and beyond the scope of our analysis of the AUD contract.

5.6 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.

In this analysis, 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.⁶¹ In order to analyze the impact of any potential merger, we conduct a similar exercise as before, but consider the incentives of the merged firm.

Table 16 parallels Table 14, but measures how upstream firms might respond to an upstream merger.⁶² The first column duplicates Table 14, while in the second, we assume that the Hershey product (Reeses Peanut Butter Cup) is priced at the Mars wholesale price and included in Mars' rebate contract after the merger. 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).⁶³ The merged firm faces competition from Nestle (Crunch and Butterfinger), which charges lower wholesale prices but sells less popular products.⁶⁴ In the absence of an AUD, the Retailer maximizes profits by stocking the two Nestle products (earning \$36,594), but the AUD induces the retailer to choose (H,M), as well as the effort level that would be set by the vertically-integrated firm (earning \$36,340 + \$2,105 = \$38,445). We find that the after the Mars-Hershey merger, because the rebate could be used to induce the retailer to stock (H, M) and set the vertically integrated effort level, the effect of the rebate is unambiguously positive. It increases $\Delta PS = 1,251$ and $\Delta CS = 2,473$, in part because the alternative to the rebate (N, N) is less popular than (H, H).

We continue to perform the same exercise as in Table 14, and allow Nestle to cut its price in order to avoid having Butterfinger and Crunch foreclosed. This is impossible as it would require the wholesale price charged by Nestle to the retailer to be negative. This is not surprising, as Nestle would be trying to induce the retailer to stock a less popular assortment (similar to condition (A3)). The likely response from Mars to the merger would be to decrease the generosity of the rebate. Pre-Merger we found that the rebate was only 3.53% too generous, after the merger it is 43.4% too generous. This implies that Mars could

⁶¹For a related analysis of diversion ratios in this market, see Conlon and Mortimer (2013b).

⁶²For a full accounting of post-merger profits at all $\pi(a, e)$ please consult Appendix A.6.

⁶³We assume that the AUD retains λ at the pre-existing level, and sets $\bar{\pi}^M = \pi^M(e^{VI}(H, M))$ to induce the vertically integrated optimal level of effort.

⁶⁴In the base case, we assume Nestle's wholesale prices do not adjust after the Mars-Hershey merger.

decrease the transfer to the retailer by around \$900.

We may also be interested in the direct effects of a merger in the presence of the AUD. We compare the pre-merger outcome of $e^{VI}(M, M)$ and the post-merger equilibrium outcome $e^{VI}(H, M)$.⁶⁵ The merger would increase $\Delta PS = 269$ and $\Delta CS = 110$ (assuming $\epsilon = -2$), primarily through the improved product assortment.⁶⁶ The somewhat paradoxical result is that merger undoes the foreclosure incentive under the AUD and is thus welfare improving.

We perform a similar exercise, where we allow Mars and Nestle to merge (third column). The main difference is that Mars has access to the profits of Nestle’s Raisinets, and is able to include Raisinets profit in the rebate. This leads Mars to reduce the λ of the rebate, though because of the larger base, the overall size of the transfer changes by less than \$20.⁶⁷ We also perform an exercise where we allow Hershey and Nestle to merge (final column). Giving Hershey access to the profits of Raisinets does very little, because Raisinets are not in danger of being foreclosed, and it more or less resembles our baseline (No Merger) scenario.

Throughout the paper, we report the variable profits for the retailer; it is likely that his overall operating profits after accounting for administrative and overhead costs, are substantially lower. In the *Intel* case, the rebate program was reported to account for more than one quarter of Dell’s operating profits. Based on communication with industry participants, we think that the Mars rebate may be an even larger fraction of operating profits in the vending industry. This means that a 42% rebate reduction (implied by the hypothetical Mars-Hershey merger) may represent a substantial fraction of the overall operating profits of the retailer.

6 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.

⁶⁵Both of these outcomes satisfy our (A1)-(A3) conditions, whether the alternative is (H, H) or (N, N) respectively. There is ambiguity about the equilibrium effort level, but we choose e^{VI} for simplicity and because it maximizes bilateral surplus.

⁶⁶If we allow the retailer to consider the consumer surplus when making restocking decisions as we do in Appendix A.5 (as a reduced form way to model competition for vending machine locations), the results are nearly unchanged $\Delta PS = 261$ and $\Delta CS = 116$.

⁶⁷The only difference comes to the effort channel as Mars prefers less effort once it internalizes substitution to Raisinets.

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 discrete-choice demand model 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 demand and retailer-effort models benefit 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 by roughly 9-11%, but these rents are mostly captured by consumers. The rebate also enables the dominant firm, Mars, to foreclose Hershey by leveraging profits from dominant brands such as Snickers and Peanut M&Ms, and to obtain shelf-space for brands 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 does not lead to a product assortment that maximizes industry profits. We note that in the absence of the vertical rebate, manufacturers may charge different wholesale prices. In a limited comparison of Mars' optimal linear wholesale prices to the AUD contract, we find that the primary difference between Mars' AUD and linear wholesale pricing is the allocation of profits between the dominant upstream firm and the retailer. The differential impact on social welfare is small, and depends on how the dominant firm sets the quantity threshold in the AUD. Finally, we explore the potential impact of three potential 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 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.

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Figure 1: Mars Vend Operator Rebate Program

The Only Candy You Need To Stock In Your Machine!

Spinal#1	Spinal#2	Spinal#3	Spinal#4	Spinal#5	Spinal#6	Spinal#7	Spinal#8
							
#1 Selling Confection Item in Vending!	#2 Selling Confection Item in Vending!	#3 Selling Confection Item in Vending!	#4 Selling Confection Item in Vending!	#11 Selling Confection Item in Vending!	#6 Selling Confection Item in Vending!	#5 Selling Confection Item in Vending!	#9 Selling Confection Item in Vending!

- Based on the current business environment, vend operators are looking for one supplier to cover all of their Candy needs
 - MARS - 100% Real Chocolate!
 - MARS - 100% Real Sales!



Proven 52 Weeks Ending 10/4/09

MARS chocolate north america

2010 Vend Operator Program

Platinum Rebate Level

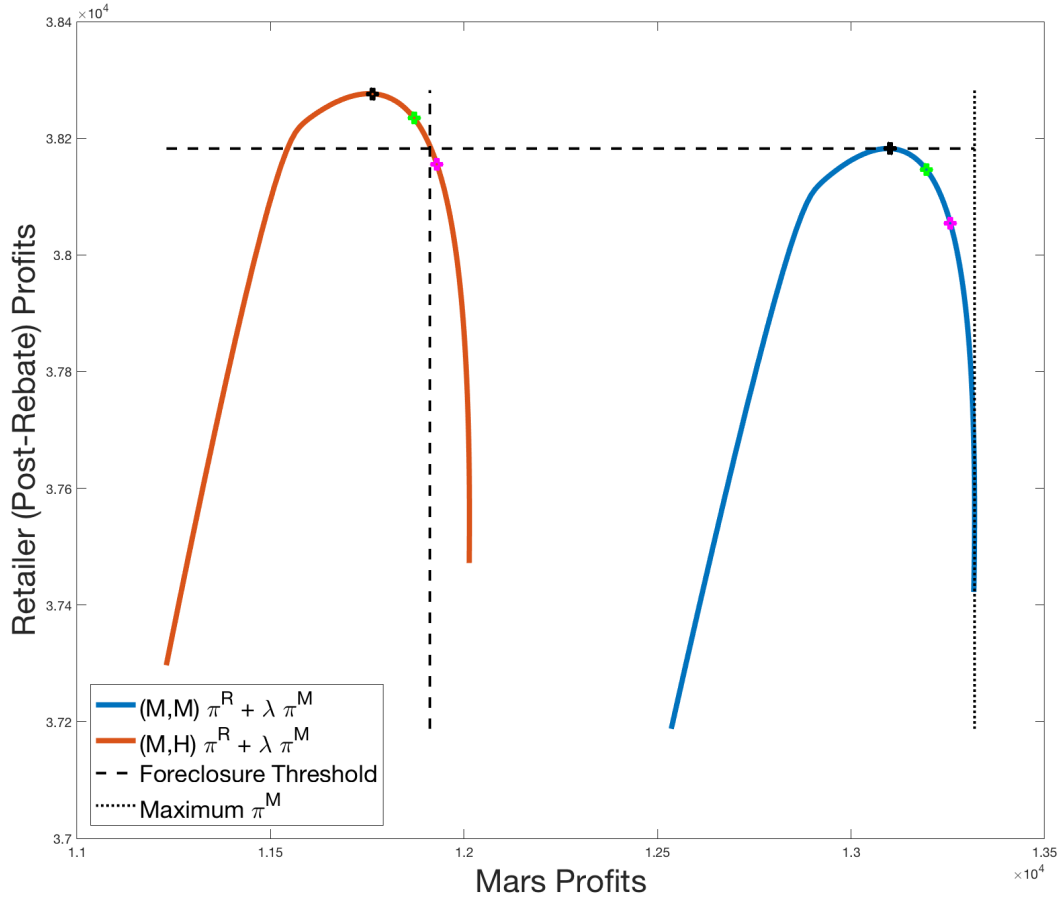
- Receive a great Every Day Low Cost from your Authorized Vend Product Distributor
- Purchase brand level targets for 6 singles or king size items
 - Reduction from 7 must-stock items in 2009!
 - You pick the six items!
 - Will consolidate item variants to qualify (by brand, excluding SNICKERS® Bar and M&M's® Peanut Candies)
- No Growth Requirement
- PLUS a Rebate Payment Low Cost PLUS Rebate:

Item	Rebate %	Rebate \$ Per Bar (singles)
All Items	8%	4.0¢

MARS chocolate north america

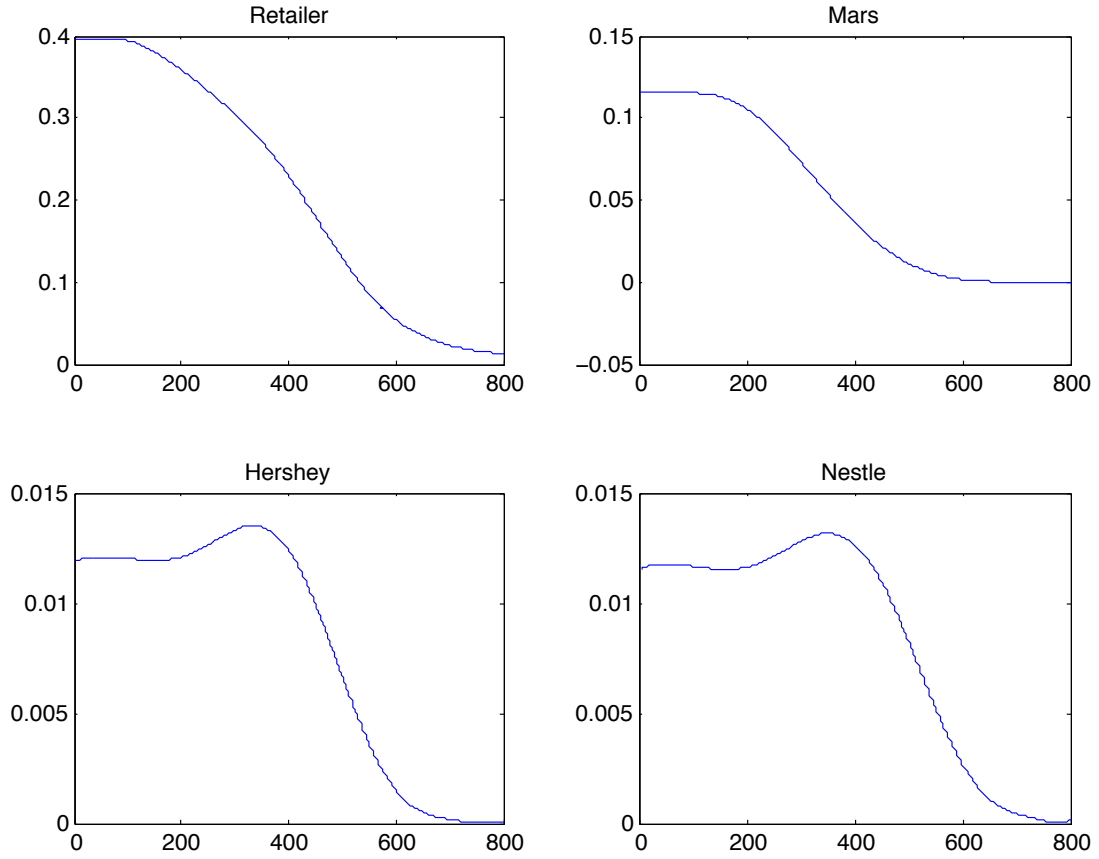
Notes: From '2010 Vend Program' materials, dated December 21, 2009; last accessed on February 2, 2015 at <http://vistar.com/KansasCity/Documents/Mars%202010%20Operatorpr%20rebate%20program.pdf>.

Figure 2: Impact of AUD Quantity Threshold on Retail Assortment Choice



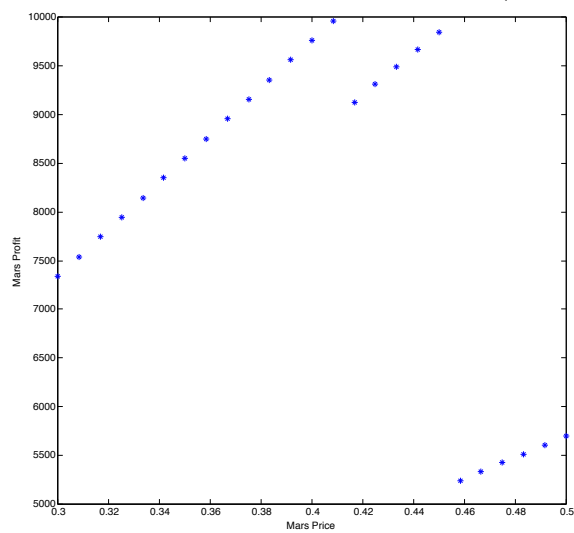
Notes: Figure reports retailer profit under two assortment choices ((H,M) on the left and (M,M) on the right), against sales of Mars products. For a threshold $\bar{\pi}^M \geq 11,912$ (noted by the vertical dashed line), the retailer prefers to switch his assortment from (H,M) to (M,M).

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



Notes: Reports the profits 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.

Figure 4: Mars Profits as a Function of Price (Linear Pricing)



Notes: Reports Mars' profit at different linear wholesale prices, holding fixed the wholesale prices of Hershey and Nestle. The discontinuities reflect prices at which the retailer drops a Mars product from its assortment.

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

Manu- facturer	Product	National:			Mark Vend:		Experimental:	
		Rank	Avail- ability	Share	Avail- ability	Share	Avail- ability	Share
Mars	Snickers	1	89	12	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	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 2007q1-2008q1 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	
	Mars	Hershey	Nestle	Milkyway	3 Musketeer	PB Cup	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*** (0.410)	0.857*** (0.0690)
Observations	117,428	117,428
R-squared	0.361	0.154
Machine FE	YES	YES
Week of Year FE	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes:

Table 5: Downstream Profit Impact

			Without Rebate			With Rebate		
Exogenous Removal	Vends	Obs	Difference In:		T-Stat	Difference In:		T-Stat
			Margin	Profit	of Diff	Margin	Profit	of Diff
Snickers	-216.82	109	0.39	-56.75	-2.87	0.24	-73.26	-4.33
Peanut M&Ms	-197.58	115	0.78	-10.74	-0.58	0.51	-39.37	-2.48
Double	-282.66	89	1.67	-4.54	-0.27	1.01	-54.87	-3.72

Notes: Calculations by authors, using exogenous product removals from the field experiment.

Table 6: Upstream (Manufacturer) Profits

Exogenous Removal					% Borne by Mars	
	Mars	Hershey	Nestle	Other	Without Rebate	With Rebate
Snickers	-26.37	5.89	19.32	-20.26	31.7%	11.9%
Peanut M&Ms	-68.38	32.76	11.78	-9.36	86.4%	50.2%
Snickers + Peanut M&Ms	-130.81	61.43	20.22	37.10	96.7%	59.5%

Notes: Calculations by authors, using exogenous product removals from the field experiment. The ‘% 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	
σ_{Salt}	0.506 [.006]	0.458 [.010]
σ_{Sugar}	0.673 [.005]	0.645 [.012]
σ_{Peanut}	1.263 [.037]	1.640 [.028]
# Fixed Effects ξ_t	15,256	2,710
LL	-4,372,750	-4,411,184
BIC	8,973,960	8,863,881
AIC	8,776,165	8,827,939

Notes: The random coefficients estimates correspond to the choice probabilities described in section 4, equation 5. Both specifications include 73 product fixed effects. Total sales are 2,960,315.

Table 8: Products Used in Counterfactual Analyses

'Typical Machine' Stocks:	
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	
Kar Sweet & Salty Mix	
Farley's Mixed Fruit Snacks	
Planter's Salted Peanuts	
Zoo Animal Cracker Austin	

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: Assortment Decisions with Fixed Effort

	(H,H)	(H,M)	(M,M)
e^R	257	261	259
π^R	36,656	36,394	36,086
$\lambda\pi^M$	1,617	1,882	2,096
π^M	10,106	11,763	13,101
π^H	2,167	1,299	0
$\pi^R + \pi^M$	46,762	48,157	49,187
$\pi^R + \pi^M + \pi^H$	48,929	49,456	49,187
from	(H, H)	(H, M)	(H, H)
to	(H, M)	(M, M)	(M, M)
$\Delta\pi^R$	-262	-308	-570
$\Delta\pi^M$	1,657	1,338	2,995
$\Delta\pi^{M+R}$	1,395	1,030	2,425
$\Delta\pi^H$	-868	-1,299	-2,167
	Rebates		
Feasible	262 -1657	308-1338	570-2995
Observed	1,882	2,096	2,096
ΔPS	501	-272	229
ΔCS	261	-110	150
ΔSS	762	-383	379

Table 10: Critical Thresholds and Foreclosure at Observed λ

$\bar{\pi}_M^{MIN}$	$\bar{\pi}_M^{MAX}$	Assortment	Effort
0	10,106	(H,M)	$e^R(H, M)$
10,106	10,420	(H,M)	$e^R(H, M)$
10,420	11,763	(H,M)	$e^R(H, M)$
11,763	11,912	(H,M)	$e(\bar{\pi}_M(H, M))$
11,912	12,014	(M,M)	$e^R(M, M)$
12,014	13,101	(M,M)	$e^R(M, M)$
13,101	13,319	(M,M)	$e(\bar{\pi}_M(M, M))$
13,320	∞	(H,H)	$e^{NR}(H, H)$

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

	(H,H)	(H,M)	(M,M)
e^{NR}	263	267	264
e^R	257	261	259
e^{VI}	237	244	243
e^{IND}	241	247	244
$e^{SOC}(\epsilon = -4)$	233	238	235
$e^{SOC}(\epsilon = -2)$	227	232	229
$e^{SOC}(\epsilon = -1)$	220	224	222

Notes: Social optimum effort levels reported for different calibrated median own price elasticities of demand. For further details, see Appendix A.4.

Table 12: Potential Gains from Effort

	Vertically Integrated			Socially Optimal		
	(H,H)	(H,M)	(M,M)	(H,H)	(H,M)	(M,M)
$\% \Delta(e^{NR}, e^{Opt})$	9.89	8.61	7.95	13.69	13.11	13.26
$\% \Delta(e^R, e^{Opt})$	7.78	6.51	6.18	11.67	11.11	11.58
$\Delta \pi^R$	-83	-63	-55	-163	-152	-157
$\Delta \pi^M$	195	152	128	251	211	190
ΔPS	76	65	63	39	24	17
$\Delta CS(\epsilon = -2)$	228	210	192	289	290	284
ΔSS	304	275	255	329	313	301

Notes: Percentage change in policy is calculated as increase required from baseline policy e^{NR} to vertically integrated or socially optimal policy. Social optimum assumes α corresponding to a median own price elasticity of demand of $\epsilon = -2$. For robustness, see Appendix A.4.

Table 13: Net Effect of Efficiency and Foreclosure

Base: to (M, M) and	(H, M) and e^{NR}			(H, H) and e^{NR}		
	e^R	e^{VI}	e^{SOC}	e^R	e^{VI}	e^{SOC}
$\Delta \pi^R$	-312	-364	-466	-575	-626	-728
$\Delta \pi^M$	1,382	1,476	1,538	3,045	3,140	3,201
ΔPS	-239	-203	-250	267	302	255
$\Delta CS(\epsilon = -2)$	-49	92	185	211	352	444
ΔSS	-287	-111	-65	477	654	700

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

Table 14: Potential Upstream Deviations

Base: to (M, M) and	(H, M) and e^{NR}			(H, H) and e^{NR}		
	e^R	e^{VI}	e^{SOC}	e^R	e^{VI}	e^{SOC}
$\Delta\pi^R$	-312	-364	-466	-575	-626	-728
$\Delta\pi^M$	1,382	1,476	1,538	3,045	3,140	3,201
$\Delta\pi^H$	-1,302	-1,302	-1,302	-2,173	-2,173	-2,173
$\lambda\pi^M$	2,096	2,111	2,120	2,096	2,111	2,121
w_h to avoid Foreclosure	-15.83	-14.61	-11.59	12.83	13.54	15.35
Reduction in λ ($w_h = 0.15$)	44.79%	42.72%	38.18%	5.27%	3.53%	-0.84%

Table 15: Linear Pricing vs. AUD (Assortment is (M,M))

	e^R	e^{VI}	Linear Pricing
$\bar{\pi}^M$	$\in [11912, 13101]$	=13,195	=0
e	259	243	257
$\pi^R + \lambda\pi^M$	38,182	38,146	39,103
$(1 - \lambda)\pi^M$	11,005	11,084	10,094
PS	50,441	50,476	50,450
CS ($\epsilon = -2$)	24,812	24,953	24,832

Notes: The optimal wholesale price under linear pricing is estimated to be 41.36 cents per unit. Hershey is excluded in the (M,M) assortment for all three arrangements, and earns zero profit. The changes in producer surplus include small changes in Nestle's profits due to the effect of changes in the retailer's choice of restocking policy on the sales of Raisinets.

Table 16: Comparison under Alternate Ownership Structures

	No Merger	M-H Merger	M-N Merger	H-N Merger
AUD Assortment	$e^{VI}(M, M)$	$e^{VI}(H, M)$	$e^{VI}(M, M)$	$e^{VI}(M, M)$
Alternative	$e^{NR}(H, H)$	$e^{NR}(N, N)$	$e^{NR}(H, H)$	$e^{NR}(H, H)$
$\Delta\pi^R$	-626	-254	-621	-626
$\Delta\pi^M$	3,140	2,962	3,095	3,140
$\lambda\pi^M$	2,111	2,105	2,310	2,111
$\Delta\pi^{Rival}$	-2,173	-1,458	-2,173	-2,212
Price to Avoid Foreclosure	13.54	-11.31	9.52	13.79
% Reduction in Rebate ($c = 0.15$)	3.53%	43.42%	12.67%	3.01%
ΔPS	302	1,251	302	302
ΔCS	444	2,473	436	444

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 level in order to maximize efficiency gains.

Appendix

A.1: Proof of Theorems

Proof of Theorem 1:

Note: We can relate our (linear) delta operators to one another via:

$$\Delta\pi^* = \Delta_M\pi^* + \Delta_H\pi^*$$

(A3) provides that $\pi^I(M, M) > \pi^I(H, H)$. (B3) provides $\pi^I(M, H) > \pi^I(H, H)$ and (C4) provides that $\pi^I(M, H) > \pi^I(M, M)$. Thus $\pi^I(M, H) > \pi^I(M, M) > \pi^I(H, H)$.

Absent transfers, if R selects the assortment then $\pi^R(H, H) > \pi^R(M, H) > \pi^R(M, M)$ implies that the equilibrium assortment will be (H, H) . If we temporarily ignore (M, H) then (A1)-(A3) say that in a choice between (M, M) and (H, H) it is possible to design a transfer T which leads to assortment $(H, H) \rightarrow (M, M)$ in equilibrium. Likewise, if we temporarily ignore (M, M) , then under (B1)-(B3) it is possible to design a transfer that leads to assortment $(H, H) \rightarrow (M, H)$ in equilibrium. Thus there are two possible assortments in equilibrium: $\{(M, M), (M, H)\}$.

If M gets to choose the contract and the transfer T then for (M, M) to be the equilibrium outcome, it remains to show that:

$$\pi^M(M, M) - T \geq \pi^M(M, H) - T_h$$

The dominant manufacturer M should choose the smallest such T in each case so that (A1) or (B1) binds.

$$\begin{aligned} \pi^M(M, M) - (-\Delta\pi^R) &\geq \pi^M(M, H) - (-\Delta_H\pi^R) \\ \pi^M(M, M) + \Delta\pi^R &\geq \pi^M(M, H) + \Delta_H\pi^R \\ \underbrace{\pi^M(M, M) - \pi^M(M, H)}_{\Delta_M\pi^M} + \underbrace{\Delta\pi^R - \Delta_H\pi^R}_{\Delta_M\pi^R} &\geq 0 \end{aligned}$$

This gives us the sensible condition that (M, M) is preferred by M to (M, H) when such a change would increase the bilateral surplus between M and R , which is guaranteed by (C4) \square .

Proof of Theorem 2:

Using (C3) instead of (C4) ensures that $\pi^I(M, H) < \pi^I(M, M)$. Thus $\pi^I(M, M) > \pi^I(M, H) > \pi^I(H, H)$. In the final line, (C3) guarantees that $\Delta_M\pi^M + \Delta_M\pi^R \geq -\Delta_M\pi^H \geq 0$. Thus (M, M) is the unique equilibrium and it maximizes overall industry profits \square .

A.2: Effort Derivation

Consider the effort choice of the retailer faced with an AUD contract from (2):

$$\begin{cases} \pi^R(e) - c(e) + \lambda \cdot \pi^M(e) & \text{if } \pi^M(e) \geq \overline{\pi^M} \\ \pi^R(e) - c(e) & \text{if } \pi^M(e) < \overline{\pi^M} \end{cases}$$

In the case where the rebate is paid, we can express the retailer's problem as:

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

The solution to the constrained problem is given by:

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

If the rebate is not paid then:

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

The retailer's IC constraint:

$$\pi^R(e_1) - c(e_1) + \lambda \pi^M(e_1) \geq \pi^R(e_0) - c(e_0) \quad (\text{IC})$$

and the dominant firm M 's IR constraint:

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

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 :

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

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

A.3: Alternative Contracts

Some readers may find it helpful to compare the AUD contract to other contracts, this section is meant to be expositional and does not present new theoretical results:

Quantity Discount

A discount d , can be mapped into λ (a share of M 's variable profit margin). However the dis-

count no longer applies to all q_m , only those units in excess of the threshold so that $\gamma(\overline{\pi^M}) = \max\left\{0, \frac{\pi^M - \overline{\pi^M}}{\pi^M}\right\}$. This implies $T \equiv \gamma(\overline{\pi^M}) \cdot \lambda \cdot \pi^M$, so that as the threshold increases, M is limited in how much surplus he can transfer to R . (At least when we require the post-discount wholesale price to be 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, $\bar{e} \geq e^{reb}$ implies that M can directly set the retailer's effort). This means that high effort levels, $e > e^{reb}$, 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 $d = w_m - c_m$ such that M earns no profit on the marginal unit, and some \bar{q}_m significantly less than the vertically integrated quantity.

Quantity Forcing Contract

The quantity forcing contract is similar to a special case of the AUD contract. If we start with a conventional AUD (w_m, d, \bar{q}_m) :

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

We can increase the wholesale price w_m by one unit, and increase the generosity of the rebate by one unit. If we continue with this procedure, the retailer profits when the threshold is met $q_m \geq \bar{q}_m$ remain unchanged, while the profits when the firm does not receive the rebate $q_m < \bar{q}_m$ eventually tend toward zero as $w_m \rightarrow p_m$. This has the effect of “forcing” the retailer to accept a quantity at least as large as \bar{q}_m . By choosing the threshold, the QF contract can achieve the vertically integrated level of effort, just like the AUD. For quantities $q_m > \bar{q}_m$, the AUD works like a quantity forcing contract plus a uniform wholesale price on “extra” units.⁶⁸ Without some outside constraint on d or w_m , and absent uncertainty about demand, the dominant firm has an incentive to increase d and w_m together and replicate the QF contract.

Two Part Tariff

We can also construct a two part tariff, which we can write as a share of M 's revenue λ and a fixed transfer T from $R \rightarrow M$. The retailer chooses between the 2PT contract and the standard wholesale price contract.

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

⁶⁸For 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)

We can 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 both 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 $T = (1 - \lambda_{AUD}) \cdot \bar{\pi}^M$ (the dominant firm's profits under the AUD) so long as the retailer is willing to choose the 2PT contract.

This indicates 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 effort levels in excess of the vertically integrated optimum e^{VI} which result 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.⁶⁹ It may be easier in practice to tailor sales thresholds to the size of individual retailers (as opposed to fixed fee transfer payments).⁷⁰

A.4: Consumer Surplus and Welfare Calculations

We calculate the expected consumer surplus of a particular assortment and policy (a,e) as follows. The approach parallels how we calculate the profits of the retailer. 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 :

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

Using the exogenous arrival rate, $f(x'|x)$, which denotes the expected daily number of consumer arrivals (from x cumulative likely consumers today to x' cumulative likely consumers tomorrow)

⁶⁹Kolay, Shaffer, and Ordovery (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.

⁷⁰Another 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).

and a policy $x^*(e)$, 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 $CS^*(a, e)$ is in arbitrary units of consumer utility, rather than dollars. Recall our utility specification from (4), with $\theta = [\delta, \alpha, \sigma]$:

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

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

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

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

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

$$SS(a, e) = PS(a, e) + \frac{1}{\alpha} CS^*(a, e)$$

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

In the following Table 17, we show robustness to assumptions about the median own price elasticity of demand (and the corresponding α parameter). As consumers become more inelastic, the social planner places more weight on consumer utility in calculating the socially optimal stocking rule. This means that in the case where more than half of consumers have an inelastic own price elasticity $\epsilon = -1$, which we view as an extreme upper bound on the potential efficiencies. The socially optimal stocking policy is to restock after (220 – 224) consumers (depending on the assortment). This represents an approximate 16% decrease in the number of consumers between

Table 17: Socially Optimal Effort Policies (under various elasticities)

	$\epsilon = -1$			$\epsilon = -2$			$\epsilon = -4$		
e^{SOC}	220	224	222	227	232	229	233	238	235
$\% \Delta(e^{NR}, e^{SOC})$	16.35	16.10	15.91	13.69	13.11	13.26	11.41	10.86	10.98
$\% \Delta(e^R, e^{SOC})$	14.40	14.18	14.29	11.67	11.11	11.58	9.34	8.81	9.27
$\Delta \pi^R$	-238	-234	-230	-163	-152	-157	-112	-102	-106
$\Delta \pi^M$	285	242	213	251	211	190	219	183	166
ΔPS	-12	-35	-36	39	24	17	66	51	46
ΔCS	645	659	637	289	290	284	128	126	124
ΔSS	633	624	601	329	313	301	193	178	170

restocking visits when compared to the no-rebate case, and the potential gains to consumer surplus are large ($\Delta SS \geq \$600$) at the cost of total producer surplus. When consumer demand is more elastic (median own price elasticity $\epsilon = -4$) the socially optimal policy is in the range of (233 – 238) representing a 10-12% reduction in the number of consumers between visits. The planner places less weight on consumer surplus, and the gains from implementing the socially optimal stocking policy are much smaller ($\Delta SS \leq 200$).

The main case that we report in the text of the paper assumes that median own price elasticity is $\epsilon = -2$. We choose this because it is relatively inelastic when compared to own price elasticities recovered from demand systems in the literature, and is meant to represent an “upper bound” on potential efficiency effects from increased restocking.

A.5: Retailer Optimizes Retailer/Consumer Joint Surplus

As a robustness test, we allow the retailer to jointly 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).

Table 18 reports the optimal effort policies of a joint Retailer-Consumer entity. The main distinction is that the retailer exerts far more effort when maximizing his own profit when compared to when he did not take consumer surplus into account. This has the effect of substantially reducing the gap between the social optimum e^{SOC} and the retailer optimum (absent the rebate) e^{NR} to 9 consumers or less in the $\epsilon = -2$ case. The gap is smaller as consumers become more inelastic at most 5 consumers for the $\epsilon = -1$ case, and larger as consumers become more elastic as many as 12 in the $\epsilon = -4$ case. Once retailers take into account consumer surplus, there is no longer a distinction

Table 18: Effort Decisions of Joint Retailer-Consumer

	$\epsilon = -1$			$\epsilon = -2$			$\epsilon = -4$		
e^{NR}	225	228	226	236	239	237	245	249	247
e^R	224	227	225	234	237	235	242	246	244
e^{VI}	219	223	221	225	230	229	230	236	234
e^{IND}	220	224	222	227	232	229	233	238	235
e^{SOC}	220	224	222	227	232	229	233	238	235

Table 19: Socially Optimal Effort Policies (Joint Retailer-Consumer)

	$\epsilon = -1$			$\epsilon = -2$			$\epsilon = -4$		
$\% \Delta(e^{NR}, e^{OPT})$	2.22	1.75	1.77	3.81	2.93	3.38	4.90	4.42	4.86
$\% \Delta(e^R, e^{OPT})$	1.79	1.32	1.33	2.99	2.11	2.55	3.72	3.25	3.69
$\Delta \pi^R$	-10	-6	-7	-19	-13	-16	-29	-23	-26
$\Delta \pi^M$	23	14	13	50	33	33	77	60	59
ΔPS	7	5	4	19	13	13	31	26	27
ΔCS	46	37	38	54	44	49	43	41	44
ΔSS	53	42	42	73	57	62	75	67	71

between the industry optimal policy and the socially optimal policy. Also, the gap between the vertically integrated policy and the socially optimal (or industry optimal) policy depends only on the profits of the competing firms, and is generally 3 customers or fewer.

We report the potential gains from socially optimal effort levels for the joint Retailer-Consumer in Table 19. 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.

In Table 20, we calculate the optimal assortment decision of a joint Retailer-Consumer pair. We find that the assortment choice depends on how much weight the retailer places on consumer surplus, or how elastic consumers are. Assuming the retailer places full weight on consumer surplus, at a median own price elasticity of $\epsilon = -2$ the retailer is more or less indifferent between the (M, H) assortment and the (H, H) assortment. As consumers become more elastic, the retailer-consumer pair prefers (H, H) , and as they become less elastic the retailer-consumer pair prefers the consumer-

Table 20: Joint Retailer-Consumer Optimal Assortment (under various elasticities)

	(M,H)	(H,H)	(M,M)
Median Elasticity $\epsilon = -1$			
π^R	36,176	36,507	35,904
CS	50,372	49,771	50,122
$\pi^R + CS$	86,548	86,278	86,026
Median Elasticity $\epsilon = -2$			
π^R	36,281	36,591	35,998
CS	25,126	24,815	24,997
$\pi^R + CS$	61,407	61,406	60,995
Median Elasticity $\epsilon = -4$			
π^R	36,340	36,637	36,053
CS	12,532	12,368	12,461
$\pi^R + CS$	48,872	49,005	48,514

Table 21: Joint Retailer-Consumer Net Foreclosure/Efficiency Effect

	$\epsilon = -1$	$\epsilon = -2$	$\epsilon = -2$	$\epsilon = -4$	$\epsilon = -4$
From	$e^{NR}(H, M)$	$e^{NR}(H, M)$	$e^{NR}(H, H)$	$e^{NR}(M, H)$	$e^{NR}(H, H)$
To	$e^{VI}(M, M)$	$e^{VI}(M, M)$	$e^{VI}(M, M)$	$e^{VI}(M, M)$	$e^{VI}(M, M)$
$\Delta\pi^R$	-329	-348	-658	-357	-654
$\Delta\pi^M$	1326	1345	3019	1368	3064
$\Delta\pi^H$	-1280	-1285	-2151	-1290	-2160
ΔPS	-286	-293	177	-287	215
ΔCS	-203	-81	230	-27	137
ΔSS	-490	-374	407	-313	351

optimal assortment (M, H) .

We combine foreclosure and efficiency effects where we treat the retailer-consumer as a jointly maximizing pair in Table 21. When consumers are sufficiently inelastic, and the retailer accounts for consumer utility when choosing the assortment, he selects (M, H) . In this world, any rebate which induces a switch to (M, M) decreased both producer and consumer surplus. As consumers become more elastic (or the retailer places less weight on consumer surplus) the retailer chooses (H, H) absent the rebate, and the results qualitatively match the results in the main text: the rebate can increase both producer and consumer surplus relative (H, H) but full foreclosure is inefficient in that it fails to implement the optimal (M, H) assortment, and efficiency gains from additional stocking (smaller when considering retailer-consumers jointly) are not sufficient to compensate for foreclosure.

Though it is likely in practice that our retailer at least partially considers consumer surplus when choosing his 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 interested in whether some efficiency effect might outweigh potential foreclosure effects, and we design our baseline estimates to be an “upper bound” on such effects.

A.6: 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 representative machine. Annualized, enterprise-level profits are approximately 20-50x larger.

Table 22: Profits under Alternate Product Assortments and Stocking Policies

Policy	π^R	$\lambda\pi^M$	π^M	π^H	π^N	$\pi^R + \pi^M$	PS	CS
(H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers								
e^{NR} (267)	36,399	1,875	11,719	1,302	1,260	48,117	50,679	24,861
e^R (261)	36,394	1,882	11,763	1,299	1,257	48,157	50,713	24,923
e^{VI} (244)	36,335	1,899	11,871	1,290	1,249	48,206	50,744	25,071
(H,H) Assortment: Reeses Peanut Butter Cup and Payday								
e^{NR} (263)	36,661	1,609	10,055	2,173	1,285	46,716	50,174	24,601
e^R (257)	36,656	1,617	10,106	2,167	1,282	46,762	50,211	24,662
e^{VI} (237)	36,578	1,640	10,251	2,149	1,272	46,829	50,250	24,830
(M,M) Assortment: Three Musketeers and Milkyway								
e^{NR} (264)	36,090	2,091	13,067	0	1,256	49,156	50,412	24,761
e^R (259)	36,086	2,096	13,101	0	1,254	49,187	50,441	24,812
e^{VI} (243)	36,035	2,111	13,195	0	1,246	49,230	50,476	24,953

Table 23: Profits after Mars-Hershey Merger

Policy	π^R	$\lambda\pi^M$	$\pi^M + \pi^H$	π^N	$\pi^M + \pi^H + \pi^R$	PS	CS
(H,M) Assortment: Reeses Peanut Butter Cup and Three Musketeers							
e^{NR} (267)	36,399	2,083	13,021	1,260	49,419	50,679	24,861
e^R (262)	36,395	2,089	13,055	1,257	49,451	50,708	24,913
e^{VI} (245)	36,340	2,105	13,155	1,249	49,496	50,745	25,064
(N,N) Assortment: Butterfinger and Crunch							
e^{NR} (257)	36,594	1,631	10,193	2,707	46,787	49,494	24,295
e^R (251)	36,589	1,639	10,246	2,700	46,835	49,535	24,355
e^{VI} (232)	36,514	1,662	10,386	2,681	46,900	49,581	24,512

Table 24: Profits after Mars-Nestle Merger

Policy	π^R	$\lambda\pi^M$	$\pi^M + \pi^N$	π^H	$\pi^M + \pi^N + \pi^R$	PS	CS
Reeses Peanut Butter Cup (H), Three Musketeers (M)							
e^{NR} (267)	36,399	2,077	12,978	1,302	49,377	50,679	24,861
e^R (262)	36,395	2,082	13,013	1,299	49,409	50,708	24,913
e^{VI} (245)	36,340	2,098	13,114	1,290	49,455	50,745	25,064
Reeses Peanut Butter Cup (H), Payday (H)							
e^{NR} (263)	36,661	1,815	11,341	2,173	48,001	50,174	24,601
e^R (257)	36,656	1,822	11,388	2,167	48,045	50,211	24,662
e^{VI} (239)	36,591	1,842	11,511	2,151	48,102	50,253	24,815
Three Musketeers (M), Milkyway (M)							
e^{NR} (264)	36,090	2,292	14,323	0	50,412	50,412	24,761
e^R (259)	36,086	2,297	14,354	0	50,441	50,441	24,812
e^{VI} (244)	36,040	2,310	14,436	0	50,476	50,476	24,946

Table 25: Profits after Hershey-Nestle Merger

Policy	π^R	$\lambda\pi^M$	π^M	$\pi^H + \pi^N$	$\pi^M + \pi^R$	PS	CS
Reeses Peanut Butter Cup (H), Three Musketeers (M)							
e^{NR} (267)	36,399	1,875	11,719	2,562	48,117	50,679	24,861
e^R (261)	36,394	1,882	11,763	2,556	48,157	50,713	24,923
e^{VI} (244)	36,335	1,899	11,871	2,538	48,206	50,744	25,071
Reeses Peanut Butter Cup (H), Payday (H)							
e^{NR} (263)	36,661	1,609	10,055	3,458	46,716	50,174	24,601
e^R (257)	36,656	1,617	10,106	3,449	46,762	50,211	24,662
e^{VI} (237)	36,578	1,640	10,251	3,421	46,829	50,250	24,830
Three Musketeers (M), Milkyway (M)							
e^{NR} (264)	36,090	2,091	13,067	1,256	49,156	50,412	24,761
e^R (259)	36,086	2,096	13,101	1,254	49,187	50,441	24,812
e^{NR} (243)	36,035	2,111	13,195	1,246	49,230	50,476	24,953

Appendix B (Not for Publication)

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. This can be seen in figure 5, which plots the overall sales of all machines in our sample on a weekly basis. For example, a law firm may have a large case going to trial in a given month, and vend levels will increase at the firm during that period. In our particular setting, many of the product removals were done during the summer of 2007, which was a high-point in demand at these sites, most likely due to macroeconomic conditions. In this case, using a simple measure like previous weeks' sales, or overall average sales for $E[q_{jt}^0]$ could result in unreasonable treatment effects, such as sales increasing due to product removals, or sales decreasing by more than the sales of the focal products.

In order to deal with this challenge, we impose two simple restrictions based on consumer theory. Our first restriction is that our experimental product removals should not increase overall demand, so that $Q_t^0 - Q_s^1 \geq 0$ for treatment week t and control week s . Our second restriction is that the product removal(s) should not reduce overall demand by more than the sales of the products we removed, or $Q_t^0 - Q_s^1 \leq q_{fs}^0$. This means we choose control weeks s that correspond to treatment week t as follows:

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

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

We propose a slight modification of (13) which removes the bias. That is, we replace q_{fs}^0 with

$\widehat{q_{fs}^0} = E[q_{fs}^0 | Q_s^0]$. An easy way to obtain the expectation is to run an OLS regression of q_{fs}^0 on Q_s^0 , at the machine level, and use the predicted value. This has the nice property that the error is orthogonal to Q_s^0 , 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:

$$S_t = \{s : s \neq t, A_t \approx A_s, Q_t^0 - Q_s^1 \in [0, \hat{b}_0 + \hat{b}_1 Q_s^0]\}. \quad (14)$$

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

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

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.⁷¹

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.

⁷¹Weeks in which the other five treatments were run (for the salty-snack and cookie categories) are excluded from the set of potential control weeks.

B.2 Product-level Results of Exogenous Removal of Snickers and Peanut M&Ms

Table 27 reports the detailed product-level results of the joint Snickers-Peanut M&M removal. Nearly 123 consumers substitute to other Assorted Chocolate products within the same product category, representing an increase of 117%. This includes several products from Mars (i.e., Milky Way and Three Musketeers), but also products from other manufacturers (i.e., Nestle’s Butterfinger). Meanwhile, Raisinets (Nestle), a product that Mark Vend stocks frequently, sees an increase in sales of only 17% when Snickers and Peanut M&Ms are removed, indicating that Raisinets may not be a close competitor to the removed products.⁷² In contrast, 93 consumers substitute to Reese’s Peanut Butter Cups (an 85.6% increase in sales for the Hershey product), which Mark Vend stocks much less frequently. This provides some descriptive evidence that the rebate may lead Mark Vend to favor products that do not steal business from the major Mars brands over better-selling products that do.

B.3 Results of Nested-Logit Demand Estimation

Table 26 reports the parameter estimates for the nested logit specification, which assumes that $(\mu_{ijt} + \varepsilon_{ijt})$ is distributed generalized extreme value, so that the error terms allow for correlation among products within a pre-specified group.⁷³ In this model, consumers first choose a product category l composed of products g_l , and then choose a specific product j within that group. The resulting choice probability for product j in market t is given by:

$$s_{jt}(\delta, \lambda, a_t) = \frac{e^{\delta_{jt}/\lambda_l} (\sum_{k \in g_l \cap a_t} e^{\delta_{kt}/\lambda_l})^{\lambda_l - 1}}{\sum_{\forall l} (\sum_{k \in g_l \cap a_t} e^{\delta_{kt}/\lambda_l})^{\lambda_l}}, \quad (16)$$

where the parameter λ_l governs within-group correlation.⁷⁴ Just as we do for the random-coefficients logit model, we assume $\delta_{jt} = d_j + \xi_t$, and we use five nesting categories: Chocolate, Non-chocolate Candy, Cookie/Pastry, Salty Snack, and Other. Estimation is via maximum likelihood (ML) for the same two definitions of ξ_t used in the random-coefficients specification of table 7.

⁷²Substitution to Raisinets is only 3.3% when Snickers is removed by itself.

⁷³See McFadden (1978) and Train (2003).

⁷⁴Note that this is not the IV regression/‘within-group share’ presentation of the nested-logit model in Berry (1994), in which σ provides a measure of the correlation of choices within a nest. Roughly speaking, in the notation used here, $\lambda = 1$ corresponds to the plain logit, and $(1 - \lambda)$ provides a measure of the ‘correlation’ of choices within a nest (as in McFadden (1978)). The parameter λ is sometimes referred to as the ‘dissimilarity parameter.’

Table 26: Nested Logit Estimates

	Parameter Estimates	
$\lambda_{Chocolate}$	0.828 [.003]	0.810 [.005]
$\lambda_{CandyNon-Choc}$	0.908 [.007]	0.909 [.009]
$\lambda_{Cookie/Pastry}$	0.845 [.004]	0.866 [.006]
λ_{Other}	0.883 [.005]	0.894 [.006]
$\lambda_{SaltySnack}$	0.720 [.003]	0.696 [.004]
# Fixed Effects ξ_t	15,256	2,710
LL	-4,372,147	-4,410,649
BIC	8,972,783	8,862,840
AIC	8,774,962	8,826,873

Notes: The nested logit estimates correspond to the choice probabilities described in section 4, equation 16. Both specifications include 73 product fixed effects. Total sales are 2,960,315.

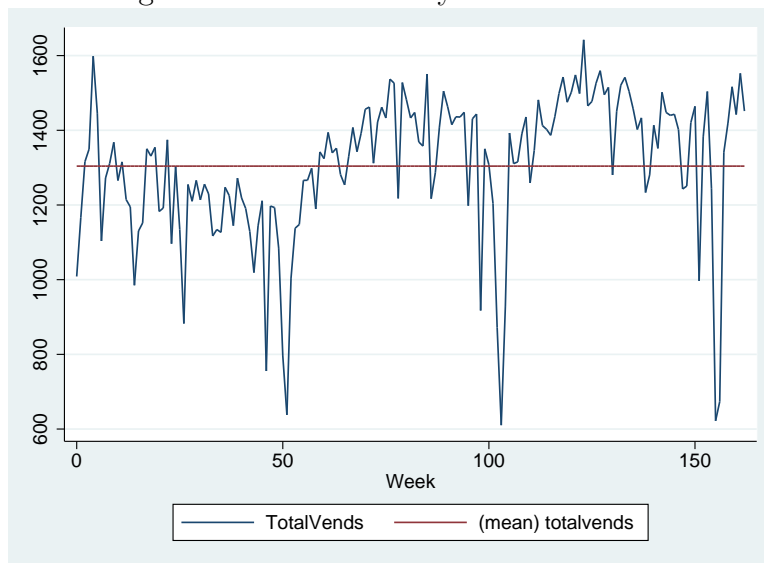
B.4: Additional Tables and Figures

Table 27: Results from Snickers and Peanut M&Ms Joint Experiment

Product	Control	Treatment	Change	% Change	Difference	T-Stat	Obs
Assorted Chocolate	104.5	227.8	123.2	117.9	1.79	6.12	69
Twix Caramel	213.0	313.3	100.3	47.1	1.43	5.64	70
Reese's Peanut Butter Cups	109.0	202.2	93.3	85.6	1.23	4.30	76
Assorted Pastry	287.4	374.2	86.9	30.2	1.16	3.60	75
Plain M&Ms	132.0	196.9	64.9	49.2	1.18	3.59	55
Assorted Nuts	359.3	415.8	56.6	15.7	0.73	2.28	78
Assorted Cookie	314.7	359.3	44.6	14.2	0.51	1.75	88
Assorted Nonchocolate Candy	263.4	301.1	37.7	14.3	0.45	1.80	83
Assorted Chips	548.2	585.6	37.4	6.8	0.43	1.35	87
Raisinets	184.0	215.9	31.9	17.3	0.44	1.99	73
Choc Chip Famous Amos	227.0	241.2	14.1	6.2	0.16	0.73	89
Raspberry Knott's	70.7	79.7	8.9	12.6	0.11	0.82	79
Assorted Pretzel/Popcorn	962.0	969.8	7.8	0.8	0.09	0.24	89
Assorted Fruit Snack	103.6	107.7	4.1	4.0	0.06	0.31	71
Dorito Nacho	284.5	282.6	-1.9	-0.7	-0.02	-0.10	89
Assorted Baked Chips	262.8	255.8	-7.0	-2.7	-0.08	-0.35	88
Assorted Cracker	114.4	93.3	-21.1	-18.5	-0.28	-1.18	75
Sun Chips	198.1	174.6	-23.5	-11.9	-0.29	-1.34	80
Cheeto	349.8	325.7	-24.1	-6.9	-0.27	-1.38	89
Assorted Salty Snack	711.9	678.1	-33.9	-4.8	-0.38	-1.16	89
Assorted Energy	272.1	229.0	-43.1	-15.8	-0.61	-1.90	71
Zoo Animal Cracker Austin	292.1	235.0	-57.1	-19.6	-0.64	-3.18	89
Snickers	379.4	13.2	-366.2	-96.5	-4.11	-16.00	89
Peanut M&Ms	425.9	9.4	-416.5	-97.8	-4.68	-18.19	89
Total	7,170.0	6887.3	-282.7	-3.9	-3.18	-12.07	89

Notes: Control weeks are defined according to the procedure described in appendix A.4.

Figure 5: Overall Weekly Sales at Site 93



Notes: Figures calculated by authors, and represent all product categories in the machines (i.e., confections, snack foods, cookies, and other).

Table 28: Summary of Sales and Revenues for Four Clusters of Machines

	Group Size	Vends/Visit		Revenue/Visit		Avg Sales/Day	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
A	4	39.0	26.1	28.3	18.7	5.8	1.4
B	7	88.9	39.5	70.6	33.4	24.9	3.0
C	27	56.9	31.5	41.5	23.2	9.2	1.4
D	28	71.6	33.8	54.3	26.8	15.1	2.0

Notes: The 66 machines in our analyses are divided into four groups of machines based on the arrival rate and the amount of revenue collected at a service visit, using a k-means clustering algorithm. Our counterfactual analyses are based on cluster D.