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Retail Competition and the Dynamics of Demand for Tied Goods

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We present a demand system for tied goods incorporating dynamics arising from the tied nature of the products and the stockpiling induced by storability and durability. We accommodate competition across tied good systems and competing downstream retail formats by endogenizing the retail format at which consumers choose to stockpile inventory. This facilitates measurement of long-run retail substitution effects and yields estimates of complementarities within, and substitution across, competing systems of tied goods. We present an empirical application to an archetypal tied goods category: razors and blades. We discuss the implications of measured effects for manufacturer pricing when selling the tied products through an oligopolistic downstream retail channel and assess the extent to which retail substitution reduces channel conflict.

Key words: tied goods; retail competition; dynamic discrete choice; durable good replacement; endogenous consumption; long-run effects; vertical channels; razor blade market

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1. Introduction

We consider the problem of estimating demand for tied good systems sold across competing retail formats. Goods and services are said to be tied when the purchase of a primary “tying” good requires consumers to purchase complementary “tied” or “aftermarket” goods from the same manufacturer. Tied good systems are common in the economy: examples include printer cartridges tied to printers, after-sales services tied to durable equipment purchases, and in the case of our application, razor blades tied to specific razor technologies. The tying of two goods imposes a complementarity such that price increases for either good decreases demand for the other through its effect on the overall price for the system. Estimating the extent of the complementarity is key to several questions of interest to firms, including the optimal pricing of the primary and aftermarket products, compatibility decisions regarding primary and aftermarket goods, as well decisions regarding optimal bundle offerings. When tied goods are sold in downstream retail channels, manufacturers also desire to understand the extent of complementarities between primary and aftermarket goods sold across competing retail formats, as well as the extent of substitution between competing systems of goods sold across those formats. Oligopolistic, downstream retail formats is a feature of many real-world tied good markets. One of the goals of this paper is to present

a parsimonious framework to measure the complex complementarity and substitution effects that arise in such contexts. A second goal of the paper is to assess the extent to which retail substitution may extenuate channel conflicts that can arise in selling tied goods in the downstream.

We define a forward-looking and dynamic discrete choice model of demand that provides a realistic characterization of the two primary phenomenon of interest: tied goods and retail format substitution. Demand for most tied goods is inherently dynamic because the choice set and prices paid of aftermarket goods are contingent upon whether a primary good has been purchased in the past. A realistic perspective on how customers substitute purchases of a single good across retail formats is also inherently dynamic if the good is durable, or storable, or both. Specifically, it is unlikely that customers know the prices of all products in a category at every store, then select the store with the lowest price. Rather, customers likely arrive at a store based on factors exogenous to the category such as distance or prices of focal products; then select to either stock up at that store at the observed prices, or postpone their purchase until a visit to a competing store with lower expected prices in the category. We therefore build the dynamics of our model around the choice set implications of tying and a stockpiling model that allows customers to endogenously determine the store at which they accumulate inventory.

Two features of the dynamic model are particularly relevant to both tying and retail substitution: usage rates and price expectations. We model usage of the aftermarket good to be endogenously determined based on consumer's current inventory levels, their price sensitivities, and the time until they expect to make another purchase to replenish their inventory. This aspect is critical for retail substitution because customers can slow their consumption to ease the process of waiting for a lower price at the current store or at a different store. Endogenous usage is also fundamental to the analysis of tied goods. Specifically, usage of aftermarket goods such as blades or printer cartridges is determined by how willing a customer is to use a depreciated blade or to read the fading ink from a nearly empty printer cartridge. Our model of endogenous usage provides an intuitive way to relate this tolerance for depreciated goods to fundamental preference parameters such as a customer's price sensitivity. Less price-sensitive customers should intuitively change their blades more often. In fact, many researchers have argued that because more sensitive customers buy fewer aftermarket goods, one way to price discriminate is to attract them through low primary good prices while extracting more surplus from higher willingness to pay customers by charging a high aftermarket price. This form of price discrimination has been referred to as metering because the aftermarket good "meters" the intensity of demand for the system (see Burstein 1960, Oi 1971, Schmalensee 1981, Klein 1996, Gil and Hartmann 2009).

Price expectations are a necessary component of any forward-looking dynamic demand analysis but have unique implications for both retail substitution and tying. The recent empirical literature on stockpiling dynamics—see Erdem et al. (2003; henceforth EIK) and Hendel and Nevo (2006)—has specified price expectations defined at the level of a single store or the entire market to endogenize whether a customer should stockpile at current prices or wait for a future price discount. When retail substitution is considered, price expectations must be defined at each retail location a customer may possibly visit. In these contexts, the temporal variation of prices faced by the customer may be driven as much by the temporal variation in store visits as it is by temporal variation in prices at a given store (e.g., Gauri et al. 2008). As described above, we model customers to only know the exact prices upon entering a store but to substitute their purchases across stores based on the expected prices at competing stores and the likelihood of visiting a competing store.

Price expectations are also a well-recognized determinant of the pricing incentives for tied goods. Early antitrust inquiries into tying arose because regulators

were concerned that high prices for tied aftermarket goods were the result of firms exploiting customers that were locked in after the purchase of a primary good (e.g., Borenstein et al. 2000, Shapiro 1995, Hall 1997). The "Chicago School" critiqued this argument, noting that if customers were to have rational expectations about future aftermarket prices, a tie only allows a firm to shift extraction of a customer's willingness to pay from the primary good to the aftermarket good (for example, see Carlton and Waldman 2008). By including customer's price expectations in the model, we avoid overstating willingness to pay for the primary good and allow the price of the aftermarket good to affect the demand for the primary good. This yields substitution patterns consistent with the complementarity implied by the tie.

An important feature to consider when tied goods are sold through competing retail formats is the presence of alternatives to the tied good. Many classic tied good examples, such as IBM computers and punch cards, and most of the theory literature, involve a monopolistic provider of the primary good. Yet retailers offering tied goods also often offer competing alternatives that may or may not be tied. For example, Hewlett-Packard printers and cartridges are typically sold adjacent to Lexmark or Epson products, and Gillette Mach razors and blades share shelf space with other Gillette tied technologies, Schick razor and blade systems, and disposable razor blades. The willingness of customers to substitute these other technologies is an important determinant of pricing at the level of both the manufacturer and the retailer.

To measure and analyze the substitution patterns implied by (1) the complementary relationship between the tied goods, (2) the substitutability between a tied good and other alternatives, and (3) the substitutability between retail providers, we apply the model to individual-level panel data on consumer purchases of razors and blades at competing retail formats in a large midwestern city in the United States. The data span 56 weeks between 2002 and 2003. During this period, the market leader, Gillette, marketed the Mach as its flagship razor technology while continuing to sell a substantial number of refill blades for its previous generation razor, the Sensor. The other significant competitor, Schick, had little market share compared to Gillette (the more successful Schick razor, the Quattro, had yet to be introduced). We observe all purchases of these two brands and disposable razor blades for every household across all store formats, including mass merchandisers and club stores. We focus on retail substitution at the format level because price expectations are likely to exhibit more variation between formats than between stores within a format. Our data also limit us to the format level because we are unable to match store-level

prices to the stores visited by consumers in our data.¹ An important caveat therefore is that any substitution we measure is likely to be conservative, providing lower bounds on retail pricing power, which is limited by additional inter-store substitution within retail formats.

We estimate the model by maximum likelihood. We accommodate a rich specification for unobserved heterogeneity via a flexible multivariate specification for the distribution of parameters in the population. The rich specification of random coefficients helps us sort the state dependence induced by inventory accumulation from persistence induced by permanent, unobserved heterogeneity (see Heckman 1981). The control for heterogeneity complicates the estimation of the dynamic model, which is facilitated by the importance sampling method proposed by Ackerman (2009). Our results reveal evidence for strong complementarities in demand between razors and blades. The estimates suggest that manufacturers may profitably shift margins between the primary and aftermarket good but cannot exploit customers in the aftermarket without suffering decreased primary good adoption. We also find evidence for strong retail substitution. Our estimates suggest that a permanent unilateral price increase at one retail format would lead to enough substitution to the other formats that a manufacturer would lose only a fraction of the sales lost by the retailer increasing prices. In spite of being conservative, the retail format competition we identify stands in contrast to much of the extant empirical literature that has either assumed monopolistic retailers or found very limited retail competition.

We believe the latter conclusion in the extant literature has been driven by two aspects: First, a typical assumption is that customers know all prices at all stores. If customers do not know all prices, but rather respond to price expectations at competing stores as in our model, a lack of responsiveness to price realizations at stores not visited could be misinterpreted as a lack of cross-store substitutability. In effect, an assumption of perfect knowledge leads to a standard attenuation bias in estimation of cross-store price effects. Second, the extant literature has used static models that measure the current period effects of prices changes. Cross-store price effects are likely to be long-term phenomena, wherein shifts in traffic and demand across stores occur over a period of time during which consumer expectations of price

distributions across stores adjust in response to permanent price changes. These are best captured by dynamic models that formally incorporate a role for price expectations across stores.

The framework we present is most closely related to the empirical models of stockpiling dynamics proposed by EIK and Hendel and Nevo (2006). We extend their work in three ways. First, we allow for dynamics arising from the tied nature of the products. Second, we endogenize per-period consumption by explicitly embedding a nested, durable good replacement policy into the solution algorithm. Third, we accommodate retail format choice in the stockpiling model and endogenize the retail format at which consumers choose to accumulate inventory. The latter component is critical to measuring retail competition for durable or storable goods and constitutes what we believe is a new approach for measuring retail substitution in single-category demand analyses. The frameworks we consider are also related to demand systems involving complementary goods such as those in the indirect network effects literature, which considers hardware platforms bought in anticipation of future software purchases (e.g., Nair et al. 2004, Dubé et al. 2009a, Lee 2007).

Finally, in discussing the results of the paper, we identify two significant channel issues that manufacturers of tied goods face when selling through an oligopolistic downstream channel. We note that double marginalization may be particularly problematic when selling tied goods because of the common desire of manufacturers to maintain low primary good prices. Furthermore, we identify what we call a “cross-product” horizontal externality that arises because the pricing incentives of the retailer, who cannot tie sales of aftermarket products to his store, are different from those of the manufacturer. If there is limited retail competition, the availability of aftermarket products at substitute stores may provide an incentive to a retailer to set primary good prices that are too high from the manufacturer’s perspective. The potential for these channel problems are relevant for managers and depend on the level of retail substitution, which our framework can be used to measure. In this respect, we believe our analysis motivates theoretical inquiry into the previously unstudied problem of selling tied goods through an oligopolistic retail channel.

The rest of the paper proceeds as follows. In §2, we present our empirical model of demand. Section 3 presents the data on consumer purchases of razors and blades used in the study. We then present parameter estimates from the model in §4 and discuss the implications for retailers and manufacturers in §5. Section 6 concludes the paper.

¹ We use the publically available Information Resources Inc. (IRI) store price files described in Bronnenberg et al. (2008). However, our proprietary panel data come from alternative sources that can only be matched to the IRI data at the format level. We chose not to use the Pittsfield and Eu-Clair panels in the Bronnenberg et al. (2008) data because they do not include club stores, which sell substantially larger pack sizes at the lowest per-blade prices.

2. Model

This section develops a dynamic model of demand for tied goods sold through competing distribution formats. The formulation of the empirical model is motivated by the considerations discussed in §1, as well as some of the specifics of our application to razors and blades.

2.1. Market

There are $R + 1$ shaving options in the market, available across K different retail formats. The options comprise of R tied razor technologies and one non-tied option, i.e., disposables. The tied razor technologies require the purchase of a razor before the corresponding blades can be used. Blades of a given razor technology are incompatible (by design) with razors of other technologies. We index the tied razor technologies by $r = 1, \dots, R$, and let $r = 0$ index disposables. We also incorporate the institutional feature that razors are always sold in packs containing blades. For each tied razor technology, we let $j = 1$ index the pack that contains the razor and index the remaining packs that contain only blades by $j > 1$. We denote the total number of pack sizes available for razor technology r at retail format k , as J_{rk} . Disposables are available in J_{0k} different packs, where each pack $j \in \{1, \dots, J_{0k}\}$ only contains disposable razors. Each pack, whether containing a razor or only blades, contains q_{rjk} blades.

In our empirical context, $R = 3$ corresponds to Gillette Mach, Gillette Sensor, and Schick brands of razors. Our empirical model considers three retail formats, corresponding to *DG* (drug and grocery), *MK* (mass merchandisers and supercenters), and *W* (wholesalers and club) stores. Thus, $K = 3$.²

2.2. Consumers and States

At the beginning of each week, a consumer owns a set of razors, a set of unused blades compatible with one of these razors, and a used blade that has depreciated from its initial quality level because of usage. In addition to these, the consumer's state also incorporates the retail format visited and the prices at that format. We describe each of these in sequence below.

Razor technology ownership (Ω). A consumer's razor technology ownership status at the beginning of each week is denoted by Ω , which is an $R \times 1$ vector of indicators for whether or not each razor type is owned. Once a razor, $r = 1, \dots, R$, is purchased, the

consumer is assumed to have it forever, and element r of Ω is permanently set to 1.³ An implication of this assumption is that consumers can own multiple razor technologies at the same time (i.e. multihoming). The data suggest multihoming because we observe several instances of consumers switching between blade packs of different brands without purchasing razors in between (see Technical Appendix A of the electronic companion to this paper, available as part of the online version that can be found at <http://mktsci.pubs.informs.org>).

Blade type currently owned (ρ). At the beginning of a week, a consumer also owns blades of a type $\rho \in \{0, 1, \dots, R\}$. Reflecting the nature of the market, a consumer can own disposable razors irrespective of his razor technology ownership status (i.e., ρ can be 0 irrespective of Ω) but can own nondisposable razor blades only if a corresponding razor is available (i.e., $\rho = r > 0$ only if $\Omega_r = 1$). The table below provides three examples to clarify the notation (e.g., in the third row, the consumer owns all three razors and is currently using disposable razors).

Ω	ρ	Razor technologies			Current blade type		
		Mach	Sensor	Schick	Disposables	Mach	Schick
(0, 1, 1)	0		×	×	×		
(1, 1, 1)	1	×	×	×		×	
(1, 1, 1)	0	×	×	×	×		

Thus, a consumer can own many razor technologies at the same time but can own only one type of blades. We make the latter assumption to keep the empirical model tractable. Relaxing this assumption would require us to add the stock of blades of each type as a state variable and to model the endogenous decision of which blade stock from which to consume.⁴

³ The perfect durability assumption is motivated by the fact that we rarely observe the same household buying the same razor brand more than once in the data. Furthermore, we also observe patterns where households buy blades of a given brand on purchase occasions that are far apart in time, without purchases of razors of that brand in between. This suggests that our no disposal assumption regarding razor ownership is reasonable. It is possible to extend the model to allow for depreciation in the quality of the primary good in other contexts where that may be more relevant. An alternative model is to assume that consumers dispose the primary good (i.e., razors) when they switch technologies. This assumption makes the model simpler but has to be evaluated on a case-by-case basis, depending on the category being studied.

⁴ In the related dynamic stockpiling literature, past researchers have also avoided modeling multiple inventory types and the associated endogenous decision of which type to consume by assuming there is a single stock. Hendel and Nevo (2006) assume all brands are identical after purchase, and EIK allow the quality of a single stock to be indexed by the proportion of each product making up the stock. Although these assumptions fit the categories they consider, both seem inappropriate here, as we expect agents to prefer to consume the blade type most recently purchased. Our assumption that agents can own only blades of the most recently purchased razor better captures this aspect of consumer behavior.

² We limit our analysis to three retail formats to manage the computational tractability of the model. We treat club stores as distinct because of their unique pack sizes but merge mass merchandisers and supercenters given their similar price levels. Although drug and grocery stores differ in their layout and perhaps the type of visit, we merge them because the prices and pack sizes offered in these stores are similar in this category.

Level of depreciation (z). We allow blades to depreciate in quality with usage (we explain how we model the depreciation rate in more detail below). The utility from usage of a blade is highest when it is new and lowest when it is dull. We capture the level of depreciation of a blade by modeling the fraction of initial per-usage utility that the blade can currently provide. Letting $z \in [0, 1]$ denote the depreciated level of the blade currently used, we model the per-usage utility from the current blade as γz , where γ denotes the utility from usage of the blade when new.

Stock of unused blades (b). We let b denote the stock of unused blades available in inventory with the consumer (i.e., total blades in inventory, including the current depreciated blade, is $b + 1$). If the consumer has no unused blades in inventory ($b = 0$), and the current blade is completely dull ($z = 0$), the consumer may be using the completely dull blade or some other technology (e.g., electric razor) for shaving. This is the outside option for the consumer.

Store visited (k). Each week, the consumer visits a retail format from one of the K different formats, $k = \{1, \dots, K\}$, or stays at home. The decision to not visit any format is denoted $k = 0$.

Prices (\mathbf{p}_k). At the visited format, k , the consumer observes a price, p_{rjk} , for each of the razor and blade packs available. The vector of prices at format k is \mathbf{p}_k , where $\mathbf{p}_k = \{p_{11k}, \dots, p_{R, Jrk}\}$.

Together, these state variables form the state vector

$$\mathbf{s} = \{\Omega, \rho, z, b, k, \mathbf{p}_k\}. \quad (1)$$

2.3. Actions

There are two types of actions in the model. The first is a decision involving the purchase of razors or blades at a visited store, and the second is a decision involving the replacement of the currently used blade at home with a new one from the available inventory. Given state \mathbf{s} at the beginning of the week, the consumer makes one of the following three purchase decisions:

1. Switch blade type to $r \neq \rho$ by buying pack $j^* \in \{1, \dots, J_{kr}\}$,
2. Stay with the current blade type ρ and not buy any blades, or
3. Stay with the current blade type ρ and buy the blade pack $j^* \in \{1, \dots, J_{k\rho}\}$ that gives him the best payoff.

If the consumer decides to stay with the current technology, the consumer also decides whether to replace his current blade or continue using it at its depreciated level. The blade replacement decision determines the consumer's consumption rate and is endogenous in our model. We model the blade replacement decision by incorporating a nested durable good replacement problem of the sort considered by Rust (1987) or Gordon (2009) for the storable

goods (see Sun 2005 for an approach that treats consumption as continuous). This decision occurs at the end of a period and affects the level of depreciation of the blade used in the next period. The blade replacement decision is therefore a component of the state transitions presented below.

Each week, the consumer chooses the actions that maximize the expected present discounted value of current and future payoffs associated with those actions.

2.4. Utilities

We define utility over the usage of blades. The utility from purchase of a razor or blades is the discounted present value of the expected stream of utility from subsequent consumption of blades. Below, we present the immediate utilities associated with each of the three purchase decisions and then later define the expected future utilities that also affect purchase incentives. We define parameters and utilities for a single agent but allow them to be heterogeneous across agents in our estimation.

2.4.1. Current Period Utility of Switching Blade Type to $r \neq \rho$. The consumer can switch his current blade type from ρ to r by buying a pack of type r from any of the K retail formats in the market. If a consumer switches his blade type in a given week, we assume he consumes a new blade that week and thus receives flow utility from consumption, γ_r (since $z = 1$). We then write the current utility from purchase of pack j of type $r \neq \rho$ as

$$u_{rj}(\mathbf{s}) = \gamma_r - \alpha p_{rjk} + \kappa + \lambda \gamma_\rho b + \varepsilon_{rj}. \quad (2)$$

Here, α is the price sensitivity, p_{rjk} is the price of the pack, and ε is an independent and identically distributed (i.i.d.) extreme-value shock to utility, unobservable to the econometrician. The term κ is a (dis)utility from making any purchase, which could be interpreted as a carrying cost or transaction cost realized at the point of purchase. Econometrically, κ helps fit the infrequent incidence of purchase of razors and blades across observed store trips. We include the term $\lambda \gamma_\rho b$ to allow the consumer to receive a salvage value for the stock of blades from the old technology, ρ . We model the salvage value as a fraction of the utility that the consumer may have attained from consuming the b blades he had available in inventory when deciding to switch. Therefore, λ can be interpreted as the share of the consumer's utility for a blade that is received when the consumer sells it in a resale market or the discounted value of using that blade at some distant future date. The salvage value serves three aspects in the model. First, the economic switching costs in this category should be bounded by the cost of a razor, which is small. A "free disposal"

assumption under which a user switching razors disposes all existing blades without realizing any value artificially increases switching costs. By allowing for a salvage value from old blades when replacing razor types, we partly address this concern. The salvage value term also generates a computational advantage since it allows us to keep track of a single stock of blades. In our empirical work, we estimate λ to be a small number; hence, the economic significance of this term for our results is small. Nevertheless, we choose to retain it here as a modeling feature that may be useful in other contexts.

2.4.2. Current Utility of Staying with Current Blade Type ρ and Not Buying Any Blades. If a consumer stays with the current blade type ρ and chooses to not buy any blades, he obtains the per-period utility of using his current blade:

$$u_0(\mathbf{s}) = \gamma_\rho z + \varepsilon_0. \quad (3)$$

If the current blade is completely depreciated, $z = 0$ and $b = 0$, the outside option is consumed and its utility is normalized to zero.

2.4.3. Current Utility of Staying with Current Blade Type ρ and Buying Blade Pack j . Finally, the consumer can decide to stay with the current blade type ρ and buy a pack of compatible blades to refill his inventory. In this case, the consumer obtains current utility:

$$u_{\rho j}(\mathbf{s}) = \gamma_\rho z - \alpha p_{\rho j k} + \kappa + \Delta + \varepsilon_{\rho j}, \quad j > 1. \quad (4)$$

In contrast to switching blade types, the consumer does not receive a salvage value when buying refills. We allow for a term Δ , which represents an increase in utility from buying the same type of blades as in the past. This is a form of habit persistence is likely the result of a psychological cost of switching brands (e.g., Roy et al. 1996, Dubé et al. 2009b).

2.5. State Transitions

Dynamics arise in this model through the transitions of the state variables $\{\Omega, \rho, z, b, k, \mathbf{p}_k\}$. The key dynamics of interest are generated by the state variables Ω, ρ, z , and b . A choice in the current period affects the razor technology and stock of blades possessed next period, as well as the level of depreciation of the blade to be used next period. To economize on notation in what follows, we denote the next period's state by a prime symbol.

Denote the set of possible purchase decisions at retail format $k > 0$, as $\mathbf{y}_k = \{y_{k0}, (y_{k01}, \dots, y_{k0J_{0k}}), \dots, (y_{kR1}, \dots, y_{kRJ_{Rk}})\}$. The indicator variable denotes y_{k0} no purchase (of razors or blades) while at store k , the indicators y_{krj} ($r \neq \rho$) denote purchase of pack j for a new technology r , and the indicators $y_{k\rho, j}$ denote purchase of blade pack j of the currently owned blade

type ρ . Finally, y_0 is an indicator of no store visit. Because of the discrete choice aspect of the problem, we have that

$$y_0 + \sum_{k=1}^K y_{k0} + \sum_{k=1}^K \sum_{r=0}^R \sum_{j=1}^{J_{rk}} y_{krj} = 1. \quad (5)$$

We now present the transitions of the state variables.

2.5.1. Transition of Razor Ownership (Ω). The law of motion for razor ownership status is governed by the purchase decision:

$$\Omega'_r = \begin{cases} 1 & \text{if } y_{kr1} = 1, r > 0, k > 0; \\ \Omega_r & \text{otherwise.} \end{cases} \quad (6)$$

Thus, the purchase of any pack $j = 1$ of a nondisposable razor technology adds r to the set of razors owned. The above specification implies that $\Omega_r = 1$ is an absorbing state.

2.5.2. Transition of Current Blade Type (ρ). The law of motion for the blade type currently owned is governed by the purchase decision:

$$\rho' = \begin{cases} r & \text{if } \sum_j y_{krj} > 0, r \neq \rho, k > 0; \\ \rho & \text{otherwise.} \end{cases} \quad (7)$$

Thus, the purchase of any pack, whether containing a razor plus blades or only blades of a new technology r , switches ρ to r .

2.5.3. Transition of Level of Depreciation (z). At the beginning of each period, the consumer's current blade is at level z . If the consumer decides to stay with the current razor technology but replaces the current blade, the level next period will be equal to its maximum value, one. If the consumer decides to stay with the current razor technology but does not replace the current blade, we assume that the level will be depreciated to δz , where δ is a parameter to be estimated from the data. Finally, if a consumer changes his blade type in that period, a new blade will be used immediately such that the next period's blade is of level δ . The transition equation is therefore

$$z' = \begin{cases} 1 & \text{if } \rho' = \rho, c = 1; \\ \delta z & \text{if } \rho' = \rho, c = 0; \\ \delta & \text{if } \sum_j y_{krj} > 0, r \neq \rho, k > 0. \end{cases} \quad (8)$$

In (8), c is an endogenous indicator for whether or not the consumer changes blades. The choice of c will be described once we define the value functions below. In the empirical application below, we allow the depreciation rate δ to be different for disposables and nondisposables.⁵

⁵ An alternative assumption to capture the replacement decisions would be to directly estimate the weekly consumption of blades

2.5.4. Transition of Stock of Unused Blades (*b*).

The transition function for the blade stock depends on whether a consumer switches his blade type, purchases refills for an existing razor, or does not make a purchase. If the consumer switches his blade type, the consumer's stock of unused blades next period equals the number of blades included in the pack minus one. We subtract one because a consumer immediately starts using one of the new blades when purchased. Old blades, b , as described earlier are not retained. When a consumer stays with the current blade type, $\rho' = \rho$, the stock is depreciated by one if he chooses to replace the current blade (i.e., if $c = 1$) and is augmented by the number of blades corresponding to the purchase decision, $q_{\rho, jk}$:

$$b'(\rho, y | c) = \begin{cases} q_{rjk} - 1, & \text{if } y_{krj} = 1, r \neq \rho, k > 0; \\ b - c + q_{\rho jk} & \text{if } y_{\rho jk} = 1, \rho' = \rho, k > 0, \\ & (b - c + q_{\rho j}) \leq \underline{B}; \\ \underline{B} & \text{if } y_{\rho jk} = 1, \rho' = \rho, k > 0, \\ & (b - c + q_{\rho j}) > \underline{B}. \end{cases} \quad (9)$$

Note that a consumer can only change blades (i.e., $c = 1$) if the current stock of unused blades is greater than zero ($b > 0$), he purchases blades ($q_{\rho, jk} > 0$), or both. We restrict the number of blades to be less than \underline{B} to keep the state space for the dynamic problem bounded. This is not a binding constraint because we set \underline{B} such that it is greater than or equal to the maximum inventory a consumer would hold.

2.5.5. Store Visited. We assume that each consumer visits only one format each week (we informally assess the implications of this restriction in §3). The probability of visiting format k is ϕ_k . We account for persistence in retail format visits by allowing the consumers' past retail visit decisions to shift ϕ_k . Given that razors and blades form a small part of the overall shopping budget, our implicit assumption is that the store visit probabilities are not shifted by prices or consumer inventories (we find support for this

assumption in the data). The current model would have to be extended to accommodate product categories that may actually drive store choice decisions (e.g., Bell and Lattin 1998). However, the decision of which retail format to purchase and accumulate inventory at is endogenous in the model and is the outcome of the dynamic choice. Letting $I(k)$ denote an indicator for whether the consumer visits retail format k , we write the format visit probabilities as

$$\phi'_k = \Pr(I'(k) = 1) = \frac{\exp(\mu_k + vI(k))}{\sum_{m=1}^K \exp(\mu_m + vI(m))}, \quad (10)$$

where v and μ_k are parameters to be estimated from the data.

2.5.6. Prices (*p*). A flexible specification of the transition density for prices would allow for prices that are correlated across products in a given week and are serially dependent over time. With a large number of products and stores, it is infeasible to estimate parametric specifications with unrestricted variance-covariance matrices that capture the comovement in product prices flexibly. Instead, we allow each price to have two support points (i.e., a base price and discount price, as frequently observed in retail scanner panel data). There are consequently $2^{\sum_r I_{rk}}$ possible combinations of prices at each format. We assume that consumers have rational expectations and expect each of these price combinations to be realized with the probability with which we observe it in the data, ψ_{km} , where m denotes a given combination of prices (in our empirical application, m is of the order of 512 at the drug and grocery format). Letting $\bar{p}_{jk} = (p_{jk}^H, p_{jk}^L)$ be a high/low pair of prices for product j at format k , and letting $p_k^{(m)}$ be the m th possible combination of all $\bar{p}_{jk} - s$ at format k , our model of expectations is $\Pr(\mathbf{p}'_k = p_k^{(m)}) = \psi_{km}$.

We believe this provides a reasonable approximation to how consumers form expectations over prices, but it should be noted that the actual price realizations we analyze in the data will not be strictly binary. Implicitly, store format prices are allowed to be flexibly contemporaneously correlated across products but assumed to be independent over time. A correlation in realized prices seen by the consumer does however arise through the state dependence in the store visit probabilities. For instance, a consumer may anticipate during a club store visit today that his chance of visiting a club store again in the immediate future is small. Hence, expected prices seen tomorrow are higher because tomorrow's visits are more likely to be to other, higher priced formats.

2.6. Value Functions

The laws of motion of the state variables imply that consumer's current actions affect their states in

as a parameter and to depreciate the stock of blades in inventory by this parameter. Relative to this approach, our specification has the advantage of endogenizing weekly consumption and also of capturing the discrete nature of replacement decisions in the blade category. The latter aspect likely better approximates the actual process of replacement decisions in this and many other tied good categories. For example, in the case of printers and cartridges—an archetypal tied good market— z captures the level of depreciation of the cartridge (how much ink is left); in the market for Polaroid cameras and films, z captures the level of depreciation of the film currently used (how many photos are left?) Once the ink runs out or all the photos are taken, a new cartridge or roll of film is used, and the stock is depleted by one, as in our model.

the future. Hence, optimal decision making involves picking the alternative that maximizes the consumer's "alternative-specific" value function (Rust 1987). In the remainder of this section, we derive the alternative-specific value functions separately for whether or not the consumer switches to a new blade type.

2.6.1. Value of Switching to Blade Type $r \neq \rho$ by Purchase of Pack j . We write the value function for switching to a new blade type as

$$\begin{aligned} V_{rj}(\rho, z, b, \Omega, \mathbf{p}_k) &= \underbrace{(\gamma_r - \alpha p_{rjk} + \lambda_\rho \gamma_\rho b)}_{\text{I}} \\ &+ \underbrace{\beta \phi_0 \mathbf{E}[V_0(r, \delta, b'(r, y), \Omega') + \varepsilon_0 | b, \Omega]}_{\text{II}} + \beta \sum_{k>0} \phi_k \sum_m \psi_{mk} \\ &\cdot \mathbf{E} \max \left\{ \underbrace{V_0(r, \delta, b'(r, y), \Omega') + \varepsilon_0}_{\text{III}}, \right. \\ &\quad \underbrace{\{V_{rj}(r, \delta, b'(r, y), \Omega', \mathbf{p}_k) + \varepsilon_{rj}\}_{j=1}^{J_{rk}}}_{\text{IV}}, \\ &\quad \left. \underbrace{\{V_{\tilde{r}j}(r, \delta, b'(r, y), \Omega', \mathbf{p}_k) + \varepsilon_{\tilde{r}j}\}_{j=1}^{J_{rk}, \tilde{r} \neq r}}_{\text{V}} \right\}. \quad (11) \end{aligned}$$

The first term (I) in the value function above captures the current period utility of switching to razor technology r today via a purchase at retail format k . The second term (II) captures the option value of potentially making no format visit (with probability ϕ_0) and staying on with the new blades r tomorrow. We define V_0 below. A switch to a new blade type today also encapsulates the discounted value of potentially visiting each format k with probability ϕ_k tomorrow and choosing to either make no purchase (term III), buying refill blade pack j for the new technology (term IV), or switching to a new blade type $\tilde{r} \neq r$ via purchase of a pack $j \in (1, \dots, J_{\tilde{r}k})$ (term V). The option value of a format visit is the expected maximum of these actions, integrated over the set of future prices possible at the format, \mathbf{p}_k , and over the distribution of unobservable shocks to utility that could be realized in the future (i.e., ε s), evaluated at the value of the other state variables tomorrow $\mathbf{s}' = \{\Omega', \rho' = r, z' = \delta, b' = b'(r, j), k, \mathbf{p}_k\}$ and discounted by one period by the factor β .

2.6.2. Value of Staying with Current Blade Type ρ : The Consumption Policy Function. The value to a consumer from staying with the current blade type depends on the choice of c . To choose c , the consumer compares the discounted future value of changing the blade with that from continuing to use the current blade. We therefore begin by specifying the discounted future value under both scenarios. If he

changes the blade currently used, he has the following expected future payoff:

$$\begin{aligned} EV_{\rho j}(\rho, z, b, \Omega | c=1) &= \beta \phi_0 \mathbf{E}[V_0(\rho, 1, b'(\rho, y | c=1), \Omega) + \varepsilon_0 | b > 0] \\ &+ \beta \sum_{k>0} \phi_k \sum_m \psi_{mk} \\ &\cdot \mathbf{E} \max \left\{ \begin{aligned} &V_0(\rho, 1, b'(\rho, y | c=1), \Omega) + \varepsilon_0, \\ &\{V_{\rho j}(\rho, 1, b'(\rho, y | c=1), \Omega, \mathbf{p}_k) + \varepsilon_{\rho j}\}_{j=1}^{J_{\rho k}}, \\ &\{V_{\tilde{r}j}(\rho, 1, b'(\rho, y | c=1), \Omega, \mathbf{p}_k) + \varepsilon_{\tilde{r}j}\}_{j=1}^{J_{\rho k}, \tilde{r} \neq \rho} \end{aligned} \right\} | b > 0. \quad (12) \end{aligned}$$

If he stays with the current blade, the consumer starts off the next period with $z' = \delta z$ and $b' = b'(\rho, y | c=0)$ and obtains the expected future payoff

$$\begin{aligned} EV_{\rho j}(\rho, z, b, \Omega | c=0) &= \beta \phi_0 \mathbf{E}[V_0(\rho, \delta z, b'(\rho, y | c=0), \Omega) + \varepsilon_0] \\ &+ \beta \sum_{k>0} \phi_k \sum_m \psi_{mk} \\ &\cdot \mathbf{E} \max \left\{ \begin{aligned} &V_0(\rho, \delta z, b'(\rho, y | c=0), \Omega) + \varepsilon_0, \\ &\{V_{\rho j}(\rho, \delta z, b'(\rho, y | c=0), \Omega, \mathbf{p}_k) + \varepsilon_{\rho j}\}_{j=1}^{J_{\rho k}}, \\ &\{V_{\tilde{r}j}(\rho, \delta z, b'(\rho, y | c=0), \Omega, \mathbf{p}_k) + \varepsilon_{\tilde{r}j}\}_{j=1}^{J_{\rho k}, \tilde{r} \neq \rho} \end{aligned} \right\}. \quad (13) \end{aligned}$$

Equations (12) and (13) jointly define a *consumption policy function* that determines the optimal consumption of blades as a function of the consumer's state. The optimal consumption policy is nested into the computation of the choice-specific value functions. The expected value of the consumer's best possible action is the maximum of the two payoffs in (12) and (13). We can therefore write the value function for staying with the current razor as

$$\begin{aligned} V_{\rho j}(\rho, z, b, \Omega, \mathbf{p}_k) &= \begin{cases} (\gamma_\rho z - \alpha p_{\rho jk}) + \max_c \left\{ \begin{aligned} &EV_{\rho j}(\rho, z, b, \Omega | c=1), \\ &EV_{\rho j}(\rho, z, b, \Omega | c=0) \end{aligned} \right\} & \text{if } b > 0 \text{ or } q > 0; \\ (\gamma_\rho z - \alpha p_{\rho jk}) + EV_{\rho j}(\rho, z, b, \Omega | c=0) & \text{if } b = 0 \text{ and } q = 0. \end{cases} \quad (14) \end{aligned}$$

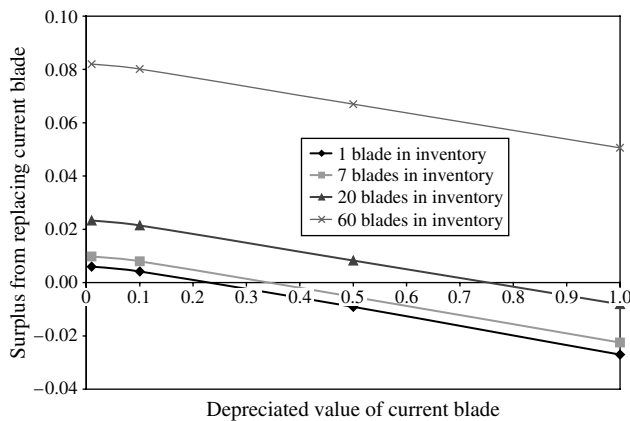
Note that the computation of c depends on partitions of the state space. If the customer has no unused blades, $b = 0$, and does not make a purchase (y_{k0} or y_0 equals 1), the customer cannot change blades (i.e., c is set to 0). The value when not visiting a store, V_0 (not presented for brevity), is defined analogously to

(14), except the current period utility excludes a price effect because nothing is purchased. In essence, (14) incorporates a durable good replacement problem analogous to Rust (1987) for the blades owned. An appealing feature of this formulation is that replacement is endogenous, driven by the consumer's preferences as well his expectations about future prices and inventory. This captures the commonly noted phenomenon that individuals may use more blades when there are many in inventory yet retain the current blade longer when the inventory is reduced. Figure 1 illustrates how the endogenous blade replacement is affected by current inventory and the depreciated value of the current blade for one of the consumers in the data. We see that when the consumer has 60 blades in inventory, the value of replacing (Equation (12)) is always greater than the value of retaining the current blade (Equation (13)). However, at inventory levels of 20, 8, and 4, the customer increases his use of the existing blade to depreciation levels of 0.75, 0.37, and 0.29 before replacement. Thus the model captures the aspect noted in the theory (Assunção and Meyer 1993) that consumption is increasing in the level of inventory.

2.7. Maximum Likelihood Estimation

We estimate the parameters of the model via maximum likelihood. We now add the subscript i denoting "consumer," and t denoting "week" to all variables. We collect the parameters specific to a consumer in a vector, $\theta_i = \{(\gamma_{ir})_{r=0}^R, \delta_{i, \text{disp}}, \delta_{i, \text{nondisp}}, \alpha_i, \lambda_i, (\phi_{ik})_{k=1}^K, v_i\}$ (here, we allow the depreciation rate δ to vary between disposables and nondisposables). As choice data alone cannot identify β , we do not estimate it and set it to 0.998. Implicitly, heterogeneity in consumer patience is not accommodated.

Figure 1 Endogenous Blade Replacement



Notes. The plots present the difference in surplus from using a new blade next period versus continuing to use the current blade, as a function of the depreciated value of the current blade (z). Each line represents a different value for the inventory of unused blades b . The plots are for a consumer currently owning a Mach razor and blades.

2.7.1. Heterogeneity. We allow for a multidimensional continuous heterogeneity distribution using random coefficients. We specify the parameters, θ_i , to be multivariate normally distributed across consumers as $\theta_i = \bar{\theta} + \Gamma \eta_i$, where Γ is the Cholesky decomposition of the covariance matrix of the parameters, Σ , and η is a vector in which each element is distributed standard normal (whereas all parameters are modeled to have a normal underlying distribution, some parameters are transformed to either restrict them to have positive or negative support, or to bound them between zero and one, as is necessary for δ). We denote the set of parameters to be estimated as, $\Theta = \{\bar{\theta}, \Gamma\}$. Given the extreme-value assumption on the stochastic terms to utility, the probability of purchase for each week t is given by a logit function in the alternative-specific values (for the exact formula, please see Technical Appendix D of the electronic companion). The likelihood function for a given individual in the data for a week t is therefore

$$l_t(y_{i0t}, \mathbf{y}_{i1t}, \dots, \mathbf{y}_{iKt} | \rho_{it}, z_{it}, b_{it}, k_{it}, \Omega_{it}, \mathbf{p}_{kt}; \theta_i) \\ = [\Pr(y_{i0t} = 1)]^{y_{i0t}} \prod_{k=1}^K [\Pr(y_{i0kt} = 1)]^{y_{i0kt}} \\ \cdot \prod_{j=1}^{J_{p_{tk}}} [\Pr(y_{ip_{tjkt}} = 1)]^{y_{ip_{tjkt}}} \cdot \prod_{r \neq p_t} \left[\prod_{j=1}^{J_{rk}} \Pr(y_{irjkt} = 1) \right]^{y_{irjkt}}. \quad (15)$$

The likelihood of the data for the individual across all weeks is then

$$L_i(\Theta) = \int \left[\prod_{t=1}^T l_t(y_{i0t}, \mathbf{y}_{i1t}, \dots, \mathbf{y}_{iKt} | \rho_t, z_t, b_t, k_t, \Omega_t, \mathbf{p}_{kt}; \theta_i) \right. \\ \left. \cdot \pi(\rho_{i0}, z_{i0}, b_{i0}, \Omega_{i0}) \right] d\Phi(\theta_i; \Theta), \quad (16)$$

where ρ_{i0} , z_{i0} , b_{i0} , Ω_{i0} are the initial current razor, current blade depreciation level, blade stock, and razor ownership, respectively, and $\pi(\rho_{i0}, z_{i0}, b_{i0}, \Omega_{i0})$ is the probability of the initial condition. An obvious issue to consider in constructing this likelihood is that b_t and z_t are not observed in the data. Consequently, for each guess of the parameter vector, we infer these according to the state transitions defined above, the model parameters, the solution of the dynamic programming problem, the blade purchases in a given week, q_{ijt} , and the initial states.⁶ The initial states are

⁶ We construct the likelihood assuming that we know the unobserved state with certainty. For example, if a consumer randomly decides not to shave for a few days, the current blade will not actually depreciate even though we assume it does. Ideally, one would integrate over all possible values of the unobserved states to account for random variation in depreciation, but this is significantly burdensome. Using our best prediction of the unobserved state as specified by the model, we are able to model interpurchase times in a functional form of past purchases that, although not exact, is consistent with the behavioral primitives of purchase timing.

unobserved, which creates a standard initial conditions problem. We derive the initial states based on model parameters and the weeks until the consumer is observed to make his first purchase.

Specifically, to obtain the initial razor ownership Ω_{i0} , we assume that all consumers own Schick and Sensor razors from the beginning of the data. This assumption is motivated by the fact that although we see very few observations of purchases of razors of these technologies in our data, we nevertheless observe many purchases of blade packs of these technologies. We also add Mach to initial razors owned if the first Mach purchase observed for that consumer is a blade pack that does not contain Mach razors. We obtain the initial blade type ρ_{i0} as follows. If the first observed purchase for a consumer is a blade pack, we set ρ_{i0} to the type of that blade pack. If the first observed purchase for a consumer is a razor-plus-blade pack, we assume that the initial blade type owned is a disposable. We recompute the initial stock b_0 for each consumer for each guess of the parameters, based on a customer having an approximate stock of zero in the first week we observe him purchasing any packs. Specifically, if a consumer i is observed to make his first purchase T_i weeks after the beginning of the data, we assume that the initial stock is $T_i(1 - \delta_i)$, where δ_i is the current guess of the depreciation rate for the consumer.⁷ Finally, we assume consumers start with a new blade at the beginning of the data—i.e., we set $z_{i0} = 1$.

The rich specification of heterogeneity increases the computational burden of the estimator significantly. To estimate random coefficients in this dynamic model we use the change of variables and importance sampling technique proposed by Akerberg (2009). In a first step, we solve the value functions over a set of 2,000 simulated parameter values. In subsequent iterations, we use this initial solution to obtain the likelihood at the new guesses of the parameter vector while avoiding the computational burden of resolving for the value functions.

2.7.2. Identification. We now present a brief informal discussion of identification in this model. The availability of panel data, including both the product choice as well as the quantity choices (i.e., pack sizes) of consumers, facilitates identification of preferences and heterogeneity. The usage utility parameters of each consumer, γ_r , are identified from his average propensity to purchase in the data, in addition to the total number of units of a given razor type that are observed to be purchased across all time

periods. The purchase disutility, κ , is separately identified from γ_r , as κ only affects utility during purchase, whereas γ_r affects utility even in periods with no purchase. The incidence of temporary price cuts in scanner data provides price variation to identify price sensitivities. The salvage value fractions, λ , are identified from the time elapsed as well as the pack sizes that are bought prior to purchase occasions that involved a change of blade types (i.e., holding consumption and usage utilities fixed, if we see a switch to a new blade type occurring soon after a large pack of a different blade type was bought, we infer that λ is high). Consumption is unobserved in the data and is identified by the joint distribution of interpurchase times and quantity choices; i.e., large pack size choices interspersed with short interpurchase times imply high consumption rates. We also allow for heterogeneous depreciation rates of stockpiles on multiple razor types. These are intuitively identified in the following way. If we see that the time to purchase of disposable blade packs following a disposables purchase is small, we infer depreciation of disposables is high. If we see that time to purchase of blade packs following a nondisposable blade pack purchase is small, we infer depreciation of nondisposable razor blades is high. Finally, the frequency of observed format visits for a given consumer identifies his format visit probabilities. Persistence in retail visit probabilities for the consumer is identified from any persistence in the temporal distribution of his observed format visits.

3. Data and Descriptive Analysis

Our data contain the complete purchase history of razors and blades for a panel of consumers in a large midwestern city in the United States. An advantage of the data is that all purchases of products in this category at every retail outlet in the city are observed. To avoid confounds related to purchases of razors and blades for different members of the household, we restricted attention to purchases of only male razors and blades. Our final data set contains the purchase patterns of male razors and blades for a panel of 725 consumers over a period of 56 weeks beginning in mid-September 2002 and ending in the beginning of October 2003. These data were augmented with a price file from the IRI data set (see Bronnenberg et al. 2008) that provided prices for all retail formats in the city (except club stores).

The period of our data includes the Gillette Mach razor, the Gillette Sensor razor, as well as the Schick Xtreme3 and Tracer razors (the data do not include the Schick Quattro, which was introduced in late 2003). In the data, we observe several purchases of Mach razors and blades but observe little or few purchases of Gillette Sensor or Schick razors, in spite of

⁷ Recall that if $\delta = 0$, a new blade will have to be used the next period. If $\delta = 1$, no replacement is necessary because the current blade has no depreciation. Hence, the expected blades used per period is roughly $(1 - \delta)$.

observing blades bought. Hence, although we model blade demand for all brands, we model razor adoption of only the Mach razor; Sensor and Schick razors are assumed to be owned prior to the beginning of the data. The reader is pointed to Technical Appendix B of the electronic companion, which discusses these issues extensively.

3.1. Data Cleaning

To obtain a data set suitable for estimation, we undertook several steps to clean the raw data. A detailed discussion of the data cleaning steps is provided in Technical Appendix B of the electronic companion. We briefly summarize the steps below. First, we restrict attention to households that purchased at least one male razor or blade pack during the period of the data. This reduced our data set from 2,786 observed purchases to 1,675. Second, for parsimony, we combine some of the infrequently purchased packs with commonly purchased pack sizes. This further reduced the number of observed purchase occasions to 1,565 in our final data set. Third, we also model consumers to make a discrete choice over the retail format visited. We use specific thumb-rules to assign consumers observed to be visiting multiple retail formats in the same week to a single format. We find 34,610 observations in which a format was visited. This aggregates a total of 96,217 format visits in the raw data. Most of the aggregation is multiple visits at the same format. In cases where different formats were visited in the same week, typically a nonrazor category purchasing DG visit was aggregated into an M or W visit (32% and 11%, respectively, of the aggregated visits). Finally, we do not have an actual price charged at club stores because these stores do not share data with syndicated vendors. Thinness of purchase data precluded inferring these weekly from observed purchases. Instead, we compute the mean price paid of each product across all consumers and across all weeks in the data, and use these as a proxy for the prices not observed. This methodology is admittedly imperfect and is a limitation of the paper.

3.2. Summary Statistics of Individual-Level Data

We first describe the distribution in the raw data of the implied state variables from the model. Recall that in our framework, we model a customer beginning each week with a current razor technology and visiting one of the three store types or staying home. We summarize the incidence of each of these in Table 1.

The bottom panel of Table 1 presents the distribution of razor ownership across consumers and weeks. Interestingly, about 31% of consumer weeks involve ownership of a Gillette Mach razor, whereas only 29% of consumer weeks involve ownership of Mach blades in inventory, suggesting that there are some instances

Table 1 Summary Statistics: Store Visits and Razor Technology Ownership

	Obs.	Mean	Std. dev.	Min.	Max.
Store visits					
No store	40,600	0.15	0.35	0	1
Grocery or drug	40,600	0.44	0.50	0	1
Mass merchandiser	40,600	0.30	0.46	0	1
Club store	40,600	0.11	0.31	0	1
Mach razor owned	40,600	0.31	0.46	0	1
Blade type in consumer inventory					
Gillette-Sensor	40,600	0.09	0.28	0	1
Gillette-Mach	40,600	0.29	0.45	0	1
Schick	40,600	0.04	0.21	0	1
Disposable	40,600	0.58	0.49	0	1

in which a consumer chooses to use blades of another technology while owning a Mach razor. This partly motivates our model formulation that allows multiple razor ownership by consumers. Figure 2 plots the distribution of the total blades purchased in all months in the data across customers. This is an indirect measure of the distribution of consumption rates and suggests significant heterogeneity.

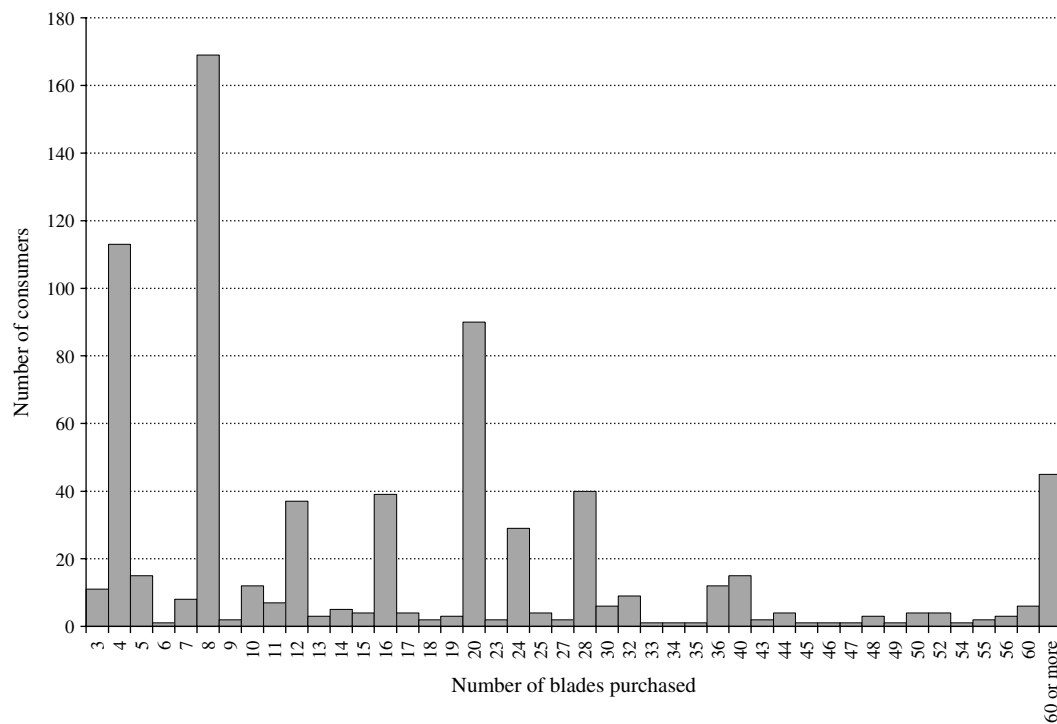
3.3. Stocking and Sales of Pack Sizes by Retail Format

In Table 2, we list the pack sizes available at each retail format, as well as the prices of each of the packs by retail format. Our data include 15 pack types across three retail formats. The grocery and drug format and mass merchandiser format carry similar packages, whereas the club stores only sell Gillette brands or disposables and only carry large package sizes. The differences in product availability across differing retail formats provides an incentive for consumers of differing tastes to self-select into visiting and accumulating inventory at each retail format.⁸

In general, Mach blades tend to be priced higher. Consistent with the notion that primary goods (i.e., razors) are priced cheaply, we do not see much evidence for higher prices on packs that contain razors. Table 2 also provides information in the differences in prices across retail formats. Consistent with the conventional wisdom, comparable pack sizes are priced lower at mass merchandisers than at grocery stores. The club stores stock only large pack sizes that have low prices on a per-blade basis, which make them

⁸ A related concern here may be that the set of products available at a retail format is itself endogenous, enabling the manufacturer to price discriminate across retail formats. Modeling the endogenous selection of products at the retail level to address this issue is beyond the scope of the current analysis. Furthermore, across the year of weekly data that we have, we do not see any variation in the set of products available at the formats in our data. Hence, our approach is to condition on retail product availability in our analysis.

Figure 2 Distribution of Blade Usage in Data



more attractive to high-consumption consumers. We also see some broad evidence for pack size-based price discrimination via quantity discounts in this category. This aspect of price discrimination is accommodated in our empirical model because we explicitly model choices over pack sizes.

3.4. Descriptive Statistics About Retail Format Switching

An important piece of our analysis involves the measurement of retail substitution. Our model specifies retail substitution to occur through consumers endogenous decisions of which store to purchase their durable and storable goods. Hence, a necessary condition for cross-format substitution is that consumers visit multiple formats. Figure 3 illustrates that almost all consumers visit each format with a probability greater than one. For instance, the lower left plot in Figure 3 depicts very little mass of consumers at both 0% and 100% visit probabilities for DG stores, whereas most of the mass is between 20% and 80% visit probabilities. Figure 4 focuses on the subset of consumers that bought blades on at least two occasions and depicts the proportion of blades bought at a given retail format on the horizontal axis. We see that there is a significant mass of consumers that buy either all or none of their blades at drug and grocery stores and mass merchandiser stores. There is also a positive mass of consumers buying blades in these retail formats with some probability between zero and

one. At club stores, we see that no consumers who purchased at least twice bought all blades at club stores. Many consumers never bought blades at club stores, but there is a mass of consumers that bought blades at all three formats. Together, Figures 3 and 4 illustrate that customers visit multiple retail formats and exhibit some switching of the retail format at which they buy blades.

We now present the results from the estimation of the model on these data.

4. Model Estimates

The goal of our analysis is to estimate the model defined in §2 with the data to conduct counterfactual changes in long-run price distributions to measure substitutability, or complementarities, or both, between goods and retail formats. Our structural approach is necessary for analysis of these scenarios that are unobserved in the data, and we also estimate several alternative models to assess the fit of our model. These models include a static logit model without unobserved heterogeneity, a myopic version of our model with discount factor set = 0, a static “reduced-form” model with unobserved heterogeneity and with functions of past quantities and inter-purchase times as covariates, the dynamic structural model without the state dependence term, as well as our full model. In general, we find that our preferred full model provides the best fit to the data and also

Table 2 Pack Size Average Prices by Razor Technology and Store Type

	Drug and grocery stores (\$)	Mass merchandisers (\$)	Club stores (\$)
Gillette Mach			
3-pk razor	8.10 (2.70)	7.36 (2.45)	
7-pk razor			14.70 (2.10)
4-pk blades	8.20 (2.05)	7.57 (1.89)	
8-pk blades	15.51 (1.94)	14.42 (1.80)	
16-pk blades			26.33 (1.65)
20-pk blades			28.03 (1.40)
Gillette sensor			
5-pk blades	7.13 (1.43)	6.42 (1.28)	
10-pk blades	13.31 (1.33)	12.06 (1.21)	
25-pk blades			25.46 (1.02)
Schick			
4-pk blades	6.57 (1.64)	6.26 (1.56)	
8-pk blades	13.13 (1.64)	12.51 (1.56)	
Disposables			
4-pk blades	2.12 (0.53)	1.92 (0.48)	
8-pk blades	4.25 (0.53)	3.85 (0.48)	
20-pk blades	10.62 (0.53)	9.62 (0.48)	
60-pk blades			16.18 (0.27)

Note. Average price per unit in parentheses.

beats the other models on the Bayesian information criteria, which penalizes parameter proliferation. We find that accounting for unobserved heterogeneity as well as allowing for dependence of current purchases on past purchase history are both important to fit the patterns observed in the data. We also conduct extensive tests to assess the ability of our model to fit the observed patterns of the data (brand and format shares) both in and out of sample. We find that the fit is extremely good. To see these results, please see Technical Appendix C of the electronic companion.

Table 3 reports the estimates of our structural model. The brand utilities represent the value per-period of consumption of blades compatible with each razor technology (note that an exponent of the reported value must be taken to obtain the actual brand value). The estimates indicate that the mean utility from shaving with Mach is greater than shaving with other types of blades. The depreciation val-

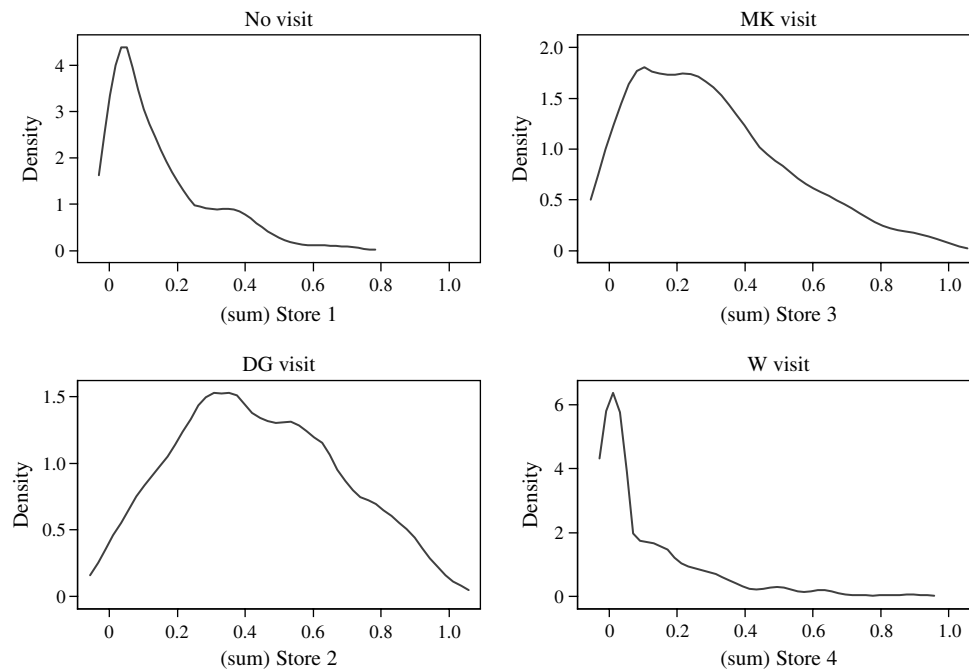
ues for nondisposable and disposable razors can be calculated by taking the exponents of the reported values and dividing by one plus this exponent. They are nearly identical at 0.07 and 0.08, respectively. Thus, for the average consumer, blades typically last one or two weeks.

As described in the model above, we also estimate a parameter that helps quantify the resale value of old blades when adopting a new type of blade inventory. The mean of this parameter is about 0.5% (transforming -5.256 by its exponent divided by one plus its exponent). Even after considering the heterogeneity in this parameter, most of the customers' salvage values are 3% or less. It seems that buying new blade types while still having old blades in stock is not a substantial factor in the decision process for these data. Although not quantitatively significant, we retain this parameter because it is a useful modeling aspect that could be considered in applications with other data sets.

The price coefficient is 1.372 (i.e., $\exp(0.317)$) for the average consumer. We also find evidence of significant heterogeneity in the price effects in the population. This is a primary reason we estimate this parameter to be log-normally distributed. When estimating it to be normally distributed, we found it to be significant (with the proper sign) but also found that imposing a symmetric heterogeneity distribution led to some consumers in the tail with an improperly signed price coefficient. These price effects, along with the format visit probabilities, will be primary determinants of the cross-store price elasticities.

The retail format visit parameters represent the average probability of visiting each of the formats (drug and grocery, mass merchandiser, and club stores). We can see that consumers are estimated to visit the drug and grocery retail format most frequently, with the mass merchandisers and then club stores following. The negative parameter on club store visits simply indicates that no visit is more frequent than club store visits. The estimated visit probabilities are informative about the degree of retail market power over consumers. Grocery stores, which are visited most often, may have more market power over consumers because a consumer facing a price increase in that retail format today anticipates that he has a high likelihood of returning to the same format tomorrow and facing a similar high price. This makes him more likely to buy at that high price, *ceteris paribus*. The high market power of grocery stores is also partly reflected in Table 2, where average prices per blade in those retail formats were higher. We also see that there is significant positive state dependence in the retail format choice decisions. The standard deviations in these parameters indicate significant unobserved heterogeneity in retail format visit probabilities.

Figure 3 Distribution of Store Visits Across Consumers



Notes. This plot shows the distribution of store visits by consumers. The plot is generated in the following way: for each consumer, we calculate the proportion of weeks in which either no store was visited, or one of the DG, MK, or W stores were visited. The figure plots the density of these proportions across consumers. For example, the first plot (top left) shows that most consumers do not have a large proportion of weeks in which no store is visited; the plots on the top right and bottom left show that many consumers are likely to make a large proportion of DG and MK visits; the bottom-right panel shows that across most consumers, W store visits is liable to be <10% of total visits.

4.1. Correlations Between Parameters

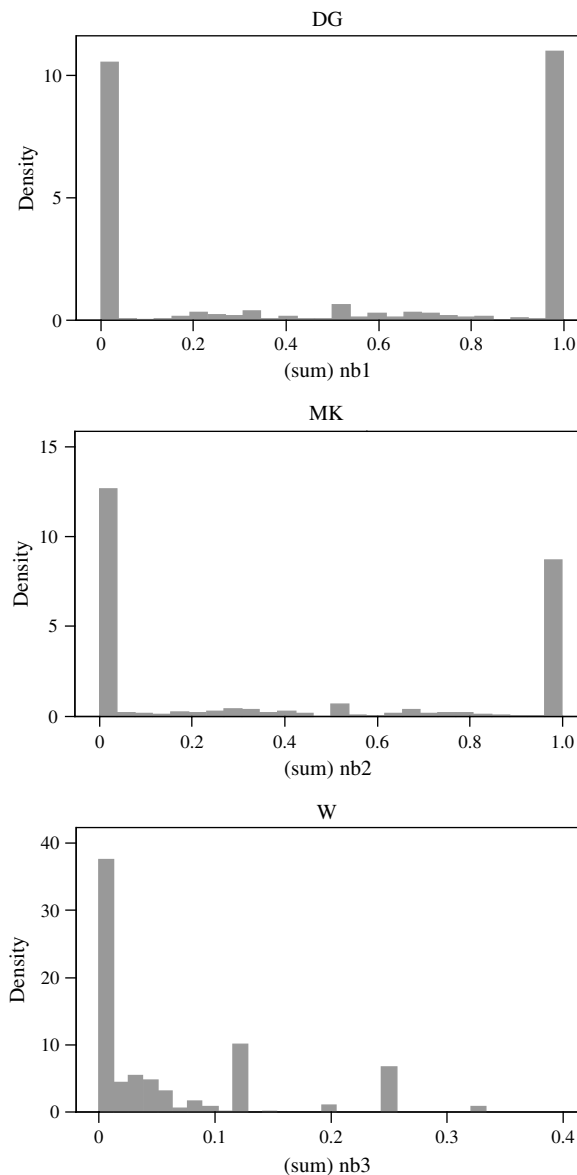
The correlations represent an important determinant of the substitutability between retail formats. In particular, the format visit probabilities could reflect the distribution of customers that are very loyal to each retail format, or customers that are very similar and visit all retail formats with some probability. Strong positive correlations between format utilities therefore indicate more interformat substitution, whereas negative correlations indicate little interformat substitution. These correlations are presented in Table 4. We see that mass merchandising formats are substitutable with both drug and grocery stores and club store formats, based on positive correlations in preferences of 0.59 and 0.38, respectively. Yet drug and grocery stores and club stores are not very substitutable with one another, indicated by a correlation of 0.09. Drug and grocery stores and club stores may therefore serve different segments of consumers. The estimated correlation in format preferences with price sensitivity also suggest that club stores may be attracting slightly less price-sensitive consumers. Many of the other correlations between heterogeneous parameters were estimated but are not reported here.

4.2. Implications of Model Parameters

To get some intuition for what the model implies about purchase dynamics, we present plots of the

value functions computed at the estimated parameter values. For illustration purposes, we pick a customer that uses about one Mach blade every two weeks (i.e., his net consumption is 26 blades in a year). We consider a situation where this consumer currently owns a Mach razor, and the currently owned blade is completely dull (i.e., $z = 0$). In the three panels of Figure 5, we present plots of the value of purchasing a blade pack to this consumer relative to the value of no purchase at drug and grocery stores, mass merchandisers, and club stores, respectively. In each of the panels, the horizontal axis is the number of unused blades in stock, b , and the vertical axis is the dollar value of surplus obtained when choosing the specified pack size relative to buying nothing. Looking at Figure 5, we see that the model implies that the more unused blades a consumer has, the less likely he is to buy any blades.

We now discuss how the model generates differing incentives for the same customer to purchase products at the different retail formats. To make the discussion concrete, we compare the incentive of this customer to purchase a Mach blade pack at each of the three formats when owning zero blades. Looking at the first panel, we see that the customer faces about a \$4 disincentive to purchase either of the Mach blade packs at a drug and grocery store (about \$2.50 of

Figure 4 Proportion of Blade Purchases by Format

Notes. These plots show the distribution of the proportion of blade purchases made by consumers across formats. For each consumer, we calculate the proportion of blades bought at one of the DG, MK, or W stores. The figure plots the density of these proportions across consumers. We see that there are many consumers that have made all their blade purchases at a DG or an MK store (significant mass at one in the panels on the left). At the same time, we also see that there are many consumers who have shopped for blades across the three formats.

this is due to the purchase disutility). However, for a large unobserved purchase incentive arising through a logit error, the customer will on average not purchase. A similar pattern holds at the mass merchandiser stores; the disincentive to purchase a Mach 4 pack is about \$3.50, implying that the customer will not refill at the mass merchandiser on average. However, looking at the third panel for club stores, we observe that the customer obtains a positive surplus

Table 3 Model Estimates

	Random coefficients	
	Mean	Std. dev.
Brand utilities		
Sensor	−1.271 (0.138)	1.016 ^a (0.020)
Mach	−0.176 (0.074)	0.888 ^a (0.020)
Schick	−2.015 (0.114)	1.423 ^a (0.025)
Disposables	−1.317 (0.159)	2.349 ^a (0.029)
Price coefficient	0.317 (0.120)	1.787 ^a (0.022)
Blade depreciation rate		
Nondisposables	−2.577 (0.115)	1.506 ^b (0.027)
Disposables	−2.377 (0.127)	1.881 ^b (0.023)
Resale percentage	−5.256 (0.144)	1.462 ^b (0.035)
Habit persistence	0.153 (0.007)	0.114 (0.005)
Purchase disutility	−3.483 (0.017)	0.238 (0.014)
Store 1	1.435 (0.104)	1.464 (0.030)
Store 2	0.713 (0.102)	1.658 (0.046)
Store 3	−1.463 (0.332)	2.819 (0.085)
Store choice	0.095 (0.029)	0.233 (0.010)
Persistence		

Notes. Standard errors in parentheses.

^aThe variable is log-normally distributed. The coefficient for these variables can be obtained by taking the exponent of the reported value.

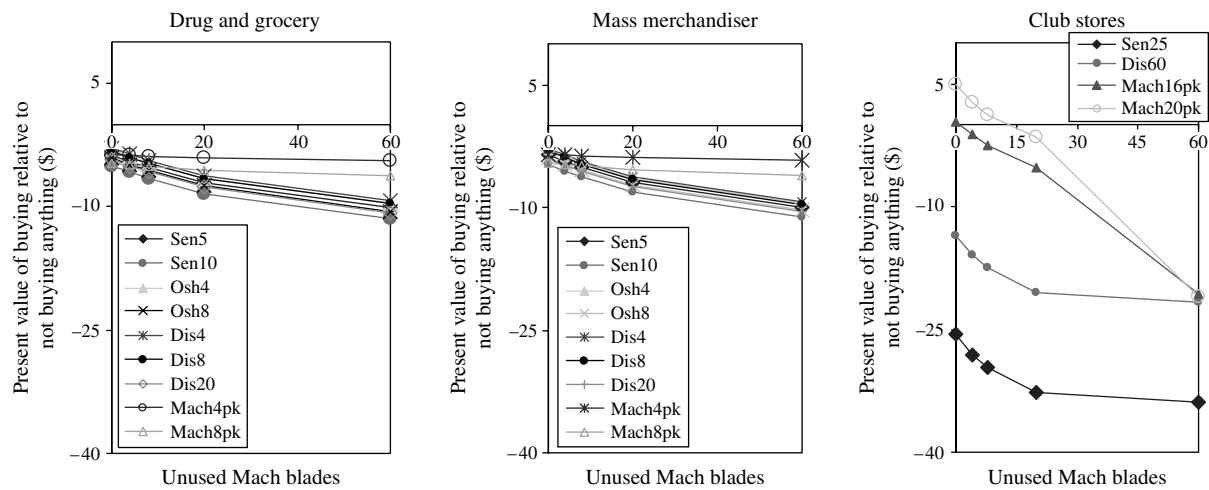
^bThe variable is constrained to be between zero and one. The coefficient for these variables can be obtained by taking the exponent of the reported value and dividing it by one plus this exponent.

when buying Mach refill blades at a club store. With zero unused Mach blades in inventory, this surplus is about \$0.26 for a Mach 16-pack and \$4.88 for a Mach 20-pack. Even when the customer has eight Mach blades, he still realizes a surplus of about \$1.25 when refilling with a 20-pack at a club store. Given the large pack sizes available at the club store and the low prices, the model implies that the customer

Table 4 Correlations in Store Visit Probabilities and Price Sensitivity

Store choice	Grocery and drug	Mass merch.	Club stores
Store choice			
Grocery and drug	1	0.59	0.09
Mass merch.	0.59	1	0.38
Club stores	0.09	0.38	1
Price sensitivity	0.07	0.00	−0.06

Figure 5 Relative Value of Buying a Pack at Each Retail Format for a Biweekly Mach Blade User Currently Owning a Mach Razor and Blades



Note. The plots present the value of buying a pack relative to the value of no purchase as a function of the current blade stock b , evaluated at $z = 0$, at each retail format, for a consumer currently owning a Mach razor and blades who replaces his blades on a biweekly basis.

at this state will strongly prefer to buy Mach blades only at club stores. On average, the model will predict that the customer would want to wait when at a drug, grocery, or mass merchandising store so that he can refill his blades during a future visit to a club store, where per-blade prices are lowest.

4.3. Discussion

To summarize the demand estimates, we find strong evidence for heterogeneity in the data, as well as preferences for format visits that are correlated with consumer tastes and consumption rates. Furthermore, the above discussion illustrates that the estimated model captures incentives for customers to optimally choose which store to purchase their refill blades from despite the fact that stores do not provide any direct utility to the consumer. Stores serve as a vehicle to obtain low prices if the customer is likely to visit. Our model illustrates that club stores, which specialize in selling large pack sizes at low per-unit prices, increase the incentive to stockpile and decrease incentives to purchase at other stores particularly for high-volume customers like the biweekly blade user considered above.

5. Substitution Patterns for Tied Goods Sold Through Competing Retail Formats

In this section, we used the estimated model to measure (1) complementarities between tied goods and (2) substitution patterns between shaving alternatives and retail formats. We measure each of these by simulating long-run own and cross-price elasticities across products and across retail formats. By *long run*, we

mean elasticities that incorporate the demand effects as a result of a change in current prices, as well as the substitution across stores and time because of changes in the price expectations of consumers. We measure these long-run effects by simulating consumer demand in response to a permanent change in the price distribution (e.g., EIK). In Technical Appendix D of the electronic companion, we provide a description of the procedure to simulate these values using the dynamic structural model we develop.

5.1. Complementarities Between Razors and Blades

We are interested in measuring complementarities between razors and blades as these determine the relative pricing of the primary and aftermarket goods for the manufacturer. The theory of pricing for tied goods suggests that under most plausible scenarios, the optimal strategy for the manufacturer is to lower margins on the primary good and make up margins on the aftermarket good. This razor/razor blades pricing model is motivated by two arguments. The first flows from the existence of switching costs that partially prevent locked-in consumers from switching away from the system after their purchase of the primary good, thereby enabling the firm to extract rents through the sales of the aftermarket good. The second motivation arises from the potential for second-degree price discrimination. By pricing the primary good low, the seller can attract low willingness-to-pay customers that demand few aftermarket goods. Pricing the aftermarket good higher then allows the seller to extract more surplus from higher willingness-to-pay customers who consume more of the aftermarket goods. We cannot sort between these two

explanations; however, we will use our estimates to informally assess the empirical significance of either considerations.

A priori, economic switching costs in this category are likely to be low because they should be bounded by the price of buying a new razor, which is low (the razor component of a Mach razor pack sold at drug and grocery stores or mass merchandisers is something less than \$1.95 and \$1.69, respectively). A psychological switching cost, related to habit persistence can, however, exist. Our estimates from Table 3 reveal that the switching cost from habit persistence is of the order of \$0.11, which we believe is not quantitatively large enough to support the switching cost explanation.

We now consider the long-run elasticity of demand of Mach razors and blades with respect to manufacturer prices. We estimate these by simulating a permanent 1% price change by all retailers in the market. From the bottom two panels of Table 5, we see that if prices of Mach razor packs were increased by 1%, overall manufacturer-derived demand from

the market would decrease by 0.84%. A 1% permanent reduction in Mach blade prices, on the other hand, reduces Mach blade demand by 2.85%. Thus, our estimates reveal that Gillette is pricing Mach razors in the inelastic region of the demand curve and pricing blades on the elastic region, which is consistent with the price discrimination incentive. Although this is not a test of price discrimination per se, in conjunction with the low estimated switching costs, this does suggest that discrimination is likely one of the primary forces driving pricing in this industry. Table 5 also finds evidence for significant complementarities between razors and blades in this industry.

5.2. Substitution Between Competing Shaving Systems

The elasticities are also informative of substitution amongst competing systems. Given that Gillette sells multiple generations of tied good technologies, we explore how the pricing of their flagship tied good technology, the Mach, affects the demand of their

Table 5 Long-Run Demand Elasticities with Respect to Mach Razor and Blade Prices

	Retail channels			Manufacturer
	Drug and grocery	Mass merchandiser	Club stores	
Drug and grocery: Mach razor pack price				
Mach razor pack demand	−2.25	1.21	0.55	−0.31
Mach blade refill demand	−0.14	−0.08	−0.06	−0.08
Sensor blade demand	0.01	−0.01	0.00	0.00
Schick blade demand	0.27	−0.05		0.11
Disposable blade demand	0.26	−0.05	−0.02	0.10
Drug and grocery: Mach blade refill price				
Mach razor pack demand	−0.45	−0.26	−0.07	−0.31
Mach blade refill demand	−4.20	0.57	0.28	−0.70
Sensor blade demand	0.02	0.00	0.00	0.01
Schick blade demand	0.64	0.14	0.00	0.38
Disposable blade demand	0.20	0.00	0.81	0.10
Club stores: Mach blade refill price				
Mach razor pack demand	−0.11	−0.08	0.08	−0.08
Mach blade refill demand	0.58	0.67	−3.13	−1.28
Sensor blade demand	0.00	0.00	0.04	0.01
Schick blade demand	0.13	0.12	0.00	0.13
Disposable blade demand	0.11	0.08	1.80	0.11
All stores: Mach razor pack price				
Mach razor pack demand	−0.88	−0.54	−1.77	−0.84
Mach blade refill demand	−0.23	−0.19	−0.05	−0.13
Sensor blade demand	0.00	0.01	0.01	0.01
Schick blade demand	0.25	0.24	0.00	0.24
Disposable blade demand	0.22	−0.07	2.05	0.08
All stores: Mach blade refill price				
Mach razor pack demand	−0.91	−0.74	−0.04	−0.72
Mach blade refill demand	−3.53	−3.06	−2.42	−2.85
Sensor blade demand	0.02	0.03	0.03	0.02
Schick blade demand	0.95	0.73	0.00	0.84
Disposable blade demand	0.29	0.34	2.97	0.33

Note. This table reports the percentage change in long-run demand as a result of a 1% change in row prices.

previous generation technology, the Sensor, relative to demand for competing alternatives (Schick and disposables). Looking at the bottom two panels of Table 5, we see that is evidence that increases in price for Mach blades results in substitution to blades of other technologies. A cursory reading of the elasticities suggests that substitution to Schick blades is the largest. This is, however, misleading because the Schick market share is quite small. In a separate calculation (not reported), we find that in terms of unit sales increases, about 83% of the increase in competing system blade sales induced by the 1% increase in Mach blade prices consists of Sensor blades. This suggests that Gillette's pricing is influenced more by its decision to segment customers between its flagship technology and previous generations than it is by pressures from competing manufacturers. Taken together, these elasticity results suggest that during this time period, Gillette may be best characterized as a monopolistic seller of razor systems that price discriminates by introducing newer generations targeted at the highest value customers. Although analyzing product introductions is beyond the scope of this paper, it suggests that this is an interesting area of research for this market and perhaps other tied good systems.

5.3. Retail Substitution Patterns

We now use the model to study retail substitution effects in our data. We are primarily interested in these as they are informative of the extent to which downstream retail competition may distort the desired pricing of the manufacturer. Because this aspect has not been identified in the literature, we provide a brief discussion and then present our empirical results.

In particular, the presence of an oligopolistic retail channel introduces new avenues for channel conflict that are not present in nontied product markets. Fundamentally, tying is difficult to sustain in the downstream. Although the manufacturer is able to enforce a tie between the goods via, say, product design, the retailer has trouble enforcing a tie because consumers can buy the aftermarket goods elsewhere. In the presence of retail market power, this aspect creates two problems for the manufacturer. The first, double marginalization, is exacerbated by the tied goods nature of the products because higher prices reduce adoption of the primary good either directly or indirectly through complementary aftermarket goods. The second issue, which we call "cross-product horizontal externalities," arises when one store's price increase reduces the demand of complementary goods sold at another store. Although many tied good products are sold through retail channels, surprisingly, to our knowledge, both the theory literature and the empirical work on tied goods so far has ignored the role

of downstream retail competition we consider. Exploring a dynamic channel game formally is beyond the scope of this paper; however, by empirically analyzing substitution patterns at the retail level, we hope to shed light on these channel problems and motivate future work modeling the supply-side implications of selling tied goods through oligopolistic downstream channels.

Double marginalization is particularly problematic for tied goods because the manufacturer requires a low price for the primary good to serve as a customer acquisition device to drive a flow of profitable aftermarket sales. A retailer with sufficient market power to raise razor prices could harm the manufacturer by generating a demand contraction in the razor market that cuts off all of the manufacturer's profitable blade sales associated with the lost razor sales. This is plausible in the razor and blades market we consider because one downstream format (drug and grocery stores) sells a large number of razors and may have significant market power. Retail market power in the aftermarket is problematic as well, because this implies "too-high" blade prices from the manufacturers' point of view. This results in reduced blade output and possibly a contraction in razor sales because of the reduced demand for razors from forward-looking consumers who anticipate high blade prices following purchase. Consequently, tied good manufacturers, such as Gillette in the razor blade market, desire retail competition in both the razor market and the blade market.^{9,10}

⁹ Competition in either one of the markets does not eliminate the distortion. Suppose the tying good is sold through a perfectly competitive retail channel but the tied good is sold through retailers with market power. Perfect competition in the tying good enables the manufacturer to pass through desired low razor prices, but the presence of market power in the blade channel implies that blade prices will be too high, and blade output too low from his perspective. Given higher blade prices, razor demand will also be too low. The vertical externality persists if the tied good retail channel is perfectly competitive, but retailers selling the tying good have market power. The manufacturer would be able to pass through his desired high price on blades, but double marginalization in the razor market imply that razor prices will be too high from his perspective. Overall demand for razors, and thus of blades, is again too low.

¹⁰ Even if there is significant retail market power, the manufacturer can avoid double marginalization by using vertical restraints (e.g., resale price maintenance) or two-part tariffs (Moorthy 1987, Desai and Srinivasan 1995, Villas-Boas 1998; see Iyer and Padmanabhan 2003 for a review of the theory, and Villas-Boas 2007 and Lafontaine and Slade 2008 for a review of the empirical work). Evaluating the incidence or efficacy of these vertical restraints is beyond the scope of the current analysis and the available data (we do not observe wholesale prices or details of the contract between the manufacturer and the retailer). Rather, our analysis here discusses whether there exists sufficient downstream retail substitution such that this may be a quantitatively significant issue for the manufacturer.

In addition, complementarities in demand between the primary good sold at one retail format and the aftermarket good sold at a different retail format create a cross-product horizontal externalities problem. The term *horizontal externalities* has generally been used to describe channel conflicts such as classic dealer free riding, in which a discount chain sells a good at a low price with low sales support to a customer who learned about the good at a high-price, high-support channel (see Mathewson and Winter 1986, Klein and Murphy 1988, Iyer 1988). If sales support or service is not desired by the manufacturer, these externalities typically do not exist. However, in the case of tied goods, a cross-product horizontal externality can still arise if the pricing decisions of a retailer specializing in the aftermarket good significantly affects the demand at a different retailer specializing in the primary good, or vice versa. For example, if a retailer specializing in blades raises prices and consequently reduces aggregate blade demand, it will do so without internalizing the lost razor sales at other formats. Significant cross-format complementarities of this nature arise only in the presence of retail market power. For instance, in the above example, without retail pricing power in blades, a consumer's razor purchase decision at a given format is unaffected by blade price changes at another, because he can easily switch to a different retail format for his blade requirements. Razors and blades provide a particularly interesting example because, in the data, club stores primarily sell blades, whereas drug and grocery stores sell many more razors relative to blades (the ratio of Mach blades to razors sold in the data by format are as follows: 47 drug and grocery stores, 74 mass Merchandisers, and 221 club stores). To evaluate the extent of cross-product horizontal externalities, researchers must therefore assess whether any one format can reduce aggregate demand of either the primary or aftermarket good and, if so, whether the reduction is large enough to significantly impact other formats' demands for the complementary good. If the externality exists, channels will not internalize all of the negative effects of increasing prices and will therefore likely reduce adoption of the tied good system.

We now discuss how the elasticity estimates are informative of both issues.

5.4. Retailer Pricing Power

Given the lack of a formal model of pricing, we cannot assess equilibrium price responses in the downstream channel game. However, the demand model can still be used to assess substitution patterns, which form an important driver of pricing power at the retail level. Our approach is to simulate how much of the manufacturers' overall razors sales would be

lost if one of the retail formats unilaterally increased its razor price. If consumers simply switch to other stores in response to the price increase, the overall reduction in sales to the manufacturer will be small, and we may infer that retail substitution is strong, and that the format's pricing power is small. This will imply that the potential for double marginalization is low. We focus on simulation on drug and grocery stores because they are the primary sellers of razors in the data. Looking at Table 5, if DG stores raised Mach razor pack prices by 1%, they would lose 2.25% of their Mach razor demand. The cross-price effects of 1.21 and 0.55 for mass Merchandisers and club stores, respectively, indicate significant substitution within Mach to other retail formats. Put differently, in terms of unit sales, this implies that 67% of Mach razor sales that would have been lost at the drug and grocery format would be made up at the competing retail formats. Overall, the price increase results in only a 0.31% decrease in the total Mach razors sold by Gillette across all retail formats in this market. We interpret these results as suggesting that although the drug and grocery format does have some degree of pricing power, retail format competition does guard Gillette from a concern that every razor sale lost at the drug and grocery format is permanently lost.

Table 5 also reveals that long-term demand for Mach blades is highly elastic at both the drug and grocery format (own price elasticity of -4.20) and at club format stores (own price elasticity of -3.13). Although there is evidence of retail substitution in blades in response to price changes at both, club store pricing imposes the largest impact on the manufacturer, since a 1% increase in Mach blade prices at club stores can decrease the manufacturer's Mach blade sales by 1.28%. In terms of unit sales, this implies that only 19% of the Mach blade sales lost at a club store would be shifted over to competing retail formats (the rest of the 1.28% reduction in blade demand is permanently lost to Mach). The larger effect of club stores are likely driven by the larger pack sizes they sell as well as their patronage of the highest usage Mach customers. The estimates suggest there is some potential for club store pricing power in blades, depending on the mode of competition.

5.5. Cross-Product Horizontal Externalities

We now assess the potential for cross-product horizontal externalities. In particular, we test whether price increases in Mach razors sold at one format significantly affects demand for Mach blades sold at another, and vice versa. We begin by assessing the affects of razor price increases at a drug and grocery format stores. An increase in razor prices at this format can reduce blade demand at other formats by (1) delaying the purchase of the razor and

hence reducing blade consumption or (2) by eliminating the entire stream of blade sales associated with the Mach razors that may never be purchased. Referring to the top panel of Table 5, we see (1) a 1% price increase in Mach razors at the drug and grocery format has a negligible effect on the sales of blades at the mass merchandisers and club stores (cross-price effects of -0.08 and -0.06), and (2) aggregate blade demand to the manufacturer is also only slightly affected (reduction of 0.08%). Simulations of the model (not reported) indicate that this is driven by the fact that marginal customers that no longer adopt razors are lower-than-average users of blades. Blade price increases at drug and grocery stores, however, seem to have more significant effects on overall demand (reduction of 0.31%) and demand for razors at other stores. Table 5 also reports on the effects of raising blade prices at club stores. We see that a 1% increase in blade prices at club stores would reduce razor adoption by only 0.11% at drug and grocery stores and 0.08% at mass merchandisers. Overall manufacturer razor demand is only reduced by 0.08% . These small effects suggest that the effects of blade price increases are primarily to reduce blade usage by Mach customers, as opposed to reducing the number of Mach razor adopters.

5.6. Take Away

These long-run effects suggest that the downstream retail format for this industry, although oligopolistic, involves substitution between retail formats. From the manufacturer's perspective, it seems the greatest potential area of concern for pricing power at the retail level might be in blades sold by club stores and drug and grocery stores. The club format represents about 18% of Mach blade demand, and unlike drug and grocery, is also a concentrated retail format. Reputational incentives for maintaining a low price image may, however, be a countervailing force that prevent club stores from exploiting potential market power in pricing. Although our estimates suggest some pricing power at the format level among drug and grocery stores, the prevalence of a large number of drug and grocery stores also suggests additional within-format, interstore competition that may reduce the exercise of this pricing power. Overall, our results therefore suggest that retail competition in this market is such that manufacturers may be able to pass much of their desired pricing through to the downstream channel without the need for additional vertical restraints.

6. Conclusions

This paper makes three contributions. First, we develop a dynamic structural demand model for tied goods sold through competing retail formats. Second, we empirically measure retail format substitution in

a real-world market context, and discuss the potential pricing implications for primary and aftermarket goods through an oligopoly retail environment. Third, we identify the horizontal externality aspect of retail competition in tied goods, which has hitherto not been articulated in the literature.

The demand model we propose advances the literature on tied goods and on estimation of demand for durable and storable goods. Whereas modeling tied goods necessitates a model that allows the choice set to be conditional on past purchases (i.e., past purchase of a primary good), the fact that many aftermarket goods are purchased and consumed in subsequent periods requires a forward-looking model that could allow demand for the primary good to be impacted by expected future prices over the aftermarket goods. Furthermore, the large pack sizes that blades are sold in requires an underlying model of how customers stock blades in inventory and then endogenously replace them over time.

These characteristics are necessary for any dynamic tied goods context and they can be generalized to other storable or durable good contexts. For instance, the model can be simplified to measure retail substitution in many single-category demand analyses without a tying aspect. In this sense, we add to the relatively small empirical literature in marketing on measuring store substitution. Whereas we find little evidence for complementarities in demand between razors sold at one store and blades sold at another, we find significant substitutability in razors sold across retail formats. This finding contrasts with much of the past literature, which has found little or small across store price effects. We speculate that much of cross-store substitution is driven by intertemporal-switching, which would be missed by the past literature, which has primarily worked with static models in this context. Whereas these intertemporal effects are accounted for in our long-run effects, these are missing in short-run estimates of store substitution patterns.

7. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at <http://mktsci.pubs.informs.org/>.

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