

Rickert, Dennis

Conference Paper

Consumer state dependence, switching costs, and forward-looking producers. A dynamic discrete choice model applied to the diaper market

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Empirical IO, No. A02-V2

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Rickert, Dennis (2016) : Consumer state dependence, switching costs, and forward-looking producers. A dynamic discrete choice model applied to the diaper market, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Empirical IO, No. A02-V2, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

This Version is available at:

<https://hdl.handle.net/10419/145672>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Consumer state dependence, switching costs, and forward-looking producers. A dynamic discrete choice model applied to the diaper market

February 29, 2016

Abstract

This study estimates a dynamic discrete choice model to analyze the effect of switching costs on firm market power. Given the presence of switching costs for consumers in the market for disposable diapers, I show how firms apply dynamic strategies to a market for differentiated products and in a context of vertical retailer-manufacturer relationship. My findings support the existence of state dependence in consumer demand. Furthermore, I show that the firm profits would be higher in a counterfactual scenario of no switching costs.

Keywords: Dynamic Discrete Choice, Household Data, Switching Costs, Diaper Market, Vertical Relationship

JEL Classification: L1, L2, L6, C1, D1 .

1 Introduction

State dependence is an important behavioral pattern in consumer decision making and researchers have documented its existence for numerous markets.¹ If state dependence is due to brand loyalty, habit persistence or consumer inertia then consumers will stick to the most recently consumed product, even if they know that other products are of the same quality (Klemperer 1995). Switching is then associated with a loss in utility because the previous consumption occasion has altered consumer preferences in order to reduce cognitive dissonance (Brehm 1956) or because consumers face psychological costs of investing time and effort to familiarize themselves with new products (Klemperer 1995). State dependence in demand creates two countervailing incentives on firm prices. First, firms that are aware of their consumers' switching costs will have the incentive to offer products at lower price levels—compared to a scenario of no switching costs—in order to attract new consumers and increase market shares. Second, once consumers are locked in, there is an upward pressure on prices to take advantage of the inert consumer base. One of the perennial questions is assessing which of the countervailing forces is the dominant effect on equilibrium prices, profits, and market power. Evidently, the magnitude of the effects depends on the market structure. Switching costs have been analyzed theoretically for markets with either finite or infinite time horizons for both cases: differentiable and non-differentiable consumer groups.² However, even in a simple two-period model with clear beginning-game and end-game effects, it is unclear whether the upward or the downward pressure on prices and profits prevails. In this setup firms' first objective is to increase market shares by attracting new consumers in order to build up a loyal/inert consumer base. To this extent, they set low prices for new consumers in the form of penetration pricing or introductory offers. Once, consumers have been attracted and locked-in, firms realize their second objective and exploit inert consumers by raising prices for old consumer groups. Klemperer (1995) and Farrell and Klemperer (2007) note that there is a strong presumption that switching costs make markets less competitive as the incentive to raise prices in later periods is more likely to dominate the incentive to lower prices in early periods. Yet, there is no clear prediction and the question boils down to an empirical matter.

¹See, for instance, Erdem (1996), Erdem and Sun (2001), and Dubé et al. (2008).

²See Klemperer (1995) and Farrell and Klemperer (2007) who both provide broad overviews of the literature of switching costs and competition.

Just recently, the empirical literature has started to tackle the question of how switching costs affect market competitiveness. Despite a vast marketing literature on the interaction of state dependence and consumer demand, there are only a few studies investigating how equilibrium prices depend on switching costs. Viard (2007) provides evidence that switching costs make markets more competitive, whereas Dubé et al. (2008) find a negative effect of switching costs on equilibrium prices. The latter results are confirmed for the case of product differentiation (Shin and Sudhir 2008) and umbrella branding (Pavlidis and Ellickson 2012). However, the aforementioned empirical studies are concerned with markets where firms cannot discriminate between old and new consumer groups. Furthermore, they impose a game structure with an infinite time horizon. These assumptions may be suitable for market structures with steady flows of consumers, such as the markets for most retail food products, but they are unrealistic for markets where consumers remain active for limited time periods. To the best of my knowledge, there is no empirical study that investigates the hypothesis of market competitiveness in a finite setup of a structural model, where firms can discriminate between new and old consumer groups.

This paper studies a market with two distinct characteristics: (i) firms can discriminate between consumer groups and set different prices for each group, and (ii) consumers purchase repeatedly but only remain in the market for a finite time period. The objectives of this paper are threefold. The first objective is to quantify the degree of state dependence and switching costs for a market with finite time periods and distinguishable consumer groups, for which I take the market for disposable diapers. Second, I investigate the effect of switching costs on supply-side profits under two different pricing regimes. Given the dynamic structure and to examine the effect of switching costs on market competitiveness, I compare equilibrium profits to a counterfactual market structure without switching costs. Third, I show how choosing the wrong supply model and neglecting switching costs may yield erroneous conclusions for competition policymakers.

The empirical strategy consists of two steps. In the first step, I incorporate a Wooldridge (2005) approach for state dependence. To this extent, a flexible function of household heterogeneity is chosen. Notably, I add further control variables for search costs and inventory stock (package size preferences) to disentangle switching costs shaped by brand loyalty or consumer inertia from unobserved household heterogeneity. In the second step, I investigate the impact of switching costs on supply-side profits by using a dynamic supply model for a finite time horizon. The dynamic supply model accounts for the strategic behavior of retailers and manufacturers in a differentiated goods setup with multi-product

firms. This model describes the market for diapers because consumer groups are distinguishable in terms of new and old consumers by different segments for the age/weight of the baby. Thus, the structure is similar to two-period models with different observable consumer segments and explicit beginning-game and end-game effects following a clear “invest-and-harvest” structure as described by Klemperer (1995) and Farrell and Klemperer (2007).³

The results in this study show that there is a significant degree of structural state dependence in the form of brand loyalty or consumer inertia after controlling for household heterogeneity. This form of state dependence induces psychological switching costs and creates incentives for dynamic price setting. Representative household-level data enable me to quantify the magnitude of switching costs. I find that the average consumers’ willingness to pay for the state dependence is roughly 60% of the average market price. Furthermore, supply-side results show that the dynamic model better explains observed pricing patterns since the static model predicts negative marginal costs for most products. Finally, I impose a counterfactual policy experiment and find that firm profits are lower if consumers have no switching costs. The total change in producer surplus is quantified to be 6.47 million Euro.

There are manifold examples of pricing patterns consistent with the “invest-and-harvest” (Farrell and Klemperer 2007) motive in finite setups and differentiable consumer groups. This structure is given by any scenario where firms can discriminate between new and old consumer groups, such that they are able to target new consumer groups with low prices and subsequently raise prices for the locked-in consumers. For instance, banks offer higher interest rates on savings for new customers, service agencies—such as consultancies and accounting companies—charge less than the full amount of man-hours for initial projects, and firms offer introductory discounts. Furthermore, automotive insurances specify contracts where new customers pay lower contract fees than old consumers (Nilssen 2000). Klemperer (1995) mentions two further applications: First, service providers often target students at universities who are given, for instance, cheap access to operating and virus protection systems. Second, automotive full-line producers offer cheap small or compact cars—mainly targeted at young adolescents—and then raise prices for higher class cars. Moreover, switching costs also play an important role for durable goods markets accompanied by after-markets which induces related pricing schemes. Notable examples include

³This assumption of market share-driven dynamics is quite reasonable because corporate planning models often rest on the assumption that current sales affect future demand (Klemperer 1995).

markets for spare parts or repair services.⁴ Finally, markets with finitely living consumers include the broad sector of infant products, such as baby food or children's cloths, or similar sectors where product (or service) purchase is related to the consumer's age.⁵

This paper contributes to the empirical literature in two respects. First, it helps to better understand markets with switching costs. Household-level data from a representative sample documenting revealed preferences and actual substitution patterns across brands and retail formats enable me to estimate the magnitude and significance of switching costs for a specific market structure. Furthermore, I investigate the effect of switching costs on supply-side profits for a market that has not been investigated before and whose characteristics are comparable to a broad range of other markets. Second, neglecting state dependence has several important policy implications. If state dependence is present and is not recognized by the researcher then static demand models will underestimate cross-price elasticities because these models find a lack of substitution between products (see e.g., Erdem 1996). The researcher may then find that the lack of switching can be explained by dissimilarities of the brands instead of consumers' state dependence. Hence, policy experiments will predict false outcomes with potentially severe consequences. Two prominent example are the cases of market delineation tests and the full equilibrium merger analysis, which are both conducted based on cross-price elasticities. If cross-price elasticities are erroneously under-predicted, the policymaker may find that two brands do not constitute the same market and may thus overestimate the degree of market power. The remainder of this study is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and the market for diapers. Section 4 develops the econometric model of consumer demand and supply-side behavior. Section 5 presents empirical demand and supply results. Section 6 concludes the study.

⁴To some extent, the same structure is present in the market for printers and cartridges, or camera and camera films, although here switching costs are also artificially created by incompatibilities. Printers and cameras are offered at a relatively low price (first period), and cartridges and films are relatively more expensive (second period).

⁵Other market with similar finite structures may be doctoral services, rehabilitation facilities or nursing homes.

2 Literature

Researchers have documented state dependence in purchasing decisions for many markets, such as ketchup, peanut butter, liquid detergents, tissue, tuna (Erdem and Sun 2001), orange juice, margarine (Dubé et al. 2008), and cereals (Che et al. 2007).

However, modeling state dependence on retail markets is complex. First of all, the researcher has to deal with the econometric problem of disentangling unobserved household heterogeneity from structural state dependence. From an empirical viewpoint, it is difficult to relate a pattern of repeated purchases to a structural behavioral explanation, which is labeled as “structural” state dependence (Heckman 1981a). A series of repeated purchases may stem from underlying household preferences which are often not observed. A household purchases the same product repeatedly because of the limited assortment of a retailer close to a focal point (search costs) or because it has a preference for certain product characteristics, such as package size. Another explanation may be that a household is subject to a learning process, where it experiments with a variety of products at the beginning and then sticks to its preferred brand. If these drivers are present in the considered market—and not adequately accounted for—then state dependence can be “spurious” (Heckman 1981a). An econometric model should be capable of disentangling structural from observed state dependence by controlling for unobserved household heterogeneity, such as search costs, inventory or learning.

Empirical studies investigating consumer switching costs by adequately disentangling state dependence from unobserved household heterogeneity in markets with differentiated goods and strategic retailers are scarce. Most studies assume that the first purchase observation is non-random and uncorrelated with household heterogeneity (e.g., Erdem 1996, Che et al. 2007, Dubé et al. 2008). One of the few exceptions is Erdem and Sun (2001) who follow Wooldridge (2005) to allow for correlation between the initial condition and unobservable household heterogeneity.

There are only a few studies investigating how equilibrium prices depend on switching costs. Viard (2007) uses a natural experiment in the telecommunications market and he finds that lower switching costs lead to lower prices and thus evidence that switching costs make markets more competitive. Instead, Dubé et al. (2008), Shin and Sudhir (2008), and Pavlidis and Ellickson (2012) study consumable goods markets modeling firm profits in an infinite horizon single-agent dynamic decision framework and find negative effects of switching costs on equilibrium prices. However, these authors do not study switch-

ing costs in setups where consumers live a finite amount of time periods and firms can discriminate between consumer groups. As outlined in the introduction, the type of dynamics present in the market impacts the magnitude and significance of switching costs. It is important to distinguish between the dynamic problems of finite and infinite horizons because the profit-maximization problem for firms is different. Authors studying infinite time horizons explicitly attempt to avoid end-game effects in firms' profit-maximization problem (Dubé et al. 2008). That is not the aim of this paper, which examines a market where consumers are active in the market for a limited time period and firms are able to set different prices for new and old consumer groups.

Borenstein (1991) and Elzinga and Mills (1999) study markets with structures, where firms can actually price discriminate between new and old consumer groups in the markets for gasoline and wholesale cigarettes, respectively. Borenstein (1991) uses a reduced form approach and Elzinga and Mills (1999) consider markets with homogeneous goods. Neither of the studies sets up a structural model of heterogeneous goods and multi-product firms. Structural models are helpful to construct counterfactual policy scenarios in the absence of natural experiments (Reiss and Wolak 2007). However, this study uses a structural model to investigate the effect of switching costs on markets with a finite period game structure in the presence of strategic retailers, differentiated products, and multi-product firms.

Besides an adequate specification of a demand model and accounting for the type of dynamics present in the market, there exist three more important market mechanisms which interact with switching costs. First, manufacturers usually offer a set of differentiated products for certain product categories. It is by no means clear at which level consumers exhibit switching costs (Pavlidis and Ellickson 2012). This study helps to shed light on describing whether consumers are loyal toward the parent brand or toward a sub-brand of the brand manufacturers' portfolio. Second, there might also be state dependence with respect to the optimal retail choice. In this case, choice dynamics are different because retailers may face strategic consumers who plan the number of optimal stops given a particular distribution of search costs (e.g., Chen and Rey 2012, Dubois and Perrone 2015). Thus, it is important to control for this behavioral pattern. Third and last, manufacturers typically interact with retailers who again have strategic incentives to react to manufacturer strategies. In many markets, manufacturers offer a set of differentiated products in monopolistic or oligopolistic environments where they are able to exert market power (Berry et al. 1995, Nevo 2001). When manufacturers sell their products

through retailers then retailers are non-neutral intermediaries who also act strategically (Sudhir 2001, Villas-Boas 2007). The contracts between manufacturers and retailers are complex and can either be specified as linear contracts (e.g., Villas-Boas 2007, Brenkers and Verboven 2006) or non-linear contracts, e.g., as two-part tariff contracts (e.g., Bonnet and Dubois 2010, Bonnet and Dubois 2015). If the strategic role of the retailer is not adequately modeled retailer strategies are captured in the marginal cost estimate of the brand choice model, which may bias results.

As previously argued in the introduction, neglecting state dependence can lead to erroneous policy results, since price elasticities are biased. Price elasticities are the crucial ingredient in policy evaluation derived from structural models and demand biases lead to wrong inference on firm behavior. Elasticities measure consumer price sensitivity and switching behavior, and thus determine the magnitude of firm profits. Firm profits in turn are the basis for policy experiments. Dubé et al. (2008) show that ignoring loyalty leads to lower long-run total category profits, but they also find that margins for high quality goods can be lower in scenarios with switching costs. Erdem (1996) finds that not accounting for state dependence may yield erroneous results regarding the market structure with wrong implications on the competitive relationships between brands. In her setup, models neglecting state dependence overestimate the distance between brands, which leads to wrong advice on marketing policy experiments. Che et al. (2007) finds that consumers appear to be more price-sensitive when not accounting for state dependence. In addition, when observed prices are high, they show that one could falsely attribute high prices and low elasticity to tacit collusion, when in fact competitive behavior is non-cooperative.

My study provides new insights for competition and marketing policymakers as it examines the effect of switching costs on firm behavior, accounting for a vertical structure in a setup with multi-product firms with differentiated goods. The results will help us to understand market mechanisms and highlight the importance of using unbiased elasticities for conducting policy experiments, such as calculating counterfactual profits, applying market delineation tests, and the full equilibrium merger analyses, whose major ingredient are price elasticities.

3 The Market for Diapers

To assess the quantitative effect of state dependence and switching costs on prices and supply-side profits, I use data from a German representative household panel collected by the GfK Panel Services. The GfK Panel Services monitor the purchasing behavior of panel members whose characteristics are representative of the German population.⁶ These households are equipped with a home scanner device for tracking each retail sale. In contrast to scanners at the checkout counters, which can only track purchases within one store, this particular data set enables me to analyze switching behavior more precisely because each purchase at each retailer is recorded. The data set contains information on the name of the brand, product, retailer as well as the number and time of the shopping trips. Additionally, there is information on the transaction price including discounts and coupons, the package size, and type of label (premium, regular or private label).

To describe the quality of the panel in terms of representativeness, tables 1 and 2 show the descriptive statistics of the total consumer panel and of the panel members purchasing diaper products. The latter is a natural subset of the total panel since not all households are in urgent need of diaper consumption. Diaper consumers constitute 16.9% of the total panel. There are some slight differences between both panels. Consumers who buy diapers, assumably parents or future parents, have on average higher (net) household income, are of lower age, and are less unemployed. These numbers accompany the intuition that households are more willing to have children at a low age, with a sufficiently high income, and when being employed. Interestingly, there are not many singles in the panel (share of 8% in contrast to 26% in the total panel). A surprising statistic may be the share of females: 77% respectively 91%. This can be explained by the fact that we observe a household panel where the variable female represents the share of females as the head of the household, not the share of females in the panel. Qualitatively, that does not have any influence on the analysis since 92% do not live alone, and it is just a matter of definition that females are assigned to be the head of the household.

The benefits of structural models for evaluating counterfactual scenarios comes at the cost of making assumptions on consumer and firm behavior. To gain insights into the market mechanisms and on the underlying behavioral assumptions, I present detailed data on consumer shopping behavior, products, and firms, which help to understand consumers' decisions, the choice sets, and firms' pricing patterns.

⁶<http://www.gfk.com/de/loesungen/verbraucherpanel/>

First, I use the sample for the time period of 2006 for customers who purchased diapers. This ensures that we exclude major trends over the years and panel attrition issues.⁷ Next, I assume that consumers can only choose from the choice set of disposable diapers which constitute more than 95% of all used diapers.⁸ All other product types—that is cotton, mull, fleece swimming diapers, and training pants—are excluded from the sample. Furthermore, I exclude specialized retailers, such as, for instance, cash-and-carry stores, pharmacies and also Internet purchasing. Next, I only keep the 11 retail chains with a nationwide spread of stores to handle the number of observations. Thus, I focus on retailers who compete at a national level. Second, I assume that consumers decide whether to buy diapers on a monthly basis, which is a reasonable assumption as households buy on average approximately 1.2 diaper packages per month (Haucap et al. 2013). When facing their decision, consumers can choose between inside goods and an outside good. A purchasing decision of the outside good is observed when none of the inside goods is chosen. That is the case when consumers buy non-disposable diapers, diapers from a specialized or regional retailer, or decide not to purchase at all.

The outside goods and inside goods define consumers' choice sets. Inside goods are defined as bundles or combinations of brands, retailers, package size, and diaper class. These bundles are the alternatives a consumer can choose from. To build this identifier, I first look at retailers and brands. Each of the 11 national retailer offers two different labels, a manufacturer brand label and a private label. Private labels and manufacturer brands are shown to be of comparable quality in tests, thus indicating that both product types are substitutes.⁹ There is one manufacturer producing for the manufacturer label and 11 manufacturers producing for the private label. In the following I use the term labels if I mean the manufacturer brand (label) or the private label. As there are several manufacturers for the private labels, I use the term brands when describing the collection of all products from a manufacturer. Thus, there are 12 brands in total with roughly 50% of the market shares held by the leading manufacturer brand label and the remainder is held by private label producers for the various retail formats—drugstore, discounter and supermarket—with the highest market shares for discounters, and drugstores (Haucap et

⁷Furthermore, some structural changes can be observed in the market. One brand manufacturer exited the market in 2004/2005. Furthermore, the major manufacturer brand downsized the package size of its products from 2007 on. As I want to abstract from strategic market exit and downsizing effects, I chose the year 2006 for analysis.

⁸<https://www.test.de/Babywindeln-Pampers-machen-das-Rennen-1230140-0/>

⁹<http://www.oekotest.de/cgi/index.cgi?action=heft&heftnr=M1401>

al. 2013).

Each brand offers different package sizes. Based on the package size I build six different package size types. The smallest category (“Very Small”) are packages with two diapers. The second smallest category (“Small”) contains all alternatives with a package size of less than 18. The remaining package types are categorized according to the label of the leading manufacturer brand (Normal, Big, Jumbo, Mega, Giga). To define the package type, I take the package size type label of the brand manufacturer and assign the same label to all private label products if they have the same package size. Since in some cases package sizes may differ among brands, I apply the rule that two alternatives are of the same package size type if the difference in the size is less than ten diapers.

To complete the definition of the choice alternatives, let us turn to some specific product characteristics which help to determine whether consumers are classified as new or old. As illustrated in table 3 retailers may offer a particular package size of a brand for different ages or weight of the baby. This is the so-called diaper class, which indicates at which point of the life-cycle the consumer is. When purchasing a product from a newborn category, it is assumed that the consumer has just recently entered the market and is thus classified as a new consumer. When observing that a consumer purchases a product from a diaper class for older infants, it is assumed that the consumer will leave the market soon. To sum up, households can choose between *Retailer x Brand x Package Size x Diapclass* combinations. In other words, the same brand may be offered in different package sizes or at different retail outlets, which represents different choice options. Furthermore, the same *Retailer x Brand x Package Size* combination may or may not be offered in different diaper classes, which is varying with the age of the child. This diaper class can be considered as the state of the household or the stage at the life-cycle.

Building this unique identifier for the choice sets and dropping all niche products which are sold less than 28 times per year leaves me with 156 different alternatives including the outside option. Finally, it is worth mentioning that a more exact definition of the product bundle would include the distinction between regular diapers and diaper pants, which could not be implemented here because of insufficient information on this distinction.

An overview on the market structure is given by table 3. There are seven different diaper classes on the market, where the lowest is for children between 2–5 kg and the highest for children between 16–30 kg. These classes determine the state of the household by the weight (or age) of the infants or the stage of the life-cycle. Within each diaper class, there are a different number of alternatives. The lowest numbers of choices are found in classes

1, 2, and 7, where there are 9, 15, respectively 1 different alternative(s). Consumers can choose between 41, respectively 43 different alternatives in classes 4 and 6. The diaper classes are overlapping regarding weight description, which leads to the need to define heterogeneous choice sets. The third column of the table shows the number of different choices for a household that purchased an alternative within a diaper class. For instance, a choice set for a household purchasing a product from the first diaper class not only consists of the nine alternatives of the first diaper class but also the 15 alternatives of the second class and 27 alternatives of the third class. Thus, the household faces a choice set containing 51 different alternatives. The same logic can be applied for the remaining classes.

Table 3 shows descriptive statistics per diaper class. Columns 4–6 show the number of distinct retailers, brands, and package size types leading to the number of choices within a diaper class. Columns 7–9 show average descriptive statistics for products within a diaper class and the last column shows the total amount of diapers purchased. In general, prices increase over the diaper classes, a pattern which is confirmed by the descriptive statistics conditional on the brand label and package size in table 4. There may be several explanations for this pricing pattern, such as the difference in demand or competition in each class. Differences in competition and demand may explain why prices in the second class are lower than in the first class, but prices in the fourth class are higher than in the second class, despite the fact that demand is higher and competition is higher. This already shows some evidence that dynamic price setting may play a role according to the “invest-and-harvest-motive,” where firms set higher prices over the life-cycle of the consumer. Another explanation might be that the price differences are driven by lower unit costs. Older children need larger diapers, which can be produced at lower unit costs. While this is undoubtedly true, the major determinant of costs are material costs, but costs for R&D expenditures and for advertising. Diapers are high-tech products which contain up to 30 different components. The leading manufacturer brand invests two billion Euros each year into product development at various laboratories from which there are three in Germany.¹⁰ Furthermore, differences in unit costs should not be able to explain the per-diaper price differences of the third and the last diaper class, where the price per diaper in class 7 is almost twice as high as the price in class 3.

The pricing pattern in classes 3 to 7 seems to be the most convincing for switching costs. In classes 1 and 2, forces other than switching costs play a role. Consumers may face

¹⁰see <http://www.welt.de/wirtschaft/article117203610/Das-lukrative-Geschaef-mit-Babys-Po.html>

higher opportunity costs of time or be under pressure immediately after delivery and may thus be less informed since they cannot acquire the sufficient amount of information (Calzolari et al. 2012). As a consequence, they are less price elastic than standard more experienced consumers.¹¹ This gives firms incentives to raise prices and might be one explanation for higher prices in the first two classes (see tables 3 and 4). For a clean identification strategy on the supply side, I exclude the first two classes for the calculation of retailer and manufacturer profits.

Finally, table 5 highlights the heterogeneity in retail strategies. Retailers may apply very different strategies regarding the category depth. There are differences in the number of total products stocked (column 2), the number of labels offered (column 3), the number of distinct diaper classes (column 4), and the number of distinct package sizes (column 5). Furthermore, retailers are heterogeneous regarding prices and number of diapers per package (columns 6 and 7), where these parameters could differ significantly for the offered manufacturer labels and private labels (columns 8 and 9).

4 The Econometric Model

The empirical strategy is to define a structural model of demand and supply in order to answer the research question of interest. The general timing of the game is as follows

- *Stage 1* Manufacturers choose their wholesale prices.
- *Stage 2* Given the wholesale prices retailers set retail prices.
- *Stage 3* Consumers choose their utility-maximizing product.

The whole equilibrium system is solved by backward induction. Demand is estimated first then retail profits, and subsequently manufacturer profits can be derived given the estimated demand function. For a consistent demand model with state dependence disentangled from household heterogeneity, I incorporate a Wooldridge (2005) approach where I also control for the endogeneity of prices. When consumer demand is state dependent, this provides incentives for firms to apply profit-maximizing strategies with respect to this

¹¹This is consistent with my estimates of price elasticities, where I get elasticities of below 1 for the first two diaper classes.

particular behavioral pattern, even when consumers are not forward-looking. Assuming myopic consumers and forward-looking firms seems reasonable since one might argue that firms are able to solve complicated dynamic decisions rather than consumers.

To model the dynamic supply-side decision, I exploit a special characteristic of the diaper market. Consumers enter the market once they have a newborn child, stay in the market for a limited time span, and then exit the market when the child is old enough to retire from diapers.¹² Although manufacturers do not have complete information on consumer characteristics, they can identify each stage of the life cycle because consumers need different products with the changing age/weight of the baby. These are the seven diaper classes in table 3. Thus, firms are able to control the stock of consumers by their dynamic pricing decisions in a finite horizon. When new consumer groups enter the market—that is, they buy from a newborn category—firms have incentives to lower prices to invest in market shares. If consumers mature in the market—that is, the infant ages and consumers buy from a product category for older children—the incentives to invest decrease and the incentives to harvest increase. At the end of the consumer life cycle, there is no incentive to further invest and firms charge the highest prices. The logic is according to the Klemperer (1987) model where firms set low prices at the beginning to attract consumers and build up a base of loyal consumers. This gives firms pricing power over the state dependent, i.e., locked-in, consumers who are inert to switching brands. Klemperer (1995) argues that firms are likely to engage in price wars when “a new group of consumers enter the market and can be sold separately to others.” Then each cohort can be treated as a sub-group and is separately priced.¹³ Still, the direction of the net effect is not clear. I investigate the dynamic pricing decision in a vertical market structure with upstream and downstream competition and differentiated products.

4.1 Demand Model

The researcher’s main challenge is to disentangle structural from spurious state dependence. In the presence of state dependence, the most common approach is to include a dummy variable in the utility model to indicate whether the product was purchased on

¹²The implicit assumption is that (i) state dependence does not differ with respect to the number of children, and (ii) firms do not set prices in order to discriminate between the first and the second child.

¹³When consumer groups are not identifiable there is a trade-off for firms between lowering prices to gain market shares and raising the price to exploit existing consumers.

the previous occasion. This generates simple dynamics and measures the effect of past choices on current purchasing decisions because the last purchase delivers sufficient information on the purchasing history (Dubé et al. 2008). However, the inclusion of the lag variable generates some complications in the estimation procedure, which has to be accounted for. The first and main problem is that the lagged variable is correlated with unobserved heterogeneity. An intuitive solution to this problem is to assume a functional form for the unobserved household heterogeneity and to condition on this heterogeneity (Train 2009), e.g., by assuming random coefficients. The random coefficients determine the degree of household heterogeneity and state dependence is exogenous conditional on the household heterogeneity.

However, even if a functional form for unobserved household heterogeneity is specified, another major problem remains, which is often referred to as the initial condition problem. If household choices are not observed from the beginning then the first choice depends on previous unobserved choices. As Wooldridge (2005) points out, there are several ways to tackle this problem in a parametric framework.¹⁴ One could (i) assume that the initial conditions are non-random variables, or (ii) treat them as random variables and specify the joint distribution of initial conditions and unobserved heterogeneity. Despite being often assumed in the literature, (i) implies that the first purchase is independent of household heterogeneity. There are two ways to introduce correlation: a) approximate the initial distribution conditional on unobserved heterogeneity and exogenous variables (Heckman 1981b, Heckman 1981a), or b) model the distribution of the unobserved effect conditional on the initial value and exogenous variables (Wooldridge 2005). I follow Wooldridge (2005) to specify a distribution of heterogeneity conditional on initial conditions as it has the advantage that partial effects—and thus elasticities—are identified. It can further be combined with the random coefficient logit model, which yields flexible substitution patterns. However, the Wooldridge (2005) approach assumes strict exogeneity, which is not given if the price is included as a regressor. Thus, the third challenge is to control for this potential source of endogeneity. Here, I combine the control function approach for the random coefficient logit model, as proposed by Petrin and Train (2010), with the Wooldridge (2005) approach. This is similar to the method of Papke and Wooldridge (2008) and Giles and Murtazashvili (2013). This approach also allows household heterogeneity to be a function of observables and the initial condition, not only

¹⁴I focus on parametric solutions because in many non-parametric frameworks partial effects on response variables are not identified (Wooldridge 2005).

controlling for the correlation of unobserved heterogeneity and observables, but also for the correlation between prices and the error term.

We begin by the defining the household decision. Let us define the (latent) utility y^* for household n from purchasing product j at time t as:

$$y_{njt}^* = \rho_n y_{nj,t-1} + \alpha_n p_{jt} + X_{jt} \beta_n + h_{nj} + \epsilon_{njt}, \quad (1)$$

Utility depends on an endogenous price variable p_{jt} with coefficient α_n varying over n households and a vector of exogenous observable variables X_{njt} . Let $y_{nj,t-1}$ define a lagged variable indicating the last brand choice with coefficient ρ_n randomly varying among n households. The parameters for prices and lagged brand choice are the structural parameters of interest which determine price sensitivity and the magnitude of switching costs, respectively. Furthermore, utility is shaped by unobserved household heterogeneity h_{nj} and unobserved product characteristics ξ_{jt} —such as promotion and quality—captured by the error term ϵ_{njt} . The presence of these unobserved demand shifters poses a challenge to the identification strategy because unobserved household heterogeneity is correlated with the lagged brand choice variable and the price is correlated with unobserved product characteristics.

To tackle the challenges to the identification strategy, I assume the following general structure of the demand problem:

$$D(y_{njt} = 1 | y_{nj,t-1}, \dots, y_{nj0}, p_{jt}, X_{jt}, h_{nj}, \xi_{jt}) = L(\rho_n y_{nj,t-1} + \alpha_n p_{jt} + X_{jt} \beta + h_{nj} + \xi_{jt}), \quad (2)$$

The aim is to estimate the conditional expectation of y_{njt} given the observed purchasing history, the price, other observed variables, unobserved household heterogeneity, and unobserved marketing variables. I make three key identification assumptions on the distribution of interest, which are summarized on the right-hand side of equation 2. First, h_{nj} is additive inside $L(\cdot)$, which I specify as a logit distribution. Second, I assume that demand dynamics are correctly specified as a first-order process once X_{jt}, p_{jt}, h_{nj} are conditioned on. Third, X_{jt} is strictly exogenous conditional on the unobserved heterogeneity h_{nj} .

Next, assume a reduced form equation for the endogenous variable, which is independent of h_{nj} :

$$p_{jt} = X_{jt} \delta_1 + Z_{jt} \delta_2 + u_{jt} \quad (3)$$

where Z_{it} are exogenous instruments that are not in the utility function and u_{jt} is a serially uncorrelated idiosyncratic error with constant variance. Furthermore, it has to hold that

($E[Z_{jt}u_{jt}] = 0$). Defining ϵ_{njt} as the error term of the structural equation of interest—given by equation 1—and assuming that the exclusion restriction holds ($E[Z_{jt}\epsilon_{njt}] = 0$), the linear projection of ϵ_{njt} on u_{jt} is $\epsilon_{njt} = \lambda u_{jt} + \tilde{\epsilon}_{njt}$, which is the error from the first stage and an unobservable leftover. By construction $E[u_{jt}\tilde{\epsilon}_{njt}] = 0$ because of the linear projection. $\tilde{\epsilon}_{njt}$ is a linear combination of ϵ_{njt} and u_{jt} , and thus uncorrelated with Z_{jt} and X_{jt} . $\tilde{\epsilon}_{njt}$ is further uncorrelated with p_{jt} because p_{jt} is a linear function of Z_{jt} and u_{jt} . As the control function is uncorrelated with observable variables, instruments, household heterogeneity, and the new iid error term, ϵ_{njt} from the structural estimation equation is replaced by the linear projection: in other words, u_{jt} enters as an additional explanatory variable to control for endogeneity.

Next, I have to account for the initial condition problem. Instead of assuming that the initial condition is a non-random variable, which would imply that it is independent of household heterogeneity, I follow Wooldridge (2005) to form the joint distribution $(y_{nj1}, y_{nj2}, \dots, y_{njT})$ given the initial condition y_{nj0} and the observed variables X_j , i.e., $f[(y_{nj1}, y_{nj2}, \dots, y_{njT})|y_{j0}, X_j]$. Then, the density for unobserved household heterogeneity conditional on the initial condition and observed explanatory variables $f(h_{nj}|y_{j0}, X_j)$ is specified. Having specified this distribution, h_{nj} can be integrated out of the joint density $f[(y_{nj1}, y_{nj2}, \dots, y_{njT})|y_{j0}, X_j, h_n]$.

Similar to Wooldridge (2005) and Erdem and Sun (2001) the functional form of unobserved household heterogeneity is assumed to be:

$$\begin{aligned} h_{nj}|y_{n0}, X_{jt} &= h_j + \gamma_n y_{nj0} + Y_{njt-1}^c \rho_n^c + Y_{nj0}^c \gamma_n^c + a_{nj} \\ a_{nj}|y_{n0}, X_{jt}, Y_{njt-1}^c, Y_{nj0}^c &\sim Normal(0, \sigma_a^2), \end{aligned} \quad (4)$$

where y_{nj0} is the initial condition for the brand choice and α_{nj} is assumed to be independent of y_{nj0} . To introduce some more flexibility, I assume that household heterogeneity is further determined by additional household-specific control variables $Y_{njt-1}^c \rho_n^c + Y_{nj0}^c \gamma_n^c$, with $Y_{njt-1}^c \rho_n^c = \rho_n^{re} y_{nj,t-1}^{re} + \rho_n^{ps} y_{nj,t-1}^{ps}$ and $Y_{nj0}^c \gamma_n^c = \gamma_n^{re} y_{nj0}^{re} + \gamma_n^{ps} y_{nj0}^{ps}$. Put differently, the lag retail choice $\rho_n^{re} y_{nj,t-1}^{re}$ and the lag package size choice $\rho_n^{ps} y_{nj,t-1}^{ps}$ with their corresponding initial conditions are part of the household equation which enters as a control for retail search costs and package size preferences. However, it is worth noting that we let these controls enter to estimate the structural parameter of interest ρ_n of the lag brand choice variable $y_{nj,t-1}$ in equation 1.

Evidently, equation 4 is a restrictive assumption as the functional form for unobserved household heterogeneity is explicitly assumed, but it does allow for correlation between the initial conditions and the unobserved household heterogeneity, which is a more real-

istic assumption than non-randomness (Wooldridge 2005). Thus, the initial conditions flexibly enter the demand equation to influence decisions not only in the initial period, but also in subsequent periods.¹⁵

By assuming a functional form of the relationship between price and unobserved marketing variables, and of unobserved household heterogeneity, the causal effect of p_{jt} and y_{njt-1} on the response variable y_{njt} can be inferred while holding fixed the unobserved factors. Thus, household heterogeneity h_{nj} and the control function can be plugged into equation 1:

$$y_{njt}^* = \rho_n y_{nj,t-1} + \alpha_n p_{jt} + X_{jt} \beta_n + h_j + \gamma_n y_{nj0} + Y_{njt-1}^c \rho_n^c + Y_{nj0}^c \gamma_n^c + a_{nj} + \lambda u_{jt} + \tilde{\epsilon}_{njt}, \quad (5)$$

which is the estimation equation. As explained above, $\epsilon_{njt} = \lambda u_{jt} + \tilde{\epsilon}_{njt}$, and thus μ_{jt} enters the estimation equation as an additional explanatory variable with coefficient λ . Then $\tilde{\epsilon}_{njt}$ is assumed to be an iid generalized extreme value, in which case the choice probabilities follow the typical logit distribution.

It may be useful to state the parameters of the model differently. Note that coefficients can be decomposed into a population mean $(h_j, \rho, \alpha, \beta, \gamma)$ and a deviation from the mean $\eta_n = (a_{nj}, \eta_n^\rho, \eta_n^\alpha, \eta_n^\beta, \eta_n^\gamma)$, which are assumed to be normally distributed with a zero mean and variances $(\sigma_a^2, \sigma_\rho^2, \sigma_\alpha^2, \sigma_\beta^2, \sigma_\gamma^2)$. That means that households can have different effects of price disutilities, different effects of state dependence or different degrees of correlation between household heterogeneity and initial conditions. Hence, the degree of household heterogeneity is determined by the individual deviations from the mean.

Choice Probabilities

Households choose their utility-maximizing product and purchase j if the utility is higher than from purchasing other products k , i.e., $U_{njt}(\cdot) \geq U_{nkt}(\cdot)$. Following Nevo (2001) indirect utility can be expressed as $U_{njt} = V_{njt}(\theta, \eta_n) + \tilde{\epsilon}_{njt}$ to derive the choice probabilities conditional on the control function as

$$Pr_{njt}(\theta, \eta_n) = \frac{e^{V_{njt}(\theta, \eta_n)}}{1 + \sum_{j=1}^J e^{V_{nkt}(\theta, \eta_n)}}, \quad (6)$$

where θ is a vector collecting all estimated parameters (means and their standard deviations), and η_n is the vector of household-specific random effects. These are known to

¹⁵The idea is similar to Papke and Wooldridge (2008) and Giles and Murtazashvili (2013) who propose specifying the distribution for unobserved heterogeneity given the initial condition, observed variables, and the control function, but in their approach the endogenous variable is also a function of household heterogeneity.

the consumer, but not to the researcher, and it is assumed that they randomly vary over consumers.

Denoting I as an indicator of the sequence of decisions, the probability that a household makes a sequence of decisions is

$$Pr_n(\theta, \eta_n) = \prod_{t=1}^T \prod_{j=1}^J Pr_{njt}(\theta, \eta_n)^{I_{njt}}. \quad (7)$$

The unconditional probability is found by taking the integral over the household random effects η_n :

$$Pr_n(\theta) = \int_{\eta_n} Pr_{njt}(\theta, \eta_n) f(\eta_n | \theta_s) d(\eta_n), \quad (8)$$

where $f(\eta_n | \theta_s)$ is the multinomial probability distribution function for η_n conditional on the subset of the parameter vector θ_s , which is a subset of θ containing household variances.

The parameters of θ can be found by maximizing the simulated log-likelihood function:

$$SLL(\theta) = \sum_{g=1}^G \left\{ \frac{1}{H} \sum_{h=1}^H Pr_n(\theta) \right\}, \quad (9)$$

where G is the total number of households in the panel and H the number of Halton draws. To calculate the simulated choice probability, I take a draw of the distribution $f(\eta_n | \Sigma)$ representing the household random effects η_n , plug this draw into the logit formula in equation 6 and calculate the probability with this draw. As suggested by Train (2009) this is done $H = 100$ times and the results are the average of the 100 draws.

4.2 Static Supply

To derive profit margins, it is assumed that prices and market shares are the equilibrium outcomes of demand and supply conditions. The demand equation relates market shares to prices and unobserved demand determinants, whereas the supply equation relates retail and wholesale prices to markups and costs (Villas-Boas and Hellerstein 2006). The magnitude of the markups and costs depend on the estimated consumer price sensitivity as well as the type of horizontal interaction between retailers, respectively manufacturers, and the type of horizontal interaction. In the static version of the game, retailers and manufacturers make profits in a certain diaper class (the consumer state), which can be

interpreted as different product categories, by setting optimal prices separately for each class. Total profits in the diapers market are defined as the sum of profits for each product i from retailer product portfolio θ_d^r in state d which is equal to the sum over all products j in retailer product portfolio θ^r :

$$\pi = \sum_{d=1}^D \sum_{i \in \theta_d^r} \pi_d(p_{id}) = \sum_{j \in \theta} = \pi^r(p_j).$$

The profits in each diaper class depend on the type of contract between retailers and manufacturers. Suppose retailers and manufacturers agree on contracts with linear prices, where manufacturers make their pricing decision first and retailers take manufacturers' decisions as given. They set retail prices given the optimal wholesale prices.

Retailer Profits

There are R retailers in the market and each retailer chooses whether to stock the product j in its product category portfolio class θ^r . Profits for retailers are defined as:¹⁶

$$\pi^r = \sum_{j \in \theta^r} [p_j - w_j - c_j] s_j(p) \quad \forall r = 1 \dots, R, \quad (10)$$

where the retail profits of diaper class d are defined as the sum of the per-product margin over all products i in retail diaper class portfolio θ_d^r , and total profits over all classes are the sum over the diaper classes. The margin for any product j from the total retail portfolio is given by retail price p_j , the wholesale price w_j , the retail costs c_j , and the market share s_j , which is a function of all retail prices. In total, there are N observations given by the product of the total amount of differentiated products J and time periods T .¹⁷

Optimal prices are the outcome of Bertrand-Nash equilibrium in pure price strategies. Thus, the first-order conditions w.r.t. prices is given by:

$$\frac{\partial \pi^r}{\partial p_j} = \sum_{k \in \theta^r} \frac{\partial s_k(p)}{\partial p_j} [p_k - w_k - c_k] + s_j(p) = 0 \quad \forall i = 1, \dots, J. \quad (11)$$

The equation shows that retailers are category profit-maximizers, where they optimize prices over all their products in their product category portfolio. Profits not only depend

¹⁶The time subscript is dropped for convenience.

¹⁷Please note that for actual total profits, one has to multiply equation 10 with the market size, which is normalized to $MS = 1$ for convenience. Then, the profit equation can be interpreted as the sum of the per-product margins.

on market shares and the number of products in the category stock, but also on the derivatives $\frac{\partial s_k}{\partial p_j}$, which measure how all market shares change with j 's price changes. Since products are substitutes, cross-price marginal effects are positive, which leads to higher optimal prices in the case of multi-product firms compared to single-product firms given that the number of products is fixed. However, consumers face a different choice set in each diaper class d because retailers and manufacturers offer different product ranges θ_d . The relevant choice set of a consumer who aims at buying a product from diaper class 1 also consists of products from diaper classes 2 and 3. Columns 1–4 of table 3 illustrate the logic of the competitive set. Thus, firms are constrained in their price setting not only by products from class 1, but also from the products of other classes. We see this constraint in the price setting by the fact that firms account for cross-effects in their optimization problem, which is given by the sum of the market share derivatives over all $k = 1, \dots, J$ products, where J is the maximum number of products in the complete diaper market. However, as consumers have different choice sets, where they cannot substitute freely between all classes, cross-price effects are zero if products are not in the relevant choice set of consumers. Hence, the optimal prices of a product j affect only market shares for a product from the same competitive set. For instance, prices in state 1 only affect market shares in classes 2 and 3

The equation for the price-cost margin of product j can be solved to get

$$p_j - w_j - c_j = -\frac{s_j(p)}{\sum_{k \in \Theta_r} \frac{\partial s_k(p)}{\partial p_j}} \quad \forall j = 1, \dots, J. \quad (12)$$

To better understand the profit-maximization problem of multi-product firms, let us gather all price derivatives in a matrix, which is the market share response matrix:

$$\frac{\partial s_k(p)}{\partial p_j} = \begin{pmatrix} \frac{\partial s_{k=1}(p)}{\partial p_{j=1}} & \dots & \frac{\partial s_{k=J}(p)}{\partial p_{j=1}} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_{k=1}(p)}{\partial p_{j=J}} & \dots & \frac{\partial s_{k=J}(p)}{\partial p_{j=J}} \end{pmatrix}$$

The market share response matrix is a $J \times J$ matrix collecting the first derivatives of product i 's market share with respect to all $j = 1, \dots, J$ prices. The derivatives given by the demand specification, which is assumed to be a random coefficient logit model, are straightforward to obtain (see Train 2009, Wooldridge 2005). Note that α_n is the estimated price-sensitivity parameter from equation (5) for a specific Halton draw n , which determines, along with the market shares and the Halton draws, the magnitude

of consumer switching. In the absence of Halton draws, the model would reduce to the simple logit specification with the price-sensitivity parameter α , not varying over unobserved household heterogeneity. Given the matrix of derivatives and defining two $J \times 1$ vectors, in which all market shares and price cost margins are collected respectively:

$$\begin{pmatrix} m_{j=1} \\ \vdots \\ m_{j=J} \end{pmatrix} = \begin{pmatrix} p_{j=1} - w_{j=1} - c_{j=1} \\ \vdots \\ p_{j=J} - w_{j=J} - c_{j=J} \end{pmatrix} = -\Omega_r \star \begin{pmatrix} \frac{\partial s_{k=1}(p)}{\partial p_{j=1}} & \dots & \frac{\partial s_{k=J}(p)}{\partial p_{j=1}} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_{k=1}(p)}{\partial p_{j=J}} & \dots & \frac{\partial s_{k=J}(p)}{\partial p_{j=J}} \end{pmatrix}^{-1} \begin{pmatrix} s_{j=1}(p) \\ \vdots \\ s_{j=J}(p) \end{pmatrix}$$

Because the FOC indicates that optimal prices are found by taking the sum over all products in the retailer stock $\sum_{j \in \Theta_r}$ and not over all products, $\Omega_r \star$ is introduced to select rows and columns with products of the same retailers. Ω_r is a $J \times J$ (symmetric) diagonal matrix with the general element (i, j) equal to 1 if products are stocked by the retailer and 0 otherwise. The symbol \star is used to express the Hadamard product of two matrices, which is the element-wise multiplication of the cell entries of matrices. Now it can be solved for the price-cost margin, which is done by using matrix and vector notation:

$$m_r = p - w - c = -[\Omega_r \star \Delta^{sp}]^{-1} s(p). \quad (13)$$

$p - w - c$ is now a $J \times 1$ vector containing retail margins for each product, $s(p)$ a $J \times 1$ vector of market shares, Δ^{sp} is a $J \times J$ matrix of first-order price derivatives.

Manufacturer Profits

I assume that retailers set their prices given the manufacturer decision and thus their margins are independent of the manufacturer decision. Manufacturers set their prices first and anticipate how retail prices are correlated with wholesale prices, i.e., how retail prices change in response to optimal wholesale prices and manufacturer profits depend on the pass-through rate at which wholesale price changes are translated into retail prices. Hence, retail prices are then a function of wholesale prices $p(w)$. Suppose there are M manufacturers in the market, either brand label manufacturers or private label manufacturers, who offer a set of differentiated products θ_d^m in a given diaper class:

$$\pi^m = \sum_{j \in \theta^m} [w_j - \mu_j] s_j(p) \quad \forall m = 1, \dots, M, \quad (14)$$

where μ_j is the wholesale cost, w_j is the wholesale price and the remainder is defined as above. Taking the first-order conditions w.r.t. w_j results in:

$$\frac{\partial \pi^m}{\partial w_j} = \sum_{k \in \Theta_m} \sum_{l=1}^J \frac{\partial s_k(p)}{\partial p_l} \frac{\partial p_l}{\partial w_j} [w_k - \mu_k] + s_j(p) = 0 \quad \forall j = 1, \dots, J.$$

In the manufacturer first scenario retail prices change in response to wholesale prices. Hence, the additional derivative $\frac{\partial s_k(p)}{\partial p_i} \frac{\partial p_i}{\partial w_j}$ appears in the FOC. Using vector notation, the margins are then given by

$$m_m = w - \mu = - [\Omega_m \star (\Delta^{sp} \Delta^{pw})]^{-1} s(p), \quad (15)$$

where everything except Δ^{pw} is defined above. Δ^{pw} is a JxJ matrix capturing the pass-through of retail price changes after wholesale price changes. As in Sudhir (2001), I assume full pass-through where changes in the wholesale price are fully translated into retail prices and there are no cross-brand pass-through effects. Thus, Δ^{pw} is the identity matrix because the pass-through rate is equal to 1.

4.3 Dynamic Supply

In the market, there are $D = 7$ consumer life-cycle stages defined by the seven diaper classes, which are the diaper products for different ages/weight of the baby. Recall that product bundles are defined as *brand x package size x retailer x diaper class* bundles and thus a *brand x package size* combination may (or may not) be offered for several stages of the life-cycle. Furthermore, retailers may have different assortments of *brand x package size x diaper class* combinations.

Retailer Profits

When retailers' behavior is dynamic, each retailers' total profit depends on current profits and the discounted value of future profits. Retailers set optimal prices in order to maximize profits for one particular diaper class, which is the current stage of the consumer life-cycle and the sum of discounted profits from future stages. Thus, the maximization is over all possible stages of the consumers' life-cycles, where profits from a given stage are influenced by profits from future stages. The objective function is given by the sum of the profits from the current diaper class d and the discounted sum of all subsequent future stages $c = 1, \dots, C$.

$$V^r = \pi_d^r(p_d) + \sum_{c=1}^C \delta^c \pi_c^r(p_c).$$

Total profits are the sum of the profits in the class/stage d and the sum of the discounted values of future profits. c counts the class $d + 1$ as period 1 and C is the last stage.

For instance, if the individual is in class 1 then class 2 is counted as $c = 1$ and the consumer remains for $C = D - 1 = 6$ more periods on the market. If she is in the last class $d = D = 7$ then the second part of the equation disappears and the maximization problem is equal to a static one. After this last stage, there is no other stage and consumers leave the market.

If price dynamics are at play, there are two countervailing forces, on the one hand retailers want to set high prices in order to extract high profits, on the other hand there is another control option. Retailers can control the stock of consumers by choosing prices. Retailers may set low prices aiming to attract consumers. If demand is state dependent and consumers are inert or brand loyal, lowering the price is an investment in market shares. With a larger consumer base, firms can take advantage of consumer inertia at a later stage of the consumer life cycle. When consumers approach the end of their life cycle, the incentive to invest decreases and the incentive to raise price increases. At the end of the life cycle, there is no incentive to set low prices as consumers exit at the next stage.

In the final stage (which is $D=7$) the derivative of the objective function is

$$\frac{\partial V^r}{\partial p_{i7}} = \frac{\partial \pi_7^r(p_7)}{\partial p_{i7}} = 0,$$

with an FOC which is equivalent to the static optimization problem in equation 12. Retailers know that consumers will leave the market and have no incentives to keep them for future periods.

In stage $D - 1 = 6$ the derivative of the objective function is:

$$\frac{\partial V^r}{\partial p_{i6}} = \frac{\partial \pi_6^r(p_6)}{\partial p_{i6}} + \delta \sum_{k \in \Theta^r} \frac{\partial \pi_7^r(p_7)}{\partial s_{k7}(p_7)} \frac{\partial s_{k7}(p_7)}{\partial s_{k6}(p_6)} \frac{\partial s_{k6}(p_6)}{\partial p_{i6}} = 0.$$

At this stage, optimal profits depend on expected future profits. The second part of the equation basically determines the degree to which retailers will lower the price in anticipation of higher future gains from higher market shares when consumers are inert. Future profits depend on future market shares $\frac{\partial \pi_7^r(p_7)}{\partial s_{k7}(p_7)}$, and future market shares depend on current market shares $\frac{\partial s_{k7}(p_7)}{\partial s_{k6}(p_6)}$, which is the transition probability of continuing to buy the same brand after the transition. Finally, current market shares depend on current prices $\frac{\partial s_{k6}(p_6)}{\partial p_{i6}}$. The latter is the market share response matrix which accounts for future profits, depending on current market shares, where current market shares depend on current prices.

In class $D - 2 = 5$ the derivative of the objective function is:

$$\begin{aligned} \frac{\partial V^r}{\partial p_{i5}} &= \frac{\partial \pi_5^r(p_5)}{\partial p_{i5}} + \delta \sum_{k \in \Theta^r} \frac{\partial \pi_6^r(p_6)}{\partial s_{k6}(p_6)} \frac{\partial s_{k6}(p_6)}{\partial s_{k5}(p_5)} \frac{\partial s_{k5}(p_5)}{\partial p_{i5}} \\ &+ \delta^2 \sum_{k \in \Theta^r} \frac{\partial \pi_7^r(p_7)}{\partial s_{k7}(p_7)} \frac{\partial s_{k7}(p_7)}{\partial s_{k6}(p_6)} \frac{\partial s_{k6}(p_6)}{\partial s_{k5}(p_5)} \frac{\partial s_{k5}(p_5)}{\partial p_{i5}} = 0, \end{aligned}$$

In class 1 (this is $d = 1$) the equation becomes

$$\begin{aligned} \frac{\partial V^r}{\partial p_{i1}} &= \frac{\partial \pi_1^r(p_1)}{\partial p_{i1}} + \delta \sum_{k \in \Theta^r} \frac{\partial \pi_2^r(p_2)}{\partial s_{k2}(p_2)} \frac{\partial s_{k2}(p_2)}{\partial s_{k1}(p_1)} \frac{\partial s_{k1}(p_1)}{\partial p_{i1}} \\ &+ \delta^2 \sum_{k \in \Theta^r} \frac{\partial \pi_3^r(p_3)}{\partial s_{k3}(p_3)} \frac{\partial s_{k3}(p_3)}{\partial s_{k2}(p_2)} \frac{\partial s_{k2}(p_2)}{\partial s_{k1}(p_1)} \frac{\partial s_{k1}(p_1)}{\partial p_{i1}} + \dots \\ \dots &+ \delta^6 \sum_{k \in \Theta^r} \frac{\partial \pi_7^r(p_7)}{\partial s_{k7}(p_7)} \frac{\partial s_{k7}(p_7)}{\partial s_{k6}(p_6)} \dots \frac{\partial s_{k3}(p_3)}{\partial s_{k2}(p_2)} \frac{\partial s_{k2}(p_2)}{\partial s_{k1}(p_1)} \frac{\partial s_{k1}(p_1)}{\partial p_{i1}} = 0, \end{aligned}$$

As in the static model, market shares and prices are observed. The market share response matrix is given by the estimated demand function. To solve the optimization problem, the following analytical expressions have to be defined. The derivatives of profits w.r.t. retail prices ($\frac{\partial \Pi_d^r}{\partial p_{id}}$) are given by equation 11 and the derivative of profits w.r.t. market shares are:

$$\frac{\partial \Pi_d^r}{\partial s_{id}(p)} = (p_{id} - w_{id} - c_{id}) \quad (16)$$

Furthermore, there is the need to define an expression as to how the relationship how market shares of a given class change class w.r.t. the preceding class. Analogous to Che et al. (2007), I assume the following relationship holds for the transition between two diaper classes:

$$\Lambda_d = \omega_{btt+1,d} - \sum_{\substack{a=1, \\ a \neq b}}^B \omega_{atb+1,d} + \sum_{\substack{c=1, \\ c \neq d}}^D \omega_{btt+1,c} - \sum_{\substack{a=1, \\ a \neq b}}^B \sum_{\substack{c=1, \\ c \neq d}}^D \omega_{atb+1,c}, \quad (17)$$

where ω is the transition probability of moving from one period to another. For instance, $\omega_{btt+1,d}$ is the transition probability of continuing to purchase the same brand in $t + 1$ as in t given that the consumer does not change the class d . Accordingly, we can calculate the share of consumers who do not switch the diaper class between two time periods, but switch from another brand to it (part *ii*), all consumers switching the diaper class between two time periods, but continuing to buy the same brand (part *iii*), and all consumers switching the diaper class between two time periods and switching from another brand

to it (part *iv*). The transition probability ω is given by the marginal effect of the state dependence parameter in the demand function, which measures the share of consumers continuing to purchase the same brand and also the substitution among brands and classes between two shopping occasions.

Hence, for the last period $D = 7$, the margins expressed in matrix notation are given by

$$m_6^r = w_7 - \mu_7 = - [\Omega_7^m \star \Delta_7^{sp}]^{-1} s_7(p), \quad (18)$$

which is exactly the margin derived from the static maximization problem in 15. The margin from class 6 can be written as:

$$\begin{aligned} m_6^r &= - [\Omega_6^r \star \Delta_6^{sp}]^{-1} s_6(p) - \delta [\Omega_7^r \star \Delta_7^{sp}]^{-1} s_7(p) \Lambda_7, \\ &= (p_6 - w_6 - c_6) - \delta \Lambda_7 (p_7 - w_7 - c_7) \end{aligned} \quad (19)$$

Following the same logic, margins in class 5 are:

$$m_5^r = (p_5 - w_5 - c_5) - \delta \Lambda_6 (p_6 - w_6 - c_6) - \delta^2 \Lambda_7 (p_7 - w_7 - c_7) \quad (20)$$

and for the first class:

$$m_1^r = (p_1 - w_1 - c_1) - \delta \Lambda_2 (p_2 - w_2 - c_2) - \dots - \delta^7 \Lambda_7 (p_7 - w_7 - c_7) \quad (21)$$

Manufacturer Profits

Analogous to the manufacturer case, dynamic retail profits are given by

$$V^m = \pi_d^m(w_d) + \sum_{c=1}^C \delta^c \pi_c^m(w_c),$$

In the final class (which is $D=7$) the derivative of the objective function is

$$\frac{\partial V^m}{\partial w_{i7}} = \frac{\partial \pi_7^m(w_7)}{\partial w_{i7}} = 0,$$

which is equivalent to the static optimization problem. Manufacturers know that consumers will leave the market after the last class and have no incentives to keep them for future periods. The only constraint is given by the competitive products for this class and the outside option.

In stage $D - 1 = 6$ the derivative of the objective function is:

$$\frac{\partial V^m}{\partial w_{i6}} = \frac{\partial \pi_6^m(w_6)}{\partial w_{i6}} + \delta \sum_{k \in \Theta^m} \sum_{l \in \Theta^m} \frac{\partial \pi_7^m(w_{i6})}{\partial s_{k7}(p_7)} \frac{\partial s_{k7}(p_7)}{\partial s_{k6}(p_6)} \frac{\partial s_{k6}(p_6)}{\partial p_{l6}} \frac{\partial p_{l6}(w)}{\partial w_{i6}} = 0,$$

In stage $D - 2 = 5$ the derivative of the objective function is:

$$\begin{aligned} \frac{\partial V^m}{\partial w_{i5}} &= \frac{\partial \pi_5^m(w_5)}{\partial w_{i5}} + \delta \sum_{k \in \Theta^m} \sum_{l \in \Theta^m} \frac{\partial \pi_6^m(w_6)}{\partial s_{k6}(p_6)} \frac{\partial s_{k6}(p_6)}{\partial s_{k5}(p_5)} \frac{\partial s_{k5}(p_5)}{\partial p_{l5}} \frac{\partial p_{l5}(w)}{\partial w_{i5}} \\ &+ \delta^2 \sum_{k \in \Theta^m} \sum_{l \in \Theta^m} \frac{\partial \pi_7^m(w_7)}{\partial s_{k7}(p_7)} \frac{\partial s_{k7}(p_7)}{\partial s_{k6}(p_6)} \frac{\partial s_{k6}(p_6)}{\partial s_{k5}(p_5)} \frac{\partial s_{k5}(p_5)}{\partial p_{l5}} \frac{\partial p_{l5}(w)}{\partial w_{i5}} = 0, \end{aligned}$$

In stage 1 (this is $d = 1$) the equation becomes

$$\begin{aligned} \frac{\partial V^m}{\partial w_1} &= \frac{\partial \pi_1^m(w_1)}{\partial w_{i1}} + \delta \sum_{k \in \Theta^m} \sum_{l \in \Theta^m} \frac{\partial \pi_2^m(w_2)}{\partial s_{k2}(p_2)} \frac{\partial s_{k2}(p_2)}{\partial s_{k1}(p_1)} \frac{\partial s_{k1}(p_1)}{\partial p_{l1}} \frac{\partial p_{l1}(w)}{\partial w_{i1}} \\ &+ \delta^2 \sum_{k \in \Theta^m} \sum_{l \in \Theta^m} \frac{\partial \pi_3^m(w_3)}{\partial s_{k3}(p_3)} \frac{\partial s_{k3}(p_3)}{\partial s_{k2}(p_2)} \frac{\partial s_{k2}(p_2)}{\partial s_{k1}(p_1)} \frac{\partial s_{k1}(p_1)}{\partial p_{l1}} \frac{\partial p_{l1}(w)}{\partial w_{i1}} + \dots \\ \dots &+ \delta^6 \sum_{k \in \Theta^m} \sum_{l \in \Theta^m} \frac{\partial \pi_3^m(w_{i3})}{\partial s_{k3}} \frac{\partial s_{k7}(p_7)}{\partial s_{k6}(p_6)} \dots \frac{\partial s_{k3}(p_3)}{\partial s_{k2}(p_2)} \frac{\partial s_{k2}(p_2)}{\partial s_{k1}(p_1)} \frac{\partial s_{k1}(p_1)}{\partial p_{l1}} \frac{\partial p_{l1}(w)}{\partial w_{i1}} = 0, \end{aligned}$$

Hence, for the second last period $D = 7$, manufacturer margins in matrix notation are

$$m_7^m = w_7 - \mu_7 = - [\Omega_7^m \star (\Delta_7^{sp} \Delta_7^{pw})]^{-1} s_7(p), \quad (22)$$

which is exactly the margin derived from the static maximization problem in 15. The manufacturer margin in period 6 can be written as:

$$\begin{aligned} m_6^m &= w_6 - \mu_6 = - [\Omega_6^m \star (\Delta_6^{sp} \Delta_6^{pw})]^{-1} s_6(p) - \delta [\Omega_7^m \star (\Delta_7^{sp} \Delta_7^{pw})]^{-1} s_7(p) \Lambda_7, \\ &= (w_6 - \mu_6) - \delta \Lambda_7 (w_7 - \mu_7) \end{aligned} \quad (23)$$

Following the same logic, the manufacturer margins at stage 5 are expressed as:

$$m_5^m = (w_5 - \mu_5) - \delta \Lambda_6 (w_6 - \mu_6) - \delta^2 \Lambda_7 (w_7 - \mu_7) \quad (24)$$

and for the first stage:

$$m_1^m = (w_1 - \mu_1) - \delta \Lambda_2 (w_2 - \mu_2) - \dots - \delta^7 \Lambda_7 (w_7 - \mu_7) \quad (25)$$

5 Empirical Analysis

The following subsections outline results from demand estimation (5.1) and report supply-side results (5.2). Finally, a counterfactual analysis is implemented to determine the effect of switching costs on firm profits (5.3).

5.1 Demand-Side Results

To construct the control function, additional data on cost shifters are obtained. I use two cost shifters, a plastic and a paper price index, which are both obtained from Thomson Reuters. Polyethylen spot prices from the Thomson Reuters ICIS pricing database are used as a proxy variable for plastic prices and the FOEX-PIX paper index from the Thomson Reuters FOEX Indexes is used as a proxy for paper costs. The estimation (table 6) shows the results from the first stage and all cost shifters are significant. The R^2 is around 98%.

The parameter estimates of the demand model are reported in table 7. The table presents five models, each in one column which divides parameter estimates in a mean coefficient and standard deviation of the coefficient. Model 1 is a simple model without state dependence, but with price variable p_{jt} , control function u_{jt} and control variables X_j . X_j are a number of fixed effects for brand, retailer, package size, and diaper class. These serve as proxies for unobserved characteristics which are constant over time, such as the number of products in a given diaper class, product quality, and retail store size. The price is defined as the price paid at the checkout counter, less the monetary amount of any promotion activity (i.e., discounts or coupons). The price coefficient α can be disentangled in a population mean α and a standard deviation of the price coefficient σ_α . The estimated standard deviation is significant and is about half of the magnitude of the mean coefficient, indicating that there is a significant amount of household heterogeneity. The control function, which is the error term from the first stage, enters the demand equation with a positive and significant coefficient, indicating that the price is indeed endogenous. Hence, the control function controls for unobservable characteristics which are positively correlated with the price.

Model 2 adds the state dependence parameter for the brand choice plus additional controls for the previous retailer choice, the previous package size choice, and a dummy variable indicating whether consumers have switched the diaper class. All coefficients are positive and significant, showing that the omission of these variables would be wrong. The positive sign of the brand choice variable suggests that consumers may be subject to some kind of behavioral dynamic process which is shaped by psychological switching costs rather than variety-seeking behavior. In the case of variety-seeking behavior, the sign of the coefficient would be negative because purchasing the same brand repeatedly negatively impacts utility. Including variables for the lagged retailer choice and lagged

package size choice capture the positive effects of unobserved household preferences which would be erroneously attributed to brand loyalty. Model 3 adds standard deviations for the lag variables. The standard deviations are significant for all lagged variables, which highlights the degree of heterogeneity.

However, the state dependence parameter could also capture unobserved household heterogeneity, in which case the state dependence would be spurious. Models 4 and 5 include the initial conditions of the lag variables and further add to the flexibility of the household heterogeneity. Conditioning on the initial purchases is appropriate because the estimated coefficients of the initial conditions are positive and significant. A model neglecting this conditioning would also erroneously assume that the initial purchase is independent of household heterogeneity. As the initial conditions in the final model are part of the household equation, correlation between household heterogeneity and the first purchase of households is introduced, which has a different impact on utility in every period. It is conditioned not only on the first brand choice, but also on the first choice of retailer and package size. These two variables also determine the degree of household heterogeneity since they control for household preferences for retailers and package size. The former thus picks the consumer behavior related to search costs and the latter acts as a control for inventory behavior.

The magnitude of the coefficients in discrete choice models, in contrast to the sign, are not interpretable. Hence, demand parameters have to be applied in terms of marginal effects and elasticities to better understand the influence on consumer behavior. Table 8 shows the difference in the price elasticities over the five demand models. The importance of including the state dependence parameters can be seen by the difference in magnitudes of the elasticities between Model 1 and Models 2 to 5. The mean price elasticity of the model without state dependence is -2.36, whereas the other models' mean elasticities range between -3.43 and -3.56. Compared to the full model, the elasticities of Model 1 are roughly 32% lower. Hence, neglecting state dependence leads to a non-trivial bias in price elasticities. Consumers appear less price elastic than they actually are, which also leads to biased supply-side results and thus to biased policy implications. If state dependence is present and is not recognized by the researcher then the static demand models also underestimate cross-price elasticities between brands because it seems that consumers hardly switch between two brands. But the absence of switching is due to any kind of state dependence and not to dissimilarities of the brands. Hence, policy experiments predict false outcomes with potentially severe consequences for market definition and merger

analysis.

Table 9 shows the detailed dispersion of own-price elasticities over brands, diaper classes, package sizes, and retailers for Model 5. Generally, the table shows an interesting pricing pattern, which is observed for manufacturer brands, private labels, and also all package sizes, except for small and very small. Consumers are least price elastic in diaper classes 1 and 2. The price elasticity increases from class 3 to class 4 and then remains relatively stable. However, price elasticities are heterogeneous over retailers, indicating that these retailers apply heterogeneous strategies. Two more general statements can be made. First, the average price elasticity of manufacturer brands is higher than for private label brands, which is driven by the fact that the average price of manufacturer brands is higher than for private labels and consumers of both product types are at different points of the demand curve. Second, consumers of larger package sizes are less price elastic than consumers of smaller package sizes.

5.2 Supply-Side Results

Table 10 shows the results from the supply side. I calculate retail margins and manufacturer margins for two different pricing models. The static pricing model and the dynamic pricing model, both for the estimates of demand model 5, which is the model with state dependent consumer demand and the flexible control of household heterogeneity.

Static retail margins are indicated by rows with S for each label and dynamic margins with D . Estimated static manufacturer margins for the branded label are relatively stable over the classes.¹⁸ Absent any dynamic decision, the magnitude of the static margins depends on the estimated own and cross-price elasticities of demand as well as the number of products offered in the competitive set and the number of products owned by a firm. The intuition behind that is quite obvious. The competitive set, which comes from the heterogeneous choice sets for each consumer depending on the diaper class, has an influence on the prices because firms internalize only the cross-effects of products within the competitive set. The more products within this set are owned by the same firm, the more cross effects are internalized and the higher the price and the margin. The estimated margins are rather constant over the diaper classes because firms lack dynamic strategies. Besides static conditions, dynamic margins depend on the level of state dependence, con-

¹⁸The estimated margins for the private label vary, but this is due to the fact that the term gathers the products of all private label manufacturers.

sumer inertia or switching costs. To be more precise, the magnitude of the dynamic margins depend on the static margins in a given diaper class, the static margins from the future stages, and the transition probability. The transition probability is determined by the share of consumers who continue to buy the product minus the share of consumers who did not buy the product and who will switch to it within the same class and from other classes.

Thus, the transition probability parameter captures several forces on prices. The higher the share of consumers continuing to buy the product, the lower the prices. But it also depends on the total number of products offered in a particular diaper class. The higher the number of products offered by other brands the higher the probability that firms will lose their consumers. Another force on the pricing decision comes from the strategic marketing decisions chosen by firms. The transition probability decreases with the share of consumers who did not buy the brand but who switch to it. This force generates an upward pressure on prices.

In general, I find that the absolute level of price reduction in order to lock in consumers and invest in market shares is higher for the branded label than for the private labels. The driver behind the result is the difference in the number of products offered. The branded label offers a product line with a larger product set and thus internalizes future margins of a certain product type to a larger extent. This leads to comparatively low margins at the beginning of each consumer life cycle, which are about half of the magnitude of static margins. Over the life cycle the investment incentive vanishes because there are fewer stages following. At the last stage of the consumer life cycle, static and dynamic margins are identical.

Table 11 show the results for each retailer. As table 3 with the descriptive statistics has indicated, there are very different retail strategies for the assortment regarding both choices for package size choice and for diaper class with immediate effects on dynamic margins. Discounters have the lowest category range on average (10 resp. 8) of all retail formats, giving them small incentives for dynamic pricing decisions. Drugstores, with the exception of drugstore 2, have the broadest category depths, ranging between 21 products for drugstores 3 and 4 and 32 products for drugstore 1. Supermarkets are more heterogeneous in their strategy. Supermarkets 2 and 4 offer 19, respectively 22, different products, whereas supermarkets 1, 3 and 5 have category depths of 9, 6 and 4, which is similar to or below the range of discounters. As seen in the table, this gives very different incentives for dynamic pricing decisions.

The results already provide insight into how the effect of state dependence affects inference on supply models. To further examine the effects on product differentiation, I focus on the firm decision of a particular brand manufacturer who offers a high number of differentiated labeled products (table 12). An implication of the dynamic model is that the incentive to lower prices with the intention of investing in market shares is higher for firms who offer a full set of differentiated products. First, the manufacturer can then occupy every stage of the consumer life cycle with products. Second, the higher the variety of products within a stage, the higher the probability that consumers will switch to another product of the same manufacturer portfolio if they have preferences for variety.

Table 12 shows the comparison of static marginal costs, dynamic marginal costs, static margins, and dynamic margins for the label brand. Marginal costs can be recovered from the structural supply model. The channel margin can be defined as the sum of retail and manufacturer margins. Total marginal costs can be recovered by the price minus total margins. The static model predicts negative marginal costs in many cases, whereas the dynamic marginal costs, corrected by the dynamic pricing decision, predicts marginal costs which are approximately of the same magnitude at each stage. The table also shows the retailer margins for the branded product. Retailer margins are fairly lower, on average, than manufacturer margins. The difference is due to the fact that, on average, the retailers have a lower assortment depth of labeled products than the manufacturer, i.e., they do not stock all of the labeled products. Their ability to conduct dynamic pricing strategies is also limited. This is an immediate effect of the retail strategies of also offering private labels and offering a limited product assortment of a certain product category. However, I find unplausible marginal cost estimates for the largest package sizes. This indicates that the switching cost model is not completely adequate for these large package sizes and other forces may be at play, such as consumer inventory planning.

5.3 Counterfactual Analysis

To get an estimate of the magnitude of the switching costs, I calculate the compensating variation of removing switching costs, which can also be interpreted as consumers' willingness to pay for their state dependence. More precisely, the compensation is given by the difference of the consumer surplus of both scenarios with and without switching costs, divided by a cost measure. Small and Rosen (1981) derive a formula for the logit model

which can be used to measure changes in utility when certain attributes of the systematic part of the utility change (the compensating variation). That formula is given for the random coefficient model as

$$CV_n = -\frac{1}{\alpha_n} \left\{ \ln \sum_{j=1}^J e^{V_{jn}^0} - \ln \sum_{j=1}^J e^{V_{jn}^1} \right\}, \quad (26)$$

where α is the price coefficient used as a cost measure. We compare the systematic part of the utility gained from a scenario with switching costs V^1 to a scenario without switching costs V^0 by calculating the difference of the logsums and dividing it by the negative price coefficient.¹⁹ Results show that the average consumer has to be compensated by 11.28 cents per diaper if the regime is changed from switching costs to no switching costs. Put differently, on average, the consumer is willing to pay 11.28 cents per diaper for its state dependence, which gives a quantitative measure of the magnitude of the switching costs. Given an average price of 19.89 cents per diaper, the magnitude of the average switching costs can be quantified as roughly 60% of the average price for diapers.²⁰

One of the perennial questions is how switching costs impact the competitiveness of markets. To assess whether markets are more or less competitive without switching costs, channel profits in a switching cost regime are compared to profits hypothetically earned in the counterfactual scenario where switching costs are absent. The difference in producer surplus is then given by

$$\Delta PS = \{(\pi_1^r + \pi_1^m) - (\pi_0^r + \pi_0^m)\}, \quad (27)$$

where I assume that manufacturer and retailer marginal costs are the same for both regimes. For the calculation of the counterfactual profits, I set the switching cost parameter to zero and assume uniform prices of sub-brands at each retailer. Furthermore, I assume that the total market size is 2.3 billion diapers, which corresponds to total sales in the year 2004.²¹ Table 13 shows that the manufacturer brand profits under the switching cost regime are always lower in the first classes and always higher in the last classes

¹⁹As for the calculation of counterfactual supply-side profits, I assume that counterfactual prices are the mean of a particular sub-brand at each retailer.

²⁰As an alternative way to calculate the amount of switching costs, I take the total derivative of the utility function w.r.t. the brand loyalty attribute and the cost measure and set this to zero to see how brand loyalty changes with price changes. It turns out that this is just the ratio of the price coefficient and brand loyalty coefficient (assuming that the price coefficient is fixed). However, I get similar results in the magnitude of switching costs, which are about half of the average price.

²¹<http://www.brandeins.de/archiv/2004/der-plan/wenn-der-markt-schrumpft/>

compared to the no-switching cost regime. This is due to the fact that prices with switching costs are lower in first classes than in last classes. To see for a particular sub-brand whether total channel profits are higher with or without switching costs, columns 9 and 10 list the total profits and the difference in the profits between two scenarios. Specifically, we are interested in the sign of the profit change. For most sub-brands, profits are lower under the switching cost regime, indicating that switching costs make markets more competitive. The intuition behind this is simple. The lower profits in the first classes cannot be compensated by the higher profits in later periods. Due to competitive effects between manufacturer brands and the private labels which both have incentives to attract higher shares of consumers, firms engage in a price war which causes firms to lower prices below a point which is optimal for them. In total, this leads to a loss in producer welfare of 2.3 million Euro. Nevertheless, it is evident that the results depend on the specification of the dynamic problem. The presented results are calculated for a discount factor of $\delta = 1$ and assuming that state dependence is at the brand level, meaning that firms incorporate brand market share changes in their profit function. Whereas the latter assumption is quite reasonable and can be supported by results from Pavlidis and Ellickson (2012), the former assumption has to be questioned. Lower discount factors will lead to higher total dynamic profits because the incentive to decrease prices is lower as the future is then less valuable for firms. However, the quality of the results remain unchanged if discount factors of 0.99, 0.95 or 0.90 are assumed.²²

6 Conclusion

This study examines the degree of state dependence and switching costs for a market where firms can discriminate between new and old consumer groups. Firms are forward-looking in the sense that they set dynamic prices for the different groups in a setup with finite time periods. Switching costs stem from state dependence in demand, where consumers are noted to experience utility gains when purchasing the same brand repeatedly. This type of state dependence is often referred to as demand inertia, brand loyalty or habit persistence, which creates psychological switching costs to purchase a brand different to the most recently purchased. When consumers have switching costs, firms have incentives to build up a loyal/inert consumer base by investing in market shares via reducing prices

²²Results are not reported, but are available upon request.

for new consumer groups compared to a scenario of no switching costs. Once consumers are locked-in, firms are able to exploit their market power and set prices which are above the level of the no-switching costs regime.

Given switching costs in consumer demand, the effect on supply-side profits is evaluated. To this extent an equilibrium model of demand and supply is developed. The demand model explicitly disentangles structural state dependence from unobserved household behavior. The supply model accounts for the strategic behavior of retailers and manufacturers in a differentiated goods set-up with multi-product firms. As the net price effect of investing in market shares and exploiting consumer inertia is not clear, I impose a counterfactual analysis to analyze market competitiveness with and without switching costs. Results show that there is a significant degree of structural state dependence in the form of brand loyalty or consumer inertia, even after controlling for household heterogeneity. The magnitude of switching costs is quantified by comparing changes in consumer welfare for two different market scenarios: demand with and demand without switching costs. I find that the average consumer has to be compensated with roughly 60% of the retail price if switching costs are removed, which gives a willingness-to-pay measure for switching costs. Furthermore, I find that the dynamic model better explains observed pricing patterns. Finally, the counterfactual supply-side analysis yields that firms are worse off with than without switching costs. Firms engage in price wars in order to attract new consumer groups and increase market shares, which cannot be compensated by the profit gains from the locked-in consumer groups.

Neglecting state dependence has several important implications. If state dependence is present and is not recognized by the researcher then static demand models will underestimate cross-price elasticities because these models find a lack of substitution between products. The researcher may then find that the lack of switching can be explained by dissimilarities of the brands instead of state dependence. Hence, policy experiments will predict false outcomes with potentially severe consequences. Two prominent examples are the cases of market delineation tests and the full equilibrium merger analysis, which are both conducted based on cross-price elasticities. If cross-price elasticities are erroneously under-predicted, the policymaker may find that two brands do not constitute the same market and may thus overestimate the degree of market power.

The results apply not only to the market for diapers, but also to a range of markets with similar market structures with finite amount of time periods and differentiable consumer groups. Applications include the market for banks which offer higher interest rates on

savings for new customers, service agencies such as consultancies and accounting companies that charge less than the full amount of man-hours for the first projects, and markets which offer introductory discounts. Further applications can be the market for automotive insurances where new customers pay lower contract fees than old consumers, service providers targeting students at universities with cheap access to their services, and automotive full-line producers offering cheap small or compact cars targeted at young adolescents in expectation of raising prices for higher class cars.

Given the complexity of the market structure and the interaction of behavioral patterns in consumer demand, several tasks are left for future research. First, there may be two other important behavioral patterns in consumer demand: consumer learning and inventory stockpiling. Second, the type of vertical structure imposed by the equilibrium model in this paper is assumed to be agreed on as linear pricing contracts. However, the vertical relationship may be of a non-linear type. Furthermore, as results show, retailers may apply different strategies than manufacturers. In particular, retailers offer multiple categories, where they optimize prices for multiple categories subject to consumer search costs and one-stop behavior.

References

- Berry, S. T., J. Levinsohn, and A. Pakes**, “Automobile Prices in Market Equilibrium,” *Econometrica*, 1995, *63* (4), 841–890.
- Bonnet, C. and P. Dubois**, “Inference on Vertical Contracts between Manufacturers and Retailers Allowing for Nonlinear Pricing and Resale Price Maintenance,” *The RAND Journal of Economics*, 2010, *41* (1), 139–164.
- and —, “Identifying Two Part Tariff Contracts with Buyer Power: Empirical Estimation on Food Retailing,” *CEPR Discussion Paper No. DP10623*, 2015.
- Borenstein, S.**, “Selling Costs and Switching Costs: Explaining Retail Gasoline Margins,” *RAND Journal of Economics*, 1991, pp. 354–369.
- Brehm, J. W.**, “Postdecision Changes in the Desirability of Alternatives,” *Journal of Abnormal and Social Psychology*, 1956, *52* (3), 384.
- Brenkers, R. and F. Verboven**, “Liberalizing a Distribution System: The European Car Market,” *Journal of the European Economic Association*, 2006, *4* (1), 216–251.
- Calzolari, G., A. Ichino, F. Manaresi, and V. Nellas**, “When the Baby Cries at Night: Uninformed and Hurried Buyers in Non-Competitive Markets,” 2012.
- Che, H., K. Sudhir, and P.B. Seetharaman**, “Bounded Rationality in Pricing under State-Dependent Demand: Do Firms Look Ahead, and if so, How Far?,” *Journal of Marketing Research*, 2007, *44* (3), 434–449.
- Chen, Z. and P. Rey**, “Loss Leading as an Exploitative Practice,” *American Economic Review*, 2012, pp. 3462–3482.
- Dubé, J.-P., G. J. Hitsch, P. E. Rossi, and M. A. Vitorino**, “Category Pricing with State-Dependent Utility,” *Marketing Science*, 2008, *27* (3), 417–429.
- Dubois, P. and H. Perrone**, “Price Dispersion and Informational Frictions: Evidence from Supermarket Purchases,” 2015.
- Elzinga, K. G. and D. E. Mills**, “Price Wars Triggered by Entry,” *International Journal of Industrial Organization*, 1999, *17* (2), 179–198.

- Erdem, T.**, “A Dynamic Analysis of Market Structure Based on Panel Data,” *Marketing Science*, 1996, 15 (4), 359–378.
- and **B. Sun**, “Testing for Choice Dynamics in Panel Data,” *Journal of Business & Economic Statistics*, 2001, 19 (2), 142–152.
- Farrell, J. and P. Klemperer**, “Coordination and Lock-in: Competition with Switching Costs and Network Effects,” *Handbook of industrial organization*, 2007, 3, 1967–2072.
- Giles, John and Irina Murtazashvili**, “A Control Function Approach to Estimating Dynamic Probit Models with Endogenous Regressors,” *Journal of Econometric Methods*, 2013, 2 (1), 69–87.
- Haucap, J., U. Heimeshoff, G.J. Klein, D. Rickert, and C. Wey**, *Inter-Format Competition Among Retailers: The Role of Private Label Products in Market Delimitation*. number 101, DICE Discussion Paper, 2013.
- Heckman, J. J.**, “Heterogeneity and State Dependence,” in “Studies in Labor Markets,” University of Chicago Press, 1981, pp. 91–140.
- , “The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process,” in “Structural Analysis of Discrete Data with Econometric Applications,” Manski C.F., McFadden D, 1981, pp. 179–195.
- Klemperer, P.**, “Markets with Consumer Switching Costs,” *Quarterly Journal of Economics*, 1987, pp. 375–394.
- , “Competition When Consumers Have Switching Costs: An Overview with Applications to Industrial Organization, Macroeconomics, and International Trade,” *Review of Economic Studies*, 1995, 62 (4), 515–539.
- Nevo, A.**, “Measuring Market Power in the Ready-to-Eat Cereal Industry,” *Econometrica*, 2001, 69, 307–342.
- Nilssen, Tore**, “Consumer Lock-In with Asymmetric Information,” *International Journal of Industrial Organization*, 2000, 18 (4), 641–666.

- Papke, L. E. and J. M. Wooldridge**, “Panel Data Methods for Fractional Response Variables with an Application to Test Pass Rates,” *Journal of Econometrics*, 2008, *145* (1), 121–133.
- Pavlidis, P. and P. B. Ellickson**, “Switching Costs and Market Power Under Umbrella Branding,” 2012.
- Petrin, A. and K. Train**, “A Control Function Approach to Endogeneity in Consumer Choice Models,” *Journal of Marketing Research*, 2010, *47*, 1–11.
- Reiss, P. C. and F. A. Wolak**, “Structural Econometric Modeling: Rationales and Examples from Industrial Organization,” *Handbook of Econometrics*, 2007, *6 (A)*, 4277–4415.
- Shin, J. and K. Sudhir**, “Switching Costs and Market Competitiveness: Deconstructing the Relationship,” 2008.
- Sudhir, K.**, “Structural Analysis of Manufacturer Pricing in the Presence of a Strategic Retailer,” *Marketing Science*, 2001, *20* (3), 244–264.
- Train, K.**, *Discrete Choice Methods with Simulation*, Cambridge University Press, 2009.
- Viard, V. B.**, “Do Switching Costs Make Markets More or Less Competitive? The Case of 800-Number Portability.,” *RAND Journal of Economics*, 2007, *38* (1), 146–163.
- Villas-Boas, S. and R. Hellerstein**, “Identification of Supply Models of Retailer and Manufacturer Oligopoly Pricing,” *Economics Letters*, 2006, *90* (1), 132–140.
- Villas-Boas, S. B.**, “Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data,” *Review of Economic Studies*, 2007, *74*, 625–652.
- Wooldridge, J.M.**, “Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity,” *Journal of Applied Econometrics*, 2005, *20* (1), 39–54.

A Appendix

Table 1: **Summary Statistics Total Panel**

variable	mean	p50	sd	min	max
income	2224.34	2125.00	937.74	400.00	4250
age	44.95	42.00	14.93	18.00	79.00
female	0.77	1.00	0.41	0.00	1.00
nojob	0.05	0.00	0.21	0.00	1.00
single	0.26	0.00	0.43	0.00	1.00
hhsz	2.49	2.00	1.22	1.00	8.00
child	0.59	0.00	0.91	0.00	6.00

Table 2: **Summary Statistics Diaper Panel**

variable	mean	p50	sd	min	max
income	2367.36	2375.00	845.00	400.00	4250.00
age	35.69	32.00	11.19	18.00	79.00
female	0.91	1.00	0.28	0.00	1.00
nojob	0.04	0.00	0.20	0.00	1.00
single	0.08	0.00	0.27	0.00	1.00
hhsz	3.28	3.00	1.13	1.00	8.00
child	1.28	1.00	1.03	0.00	6.00

Table 3: Descriptive Statistics

Class	Label	Choices	ChoiceSet	Ret.	Bra.	Sizes	Size	Price	PackPrice	Demand
1	2-5kg	9	51	6	2	2	29.54	18.59	538.38	12,592
2	3-6kg	15	51	6	2	2	48.6	16.23	786.78	176,298
3	4-10kg	27	112	10	2	4	76.64	14.87	1,135.96	161,260
4	7-18kg	41	132	11	2	6	63.29	16.95	1,048.88	860,628
5	9-20kg	20	132	9	2	4	67.62	19.63	1,309.58	97,252
6	13-27kg	43	105	10	2	6	49.08	21.76	1,007.15	345,848
7	16-30kg	1	105	1	1	1	69.83	23.12	1,615.87	1,238

Table 4: Price Dispersion over Package Size, Diaper Class, Brand, and Retailer

Label	PackSize	1	2	3	4	5	6	7
MB	NORMAL	21.26	16.81	18.51	21.01	23.76	27.4	
		1.14	0.25	1.03	1.62	1.52	2.53	
	JUMBO			14.46	17.24	20.44	21.89	23.12
				0.40	0.34	0.38	0.22	0.00
MEGA			16.08	18.97	19.7	22.15		
			0.61	1.04	0.28	0.65		
PL	VERYSMALL				29.3		37.53	
					0.00		0.00	
	SMALL				27.47		30.41	
					1.1		1.57	
	NORMAL	17.35	17.55	13.8	15.64	18.23	21.53	
		0.31	0.00	0.00	0.32	0.57	3.85	
	BIG	12.51	13.34	13.58	14.91	15.3	17.5	
		0.00	0.61	0.46	0.42	0.00	0.29	
JUMBO			12.86	14.54	15.87	17.06		
			0.94	0.95	1.06	0.82		

Table 5: Descriptive Statistics per Retailer

Retailer	Products	Labels	Class	Packtypes	Price	Size	PriceDiff	SizeDiff	Demand
Disc 1	10	1	4	3	16.06	55.67			510,540
Drug 1	32	2	7	5	18.46	58.81	2.82	9.02	411,502
Super 1	9	2	4	3	18.78	95.31	2.85	59.21	496,108
Super 2	22	2	6	3	19.21	59.54	2.84	19.72	429,076
Disc 2	8	2	3	3	19.46	41.93	2.21	3.13	549,643
Super 3	6	2	4	3	20.03	114.89	-8.85	105.93	453,583
Drug 2	4	2	4	2	14.44	44.27	6.25	1.04	244,495
Super 4	19	2	6	4	18.93	100.86	2.1	61.52	477,899
Super 5	4	2	3	2	17.84	66.34	2.57	38.96	523,744
Drug 3	21	2	6	4	16.24	52.83	3.08	8.36	461,455
Drug 4	21	2	6	4	19.98	42.89	3.4	0.69	358,826

Table 6: Control Function

	b/se
PaperIndex	0.0244*** (0.0026)
PlasticIndex	2.3842
Retailer FE	Yes
Label FE	Yes
Class FE	Yes (1.5444)
R2	0.9588
F	2041.0221
N	1772

Standard errors in parentheses.

*Significant at 1% ***,*

*significant at 5 % **,*

*significant at 10% *.*

Table 7: Demand Estimation Results

	Model 1	Model 2	Model 3	Model 4	Model 5
	b/se	b/se	b/se	b/se	b/se
<u>Mean</u>					
price	-0.1497*** (0.0021)	-0.2298*** (0.0020)	-0.2310*** (0.0021)	-0.2281*** (0.0107)	-0.2344*** (0.0111)
CF		0.1679*** (0.0033)	0.1614*** (0.0035)	0.2129*** (0.0036)	0.2167*** (0.0040)
retailerloy		2.3802*** (0.0266)	2.5508*** (0.0436)	2.0559*** (0.0290)	2.0188*** (0.0490)
brandloy		1.6747*** (0.0383)	2.3075*** (0.0819)	1.6296*** (0.0400)	2.1526*** (0.0755)
packsizeloy		1.4108*** (0.0245)	1.4697*** (0.0371)	1.3584*** (0.0253)	1.3526*** (0.0394)
diapclassloy		1.8986*** (0.0285)	2.0079*** (0.0375)	1.9113*** (0.0287)	2.0149*** (0.0355)
meanprice hh				-0.0472*** (0.0105)	-0.0576*** (0.0109)
initcond brand				0.6867*** (0.0290)	0.7854*** (0.0378)
initcond retailer				1.6068*** (0.0256)	1.9161*** (0.0382)
initcond packsize				0.5561*** (0.0234)	0.7593*** (0.0363)
<u>SD</u>					
price	0.0690*** (0.0018)	-0.0307*** (0.0022)	-0.0350*** (0.0023)	-0.0336*** (0.0021)	-0.0245*** (0.0034)
retailerloy			1.2263*** (0.0605)		1.5308*** (0.0696)
brandloy			1.4437*** (0.0888)		1.2660*** (0.0865)
packsizeloy			1.1564*** (0.0507)		1.1691*** (0.0565)
diapclassloy			0.7348*** (0.0639)		0.6010*** (0.0721)
initcond brand					0.5805*** (0.0698)
initcond retailer					1.0340*** (0.0562)
initcond packsize					1.1321*** (0.0539)
Retailer FE	Yes	Yes	Yes	Yes	Yes
Brand FE	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes
aic	118160.6567	85189.9969	83934.5293	79824.6084	77843.5979
N	1833520	1833520	1833520	1833520	1835173

Standard errors in brackets.

Significant at 1% ***, significant at 5% **, significant at 10% *

Table 8: Overview Elasticities over Models 1–5

	Mean	Std. Dev.	Min	Max
Own-Price Elast. Model 1	-2.36	0.46	-3.47	-1.40
Own-Price Elast. Model 2	-3.47	0.88	-5.71	-1.87
Own-Price Elast. Model 3	-3.45	0.88	-5.61	-1.87
Own-Price Elast. Model 4	-3.43	0.85	-5.58	-1.86
Own-Price Elast. Model 5	-3.56	0.94	-5.98	-1.89

Table 9: Dispersion of Elasticities over Package Size, Diaper Class, Brand, and Retailer

Label	Pack.Size	3	4	5	6	7
MB	NORMAL	-3.22	-4.2	-4.43	-4.31	
		0.43	0.76	0.49	0.6	
	JUMBO	-2.46	-3.25	-4.1	-3.54	-3.59
		0.15	0.19	0.54	0.28	
	MEGA	-2.73	-3.96	-3.77	-3.56	
		0.25	0.79	0.12	0.37	
PL	VERYSMAL		-5.22		-5.35	
			0.00		0.00	
	SMALL		-5.04		-4.68	
			0.29		0.34	
	NORMAL	-2.31	-2.99	-3.44	-3.47	
			0.08	0.12	0.64	
	BIG	-2.27	-2.91	-2.98	-2.78	
		0.1	0.12		0.08	
	JUMBO	-2.08	-2.8	-2.92	-2.72	
		0.24	0.21	0.31	0.21	

Table 10: Static and Dynamic Margins for each Label

Label	Type	Size	3	4	5	6	7
MB	S	NORMAL	9.42	8.68	9.10	9.63	
	D		4.00	5.01	7.20	9.63	
	S	JUMBO	10.79	10.22	11.84	10.61	9.67
	D		2.42	3.93	7.81	8.69	9.67
	S	MEGA	15.03	14.65	14.87	14.13	
	D		6.33	8.87	12.04	14.13	
PL	S	VERYSMAL		6.01		11.85	
	D			6.01		11.85	
	S	SMALL		9.39		13.39	
	D			8.85		13.39	
	S	NORMAL	11.44	7.58	7.46	4.64	
	D		9.50	7.22	7.47	4.64	
	S	BIG	6.71	6.79	3.73	7.25	
	D		6.23	6.58	3.73	7.25	
	S	JUMBO	7.81	5.85	6.42	5.09	
	D		6.94	5.53	6.16	5.09	

Table 11: Static and Dynamic Retail Margins for Banded Product

Retailer	Size	Type	3	4	5	6	7	
Disc 1	NORMAL	S	11.44	12.87		5.89		
		D	9.5	12.28		5.89		
	BIG	S	9.31	9.97		11.58		
		D	7.03	8.77		11.58		
	JUMBO	S		7.55		6.01		
		D		6.94		6.01		
Drug 1	VERYSMAL	S		7.48				
		D		7.48				
	SMALL	S		12.67		13.07		
		D		11.8		13.07		
	NORMAL	S	7.46	7.39	8.35	7.11		
		D	3.38	5.17	7.42	7.11		
	BIG	S	10.07			6.31		
		D	9.67			6.31		
	JUMBO	S	10.77	9.89	9.5	9.41	8.75	
		D	6.26	6	6.91	8.55	8.75	
	Super 1	NORMAL	S		2.52		5.37	
			D		2.62		5.37	
JUMBO		S		5.76		6.04		
		D		4.55		6.04		
MEGA		S	8.29	7.34	6.59	5.6		
		D	4.38	4.91	5.47	5.6		
Super 2	NORMAL	S	6.23	6.08	6.16	6.93		
		D	2.4	3.48	4.77	6.93		
	BIG	S	5.72	7.67		6.93		
		D	5.93	7.79		6.93		
	JUMBO	S	9.78	7.25	8.67	7.62		
		D	5.11	4.09	7.16	7.62		
Disc 2	SMALL	S		10.24		17.23		
		D		9.39		17.23		
	NORMAL	S	2.87	3.89		5.03		
		D	1.14	2.94		5.03		
	BIG	S	6.46	9.59		10.83		
		D	5.53	9.15		10.83		
Super 3	SMALL	S				13.27		
		D				13.27		
	NORMAL	S				2.06		
		D				2.06		
	MEGA	S	10.68	10.2	7.49	8.14		
		D	5.52	7.09	5.86	8.14		
Drug 2	NORMAL	S		4.66				
		D		4.66				
	BIG	S	3.96		3.75			
		D	4.06		3.75			
Super 4	NORMAL	S				6.52		
		D				6.52		
	BIG	S		3.84				
		D		3.84				
	JUMBO	S	7.18	4.98	6.65	6.65		
		D	3.36	3.24	5.33	6.65		
	MEGA	S	10.54	10.56	14.57	11.78		
		D	3.21	5.32	12.22	11.78		
Super 5	BIG	S		2.91		3.57		
		D		3.02		3.57		
	JUMBO	S		5.13	9.35			
		D		3.26	9.35			
Drug 3	VERYSMAL	S				12.15		
		D				12.15		
	NORMAL	S	6.34	5.23	4.03	5.04		
		D	3.53	3.47	3.06	5.04		
	BIG	S	8.11	10.64		6.47		
		D	7.97	10.6		6.47		
	JUMBO	S	5.37	6.04	4.46	4.68		
		D	4.28	5.55	4.42	4.68		
Drug 4	SMALL	S		7.36		12.15		
		D		7.35		12.15		
	NORMAL	S	7.15	6.93	6.85	6.76		
		D	2.92	4.12	6.19	6.76		
	BIG	S	6.72	5.51				
		D	6.73	5.51				
	JUMBO	S		4.31		2.86		
		D		4.32		2.86		

Table 12: Static and Dynamic Margins for Banded Product

	Class	Price	MC	MC Dyn	M.Marg	M.Marg Dyn	R.Marg	R.Marg Dyn
NORMAL	3	19.66	3.79	12.88	9.42	4.00	6.45	2.78
	4	22.54	7.96	13.68	8.68	5.01	5.90	3.86
	5	23.95	8.60	11.82	9.10	7.20	6.25	4.93
	6	28.63	12.36	12.36	9.63	9.63	6.64	6.64
JUMBO	3	14.56	-4.06	8.71	10.79	2.42	7.83	3.42
	4	16.96	-0.01	9.18	10.22	3.93	6.75	3.85
	5	21.91	1.54	7.49	11.84	7.81	8.54	6.61
	6	22.67	5.02	7.22	10.61	8.69	7.04	6.76
	7	23.00	4.58	4.58	9.67	9.67	8.75	8.75
MEGA	3	16.27	-8.77	5.86	15.03	6.33	10.01	4.08
	4	21.11	-3.38	6.64	14.65	8.87	9.85	5.59
	5	19.84	-4.58	-0.06	14.87	12.04	9.55	7.85
	6	22.81	-0.65	-0.65	14.13	14.13	9.33	9.33

Table 13: Profits with and without Switching Costs

Label	PackSize	3	4	5	6	7	Rowsum	Difference	
MB	NORMAL	D	3,536,368	5,252,102	4,015,741	9,060,534	21,864,745		
		S	6,322,995	6,596,597	4,131,866	6,940,813	23,992,271	-2,127,526	
	JUMBO	D	1,816,218	6,938,298	6,665,971	6,766,400	618,992	22,805,879	
		S	3,305,869	8,944,171	6,239,909	5,621,850	518,463	24,630,262	-1,824,383
	MEGA	D	3,026,528	7,768,618	5,799,374	7,452,712	24,047,232		
		S	4,399,730	8,565,457	6,078,324	6,955,920	25,999,431	-1,952,199	
PL	VERYSMAL	D		543,767		725,736	1,269,503		
		S		550,836		722,437	1,273,273	-3,770	
	SMALL	D		8,355,284		22,319,953	30,675,237		
		S		8,881,012		21,300,813	30,181,825	493,412	
	NORMAL	D	5,268,995	27,767,974	7,581,016	5,276,600	45,894,585		
		S	6,424,501	30,508,609	7,284,397	4,614,356	48,831,863	-2,937,278	
BIG	D	13,407,248	38,211,897	238,604	35,936,490	87,794,239			
	S	14,895,935	38,695,281	186,059	31,784,197	85,561,472	2,232,767		
JUMBO	D	5,153,839	15,320,480	4,346,734	6,178,655	30,999,708			
	S	5,779,341	16,075,332	4,106,559	5,393,853	31,355,085	-355,377		
Total Change								-6,474,354	