An Empirical Analysis of Consumer Purchase Behavior of Base Products and Add-ons Given Compatibility Constraints

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Abstract

Despite the common practice of multiple standards in the high-technology product industry, there is a lack of knowledge on how compatibility between base products and add-ons affects consumer purchase decisions at the brand and/or standard level. We recognize the existence of compatibility constraints and develop a dynamic model in which a consumer makes periodic purchase decisions on whether to adopt/replace a base and/or an add-on product under the expectation of future price, quality, and compatibility. Dynamic and interactive inventory effects are included by allowing consumers to account for the long-term financial implications when planning to switch to a base product that is incompatible with their inventory of add-ons. Applying the model to the consumer purchase history of digital cameras and memory cards from 1998 to 2004, we demonstrate that the inventory of add-ons significantly affects the purchase of base products. This "lock-in" effect is enhanced when future prices of add-ons increase. Interestingly, it is more costly for consumers to switch from Sony to other brands than vice versa. In two policy simulations, we explore the impact of alternative compatibility policies. For example, if Sony had not created its proprietary Memory Stick the market share of its cameras would have been reduced by 6 percentage points. This result provides important insights that leading brands and early movers should implement a proprietary standard.

Keywords: compatibility and standard, base product, add-on product, dynamic structural model, product adoption, product line pricing

1. Introduction

In high-tech markets, firms often rely on a variety of add-on products in addition to their base products to deliver value to consumers. In these markets, "add-ons refer to any ancillary or complementary product that is offered in addition to firms' core product market" (Choudhary and Zhang, 2016). In markets such as video games, smartphone, cameras, et cetera, consumers often purchase multiple add-on products over time, creating a valuable inventory. Moreover, it is a common strategy for firms to leverage this accumulation of add-ons to "lock in" consumers to the base product by linking add-ons and base products via proprietary standards. In the video game market, games are developed and produced for a particular console (base product), ensuring compatibility between only designated base and add-on products.[1] Yet, in the smartphone and digital camera market, where add-on inventories also exist, compatibility is not as simple, as each market has both open and closed add-on standards. For instance, at the initial release of the digital camera, the industry produced multiple different memory card standards, with multiple camera brands adopting the same memory card standard. Some twenty years and multiple memory standards later, this incompatibility does not exist, as all camera brands use the same SD memory card standard.

Given the importance of add-on inventory and its compatibility with base products in many high-tech markets, we believe there is a need to understand the impact of each on consumers' purchase decisions. Specifically, we seek to understand the impact of incompatibility of add-ons with base products and the role past purchases (state dependence) play to locking-in consumers in a dynamic environment.

[1] Compatibility between the base products and the consumer's inventory of add-ons makes the consumer's purchase/upgrade/replacement decisions interconnected, both across time and across categories. For example, in the video game industry, many games are tied to only one type of console, e.g., Xbox or PlayStation. Gamers accumulate many games over time. When a console needs to be replaced, the gamers may prefer to stay with the same brand of console because they can continue to play their games (in inventory) and avoid re-purchasing all the games in inventory in order to achieve the same entertainment value offered by the old console and games in their possession.

We also evaluate the switching cost associated with purchasing a different base product that employs a different add-on standard than the consumer's existing inventory, by deconstructing the impact into the following key issues: First, does the inventory of add-ons affect the replacement purchase of base products at the standard level? If so, how large is the cost of switching due to a consumer's current inventory of add-ons compared to the cost associated with previous base product purchases (state dependence)? Moreover, does the cost of switching vary with consumers' future expectations of compatibility constraint? Lastly, how does the price of add-ons influence a consumer's add-on inventory effect and impact her choice of a base product?

This paper provides a framework to explicitly model consumer brand and standard choices of base and add-on products and investigates the dynamic dependence between two product categories, when multiple incompatible standards exist. It also accounts for consumers' expectations of future price and compatibility. Our dynamic structural model characterizes two new inter-temporal trade-offs of consumers simultaneously: the cross-category price effect and the cross-category dynamic inventory effect. For instance, a forward-looking consumer may sacrifice the gain from switching to a cheaper but incompatible base product in exchange for the saved costs from not purchasing new add-ons, by continuing with a compatible base product. We name this effect the "add-on inventory effect." It captures the notion that the more add-ons a consumer has accumulated, the less the consumer is willing to switch to other incompatible base products. Additionally, these forward-looking consumers also account for the price of memory cards in their purchase of cameras. This effect is denoted as a cross-category price effect.

We apply the model to a unique panel data with 828 households and their purchase history of digital cameras and memory cards from December 1998 to November 2004. During the six-year observation period, manufacturers of digital cameras adopted (at least) three memory card standard families: Memory Stick (Standard 1) for Sony, SmartMedia and xD Card (Standard 2) for Olympus and Fujifilm, and CompactFlash and SD Card (Standard 3) for Canon, Kodak, Nikon, and HP. The unique structure of this industry provides an ideal opportunity to examine brand competition in the face of standard compatibility constraints.

Our empirical results indicate that the largest component of the consumer's lock-in effect is his own prior purchase behavior. The existing literature has shown that a consumer's past purchase decisions can create consumer inertia (e.g., Seetharaman, Ainslie, and Chintagunta (1999) and Dubé, Hitsch, and Rossi (2010)). Yet, we also find strong empirical evidence of an "add-on inventory effect," which has been overlooked by the existing literature. Consumers are indeed locked in by the utility that compatible add-ons provide. Interestingly, the cost to switch is asymmetric: it takes more for Standard 2 and Standard 3 to steal Sony consumers ($19.34 and $17.15) than for Sony to steal the consumers from the other two standards ($14.84 and $15.01). However, the cost of switching decreases substantially when consumers expect future incompatibility at the time of new standard introduction. The structural model further permits us to investigate the interaction between the "cross-category price effect" and the "add-on inventory effect." We show that the add-on inventory effect is enhanced when future prices of add-ons are higher (i.e., when the expected future price of a memory card increases).

Additionally, we provide insights on competition in a hybrid market with both open and closed standards. Such a unique context allows us to examine both within-standard competition and cross-standard competition. We find that within-standard competition is stronger than cross-standard competition, and that consumers are attracted by openness when determining whether to switch between standards.

With the use of a counterfactual simulation we also discover that when incompatibility is removed among standards, the manufacturer of a premium memory card cannot reap the profit from camera transactions. For instance, if Sony had not created its proprietary memory card standard the market share of its cameras would have been reduced by 6 percentage points. This result provides important insights into when a brand should implement a proprietary standard. Our results determine that weak brand equity firms should elect to either be compatible with the leading brand or create a union with other players in the market to diminish the market power of the leading brand in order to remain competitive in the market place, while strong brands can elect the go it alone strategy and garner sizeable market share in both complementary markets. Additionally, entry timing plays an important role in an open standards market—late movers are at significant disadvantage over their early mover counterparts.

2. Literature Review

Our paper is related to several streams of literature: durable goods adoption and replacement decision-making, multi-category purchase analysis, switching cost, network effects, and compatibility. However, we contribute most notably to the literature on multi-category purchases, switching costs, and compatibility.

Papers investigating the complementary relationship between products in different categories have seen a growth of interest over the last few years, particularly when analyzing technology products.[2]

In our paper, the add-on inventory effect is consistent with the literature that recognizes complementarity between product categories (Sriram, Chintagunta, and Agarwal (2009) and Liu, Chintagunta, and Zhu (2010)). Previous models, however, define the complementary term only as time-invariant and at the category level. We advance the literature by making such a term time-varying. Our approach also allows us to investigate the dynamic and interdependent consumer decision process and is similar to that of Hartmann and Nair (2010), which studies how expectations about the future

[2] Seetharaman et al. (2005) provides an excellent review of models of multi-category choice behavior, including three outcomes: purchase incidence, brand choice, and quantity consideration.

prices of the aftermarket goods influence the initial purchase of the primary good. Our study goes further by analyzing how brand choice of a base product is driven by past, current, and future choices of add-on products. We also allow the add-on inventory effect to depend on the number and size of the add-on products owned. Therefore, the add-on inventory effect can vary across time and affect the inter-temporal decision-making of forward-looking consumers—because the more compatible memory cards accumulated, the higher the per-period add-on inventory effect. This implies that the accumulation of add-on products creates a higher cost of switching for consumers to abandon the compatible base product.

Switching costs are an important area of research, particularly for markets that have network effects or complementary products associated with them. Farrell and Klemperer (2005) describe the cost as the expense that "arise[s] if a buyer…purchase[s] follow-on products such as service and repair, and…find[s] it costly to switch from the supplier of the original." In other words, the authors consider the situation when a buyer wants to purchase an add-on product but is constrained by the switching cost from the base product. Forman and Chen (2005) and Chen and Forman (2006) study the role of product compatibility in creating switching costs in the market for telecommunications equipment. Specifically, Chen and Forman (2006) determine that the presence of switching costs can lead to inefficient adoption of new information technology and that vendors may be able to influence the speed of new information technology adoption. Additional empirical switching cost papers have analyzed the impact of switching costs and network effects on competition between online, traditional, and hybrid firms (Viswanathan, 2004) and procurement decisions in government agencies (Greenstein, 1993). In contrast, we extend this literature by documenting a new form of switching cost that originates from the inventory of the add-on product and takes place at the time of base product replacement. The intuition is that if the consumer switches to a different standard of the base product, he has to forgo all the inventory of the add-ons and purchase new add-on products, hence suffering from what possibly could be a large switching cost. Moreover, we separately account for consumers' past purchases in the form of state dependence.[3]

The empirical literature that incorporates the estimation of state dependence when studying and quantifying switching cost is scant. Greenstein (1993), however, does determine that both state dependence and compatibility impact purchase decisions. Specifically, he finds that an agency is likely to acquire a system from an incumbent vendor (state dependence) and that the (in)compatibility between a buyer's installed base and a potential system also influences the vendor choice. Zhu, Kraemer, Gurbaxani, and Xu (2006) analyze whether switching costs are significant barriers to entry of a new open standard and determine that adoption costs are, in fact, a significant barrier. In the context of electronic interorganizational systems and the entry of a new open standard, they find that EDI users are much more sensitive to the costs of switching to the new standard. Their finding illustrates that experience with older standards may create switching costs and make it difficult to shift to open and potentially better standards, a phenomenon called "excess inertia" in technology change.

The incorporation of the add-on inventory effect to our model of consumer purchase is similar to indirect network effects (Katz and Shapiro, 1985) where the utility a user derives from the good depends upon the number of other complementary products that are in the same "network" and that the number/variety of complementary products depends upon the adoption of the primary product, but is not exact. In our setting, the linkage between categories focuses on the cards (complementary products) in inventory rather than on what is available or could possibly be in inventory, as most research on indirect network effects does. In our paper, the indirect network effect does not exist, as the effect is only unidirectional (memory card to camera). Second, we allow the add-on inventory effect to depend on not only the number, but also the size of the add-on products owned. This is a

[3] Most studies of state dependence rely on the first purchase occasion being non-random and uncorrelated with consumer purchase behavior (Erdem, 1996; Che et al.., 2007; Dube et al., 2008). A paper by Erdem and Sun (2001) does allow for correlation between the initial condition and consumer heterogeneity.

movement forward from the Katz and Shapiro definition of network effects, which abstracts away the idea of product heterogeneity. Similar steps forward have been taken by Lee (2013), Derdenger and Kumar (2013), and Derdenger (2014). In doing so, the add-on inventory effect can vary across time and affect the inter-temporal decision-making of forward-looking consumers—the more compatible memory cards that are accumulated, the higher the per-period add-on inventory effect. This implies that the accumulation of add-on products creates a higher cost of switching for consumers to abandon the compatible base product. Such costs lock in consumers to one particular standard. In markets with strong indirect network effects, this may lead to the market tipping toward one standard as shown in Dube, Hitsch, and Chintagunta (2010).

Finally, our paper is related to the literature on compatibility and standards. Prior economics literature, mostly analytical works, claims that if products are incompatible, the costs of switching bind customers to vendors. Such costs of switching not only involve direct efficiency losses but also soften competition and magnify incumbency advantages (see Farrell and Klemperer (2005) for a review). Therefore, consumers as well as economists favor compatibility, or standardization (see Farrell and Simcoe (2012) for benefits of compatibility). Katz and Shapiro (1985) found that firms with good reputations or large existing networks tend to be against compatibility, whereas firms with weak reputations tend to favor product compatibility. Additionally, our policy simulations reinforce and extend the findings in this analytical literature by showing that the manufacturers with high brand equity or good reputations prefer maintaining proprietary standards versus joining open standards coalitions.

Our simulation results also expand on the literature on compatibility and, in particular, on open versus closed standards, by specifically analyzing the impact of the initial brand equity condition on a firm's decision to implement a proprietary standard. David and Greenstein (1990) highlight that "initial conditions can matter a great deal in determining firms' strategies when compatibility is a design decision. This is because asymmetries in market position give firms who sponsor alternative standards quite different payoffs from providing for 'interoperability' (or realized technical complementarity) with competitors' products."

3. Industry Background and Data Description

3.1. Digital Camera and Memory Card Industries

Since 1994, the digital camera industry has seen constant technology improvements: higher pixel counts, larger sensors, shorter shutter lag, smaller and lighter bodies, and more optical zoom options. The market has also seen a substantial increase in models and brands, with Canon, Casio, Fujifilm, Kodak, Nikon, Olympus, and Sony as the leading players. As digital cameras began taking higher quality pictures, consumers demanded larger memory devices to capture photos. It was in this memory card territory that competition increased, creating multiple manufacturers of proprietary memory card standards.

We categorize memory cards into three standard families, each with two generations. The Standard 1 family includes the Memory Stick (MS)[4], Memory Stick PRO, and Memory Stick PRO Duo. Only Sony cameras are compatible with the Standard 1 cards. Within this family, the Memory Stick PRO Duo is the second generation, not backward compatible with cameras that use the first generation cards. The Standard 2 family includes SmartMedia cards (SM) and xD cards (XD). Olympus and Fujifilm cameras are compatible with Standard 2 cards. We regard the SmartMedia card as the first generation and the xD card as the second generation. The Standard 3 family includes CompactFlash (CF) and SD cards. The CompactFlash is the first generation and the SD card is the second generation. Kodak, Canon, HP, and Nikon cameras all adopt the Standard 3 memory cards. Given the complex standard family and generation structure, we present the industry timeline in Table

[4] For more details about the memory card timeline, please see Appendix A1.

1. In addition, in Table 2 we present our labeling employed in the model section to avoid confusion: Standard 1-1, Standard 1-2, Standard 2-1, Standard 2-2, Standard 3-1, and Standard 3-2 refer to the Memory Stick (including Memory Stick Pro), Memory Stick Pro Duo, SmartMedia, xD, CompactFlash, and SD, respectively.

[Insert Table 1 and Table 2 about Here]

3.2. Data Description

The data comprise an individual level scanner panel provided by an anonymous major electronic retailer in the United States. Our sample consists of the complete purchase records of 828 randomly selected households that purchased at least one camera in six years, from December 1998 to November 2004. The transaction record includes detailed information about purchases of products, such as brand name, UPC, product type, price paid, and time and location of purchases. In addition, we collect information on digital cameras at the brand-model level from a camera database website that tracks detailed information of all camera models.[5] [6] The quality information on memory cards is obtained from annual reports of major memory card manufacturers at the standard level.[7] Following Song and Chintagunta (2003), we use effective pixels (in megapixels) as a proxy of camera quality because it is the most important factor in determining camera performance. The quality of a memory card is measured by capacity (in megabytes).[8] Finally, note that the cameras compatible with the new generation of memory cards are not compatible with the old generation of memory cards in other standard families.

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5 www.dpreview.com/products

6 The data contain the product UPC as a unique identifier, despite missing the model name information. We further collected the initial introduction price for all cameras from dpreview. For example, from this review article, https://www.dpreview.com/reviews/sonydscp1/, we found that the initial price of Sony DSC-P1 is $799. We then identify the exact model of each camera by matching the price information from dpreview with the price for that UPC when the UPC first appeared in the dataset.

7 www.dpreview.com/products

8 Given the fact there are many distinct models for each brand, we assume that consumers can choose any model from any brand. We calculate price and quality indices for each brand of camera and standard of memory card. The price and quality indices are weighted by the market share of the camera model. We use observed prices to generate the price index. We deduct the price promotion amount from the list price to obtain the paid price. The price of the memory card is normalized by the size of the memory card.

[Insert Tables 3A, 3B, 3C, and 3D about Here]

We prepare the data in the time frequency of a quarter because consumers seldom purchase cameras and memory cards more frequently than that. During the six-year sample period, the 828 households made 1059 transactions of cameras and 1043 purchases of memory cards.

Table 3A presents market shares of different brands of cameras and memory cards. In the digital camera market, Sony had the largest market share: 27.86%. Olympus and Fujifilm together took up 23.89%, and the remaining 48.15% was left to other brands. Consistently, Standard 1 memory cards (compatible with Sony cameras) had a market share of 29.63%, Standard 2 memory cards (compatible with Olympus and Fujifilm cameras) had a market share of 23.11%, and Standard 3 memory cards (compatible with Kodak, Canon, HP, and Nikon cameras) occupied 47.27%.

Table 3B reports the total purchase incidences for 828 consumers. 15.22% of consumers replaced cameras, while 84.78% of consumers purchased one camera; 18.97% of consumers purchased more than one memory card. The maximum number of camera purchase incidences is three, and the maximum number of memory card purchase incidences is four. These numbers are consistent with the nature of cameras and memory cards as durable goods.

Table 3C and 3D report the summary statistics of price and quality information. Sony's camera average price is the highest, and HP's cameras are the lowest. Interestingly, the quality measure is not quite aligned with price, as Nikon, rather than Sony, has the highest average quality. For memory card, Standard 2 is the highest priced with lowest average quality, whereas Standard 3 charges the lowest price with the highest average quality.

[Insert Figures 1A, 1B, Figures 2A and 2B about Here]

Figure 1A and 1B exhibit the price trend of cameras and memory cards. We find that the price of Sony cameras decreased over time. Prices of Olympus and Fujifilm cameras increased in 2000 and 2001 and then decreased for the rest of the sample periods. Prices of Kodak, Cannon, Nikon, and HP decreased at the beginning and then stabilized (or slightly increased for Kodak). In terms of memory cards, Standard 1 almost always had the highest average price except after 2002, when Standard 2 increased. Standard 3 charged a lower average price than Standard 2 after the second quarter of 2002 and stayed with the lowest price among the three standards.

Figure 2A and 2B show the corresponding quality trends of cameras and memory cards. During our sample period, technology improved dramatically and all products saw a significant quality upgrade. Interestingly, there's no clear quality differentiation among brands of cameras—in other words, no brand had a dominant quality throughout time.

[Insert Figures 3A, 3B and Figures 4A and 4B about Here]

For technology goods like cameras and memory cards, prices highly depend on features of the model. Prices alone do not provide the true nature of the product; thus, we need to use quality-adjusted price. Figure 3A illustrates how purchase incidence of cameras evolved over time, whereas Figure 3B shows the quality-adjusted price trends for each camera brand. We also present purchase incidence and quality-adjusted price trends of memory cards in Figures 4A and 4B.

4. Model Free/Reduced Form Evidence of Cross-Category Inter-temporal Dependence

Below we present evidence of the existence of cross-category, inter-temporal dependence. We specifically highlight three effects: i) cross-category price effect, ii) add-on inventory effect, and iii) future memory card compatibility expectations.

Cross-Category Price Effect

[Insert Table 4 about Here]

We first provide evidence for a "cross-category dynamic price effect." More specifically, if consumers anticipate the price of future add-on products as rising, they will switch brands in the base product category to minimize the total financial burden of the product portfolio. In order to analyze the presence of this effect, we run a reduced form regression

$$\log(CameraSales_{jt}) = \beta_0 + \beta_1 \log(CameraPrice_{jt}) + \beta_2 \log(MemoryPrice_{jt}) + \beta_3 \log(MemoryPrice_{jt+1}) + \epsilon_{jt}$$

where $j \in \{1,2,3\}$ represent the three standard families and t represents a month in our sample period, and ϵ_{jt} , is the normally distributed error term, $\epsilon_{jt} \sim N(0, \sigma^2)$ to test if the sales of camera brands are affected by future memory card prices. In Table 4, we present the regression estimates of the following log-log specification. As we can see, the coefficient for the future price of a memory card is significant and negative. This suggests that consumers may be forward-looking with respect to the future price of memory cards when purchasing cameras in the current period.

Add-on inventory Effect (Cross-category Dynamic Inventory Effect)

[Insert Figure 5A and 5B about Here]

In addition to the above memory card price effect on camera purchase incidence, we conjecture that perhaps the inventory of memory cards also plays an important role in camera purchases—what we call the "add-on inventory effect." The intuition is that a consumer who owns a memory card should be more reluctant to switch to a camera that is incompatible with her existing stock of memory inventory. In contrast, a consumer who has zero inventory is not "locked-in" to a particular camera brand. Figure 5A illustrates the purchase incidences for each camera brand, conditional on consumer inventory levels of compatible memory cards. We see that for all camera brands, purchase incidence increases as the inventory level of compatible memory cards increases. This is particularly true for Sony, and is perhaps due to consumers facing a higher cost of switching or add-on inventory effects associated with existing memory card inventory than that faced by consumers who own other standards. We further decompose this data and illustrate with Figure 5B the purchase probability of repurchasing a camera of the same brand. Figure 5B highlights that loyalty probability of upgrading to the same brand increases as the number of memory cards a consumer owns increases. Note that the qualitative analysis would also hold if we were to show it at the standard level.

Future Compatibility Expectation

[Insert Figure 6 about Here]

The presence of the add-on inventory effect relies on an assumption that the memory cards in inventory are compatible with new cameras. However, when firms launch new memory cards, they usually make the new cameras compatible with only the new memory cards, not the old. We conjecture that current camera purchase decisions are impacted by a consumer's expectation about the release of future memory card standards. This conjecture is supported by evidence in the data. During our sample period, all three standard families introduced new memory cards. For example, in 2001, the SD card was launched; in 2002, the xD card was introduced for the Standard 2 cameras; and in early 2003/late 2002, Sony introduced the Memory Stick Pro Duo. In Figure 6 we plot the time series of memory card market share. For each standard, we use a vertical bar to mark the time (year) a new card type was introduced. Across the three standards, roughly a year before a new memory card was released, the market share of the old memory card declined. We believe this is because consumers' expectations were correct that the old generation memory cards would not be compatible with future cameras.[9]

In summary, the presented data patterns show the cross-category, inter-temporal interdependence between purchases of base and add-on products. It is evident that forward-planning consumers take into account the price and quality of add-ons as well as financial implications of discarding their existing add-ons when comparing long-term utilities of alternative choice sequences. In the next section, we develop a model to explicitly describe this decision process.

[9] This data pattern reflects the fact that consumers have form correct expectations about future releases. We do not specify the mechanism for why or how consumers formed these correct expectations.

5. Model

In the case of base products that are durable in nature and that allow for subsequent purchase of add-on products, consumers tend to be forward-looking when making purchasing decisions (Nair, Chintagunta, and Dubé, 2004, Derdenger and Kumar, 2013). The forward-looking behavior of consumers and the issue of compatibility between camera and memory cards imply that a consumer's decision to purchase the base product depends on the anticipated purchase(s) of the add-on products. Therefore, the purchase decision for the base product would depend not only on the expected price and quality trajectories of that product, but also on the anticipated price and quality of the add-on product, in addition to the future compatibility between the two categories. To approximate a consumer’s decision process that accounts for the above characteristics, we develop a model of consumers’ joint purchase (adoption and replacement) decisions of base and add-on products as a dynamic optimization problem with price, quality, and compatibility uncertainty.

5.1. Assumption

In light of the available data and the specific industry we study, we make several assumptions regarding consumer behavior for model parsimony. First, we assume that consumers can buy only at the focal electronic retail chain[10]. Second, we assume that there is no resale market for cameras and a discarded camera cannot be exchanged for its residual value. This implicitly assumes that consumers only derive utility from their most recently purchased camera. Finally, we assume that consumers keep all memory cards—i.e., memory cards are accumulated, not replaced. Past research ignores the memory card in inventory, which is equivalent to assuming that consumers discard all the add-on products that they previously purchased and ignore those products when making decisions about base product replacement choices. In contrast, we relax the assumption and allow inventory to be cumulative.

[10] Please find our justifications for this assumption in Appendix A4.

5.2. Consumer Choices and Flow Utility

Our model follows the large literature pertaining to choice models (Guadagni and Little, 1983). In each period t $(t = 1,2,..,T)$, the consumer i $(i = 1,2,...,I)$ makes purchase decisions about both the base product (camera of brand $c \in \{1, ... C\}$) and the add-on (memory card of standard $m \in \{1, ... M\}$) jointly. Let the consumer's choice for the camera be $DC_{it} \in \{0,1, ..., C\}$ and her choice for the memory card be $DM_{it} \in \{0,1, ... M\}$. When $DC_{it} = 0$, it denotes that the consumer chooses not to purchase any brand of camera in period t. Similarly, when $DM_{it} = 0$, the consumer chooses not to purchase any standard of memory card. Here, C denotes the total number of camera brands and M is the total number of memory card standards. In our data, $c = 1,2,3,4,5,6,7$ represents Sony, Olympus, Fujifilm, Kodak, Canon, HP, and Nikon respectively, while $m = 1,2,3$ corresponds to Standard 1 (Memory Stick/Memory Stick Pro Duo), Standard 2 (SmartMedia/xD card), and Standard 3 (CompactFlash/SD card), respectively. Thus, during each time period, a consumer faces 18 choice alternatives altogether.[11]

Given these choices, the consumer's per-period utility U_{it} can be decomposed into a deterministic part $\overline{U}_{it}$ and an idiosyncratic error term ε_{it} that follows a generalized extreme value distribution and allows for correlation of errors within categories. This error term captures any unobserved factors that may affect a consumer's purchase decision. This could be caused by holiday demand spikes, word of mouth advertising, store closure in the retail chain, unobserved promotions, or local demand shocks.

$$U_{it}(DC_{it}, DM_{it}) = \overline{U}_{it}(DC_{it}, DM_{it}) + \varepsilon_{it}(DC_{it}, DM_{it}) \quad (1)$$

We adopt a utility specification that follows a large body of literature of complementary good and multi-category purchase.[12] This function allows for the added utility of consuming goods A and

[11] Utility functions for each of the 18 choice alternatives of this full model are shown in Table A1 of the Appendix A2.

[12] Gentzkow (2007); Sriram, Chintagunta and Agarwal (2009); Liu, Chintagunta and Zhu (2010) to name a few.

B together. The deterministic part of the per-period utility $\overline{U}_{it}(DC_{it}, DM_{it})$ is the sum of the three elements i) basic utility of using the camera, ii) enhanced utility that is associated with the compatible add-ons, and iii) cost of purchasing/replacing the products. We discuss each during a more formal discussion of the specific utility function below.

In modeling two category choice decisions, we must specify four types of choice alternatives: (1) purchase camera and memory card together, (2) purchase (adopt or replace) only a camera of brand c, (3) purchase only a memory card of standard m, or (4) purchase neither product. Below we demonstrate the utility specification for the four cases, respectively[13].

Case 1: Camera and Memory

When a consumer simultaneously purchases a camera $DC(> 0)$ and a memory card $DM(> 0)$, the utility function has all three of the above components.[14]

$$\begin{aligned}
&\overline{U}_{it}(DC_{it} = c, DM_{it} = m) \\
&= \underbrace{\alpha_i^c + \phi_i QC_t^c + \mu_i^c * Y_t + \beta_i * I\left(DC_{it} = DC_{iR_{it}}\right)}_{basic\ utility} \\
&+ \underbrace{\left\{\left[\theta_i^{mv_t} + \psi_i * Size_t^m\right] * I(m \sim_t c) + \sum_{m'=1}^{M} \sum_{\tau=0}^{t-1} \rho_i^{t-\tau} * I(DM_{i\tau} = m') * \psi_i * Size_\tau^{m'} * I(m' \sim_t c)\right\}(1 + \delta_i * QC_t^c)}_{enhanced\ utility} \qquad (2) \\
&+ \underbrace{\lambda_i * (PC_t^c + PM_t^m)}_{financial\ cost}
\end{aligned}$$

In equation (2), the component associated with the basic consumption utility of the camera is

$$\alpha_i^c + \phi_i QC_t^c + \mu_i^c * Y_t + \beta_i * I\left(DC_{it} = DC_{iR_{it}}\right) \qquad (3)$$

A camera can create basic utility because most camera models have a small allocation of internal memory or come with a free small-capacity memory card at the time of the purchase. Therefore, the cameras can function by themselves and provide the utility of shooting photos. Equation (3) implies

[13] The specification that covers all four cases is included in Appendix A2.
[14] They must be compatible, because no consumer purchased an incompatible base product and add-on at the same time in our data.

that when the consumer makes a purchase of the camera brand c, her utility is summarized by the brand-specific constant (α_i^c), brand preference time trend ($\mu_i^c * Y_t$), quality ($\phi_i QC_t^c$), and state dependence ($\beta_i * I(DC_{it} = DC_{iR_{it}})$). The first term α_i^c is the brand-specific fixed effect, which represents a persistent form of product differentiation that captures the household's intrinsic brand preferences of camera brand c. In the third term, QC_t^c is the quality of the camera c at its purchase time t. Quality is measured by megapixels as in Song and Chintagunta (2003). The coefficient ϕ_i is the marginal utility for a single unit of quality increment. Since camera a complicated product and consumers might care about multiple attributes which improve over time, we use the third term to capture the time-varying brand preference as well as the unobserved quality upgrades. Here Y_t is the number of years lapsed since the inception of the digital camera market and μ_i^c is the brand specific time trend parameter. The next term, $\beta_i * I(DC_{it} = DC_{iR_{it}})$, denotes state dependence (Dubé, Hitsch, and Rossi, 2010); that is, if the consumer purchases a camera (brand DC_{it}) of the same brand, she can receive an extra utility β_i compared to other brand choices. Here, the subscript R_{it} denotes the time of the recent camera purchase. For example, if before this period t, the most recent camera purchase took place in period 2, then $R_{it} = 2$[15]. It's possible that different behavioral mechanisms generate a consumer's state dependence. One such mechanism is that consumers have become loyal to a brand because of their past user experiences, and would thus incur a psychological cost by switching to another brand. Another possibility is that a consumer learns that she has a high match value with the brand. The purpose of this paper is not trying to differentiate these explanations, but to simply capture the "state dependence" effect.

[15] From this definition, it is easy to know that RP_{it} can be constructed as follows $R_{it} = \begin{cases} t-1, & if\ DC_{it-1} \in \{1, \ldots C\} \\ R_{it-1}, & if\ DC_{it-1} = 0 \end{cases}$. That is, if the consumer made a purchase in the previous period, then R_{it} records the last period. But if the consumer did not make a purchase in the previous period, R_{it} will be the same as its predecessor, which recorded the prior purchase time.

Next, the component in equation (2) that characterizes the enhanced utility of the memory card is

$$\left\{\left[\theta_i^{mv_t} + \psi_i * Size_t^m\right] * I(m\sim_t c) + \sum_{m'=1}^{M}\sum_{\tau=0}^{t-1}\rho_i^{t-\tau} * I(DM_{i\tau} = m') * \psi_i * Size_\tau^{m'} * I(m'\sim_t c)\right\}(1 + \delta_i * QC_t^c) \qquad (4)$$

We further decompose this long equation (4) to the three subcomponents below:

$$\left[\theta_i^{mv_t} + \psi_i * Size_t^m\right] * I(m\sim_t c) \qquad (4\text{-}1)$$

$$\sum_{m'=1}^{M}\sum_{\tau=0}^{t-1}\rho_i^{t-\tau} * I(DM_{i\tau} = m') * \psi_i * Size_\tau^{m'} * I(m'\sim_t c) \qquad (4\text{-}2)$$

$$(1 + \delta_i * QC_t^c) \qquad (4\text{-}3)$$

Equation (4-1) represents the consumer's enhanced utility from a newly purchased memory card. Equation (4-2) is the consumer's enhanced utility from the memory cards in inventory. Equation (4-3) allows the previous two subcomponents to be interacted with the consumption utility of the camera.

For a newly purchased memory card of standard m, the enhanced utility (equation (4-1)) is summarized by $\theta_i^{mv_t}$, the standard-specific fixed effect and size, $Size_t^m$, measured by megabytes. We allow the standard-specific fixed effect to vary by generation $v_t \in \{1,2\}$, in order to capture the differential utility from different generations (see Table 2 for details) of the memory card standards. For example, θ^{11} represents the fixed effect for the first generation of standard 1 memory cards, which is the Memory Stick and Memory Stick Pro while θ^{12} is the fixed effect for the second generation of standard 2 memory cards, i.e. Memory Stick Pro Duo. The coefficient ψ_i is consumer i's sensitivity to memory card storage capacity. Recall that add-on products provide consumption value only to the compatible base product. The indicator $I(m\sim_t c)$ in equation (4) denotes that only compatible memory cards can enhance the utility of a camera. That is, $I(m\sim_t c) = \begin{cases} 1, & \text{if } m \textit{ and } c \textit{ are compatible} \\ 0, & \textit{otherwise} \end{cases}$. The subscript t next to the $\sim$ symbol captures the notion that the compatibility relationship between camera and memory card changes with time. For example, if a consumer purchases a CompactFlash (Standard 3-1) in 2003, it won't be compatible with the Canon cameras on the market then, because the Canon cameras switched to the SD cards (Standard 3-2) in 2001. This t subscript becomes handy later when we discuss consumers' forward-looking behavior with respect to future compatibility.

In addition to using the newly purchased memory cards, the consumer can also enjoy the enhanced utility from the memory cards in inventory, as summarized in equation (4-2). Notice that equation (4-1) and (4-2) have a few differences. First, the memory cards in inventory were purchased at a different time period τ than the current period t. Second, the memory cards in inventory depreciated by a factor of $\rho_i^{t-\tau}$. This represents the wear and tear as well as the effect that consumers might be less likely to use the memory cards in inventory than to use the new memory card. The older the memory card, the more it depreciates. Last, the intercept θ_i^m is present only for the current memory card but not the memory cards in inventory. We choose this specification because the intercept term captures consumers' standard preference, hence influencing consumer preference only at the standard level, not at the unit level. The summation sign over m' and τ assumes that the enhanced utility of all the previously purchased memory cards is accumulated, as long as they are compatible with the currently used camera, $DC_{iR_{it}}$.

Furthermore, it is possible that the consumer's utility of the memory card depends on the quality of the camera, because if the camera takes a better picture, there is a higher value of capturing pictures. To take into account this potential interdependence (complementarity) between a camera and memory card, we allow for an interaction effect between the consumption utility of memory cards, both new and in inventory, and the quality of the camera, in equation (4-3). The camera-memory interaction coefficient δ_i captures the nonlinear effect of the inventory of memory cards and the quality of camera purchased.

Finally, the cost of purchasing is the sum of PC_t^c, the price for the camera of brand c, and PM_t^m, the price for the memory card of standard m. The coefficient λ_i is the price sensitivity.

Case 2: Purchase Camera Only

When the consumer purchases a camera but no memory cards, she obtains basic consumption utility from the camera and pays for the purchase. In addition, she obtains the enhanced utility associated with the compatible add-ons in inventory. Consequently, for $c \in \{1,2,\dots,C\}$,

$$\begin{aligned}
&\bar{U}_{it}(DC_{it} = c, DM_{it} = 0) \\
&\quad = \underbrace{\alpha_i^c + \phi_i QC_t^c + \mu_i^c * Y_t + \beta_i * I\left(DC_{it} = DC_{iR_{it}}\right)}_{basic\ utility} \\
&\quad + \underbrace{\left\{\sum_{m'=1}^{M}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')\left[\theta_i^{m' v_\tau} + \rho_i^{t-\tau} * \psi_i * Size_\tau^{m'} * I(m' \sim_t c)\right]\right\}(1 + \delta_i * QC_t^c)}_{enhanced\ utility} + \underbrace{\lambda_i * PC_t^c}_{financial\ cost}
\end{aligned} \tag{5}$$

Case 3: Purchase Memory Only

When a consumer buys only a memory card, she must own a compatible camera. Her utility originates from the consumption utility of using the camera in inventory and the enhanced utility from the memory card in inventory and the purchase of a new memory card. For $m = 1,2,3,$ the utility function for the purchase of memory takes only the form

$$\begin{aligned}
&\bar{U}_{it}(DC_{it} = 0, DM_{it} = m) \\
&= \underbrace{\alpha_i^{DC_{iR_{it}}} + \phi_i * QC_{R_{it}}^{DC_{iR_{it}}} + \mu_i^{DC_{iR_{it}}} * Y_{R_{it}}}_{basic\ utility} \\
&+ \underbrace{\left\{\left[\theta_i^{m v_t} + \psi_i * Size_t^m\right] * I\left(m \sim DC_{iR_{it}}\right) + \sum_{m'=1}^{M}\sum_{\tau=0}^{t-1} \rho_i^{t-\tau} * I(DM_{i\tau} = m') * \psi_i * Size_\tau^{m'} * I\left(m' \sim DC_{iR_{it}}\right)\right\}\left(1 + \delta_i * QC_{R_{it}}^{DC_{iR_{it}}}\right)}_{enhanced\ utility} \\
&+ \underbrace{\lambda_i * PM_t^m}_{financial\ cost}
\end{aligned} \tag{6}$$

In the above equation (6), the camera consumption utility is $\alpha_i^{DC_{iR_{it}}} + \phi_i QC_{R_{it}}^{DC_{iR_{it}}} + \mu_i^{DC_{iR_{it}}} * Y_{R_{it}}$. The superscript $DC_{iR_{it}}$ denotes the camera brand bought previously at time R_{it}. The associated quality of this previously purchased camera is $QC_{R_{it}}^{DC_{iR_{it}}}$.[16] Note that when the consumer purchases only the memory card, she picks the standard that is compatible with the camera in inventory ($I\left(m \sim DC_{iR_{it}}\right) = 1$) because other memory card standards cannot be used with the camera in hand.

Case 4: No Purchase

If a consumer does not own a camera and she decides not to make a purchase of any product at time *t*, we normalize the utility to zero.

$$\bar{U}_{it}(DC_{it} = 0, DM_{it} = 0) = 0 .$$

However, if the consumer owns a camera and decides not to replace it with a new one, she continues to receive utility from the camera and the compatible memory cards in inventory (if there are any) without paying additional cost. Thus, the utility function has two components: possession of a camera $DC_{iRP_{it}}$, and the add-on inventory effect provided by the inventory of compatible memory cards.

$$\begin{aligned} \bar{U}_{it}(DC_{it} = 0, DM_{it} = 0) \\ &= \underbrace{\alpha_i^{DC_{iR_{it}}} + \phi_i * QC_{R_{it}}^{DC_{iR_{it}}} + \mu_i^{DC_{iR_{it}}} * Y_{R_{it}}}_{basic\ utility} \\ &+ \underbrace{\left\{\sum_{m'=1}^{M} \sum_{\tau=0}^{t-1} I\left(DM_{i\tau} = m'\right)\left[\theta_i^{m' v_t} + \rho_i^{t-\tau} * \psi_i * Size_\tau^{m'} * I\left(m' \sim DC_{iR_{it}}\right)\right]\right\}\left(1 + \delta_i * QC_{R_{it}}^{DC_{iR_{it}}}\right)}_{enhanced\ utility} \end{aligned} \tag{7}$$

Before progressing to the discussion of consumer expectations, it is worth noting several model features that characterize the cross-category intertemporal trade-offs. First, as the equation shows (4-2), the more memory cards (larger $\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')$) a consumer has, and/or the larger the total storage space of the memory cards (larger $Size_\tau^{m'}$) is, the higher enhanced utility a consumer

[16] Based on its definition, we can construct $QC_{R_{it}}^{DC_{iR_{it}}}$ iteratively as $QC_{R_{it}}^{c} = \begin{cases} QC_t^c \ , \ if\ DC_{it} = c \\ QC_{R_{it}}^{c}, \ if\ DC_{it} = 0 \end{cases}$. Intuitively, this means that when the consumer makes a purchase, the quality of the memory card in inventory will be updated to the quality of the newly purchased. Otherwise, this term will remain the same as its predecessor.

can derive from the inventory. Second, the term $I(m' \sim_t c)$ indicates the "add-on inventory effect," which links the consumer purchase decision about a camera and the decision about memory cards into a single framework. A forward-looking consumer who makes a purchase decision about a camera at time *t* will consider not only the price and quality of the cameras, but also the future price and quality of the memory cards. This is because, if a consumer chooses to switch to a camera that is incompatible with the memory cards in inventory, i.e., $I(m' \sim_t c) = 0$, she will lose the utility provided by these memory cards and must re-invest in more memory cards to enhance the consumption value of the camera in the future. But if she stays loyal to the camera brand that is compatible with the current memory cards in inventory, the cost of new memory cards can be saved. Note that without this compatibility term, the purchase decisions of the two categories will be separated.

5.3. Dynamic Optimization Problem and Inter-temporal Tradeoffs

Given that the base products and add-ons are durable in nature, we follow the standard literature and assume that the objective of consumer i is to maximize the expected present value of utility over the infinite planning horizon $t = 1,2,\dots,\infty$

$$\max_{\{DC_{i\tau},DM_{i\tau}\}_{\tau=t}^{\infty}} \{E[\sum_{\tau=t+1}^{\infty} \Upsilon_i^{\tau} U_{i\tau}(DC_{i\tau}, DM_{i\tau})|\Omega_{it}]\} \tag{8}$$

where δ is the discount factor. The state space for the dynamic optimization problem at time t for consumer i is Ω_{it}, which consists of the set of prices and qualities of current cameras, prices and sizes of memory cards, inventory of cameras and memory cards, the consumer's purchase time of each, and their qualities and the vector of unobserved taste shocks, so

$$\Omega_{it} = \{\{PC_t^c\}_{c=1}^{C}, \{PM_t^m\}_{m=1}^{M}, Y_t, Y_{R_{it}}, \{QC_t^c\}_{c=1}^{C}, \{Size_t^m\}_{m=1}^{M}, DC_{iR_{it}}, R_{it}, \left\{QC_{R_{it}}^c\right\}_{c=1}^{C}, \{DM_{i\tau}\}_{\tau=1}^{t-1}, \{\{Size_\tau^m\}_{m=1}^{M}\}_{\tau=1}^{t-1}, \boldsymbol{\varepsilon_{it}}\} \tag{9}$$

with letters in bold denoting vectors of all choice alternatives.

Our model inherently allows for three important inter-temporal tradeoffs. First, within each product category, a consumer faces the trade-off of purchase timing due to declining price and improving quality. This buy-now-or-later trade-off is well documented in marketing literature (Song and Chintagunta, 2003; Gordon, 2009; Gowrisankaran and Rysman, 2012). Second, given that a consumer makes purchase decisions about both base products and add-ons simultaneously, she must consider prices in both markets to achieve an optimal purchasing strategy. For example, assume that a consumer has two alternative camera brands to choose from: brand A with high quality-adjusted price and brand B with low quality-adjusted price. She anticipates the future price of memory cards compatible with brand A will be much lower than those compatible with brand B. She may sacrifice a high price in the camera category and buy brand A in order to gain more utility in the memory card category so that the financial cost of the portfolio is minimized. We refer to this trade-off as cross-category dynamic price and quality effects (Hartmann and Nair, 2010; Derdenger and Kumar, 2013). Third, a compatibility constraint between a camera and memory cards creates a trade-off of switching standards (Farrell and Klemperer, 2005). For example, assume that a consumer who owns a Sony Memory Stick is deciding which camera to purchase in a replacement occasion. If the consumer switches to a camera that uses a different standard of memory card, the consumer forgoes the continuous future consumption utilities provided by the Memory Stick. Moreover, she has to incur an added financial cost to purchase new memory cards to enhance the utility of the new camera. These losses can be offset only by higher total future utilities from the new brand of camera by offering higher quality at a lower price than Sony's. Fourth, the cost of switching associated with compatibility is moderated by the consumer's expectation of future compatibility. If the consumer expects that future cameras are incompatible with the memory cards in inventory, then the cost of switching vanishes. In summary, our model incorporates trade-offs regarding own-product inter-temporal price and quality effects, cross-category price and quality effects, and a cross-category dynamic inventory effect moderated by future compatibility expectations. To our knowledge, this is the first paper to study these effects simultaneously.

5.4. Expectations

Price and Quality Process

We assume that consumers have rational expectations about the stochastic processes governing the evolution of price and quality, which follow a first-order vector autoregressive process. We also take into account competitive reaction; i.e., the price and quality expectation of one brand/standard depends not only on its own lag price and quality, but also on that of all other competitors in the market. Furthermore, we capture the cross-category effect where the price and quality of a product in one category (e.g., cameras) depends on the lagged price and quality of all products in the other category (memory cards, including both compatible and incompatible ones).

$$\boldsymbol{H_t} = \begin{pmatrix} \boldsymbol{P_t} \\ \boldsymbol{Q_t} \end{pmatrix}$$
$$E(\ln \boldsymbol{H_t} \,|\Omega_{t-1}) = \boldsymbol{\Lambda} \ln \boldsymbol{H_{t-1}} + \omega Holiday_t + \boldsymbol{\eta_t} \tag{10}$$

Letters in bold denote vectors of all choice alternatives. More specifically, $\boldsymbol{P_t}$ is a column vector that includes all prices of cameras and memory cards; i.e., $\boldsymbol{P_t} = [PC_t^1\ PC_t^2\ PC_t^3\ PC_t^4\ PC_t^5\ PC_t^6\ PC_t^7\ PM_t^1\ PM_t^2\ PM_t^3]^T$ (T denotes transpose) and $\boldsymbol{Q_t}$ is a column vector that includes all qualities of cameras and memory cards, $\boldsymbol{Q_t} = [QC_t^1\ QC_t^2\ QC_t^3\ QC_t^4\ QC_t^5\ QC_t^6\ QC_t^7\ Size_t^1\ Size_t^2\ Size_t^3]^T$. $\underbrace{\boldsymbol{\Lambda}}_{2(C+M)\times 2(C+M)}$ is a matrix that captures the influence of competitors' price and quality, the interdependence between categories and between price and quality. We include $Holiday_t$, a dummy that indicates the fourth and first quarters of the year, because we observe significant discounts during the holiday season (Figure 1A). $E(.\,|\Omega_{t-1})$ is the conditional expectation given a set of state variables Ω_{t-1}. $\boldsymbol{\eta_t}$ is a column vector of random price shocks at time t. We assume that random shocks in prices/qualities follow a multivariate normal distribution:

$$\boldsymbol{\eta_t} \sim N\left(0, \Sigma_\eta\right) \tag{11}$$

Allowing random shocks to be correlated can further capture the co-movement of prices (qualities) of the competing brands. In this fashion, we utilize all past variables (price and quality) to characterize market dynamic interaction in a reduced form representation. The price (quality) process parameters are estimated using the price (quality) data prior to the estimation of the model. They are then treated as known in the model estimation when we solve the consumer's dynamic optimization problem.

Inventory Process

According to our assumptions, a consumer uses only the latest purchased camera. When the consumer buys a new camera c, its inventory switches from $DC_{iRP_{it}}$ to c. When no camera is purchased at time t, the inventory remains the same as in the last period[17].

As for the inventory process for the memory card, we keep track of all the memory cards ever purchased. For each memory card, we track its purchase time and size information. When the consumer is forming an expectation of future memory card inventory, we assume that the she will purchase a maximum of 4 cards[18], as observed in the data.

We also assume that consumers form a fully rational expectation of the compatibility status between cameras and memory cards. In other words, consumers can correctly expect that inventory of the memory cards will stop providing enhanced consumption utility when future cameras become incompatible with the old memory cards.

[17] So the inventory process for cameras is (after dropping the consumer index i)

$$DC_{iR_{it}} = \begin{cases} c, & if\ DC_{it} = c \\ DC_{iR_{it-1}}, & if\ DC_{it} = 0 \end{cases}$$

where DC_{it} is the indicator of a consumer's choice, with $DC_{it} = c$ denoting the consumer's purchasing brand c $(c = 1,2,3,4,5,6,7)$ as the base product and any memory card (including no purchase) as an add-on product. $DC_{iR_{it-1}}$ is the beginning camera inventory at time t.

[18] We offer a robustness check for this assumption in Appendix A6.

6. Estimation and Identification

We adopt a hierarchical Bayes approach (Imai, Jain, and Ching, 2009) to incorporate unobserved heterogeneity. Let the parameter vector be $\Theta_i = \{\alpha_i^1, \alpha_i^2, \alpha_i^3, \alpha_i^4, \alpha_i^5, \alpha_i^6, \alpha_i^7, \theta_i^{11}, \theta_i^{12}, \theta_i^{21}, \theta_i^{22}, \theta_i^{31}, \theta_i^{32}, \phi_i, \psi_i, \lambda_i, \kappa_i, \rho_i, \delta_i\}$. It is assumed to follow a multivariate normal distribution $\Theta_i \sim N(\bar{\Theta}, \sigma_\Theta^2)$.[19]

The maximization of (8) is accomplished by choosing the optimal sequence of control variables for $DC_{it} \in \{0,1,\dots,C\}, DM_{it} \in \{0,1,2,\dots,M\}$ and $\tau \in \{1,2,\dots,\infty\}$. Define the maximum expected value of discounted lifetime utility as

$$V_{it}(\Omega_{it}) = \max_{\{DC_{it}, DM_{it}\}} \{U_{it}(DC_{it}, DM_{it}) + \Upsilon E[\sum_{\tau=t+1}^{\infty} \max_{\{DC_{i\tau}, DM_{i\tau}\}} \Upsilon_i^{\tau} U_{i\tau}(DC_{i\tau}, DM_{i\tau}) | \Omega_{it}, DC_{it}, DM_{it}]\} \tag{12}$$

We discuss the details of value function and likelihood calculation in Appendix A7. To estimate the dynamic model, we follow the convention and fix the discount factor Υ at 0.95, for all consumers[20]. To handle the problem of a large state space, we use the random sampling method suggested in IJC (2009) and calculate the value functions only once in each MCMC iteration.

Next, we explain the source of identification for each of the model parameters. For some parameters, the identification intuition is straightforward. For instance, camera brand and memory card standard intercepts $(\alpha_i^1, \alpha_i^2, \alpha_i^3, \alpha_i^4, \alpha_i^5, \alpha_i^6, \alpha_i^7, \mu_i^1, \mu_i^2, \mu_i^3, \mu_i^4, \mu_i^5, \mu_i^6, \mu_i^7, \theta_i^{11}, \theta_i^{12}, \theta_i^{21}, \theta_i^{22}, \theta_i^{31}, \theta_i^{32})$ are identified by (time-varying) market shares[21]. Camera quality (ϕ_i), memory card quality (ψ_i) as well

[19] With our data originating near the inception of the digital camera industry, we set the initial state variables for camera and memory card inventories to be zeroes for nearly all consumers. Please find the evidence that supports this assumption in Appendix A7.

[20] We offer a robustness check for this assumption in Appendix A6.

[21] Although there is a 1:1 mapping between cameras and memory card standards, the purchase frequency ratio between cameras and compatible memory cards is not 1:1. This is because of repeated purchases of memory cards. And this fact can help us identify the memory card standard utility above and beyond the camera intercept. In our model, a consumer can purchase multiple memory cards to work with a single camera. This is demonstrated in Case 3: Purchase Memory Only. So the extent that different memory card standards have different repeat purchase probabilities can identify the intercept of memory card. Therefore, the market shares of cameras identify the intercepts of cameras while the market shares of memory cards identify the intercepts of memory cards.

as the camera-memory interaction coefficients (δ_i) are identified from the variations of the quality of the cameras and memory cards. The price coefficient (λ_i) is identified from price variations of both cameras and memory cards. We discuss only the last two parameters, state dependence (κ_i) and depreciation factor (ρ_i) in detail below.

The depreciation factor governs the add-on inventory effect and plays an important role in our model. If the depreciation factor is extremely low (≈ 0), the add-on inventory effect vanishes. In other words, when memory cards in inventory fully depreciate, they have no impact on a consumer's camera replacement decision, because the value of the memory cards in inventory is zero. Consequently, the consumer suffers the re-investment cost of purchasing new memory cards. Considering the role of the depreciation factor and the further incorporation of state dependence and heterogeneous consumer brand preference, identification of the depreciation factor is challenging, but possible. The depreciation parameter, which is pooled across memory standards, relies on the variation in time-to-purchase of any subsequent memory card after the purchase of a camera and the first compatible card. For instance, if the time-to-purchase a second memory card after the purchase of the first is short, the depreciation factor of that memory is low (closer to zero), given price and quality expectations. If such time-to-purchase is long, its depreciation factor is high (this strategy is similar to that of Hartmann and Nair (2010)). Variation in switching probabilities with the variation in the value of inventory also aids identification. If switching probabilities are flat as inventory varies, it means that the depreciation factor is small (close to zero), as memory has little impact on camera purchase decision. If switching probabilities decrease as the inventory size grows, then this indicates that the factor is large and that consumers value all memory, old and new. It is important to note that this data variation not only aids in identifying the depreciation term but also in quantifying the total add-on inventory effect. Next, we discuss how the state dependence parameter is identified separately from the above depreciation factor.

Theoretically, the identification of add-on inventory effect (depreciation factor), state dependence, and brand intercepts originates from distinct sources of data variation. Given that we have discussed the depreciation factor above, we move to discuss what other data variation separately identifies state dependence. Identification of state dependence employs all the purchase incidence data of cameras at the brand level but is agnostic to the number of memory cards one holds. Put differently, state dependence is manifested in persistent purchases of the same brand of cameras, regardless of the memory card inventory accumulation. It also uses only brand data where the depreciation term above uses the same purchase incidence data, but is leveraged at the standard level. Consider two consumers (X and Y), neither of whom has a memory card. X has a Sony camera and Y has no camera. If X is more likely to buy another Sony camera than Y, the state dependence factor is identified. Furthermore, it is well documented in the marketing and economics literature (Dubé et al., 2010; Paulson, 2012) that structural state dependence can be separately identified from unobserved heterogeneity if consumers' initial brand choices are known and there exists enough price variation to induce switching behavior. In our case, we are fortunate that the sample was collected at the beginning of the digital camera and memory card market. Hence we observe consumers' initial brand choice directly from the data. After carefully accounting for unobserved heterogeneity, we are able to identify both state dependence and brand intercepts. In summary, different dimensions of data variation allow us to pin down the depreciation factor, state dependence, and unobserved brand preference.

Finally, we discuss the number of data observations that are used to identify each of the above effects. In our sample, there are 231 repeat camera purchase incidences. Of those, 98 consumers have switched from a favorite brand to a less favorite brand of camera for the replacement choice, whereas 157 stayed loyal. The purchase incidences of these consumers help identify the state dependence effect. The depreciation term employs 157 repeat memory card purchase incidences for identification. It also uses the 231 repeat camera purchase incidences, but broken down by camera standard. These data are at the focus of the standard level, while the state dependence data are at the brand level. Last, brand preferences are identified by the average market share. All purchase incidences in the sample contribute to identification of the brand preference. Given this information, we strongly believe that we have enough data variation to identify the parameters of interest. To further support this claim we highlight the ability to recover model primitives via Monte Carlo simulations with the results presented in the Appendix A3.

7. Results and Discussion

7.1. Model Comparison

In order to evaluate the importance of incorporating the dynamic add-on inventory effect, we compare the data fitting performance of our proposed model with several alternative benchmark models. The first assumes a zero discount factor, no add-on inventory effect, and homogeneous consumers. This is a myopic model in which homogenous consumers are assumed to make independent purchase decisions about base and add-on products to maximize current utility—consumers do not consider the inter-temporal dependence between these two products. The second model adds to the first by incorporating forward-looking consumers. Even though customers are allowed to take into account future trends of prices and quality, their purchases of base products and add-ons are assumed to be independent, because this model does not recognize compatibility. The third benchmark adds the add-on inventory effect but assumes it is a constant, similar to Sriram, Chintagunta and Agarwal's (2009) estimated model. It is important to note that this model implicitly assumes that the add-on and base products are not required to be purchased simultaneously like those in Sriram et. al. for consumers to recover the additional benefit from memory. The fourth benchmark is the aforementioned model without heterogeneous consumers. The last model adds heterogeneous consumers and is our proposed model.

[Insert Table 5 about Here]

Table 5 presents the log marginal density (Kass and Raftery, 1995) of the five alternative models. All of our dynamic models (Models 2-5) outperform the myopic model (Model 1). This implies that there is an inherent dynamic process associated with the data generating process. Similarly, models recognizing the add-on inventory effect (Models 3-5) outperform the ones that treat the purchase decisions about base and add-on products independently (Models 1 and 2). Model fit further improves when we replace the add-on inventory effect in Model 3 with the cumulative inventory term of memory cards in Model 4. Such a result shows that a model taking into account all previously purchased memory cards better approximates the dynamic decision process than a model with a simple constant effect. Finally, our proposed model is superior because it captures the dynamic impact of add-ons on the purchase of the base product: when making brand/standard choices about base products, a consumer takes into account the quantity (and quality) of add-ons for each standard to evaluate the stream of future consumption utilities net of future re-investment costs.

7.2. Model Results

Below we discuss our model results. However, given the complexities of our model, we also focus on succinctly summarizing the findings through illustration. We focus on the two inter-temporal tradeoffs consumers face when making a purchase of a base and/or add-on product: (i) a cross-category pricing effect and (ii) the cross-category inventory effect. We first describe how consumers' brand choices of cameras are driven by inventory as well as by prices of memory cards. Next, we discuss how consumer inventory levels of a given memory card standard lock in consumers to a specific camera standard, due to the incompatibility of memory across camera standards. We finish with a discussion of dynamic price effects with the presentation of consumer price elasticities (we focus on the cross-category price effects, as within prices effects are less germane to our analysis).

[Insert Table 6 about Here]

In Table 6, we report the estimated coefficients for the proposed model. All the parameter estimates are statistically significant at the 0.05 level. The intercept terms represent consumer intrinsic preference for the seven brands of camera and three standards of memory cards. Comparison of these intercepts reflects the relative attractiveness of different brands within each category. For example, all else equal, consumers prefer Sony and Kodak, followed by Olympus, Canon, Fuji, Nikon, and HP in sequential order for cameras and Standard 1, Standard 2, and Standard 3 for memory cards. The camera time trend parameters ($\mu^1, \dots, \mu^7$) are all significantly positive, which indicates that the unobserved quality or brand intrinsic value is improving over time. And for memory cards, the newer generations always have a higher intrinsic value (intercept) than the older generations do.

The coefficients of quality for camera and memory cards are positive, implying that consumers care about the quality of the products. Not surprisingly, the coefficient of the state dependence term is positive, which suggests that consumers are more likely to purchase the same brand of camera as the one they have in hand. This estimate also can be interpreted as a measure of consumer inertia. As expected, the price coefficient is estimated to be negative, showing that consumers are price sensitive to the base and add-on products. The estimated depreciation effect is 0.92 per quarter. This corresponds to an annual depreciation rate of 0.72, which implies that after three years, the utility of a memory card in inventory will be only about one third of its initial utility at purchase time. This depreciation can be attributed to the fast quality improvement in the memory card industry over the sample period. Finally, we find that the interaction term between memory card utility and camera quality is significantly positive. This suggests that the consumer's utility of the memory card depends on the quality of the camera, possibly owing to the fact that if the camera takes a better picture, there is a higher value of capturing such.

7.3. Add-on Inventory Effect and Cross-category Dynamic Price Effect

Dynamic Add-on Inventory Effect and Interaction with Future Prices of Add-ons

[Insert Figure 7 about Here]

Figure 7 characterizes a consumer's decision rule describing how forward-looking consumers make a dynamic choice about cameras based on current inventory and the expected future price sequence of compatible memory cards. The purchase probability of a new camera increases with the inventory of compatible memory cards. This is because when planning her future purchase sequence, a consumer with a higher inventory of memory cards not only enjoys a long-term consumption utility stream, but also avoids a stream of future spending on new memory cards. This is the dynamic add-on inventory effect captured by our model. Interestingly, the dynamic add-on inventory effect is most prominent for Standard 1 (Sony) and Standard 3 cameras, in the sense that the purchase probability increases faster for the same amount of accumulation in memory card inventory. This is because when compared with those of Standard 2, Sony's memory cards offer a higher consumption utility stream, whereas Standard 3 memory cards offer a lower financial commitment. This implies that when switching to an incompatible camera, consumers incur not only a camera price, but also a future of purchasing additional memory cards of another standard and a loss of long-term consumption utility from existing cards.

Figure 7 also presents how a current purchase decision about a camera is driven by the future price trend of compatible memory cards. As expected, for all brands, when the expected future price of a memory card decreases, the purchase probability of the compatible camera increases because the financial commitment related to the planned purchase sequence for owning a composite of camera and memory card(s) is lower compared with other pairs.

Finally, it is important to discuss how the future price expectations interact with the aggregate dynamic add-on inventory effect. Although the add-on inventory effect does not explicitly account for the price of the memory cards, the inventory effect does indirectly, through a consumer's accumulation. The model determines, and we illustrate in Figure 7, that the add-on inventory effect becomes more prominent when consumers expect future prices of compatible memory cards to be higher, as consumers must spend more on purchasing new memory cards. Consequently, consumers are locked in and are more likely to purchase compatible cameras, to avoid incurring a higher switching cost. To summarize, higher future prices of memory cards can enhance the dynamic add-on inventory effect for compatible cameras.

Quantify Purchase "Lock-In" due to Compatibility

In order to demonstrate how a consumer's dynamic decision process is affected by compatibility, we quantify the amount of financial incentive each brand needs to offer in order to persuade a consumer to switch to a camera that is incompatible with a consumer's current inventory of memory cards. We define the cost of switching to be the minimum lump-sum payment needed for a manufacturer to induce a consumer to switch to its brand of camera as a replacement. Because the consumer is forward-looking, this cost of switching measures the difference between the total discounted values of two streams of utilities associated with the purchasing of two different cameras. More specifically, it is the difference between the continuation value of purchasing a compatible camera and the continuation value of switching to an incompatible brand, divided by the price sensitivity coefficient (we divide by the price coefficient in order to convert the measure into dollars).[22]

[Insert Table 7 about Here]

We report the cost of switching for the three brand groups in Table 7. On average, Olympus or Fujifilm need to offer a \$19.38 discount and Kodak/Canon/HP/Nikon need to offer a \$17.13

[22] Given this definition, the cost of switching is time and state-dependent. We pick an arbitrary period, period ten, and calculate the monetary equivalent of switching under the scenario of a representative consumer who has only one compatible memory card in inventory.

discount to induce consumers to switch from Sony. However, Sony has to offer only $14.82 to steal a consumer from Olympus/Fujifilm and $15.04 to induce brand switching from Kodak/Canon/HP/Nikon. From the above comparison, we see that Sony (the first row) has the highest cost of switching. For consumers who hold the same amount of memory cards in inventory, it is more costly to attract consumers from Sony to other brands than vice versa. Thus, Sony enjoys the highest rate of "lock in" or loyalty partly because of its incompatibility with rival products—Sony owners enjoy higher total discounted future utility from memory cards in inventory by purchasing a compatible camera than purchasing a non-compatible camera. Consequently, when product replacement becomes more frequent as product quality improves over time, such a lock-in effect creates continuous sales for Sony.

A comparison of switching costs also indicates that it takes a larger discount to incentivize consumers to switch from Standard 3 cameras ($15.04 and $16.53) than from Standard 2 cameras ($14.82 and $14.18). This is because Standard 3 cameras have a higher add-on inventory effect, due to the lower future prices of Standard 3 memory cards than those of Standard 2. This enhances the dynamic add-on inventory effect and competitiveness of Standard 3 cameras.

We decompose the total cost of switching in order to measure the relative contribution of the add-on inventory effect. We also further decompose the switching cost due to i) price and quality differences between camera brands and ii) state dependence.[23] Because the cost of switching varies with the consumers' expectations on the future compatibility, we perform the decomposition analysis at two representative periods: one right before a standard compatibility change and the other over a year prior. Specifically, we pick period fifteen (second quarter of 2002), the quarter before Standard 1 changed from the Memory Stick to the Memory Stick Pro Duo, and period ten (first quarter of 2001), which is over a year away from the compatibility change.

[23] Please find the detailed procedure in Appendix A5.

[Insert Table 8A and 8B about Here]

Table 8A above shows the result of decomposition at time period ten. We find that it requires 2.96 dollars of compensation for a Sony owner to switch to Olympus or Fujifilm (cameras that are compatible with Standard 2 memory cards) when consumers lack loyalty (state dependence) to the camera brand or have no add-on inventory effect. This is because Sony cameras provide higher utility to consumers than alternative brands (higher intercept net of price and quality effect from Table 6). However, the price and quality differences only account for a very small portion (15%=2.96/19.38) of the switching cost. In contrast, state dependence accounts for 57% (=11.13/19.38) of the cost of switching, while the add-on inventory effect accounts for the other 28% (=1-15%-57%). Similarly, the decomposition of the cost of switching from Sony to cameras compatible with Standard 3 memory cards shows that 16% of the cost comes from price/quality effect, 65% comes from the state dependence, and 19% comes from the add-on inventory effect. Note that there is no variation in the state dependence factor, because our model sets the state dependence coefficient to be the same across all brands.[24]

The results differ for time period fifteen (Table 8B), the period before the Memory Stick (Standard 1-1) was upgraded to the Memory Stick Pro Duo (Standard 1-2). This is due to consumers expecting that the Memory Stick in inventory would not be compatible with new cameras when the Memory Stick Pro Duo was introduced. As a result, the add-on inventory effect vanished. The cost of switching dropped to $14.09 (from Standard 1 to Standard 2) and $13.86 (from Standard 1 to Standard 3), respectively.

It is evident that the add-on inventory effect is an important source of the cost of switching, above and beyond the state dependence effect.

[24] We do not have enough degrees of freedom to identify standard-specific or brand-specific state dependence from the data.

Price Elasticity

With our model built at the brand and standard choice level, we are able to examine how price affects brand or standard switching decisions. In addition, our model takes into account the inter-temporal dependence of base and add-on products. In Table 9A and Table 9B, we report the percentage changes in sales[25] when the price increases by 1% for both camera brands and memory card standards, at the (a) standard and brand (b) levels. There are many notable results; however, we focus on the most interesting ones related to cross-category elasticities.

[Insert Table 9A and 9B about Here]

First, Table 9A[26] shows that for cameras, the within-standard competition is stronger than the cross-standard competition. For example, when the price of Olympus cameras increases, the demand percentage increase for the other camera brands that are also compatible with Standard 2 memory cards (0.538) are higher than the demand percentage increase for cameras that are incompatible with the Standard 2 memory cards ({0.453, 0.511, 0.184, 0.159, 0.372}). This implies that consumers are more likely to switch to a different camera brand within the same standard family than to switch to other incompatible standards. This pattern is consistent across all cameras compatible with the Standard 2 and Standard 3 memory cards (i.e., Olympus, Fujifilm, Kodak, Canon, HP, and Nikon).

Moreover, it is interesting to note in Table 9B that own-category price effect dominates cross-category price effect for all brands with the exception of Sony. For instance, the purchase probability of the Sony camera decreases by 1.268% when the price of Sony memory increases by 1% but only by 1.065% when the price of the Sony camera increases by 1%. In other words, the change of purchase probability for the Sony camera decreases more when the price of the compatible Standard 1 memory

[25] We consider both short-term and long-term price elasticities by taking an average over all periods. Specifically, in a particular period, we increase the price of each camera (and memory card) by 1%, then calculate the average change in sales in the subsequent periods (up to six years). We repeat this process for all the time periods and then calculate the average price elasticities.

[26] Here are the interpretations of the row labels: "C1" denotes the price elasticity of Sony; C2-own and C3-own denote the own price elasticity of cameras compatible with the standard 2 and standard 3 memory cards respectively; ; C2-cross and C3-cross denote the cross price elasticity of cameras compatible with the standard 2 and standard 3 memory cards respectively.

card decreases than when its own price decreases. This is because the high price charged by Sony for its memory card prevents consumers from purchasing more memory cards, thus eroding the dynamic add-on inventory effect to a point that consumers become highly sensitized to the price of memory cards.

Furthermore, when examining the cross-category elasticities listed in the last three columns, we find that when the price of a Standard 1 or 2 memory cards increases, most sales transfer to Standard 3 cameras. For example, when Sony increases the price of its memory card, the sales of Standard 3 cameras (Canon and Kodak) increase more than those of Olympus and Fuji. Similarly, when the price of a Standard 2 memory card increases by 1%, the sales of Standard 3 cameras also increase more than those of Sony. Consequently, higher memory card prices drive consumers to a more open standard in which more cameras can share the same memory card (emphasis added).

8. Counterfactual Simulations

In order to address the impact of several important research questions pertaining to compatibility, we employ the above estimated model primitives in two counterfactual simulations. In the first, we attempt to understand how the market changes when all compatibility constraints are eliminated. Consequently, what role does incompatibility play on market share? Next, we ask the question: is incompatibility or a closed system beneficial for all firms? Specifically, how does brand equity moderate the effects of incompatibility on market share? It is important to highlight the fact that the simulations below recover only partial equilibrium effects. We do not fully account for changes in product quality or rival firms responding to changes in compatibility across standards. The results are therefore partial equilibrium effects.

8.1. What If All Standards are Compatible?

To investigate the implication of compatibility, we carry out a simulation wherein we estimate average choice probabilities of cameras and memory cards of different standards under the assumption that all cameras and memory card standards are compatible. For instance, a previously purchased Sony Memory Stick can be used on any newly purchased cameras from Olympus, Fujifilm, Kodak, Canon, HP, and Nikon, in addition to Sony. Thus, all memory cards in inventory will exert the add-on inventory effect for the purchased camera. To approximate this scenario, we set the add-on inventory effect to be the sum of inventory of all memory cards, as if no compatibility constraints exist across standards.

[Insert Table 10 about Here]

In columns 2 and 3 of Table 10, we compare the purchase probabilities with those generated by the counterfactual simulation; from this we can understand the extent to which compatibility changes the purchase probabilities of base products. The results suggest that if the Sony Memory Stick were compatible with the products of all its competitors, its camera market share would drop by 6.22 percentage points (from 30.83 percentage points to 24.61 percentage points) and by roughly 4.83 percentage points (from 31.79% to 26.96%) for memory. On the other hand, the market shares for Kodak, Canon, HP, and Nikon jump by 6.81 percentage points (from 47.87 percentage points to 54.68 percentage points), and the share for Standard 3 memory cards increases by 4.77 percentage points (from 47.32 percentage points to 52.09 percentage points).

These changes occur because consumers are no longer locked-in by the memory standards. Without the compatibility constraint, consumers are free to choose whatever brand of new camera and memory they like for their next purchase. Given full compatibility, competition in the memory card and camera markets increases. For instance, consumers now have more options in the memory card choice set to choose from.[27] Furthermore, because markets are now less connected to one another and the switching cost consists only of price/quality differences and excess inertia (state dependence), consumer demand for camera brands should more closely follow the quality adjusted price. This latter fact is especially true for the memory card market. Figure 4B highlights the quality adjusted price for cameras and memory cards, respectively. Starting with memory cards, it clearly highlights that Standard 3 has, on average, the lowest quality adjusted price of the three and is followed by Standards 2 and 1, respectively. This informs us that Standard 3 should dominate the other two standards and that the market could perhaps tip in its favor, given the lack of compatibility constraints. Yet, brand equity (intercept terms) plays an important role, as it enables brands to retain market share when faced with more intense competition. For instance, Sony's large brand equity value in memory allows it to retain some market share, even though its quality adjusted price is not the lowest. As for camera shares, the large measure of brand equity also seen for Sony in the camera market enables the brand to retain market share given its high quality adjusted price. The impact of this, along with the role of inertia (state dependence), enables Sony to retain a higher level of market share.

8.2. Is Incompatibility Beneficial for All Firms?

From section 5.1 we know that Sony has the largest intrinsic brand preference, or the strongest brand equity in the camera market. Such strong brand equity lays the foundation for its success. But what if this were not the case? What if its brand equity were not as strong? Would the aid of the add-on inventory effect stemming from incompatibility be marginalized and thus have less influence on the market for base products? We find it necessary to examine how brand equity moderates the effects of incompatibility in order to answer these questions. We run a series of policy simulations where Sony's brand-specific intercept is set to that of the brand that ranks 2nd to 7th in the market. We compare the market share of Sony before and after eliminating incompatibility between memory cards and cameras

[27] A full equilibrium effect in this market may incorporate a price decline in memory cards due to the increased competition.

(as done in section 6.1). Figure 8 depicts how the effect of incompatibility varies with Sony's brand equity rank. As we can see, when Sony had the strongest brand equity, creating compatibility with other standards had a significant impact on its market share—a decrease of 6.3 percentage points. This effect of compatibility diminishes as Sony's brand equity advantage vanishes (from rank 1 to rank 4). Strikingly, Sony's market share increases if it creates an open memory card format when Sony's brand equity falls below the industry average (rank 5 to rank 7). In other words, a market follower should not set up a compatibility constraint to bind itself (Katz and Shapiro, 1985).

[Insert Figure 8 about Here]

8.3. Managerial Recommendations

The results of the above counterfactual exercises provide important insights into when a brand should implement a proprietary standard. We determine that a weak brand equity firm should not develop a proprietary memory standard (impose a compatibility constraint) and bind itself to one particular memory form as such a constraint restricts the firm's demand due to consumers valuing openness. However, a high brand equity firm can increase its market share if it creates a proprietary memory card format, as it enables the brand to overcome the preference for openness as well as, and most importantly, locks consumers into its standard. In summary, weak brand equity firms should elect to either be compatible with the leading brand or create a union with other players in the market to diminish the market power of the leading brand in order to remain competitive in the market place, while strong brands can elect the go it alone strategy and garner sizeable market share in both complementary markets.

Additionally, when firms face a market with open standards, competition is quite fierce. As such it is quite difficult for a follower to enter into the market place. In such a setting what allows firms to retain profits and market share is the accumulated brand equity. With late movers/followers have little brand equity, they are thus forced to compete on price and quality dimensions, which are costly. Therefore, in an open standards market, late movers are at significant disadvantage over their early mover counterparts.

In addition to the above managerial insights we also discuss how a firm can further leverage the camera-memory compatibility constraints to its competitive advantage. Our model illustrates that a firm has a strong incentive to lock customers into its camera-memory standard and does so by capitalizing on a consumer's inventory of memory cards and their lack of compatibility with other camera-memory standards. Once locked-in, consumers are significantly more likely to upgrade to a brand within the same standard. Consequently, an important question to address is whether a firm can use price to create greater switching costs and thereby strengthen the consumer lock-in effect.

In markets with complementary products such as razors and blades, printer and ink, eReaders and eBooks, firms traditionally follow a razor and blades pricing model and subsidize the base product to extract rents from the add-on. However, these models usually ignore the durable nature of the add-on/complementary product (e.g. ink; blades, eBooks). In the case of durable add-ons, the durable nature of the product puts an even greater incentive to lower the price of the base product than the typical razor and blade model. For instance, in our setting, this is due to the role the memory inventory and system compatibility plays in creating switching costs and locking customers into a particular camera-memory standard. In the non-durables case, a consumer does not have this lock-in effect as blades, ink and books are discarded after use, which allows a consumer to quickly change standards if so desired. One potential pricing strategy for a firm, which owns both the camera and memory, is to set an initial low price for the memory that increases the likelihood of purchasing its camera brand. Doing so also pulls forward the purchase timing, allowing the consumer to enjoy the stream of utility from the camera and memory cards for a longer duration. Once, the market has been saturated, the firm, in theory, is then able to increase its memory (or camera) price to extract larger rents from consumers who are locked-in to its standard.

9. Conclusions, Limitations and Future Research

High-technology durable products often comprise base products and add-ons. When making purchase decisions, forward-looking consumers take into account price and quality, as well as compatibility, and make joint inter-temporal decisions across categories. We develop a framework in which forward-looking consumers make joint choice decisions regarding the base and add-on products when multiple incompatible standards exist. We model consumers' repeated choices at the brand and standard level given compatibility constraint. Compatibility makes the purchase behavior of two categories dynamically interdependent, because when choosing which base product to buy, a consumer must take into account the effect of forgoing future consumption utilities and incurring future financial costs for the add-ons if she switches standards. This novel model feature enables us to calibrate cross-brand, cross-standard, and cross-category price elasticity and compare the relative magnitude of each. After establishing these elasticities, we further examined consumers' switching propensity in brand and standard, as well as interdependence across categories. Our results enrich the current literature by further probing the effect of compatibility on consumer choices at the standard and category level.

We found that when making a purchase decision for the base product, consumers take into account future prices of the add-on product, because the financial commitment is related to the planned purchase sequence of both categories. Moreover, consumers are locked in to the base product brand by the dynamic add-on inventory effect, which becomes stronger with greater inventory levels of add-ons. Furthermore, the dynamic add-on inventory effect can be enhanced by higher future prices of add-ons. These interesting consumer behaviors have important firm strategy implications. We found that among three standards, Sony's Memory Stick has the highest cost of switching and greatest lock-in effect. Following this, we demonstrated that Sony gained profits from developing its proprietary standard of memory card (the Memory Stick). We also found that such a strategy might not be as profitable for a manufacturer with lower brand equity.

The above results are important to the switching cost literature, but we also find it important to highlight key limitations or constraints on the model, which restrict the generalizability of our results. A key feature/parameter of our model is the depreciation factor associated with memory cards in inventory. It plays a vital role in formulating a consumer lock-in effect. If the depreciation factor were zero, the lock-in effect would be negligible. Given this, we believe it is important to discuss several factors that would lead to a small estimate of the depreciation parameter or a high rate of depreciation of memory cards in inventory as well as other factors that would diminish the size of the lock-in effect. The first factor is the nature of the add-on product—is it a durable or non-durable? Non-durable add-ons such as ink (with printers) or blades (with razors) will have high depreciation rates due to the fact that once ink or blades are used they cannot be used again. Thus, having a durable add-on is a necessary condition to create a lock-in effect from add-on inventory. Factor two is related to the degree of innovation. For example, if the change in quality of memory cards from one innovation cycle to the next is large, the value of the existing memory in inventory will depreciate fast. Two additional factors unrelated to depreciation impact the lock-in effect: i) compatibility of the add-on inventory with upgraded camera and ii) the replacement cost of add-ons. Compatibility is a vital feature and the main driver of the lock-in effect. The fact that a new camera is compatible with one's memory inventory provides a consumer a strong incentive to purchase a camera within the same standard. Furthermore, the replacement cost of add-ons impacts the consumer's switching cost/lock-in effect. A high replacement cost leads to a greater total financial cost associated with a new camera of a differing standard, which creates another incentive to remain with the consumer's current camera/memory standard.

Our research is subject to limitations that open areas for future research. First, in the high-technology product market with frequent innovations, consumer brand preferences might evolve over time. Researchers might want to model ever-changing consumer intrinsic brand preference to better capture the demand dynamic. Second, the current paper assumes that price and quality are exogenously given. A very interesting topic to explore is how firms design the full product line by deciding price trajectories for both base products and add-ons, taking consumers' dynamic decision-making processes into consideration. A full equilibrium model is needed to solve this problem from both sides of supply and demand. Third, Gabaix and Laibson (2006) reveal interesting phenomena regarding base product and add-ons where firms shroud information about add-ons to consumers. Only sophisticated consumers take advantage of the firm that shrouds information by avoiding add-on purchases; the unsophisticated fall into the trap of high add-on prices. Our paper supports the decision-making process of sophisticated consumers with evidence of their consideration of base products and add-ons at the same time. Future research can modify our model to allow only part of the consumers to be forward-looking, whereas the rest will be short-sighted. Fourth, we keep other firm strategies—for example, product design, pricing, and cost structure—exogenous. But in reality, making add-on products compatible with base products involves engineering design, which will affect other firm decisions.

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Table 1. Memory Card Timeline

<table>
<tr><th></th><th>Std. 1(SON)</th><th>Std. 2(OLY/FUJ)</th><th>Std. 3(KOD/CAN/HP/NIK)</th></tr>
<tr><td>1996</td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="2">PCMCIA</td></tr>
<tr><td>1997</td></tr>
<tr><td>1998</td><td>DISK/MS</td><td rowspan="4">SM</td><td rowspan="3">CF</td></tr>
<tr><td>1999</td><td rowspan="4">MS</td></tr>
<tr><td>2000</td></tr>
<tr><td>2001</td><td>CF/SD</td></tr>
<tr><td>2002</td><td>SM/XD</td><td rowspan="3">SD</td></tr>
<tr><td>2003</td><td rowspan="2">MS Pro
/MS Pro Duo</td><td rowspan="2">XD</td></tr>
<tr><td>2004</td></tr>
</table>

Note: DISK: 3.5 floppy disk, MS: Memory Stick, SM: SmartMedia card, XD: xD card, CF: CompactFlash, SD: SD card. We exclude the 3.5" floppy disk because our sample period starts from the fourth quarter of 1998, after the Memory Stick was launched.

Table 2. Memory Card Referred Names

Standard	Generation	Referred Name	Card Type
1	1	Standard 1-1	Memory Stick and Memory Stick Pro
	2	Standard 1-2	Memory Stick Pro Duo
2	1	Standard 2-1	SmartMedia
	2	Standard 2-2	xD
3	1	Standard 3-1	CompactFlash
	2	Standard 3-2	SD (Secure Digital)

Table 3A. Summary of Purchase Incidences of Cameras and Memory Cards

Camera Purchases			**Memory Purchases**		
Brand	**Frequency**	**Percentage**	**Standard**	**Frequency**	**Percentage**
Sony	295	27.86%	**1 (Sony)**	309	29.63%
Olympus	172	16.24%	**2 (Olympus, Fuji)**	241	23.11%
Fuji	81	7.65%	**3 (Kodak, Canon, HP, Nikon)**	493	47.27%
Kodak	212	20.02%			
Canon	114	10.76%			
HP	89	8.40%			
Nikon	96	9.07%			

Table 3B. Total Purchase Incidences

Camera\Memory	0	1	2	3	4	5	Total
1	17	621	56	5	3	0	702
	2.05%	75.00%	6.76%	0.60%	0.36%	0.00%	84.78%
2	11	8	6	2	0	0	27
	1.33%	0.97%	0.72%	0.24%	0.00%	0.00%	3.26%
3	4	10	26	47	5	1	93
	0.48%	1.21%	3.14%	5.68%	0.60%	0.12%	11.23%
4	0	0	0	0	1	5	6
	0.00%	0.00%	0.00%	0.00%	0.12%	0.60%	0.72%
Total	32	639	88	54	9	6	828
	3.86%	77.17%	10.63%	6.52%	1.09%	0.72%	100.00%

Table 3C. Summary Statistics of Price and Quality for Camera

	Sony	**Olympus**	**Fuji**	**Kodak**	**Canon**	**HP**	**Nikon**
Price	521.577	429.172	339.028	387.213	504.043	256.239	342.537
Quality (Megapixel)	3.898	3.895	3.547	3.889	4.082	3.316	4.444

Table 3D. Summary Statistics of Price and Quality for Memory Card

	M 1	**M 2**	**M 3**
Price	65.182	72.989	62.230
Quality (Megabyte)	3.058	2.900	3.089

Table 4. Cross-category Price/Quality Effect

	Log(Sales_C) (S.E.)
Intercept	1.2087***
	(0.3510)
Log(Price of Camera)	-0.1191*
	(0.0521)
Log(Current Price of Memory Card)	-0.0655**
	(0.0265)
Log(Future Price of Memory Card)	-0.0135*
	0.0062
Number of Observations	939
R2	0.065

Table 5. Model Comparison

	Model 1: No Dynamics	**Model 2: No Compatibility**	**Model 3: Static Compatibility**	**Model 4: No Heterogeneity**	**Proposed Model**
Log-Marginal Density	-5660.15	-5584.56	-5371.93	-5100.91	-4836.31

Table 6. Estimation Results

Parameters	Posterior Mean	Credible Interval of Mean	Standard Deviation	Credible Interval of Standard Deviation
Intercept: Sony ($\boldsymbol{\alpha^1}$)	-0.275	[-0.362,-0.188]	0.095	[0.081,0.109]
Intercept: Oly ($\boldsymbol{\alpha^2}$)	-0.638	[-0.776,-0.500]	0.048	[0.040,0.055]
Intercept: Fuji ($\boldsymbol{\alpha^3}$)	-1.241	[-1.291,-1.191]	0.047	[0.040,0.054]
Intercept: Kodak ($\boldsymbol{\alpha^4}$)	-0.586	[-0.693,-0.479]	0.249	[0.223,0.275]
Intercept: Canon ($\boldsymbol{\alpha^5}$)	-0.709	[-0.802,-0.616]	0.201	[0.168,0.234]
Intercept: HP ($\boldsymbol{\alpha^6}$)	-1.964	[-2.086,-1.842]	0.135	[0.107,0.162]
Intercept: Nikon ($\boldsymbol{\alpha^7}$)	-1.709	[-1.808,-1.610]	0.080	[0.068,0.092]
Time: Sony ($\boldsymbol{\mu^1}$)	0.018	[0.012,0.024]	0.016	[0.012,0.020]
Time: Oly ($\boldsymbol{\mu^2}$)	0.025	[0.017,0.033]	0.007	[0.005,0.009]
Time: Fuji ($\boldsymbol{\mu^3}$)	0.079	[0.054,0.104]	0.005	[0.004,0.006]
Time: Kodak ($\boldsymbol{\mu^4}$)	0.003	[0.002,0.003]	0.057	[0.046,0.069]
Time: Canon ($\boldsymbol{\mu^5}$)	0.001	[0.001,0.002]	0.029	[0.023,0.035]
Time: HP ($\boldsymbol{\mu^6}$)	0.061	[0.040,0.082]	0.050	[0.040,0.061]
Time: Nikon ($\boldsymbol{\mu^7}$)	0.035	[0.024,0.047]	0.009	[0.007,0.011]
Intercept: Stdrd 1-1 ($\boldsymbol{\theta^{11}}$)	2.548	[2.433,2.663]	0.216	[0.215,0.216]
Intercept: Stdrd 1-2 ($\boldsymbol{\theta^{12}}$)	3.949	[3.910,3.987]	0.198	[0.197,0.199]
Intercept: Stdrd 2-1 ($\boldsymbol{\theta^{21}}$)	-0.534	[-0.684,-0.384]	0.209	[0.169,0.249]
Intercept: Stdrd 2-2 ($\boldsymbol{\theta^{22}}$)	-0.294	[-0.393,-0.194]	0.210	[0.170,0.250]
Intercept: Stdrd 3-1 ($\boldsymbol{\theta^{31}}$)	-2.459	[-3.020,-1.898]	0.092	[0.079,0.105]
Intercept: Stdrd 3-2 ($\boldsymbol{\theta^{32}}$)	-1.726	[-1.913,-1.539]	0.083	[0.070,0.096]
Cquality ($\boldsymbol{\phi}$)	0.598	[0.500,0.696]	0.069	[0.067,0.070]
Mquality ($\boldsymbol{\psi}$)	0.128	[0.082,0.174]	0.085	[0.084,0.086]
Price ($\boldsymbol{\lambda}$)	-2.225	[-2.232,-2.218]	0.001	[0.000,0.002]
State Dep ($\boldsymbol{\kappa}$)	0.045	[0.027,0.063]	0.020	[0.015,0.025]
Depreciation ($\boldsymbol{\rho}$)	0.915	[0.701,1.129]	0.061	[0.056,0.066]
CMInteraction ($\boldsymbol{\delta}$)	0.024	[0.015,0.033]	0.013	[0.011,0.014]

Table 7. Cost of switching

Average	Sony	Olympus/Fuji	Kodak/Canon/HP/Nikon
Sony	$0	$19.38	$17.16
Olympus/Fuji	$14.88	$0	$14.26
Kodak/Canon/HP/Nikon	$15.04	$16.62	$0

Table 8A. Decomposition of Cost of Standard Switching at T=10 for A Consumer with One Memory Stick

Switching Direction	Cost of switching	Camera Price/Quality	State dependence[28]	Memory Inventory
Son (Standard 1)→ Oly/Fuj (Standard 2)	$19.38	$2.96	$11.13	$5.29

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[28] Note that switching cost derived from state dependence is the same across brands. This is because in the utility function, the state dependence parameter SD_i, is not brand specific, as there are not enough replacement purchases to identify different SD_is for different brands.

Son (Standard 1)→Kod/Can/HP/Nik (Standard 3)	$17.16	$2.73	$11.13	$3.30

Table 8B. Decomposition of Cost of Standard Switching at T=15 for A Consumer with One Memory Stick

Switching Direction	Cost of switching	Camera Price/Quality	State dependence	Memory Inventory
Son (Standard 1)→ Oly/Fuj (Standard 2)	$14.09	$2.96	$11.13	$0
Son (Standard 1)→Kod/Can/HP/Nik (Standard 3)	$13.86	$2.73	$11.13	$0

Table 9A. Price Elasticities at Standard Level

	SonC	OlyC	FujC	KodC	CanC	HPC	NikC	M1	M2	M3
C1	-1.057	0.472	0.302	0.598	0.381	0.195	0.386	-1.243	0.050	0.635
C2-own	0.453	-2.789	-14.069	0.511	0.184	0.159	0.372	0.255	-3.298	0.829
C2-cross		0.538	0.510							
C3-own	0.460	0.311	0.171	-1.536	-3.561	-4.480	-3.580	0.408	0.314	-1.101
C3-cross				0.608	0.401	0.211	0.401			

Table 9B. Price Elasticities at Brand Level

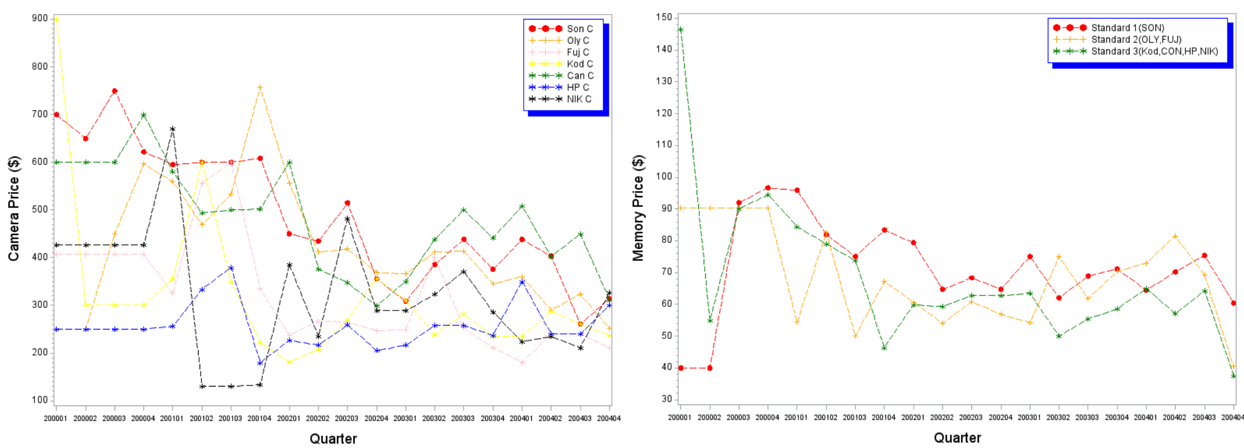
	SonC	OlyC	FujC	KodC	CanC	HPC	NikC	M1	M2	M3
SonC	-1.065	0.480	0.294	0.594	0.388	0.194	0.380	-1.268	0.052	0.613
OlyC	0.456	-2.799	0.505	0.492	0.287	0.019	0.273	0.278	-1.679	0.672
FujC	0.432	0.515	-14.073	0.823	-0.054	0.483	0.591	0.194	-7.055	1.167
KodC	0.713	0.195	0.167	-1.543	0.397	0.188	0.068	0.235	0.221	-1.148
CanC	0.303	0.287	0.125	0.677	-3.559	0.251	0.429	0.680	0.392	-0.723
HPC	0.247	0.500	0.325	0.211	0.116	-4.498	0.016	0.407	0.541	-1.030
NikC	0.169	0.468	0.041	0.371	0.128	0.134	-3.579	0.389	0.149	-1.793
OutC	0.016	0.085	0.035	0.058	-0.207	-0.011	0.009	-0.090	0.147	0.030
M1	-1.272	0.275	0.308	0.512	0.314	0.275	0.070	-3.267	0.396	0.620
M2	0.127	-2.961	-0.598	0.277	0.217	0.144	0.254	0.182	-4.560	0.780
M3	0.262	0.380	0.144	-0.704	-0.091	-0.212	-0.479	0.480	0.410	-2.441
OutM	-0.139	-0.149	-0.029	-0.006	-0.004	-0.050	0.052	0.085	0.018	0.156

Table 10. Policy Simulations

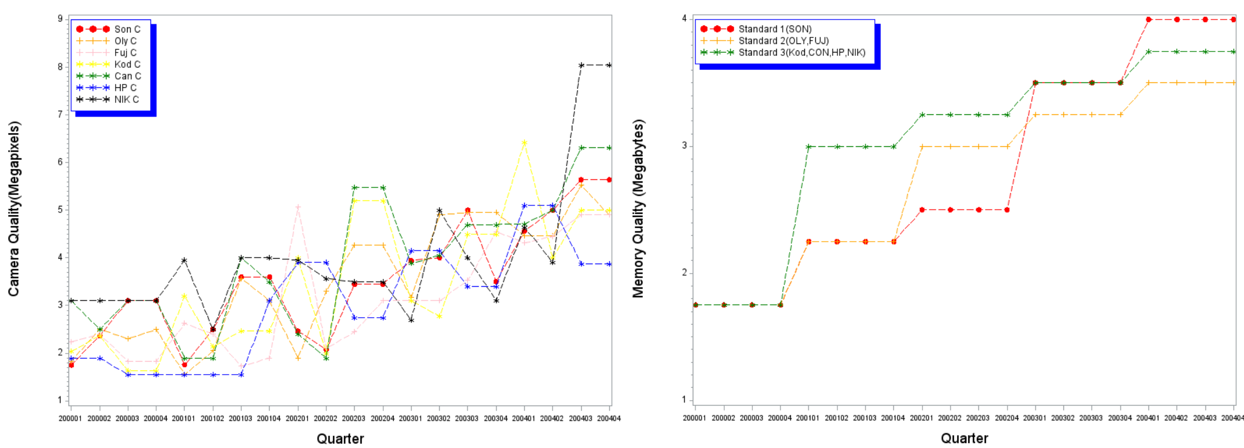
	Market Share of Cameras		
	Benchmark	**No Compatibility**	
Son	30.83%	24.61%	-20.18%
Oly	15.04%	14.67%	-2.42%
Fuji	6.26%	6.04%	-3.61%
Kod	21.53%	26.42%	22.68%
Can	11.45%	12.48%	9.00%
HP	8.81%	9.22%	4.62%
Nik	6.07%	6.56%	8.07%

	Market Share of Memory Cards		
	Benchmark	No Compatibility	
Std1	31.79%	26.96%	-15.19%
Std2	20.90%	20.14%	-3.61%
Std3	47.32%	52.90%	11.80%

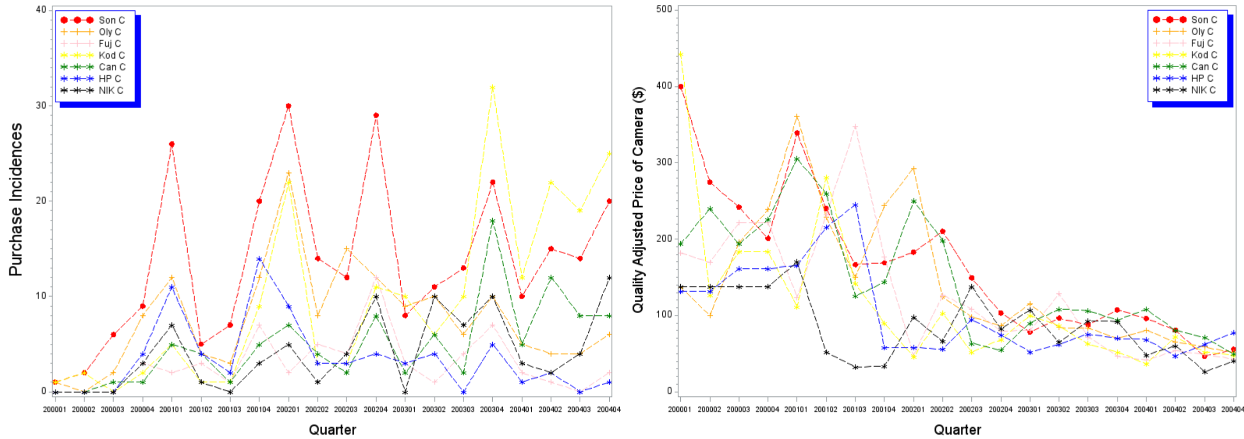
Figures 1A and 1B. Original Price Trend of Camera and Memory Card by Quarter



Figures 2A and 2B. Quality Trend of Camera and Memory Card



Figures 3A and 3B. Purchase Incidences and Price (Adj. by Quality) Trend of Camera by Quarter



Figures 4A and 4B. Purchase Incidences and Price (Adjusted by Quality) Trend of Memory Card by Quarter

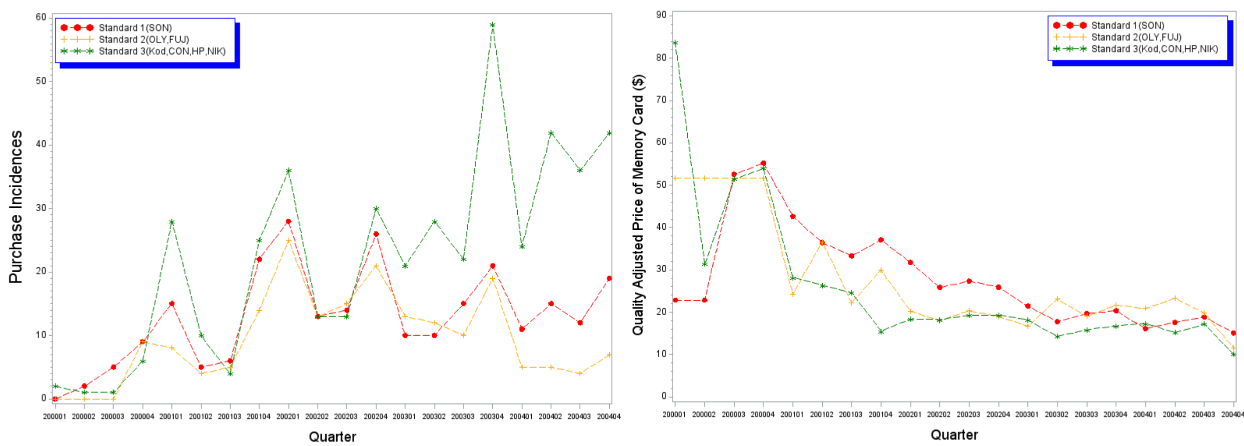


Figure 5A. Percentage of Camera Purchases at Memory Card Inventory

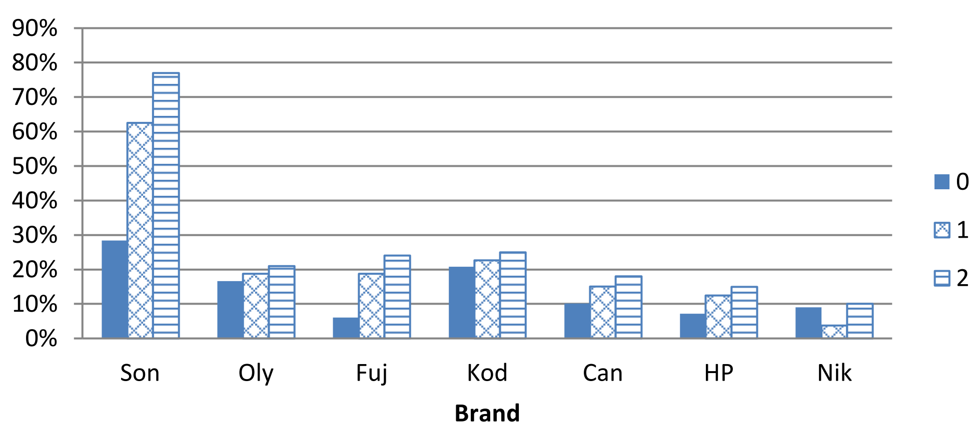


Figure 5B. Percentage of *Repeat* Camera Purchases at Memory Card Inventory

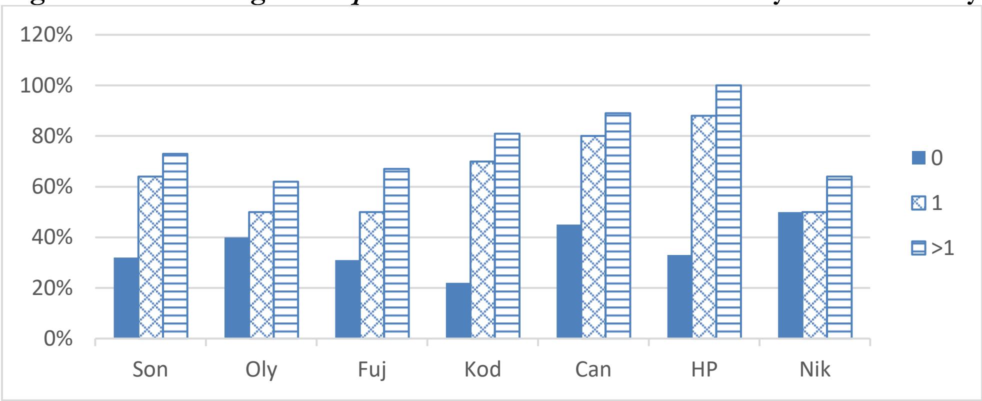


Figure 6. Expected Future Incompatibility Reduces Memory Card Market Share

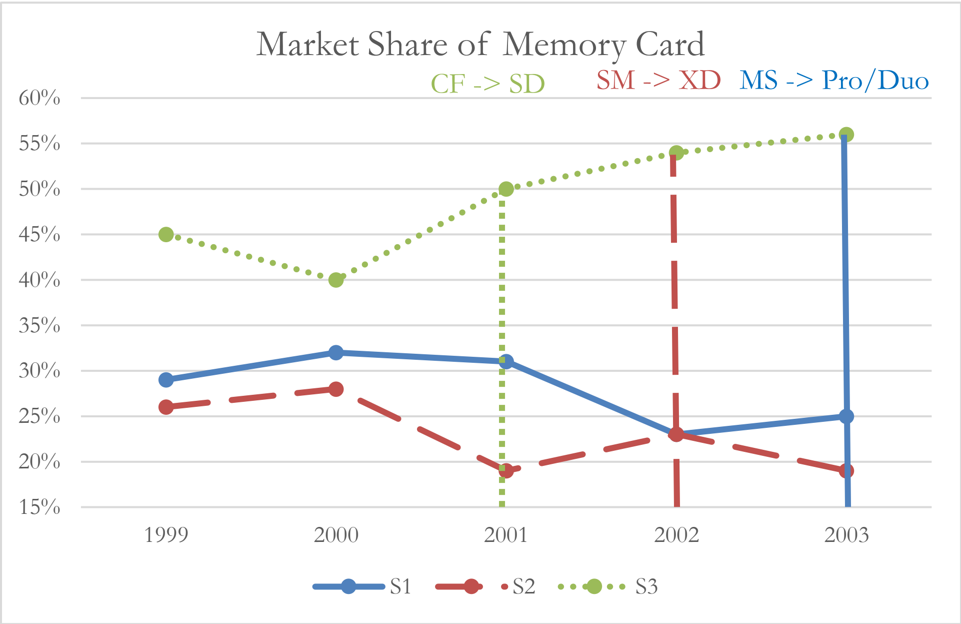


Figure 7. Purchase Probability of Camera is Driven by the Expected Future Price and Current Inventory of Memory Card

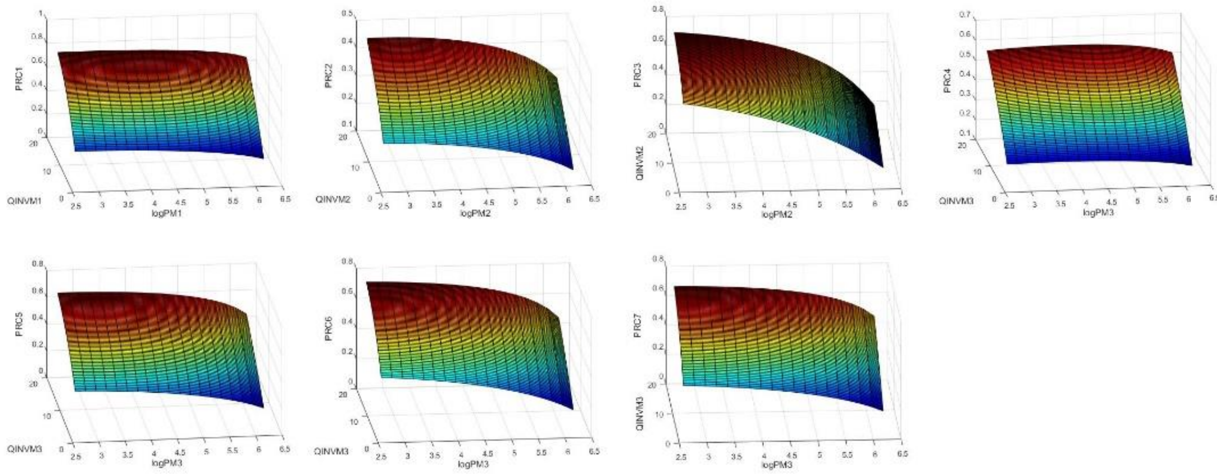
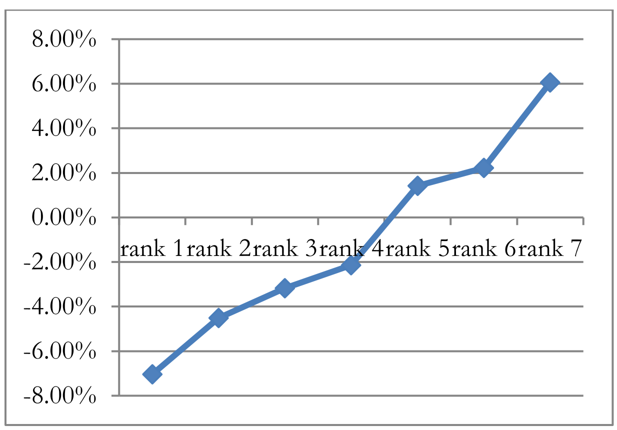


Figure 8. Sony's Market Share Loss of Eliminating Incompatibility at Different Brand Equity Ranks



Appendix A1. Memory Card Timeline

Table 1 is the adoption timeline of memory cards for different manufacturers.

[Insert Table 1 about Here]

As shown in Table 1, accompanying Sony's first digital camera was a 3.5" floppy disk storage device. The desire for smaller cards led Sony to invest R&D resources to create its own memory card format, the Memory Stick, which was launched in October 1998. After its introduction, from 1999 to 2001, the Memory Stick embraced a market expansion from 7% to 25%.[29] Meanwhile, from 1998 to 2004, the market share of Sony's cameras increased from 17% to 23%.[30] Since then, Sony has been using its proprietary standard and its extensions, such as the Memory Stick PRO, Memory Stick Duo, and Memory Stick PRO Duo as its compatible storage devices. Among them, the Memory Stick PRO Duo, introduced in early 2003,[31] is smaller than the others, hence backward incompatible.

Olympus and Fujifilm, on the other hand, employed SmartMedia cards for their first few cameras, and in July 2002, they jointly invented another standard, the xD card,[32] as the primary storage device to compete with Sony.

The success of the Sony Memory Stick also motivated SanDisk, Matsushita, and Toshiba to develop and market the SD (Secure Digital) memory card.[33] Early samples of the SD card became available in the first quarter of 2000. Later, in March 2003, SanDisk Corporation announced the introduction of the miniSD, a variant of the original SD Card. Because SD cards are ultra-compact, reliable, interoperable, and easy to use, many of leading digital camera manufacturers, including Canon, Kodak, Nikon, and HP, all of which originally used the CompactFlash card format, switched to SD cards in their consumer product lines in 2002.

Appendix A2. Model Details

The utility specification that embraces all the four cases is

$$\bar{U}_{it}\left(DC_{it}, DM_{it} | \{QC_t^c\}_{c=1}^C, R_{it}, \{QC_{R_{it}}^c\}_{c=1}^C, \{Size_t^m\}_{m=1}^M, DC_{iR_{it}}, \{DM_{i\tau}\}_{\tau=1}^{t-1}, \{\{Size_\tau^m\}_{m=1}^M\}_{\tau=1}^{t-1}, \{PC_t^c\}_{c=1}^C, \{PM_t^m\}_{m=1}^M, Y_t, Y_{R_{it}}\right)$$

$$= \underbrace{\sum_{c=1}^{C} I(DC_{it} = c) * \left\{\alpha_i^c + \mu_i^c * Y_t + \phi_i QC_t^c + \beta_i * I\left(DC_{it} = DC_{iR_{it}}\right)\right\} + I(DC_{it} = 0) * \left[\alpha_i^{DC_{iR_{it}}} + \mu_i^{DC_{iR_{it}}} * Y_{R_{it}} + \phi_i QC_{R_{it}}^{DC_{iR_{it}}}\right]}_{camera\ consumption}$$

$$+ \underbrace{\begin{matrix}\left\{\sum_{m=1}^{M} \{I(DM_{it} = m) * [\theta_i^m + \psi_i * Size_t^m] * I\left(DM_{it} \sim_t DC_{iR_{it}}\right)\} + \sum_{m'=1}^{M} \sum_{\tau=0}^{t-1} [I(DM_{i\tau} = m')\{I(DM_{it} = 0) * \theta_i^{m'} + \rho_i^{t-\tau} * \psi_i * Size_\tau^{m'} * I\left(m' \sim_t DC_{iR_{it}}\right)\}]\right\} \\ * \left\{1 + \delta_i \sum_{c=1}^{C} \left[I(DC_{it} = c) * QC_t^c + I(DC_{it} = 0) * QC_{R_{it}}^{DC_{iR_{it}}}\right]\right\}\end{matrix}}_{enhanced\ consumption\ interaction}$$

$$+ \underbrace{\lambda_i * \left(\sum_{c=1}^{C} I(DC_{it} = c) * PC_t^c + \sum_{m=1}^{M} I(DM_{it} = m) * PM_t^m\right)}_{financial\ cost}$$

We use Table A1 to exhibit the counterpart for each of the 18 choice alternatives.

Table A1 Summary of Mean Utility Functions

1.only c1: $u_{it}^{1,0} = \alpha_i^1 + \phi_i QC_t^1 + \mu_i^1 * Y_t + \beta_i * I(1 = DC_{iR_{it}}) + \{\sum_{\tau=0}^{t-1} I(DM_{i\tau} = 1)(\theta_i^{1 v_t} + \rho^{t-\tau} * \psi_i * Size_\tau^1)\}(1 + \delta_i QC_t^1) + \lambda_i PC_t^1$
2.only c2: $u_{it}^{2,0} = \alpha_i^2 + \phi_i QC_t^2 + \mu_i^2 * Y_t + \beta_i * I(2 = DC_{iR_{it}}) + \left\{\sum_{m'=2}^{3} \sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\theta_i^{m' v_\tau} + \rho^{t-\tau} * \psi_i * Size_\tau^{m'})\right\}(1 + \delta_i QC_t^1)$
3.only c3: $u_{it}^{3,0} = \alpha_i^3 + \phi_i QC_t^3 + \mu_i^3 * Y_t + \beta_i * I(3 = DC_{iR_{it}}) + \left\{\sum_{m'=2}^{3} \sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\theta_i^{m' v_\tau} + \rho^{t-\tau} * \psi_i * Size_\tau^{m'})\right\}(1 +$

[29] http://news.cnet.com/2100-1040-268460.html

[30] http://www.pcworld.com/article/114711/sony_unveils_digicams_photo_printer.html

[31] https://www.pctechguide.com/portable-ram/sony-memory-stick-technology-and-background

[32] http://en.wikipedia.org/wiki/XD-Picture_Card

[33] http://en.wikipedia.org/wiki/Secure_Digital

$\delta_i QC_t^2) + \lambda_i PC_t^3$
4.only c4:$u_{it}^{4,0} = \alpha_i^4 + \phi_i QC_t^4 + \mu_i^4 * Y_t + \beta_i * I(4 = DC_{iR_{it}}) + \left\{\sum_{m'=4}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\theta_i^{m'v_\tau} + \rho^{t-\tau} * \psi_i * Size_\tau^{m'})\right\}(1 + \delta_i QC_t^4) + \lambda_i PC_t^4$
5.only c5:$u_{it}^{5,0} = \alpha_i^5 + \phi_i QC_t^5 + \mu_i^5 * Y_t + \beta_i * I(5 = DC_{iR_{it}}) + \left\{\sum_{m'=4}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\theta_i^{m'v_\tau} + \rho^{t-\tau} * \psi_i * Size_\tau^{m'})\right\}(1 + \delta_i QC_t^5) + \lambda_i PC_t^5$
6.only c6:$u_{it}^{6,0} = \alpha_i^6 + \phi_i QC_t^6 + \mu_i^6 * Y_t + \beta_i * I(6 = DC_{iR_{it}}) + \left\{\sum_{m'=4}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\theta_i^{m'v_\tau} + \rho^{t-\tau} * \psi_i * Size_\tau^{m'})\right\}(1 + \delta_i QC_t^6) + \lambda_i PC_t^6$
7.only c7:$u_{it}^{7,0} = \alpha_i^7 + \phi_i QC_t^7 + \mu_i^7 * Y_t + \beta_i * I(7 = DC_{iR_{it}}) + \left\{\sum_{m'=4}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\theta_i^{m'v_\tau} + \rho^{t-\tau} * \psi_i * Size_\tau^{m'})\right\}(1 + \delta_i QC_t^7) + \lambda_i PC_t^7$
8.only m1:$u_{it}^{0,1} = I(DC_{iR_{it}} = 1)(\alpha_i^{DC_{iR_{it}}} + \phi_i * QC_{R_{it}}^{DC_{iR_{it}}} + \mu_i^{DC_{iR_{it}}} * Y_{R_{it}}) + \{(\theta_i^{1v_t} + \psi_i * QM_t^1) I(1 \sim_t DC_{iR_{it}}) + \sum_{\tau=0}^{t-1} I(DM_{i\tau} = 1)(\rho^{t-\tau} * \psi_i * Size_\tau^1) I(DM_{i\tau} \sim_t DC_{iR_{it}})\}\left(1 + \delta_i QC_{R_{it}}^{DC_{iR_{it}}}\right) + \lambda_i PM_t^1$
9.only m2:$u_{it}^{0,2} = I(DC_{iR_{it}} = 2,3)(\alpha_i^{DC_{iR_{it}}} + \phi_i * QC_{R_{it}}^{DC_{iR_{it}}} + \mu_i^{DC_{iR_{it}}} * Y_{R_{it}}) + \{(\theta_i^{2v_t} + \psi_i * QM_t^2) I(2 \sim_t DC_{iR_{it}}) + \sum_{m'=2}^{3}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\rho^{t-\tau} * \psi_i * Size_\tau^{m'}) I(DM_{i\tau} \sim_t DC_{iR_{it}})\}\left(1 + \delta_i QC_{R_{it}}^{DC_{iR_{it}}}\right) + \lambda_i PM_t^2$
10.only m3:$u_{it}^{0,3} = I(DC_{iR_{it}} = 4,5,6,7)(\alpha_i^{DC_{iR_{it}}} + \phi_i * QC_{R_{it}}^{DC_{iR_{it}}} + \mu_i^{DC_{iR_{it}}} * Y_{R_{it}}) + \{(\theta_i^{3v_t} + \psi_i * QM_t^3) I(3 \sim_t DC_{iR_{it}}) + \sum_{m'=4}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\rho^{t-\tau} * \psi_i * Size_\tau^{m'}) I(DM_{i\tau} \sim_t DC_{iR_{it}})\}\left(1 + \delta_i QC_{R_{it}}^{DC_{iR_{it}}}\right) + \lambda_i PM_t^3$
11.c1 & m1:$u_{it}^{1,1} = \alpha_i^1 + \phi_i QC_t^1 + \mu_i^1 * Y_t + \beta_i * I(1 = DC_{iR_{it}}) + \{(\theta_i^{1v_t} + \psi_i * QM_t^1) + \sum_{\tau=0}^{t-1} I(DM_{i\tau} = 1)(\rho^{t-\tau} * \psi_i * Size_\tau^1) I(DM_{i\tau} \sim_t DC_{it})\}(1 + \delta_i QC_t^1) + \lambda_i(PC_t^1 + PM_t^1)$
12.c2 & m2:$u_{it}^{2,2} = \alpha_i^2 + \phi_i QC_t^2 + \mu_i^2 * Y_t + \beta_i * I(2 = DC_{iR_{it}}) + \{(\theta_i^{2v_t} + \psi_i * QM_t^2) + \sum_{m'=2}^{3}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\rho^{t-\tau} * \psi_i * Size_\tau^{m'}) I(DM_{i\tau} \sim_t DC_{it})\}(1 + \delta_i QC_t^2) + \lambda_i(PC_t^2 + PM_t^2)$
13.c3 & m2:$u_{it}^{3,2} = \alpha_i^3 + \phi_i QC_t^3 + \mu_i^3 * Y_t + \beta_i * I(3 = DC_{iR_{it}}) + \{(\theta_i^{2v_t} + \psi_i * QM_t^2) + \sum_{m'=2}^{3}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\rho^{t-\tau} * \psi_i * Size_\tau^{m'}) I(DM_{i\tau} \sim_t DC_{it})\}(1 + \delta_i QC_t^3) + \lambda_i(PC_t^3 + PM_t^2)$
14.c4 & m3:$u_{it}^{4,3} = \alpha_i^4 + \phi_i QC_t^4 + \mu_i^4 * Y_t + \beta_i * I(4 = DC_{iR_{it}}) + \{(\theta_i^{3v_t} + \psi_i * QM_t^3) + \sum_{m'=4}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\rho^{t-\tau} * \psi_i * Size_\tau^{m'}) I(DM_{i\tau} \sim_t DC_{it})\}(1 + \delta_i QC_t^4) + \lambda_i(PC_t^4 + PM_t^3)$
15.c5 & m3:$u_{it}^{5,3} = \alpha_i^5 + \phi_i QC_t^5 + \mu_i^5 * Y_t + \beta_i * I(5 = DC_{iR_{it}}) + \{(\theta_i^{3v_t} + \psi_i * QM_t^3) + \sum_{m'=4}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\rho^{t-\tau} * \psi_i * Size_\tau^{m'}) I(DM_{i\tau} \sim_t DC_{it})\}(1 + \delta_i QC_t^5) + \lambda_i(PC_t^5 + PM_t^3)$
16.c6 & m3:$u_{it}^{6,3} = \alpha_i^6 + \phi_i QC_t^6 + \mu_i^6 * Y_t + \beta_i * I(6 = DC_{iR_{it}}) + \{(\theta_i^{3v_t} + \psi_i * QM_t^3) + \sum_{m'=4}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\rho^{t-\tau} * \psi_i * Size_\tau^{m'}) I(DM_{i\tau} \sim_t DC_{it})\}(1 + \delta_i QC_t^6) + \lambda_i(PC_t^6 + PM_t^3)$
17.c7 & m3:$u_{it}^{7,3} = \alpha_i^7 + \phi_i QC_t^7 + \mu_i^7 * Y_t + \beta_i * I(7 = DC_{iR_{it}}) + \{(\theta_i^{3v_t} + \psi_i * QM_t^3) + \sum_{m'=4}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')(\rho^{t-\tau} * \psi_i * Size_\tau^{m'}) I(DM_{i\tau} \sim_t DC_{it})\}(1 + \delta_i QC_t^7) + \lambda_i(PC_t^7 + PM_t^3)$
18.no purchase:$u_{it}^{0,0} = \sum_{j=1}^{7} I(DC_{iR_{it}} = j)\left(\alpha_i^{DC_{iR_{it}}} + \phi_i * QC_{R_{it}}^{DC_{iR_{it}}} + \mu_i^{DC_{iR_{it}}} * Y_{R_{it}}\right) + \left\{\sum_{m'=1}^{7}\sum_{\tau=0}^{t-1} I(DM_{i\tau} = m')\left(\theta_i^{m'v_\tau} + \rho^{t-\tau} * \psi_i * Size_\tau^{m'}\right) I(DM_{i\tau} \sim_t DC_{iR_{it}})\right\}\left(1 + \delta_i QC_{R_{it}}^{DC_{iR_{it}}}\right)$

Appendix A3. Identification Simulation

We conduct a Monte Carlo simulation to show the ability of our model to separately identify add-on inventory effects from state dependence and brand preference. The market structure is set to be different from real data: there are two brands of cameras and two compatible memory card standards. Our simulation scheme is as follows: First, we simulate price and quality series data, based on the following transition probability $pc_t = \begin{bmatrix} 0.76 & 0.28 \\ 0.16 & 0.56 \end{bmatrix} * pc_{t-1} + \eta_{pt}$, $\eta_{pt} \sim N\left(0, \begin{bmatrix} 0.5 & 0 \\ 0 & 0.75 \end{bmatrix}\right)$, $pm_t = \begin{bmatrix} 0.72 & 0.24 \\ 0.16 & 0.40 \end{bmatrix} * pm_{t-1} + \iota_{pt}$, $\iota_{pt} \sim N\left(0, \begin{bmatrix} 0.5 & 0 \\ 0 & 0.75 \end{bmatrix}\right)$, $qc_t = \begin{bmatrix} 0.96 & 0.36 \\ 0.24 & 0.92 \end{bmatrix} * qc_{t-1} + \eta_{qt}$, $\boldsymbol{\eta_{qt}} \sim N\left(0, \begin{bmatrix} 0.5 & 0 \\ 0 & 0.75 \end{bmatrix}\right)$, $Size_t = \begin{bmatrix} 1.078 & 0.245 \\ 0.147 & 1.029 \end{bmatrix} * Size_{t-1} + \iota_{qt}$, $\boldsymbol{\iota_{qt}} \sim N\left(0, \begin{bmatrix} 0.5 & 0 \\ 0 & 0.75 \end{bmatrix}\right)$. We generate the price and quality series for 8 time periods. We use the utility specification as in the model section. Given the price/quality series, we compute the observable part of the value functions. We then generate the value function by simulating the GEV error term

$\varepsilon_{it}^{DC_{it},DM_{it}}$. We simulate the purchasing behavior of 1200 individuals. Using the computed values of the $V_{it}{}'s$, we decide the timing of purchase by comparing $V_{it}^{DC_{it},DM_{it}}$ with $V_{it}^{0,0}$ (outside option of no purchase). We generate 50 data sets for the same values of the parameters.

The results are shown in Table A2. All estimates are within two standard deviations from the true values. This result demonstrates the ability of our model to recover the quality, inventory, and price coefficients, as well as state dependence.

The simulation result reveals that our model can separately identify add-on inventory effect from state dependence. Essentially, the add-on inventory effect is identified by the variance in inventory of memory card conditional on the camera inventory. For example, let us consider two consumers (X and Y) who both adopted a Sony camera. X has 1 Memory Stick and Y has 2 Memory Sticks. Our model implies that Y is more likely to continue purchasing Sony cameras than X. This suggests that when we control for state dependence, the add-on inventory effect still exists and can be identified, given enough variation in memory card inventory level.

Table A2 Simulation Results

Parameters	TRUE	Estimates	Std
Intercept: C1	-2	-2.622	0.407
Intercept: C2	-3.6	-3.851	0.636
Intercept: M1	-0.2	-0.220	0.060
Intercept: M2	-0.5	-0.438	0.199
Cquality	1.7	1.827	0.184
Mquality	0.3	0.289	0.042
Price	-5	-5.013	0.158
State Dep	0.1	0.134	0.061
Depreciation	0.8	0.852	0.076
CMInteraction	0.05	0.058	0.013

Table A3 Summary of Purchase Incidences of Cameras and Memory Cards

Brand	**Frequency**	**Percentage**	**Standard**	**Frequency**	**Percentage**
C1	297	21.60%	M1	358	23.88%
C2	1078	78.40%	M2	1141	76.12%

Similar to Table 2B in the paper, Table A4 below summarizes the total incidences, where around only 15% of consumers repeated camera purchases and 25% of consumers purchased more than one memory card. We believe that this is consistent with the patterns in the real data.

Table A4 Total Purchase Incidences

Camera\Memory	**0**	**1**	**2**	**3**	**Total**
1	26	743	232	24	1025
	2.2%	61.9%	19.3%	2.0%	85.4%
2	1	132	38	4	175
	0.1%	11.0%	3.2%	0.3%	14.6%
Total	27	875	270	28	1200
	2.3%	72.9%	22.5%	2.3%	100.00%

The generated price and quality processes also resemble those in the real data. Please see Table A5 below.

Table A5 Summary Statistics of Price and Quality

	C1	C2	M 1	M 2
Price	688.697	235.936	46.225	12.350
Quality	5.537	5.385	2.030	2.429

Finally, we show that with the current variations in the data, the intrinsic brand preference, add-on inventory effect, and state dependence effect can all be identified (Table A2). Notice that the standard deviations for the intrinsic brand preference and state dependence parameters are rather large. Should we have more data, the standard deviations will be much smaller, which will give us more accurate estimates.

Appendix A4. Focal Chain Assumption

This assumption may seem quite restrictive, as consumers may often purchase at several electronic retail chains. However, this concern is mitigated in our sample for several reasons. One, all households are holders of loyalty cards of the observed retail chain and consequently are assumed to be frequent buyers. Two, the focal chain offers a "low-price guarantee" that will beat any price from another retail chain stocking the same item. This highly competitive pricing strategy provides a large disincentive for these loyal consumers to purchase at rival chains. Three, we delete households that purchased memory cards only from the observed retail chain. These consumers are more likely to purchase from multiple chains rather than one. Lastly, our observed data pattern from this chain is representative of the industry average (See next paragraph). For example, we observe a camera replacement cycle of 4.67 years, while the industry average is 4.30 years with a standard deviation of 2.28 years. Above all, we acknowledge the data limitation and claim that we provide insight only on loyal consumers' brand and standard choice behavior within a chain. Chain competition is beyond the scope of this research. Our second assumption treats a consumer who buys multiple memory cards on a single trip as only one purchase incidence. This assumption is reasonable because only a very small portion (0.6%) of the purchases in our sample involve multiple items.[34]

To justify that our observed data pattern from this chain is representative of the industry average, we collected evidence that suggests that consumers generally replace cameras every three years. For example, Walmart has a 3 Year Replacement Plan for a Camera/Camcorder (http://www.walmart.com/ip/3-Year-Replacement-Plan-for-a-Camera-Camcorder/10227063). Our sample ranges from the 4th quarter of 1998 to the 4th quarter of 2004. However, from 1998 to 2000, only 115/1059=10.9% camera transactions took place. Therefore, the majority of the transactions happened within the four year range between 2001 and 2004. In this sense, most consumers (75.00%) bought only one camera and one memory card, which is consistent with the industry average. We collect additional information from consumer online forums to confirm that the purchase frequency observed in our data set is consistent with reality. In our sample, the average length for a consumer to replace a camera is 4.67 years. From four digital camera forums,[35] we obtain a sample of 26 data points. The average replacement cycle is 4.30[36] years and the standard deviation is 2.28 years. This gives us more confidence

[34] When multiple memory cards are bought, we treat each item as a separate purchase incidence. The state variable, inventory of the memory cards, is cumulated by the number of items bought. We delete the consumer who purchased multiple cameras, because this might be a case of several family members adopting together. We examine the behavior of only an individual consumer.

[35] http://www.dpreview.com/forums/thread/3085393, http://www.travelblog.org/Topics/18677-1.html, http://forums.steves-digicams.com/general-discussion/44234-how-often-do-you-buy-new-digital-camera.html#b, http://www.twopeasinabucket.com/mb.asp?cmd=display&thread_id=3092220

[36] One thing to know is that many consumers on these forums are photographers who replace more frequently than the average consumer.

that our data pattern is consistent with reality. That said, we also want to repeat that our data are collected at the beginning of the digital camera industry and from the chain store that has the largest market share. Thus, the missing data problem is probably negligible.

Appendix A5. Procedure for Decomposition Analysis

Below we use the $19.34 cost of switching from Sony to Fujifilm as an illustration of the procedure of decomposition.

1) Price/Quality difference between brands: We assume that Fujifilm and Sony form a similar user experience and are compatible with the same Standard 1 memory card. Therefore, after switching to Fujifilm, the consumer keeps her state dependence effect and the add-on inventory effect (memory card inventory) in her utility. The only difference is that Fujifilm charges a different price at a different quality level from Sony.

2) State dependence: We assume that Fujifilm matches Sony's price and quality strategy and is compatible with the Standard 1 memory card that Sony uses. But because Fujifilm provides a different user experience than Sony, the state dependence term in the consumer's utility function vanishes.

3) Add-on inventory effect: We assume that Fujifilm provides a similar user experience as Sony's and matches price and quality with Sony. However, it is compatible with the Standard 2 memory card rather than Standard 1. When switching to Fujifilm, the consumer can no longer use her Standard 1 memory card in inventory.

We repeat the same exercise for all the other brands.

Appendix A6. Robustness Check

Maximum Number of Cards

When estimating the model, we set a restriction that the maximum number of memory cards purchased in the entire sample period is 4. Here we test whether the estimation result is sensitive to this restriction by changing this maximum from 4 to 5.[37] Table A6 below displays the policy simulation result.[38] The result remains qualitatively similar to the original one.

Table A6 Policy Simulations When Maximum Memory Card Inventory is 5

	Market Share of Cameras		
	Benchmark	**No Compatibility**	
Son	30.75%	23.35%	-24.08%
Oly	15.06%	14.36%	-4.63%
Fuji	6.49%	6.24%	-3.87%
Kod	21.07%	24.76%	17.51%
Can	11.88%	12.09%	1.80%
HP	8.58%	8.77%	2.19%
Nik	6.18%	6.63%	7.30%
	Market Share of Memory Cards		
	Benchmark	**No Compatibility**	
Std1	31.67%	26.95%	-14.90%
Std2	20.75%	21.51%	3.67%
Std3	47.58%	54.09%	13.69%

Discount Factor

[37] We also tried other values, from 6 to 10. The results remain qualitatively similar.
[38] Most of the model coefficients also remain unchanged.

We also perform a robustness test for the choice of the discount. Table A7 presents the policy simulation result[39] when we fix the discount factor at 0.9 instead of 0.95 as in the main text. Comparing the results in Table A7 and Table 10, we can see that the results are qualitatively identical.

Table A7 Policy Simulations When Discount Factor is 0.9

	Market Share of Cameras		
	Benchmark	**No Compatibility**	
Son	30.75%	23.66%	-23.07%
Oly	15.06%	13.96%	-7.28%
Fuji	6.49%	6.10%	-6.07%
Kod	21.07%	26.47%	25.65%
Can	11.88%	12.67%	6.64%
HP	8.58%	9.70%	13.03%
Nik	6.18%	7.21%	16.71%
	Market Share of Memory Cards		
	Benchmark	**No Compatibility**	
Std1	31.67%	27.23%	-14.01%
Std2	20.75%	22.79%	9.84%
Std3	47.58%	53.08%	11.55%

Appendix A7. Value Function, Likelihood and Initial Values

The value function V depends on the state at t and, given that t takes values from an interval of infinite length, the value function can be written as

$$V_{it}(\Omega_{it}) = \max_{DC_{it}, DM_{it}} (V_{it}^{DC_{it}, DM_{it}}(\Omega_{it})). \tag{13}$$

Based on the Bellman equation (Bellman 1957),

$$\begin{aligned} V_{it}^{DC_{it}, DM_{it}}&(\Omega_{it}) \\ &= \bar{U}_{it}(DC_{it}, DM_{it}) + \varepsilon_{it}(DC_{it}, DM_{it}) \\ &+ \Upsilon E \max_{DC'_{it}, DM'_{it}} [V_{it+1}^{DC'_{it}, DM'_{it}}(\Omega_{it+1}) | \Omega_{it}, DC_{it}, DM_{it}] \end{aligned} \tag{14}$$

We assume that the error term associated with deterministic components of utility above is $\varepsilon_{it}(DC_{it}, DM_{it})$ and jointly follow the Generalized Extreme Value (GEV) distribution across choice alternatives but i.i.d across consumers and time. We choose the GEV distribution because it allows for correlations of the errors within each product category.

$$F(\boldsymbol{\varepsilon}_{it}) = exp\{-G(e^{-\boldsymbol{\varepsilon}_{it}})\}$$

$$G(e^{-\varepsilon_{it}}) = \left[\sum_{DC_{it}=1}^{C} \sum_{DM_{it}=0}^{M} exp\left(\frac{-\varepsilon_{it}(DC_{it}, DM_{it})}{1-\gamma_c}\right)\right]^{1-\gamma_c} + \left[\sum_{DM_{it}=0}^{M} exp\left(\frac{-\varepsilon_{it}(0, DM_{it})}{1-\gamma_m}\right)\right]^{1-\gamma_m}$$

The choice probability for consumer i at time t has a closed-form solution:

$$P_{it}^{DC_{it}, DM_{it}} = \frac{\exp(\bar{V}_{it}^{DC_{it}, DM_{it}}/\gamma_c)\left(\sum_{DC_{it}=1}^{C} \sum_{DM_{it}=0}^{M} exp(\bar{V}_{it}^{DC_{it}, DM_{it}}/\gamma_c)^{\gamma_c - 1}\right)}{\sum_{DC_{it}=1}^{C} \sum_{DM_{it}=0}^{M} exp(\bar{V}_{it}^{DC_{it}, DM_{it}}/\gamma_c)^{\gamma_c - 1} + \sum_{DM_{it}=0}^{M} exp(\bar{V}_{it}^{0, DM_{it}}/\gamma_m)^{\gamma_m - 1}} \tag{15}$$

[39] Some of the model coefficients change when we lower the discount factor.

$$P_{it}^{0,DM_{it}} = \frac{\exp(\bar{V}_{it}^{0,DM_{it}}/\gamma_m)\left(\sum_{DM_{it}=0}^{M} exp\left(\bar{V}_{it}^{0,DM_{it}}/\gamma_m\right)^{\gamma_m - 1}\right)}{\sum_{DC_{it}=1}^{C}\sum_{DM_{it}=0}^{M} exp\left(\bar{V}_{it}^{DC_{it},DM_{it}}/\gamma_c\right)^{\gamma_c - 1} + \sum_{DM_{it}=0}^{M} exp\left(\bar{V}_{it}^{0,DM_{it}}/\gamma_m\right)^{\gamma_m - 1}}$$

where $\bar{V}_{it}^{DC_{it},DM_{it}}$ is the deterministic part of the choice-specific value function, i.e. $\bar{V}_{it}^{DC_{it},DM_{it}} = V_{it}^{DC_{it},DM_{it}} - \varepsilon_{it}^{DC_{it},DM_{it}}$. The corresponding log-likelihood function to be maximized is

$$\mathrm{LL} = \sum_{i=1}^{I}\sum_{t=1}^{T}[\sum_{DC_{it}}\sum_{DM_{it}} I(DC_{it} = OC_{it})I(DM_{it} = OM_{it})\log(P_{it}^{DC_{it},DM_{it}})] \tag{16}$$

where OC_{it} and OM_{it} are the observed choices of cameras and memory cards in the data.

With our data originating near the inception of the digital camera industry, we set the initial state variables for camera and memory card inventories to be zeroes for nearly all consumers. We support this assumption with several facts. The penetration rate of digital cameras in the US in 1998 was a mere 0.35%.[40] Moreover, before 1998, only 9 models[41] of camera were launched, among which four models did not allow for external memory. The other five cameras were extremely expensive (average price of $1220) and had expensive compatible memory cards (SmartMedia Card: $259 for 30MB[42] or CompactFlash Card: $140 for 24MB[43]). Nevertheless, there could be rare exceptions for the very early adopters of cameras, and we accommodate this off chance in our estimation procedure. In our dataset, we observe roughly 1.09% (9/828) of the total sample occasions where a consumer buys a memory card before a camera. To rationalize this data pattern, we assume that the consumer had adopted a compatible camera before the observation period (exact purchase time is randomly assigned to a quarter between 1994 and 1998 and for a memory card standard that is compatible with multiple camera brands, we randomly assign a brand.[44])

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[40] Worldwide Digital Camera Market Review and Forecast, 1997-2003 (IDC #B99S2172)

[41] Within the seven brands we are considering, the 9 models are Olympus D-200L, Olympus D-300L, Olympus D-500L, Olympus D-600L, Fujifilm DS-300, Canon PowerShot 600, Canon PowerShot 350, Nikon Coolpix 100, Nikon Coolpix 300.

[42] http://www.epi-centre.com/reports/9802seye.html

[43] http://zonezero.com/magazine/dcorner/texto8.html

[44] Note that our model has already taken care of the state-dependence effect. So any missing value of initial purchases of cameras will not bias our estimated add-on-to-base effect. We admit that if, unfortunately, there is a missing value of memory card purchases before the sample started, we might overestimate the add-on-to-base effect. But given so much evidence, we do not think the problem is severe enough to overturn our results.