The ISMS Durable Goods Datasets

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Abstract

This paper describes two new data sets available to academic researchers (at the following website: http://www.informs.org/Community/ISMS). The first data set is a panel dataset containing the transactions of 19,936 households made over the period December 1998 – November 2004 at a major U.S. consumer electronics retailer. There are a total of 173,262 transactions, including purchases and returns of products as well as extended warranties. There are 292 product categories, ranging from big ticket items such as televisions to small ticket items such as CDs and batteries. The second data set features a field experiment for a Christmas promotion, which took place in December 2003 in the form of a direct mailing sent to a randomly selected group of households at the end of November 2003. We describe the data and the research issues that can be potentially studied using these two durable good data sets.

Key words: retailer, durable goods, panel data, product adoption, holiday promotion, sales forecasting
1. Introduction

Durable goods play a crucial role in the economy. In 2008, personal consumption expenditures on durables exceeded $1.1 trillion (Federal Reserve Bank of St. Louis, 2009). Compared with fast-moving packaged goods products, consumer decisions for durable goods are much more sophisticated, dynamic, and deliberative, and raise numerous research questions for microeconomic and marketing analysis. A thorough understanding of consumer decisions with respect to durables will help develop and test both economic and consumer behavior theories, and have important implications for managerial decisions.

During the past several decades, a rich analytical literature in both marketing and economics has examined the competitive behavior of firms that sell durable goods (Waldman, 2003). However, empirical research investigating consumer decisions about durable goods are sparse in marketing. Counting *Marketing Science* and *Journal of Marketing Research*, more than 400 papers have been published examining consumer purchase behavior of fast moving packaged goods using the IRI and ACNielsen data sets. Of these, 36 papers are about durable goods, among which 28 used aggregate sales and only 8 used individual consumer purchase history (consumer panel data) of durable goods.

The purpose of this paper is to address this disparity by introducing two distinct databases to the research community. Both are being administered by the INFORMS Society for Marketing Science (ISMS) and are called ISMS Durables Dataset 1 and ISMS Durables Dataset 2. To the best of our knowledge, the ISMS durables datasets are the most comprehensive customer-level transaction data available for researchers. We make these data sets publically available with the wish to facilitate researchers in marketing, economics, psychology, and other fields to conduct research that help understanding consumer purchase decisions about durable goods.
Both databases are provided by an anonymous major U.S. consumer electronics retailer. ISMS Durables Dataset 1 is panel data, i.e., it contains the complete transaction records of a large set of customers from most of the retailer’s stores over time. ISMS Durables Dataset 2 is also at the customer level. It is cross-sectional and features the results of a direct mail promotion field experiment. It contains a host of variables calculated before the promotion, an indicator of whether the customer received the promotion, and dollar purchases made by the customer during the promotion period. In what follows, we will devote more space to the description and possible research topics for ISMS Durables Dataset 1. However, ISMS Durables Dataset 2 is also quite valuable, and we will also describe it. Detailed documentation of the variables in each database is available at http://www.informs.org/Community/ISMS.

2. ISMS Durables Dataset 1

2.1 Data Description

The first dataset consists of the transaction records of 19,936 randomly selected customers during 6 years from December 1998 to November 2004. There are six types of transactions: product purchase, product return, service contract purchase, service contract return, sales discount, and miscellaneous. Table 1A shows the frequency counts of the various transaction types and Table 1B lists some key descriptive statistics related to purchases. Each record includes detailed information about these transactions for a particular customer at a particular date, and depending on the transaction type, information such as brand purchased, service contracts purchased, product category, price paid, lengths of coverage of service contracts, and time and location of purchases. It also contains information on product returns. Finally, each record contains customer-level demographic information such as income, gender, family size and age. Table 2 provides descriptive statistics of customer demographics.
During the six-year observation period, the 19,936 households made 173,262 transactions of durable goods and/or services from 1176 of the focal retailer’s stores located throughout the United States. There are 16 product categories, 292 sub-categories, and 22,210 specific products, ranging from big ticket items such as televisions, cameras, and PDAs, to accessories and small ticket items such as CDs and batteries. The specific products are also associated with a particular brand. A large number of categories and store locations enable the analysis of multi-store shopping from the same retailer and purchase behavior across categories.

Each household on average made 8.69 transactions and purchased 7.14 products during the six years observation period. The average expenditure per year is $158.22. The most frequent customer in the data purchased 255 times. Taking digital cameras as an example, 1953 customers made 2524 purchases of 20 brands during the six years at an average price of $311.95, and purchased on average $71.27 in extended service plans offered by the retailer. Among these purchases, 22% of customers bought extended service contract, 11.9% returned the product, 3.4% were purchased online, and 24.8% were bought during the holiday season (Thanksgiving and Christmas weeks).

Examination of the data reveals that 98% of the regular prices paid on the same day are the same across stores. This suggests that pricing decisions are made at the retailer’s headquarters. To construct a time series of store level prices, one can use the Transaction_Type and Unit_Price variables (see Data Documentation for Durables Dataset 1). Transaction_Type provides information on whether the transaction was a product purchase and also identifies possible promotional price discounts. The Unit_Price variable states the price paid or the amount of the
promotional price discount. Users can also construct a price series using data collected from other sources such as NPD.com. For example, in Figures 1 and 2, we plot the price and sales trends of Apex digital video camera models 763370 and 749912. To prepare these figures, we aggregate across customers to count the number of units sold for the product.

[Insert Figures 1 and 2 About Here]

2.2 Research Issues for ISMS Durables Dataset 1

[Insert Table 3 about Here]

In this section, we suggest research issues that can be investigated using ISMS Durables Dataset 1, and briefly summarize the marketing and economics literature on each topic (see Table 3). We later point out limitations of this dataset.

(1) Purchase of Retailers’ Extended Service Contracts

Contributing more than half of the total profits of major electronics retailers, extended service contracts (ESCs) have become a major profit engine for consumer electronics retailers such as Best Buy and Circuit City since the mid-1990s (BusinessWeek 2004). According to Warranty Week, consumers spent more than $16 billion on extended warranties in 2006. In a PC World survey of consumers who bought products from many retailers, including Best Buy, Circuit City and Dell, about 63 percent said they had bought extended warranties and on average 71 percent of these consumers are glad they purchased the extended warranty coverage (CBS News 2007). Since their introduction by large electronics stores in the late 1980s, ESCs have become a major profit engine for consumer electronics retailers (BusinessWeek 2004). In 2007, ESCs for consumer electronics generated approximately $8.3 billion sales (Bloomberg 2009). This significant contribution to the bottom line makes ESCs increasingly important, visible marketing
mix variables for retailers (Desai and Padmanabhan 2004). However, little existing research examines consumer purchase behavior with regard to ESCs offered by retailers. Moreover, little work considers whether and how ESC purchases interact with dynamic product adoption/upgrade/replacement decisions or investigates its implications on the general design and pricing of ESCs.

Existing literature focuses on the manufacturers’ basic warranty, and suggests that manufacturers provide basic warranties to signal the quality of the product. This literature uses both experimental (e.g., Boulding and Kirmani 1993, Bearden and Shimp 1982) and analytical (e.g., Spence 1977, Grossman 1981) approaches. Other research studies the manufacturer warranty’s insurance role (e.g. Heal 1977). Murthy and Djamaludina (2002) offer a thorough review of existing literature on manufacturers’ basic warranties. The sparse literature on manufacturers’ extended service contracts focus on either empirically showing the correlations between ESC purchases and demographics (Day and Fox 1985) or analytically examining competitive conditions under which offering ESCs are profitable (Padmanabhan and Rao 1993; Padmanabhan 1995; Lutz and Padmanabhan 1995) in a static setting.

Recently, Chen, Kalra, and Sun (2009) specifically investigate ESCs offered by retailers. They study consumers’ purchases of ESCs in a retail environment to determine how product characteristics, retailer environment factors, and demographic factors affect the choice context. Chen and Sun (2010) investigate the dynamic nature of consumer ESC purchase in response to the inter-temporal pricing of the product and ESCs and evaluate whether lower ESC prices across the product shelf life, as implied by current tiered ESC pricing, encourage consumers to delay their product purchases and decrease their risk. They demonstrate that when consumers anticipate
declining future ESC prices, they not only delay their product adoption, but also are less likely to purchase an ESC in the current period. Thus, the retailer’s ESC pricing policy may hurt ESC sales.

Given the increasing importance of ESCs for retailers, it is important to understand how to improve marketing mix decisions to better sell ESCs. (1) What factors affect consumer purchases of ESCs? (2) How does the consumer’s propensity to purchase ESCs change as a function of the product’s shelf life and how does this propensity relate to the time at which consumers adopt the product? (3) How is ESC purchase affected by the trend in prices? And how does the inter-temporal pricing schedule of an ESC affect consumer purchases of ESC? (4) Does current ESC pricing encourage or discourage consumers from purchasing ESC? (5) How can retailers improve ESC pricing to align it with consumer strategic and dynamic decisions?

(2) Gift Card Purchasing
Offered by banks, malls, retailers, airlines, restaurants, hotels, web sites, and state parks, gift cards are wildly popular choices as “green” holiday gifts. A gift card is like a loan: you are giving the money to the company that holds the value of the card until you use it. And they promise to give that money back when you ask for it. According to the TowerGroup research firm, sales totals for the cards will rise nearly 5 percent, to $91 billion in 2010. Analysts pointed to new technology, wider distribution and savvy marketing strategies behind the growth (Chen, Cui & Zhang 2010).

Descriptive industry analyses reveal an interesting pattern in the purchase of gift cards (Accenture 2006, Riley 2009): for example, younger people are more likely to buy gift cards. The popularity of gift cards is transforming the retailing industry. The customer decision to purchase gift cards is having a major impact on the retailing landscape. Research on purchases and usages of gift cards is rare. It is important to validate industrial observations and address issues such as who
and when do consumers purchase gift cards? How does the purchase of gift cards relate to previous purchase patterns? Are gift cards “incremental” sales for the retailer?

(3) **Product Returns**

Allowing consumers to return products encourages them to try a new product about which they have huge uncertainty. However, consumers can also abuse the return policy. When too many products are returned, retailers bear significant cost. Retailers have been imposing more and more stringent return policies such as re-Stocking fees, limited windows during which customers can return, and “no-open” requirements in order for a product to be returned.

When consumer advocates criticize retailers for imposing more restrictive and sometimes hidden return policies, it is important to understand the fundamental driving force behind product returns and how do product returns after future purchasing? For example, How does product return affect customers product adoption and their subsequent purchases? What types of products are more likely to be returned?

(4) **Migration to the Online Channel**

In this dataset we observe consumer adoption of the online channel. A rich literature is developing on the factors that influence channel adoption (e.g., see Blattberg, Kim, and Neslin 2008, Chapter 25 for a full review). However, there are still important issues that can be answered with ISMS Durables Dataset 1. For example, what types of durable products do customers buy first when they are starting to use the Internet channel? Do they focus on search as opposed to experience goods? What impact does online channel adoption have on future purchase frequency from the retailer? How does online channel purchasing relate to product returns? What customer characteristics predict online adoption for a durable goods retailer?
(5) **Black Friday and Christmas Shopping**

Holiday retail sales are generally defined as same store sales made during Black Friday and Christmas (November and December). These sales represent 25% to 30% of total year retail sales. The various holidays have a substantial impact on the economic wellbeing of retailers. For many retailers, this is the make-it or break-it period. In light of the substantive economic impact of the holiday shopping period on retailing, and the potential differential impact on retailers in urban versus suburban locations (or vice versa), the holiday shopping period deserves much closer scrutiny than has been reported in the academic literature and the popular press.

It is important to investigate issues such as how does the anticipation of the big discount on Black Friday affect consumers purchases before the holiday season? How does Black Friday or Christmas sales affect after-holiday sales volume? Is the best time to get rid of obsolete products during the holiday and introduce new product right after the holiday?

(6) **Competition Among Manufacturers**

Retailers provide an environment where manufacturers of durable goods compete with each other to maximize their own long-term profit. Many competitive marketing mix strategies such as new product introductions, pricing, promotion, and advertising can be studied. For example, when Sony lowers the prices on its digital cameras, how does Cannon adjust its prices to defend its position? Static or dynamic models can be developed to measure and test the nature of interactions among firms, to test theories of competition and for policy analysis by simulating behavior under a variety of market environments. This usually requires imposing the equilibrium conditions implied by the supply side model while estimating the parameters of the demand function. ISMS Durables Dataset 1 is particularly useful for examining manufacturer competition using customer-level data (Villas-Boas, 2007).
(7) Product Adoption Decisions

Consumer decisions about when to adopt a new product is the most important decisions for durable goods. Consumers seem to adopt a sophisticated decision process when making these decisions such as waiting for product improvements, price reductions, or a better complementary good. Recent literature established that consumer purchase and repeated purchase decisions are driven by future price expectation (Melnikov 2001, Song and Chintagunta 2003, Carranza 2006, Gowrisankaran and Rysman 2007, Nair 2007, Gordon 2009 and Sriram, Chintagunta, and Agarwal 2009), future availability of the focal product and its add-ons and/or switching cost (Song and Chintagunta 2003; Schiraldi (2009), and risk attitudes (Oren and Schwartz 1988; Chatterjee and Eliashberg 1990).

Understanding that consumer purchase decisions are driven by expectation of future price trend, information on future product introductions, and uncertainty about product quality help the firm to sharpen its dynamic pricing strategies, product line management, and product introduction strategies. For example, will retailers carry only non-high-quality units first because consumers are unable to identify high quality of new products and are thus unwilling to pay a high price for it? To what extent do firms have an incentive to introduce new products that make old units obsolete? How are the current price and marketing strategies affect the future value of products?

(8) Brand Choice and Cross-Category Purchases

Most existing literature examining the product adoption/upgrade/replacement decision is at the product category level and abstracts out consumer brand choices, with the exception of Gordon (2009) who found consumers are willing to pay much higher price for Intel processors compared to AMD when making their computer replacement decision.
In addition, not much research has examined whether purchases of one durable good leads to purchases of other durable goods within the same retail store, a finding that is well established for fast moving packaged goods. This requires more comprehensive data set like the one we make available here. In the durable goods setting, this complementary or substitution effect exists not only across categories in the same time, but also inter-temporally even within the same category (Nair, 2007). Using unique survey data, Sriram, Chintagunta and Agarwal (2009) demonstrate that consumer’s adoption decisions are not only based on the dynamic pricing arrangement from the focal category but also on other product categories sold in the same store. Chen, Kalra and Sun (2009) demonstrate that if the focal product is purchased on promotion, the consumers are more likely to purchase other products, especially when the promotion is unadvertised.

With a large number of categories and 6 years of observation, ISMS Durables Dataset 1 enables the analysis of consumer choices across brands as well as products categories. There are many issues that need to be addressed. (1) The most fundamental but important question is how consumers make brand choice decisions for durable goods. (2) What purchase patterns are associated with increasing store purchase frequency? (3) Do high-ticket or low-ticket items build store purchase frequency? (4) What is durable brand loyalty across the product line and how does it develop over time? (5) What types of products tend to be bought together (market basket analysis)? Understanding how consumers make brand and category choices in the same retail store helps retailers to better manage competition among brands and improve shopping environment to grow incremental sales.

(9) Purchase of Add-ons

As manufacturers increasingly rely on selling accessories as a source of high-margin profits, more and more add-ons (e.g. toner) are introduced to target consumers who purchased the “root product”
(e.g. printer). This makes consumers’ purchase/upgrade/replacement decisions no longer independent of all the factors affecting their purchase decisions of those add-ons. In the interesting work by Gabaix and Laibson (2006), the joint decisions of focal product and its add-on are studied by relaxing the rational expectation assumption. Assuming a heterogeneous discounting factor (hyperbolic discounting), they show that in managing high-tech products (e.g., printer) with add-ons (e.g., toner), firms exploit myopic consumers through marketing schemes that shroud high-priced add-ons. In turn, sophisticated consumers exploit these marketing schemes by pooling themselves with myopic consumers, receiving the loss-leader base good and substituting away from the add-on. With the presence of both myopic and sophisticated consumers, firms will choose not to educate the public about the add-on market, even when advertising is free.

The inter-dependence between the root product and its many add-ons has several interesting implications for manufacturers when they make dynamic marketing decisions for all products. It will be interesting to understand (1) what accessories do customers purchase, when do they purchase them, and how does this relate to subsequent purchases? (2) the cross-price elasticity of high-tech products and add-ons; (3) how does price of add-ons affect the adoption of the focal product, and vice versa? (4) how do price, availability and quality of add-ons affect the adoption of the incumbent product?

2.3 Limitations of ISMS Durables Dataset 1

With a 6-year observation window and complete household-level transaction records of a large number of electronic durable goods, this dataset is unique. However, it is also subject to limitations. First, other than in-store price promotion, it does not contain any information on non-price related promotions such as TV advertising, catalogs, store display etc. Second, it is from a single retailer. Without information on consumer purchases from other retail outlets, studies on
some consumers decisions such as product adoption, upgrade, and replacement could be subject to bias. Third, the data includes price paid, but does not provide a “store environment” file, i.e., it does not include prices for all available brands at each point in time. One can create a price time series as described earlier by looking across the 1176 stores and across all customers to find a purchase of the particular product, which will include its price. Again, this assumes, as verified earlier, that the focal retailer charges the same prices across its different stores. If the resulting price series is still sparse, we suggest collecting pricing information from other sources, which is a standard practice among economists. We caution researchers to be aware of these limitations when making assumptions, formulating models, and drawing conclusions.

3. ISMS Durables Dataset 2

3.1 Data Description

ISMS Durables Dataset 2 features a field experiment for a Christmas promotion, which took place in December 2003 in the form of a direct mailing sent to a randomly selected group of households at the end of November 2003. The promotion offer is the following – households get $10 off if they purchase during the promotional time period (12/4 – 12/15). And if they do purchase, they will get 10% off on a subsequent purchase, which is good through the end of December.

Table 4 present some sample statistics for ISMS Durables Dataset 2. Roughly half of the 176,961 households in the database (promotion group) received the Christmas holiday promotional mailer; the other half (control group) did not. ISMS Durables Dataset 2 contains cross-sectional information for all the customers in the experiment and control groups. In addition to receipt of and response to the promotion, the data contain approximately 150 “predictor” variables in the database, covering purchase history, response to previous promotions, purchase of
warranties/extended service, product returns etc. Table 4 provides statistics for a few key variables characterizing the reaction to the Christmas promotion for the promotion and control groups. Mean sales for those receiving the promotional offer is $12.38; for those not receiving the offer it is $9.65. The other statistics show the experimental and control groups were equally matched on variables available before the promotion. This of course is as it should be, given the promotion was distributed randomly.

[Insert Table 4 about Here]

3.2 Research Opportunities and Limitations

ISMS Durables Dataset 2 provides the opportunity to analyze the results of a promotional field test, plus other topics such as the direct-mail-promotion-prone consumer. Its most attractive attribute is the field test; hence the most obvious use of the database is to analyze the results of the field test – both predicting the results and understanding them. For example, what are the best methodologies for predicting customer-level incremental sales for this experiment? What variables best predict incremental sales for this promotion? In addition, since the data contain response to previous promotions – all delivered via direct mail – one could try to profile the “direct mail deal prone” customer (see Blattberg and Neslin (1990, Chapter 3) for a summary of research on the deal-prone consumer in the context of consumer-packaged goods promotions). Another topic might be, “How best to quantify RFM?” The database contains summary variables such as number of purchases in the last 12, 24, 36, or 60 months, average basket size over the last 12, 24, 36, or 60 months, time since most recent purchase, broken down by product category, etc. It isn’t clear how these variables should be combined to provide meaningful metrics for tracking customers in a retailer environment. Those who received the offer averaged almost $2.84 higher
sales levels. These variables may be used to construct a model for predicting which customers will experience the most incremental sales if mailed the promotion. It is important to identify the customers whose sales levels increased the most.

One limitation, is that the data are not longitudinal in the sense of ISMS Durables Dataset 1. The RFM variables, etc., precede the field experiment, but the data do not contain week-by-week purchase histories of each customer. While ISMS Durables Datasets 1 and 2 are offered by the same company, the data cannot be linked - the customer IDs in the two data sets do not have one-to-one mapping.

4. Process

The database is provided by the INFORMS Society of Marketing Science (ISMS), the INFORMS organization for academics and practitioners of marketing science (http://www.informs.org/Community/ISMS). The distribution of the data is controlled to ensure its use is consistent with ISMS’s mission of enabling the development, dissemination, and implementation of research based on marketing science approaches. Database documentation, purchase agreement, open forum, working paper collection, and downloading instructions are available at http://www.informs.org/Community/ISMS.

5. Summary

In sum, ISMS makes available to the marketing science community two durable goods datasets – a panel database and a field test database. We hope these databases will spark a major acceleration

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1 Plans are underway to use ISMS Durables Dataset 2 for the ISMS Incremental Direct Sales Marketing Tournament, the purpose of which is to identify the customers whose sales levels increased the most during the December promotion. Database 2 is the calibration sample for that experiment. After the tournament is completed, we will make the holdout sample available.
in research of durable goods market that will benefit the practice of marketing for many years to come.
6. References


47. Mandell, Lewis (1972), Credit Card Use in the United States, Ann Arbor, MI: Institute for Social Research, University of Michigan.  
Table 1A: ISMS Durables Dataset 1: Frequency Count of Different Types of Transactions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Freq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Purchase</td>
<td>139,580</td>
</tr>
<tr>
<td>Product Return</td>
<td>14,724</td>
</tr>
<tr>
<td>Service Contract Purchase</td>
<td>15,033</td>
</tr>
<tr>
<td>Service Contract Return</td>
<td>2,437</td>
</tr>
<tr>
<td>Product Purchases with Identified Sales Discount</td>
<td>1452</td>
</tr>
<tr>
<td>Miscellaneous Transactions</td>
<td>36</td>
</tr>
<tr>
<td><strong>Total Number of Transactions</strong></td>
<td>173,262</td>
</tr>
</tbody>
</table>

Table 1B: ISMS Durables Dataset 1: Descriptive Statistics Related to Purchases

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Amount Paid per Trip</td>
<td>$317.02</td>
<td>$497.52</td>
</tr>
<tr>
<td>Average Amount Paid per Transaction</td>
<td>$109.23</td>
<td>$295.50</td>
</tr>
<tr>
<td>Average Number of Items per Trip</td>
<td>2.39</td>
<td>3.79</td>
</tr>
<tr>
<td>Average Number of Items per Transaction</td>
<td>0.82</td>
<td>1.38</td>
</tr>
<tr>
<td>Average Number of Purchase Trips per Household</td>
<td>2.99</td>
<td>2.78</td>
</tr>
<tr>
<td>Average Number of Purchase Transactions per Household</td>
<td>8.69</td>
<td>11.67</td>
</tr>
<tr>
<td>Average Price per Item</td>
<td>$108.91</td>
<td>$295.42</td>
</tr>
<tr>
<td>Average Amount Spent on Holiday Shopping a</td>
<td>$189.77</td>
<td>$352.71</td>
</tr>
<tr>
<td>Number of Gift Card Purchases</td>
<td>1487</td>
<td>NA</td>
</tr>
<tr>
<td>Number of Online Purchases</td>
<td>2550</td>
<td>NA</td>
</tr>
<tr>
<td>Number of Different Items Purchased</td>
<td>22210</td>
<td>NA</td>
</tr>
</tbody>
</table>

a. Holiday shopping refers to purchases made on Black Friday and Christmas.

Table 2: ISMS Durables Dataset 1: Descriptive Statistics of Demographic Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations b</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age_Household.Head</td>
<td>16384</td>
<td>48.42</td>
<td>15.17</td>
<td>18</td>
<td>99</td>
</tr>
<tr>
<td>Gender_Household.Head</td>
<td>16566</td>
<td>0.64</td>
<td>0.48</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>With Child(ren) or not</td>
<td>8451</td>
<td>0.66</td>
<td>.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of Children</td>
<td>19936</td>
<td>0.40</td>
<td>0.80</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Income</td>
<td>16811</td>
<td>5.68</td>
<td>2.36</td>
<td>1</td>
<td>9</td>
</tr>
</tbody>
</table>

b. Overall there are 19936 households in the data and some demographic info is missing.
<table>
<thead>
<tr>
<th>Decision Variables</th>
<th>Existing Literature</th>
<th>Method, Major Findings &amp; Research Issues</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Adoption</td>
<td>Gowrisankaran &amp; Rysman (2009)</td>
<td>Incorporate dynamic heterogeneous consumers with rational expectation about future attributes and find different elasticity measure when incorporating dynamics.</td>
<td>Aggregate level data</td>
</tr>
<tr>
<td></td>
<td>Song and Chintagunta (2003)</td>
<td>Analyze the impact of price expectations on the diffusion patterns of new high-technology products.</td>
<td>Aggregate level data</td>
</tr>
<tr>
<td></td>
<td>Nair (2007)</td>
<td>Investigate optimal pricing over time of a firm selling a durable-good product to strategic consumers.</td>
<td>Aggregate level data</td>
</tr>
<tr>
<td>Product Replacement</td>
<td>Gordon (2009)</td>
<td>Study consumers’ adoption and replacement decision of computer CPU and the implication of firm pricing behavior.</td>
<td>Aggregate level data</td>
</tr>
<tr>
<td></td>
<td>Schiraldi (2009)</td>
<td>Study how transaction costs determines consumer replacement behavior in both primary and secondary markets for automobiles.</td>
<td>Aggregate level data</td>
</tr>
<tr>
<td>Brand Choice</td>
<td>Erdem, Keane, Öncü &amp; Strebel (2005)</td>
<td>Study how consumer forward-looking price expectations of durable goods and the process of learning about quality influence the consumer choice process of computers.</td>
<td>Survey data</td>
</tr>
<tr>
<td>Cross-Category Purchases</td>
<td>Carlton &amp; Waldman (2005)</td>
<td>Use two-period model to study complementary product (monopolist in one category vs. monopolist/oligopoly in other category), and show when with upgrades for durable goods, the firm could increase profits by tying the cross-category purchase.</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td>Sriram, Chintagunta &amp; Agarwal (2007)</td>
<td>Study consumers’ adoption of multiple categories of technology products and found strong complementary effect across categories.</td>
<td>Survey data</td>
</tr>
<tr>
<td>Purchase of Add-ons</td>
<td>Ellison (2005), and Ellison &amp; Ellison (2005)</td>
<td>The former theoretically examine price discrimination role of add-on. The latter empirically analyzes demand and markups at a retailer who use add-on strategy to sell computer parts.</td>
<td>Combine several aggregate data collected online</td>
</tr>
<tr>
<td>Topic</td>
<td>Author(s)</td>
<td>Methodology</td>
<td>Data Type</td>
</tr>
<tr>
<td>-------</td>
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</tr>
<tr>
<td>Theoretically show how firms make excess profits using add-on prices when facing bounded rational consumers</td>
<td>Gabaix &amp; Laibson (2006)</td>
<td>Theoretical model</td>
<td>NA</td>
</tr>
<tr>
<td>Use theoretical monopolist model to study why the durable goods firm has incentive to monopolize the maintenance market.</td>
<td>Morita &amp; Waldman (2006)</td>
<td>Theoretical model</td>
<td>NA</td>
</tr>
<tr>
<td>Empirically investigate the factors that affect consumers’ purchases of extended service contracts.</td>
<td>Chen, Kalra &amp; Sun (2009)</td>
<td>Individual-level panel data</td>
<td></td>
</tr>
<tr>
<td>Field experiments using Walmart gift card to estimate consumers’ discount rate and provide implication for hyperbolic discounting and consumer self-control with field data.</td>
<td>Castillo, Ferraro, Jordan, Petrie (2008)</td>
<td>Field experiments</td>
<td></td>
</tr>
<tr>
<td>Theoretically investigate the competitive and welfare implications of gift cards in a retailing setting.</td>
<td>Chen, Cui &amp; Zhang (2010)</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td>Study how credit card affect consumers’ consumption with hyperbolic discounting; Focus on self-control and consumption, not studying how usage of credit card affect durable good consumption, and show how relaxation of borrowing constraint help consumer update durable purchase.</td>
<td>Laibson, Repetto and Tobacman (2000), Angeletos, Laibson, Repetto, Tobacman &amp; Weinberg (2001)</td>
<td>Experiments and account-level data on usage of credit card</td>
<td></td>
</tr>
<tr>
<td>Use equilibrium model of durable goods oligopoly with a competitive secondary market to evaluate the bias in estimating parameters of demand and supply when durability is omitted.</td>
<td>Chen, Esteban &amp; Shum (2008); not directly study open box item</td>
<td>Aggregate level data</td>
<td></td>
</tr>
<tr>
<td>Analytical model to identify potential causes for variation among retailers’ return policies.</td>
<td>Davis, Hagerty, &amp; Gerstner (1998)</td>
<td>Survey data distributed to mall visitors to validate/ Field-data to study why return</td>
<td></td>
</tr>
<tr>
<td>Study advantage of online channel and the implication of reducing consumer search cost.</td>
<td>Goolsbee (2000), Varian (2003), Goldmanis, Hortacsu, Syverson &amp; Emre (forthcoming)</td>
<td>Individual level survey data</td>
<td></td>
</tr>
<tr>
<td>Use dynamic game to study timing decisions and strategic interaction of</td>
<td>Schmidt-Dengler (2009)</td>
<td>Aggregate level data</td>
<td></td>
</tr>
</tbody>
</table>
the adoption of nuclear magnetic resonance imaging (MRI) by US hospitals.

Table 4: ISMS Durables Dataset 2: Descriptive Statistics for Calibration Sample  
(Standard Deviation in Parentheses)

<table>
<thead>
<tr>
<th></th>
<th>Control Group (Did not Receive Promotion Offer)</th>
<th>Treatment Group (Received Promotion Offer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Size</td>
<td>88,625</td>
<td>88,336</td>
</tr>
<tr>
<td>Total Sales During December Promotion period</td>
<td>$9.73 ($104.14)</td>
<td>$12.42 ($120.85)</td>
</tr>
<tr>
<td>Number of Transactions in previous 12 months</td>
<td>1.73 (3.44)</td>
<td>1.74 (3.59)</td>
</tr>
<tr>
<td>Number of Large ticket item purchases in previous 12 months</td>
<td>0.17 (0.51)</td>
<td>0.17 (0.50)</td>
</tr>
<tr>
<td>Number of Small ticket item purchases in previous 12 months</td>
<td>0.96 (3.57)</td>
<td>0.99 (4.10)</td>
</tr>
<tr>
<td>Number of ESPs purchased in previous 12 months</td>
<td>0.16 (0.54)</td>
<td>0.16 (0.54)</td>
</tr>
</tbody>
</table>
Figure 1. ISMS Durables Dataset 1: Weekly Sales Volume and Price Trend for Apex Digital Video Model 763370

Figure 2. ISMS Durables Dataset 1: Weekly Sales Volume and Price Trend for Apex Digital Video Model 749912