Investigating Consumer Adoption of Related Technology Products

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Abstract

We present a framework for modeling consumer adoption of multiple categories of technology products that may be related as complements (or substitutes). The context of technology products as well as the relationship between categories poses some unique challenges. First, declining prices (and the corresponding increase in quality levels) over time imply that consumers anticipate these changes and make a tradeoff between adopting the product early on and consuming the product for a longer time versus adopting later at lower prices (and higher quality). Second, the durable nature of technology products implies that even if two categories are related as complements, consumers may stagger their purchases over several periods; unlike in the case of packaged goods, one cannot infer complementary relationships between these categories based on joint purchases. Third, the forward-looking consumer decision process and the durable nature of technology products imply that a consumer's adoption decision for one category will depend not only on the anticipated price and quality trajectories of that category, but also on the anticipated adoption timing of the related category. Fourth, the adoption decision for some categories (such as printers) may be contingent upon adoption of another related category (such as a personal computer). We illustrate how our proposed modeling framework is flexible enough to address these issues in the context of two related categories and discuss how it can be extended to multiple categories. We apply our modeling framework to a unique dataset that contains information on consumer adoption of three related categories of technology products- personal computers, digital cameras, and printers. The results reveal a strong complementary relationship between these categories. As a result, the probability that a consumer would adopt a given category increases significantly if she has already adopted one or more of the related categories. Policy simulations based on a temporary price decrease in any one category provide interesting insights into how consumers would modify their adoption behavior over time as well as across categories as a consequence of the price decrease.

Keywords: Technology products, consumer adoption, complementary products, forward-looking consumers, econometric models

1. INTRODUCTION

Technology companies or divisions of such companies, e.g., the consumer products division of Hewlett Packard manage product lines that, amongst others, include personal computers, printers, handhelds, televisions, digital cameras, and related accessories. The responsibility of managing such a multi-product line poses several key challenges – e.g., How does the price trajectory of personal computer affect consumer adoption of printers and digital cameras? Can a price cut on digital cameras impact the adoption of higher margin printers? The key challenge in answering these questions is that different technology products may be related to each other as complements or substitutes. This implies that whether a consumer already owns related technology products may have an influence on the utility, and hence the probability of adoption of a new product. A good understanding of these inter-category relationships will be of great value to a manager responsible for managing a product line comprising of such related products, e.g., personal computers and digital cameras. Prior ownership of one of these products could increase the value a consumer would derive from the other. As a result, a consumer's probability of adopting any one category is likely to be higher if she has already adopted the other category. This, in turn, could influence promotional incentives targeted at such consumers. Further, a price decrease in the personal computer category might influence consumers who would otherwise have adopted the digital camera before adopting personal computers to reverse their order of adoption. As a result, the adoption trajectory as well as the total number of adopters of these categories is likely to change. This can have implications for managers who need to make decisions on the price trajectories of these related products.

The objective of this study is to investigate consumers' category adoption timing decisions in multiple, possibly related categories of technology products. We address the following three questions: a) to what extent does having adopted related categories increase the probability that the consumer would adopt the focal category?; b) to what extent does the number of adopters for each category depend on the complementary relationships between categories?; and c) how does a change in the pricing policy of one category influence adoption behavior in that category as well as in related categories? We develop an econometric framework that addresses these questions. In doing so, we need to account for the following four factors relevant for technology products.[4] First, a unique aspect of technology product adoption is that the prices tend to decline over time while quality typically improves. If consumers anticipate these future price and quality trajectories while deciding when to adopt, a model of consumer adoption of technology products needs to account for such forward-looking nature of consumer decision making (Erdem et al. 2005). Second, the durable nature of the products implies the modeling framework needs to account for the utility derived by the consumer over several time periods. Hence, the consumer's decision problem relates to making a tradeoff between the stream of utilities she would derive upon adopting the technology and the one-time price she needs to pay at the time of adoption. Third, an additional consequence of the durable nature of technology products is that joint adoption of two technologies is not necessary to infer a complementary relationship. Rather, a consumer who perceives a complementary relationship between categories can stagger these purchases over several time periods. Finally forward-looking behavior of consumers and the durable nature of the product imply that a consumer's decision to adopt any one technology is also likely to depend on when she anticipates adopting the remaining technologies. Hence, the adoption decision for the focal technology should depend not only on the expected price and quality trajectories of that technology but also on the trajectories of the related technologies.

We present our framework in the context of two related technology products and discuss how it can be extended to multiple technology products. We then discuss a special case of complementary products wherein the adoption of one category is contingent upon adoption of the related product. In order to demonstrate the applicability of our modeling framework to more than two categories, we perform our empirical analysis using data on the adoption of three related categories of technology products – personal computers, digital cameras, and printers. While the adoption of printers is contingent upon adoption of the personal computer category, no such restriction exists for the adoption of the either

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[4] We elaborate on these issues in the next section.

the personal computer or digital camera categories. Thus, our empirical analysis illustrates the application of our methodology when we have both contingent and non-contingent adoption.

Using a unique dataset that contains information regarding the time when each household adopted different technology products, we estimate an adoption timing model that accounts for consumer heterogeneity in their intrinsic valuation for the three product categories. The results from our analysis reveal the presence of three distinct segments of consumers that differ in terms of their relative valuation and hence, the timing of adoption of the three categories. Furthermore, the results imply complementary relationships between the three categories. As a consequence of this complementary relationship, the probability that a consumer would adopt a given category increases if she has already adopted one or more categories. To understand the impact of the estimated complementarity effects on adoption probabilities, we simulate these probabilities by setting the complementarity parameters to zero. We find that for a consumer who has not adopted any of the three categories, personal computer adoption probability would decrease by 5.14% if there was no complementary relationship between personal computer and digital camera categories. On the other hand, for a consumer who has already adopted the digital camera category, the adoption probability of personal computers would decrease by 22.36%. Additionally, the results indicate that the effect of complementarity between digital cameras and printers on the adoption probabilities is marginally greater than the effect of PC-digital camera complementarity. Of the three categories, the probability of adopting digital cameras was most sensitive to these changes.

In order to understand how a temporary price change in one category influences the adoption behavior in that category as well as in other related categories, we perform policy simulations where we decrease the first period price of the personal computer and digital camera categories by 5%. The results from this one time price decrease reveal interesting inter-temporal substitution in adoption across categories. When we decrease the price of the digital camera (personal computer) category, some consumers who initially prefer to adopt a personal computer (digital camera) before adopting other categories prefer to start with digital cameras (personal computer) instead. Further, we find that the price changes have comparable effects in terms of magnitude on the adoption behavior of digital cameras amongst the different ownership groups – a) consumers who do not own anything before adopting digital cameras, b) consumers who have adopted the personal computer before adopting the digital camera category, and c) consumers who have adopted both the personal computer and printer before adopting digital cameras. On the other hand, in case of both the personal computer and printer categories, the change due to the price decreases is dominated by consumers who have not adopted any of the categories.

This paper makes the following contributions to the extant literatures on multi-category purchasing behavior and on the adoption of technology products. First, from a methodological point of view, we develop a framework for modeling multi-category adoption behavior by forward-looking consumers with special emphasis on adoption of technology products. Thus the paper presents an extension of the literature on consumer purchases across multiple categories (see, for example, Gentzkow 2007) to the context of durable technology products. As we discuss later in the paper, the context of durable technology products poses some unique challenges that need to be addressed while developing the framework. We believe that our framework is general enough to accommodate sequential purchases by consumers across several categories or channels. Second, from a substantive point of view, we investigate the extent to which adoption of related categories can modify the propensity of a consumer to adopt a new category. Moreover, our findings on the expected changes in consumer adoption behavior across related categories as a result of changes in price trajectory in any one category has implications for managers who design promotional campaigns across such related categories.

The rest of the paper is organized as follows. We first present the framework for modeling consumer adoption of related technology products. We then discuss the empirical application of our proposed modeling framework. Next, we describe the data used in the empirical application. We then present our empirical results based on the adoption behavior for personal computer, digital camera, and printer categories and discuss their implications. Finally, we provide some concluding comments.

2. A FRAMEWORK FOR MODELING ADOPTION OF RELATED TECHNOLOGY PRODUCTS

In this section, we present a framework for modeling consumer adoption of related technology products. First, we review related literature and discuss the features of the model that are necessitated by the context of our application. We then provide details of the model in the context of two related categories of technology products. In the following sub-section, we describe how the model can be applied when adoption of one category is contingent upon adoption of a related category. The section concludes with a generalization of the model to an arbitrary number of categories.

2.1. Related Literature and Model Features

Recent years have seen a significant number of papers that seek to understand consumer purchase behavior across multiple categories (see Seetharaman et al. 2005 for a review of this literature). The key motivation behind these studies is that if purchase decisions across two or more categories are related, a change in purchase behavior in one category, which might be induced e.g., by a change in its marketing mix, is likely to alter purchase behavior in related categories (Niraj, Padmanabhan, and Seetharaman 2007; Gentzkow 2007; Song and Chintagunta 2006; Wedel and Zhang 2004). Consequently, this can have an impact on optimal marketing mix decisions across categories. Hence, retailers and managers who need to manage multiple categories are likely to benefit from a better understanding of such cross-category effects.

Extant research has identified several factors that drive dependence in consumer purchases across multiple categories. These include heterogeneity: consumers who have a high propensity to purchase in one category may also have a high propensity to purchase in other categories (Ainslie and Rossi 1998; Kamakura et al. 2004); complementarity (or substitutability) as in e.g., Chintagunta and Haldar 1998); and co-incidence: consumers purchase products together because of factors such as similar purchase cycles, physical environment in the store (Swinyard 1993), and habit (Kahn and Schmittlein 1992). Manchanda, Ansari, and Gupta (1999) decompose the effects of these three factors in inducing dependence in purchase behavior across multiple categories. Additionally, consumer purchase across categories could be related due to shared brand names (Hansen, Singh, and Chintagunta 2006) or more generally, a common set of attributes (Hansen, Gupta, and Singh 2005).

Our application differs from these studies along several key dimensions. First, current research on multi-category purchases is restricted to static models.[5] Consequently, they do not incorporate the effect of consumers anticipating future price reductions while making purchase decisions (see Erdem et al. 2005 and Song and Chintagunta 2003 for applications that model consumer anticipation of future prices). In the context of technology product markets which are characterized by declining prices (and possibly increasing quality) over time, such a static analysis may not be appropriate. Especially, dynamics in prices and quality imply that consumers anticipate future price decreases and make a tradeoff between "enjoying" the technology for a longer time by adopting earlier and adopting it in the future at a lower price. An important consequence of ignoring such "forward looking" behavior of consumers that has been documented in the literature is that it leads to the underestimation of price elasticities. In our application, we incorporate consumers' anticipation of the future price trajectory in modeling their purchase decisions across multiple categories. However, the durable nature of these products implies that in deciding when to adopt a given category, a consumer also needs to anticipate when she is likely to adopt other related categories. Consequently, the adoption behavior of the focal category depends not only on the price (and quality) trajectory of that category, but also on the corresponding trajectories of related categories. This adds further complexity to the analysis.

Second, a key challenge when studying multi-category purchase behavior in the context of consumer packaged goods is that, very often, these categories are purchased together even when these categories are entirely unrelated. Hence researchers need to use methods that can separate out the effects of "co-incidence" in purchase behavior from possible substitution and complementary effects. One such strategy for identifying substitution and complementary effects is to make the utility of purchasing in a category at time t to be a function of the marketing mix variables of the other categories at time t (see, for example, Manchanda et al. 1999; Niraj et al. 2007). However, such an approach cannot be readily adapted to the context of technology product markets because their durability implies that joint purchase

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[5] Some studies (see, for example, Erdem and Sun 2002) have investigated purchase decisions across categories by forward-looking consumers in the context of packaged goods. However, their main focus is on spillover effects due to shared brand names across categories and do not consider complementarity between them.

is not a necessary condition for dependence. Consequently, one needs to infer dependence by seeing if the utility from adopting a category of technology products at time *t* depends on the prior ownership of the other product category. Furthermore, the durable nature of technology products implies that consumers derive utility from these products over an extended period of time. As a result, when technology products are purchased in a staggered fashion, the consumer derives incremental utility due to the complementary relationship only for the period since she has both technologies. This further complicates assessment of the magnitude of the complementary relationship.

Third, while most of the extant literature on multi-category purchases has studied consumer packaged goods markets, our study is interested in technology products. This poses a challenge since an analysis of purchase behavior across multiple categories requires household-level data on purchases across these categories over time. Clearly, no such readily available data exist even for individual technology products, let alone multiple products. The limited availability of such data can be attributed, in part, to technology products not being purchased frequently. As a result, one needs to track purchases over several years in order to yield a sufficiently large sample of respondents who have purchased across multiple categories. A plausible alternative is to ask consumers retrospectively about their ownership of technology products across multiple categories as well as the timing of these purchases. We use such an approach in our application. To ensure that our data are from a representative sample of consumers, we correlated the aggregated purchases from our data to actual aggregate sales data over time obtained from secondary data sources and verified that this correlation was high (the correlations were 0.68, 0.99, and 0.80 for the personal computer., digital camera, and printer categories, respectively). Note however, that such data limit us to the study of category level (rather than at the model or brand level) adoption decisions of consumers since information at the model or even the brand level is rarely available.

2.2. The Modeling Framework

2.2.1. Overview of the Modeling Framework

For the sake of simplicity, we first consider the adoption of two related technology products by consumer *i*, $i = 1, 2, 3, \dots I$. Later, we show that the model can be extended to multiple categories. Upon adoption of category *c*, $c = 1, 2$ at quality level q_{ic}, consumer *i* derives a per-period utility $\alpha_{ic}(q_{ic})$ from that category – the consumer's intrinsic valuation for the category. This specification of the intrinsic valuation for each category is general enough to capture three factors that can cause the intrinsic valuation to vary across consumers. First, it depends on the quality level at which the consumer adopts the product.[6] Second, it could depend on consumer-specific demographic and psychographic characteristics (sources of observed heterogeneity). Finally, one can also allow the intrinsic valuation to vary across consumers (due to unobserved heterogeneity). Hence, over her lifetime, the consumer receives $\Lambda_{ic}(q_{ic})$, the discounted infinite series of the per-period utility, $\alpha_{ic}(q_{ic})$. Let $\delta \in [0,1)$ be the discount factor. Then,

$$\Lambda_{ic}(q_{ic}) = \frac{\alpha_{ic}(q_{ic})}{1-\delta}. \tag{1}$$

In the subsequent discussion, we sometimes refer to this infinite stream of utility as the "residual value" of the product. Upon adopting both categories, the consumer derives a lifetime of utilities from both categories plus an additional term which can take non-zero values if the two categories are related as complements or substitutes. Formally,

$$\overline{\alpha_i}(q_{i1}, q_{i2}) = \alpha_{i1}(q_{i1}) + \alpha_{i2}(q_{i2}) + \Gamma \text{ and}$$

$$\overline{\Lambda}_i(q_{i1}, q_{i2}) = \Lambda_{i1}(q_{i1}) + \Lambda_{i2}(q_{i2}) + \Gamma/_{1-\delta}, \tag{2}$$

where $\overline{\alpha_i}(q_{i1}, q_{i2})$ is the per-period utility that consumer *i* derives from adopting category 1 and 2 at quality levels q_{i1} and q_{i2}, respectively. The term $\overline{\Lambda}_i(q_{i1}, q_{i2})$ is the corresponding residual value. The term Γ captures the additional per-period utility that the consumer derives from adopting both categories. If the two categories are related as complements (substitutes), we would expect Γ to be positive (negative), and for unrelated categories, $\Gamma = 0$. Note that Equation 2 has two key implications. First, a

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[6] Note that the quality level at which the consumer adopts each category will depend on the time of adoption. Increasing quality over time implies that a consumer adopting the product later would also adopt at a higher quality level. Later, we discuss the effect of quality dynamics on consumer decision-making.

consumer derives utility from each technology not just in the period when it is adopted but for any time period subsequent to adoption. Second, the consumer derives the additional utility Γ for every period since the time she adopts both products. Let {a, b} denote a consumer's adoption in the two categories; where a, b $\in$ {0, 1} denotes either non-adoption (0) or adoption (1) in categories 1 and 2, respectively. Based on whether the consumer owns each of the two categories, we can view her as being in four possible adoption levels at any give time period:

Adoption level 0: Own neither - {0, 0}

Adoption level 1: Own category 1 - {1, 0}

Adoption level 2: Own category 2- {0, 1}

Adoption level 3: Own both categories - {1, 1}.

The consumer has to decide the sequence as well as the timing of adoption of the two categories that maximizes her expected discounted stream of utilities from these categories. At any time *t*, a consumer can either stay in the current adoption level or move to a higher adoption level. A consumer in adoption level 0 has the option of staying in level 0 or moving to levels 1, 2, or 3; a consumer in adoption levels 1 or 2 has the option of staying in that level or adopting the other category and moving to adoption level 3. Once the consumer reaches adoption level 3, she exits the market.

The tradeoff that the consumer faces is between a) adopting the categories early and deriving utility over a longer period of time and b) adopting them later and paying a lower price and/or obtaining a higher quality product. Further, if the products are complements with $\Gamma > 0$, a consumer who has adopted only one category will forego the additional utility she would derive from adopting the other category. Thus, she will have an incentive to accelerate adoption of the other category. As the magnitude of the complementarity effect between the two categories increases, the consumer will reduce the time interval between their adoptions. Thus, the presence and extent of complementarity complicates the tradeoff facing the consumer in new product adoption. As a result, the relative sequence in which the consumer transitions across adoption levels is likely to depend on i) the relative intrinsic valuation of the categories, ii) the nature of the relationship between the categories (complements, substitutes or unrelated) as well as the magnitude of the complementarity or substitution effect, iii) the consumer's expectation of the future price and quality trajectories of both categories, and iv) the consumer's price sensitivity and preference for higher quality products. In what follows, we present a formal treatment of the consumer's decision problem when the two categories are related as complements or as substitutes.

2.2.2 The Case of Related Products

We first start with the case when the consumer has adopted one of the product categories (levels 1 and 2) and then finally discuss the case of a consumer in adoption level 0.

(a) Decision Process for a Consumer at Adoption Level *j*, *j* = 1, 2

Recall that a consumer who is in adoption level *j* has already adopted category *j*. Therefore, the consumer's decision problem pertains to the timing of adoption of category *k*, *k* = 1, 2, *k* ≠ *j* and thus exiting the market. Such a consumer can: a) stay in level *j* or b) move to level 3. At any time period, *t* the consumer chooses the alternative that offers the highest utility. Below, we discuss the utilities that the consumer would derive from these alternatives.

Moving from level j to level 3

A consumer who moves from level *j* to level 3 will derive the infinite stream of utilities from categories 1 and 2 as well as the infinite stream of the complementary effect. However, the consumer has to pay a one time price of category *k* in order to move to level 3 from level *j*. Hence, we have

$$W_{it}^{j3}(S_t^j) = V_{it}^{j3}(p_{kt}, q_{kt}; q_{ij}) + e_{it}^3, \tag{3a}$$

where,

$$V_{it}^{j3}(p_{kt}, q_{kt}; q_{ij}) = \overline{\Lambda}_i(q_{ij}, q_{kt}) - \beta_k p_{kt}. \tag{3b}$$

In Equation 3a, $W_{it}^{j3}(.)$ is the utility that the consumer derives from moving to adoption level 3 at time *t* from level *j* by adopting category *k* and e_{it}^3 is the error term corresponding to moving to adoption level 3 at time *t* that is unobserved by the researcher. The term S_t^j refers to the set of state variables that affect the consumer's utility at adoption level *j* at time *t*. The term $\overline{\Lambda}_i(q_{ij}, q_{kt})$ in Equation 3b captures the residual value that the consumer derives from adopting both categories and is defined as in Equation 2.

Thus, the residual value $\overline{\Lambda}_i(q_{ij}, q_{kt})$ is a function of the quality level at which the consumer had adopted category *j*, q_{ij}, and the quality level of category *k* at time *t*, q_{kt}. The term p_{kt} corresponds to the price of category *k* at time *t* and β_k is the corresponding price sensitivity parameter.

Staying in Level j

A consumer who decides to stay in adoption level *j* at time *t* derives the option value from postponing the decision of adopting category *k* to the next period. However, since she has already adopted category *j*, she derives the utility from consuming that category during that period. Thus, the observed part of the utility she derives from staying in level *j* at period *t*, $V_{it}^{jj}(p_{kt}, q_{kt}; q_{ij})$, comprises of two components: a) the value of consuming category *j* in period *t* and b) the option value of either adopting category *k* and moving to adoption level 3 in the next period or staying in adoption level *j*. Hence, we have

$$V_{it}^{jj}(p_{kt}, q_{kt}; q_{ij}) = \alpha_{ij}(q_{ij}) + \delta E[\max\{W_{it+1}^{jj}(S_{t+1}^{j}), W_{it+1}^{j3}(S_{t+1}^{j})\} \mid p_{kt}, q_{kt}]. \tag{4a}$$

Recall that the term $\alpha_{ij}(q_{ij})$ captures the per-period utility that consumer *i* derives from category *j* given that she adopted the category at quality level q_{ij}. The term $W_{it+1}^{j3}(S_{t+1}^{j})$ is defined as in Equation 3a and captures the option value of moving to adoption level 3 in the next period. Along similar lines, the term $W_{it+1}^{jj}(S_{t+1}^{j})$ captures the total utility that the consumer would derive if she were to remain in adoption level *j* in period *t*+1. As in Equation 3a, we can express the utility that a consumer derives from staying in adoption level *j* into two components – one that is observed by the researcher and an unobserved error term. Hence, the total utility that the consumer derives from staying in level 2 at time *t* can be written as

$$W_{it}^{jj}(S_t^{j}) = V_{it}^{jj}(p_{kt}, q_{kt}; q_{ij}) + e_{it}^{j}, \tag{4b}$$

where, $V_{it}^{jj}(p_{kt}, q_{kt}; q_{ij})$ is the component of utility that is observed by the researcher and e_{it}^{j} is the corresponding unobserved component. Given the formulation above, the state variables for a consumer in adoption level *j*, $S_t^{j} = \{ p_{kt}, q_{kt}, e_{it}^{j}, e_{it}^{3} \}$. Note that the set of state variables consist of two components: a)

$\Omega_t^j = \{p_{kt}, q_{kt}\}$, which is observed by both the consumer and the researcher upon realization and b) $e_{it} = \{e_{it}^j, e_{it}^3\}$, which are observed by the consumer upon realization but not by the researcher.

(b) Decision Process for a Consumer at Adoption Level 0

A consumer who is in adoption level 0 has not adopted either category. Hence, at any time period *t*, she has the option of either adopting the categories sequentially or simultaneously. If she were to decide to make sequential adoption, she can either start with category 1 or category 2. Alternatively, she can decide to postpone the adoption decision to the next period and remain in adoption level 0. Hence, a consumer in this adoption level has four possible alternatives: a) stay in level 0, b) move to level 1, c) move to level 2, and d) move directly to level 3 and thus, exit the market. We discuss the utilities associated with each of these alternatives in reverse order.

Moving from level 0 to level 3

A consumer moving from level 0 to level 3 will derive the infinite stream of utilities from categories 1 and 2 as well as the infinite stream of complementary effect. However, the consumer has to pay a one time price (of both categories) to move to level 3 from level 0. Specifically,

$$W_{it}^{03}(S_t^0) = V_{it}^{03}(p_{1t}, p_{2t}, q_{1t}, q_{2t}) + e_{it}^3, \tag{5a}$$

$$V_{it}^{03}(p_{1t}, p_{2t}, q_{1t}, q_{2t}) = \overline{\Lambda}_i(q_{1t}, q_{2t}) - \beta_1 p_{1t} - \beta_2 p_{2t}, \tag{5b}$$

where $W_{it}^{03}(.)$ is the utility that the consumer derives from moving to adoption level 3 at time *t* directly from level 0 by simultaneously adopting both product categories and e_{it}^3 is the corresponding error term which is unobserved by the researcher. The term S_t^0 refers to the set of state variables that affect the utilities of a consumer at adoption level 0 at time *t*. In Equation 5b, the term $\overline{\Lambda}_i(q_{1t}, q_{2t})$ is defined as in Equation 2 and captures the residual value that the consumer derives from adopting both categories 1 and 2 at quality levels q_{1t} and q_{2t}, respectively. The terms p_{ct}, c = 1, 2, correspond to the price of the two categories and β_1 and β_2 are the corresponding price sensitivity parameters.

Moving from level 0 to level j, j=1, 2

As in the case above, the utility that consumer *i* derives from moving to adoption level *j* from level 0 can be expressed as a sum of the components that are observed and unobserved from the researcher as

$$\begin{aligned} W_{it}^{0j}(S_t^0) &= W_{it}^{jj}(S_t^j) - \beta_j p_{jt} \\ &= V_{it}^{jj}(p_{kt}, q_{kt}; q_{ij} = q_{jt}) - \beta_j p_{jt} + e_{it}^j \end{aligned}, \tag{6}$$

where $W_{it}^{0j}(.)$ is the utility that the consumer derives from moving to adoption level *j* at time *t* from level 0 by adopting only category *j* and retaining the option of adopting category *k* ($k \neq j$) in the future. The rationale behind Equation 6 is that a consumer who moves from level 0 to level *j* at time *t* will derive the utility from being in level *j*, $W_{it}^{jj}(S_t^j)$, as defined in Equations 4a and 4b. However, the consumer has to pay a one time price (of category *j*) in order to get to level *j* from level 0. Notice that Equation 6 implies that the consumer's decision to adopt category *j* not only depends on the price and quality level of that category, $\{p_{jt}, q_{jt}\}$, but also on the anticipated price and quality trajectories of category *k*, $\{p_{kt}, q_{kt}\}$.

Utility from staying in level 0

A consumer who decides to stay in level 0 at time *t* will derive no consumption value during that period. However, the consumer retains the option value of moving to any of the higher adoption levels or staying in adoption level 0 in the next period. Hence, we can write the observed component of the consumer's utility as

$$V_t^{00}(p_{1t}, p_{2t}, q_{1t}, q_{2t}) = \delta E[\max\{W_{it+1}^{00}(S_{t+1}^0), W_{it+1}^{01}(S_{t+1}^0), W_{it+1}^{02}(S_{t+1}^0), W_{it+1}^{03}(S_{t+1}^0)\} \mid p_{1t}, p_{2t}, q_{1t}, q_{2t}], \tag{7a}$$

where, $W_{it+1}^{01}(.)$ and $W_{it+1}^{02}(.)$ are defined as in Equation 6 while and $W_{it+1}^{03}(.)$ is defined in Equation 5a. The total utility that consumer *i* derives from being in adoption level 0 at time *t* can be written as a sum of the observed and unobserved components as

$$W_{it}^{00}(S_t^0) = V_{it}^{00}(p_{1t}, p_{2t}, q_{1t}, q_{2t}) + e_{it}^0. \tag{7b}$$

Given the formulation above, the state variables for a consumer in adoption level 0, $S_t^0 =$ $\{ p_{1t}, p_{2t}, q_{1t}, q_{2t}, e_{it}^0, e_{it}^1, e_{it}^2, e_{it}^3 \}$ with the observable component, $\Omega_t^0 = \{ p_{1t}, p_{2t}, q_{1t}, q_{2t} \}$.

As mentioned earlier, the modeling framework presented above nests the case of unrelated products, wherein $\Gamma = 0$, as a special case. Under such a scenario, the adoption decision of one category will be independent of the adoption decision in the other category. A formal proof of this independence can be obtained from the authors upon request.

The above formulation presents a general structure for modeling consumer adoption of two related categories of technology products. Since such products are characterized by declining prices and increasing quality over time, the model allows for consumers' anticipation of these dynamics while making their adoption decisions. Furthermore, the model structure implies that the intrinsic value from each category would vary across consumers due to (a) the quality level at which the consumer adopts the category, (b) observed consumer heterogeneity, and (c) unobserved consumer heterogeneity. Thus, if two consumers have the same preference structure for the category in terms of their observed and unobserved heterogeneity, the consumer who adopts the category at a later time period (at a higher quality level) would derive a greater intrinsic value from the category than the consumer who adopts earlier.

2.2.3. The Case of Contingent Products

In this section, we discuss a special case of related technology products – products where the adoption of one category, say category 2, is contingent upon the adoption of category 1. In this scenario, a consumer can adopt category 1 without adopting category 2 but not vice versa. Examples of such contingent products include personal computers & printers (the contingent product) as well as hardware & software (the contingent product). In order to model consumer adoption of such contingent products in our framework, we need to impose some restrictions on the set of feasible adoption levels. Since consumers cannot adopt category 2 in the absence of category 1, we need to impose the restriction that a consumer cannot exist in adoption level 2. Consequently, a consumer in adoption level 0 has only three feasible alternatives: a) stay in adoption level 0, b) move to adoption level 1, or c) move to adoption level 3. Hence, we need to modify Equation 7a as

$$V_t^{00}(p_{1t}, p_{2t}, q_{1t}, q_{2t}) = \delta E[\max\{W_{it+1}^{00}(S_{t+1}^0), W_{it+1}^{01}(S_{t+1}^0), W_{it+1}^{03}(S_{t+1}^0)\} \mid p_{1t}, p_{2t}, q_{1t}, q_{2t}]. \qquad \text{(7a')}$$

All other utilities (except those pertaining to adoption level 2, which is not defined) are similar to the case without contingent adoption.

A key implication of the restriction that a consumer cannot exist in level 2 is that one cannot uniquely identify the complementarity effect, Γ, between these categories separately from the intrinsic valuation for category 2, α_{i2}. Rather, one can only infer the sum of these two parameters. The intuition behind this lack of identification is as follows. Assume for the time being, the absence of any price effect, thus the intrinsic utilities are the drivers of adoption. Observing transitions from adoption level 0 to level 1 (or to level 2) helps us in identifying the intrinsic utility obtained from category 1 (or category 2). Further, observing transitions from adoption level 1 (or level 2) to level 3 helps in identifying the complementarity effect since one can interpret that any increase in adoption behavior over and beyond those predicted by just the intrinsic utilities corresponding to the two categories should be due to possible complementarity between the categories. However, if adoption of category 2 is contingent on adoption of category 1, then one never observes transitions from adoption level 0 to 2, and hence the intrinsic utility of category 2 is not identified. In this case, observing the transitions from adoption level 1 to level 3 can only be attributed to some combination of the intrinsic utility of category 2 and the complementarity effect.

2.2.4. Extending the Framework to Multiple Categories

The framework presented above can be readily generalized to the context of multiple categories. Consider the case wherein a consumer is deciding on the timing and sequence of adoption of *C* categories. Hence, there are 2^C possible adoption levels in which a consumer can exist. Let $Y^l = \{y_1^l, y_2^l, ..., y_C^l\}$, be a vector such that $y_c^l = 1$ if being in adoption level *l*, *l* = 0, 2, … 2^C-1, implies that the consumer has adopted category *c*. Thus, the vector Y^l contains information on the categories that a consumer in adoption level *l* has adopted. Since a consumer who has adopted all *C* categories exits the market, there are 2^C-1 adoption levels in which the consumer is active. Let Ψ, Ψ = {0, 1, 2, …, 2^C -2}, be the set of active adoption levels. Further, let Ξ_l be the set of feasible adoption levels to which a consumer can move from each active adoption level *l*, $l \in \Psi$. Since a consumer can only move to adoption levels that have more categories than the current adoption level *l*, level *m* constitutes a feasible adoption level iff $y_c^m \geq y_c^l,\ \forall c$.[7] Thus, if $y_c^m > y_c^l$, the consumer adopts category *c* when transitioning from adoption level *l* to level *m*. Similarly, if $y_c^m = y_c^l$, the consumer decides to postpone the adoption of category *c* to a future period. Hence, the difference between vectors Y^m and Y^l contains information on the set of categories that a consumer needs to adopt in transitioning from adoption level *l* to adoption level *m*.

Let W_{it}^{lm} denote the utility that consumer *i* would derive from transitioning to adoption level *m*, $m \in \Xi_l$, from adoption level *l*, $l \in \Psi$ at time *t*. As discussed in Section 2.2.2., we have

$$\begin{aligned} W_{it}^{lm} &= V_{it}^{lm} + e_{it}^{m}, \\ V_{it}^{lm} &= V_{it}^{mm} - (Y^m - Y^l) * \mathrm{P}_t{}', \end{aligned} \text{ where} \tag{8a}$$

$$\mathrm{P}_t = \{\beta_1 p_{1t}, \beta_2 p_{2t}, ..., \beta_C p_{Ct}\}. \tag{8b}$$

In Equation 8b, the term P_t is the vector of prices of the *C* categories weighted by the corresponding price coefficients and the term $(Y^m - Y^l)$ is a vector that contains information on the set of categories that a consumer needs to adopt in transitioning from level *l* to level *m*. The observed component of utility, V_{it}^{mm}, can we written as

$$V_t^{mm}(\Omega_t^m) = u_i^m(Q_i^m) + \delta E[\max\{W_{it+1}^{mm_1^{'}}(S_{t+1}^m), W_{it+1}^{mm_2^{'}}(S_{t+1}^m), ..., W_{it+1}^{mm_M^{'}}(S_{t+1}^m)\} \mid \Omega_t^m], \tag{9}$$

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[7] For the case of contingent products, we need to impose an additional restriction. Suppose adoption of category *c'* is conditional upon adoption of category *c*, we need to have an additional restriction such that $y_c^l \geq y_{c'}^l$.

where Ω_t^m is the set of observable state variables at adoption level *m*, $u_i^m(Q_i^m)$ is the per-period utility that consumer *i* derives from being in adoption level *m*, and $\{m_1^{'}, m_2^{'}, ..., m_M^{'}\} = \Xi_m$ is the set of feasible adoption levels to which a consumer can transition from level *m*. Note that the per-period utility that the consumer *i* derives from being in adoption level m, $u_i^m(Q_i^m)$ depends on the quality level at which the consumer has already adopted the products in order to be in that level. Further, under the assumption that there are only pair-wise complementary relationships, we can write the per-period utility as

$$u_i^m(Q_i^m) = (Y^m) * (\alpha_{1i}(q_{i1}), \alpha_{2i}(q_{i2}), ..., \alpha_{Ci}(q_{iC}))' + \sum_{c,c'=1, c \neq c'}^{C} I^m(c,c') * \Gamma^{cc'}, \qquad (10)$$

where $I^m(c,c')$ is an indicator variable that takes on a value of 1 if a consumer in adoption level *m* has adopted both categories *m* and *m'* and 0 otherwise and the term $\Gamma^{cc'}$ captures the per-period pair-wise complementary effect between categories *c* and *c'*. Thus, the first term in Equation 10 corresponds to the sum of per-period utilities that the consumer would separately derive from each of the categories that she owns in adoption level *m* and the second term captures the additional complementarity effect from owning these products jointly.

Based on the discussion above, it is clear that in the case of *C* categories, there are 2^C possible adoption levels in which a consumer can exist. Hence, excluding the terminal adoption level wherein the consumer has adopted all *C* categories, there are 2^C-1 adoption levels in which the consumer is active. This will entail the computation of 2^C-1 value functions corresponding to the value that the consumer derives from being in each of these active states. This can be computationally challenging for large values of *C*. Moreover, each additional category adds more dimensions to the state space. Hence, while the extension may be conceptually straightforward, estimation can become computationally intractable as the number of categories increases. Furthermore, as the number of categories increases, it becomes increasingly likely that we have no observations for some transition alternatives from a given adoption level. In the absence of *a priori* restrictions on the feasibility of such adoption levels, we can encounter problems with identifying some of the model parameters.[8] In our empirical application, we demonstrate the applicability of the model to the case of three product categories.

3. EMPIRICAL APPLICATION

In this section, we discuss the empirical application of the modeling framework presented in Section 2. First, we recast the model in our empirical context of three related categories and then discuss the challenges in implementing the model in this context. We then present other model related details such as how we deal with consumer heterogeneity. The section concludes with a discussion of the estimation approach.

3.1. Empirical Model

In the previous section, we discussed the applicability of our modeling under two scenarios – related products with and without contingent adoption. In order to demonstrate the applicability of the framework under both these scenarios, our empirical application reflects both these scenarios. Specifically, our empirical application is based on the consumer adoption of three related categories – personal computers, digital cameras, and printers. In the subsequent discussion, we refer to these categories as 1, 2, and 3, respectively. Intuitively, one would expect to see complementary relationships between these three categories. However, as discussed in the previous section, printer adoption is contingent upon the adoption of personal computers. Nevertheless, there is no such restriction for the adoption of either personal computers or digital cameras.[9]

Given the contingent adoption restriction, at any time *t*, a consumer can exist in any of the following six adoption levels:

Adoption level 0: {0, 0, 0}	None of the 3 categories is owned
Adoption level 1: {1, 0, 0}	Only a PC is owned
Adoption level 2: {0, 1, 0}	Only a Digital Camera is owned

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[8] Given the discrete nature of the consumer choice decision, the utility derived from each transition alternative for a given adoption level is inferred based on the relative probability of transitioning to those adoption levels. If we do not observe any consumer choosing a particular alternative, the model will break down as the utility for that alternative $\rightarrow -\infty$. This will have an impact on the magnitudes of some of the parameters that are estimated.

[9] In the data section, we present evidence for these claims.

Adoption level 4: {1, 1, 0}	PC and Digital Camera are owned
Adoption level 5: {1, 0, 1}	PC and Printer are owned
Adoption level 7: {1, 1, 1}	All 3 categories are owned.

In the above notation, the first, second, and the third elements indicate whether the consumer has adopted categories 1, 2, and 3 respectively. Based on the contingent adoption condition, we impose the restriction that the consumer cannot exist in level 3 (corresponding to {0, 0, 1}) or level 6 (corresponding to {0, 1, 1}).[10] As in the two category scenario discussed above, a consumer in adoption level 7 exits the market. Thus, the set of active adoption levels, Ψ = {0, 1, 2, 4, 5}. In Table 1, we present the set of feasible adoption levels, Ξ_l, to which a consumer can move from each active adoption level l, $l \in \Psi$. From Table 1, we can see that a consumer can adopt the personal computer category from two different adoption levels – level 0 and level 2. On the other hand, a consumer can adopt the digital camera category from three different adoption levels – level 0, level 1, and level 5. Similarly, a consumer can adopt the printer from four different adoption levels – level 0, level 1, level 2, and level 4. In the appendix, we derive the consumer's decision-making process that builds on the two category scenario discussed earlier. Note that with three products, we can estimate three pair-wise complementary relationships. However, the contingent nature of printer adoption implies that we cannot identify the magnitude of the complementary relationship between personal computer and printer categories separately from the intercept for the printer category.

3.1.1. Challenges with Implementing the Model

The model presented in Section 2 provides a general structure for capturing consumer adoption of related categories of technology products. Nevertheless, implementing it poses serious challenges. The first challenge is the dimensionality of the state space. From Equation 7a, it is clear that even with two categories, the value function corresponding to being in adoption level 0 has four state dimensions –

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[10] Recently, new printer models that can be used with digital cameras without the need for personal computers have been introduced. However, during the period of our analysis, such printers were not available. Furthermore, as we discuss in the data section, we do not observe any consumers adopting printers and digital cameras in the absence of a personal computer.

prices and quality levels of the two categories. Since our empirical application deals with three categories, this value function would have six state dimensions. The high dimensionality of the state space will make the estimation computationally intensive. For consumers who adopt the categories sequentially, the value function of being in the intermediate adoption levels (i.e., already owning 1 or 2 categories) would depend on the quality levels at which the consumer adopts those other categories. For example, consider the value function corresponding to adoption level 4. A consumer in this adoption level has already adopted the personal computer and digital camera categories. Hence, there are two relevant state variables corresponding to the anticipated price and quality trajectories of printers. However, this value function, as noted previously, would also depend on the quality level at which the consumer has already adopted the personal computer and digital camera categories. Thus, we need to evaluate the value function at each combination of quality levels at which consumers could have adopted these two categories. As the number of time periods in the data increases, the number of quality levels at which we need to evaluate the value function also increases. For example, if there are T periods of data and quality changes continuously over these T time periods, consumers could have adopted the personal computer and digital cameras at T different quality levels each. Hence, we need to evaluate the value function corresponding to being in adoption level 4 for each of these T^2 possible quality levels. This can be a computationally intensive task for large values of T.

The second challenge is that the price and quality trajectories are likely to be highly collinear in most empirical settings. For example, in our empirical application, we find the correlation between price and quality trajectories to be -0.993 for personal computers, -0.827 for digital cameras, and -0.951 for printers. The high collinearity implies that separately identifying the effects of price and quality on adoption could be problematic. However, if one had variation across consumers in terms of the price or quality trajectories that they observe (e.g., data from different geographic regions), the additional cross sectional variation might help in identifying the two effects separately. Such data are not available to us.

In view of these challenges, we modify the model presented in Section 2 in two ways. First, to account for declining prices (p_{jt}) and for increasing quality levels (q_{jt}) to influence adoption decisions as well as to deal with the collinearity issue, we operationalize price as the quality adjusted price (p_{jt}/ q_{jt}) as in Song and Chintagunta (2003). Second, and as a consequence of the using quality adjusted prices in lieu of prices, the intrinsic valuation of each category in Equation (1) no longer depends upon the quality level at which a consumer adopts the category, i.e., $\alpha_{ic}(q_{ic}) = \alpha_{ic}$. We do, however, retain the variation in the intrinsic valuation across consumers due their observed and unobserved characteristics. A downside to our assumption, is that the model implies that consumers who have similar observed and unobserved heterogeneity components would derive the same intrinsic valuation for adopting a category irrespective of the quality level at which they adopt it. One can argue that this can be problematic for the types of product categories we consider. However, it is necessitated by the reasons above. In the subsequent discussion, we use "price" to refer to "quality-adjusted price."

Even if we assume, as we do above, that the intrinsic valuation of the product is invariant to the quality level at which the consumer purchases a product, it can nevertheless be the case that the product simply becomes more attractive over time to all consumers in the market. For example, consumers could eventually decide to adopt technologies as they become "indispensable." As a result of this temporal evolution in intrinsic preferences, all consumers would derive greater utilities from having adopted each category as the category becomes more indispensable over time irrespective of the quality level at which they adopted the categories. Hence, while the quality effects discussed above (i.e., $\alpha_{ic}(q_{ic})$) would "lock in" each consumer's intrinsic valuation based on the quality level at the time of adoption, the temporal evolution notion (i.e., $\alpha_{ic} + \alpha_{ct}$) would imply an ever-increasing stream of per-period utilities over time. To check whether such dynamics in intrinsic preferences exist in our application, we estimated two different myopic models that allowed for intrinsic preferences to evolve over time. First, we introduced a common time trend in the intrinsic preferences for the categories ($\alpha_{ct} = \lambda_c t$).[11] The results from this analysis did not reveal any dynamics in the intrinsic preferences of the different categories. In the second

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[11] Since a time trend in the per-period utility in the context of a dynamic model would imply an infinite utility over the lifetime, we first tested the hypothesis with the myopic version of the model.

model, we allowed for a more flexible pattern of dynamics by estimating intrinsic preferences specific to each period of our analysis ($\alpha_{ct} = \alpha_{ct}$). Once again, we failed to detect any variation in intrinsic preferences over time. We took this as evidence that the temporal evolution in the utilities was not a significant driver in our analysis.

3.2. Modeling Heterogeneity

In the model formulation, we have let the value derived from a category to vary across consumers. We allow for consumer heterogeneity in two different ways. First, we specify the intrinsic value for each category to be a function of consumer-specific psychographic variables. In our empirical application, we use each consumer's stated preference to adopt new technology to capture such observed heterogeneity. As we discuss later, the inclusion of this observed heterogeneity in the utility specification helps with identification. In addition to the observed heterogeneity, we model unobserved heterogeneity using the latent class specification with consumers belonging to different segments. Specifically, we assume that the intrinsic utility (without considering the effect of price) that consumer *i* derives from the three technology products, $\alpha_i = \{\alpha_{i1}, \alpha_{i2}, \alpha_{i3}\}$ varies across these segments. Hence, the intrinsic utility that consumer *i* belonging to segment *r* derives from adopting category *c*

$$\alpha_{cir} = \overline{\alpha}_{cr} + \chi_c d_i \text{, } c = 1, 2, 3, \text{ and } r = 1,2,\ldots, R \qquad (11)$$

where *R* is the total number of segments, $\overline{\alpha}_{cr}$ is the intrinsic preference for category *c* for a consumer belonging to segment *c* after factoring out the effect of observed heterogeneity, d_i is the consumer-specific psychographic variable capturing observed heterogeneity and χ_c is the corresponding coefficient for category *c*. Following the literature on concomitant variable latent class models (see Dayton and McReady 1988; Gupta and Chintagunta 1994), we allow the probability that a consumer *i* belongs to segment *r*, π_{ir}, to be a function of the consumer's demographic characteristics. Specifically, we have

$$\pi_{ir} = \frac{\exp(\lambda_r + \gamma_r z_i)}{1 + \sum_{r'=1}^{R-1} \exp(\lambda_{r'} + \gamma_{r'} z_i)} \qquad (12)$$

where z_i are the demographic characteristics of consumer *i* and { λ_r , γ_r } are parameters to be estimated. For identification, we set the parameters of the R^{th} segment to zero.

3.3. Estimation

We assume that the unobserved state variables (the e_{it} terms in the equations in the previous section) follow an IID Type I extreme value distribution. Given this assumption, at any time period *t*, the probability that consumer *i* belonging to segment *r* at the active adoption level *l*, $l \in \Psi$, Ψ = {0, 1, 2, 4, 5}, will remain in the same adoption level or moving to a higher feasible adoption level can be written as a logit model. Hence, the probability that a consumer belonging to segment *r* who is in one of the feasible adoption levels, *l,* will move to one of the permissible adoption levels *m*, $m \in \Xi_l$ is

$$h_{irt}^{l,m} = \frac{\exp(V_{irt}^{lm}(\Omega_t^l))}{\sum_{m' \in \Xi_l} \exp(V_{irt}^{lm'}(\Omega_t^l))} . \tag{13}$$

In the above expression, $V_{rt}^{lm}(\Omega_t^l)$ is the observed part of the utility that the consumer derives from going to adoption level *m* from adoption level *l*. The set of feasible adoption levels for a consumer who is already in adoption level *l*, Ξ_l is described in Table 1. The corresponding unconditional probability across the entire history of the consumer who belongs to segment *r* is

$$\phi_{ir} = \prod_{t=1}^{T} \prod_{l \in \Psi} \prod_{m \in \Xi_l} (h_{cirt}^{l,m})^{d_{il,mt}} , \tag{14}$$

where *T* is the total number of time periods in the data and $d_{il,mt}$ takes on the value of 1 if consumer *i* at time *t* moves from adoption level *l* to *m*, $m \in \Xi_l$, and 0 otherwise. The likelihood function across the *I* consumers across the adoption levels can be written as

$$L(\Theta) = \prod_{i=1}^{I} \sum_{r=1}^{R} \pi_{ir} \phi_{ir} , \tag{15}$$

where π_{ir} corresponds to the probability that consumer *i* belongs to segment *r*, *r* = 1, 2, …, *R*, and Θ constitutes the vector of parameters to be estimated.

3.3.1. Computing the Value Function

The evaluation of the conditional (and hence, the unconditional) probabilities of staying in each adoption level or moving to higher adoption levels require computation of the value of staying in each adoption level. Recall that with five active adoption levels, our model requires that we compute five such value functions, $V_t^{00}(.)$, $V_t^{11}(.)$, $V_t^{22}(.)$, $V_t^{44}(.)$, and $V_t^{55}(.)$. In computing these value functions, we adopt an approach similar to Rust (1987) and Song and Chintagunta (2003) by determining these values numerically. Specifically, we make two assumptions that simplify the computation of these value functions. Recall that we have assumed the error terms, e_t, to follow an IID extreme value distribution. The independence assumption further implies that the realization of the error term in period *t*+1 is independent of the realization in period *t*. Second, we assume that the transition probability of the state space is conditionally independent such that $dp(S_{t+1}^l \mid \Omega_t^l) = dp(e_{t+1})dp(\Omega_{t+1}^l \mid \Omega_t^l)$, where S_t^l is the set of all state variables that affect the value function of a consumer at adoption level l at time *t*, Ω_t^l constitutes the vector of the observable component of the state variables and e_t is the unobservable component. In our application, the set of observable state variables constitutes the (quality adjusted) prices of categories that are yet to be adopted. Based on these two assumptions, we can simplify the value function as

$$V_{ir}^{ll}(\Omega_t^l) = \delta \int \ln[\sum_{m \in \Xi_l} \exp(V_{ir}^{lm}(\Omega_{t+1}^l))] dp(\Omega_{t+1}^l \mid \Omega_t^l). \qquad (16)$$

In the above Equation, the term $V_{ir}^{lm}(.)$ corresponds to the observed component of the utility that consumer *i* who belongs to segment *r* derives from moving to adoption level *m* from the active adoption level *l*.[12] Similar to Song and Chintagunta (2003), we assume that $\ln(p_{c,t+1}) \mid \ln(p_{ct}) \sim N(\ln(p_{c,t}) + \mu_c, \sigma_c^{\ 2})$, where μ_c and σ_c^2 are estimated from the empirical distribution of the prices.

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[12] Please refer to the appendix for the formulation of these utilities.

We compute the value functions numerically at a finite number of grid points by the method of successive approximation. With three categories, the state space for $V_t^{00}(.)$ has three dimensions.[13] This high dimensionality of the state space along with the need to compute five different value functions significantly complicates the estimation. Hence, traditional value function computation methods which employ polynomial approximation turned out to be quite inefficient. In order to circumvent this problem, we used the randomized multi-grid algorithm proposed by Rust (1997). Three features of this algorithm significantly ease the computational burden. First, Rust (1997) shows that using random grid points breaks the curse of dimensionality. Consequently, we do not need an exponentially increasing number of grid points to compute the value function as the state space increases. Second, the randomized multi-grid algorithm is self approximating. This implies that once we have evaluated the value function at some set of grid points, we can easily compute the value function at any point in the state space without need for any interpolation. Since the interpolation step is subject to the curse of dimensionality (Rust 1997), this significantly reduces the computational burden. Third, the multi-grid algorithm starts by computing the value function at a small number of grid points with higher tolerances. Successive value function evaluations are performed at larger number of grid points and tighter tolerances. This implies that the algorithm spends lesser time initially when we have lesser information about the value function. Further details of the randomized multi-grid algorithm can be found in Rust (1996 & 1997).

4. DATA

We use a unique survey dataset from the year 2002 that contains information on the time of first adoption of 2005 respondents of laptop and desktop computers, computer printers, digital cameras, DVD players, personal digital assistants (PDA), and global positioning systems (GPS), etc. In the survey, each respondent is asked whether s/he owns each product and if s/he does, the year his/her household first adopted the product. Hence, the data are similar in structure to a typical multi-category scanner panel data collected on an annual basis. The key difference, however, is that the household exits the market for

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[13] This is because we use quality adjusted price instead of using price and quality separately as state variables. If we were to use price and quality separately, the state space will have six dimensions.

a given category after it adopts the category. In addition to the time of adoption, the data also contain information regarding various demographic and psychographic characteristics of the respondents.

We focus on the adoption of three related product categories – personal computers (comprising of both laptop and desktop computers), digital cameras, and computer printers. While there is likely to be a complementary relationship between them, adoption of computer printers is contingent upon personal computer adoption. However, a contingent relationship does not exist for digital cameras or personal computers. Since the data do not have information on the prices paid or the quality of various technology products over time, we used aggregate weighted (by sales of different brands and products) average market prices for each category in order to study the effects of prices on adoption. We obtained the weighted average annual price data for the three categories from the *Electronics Market Databook*.

We obtained the quality data for the three categories from three different sources. For the personal computer category, we obtained the composite quality ratings of different processor chips that were used to make personal computers from CPU scoreboard (www.cpuscoreboard.com). We then computed a weighted average of the quality ratings of the individual chips to obtain an aggregate measure of CPU quality for each year. In case of digital cameras, we used the maximum resolution (mega pixels) of the digital cameras that were surveyed in the Consumer Reports during each year. Since the Consumer Reports typically carry test results for the frontier technology during that year, our measure would be an indicator of the frontier quality trajectory. Resolution has been noted by previous researchers (e.g., Song and Chintagunta (2003) run a hedonic regression to identify this attribute) and by the trade press to be the best indicator of quality amongst the available attributes.[14] In constructing a quality measure for printers, we used an approach similar to digital cameras. However, rather than basing it on Consumer Reports, we obtained the entry and exit dates of all inkjet printers that were ever manufactured by Hewlett Packard. We then collected several objective measures of printer quality such as speed in pages per minute in color and black & white as well as the internal memory of each printer from the corresponding product manuals

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[14] For example, Consumer Reports and other trade magazines such as PC World present comparisons of digital cameras within different tiers of resolution.

from Hewlett Packard's website. Based on Consumer Reports as well as the reports in the business press, we chose printing speed (pages per minute in black and white) as a single measure of printer quality. Using these data, we constructed a panel consisting of all the models of inkjet printers (from this manufacturer) that were available each year. We then computed the mean of these quality measures amongst all the available models in a given year.

Recall that our modeling framework implies that at any time period, all product categories are available for adoption. However, the three technology products in our empirical application were introduced at different time periods. In order to ensure that the empirical application is consistent with the model, we need to restrict the data to the time period when all there technology products are available for adoption. Hence, we focus our analysis on consumers who adopted these categories during or after 1996, the year when digital cameras were available for the consumer market.[15] [16] After deleting respondents who purchased personal computers or printers prior to 1996, we ended up with a sample of 1239 respondents.[17] For the printer category, the price levels differ significantly between the two common technologies available during this period – inkjet and laser printers. Since both these technologies had significant adoption in the consumer market, the use of price and sales series corresponding to either technology may have been appropriate for our analysis. In our application, we use the price and sales data corresponding to inkjet printers.[18]

We calibrate our model based on the adoption decisions at the end of the year 2001. Hence, we have six years of data for each category. We present the summary of the cumulative number of adopters

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[15] Alternatively, if one were to use data prior to the period when digital cameras were available, we need to have different models for the period prior to and post digital camera availability (assuming that the other two technologies were available from the same year). For the period prior to the introduction of digital cameras, one needs to account for the consumer anticipation of digital camera availability. Such a model is beyond the scope of this paper.

[16] An implicit assumption here is that the decision by our sample households to postpone purchase till after 1996 does not contain any additional information on the model parameters than do the data after 1996. While this is a strong assumption, it is necessitated by the lack of availability of data prior to 1996.

[17] Most of these deletions pertained to instances where the consumers displayed inconsistency in their category ownership in two different questions in the questionnaire.

[18] The other major technology in the printer market for households was the dot-matrix which had declined significantly by 1996.

at the end of the year 2001 across the various possible adoption levels in Table 2.[19] Half the sample is in adoption level 0 as of 2001 and has not adopted either category. Amongst consumers who have adopted, the most populated adoption levels are levels 5 and 1. Hence, personal computers category exhibits the highest penetration. Furthermore, roughly 7% of the sample has adopted all three categories and exited the market by the end of 2001. Additionally, Table 2 reveals that none of the respondents owned a printer without a personal computer. A closer look at the adoption pattern for the two categories over time also revealed that none of the respondents purchased a printer prior to purchasing a personal computer – a finding consistent with our assumption of printer adoption being contingent on computer ownership.

We present the time trend in the adoption pattern for the three categories in Figure 1. The adoption pattern seems to indicate similar trends for the personal computer and printer categories with personal computers enjoying higher adoption rates. While the adoption of personal computers seems to have peaked in the year 1998 for this sample, printer adoption appears to have peaked in the year 2000. However, the adoption of digital cameras is still taking off during the period of our analysis. Overall, by the end of 2001, 629 respondents had adopted personal computers, 111 had adopted digital cameras, and 472 had adopted printers.

A related issue of interest is the ownership profile of respondents who adopted each category at the time of their adoption. For example, a consumer can adopt the personal computer category either when she has not adopted either category (from adoption level 0) or after having adopted digital cameras (from adoption level 2). It will be useful to understand what constitutes the highest fraction of personal computer adopters - those in level 0 or in level 2. In order to understand the sources of adoption of each category, we present the decomposition of adopters for each category in Table 3. The table reveals that over 95% of personal computer adopters in the sample adopted them from adoption level 0. Of these 59.78% adopted personal computers simultaneously with printers (transition from level 0 to level 5) and 36.72% adopted only personal computer (transition from level 0 to level 1). On the other hand, a large

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[19] To ensure that all three categories are available for consumer decision-making, we have restricted the analysis to the period from 1996. As a result, we have deleted respondents who had purchased either category prior to 1996. If one were to include such respondents, the cumulative penetration will be higher for the PC and printer categories.

proportion of digital camera adopters (44.14%) adopted the category after having adopted both personal computer and printer categories. Only about 26% of digital camera adopters adopted the category directly from adoption level 0. The decomposition of adopters for the printer category reveals that over 80% of its adopters adopted the category from adoption level 0 when they adopted printers simultaneously with the personal computer category. Only about 15% of printer adopters were prior owners of a personal computer. Thus, a majority of consumers adopting printers tend to do so simultaneously with personal computers. This is in contrast to the case of digital cameras where only a small fraction of adoption occurs simultaneously with the adoption of other categories with a vast majority of digital camera adoptions occurring after the adoption of other categories. Thus, if we were to infer the magnitude of the complementarity effects between digital cameras and other categories based solely on joint adoption, we will be underestimating their magnitudes. This provides further justification for our modeling framework.

4.1. Identification

Before proceeding to the results from our empirical analysis, we present a brief discussion of the intuition behind the identification of model parameters. Recall that our model requires estimation of three sets of parameters: a) category specific intercepts and complementarity effects, b) price sensitivity, and c) effect of demographic variables on segment membership probabilities. Of these, the price sensitivity parameters are identified based on the temporal variation in prices and the effect this has on the adoption behavior of the respective categories. The effect of demographic variables on segment membership probabilities is identified based on the relative propensities of consumers with a certain demographic profiles to belong to the different segments. Thus, the main issue of identification pertains to the first set of parameters. There are two issues in the identification of category-specific intercepts and complementarity effects. The first relates to identifying the category-specific intercepts separately from the complementarity effect. Moreover, since consumers may adopt multiple categories because of their intrinsic preferences for these categories even if they are not related, the second issue is identifying consumer heterogeneity separately from the complementarity effect. We discuss these identification issues in the context of two categories discussed in Section 2.2.2.

Identification of the category intercepts is accomplished based on the propensity of consumers to adopt only that category from adoption level 0. In the two category situation, the proportion of consumers that move to adoption level 1 (level 2) from adoption level 0 helps in identifying the intrinsic preference for category 1 (category 2). On the other hand, when consumers move from adoption level 1 (level 2) to adoption level 3, they derive the intrinsic utility for category 2 (category 1) as well as the complementarity effect between these categories. Thus, the proportion of consumers who move to adoption level 3 from level 1 (level 2) helps us identify the sum of a) the intrinsic value of category 2 (category 1) and b) the complementarity effect between the two categories. We can then isolate the complementarity effect by computing the difference between these composite measures and the intrinsic preference for the category. Thus, the complementarity effect between the two categories is identified based on the difference between the propensities to adopt a category from adoption level 0 and after having adopted the other category.[20]

The identification of the complementarity effect separately from heterogeneity poses a challenge. Specifically, consumers may purchase the two categories together (or in close succession) either because they have similar intrinsic preferences for these two categories or because they perceive a complementary relationship between them. In our application, two factors facilitate the identification of the complementarity effect separately from consumer heterogeneity. First, our dataset contains information of consumer's stated preference for adopting technology products. This extra information can be used to separate out consumers who have high intrinsic preference across categories from those with lower preferences and thus help in identification of the complementarity effect separately from heterogeneity. The second argument for identification is based on the exclusion restriction (Gentzkow 2007; Keane 1992) wherein some variables that enter the utility specification for one category do not enter the utility function of the other category. In our application, the price variable is a source of this exclusion

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[20] The nature of complementarity is also likely to depend on the type of product that is adopted within each category. For example, the complementary relationship between digital cameras and inkjet printers that can be used to print photos is likely to be different from the relationship between digital cameras and laser printers. However, our data do not contain information on the type of printer adopted.

restriction. The intuition behind the exclusion restriction is as follows. As stated above, if consumers have similar valuations for the two categories, we would observe them buying these categories either together or in close succession. If there is a significant decrease in the price of one category in a given period, it would increase the number of adopters in that category for that period.[21] Further, if there is no complementary relationship among the categories, the adoption behavior of the other category should remain unaffected. Hence, the extent to which one observes higher adoption behavior for the second (first) category due to an increase in the adoption behavior of the first (second) category stemming from such a price decrease helps us identify the complementary relationship between these categories separately from heterogeneity. Thus, the temporal variation in the prices of the two categories provides additional information for this identification.

5. RESULTS

As discussed above, we estimate the proposed model using data on consumer adoption of three categories of technology products – personal computers, digital cameras, and printers. As is common in the estimation of such forward-looking models, we fix the discount factor at 0.9 (see Rust 1987 for a discussion on the identification of the discount factor). Given the annual nature of our data, this corresponds to an annual discount rate of 10%. Recall that our estimation allows for latent class unobserved consumer heterogeneity. We estimated one, two, three, and four segment models. Based on the performance of these alternative models on the BIC, we picked the three segment solution. We also estimated these models by allowing for consumer heterogeneity in the intrinsic category preferences, price sensitivity parameters, as well as the complementary effects. Once again, the BIC of these alternative models supported heterogeneity only in the intrinsic category preferences (i.e., the category intercepts). Hence, we discuss the three segment model with heterogeneity only in the category intercepts. We present these results in Table 4.

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[21] Given the dynamic nature of our application, consumers in our model anticipate a decline in prices in the next period. Nevertheless, to the extent that the anticipated price decline differs from the actual decline, the price variable helps us in identifying the complementarity effect separately from consumer heterogeneity.

As expected, price has a negative effect on the utility for all three categories. Although the price coefficient is statistically significant for the personal computer and digital camera categories, it is not significant for printers. There is a significant complementarity effect between digital camera and personal computer as well as between digital camera and printer categories. However, the complementarity effect between digital camera and printer categories is marginally larger in magnitude. We discuss the implications of these complementary relationships between categories subsequently. As noted previously, the complementarity effect between personal computers and printers is not separately identified from the intrinsic preference for printers due to the contingent nature of printer adoption.

The intrinsic preferences for the categories exhibit significant variation across the three segments. In order to develop a better understanding of these intra-segment differences in category intercepts as well as the relative sizes of these segments, we assign each respondent to one of the three segments based on their posterior segment membership probabilities and summarize the adoption behavior across these segments in Table 5. Segment 1 comprises about half the sample and is the single largest segment. From Table 4, we see that consumers in this segment have a relatively low valuation for all three categories. The low number of adopters for the three categories that we see in Table 5 reflects these low preferences suggesting that these consumers are "late adopters". In contrast, consumers in segment 2 (about 20% of the sample) have the highest valuations for personal computer and digital camera categories. All consumers in this segment have adopted the personal computer. However, only a fraction of these consumers have adopted the digital camera and printer categories. Hence, it may be reasonable to characterize this segment as personal computer enthusiasts. Segment 3, which comprises of over 30% of respondents provides an interesting contrast to segment 2. Consumers in this segment have a low valuation for personal computers. However, they have a high valuation for printers. Hence, they should have a high propensity to adopt the printer category. Since printer adoption cannot happen in the absence of personal computers, the high valuation of printers influences these consumers to adopt personal computers as well. As a result, despite their low valuation for personal computers, all consumers in this segment have adopted personal computers. In addition to this unobserved heterogeneity, consumers' stated preference to adopt technology products significantly shifts their intrinsic preference for the digital camera and printer categories. However, the variable does not have a significant effect on the intrinsic preference for personal computers (|T-value| = 0.216).

The effect of the demographic variables on the segment membership probabilities in Table 4 helps us identify the consumers belonging to various segments based on their demographic profile. The significant negative effect of all three demographic variables on the probability of belonging to segment 1 imply that male households and households that subscribe to magazines or consumers reports have a low probability of belonging to segment 1. Hence, households with this demographic profile should belong to one of the segments with higher intrinsic valuation for the three categories - either segment 2 or segment 3. Since the parameters corresponding to the probability of belonging to segment 3 were constrained to zero for identification, the insignificant coefficients for segment 2 membership imply that one may not be able to use these demographic variables to discern between segments 2 and 3.

While the discussion above presents the view of the adoption scenario at the end of 2001, it will be interesting to investigate the temporal pattern in adoption for these categories across the three segments. For example, based on the temporal pattern, we can see whether the adoption of each category in a given segment is increasing or decreasing over time. In order to generate this temporal pattern, we use the model estimates in Table 4 to compute the probability of adopting each category at any given time conditional on not having adopted the category till that time. We present the temporal pattern in adoption for segments 1, 2, and 3 in Figures 2, 3, and 4, respectively. Figure 2 reveals that the adoption of the three categories is just taking off in segment 1. Hence, we see an increasing pattern for the number of adopters over time. This agrees well with the low preferences for the three categories that we discussed above.[22] In contrast to the adoption pattern for segment 1, the pattern for segment 2 reveals that personal

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[22] Note that Figure 2 implies that there are a positive number of adopters for the personal computer and printer categories during the period of our analysis. However, as shown in Table 5, none of the respondents adopted these categories during this period. This discrepancy is attributable to the fact that the adoption behavior in Figure 2 is based on the conditional probability of adoption. Since the conditional probabilities implied by the model are strictly positive, the model predicts a non-zero number of adopters each period. Alternatively, we can use the posterior segment memberships to classify each respondent to one of the segments. We can then use the actual

computer adoption peaked in 1998. As a result, there is a decreasing trend in the number of adopters for this segment after 1998. On the other hand, the number of adopters for digital cameras and printers is still increasing. Figure 4 reveals that while adoption of digital cameras is taking off for segment 3, personal computer and printer adoption peaked in 1998. Also note that the adoption curves for the personal computer and printer categories coincide with each other. Recall that consumers in this segment adopt the personal computer category because of their high valuation for printers. Hence, the constraining factor in the adoption of printers for this segment is their low personal computer valuation. As a result, consumers in this segment adopt the two categories simultaneously. Since this segment constitutes roughly 84% of all printer adopters, it would be reasonable to infer that for a vast majority of printer adopters, the main bottleneck in their adoption decision is the adoption of personal computers rather than the price of printers. This can explain the statistically insignificant effect of printer price on the adoption decision in this segment.

5.1. Effect of Prior Ownership of other Categories on the Propensity to Adopt a Given Category

An implication of the complementary relationship between categories is that the propensity of adopting a given category should increase once the consumer has adopted other related categories. From a managerial point of view, the higher probability of adoption would imply that marketing activities that are targeted at consumers who already own complementary products are likely to yield higher returns. In order to quantify the extent to which adopting one category increases the probability of adopting other categories, we compute the average probability (across individuals and over time) of adopting each category from each feasible adoption level conditional on being in that adoption level. For example, a consumer can adopt the personal computer category from two different adoption levels: a) from level 0 when she has adopted none of the three categories and b) from level 2 when she has adopted the digital camera category. Similarly, a consumer can adopt the digital camera category from three different adoption levels: a) from level 0 when she has adopted none of the three categories, b) from level 1 when

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adoption behavior of the consumers belonging to each segment to trace the temporal pattern of adoption for each segment. However, since each consumer has a non-zero probability of belonging to each of the three segments, such a temporal pattern may not be very accurate.

she has adopted the personal computer category, and c) from level 5 when she has adopted both the personal computer and printer categories. Analogously, a consumer can adopt the printer category from four different adoption levels: a) from level 0 when she has adopted none of the three categories, b) from level 1 when she has adopted the personal computer category, c) from level 2 when she has adopted the digital camera category, and d) from level 4 when she has adopted both the personal computer and digital camera categories. A comparison of the average probability of adopting each category from the higher adoption levels with those from adoption level 0 would be indicative of the extent to which having adopted one or more related categories increases the probability of adopting the focal category.

In Table 6, we present a summary of the average adoption probabilities from different feasible adoption levels for each category. Note that these probabilities are computed based on the model estimates reported in Table 4 and reflect the probabilities observed in the raw data. Overall, these results indicate that, for all categories, having adopted other related categories significantly increases the probability of adopting the focal category. For example, consider the case of the digital camera category. A consumer who has already adopted the personal computer category has a 74.38% higher probability of adopting the category compared to a consumer in adoption level 0. Further, if the consumer has already adopted both the personal computer and printer categories, the probability of adopting digital cameras increases from 0.020 (in level 0) to 0.069.

In order to understand the extent to which the different complementarity effects contribute to this increase in the probability of adoption, we carried out simulations wherein we estimated these probabilities when the complementarity effect is set to zero. Note that we estimate the magnitude of two complementarity effects in our model: a) complementarity between the personal computer and digital camera categories and b) complementarity between the digital camera and printer categories. Thus, we ran two sets of simulations wherein each complementarity effect was set to zero. By comparing the simulated probabilities with those generated under the original parameter estimates, we can understand the extent to which each complementarity effect changes the adoption probabilities from each adoption level. Below, we discuss the results from these simulations for the three categories.

5.1.1. Effect of Complementarities on PC Adoption Probabilities

We present the results from the simulation for the personal computer category in Table 7. These results reveal that on the average, personal computer adoption probability would decrease by 5.14% if there was no complementary relationship between personal computer and digital camera categories. On the other hand, the adoption probability of personal computers would decrease by 22.36% for a consumer who has already adopted the digital camera category. Overall, the results seem to indicate that the effect of complementarity between digital cameras and printers on the adoption probabilities is marginally greater than the effect of PC-digital camera complementarity. The intuition behind this is that shutting off the complementary relationship between digital cameras and printers has an adverse effect on printer adoption. Thus, some consumers who prefer to adopt personal computers along with printers find it less attractive. Especially, fewer consumers from segment 3 tend to adopt the personal computer category as a result of the policy change.

5.1.2. Effect of Complementarities on Digital Camera Adoption Probabilities

We present the results from the simulation for the digital camera category in Table 8. Overall, these results indicate that the effect of the complementary relationship between digital cameras and printers is greater than that between personal computers and digital cameras. The higher magnitude of the estimated complementarity effect between digital cameras and printers (please see Table 4) is largely responsible for the larger effect. The only exception is the effect on the digital camera adoption probability for a consumer who has already adopted the personal computer. Further, the results in Table 8 indicate that the adoption probabilities for the digital camera category are substantially more responsive to the complementarity effects than the other categories. The higher responsiveness of the digital camera adoption probabilities may attributable to the fact that consumers have a very low intrinsic preference for this category during the period of our analysis. Hence, a significant proportion of consumers adopted this category based on the complementary relationship it enjoys with other categories.

5.1.3. Effect of Complementarities on Printer Adoption Probabilities

We present the simulation results from the printer category in Table 9. These results imply the following. First, as in the case of the personal computer category, the complementarity effect between digital camera and printer categories has a higher effect than the complementarity effect between personal computers and digital cameras. Second, the effects are much smaller in magnitude compared to those in the digital camera category. As discussed earlier, most of the consumers who adopted printers in our data adopted them jointly with personal computers. Thus, personal computer adoption was the primary bottleneck in their adoption of printers. Hence, shutting off these complementarity effects affect printer adoption mostly to the extent to which they hinder the adoption of personal computers. On the other hand, we would expect the complementarity between personal computers and printers to have a large effect printer adoption. However, since we cannot separately estimate the magnitude of this complementarity effect, we cannot perform such an analysis.

5.1.4. Effect of Complementarities on total number of adopters in each category

In addition to the above analyses, we investigated the effect of shutting off these complementarity effects on the total number of adopters in each of the three categories. While the absence of complementarity effect had only a marginal effect on the number of personal computer adopters (around 3%), the effect on digital camera category was substantial (around 65%). These results echo our assessment that, during the period of our analysis, digital camera adoption relied on its perceived complementary relationship to other categories.

5.2. Effect of a One-Time Price Decrease on Adoption

The above analysis provides insights on how adoption of one or more related categories affects the consumer's adoption of the focal category. This analysis is subject to two caveats. First, the analyses presented above pertain to the change in probability of adoption for a consumer who is in a given adoption level conditional on the consumer being in that adoption level. However, the probability that a consumer will exist in that particular adoption level may be very small. As a result, the increase in the conditional probability of adoption for a consumer who is in that adoption level may be of limited managerial relevance. Thus, a more managerially useful metric might be the change in unconditional probability that also accounts for the probability that the consumer will exist in that adoption level to begin with. The second caveat concerns the fact that the conditional probability analyses do not account for segment depletion. For example, our analyses of adoption behavior by segment in Table 5 revealed that all consumers in segments 2 and 3 have adopted the personal computer. As a result, the unconditional probability would decline as the number of remaining consumers in the market is depleted. However, the corresponding conditional probabilities discussed in the previous section are expected to increase as prices continue to decline.

In order to understand how the unconditional probabilities of adopting a category change with a change in adoption behavior in related categories, we induce such a change by modifying the price trajectory of the products. Specifically, we study the effect of a one time 5% decrease in the quality adjusted price of each category in the *first period* on the adoption behavior in that category as well as in related categories. As a consequence of this initial price decrease, consumers would revise their expectation of the future price trajectory and anticipate a shallower decline in future. Hence, the price decrease will have a long-term impact on consumer adoption decisions. Since our model estimates imply significant price coefficients only for the personal computer and digital camera categories, we restrict our analysis of policy changes only to these categories.

5.2.1. Effect of a One Time Price Increase in the Personal Computer Category

We summarize the total change in adoption probabilities across all consumers in our sample for all three categories in Table 10. The values in bold indicate the net change in adoption as a consequence of the price decrease. Overall, these results imply that a one time price decrease in the personal computer category would have increased the number of adopters in all three categories during the six years of our data. Interestingly, the largest increase in adoption happens for the printer category. This is not surprising given that for a vast majority of printer adopters, the main constraint in their adoption decision was the adoption of personal computers.

What is the source of these changes? Consumers can adopt the personal computer from two different adoption levels – level 0 (adopted none of the categories) and level 2 (adopted only the digital camera category). The columns on the right hand side of Table 10 present the decomposition of the changes in adoption from these two sources, i.e., adoption levels. The temporal patterns in these changes for the three categories are in Figures 5, 6, and 7. Overall, these temporal patterns as well as the net effects in Table 10 reveal the following. First, as a result of the price decrease and the consequent expectation of shallower price decreases in the future, consumers prefer to accelerate their purchases of personal computers and printers from future periods. This leads to an initial increase in adoption of these categories followed by a decrease in later periods. However, as seen in Table 10, there is a net increase in the number of adopters during the period of our analysis. Nevertheless, if one were to extend this analysis to future periods, this net positive effect may be erased. Second, most of this change in personal computer and printer adoption comes from consumers who are yet to adopt any category (those in level 0). On the other hand, for the digital camera category, the changes in adoption behavior from the three possible adoption levels are comparable in magnitude. Third, as a result of the price decrease in the personal computer category, the number of digital camera adopters from adoption levels 1 and 5 show a net increase. Yet, a smaller number of consumers adopt the category from adoption level 0. The intuition behind this result is that as a consequence of the price decrease, some consumers who preferred to adopt digital cameras prior to adopting personal computers reverse their order of adoption. This explains the net decrease in digital camera adopters from adoption level 0 as well as the corresponding increase in the number of personal computer and printer adopters from this level. Moreover, since more consumers are available in adoption levels 1 and 5, we observe higher number of digital camera adopters from these levels. Hence, the temporary price decrease induces some interesting inter-temporal substitution patterns across the three categories.

5.2.2. Effect of a One Time Price Decrease in the Digital Camera Category

Again, we decrease the first period quality adjusted price for the digital camera category by 5%. We summarize the total change in adoption probabilities across all consumers in our sample for all three categories in Table 11. The values in bold show the net change in adoption as a consequence of the price increase. Overall, these results imply that a one time price decrease in the digital camera category would have increased the number of adopters in the digital camera category during the six years of our data. However, a marginally lower number of consumers adopt the personal computer and printer categories.

Once again, we decompose the changes originating from different adoption levels and we present the temporal pattern in these changes in Figures 8, 9, and 10. The temporal patterns for the personal computer and printer categories reveal that the price decrease induces consumers to delay their adoption of these categories. However, because consumers postpone their adoption of the personal computer and printer categories, the number of adopters in later periods increases. Nevertheless, we have a net decrease in the number of over the six year period. Moreover, the temporal patterns for these categories reveal that most of the change in adoption is dominated by consumers in adoption level 0. Thus, the price decrease in digital camera category induces consumers who would have adopted personal computer and printer categories first to begin their adoption process with digital cameras instead. For the digital camera, however, all three adoption levels contribute comparably to the increase in number of adopters. Furthermore, all three effects are positive.

Two aspects of the temporal pattern for the digital camera category are worth highlighting. First, a key difference between the digital camera and the remaining two categories is that the initial decrease (or increase) is not accompanied by an increase (or decrease) in future periods. The main reason for this difference is that the reversal in case of personal computer and printer categories happens because of segment depletion. Thus, if more (or less) consumers adopt these categories earlier, there are fewer (or more) consumers available for adoption in later periods. In other words, the pool of remaining consumers acts as a binding constraint for these categories. However, since the penetration of digital cameras is quite low, the pool of remaining consumers is not yet a constraint. Second, although the price decrease in the digital camera category brings in fewer consumers to adoption levels 1 and 5, we observe more consumers adopting digital cameras from these two adoption levels. The main reasons for these results are as follows. As a result of the price decrease, some consumers who adopted printers from adoption level 1 find it less attractive to adopt digital cameras instead. This leads to a smaller number of printer adopters from adoption level 1. Thus the substitution between printer and digital camera categories offsets the decrease that might have accrued from a smaller pool of consumers in adoption leve1 1. As regards adoption level 5, recall that most of the consumers in this adoption level belonged to segment 3. Although adoption level 5 is the "stable" adoption level for this segment, the price decrease encourages them to accelerate their digital camera adoption from future periods. The temporal pattern in Figure 9 reveals that if we were to extend our analysis to more than six years, we would observe some decrease in digital camera adopters from this level.

To summarize, the main findings from this analysis are as follows. First, change in the pricing policy in a category can have an effect on adoption behavior in that category as well as other related categories. Specifically, when the price trajectory for a category becomes flatter, consumers may find it optimal to accelerate their purchase in that category from future periods. Such intertemporal substitution can change the order in which they adopt the other related categories. Second, the source of change in adoption behavior, in terms of consumers at different adoption levels, due to a change in price trajectory varies by category.

6. CONCLUSIONS

In this paper, we present a framework for studying the adoption behavior of households across related categories of technology products. Households in the model are forward looking in the sense that they trade off adoption today and the associated utility from the product with waiting till tomorrow when the price of the product could be lower. Further, these forward-looking consumers also base their adoption decision of the focal category on the anticipated time of adoption of other related categories. Moreover, the model addresses some unique challenges posed by the durable nature of technology products. Specifically, the durable nature implies that although two categories may be related as complements, consumers may stagger their purchases over several periods. Our model is general enough to identify the complementary relationship even when consumers may not purchase them together. This is in departure from the literature on multi-category purchase behavior for packaged goods. We hope that our modeling framework will be useful in contexts other than those presented in this paper. For example, it can be extended to the case of related packaged goods where joint purchase is not necessary to infer complementarity (or substitutability). Non-perishable packaged goods categories such as shampoo and conditioners where consumers can hold products in inventory provide such a context. Furthermore, the empirical findings from this paper regarding the effect of having adopted other related categories on the adoption behavior of the focal category as well as the implications of a price change in one category on the adoption behavior in related categories can help managers in technology product firms such as HP, Dell, and IBM who manage such broad product lines.

The model and empirical application presented in this paper have some limitations that provide scope for future research. First, while the empirical application is set in the context of three related categories, extension to more categories may be computationally challenging. Second, as mentioned above, the modeling framework can be extended to the case of related packaged goods where joint purchase is not necessary to infer complementarity (or substitutability). However, since one will be studying repeat purchasing behavior in such an application, the restriction that a consumer can move only to higher adoption levels needs to be relaxed. Furthermore, while modeling the purchasing decision, one needs to account for the inventory that the consumer has in stock. Third, while the focus of this paper has been restricted to understand the demand side, it will be interesting to investigate the optimal price trajectory or inter-release time (see, for example, Luan and Sudhir 2007) for related categories. Such an application will be even more interesting if the analysis were at the brand level rather than at the category level. Fourth, while our model assumes that consumers know the utility of all the categories prior to ownership, one might argue that consumers might derive a greater appreciation for the other related products once they adopt a subset of the categories. Thus, an extension of the model by allowing for consumer learning could be a worthwhile addition.

In sum, the paper seeks to make both methodological and substantive contributions to the extant literature on multi-category purchase behavior. We anticipate that future research will benefit and hopefully build on the approach presented in this paper. Moreover, we look forward to managers in technology product firms using the substantive findings presented in this paper.

APPENDIX

Details of the Consumer Decision Process at Different Active Adoption Levels

Recall that in our empirical application based on three categories, at any time *t*, a consumer can exist in any of the following six adoption levels:

Adoption level 0: {0, 0, 0}	None of the 3 categories is owned
Adoption level 1: {1, 0, 0}	Only a PC is owned
Adoption level 2: {0, 1, 0}	Only a Digital Camera is owned
Adoption level 4: {1, 1, 0}	PC and Digital Camera are owned
Adoption level 5: {1, 0, 1}	PC and Printer are owned
Adoption level 7: {1, 1, 1}	All 3 categories are owned.

In this appendix, we present the details of the decision process for consumers in each of the five active adoption levels, Ψ = {0, 1, 2, 4, 5}. We begin with adoption levels 5 and 4 wherein the consumer has already adopted two of the three categories and then finish with the decision process for a consumer in adoption level 0.

(i) Decision Process for a Consumer at Adoption Level 5

A consumer in adoption level 5 has already adopted categories 1 and 3. Only category 2 is yet to be adopted. As seen in Table 1, a consumer in adoption level 5 has two alternatives: a) stay in adoption level 5 or b) move to adoption level 7. If she moves to level 7, the consumer will derive an infinite stream of utilities from the three categories as well as their complementarity effects. However, the consumer has to pay a one time price (of category 2) in order to move to adoption level 7. Hence, the observed component of the utility that consumer *i* derives from moving to adoption level 7

$$V_{it}^{57}(p_{2t}) = \frac{\alpha_{i1}}{1-\delta} + \frac{\alpha_{i2}}{1-\delta} + \frac{\alpha_{i3}}{1-\delta} + \frac{\Gamma^{12}}{1-\delta} + \frac{\Gamma^{23}}{1-\delta} - \beta_2 p_{2t}, \tag{A1a}$$

where, α_{ic}, *c* = 1, 2, 3 are the consumer's intrinsic valuation for category *c* reflecting the per-period utility that the consumer derives from the category, Γ^{12} is the per-period complemantarity effect between categories 1 and 2 and Γ^{23} is the corresponding complementarity effect between categories 2 and 3. As discussed in the previous section, given that the adoption of category 3 is contingent upon the adoption of category 1, we cannot identify the complementarity effect separately from the intrinsic valuation for category 3. Rather, the term α_{i3} may be viewed as the sum of both the intrinsic valuation of category 3 and the complementarity effect between category 1 and category 3. The total utility that the consumer receives from moving to adoption level 7 from level 5 can be expressed as

$$W_{it}^{57}(S_t^5) = V_{it}^{57}(p_{2t}) + e_{it}^7, \tag{A1b}$$

where, S_t^5 constitutes the set off state variables that affect the consumer's utility in adoption level 5 and e_{it}^7 is the component of utility that is unobserved by the researcher.

Alternatively, if the consumer decides to stay in adoption level 5, she will derive a one period utility from staying in that level and the option value of either moving to level 7 or staying in level 5 in the next period. Hence, we have

$$V_{it}^{55}(p_{2t}) = \alpha_{i1} + \alpha_{i3} + \delta E[\max\{W_{it+1}^{55}(S_{t+1}^5), W_{it+1}^{57}(S_{t+1}^5)\} \mid p_{2t}] \tag{A2a}$$

and

$$W_{it}^{55}(S_t^5) = V_{it}^{55}(p_{2t}) + e_{it}^5.$$

(ii) Decision Process for a Consumer at Adoption Level 4

A consumer in adoption level 4 has already adopted categories 1 and 2. From Table 1, it is evident that the alternatives are: a) stay in adoption level 4 or b) move to adoption level 7. If she moves to level 7, the consumer will derive an infinite stream of utilities from the three categories as well as their complementarity effects. However, the consumer has to pay a one time price (of category 3) in order to move to adoption level 7. Hence, the observed component of utility from moving to level 7 from level 4, V_{it}^{47}, is

$$V_{it}^{47}(p_{3t}) = \frac{\alpha_{i1}}{1-\delta} + \frac{\alpha_{i2}}{1-\delta} + \frac{\alpha_{i3}}{1-\delta} + \frac{\Gamma^{12}}{1-\delta} + \frac{\Gamma^{23}}{1-\delta} - \beta_3 p_{3t}\,. \qquad \text{(A2a)}$$

Note that Equation A2a is similar to Equation A1a. The only difference is that the consumer now has to pay the price of category 3 instead of category 2 in order to move to adoption level 7. The corresponding total utility is

$$W_{it}^{47}(S_t^4) = V_{it}^{47}(p_{3t}) + e_{it}^7\,. \qquad \text{(A2b)}$$

Similar to the case of a consumer in adoption level 5, the utility from staying in level 4 at time *t* is

$$W_{it}^{44}(S_t^4) = V_{it}^{44}(p_{3t}) + e_{it}^4, \qquad \text{(A3a)}$$

where $$V_{it}^{44}(p_{3t}) = \alpha_{i1} + \alpha_{i2} + \Gamma^{12} + \delta E[\max\{W_{it+1}^{44}(S_{t+1}^4), W_{it+1}^{47}(S_{t+1}^4)\} \mid p_{3t}]\,. \qquad \text{(A3b)}$$

(iii) <u>Decision Process for a Consumer at Adoption Level 2</u>

A consumer in adoption level 4 has only adopted category 2. Hence, the alternatives facing this consumer are: a) moving to level 7 by adopting categories 1 and 3, b) moving to level 4 by adopting category 1, or c) staying in adoption level 4. We discuss these below.

By moving to adoption level 7, the consumer derives the utility from being in that level. However, the consumer needs to pay the price of categories 1 and 3. Hence, we have

$$V_{it}^{27}(p_{1t}, p_{3t}) = \frac{\alpha_{i1}}{1-\delta} + \frac{\alpha_{i2}}{1-\delta} + \frac{\alpha_{i3}}{1-\delta} + \frac{\Gamma^{12}}{1-\delta} + \frac{\Gamma^{23}}{1-\delta} - \beta_1 p_{1t} - \beta_3 p_{3t} \qquad \text{(A4a)}$$

and $$W_{it}^{27}(S_t^2) = V_{it}^{27} + e_{it}^7\,. \qquad \text{(A4b)}$$

Similarly, by moving to adoption level 4, the consumer derives the utility from being in that state. However, the consumer has to pay the price of category 1 in order to reach level 4. Hence,

$$\begin{aligned} W_{it}^{24}(S_t^2) &= W_{it}^{44}(S_t^4) - \beta_1 p_{1t} \\ &= V_{it}^{44}(p_{3t}) - \beta_1 p_{1t} + e_{it}^4 \end{aligned}\,. \qquad \text{(A5)}$$

Note that the above Equation uses the expression for $W_{it}^{44}(S_t^4)$ in Equation A3b.

Alternatively, if the consumer decides to stay in adoption level 2, the consumer derives the per-period utility from category 2 as well as the option value of moving to any of the feasible higher levels or staying in level 2 in the next period. Thus,

$$V_{it}^{22}(p_{1t}, p_{3t}) = \alpha_{i2} + \delta E[\max\{W_{it+1}^{22}(S_{t+1}^2), W_{it+1}^{24}(S_{t+1}^2), W_{it+1}^{27}(S_{t+1}^2)\} \mid p_{1t}, p_{3t}] \qquad \text{(A6a)}$$

and $$W_{it}^{22}(S_t^2) = V_{it}^{22} + e_{it}^2\,. \qquad \text{(A6b)}$$

(iv) <u>Decision Process for a Consumer at Adoption Level 1</u>

A consumer in this adoption level has already adopted category 1. From Table 1, the consumer has four possible alternatives: a) adopt categories 2 and 3 and move to level 7, b) adopt category 3 and move to level 5, c) adopt category 2 and move to level 4, or d) stay in level 1. We discuss the utility that the consumer derives from these alternatives below.

As in instances above, by moving to adoption level 7, the consumer derives the utility from being in that level. However, the consumer needs to pay the price of categories 2 and 3. Hence, we have

$$V_{it}^{17}(p_{2t}, p_{3t}) = \frac{\alpha_{i1}}{1-\delta} + \frac{\alpha_{i2}}{1-\delta} + \frac{\alpha_{i3}}{1-\delta} + \frac{\Gamma^{12}}{1-\delta} + \frac{\Gamma^{23}}{1-\delta} - \beta_2 p_{2t} - \beta_3 p_{3t} \qquad \text{(A7a)}$$

and $$W_{it}^{17}(S_t^1) = V_{it}^{17} + e_{it}^7\,. \qquad \text{(A7b)}$$

Similarly, a consumer moving from level 1 to levels 4 or 5 will derive the utility from being in those levels. However, the consumer has to pay the price of category 2 and category 3, respectively to move to these adoption levels. Hence, we have

$$\begin{aligned} W_{it}^{14}(S_t^1) &= W_{it}^{44}(S_t^4) - \beta_2 p_{2t} \\ &= V_{it}^{44}(p_{3t}) - \beta_2 p_{2t} + e_{it}^4 \end{aligned} \tag{A8}$$

and

$$\begin{aligned} W_{it}^{15}(S_t^1) &= W_{it}^{55}(S_t^5) - \beta_3 p_{3t} \\ &= V_{it}^{55}(p_{2t}) - \beta_3 p_{3t} + e_{it}^5 \end{aligned}. \tag{A9}$$

Alternatively, a consumer who stays in adoption level 1 receives the per-period utility from category 1 and the option of making the decision again in the next period. Hence, we have

$$V_{it}^{11}(p_{2t}, p_{3t}) = \alpha_{i1} + \delta E[\max\{W_{it+1}^{11}(S_{t+1}^1), W_{it+1}^{14}(S_{t+1}^1), W_{it+1}^{15}(S_{t+1}^1), W_{it+1}^{17}(S_{t+1}^1)\} \mid p_{2t}, p_{3t}] \tag{A10a}$$

and

$$W_{it}^{11}(S_t^1) = V_{it}^{11}(p_{2t}, p_{3t}) + e_{it}^1 . \tag{A10b}$$

(v) Decision Process for a Consumer at Adoption Level 0

A consumer in adoption level 0 is yet to adopt any of the three categories. Hence, the consumer at this adoption level has six alternatives. Below, we present the utilities that the consumer derives from each alternative.

a) Utility from going to level 7 from level 0

$$W_{it}^{07}(S_t^0) = V_{it}^{07} + e_{it}^7 \tag{A11a}$$

where

$$V_{it}^{07} = \frac{\alpha_{i1}}{1-\delta} + \frac{\alpha_{i2}}{1-\delta} + \frac{\alpha_{i3}}{1-\delta} + \frac{\Gamma^{12}}{1-\delta} + \frac{\Gamma^{23}}{1-\delta} - \beta_1 p_{1t} - \beta_2 p_{2t} - \beta_3 p_{3t} . \tag{A11b}$$

b) Utility from going to level 5 from level 0

$$\begin{aligned} W_{it}^{05}(S_t^0) &= W_{it}^{55}(S_t^5) - \beta_1 p_{1t} - \beta_3 p_{3t} \\ &= V_{it}^{55}(p_{2t}) - \beta_1 p_{1t} - \beta_3 p_{3t} + e_{it}^5 \end{aligned}. \tag{A12}$$

c) Utility from going to level 4 from level 0

$$\begin{aligned} W_{it}^{04}(S_t^0) &= W_{it}^{44}(S_t^4) - \beta_1 p_{1t} - \beta_2 p_{2t} \\ &= V_{it}^{44}(p_{3t}) - \beta_1 p_{1t} - \beta_2 p_{2t} + e_{it}^4 \end{aligned}. \tag{A13}$$

d) Utility from going to level 2 from level 0

$$\begin{aligned} W_{it}^{02}(S_t^0) &= W_{it}^{22}(S_t^2) - \beta_2 p_{2t} \\ &= V_{it}^{22}(p_{1t}, p_{3t}) - \beta_2 p_{2t} + e_{it}^2 \end{aligned}. \tag{A14}$$

e) Utility from going to level 1 from level 0

$$\begin{aligned} W_{it}^{01}(S_t^0) &= W_{it}^{11}(S_t^1) - \beta_1 p_{1t} \\ &= V_{it}^{11}(p_{2t}, p_{3t}) - \beta_1 p_{1t} + e_{it}^1 \end{aligned}. \tag{A15}$$

f) Utility from going to level 4 from level 0

$$W_{it}^{00}(S_t^0) = V_{it}^{00}(p_{1t}, p_{2t}, p_{3t}) + e_{it}^0 \quad \text{where}$$

$$V_t^{00}(p_{1t}, p_{2t}, p_{3t}) = \delta E[\max\{W_{it+1}^{00}(S_{t+1}^0), W_{it+1}^{01}(S_{t+1}^0), W_{it+1}^{02}(S_{t+1}^0), W_{it+1}^{04}(S_{t+1}^0), W_{it+1}^{05}(S_{t+1}^0), , W_{it+1}^{07}(S_{t+1}^0)\} \mid p_{1t}, p_{2t}, p_{3t}] .$$

(A16)

To summarize, the above model describing consumer adoption of three related products implies that a consumer can exist in six possible adoption levels at any time period *t*. Of these six adoption levels, a consumer in terminal adoption level 7 has already adopted all three categories and exits the market. Hence, five out of these six adoption levels correspond to active consumers. Thus, the model requires computation of five different value functions, $V_t^{00}(.)$, $V_t^{11}(.)$, $V_t^{22}(.)$, $V_t^{44}(.)$, and $V_t^{55}(.)$, which correspond to the value that a consumer derives from being in any of these active adoption levels.

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Table 1

Summary of Feasible Adoption Levels

Active Adoption Level (l)	Categories Adopted	Possible Levels in the Consumer's Set of Alternatives (Ξ_l)	Components of the Observable State Space (Ω_t^l)
0	None	0, 1, 2, 4, 5, 7	p_{1t}, p_{2t}, p_{3t}
1	PC	1, 4, 5, 7	p_{2t}, p_{3t}
2	Digital Camera	2, 4, 7	p_{1t}, p_{3t}
4	PC & Digital Camera	4, 7	p_{3t}
5	PC & Printer	5, 7	p_{2t}

Table 2

Distribution of Respondents across Adoption Levels as of 2001			
Ownership	Adoption Level	Number of Respondents	Percentage of the Sample
Own Neither Category	0	602	48.59%
Own only Personal Computer	1	138	11.14%
Own only Digital Camera	2	8	0.65%
Own only Printer	3	0	0.00%
Own Personal Computer & Digital Camera	4	19	1.53%
Own Personal Computer & Printer	5	388	31.32%
Own Digital Camera & Printer	6	0	0.00%
Own all Three Categories	7	84	6.78%

Table 3

Sources of Adoption for the Three Categories				
		Personal Computer	Digital Camera	Printer
Total # Adopters		629	111	472
From Level 0	Transition from 0-1	36.72%		
	Transition from 0-2		9.91%	
	Transition from 0-4	0.48%	2.70%	
	Transition from 0-5	59.78%		79.66%
	Transition from 0-7	2.54%	14.41%	3.39%
From Level 1	Transition from 1-4		16.22%	
	Transition from 1-5			12.92%
	Transition from 1-7		12.61%	2.97%
From Level 2	Transition from 2-4	0.16%		
	Transition from 2-7	0.32%		0.42%
From Level 4	Transition from 4-7			0.64%
From Level 5	Transition from 5-7		44.14%	

Table 4

ESTIMATES FROM THE FORWARD-LOOKING MODEL WITH 3 SEGMENTS (DISCOUNT FACTOR = 0.9)				
	Parameter	Estimate	Std Error	T Value
PC	PRICE	-2.350	0.849	-2.768
	SEGMENT 1 INTERCEPT	-0.785	0.327	-2.398
	SEGMENT 2 INTERCEPT	1.210	0.574	2.107
	SEGMENT 3 INTERCEPT	-2.286	0.733	-3.121
	TECHNOLOGY PREFERENCE	-0.063	0.289	-0.216
DIGITAL CAMERA	PRICE	-1.793	0.618	-2.901
	SEGMENT 1 INTERCEPT	-1.154	0.528	-2.185
	SEGMENT 2 INTERCEPT	-0.794	0.390	-2.033
	SEGMENT 3 INTERCEPT	-1.146	0.475	-2.415
	TECHNOLOGY PREFERENCE	0.069	0.042	1.661
PRINTER	PRICE	-0.111	0.440	-0.253
	SEGMENT 1 INTERCEPT	-0.613	3.497	-0.175
	SEGMENT 2 INTERCEPT	-0.282	0.113	-2.494
	SEGMENT 3 INTERCEPT	3.582	1.861	1.924
	TECHNOLOGY PREFERENCE	0.167	0.101	1.657
COMPLEMENTARITY EFFECT	PC-DIGITAL CAMERA	0.355	0.123	2.881
	DIGITAL CAMERA-PRINTER	0.548	0.314	1.745
SEGMENT 1 MEMBERSHIP	INTERCEPT	0.443	0.319	1.390
	MALE HH	-0.248	0.149	-1.659
	MAGAZINE	-0.305	0.166	-1.842
	CONSUMER REPORTS	-0.746	0.368	-2.025
SEGMENT 2 MEMBERSHIP	INTERCEPT	-0.690	0.348	-1.980
	MALE HH	0.081	0.237	0.340
	MAGAZINE	0.238	0.294	0.809
	CONSUMER REPORTS	-0.092	0.700	-0.131
	LL	-3012.490		

Table 5

Adoption Behavior Across the Three Segments			
	Segment 1	Segment 2	Segment 3
# of Respondents	608	237	394
% of the Sample	49.07%	19.13%	31.80%
# Owning Personal Computer	0	235	394
# Owning Digital Camera	6	51	59
# Owning Printer	0	78	394

Table 6

Change in Conditional Adoption Probabilities due to Adoption of Other Categories					
	Avg. Adoption Probability from Level 0	Avg. Adoption Probability After Adopting PC	Avg. Adoption Probability After Adopting Digital Camera	Avg. Adoption Probability After Adopting PC & Digital Camera	Avg. Adoption Probability After Adopting PC & Printer
PC	0.179		0.334		
Digital Camera	0.020	0.035			0.069
Printer	0.115	0.367	0.244	0.457	

Table 7

EFFECT OF COMPLEMENTARITY ON PC ADOPTION PROBABILITIES

		Effect of Dropping PC-Digital Camera Complementarity		Effect of Dropping Digital Camera-Printer Complementarity	
	Avg. Adoption Probability with Complementarity	Avg. Adoption Probability After Dropping the Complementarity	% Change Due to Dropping the Complementarity	Avg. Adoption Probability After Dropping the Complementarity	% Change Due to Dropping the Complementarity
From Adoption Level 0	0.179	0.170	5.14%	0.165	7.67%
After Adopting Digital Camera	0.334	0.259	22.36%	0.239	28.38%

Table 8

EFFECT OF COMPLEMENTARITY ON DIGITAL CAMERA ADOPTION PROBABILITIES

		Effect of Dropping PC-Digital Camera Complementarity		Effect of Dropping Digital Camera-Printer Complementarity	
	Avg. Adoption Probability with Complementarity	Avg. Adoption Probability After Dropping the Complementarity	% Change Due to Dropping the Complementarity	Avg. Adoption Probability After Dropping the Complementarity	% Change Due to Dropping the Complementarity
From Adoption Level 0	0.020	0.007	67.08%	0.006	68.80%
After Adopting PC	0.035	0.009	74.29%	0.010	71.56%
After Adopting PC & Printer	0.068	0.021	69.31%	0.009	87.17%

Table 9

EFFECT OF COMPLEMENTARITY ON PRINTER ADOPTION PROBABILITIES

		Effect of Dropping PC-Digital Camera Complementarity		Effect of Dropping Digital Camera-Printer Complementarity	
	Avg. Adoption Probability with Complementarity	Avg. Adoption Probability After Dropping the Complementarity	% Change Due to Dropping the Complementarity	Avg. Adoption Probability After Dropping the Complementarity	% Change Due to Dropping the Complementarity
From Adoption Level 0	0.115	0.109	5.87%	0.103	10.69%
After Adopting PC	0.367	0.356	3.21%	0.340	7.46%
After Adopting Digital Camera	0.244	0.194	20.40%	0.145	40.77%
After Adopting PC & Digital Camera	0.457	0.457	0.00%	0.337	26.31%

Table 10

EFFECT OF A 5% DECREASE IN THE FIRST PERIOD PC PRICE

	TOTAL CHANGE	TOTAL CHANGE AS A % OF AVG. # ADOPTERS EACH PERIOD	FROM LEVEL 0	FROM LEVEL 1	FROM LEVEL 2	FROM LEVEL 4	FROM LEVEL 5
PC ADOPTION	**2.594**	2.44%	2.864		-0.270		
DIGITAL CAMERA ADOPTION	**0.961**	3.10%	-0.777	0.401			1.337
PRINTER ADOPTION	**2.789**	3.43%	1.764	1.065	-0.168	0.127	

Table 11

EFFECT OF A 5% DECREASE IN THE FIRST PERIOD DIGITAL CAMERA PRICE							
	TOTAL CHANGE	TOTAL CHANGE AS A % OF AVG. # ADOPTERS EACH PERIOD	FROM LEVEL 0	FROM LEVEL 1	FROM LEVEL 2	FROM LEVEL 4	FROM LEVEL 5
PC ADOPTION	**-0.093**	-0.09%	-0.451		0.358		
DIGITAL CAMERA ADOPTION	**1.662**	5.36%	0.928	0.296			0.437
PRINTER ADOPTION	**-0.069**	-0.09%	-0.178	-0.345	0.210	0.245	

Figure 1

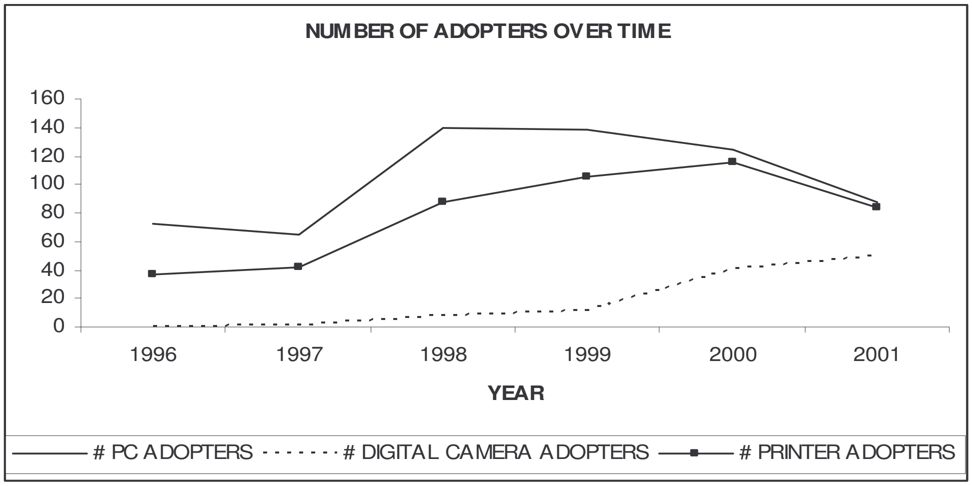


Figure 2

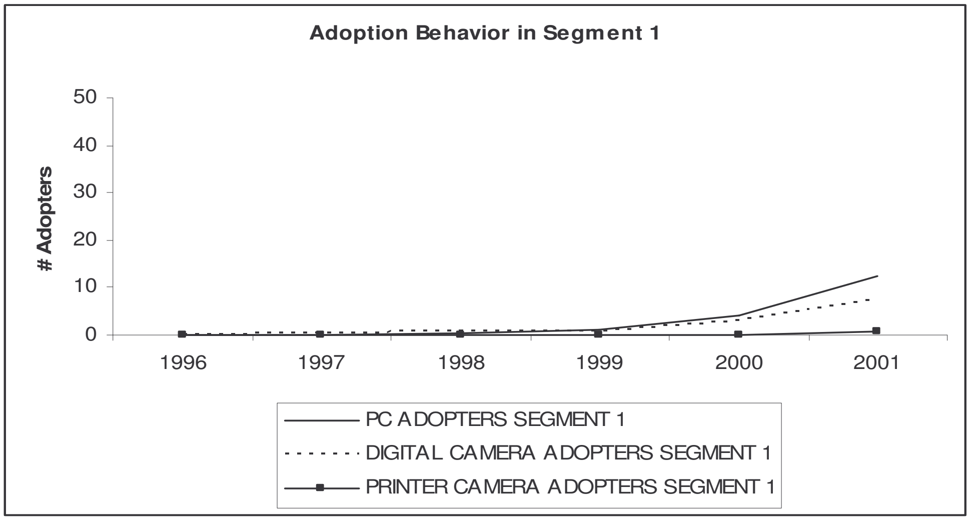
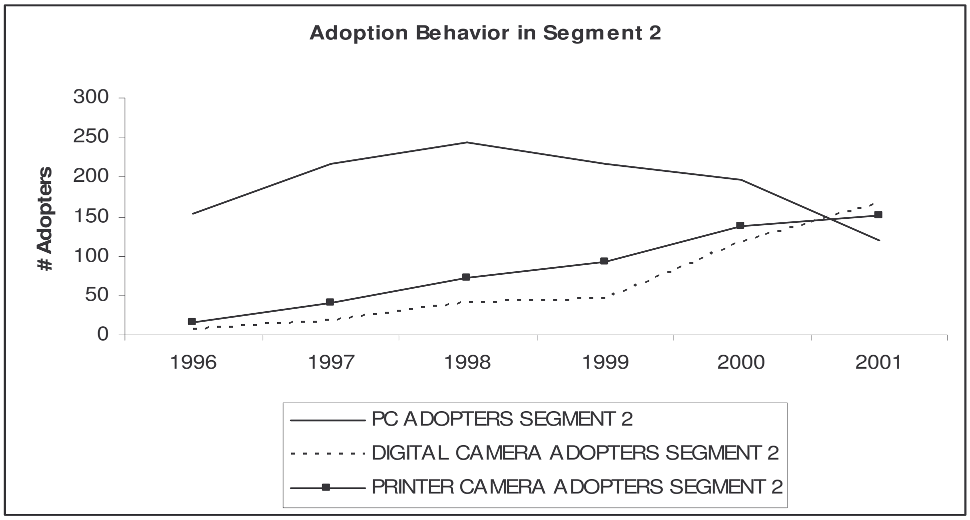


Figure 3



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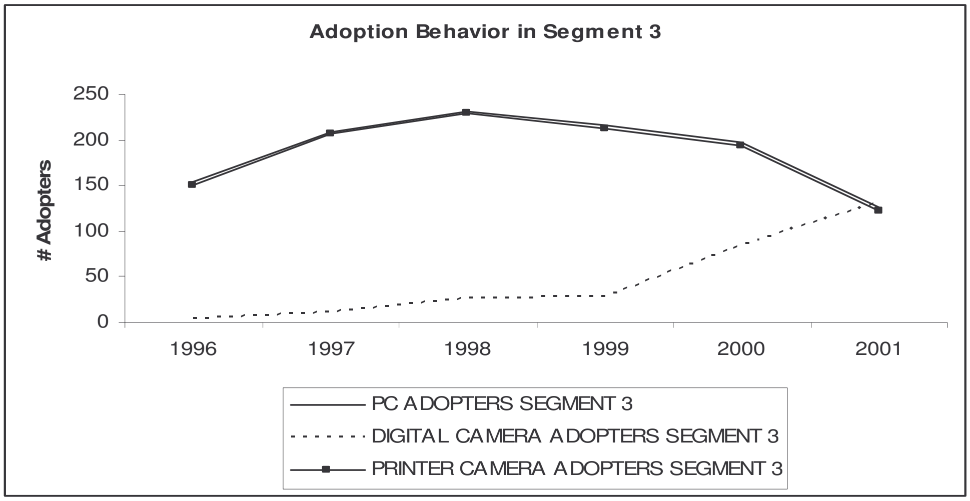

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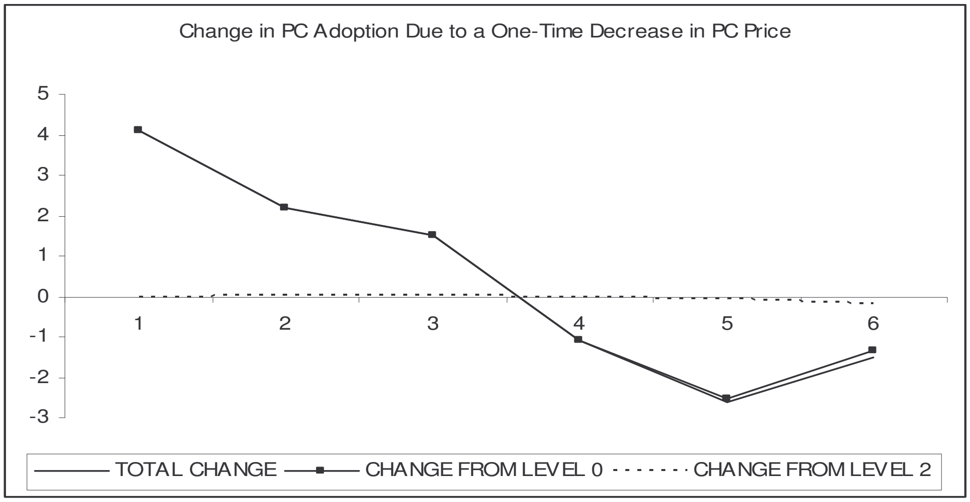

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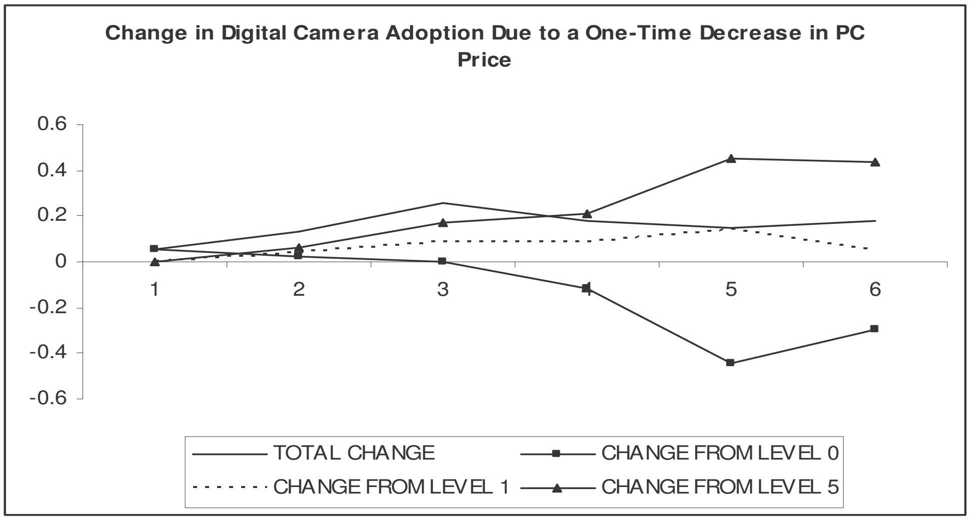

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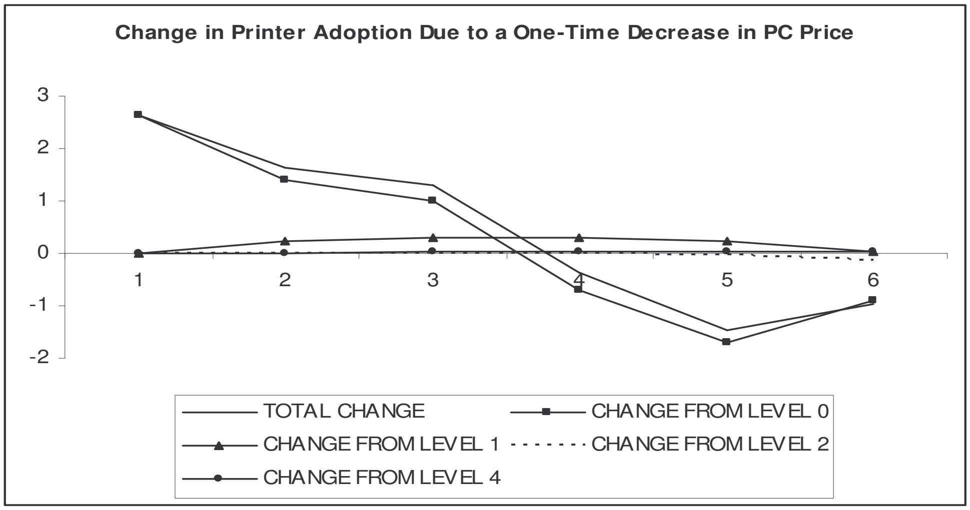


Figure 8

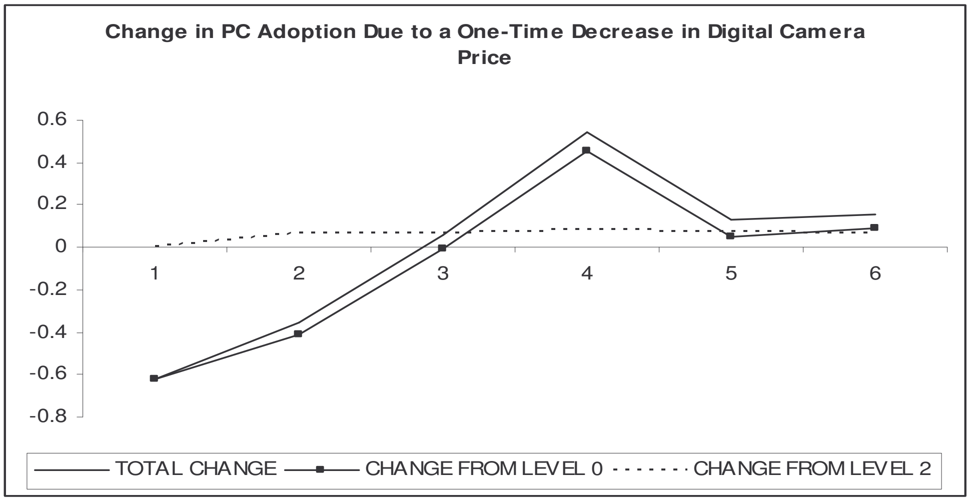


Figure 9

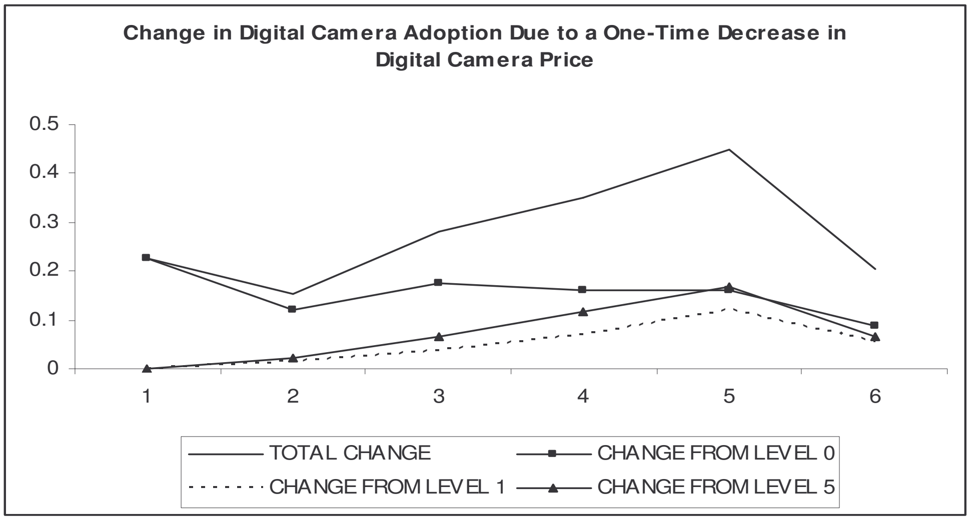
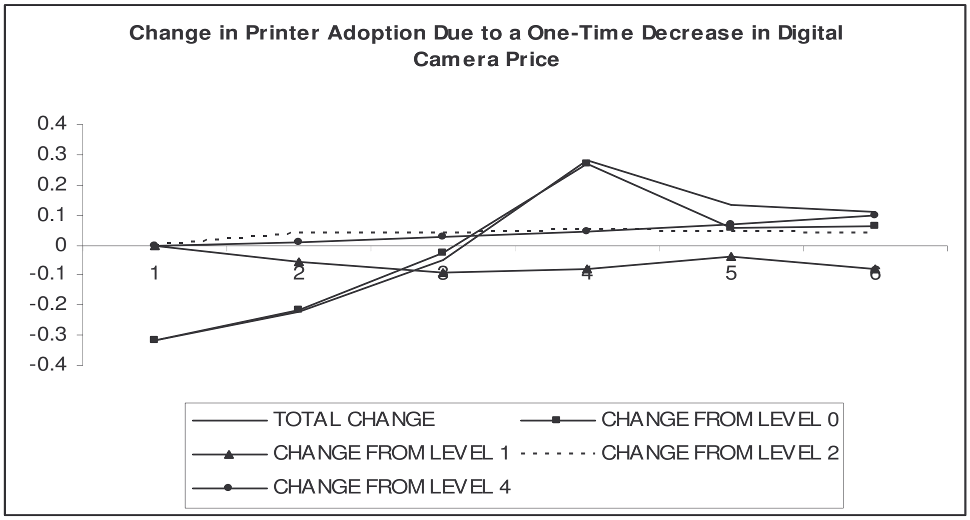

Change in Digital Camera Adoption Due to a One-Time Decrease in Digital Camera Price
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
TOTAL CHANGE
CHANGE FROM LEVEL 0
CHANGE FROM LEVEL 1
CHANGE FROM LEVEL 5

Figure 10


Change in Printer Adoption Due to a One-Time Decrease in Digital Camera Price
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
1
2
3
4
5
6
TOTAL CHANGE
CHANGE FROM LEVEL 0
CHANGE FROM LEVEL 1
CHANGE FROM LEVEL 2
CHANGE FROM LEVEL 4