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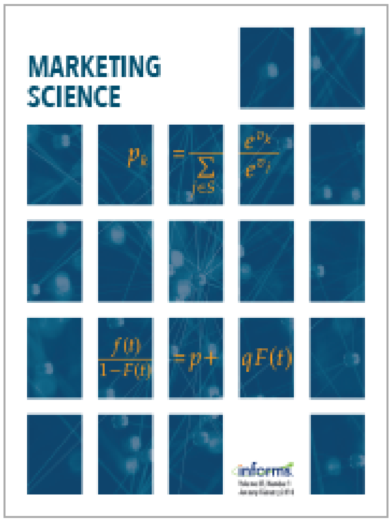

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Investigating Consumer Purchase Behavior in Related Technology Product Categories

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We present a framework of durable goods purchasing behavior in related technology product categories that incorporates the following aspects unique to technology product purchases. First, it accounts for consumers' anticipation of declining prices (or increasing quality) over time. 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. Third, the forward-looking consumer decision process, as well as the durable nature of technology products, implies that a consumer's purchase in one category will depend on the anticipated price and quality trajectories of all categories. As a potential aid to future researchers, we also lay out the data requirements for empirically estimating the parameters of our model and the consequences of not having various elements of these data on our ability to estimate the parameters. The data available for our empirical analysis are household-level information on *category*-level first-time *adoption* decisions in three categories—personal computers, digital cameras, and printers. Our results reveal a strong complementary relationship between the three 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 and also across categories as a consequence of the price decrease.

Key words: technology products; consumer adoption; complementary products; forward-looking consumers; econometric models
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1. Introduction

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 (Manchanda et al. 1999, Niraj et al. 2008, 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. Most of the research on such multicategory purchases has focused on packaged goods or nondurable categories.

In this paper, we present a framework for modeling consumer purchase behavior in related technology product categories. Purchases in such categories can entail both adoption and replacement. The context of technology products poses some unique challenges compared to packaged goods markets. First, prices of technology products tend to decline over time while quality typically improves. If consumers anticipate these future price and quality trajectories while deciding when to purchase, 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 trade-off between the stream of utilities she would derive upon buying the technology and the one-time price she needs to pay at the time of purchase. Third, an additional consequence of the durable nature of technology products is that a simultaneous purchase 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 purchase any one technology is also likely to depend on when she anticipates purchasing the other technologies. Hence, the purchase decision for a focal technology would depend not only on the expected price and quality trajectories of that technology, but also on the anticipated timing of the purchase of the related technologies.

We present a general framework of durable goods adoption and replacement behavior in the context of two related technology product categories with each category containing multiple alternatives. Next, we discuss the data requirements for empirically estimating the parameters of our general model and the specific restrictions that need to be imposed when such data are unavailable. It is particularly important to understand these restrictions in light of the data we have for our empirical analysis—household-level information on *category*-level *adoption* decisions in three categories—personal computers (PCs), digital cameras, and printers. An interesting aspect of these categories is that while the adoption of printers is contingent upon adoption of the personal computer category, no such restriction exists for the adoption of the either the personal computer or digital camera categories. As we discuss subsequently, our framework is flexible enough to accommodate consumer purchase decisions in such contingent product categories. A consequence of the nature of our data is that we cannot explore replacement purchase behavior or consumer choice within each category.

The empirical specification of our multicategory adoption model accounts for consumer heterogeneity in the intrinsic valuation for the three product categories. The results from our empirical 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. For example, the estimated probability of PC adoption for consumers who have not adopted the other two categories is 0.179, and this increases to 0.334 after the adoption of a digital camera. 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 from 0.179 to 0.170 (about 5%) 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 estimated adoption probability of personal computers would decrease from 0.334 to 0.259 (about 22%). 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 is most sensitive to these changes.

Furthermore, we also perform policy simulations wherein we modify the price trajectory of the personal computer category to be declining at a slower rate than the observed levels. These simulations help us understand the role of the actual price levels as well as consumer expectations of the price trajectory in inducing adoption in the personal computer and related categories. On the other hand, in a myopic model, the adoption decision will be driven solely by the current price levels with anticipation of future prices playing no role. This highlights the benefit of modeling the forward-looking nature of the adoption decision in technology product categories.

This paper makes the following contributions to the literatures on multicategory purchasing behavior and on the purchase of technology products. First, from a methodological point of view, we develop a framework for modeling multicategory purchase behavior by forward-looking consumers in the context of technology products. We discuss the implications for purchasing from our model and articulate the data required to estimate the model. We lay out the restrictions that need to be imposed on the general model when some aspects of the data are missing. Thus the paper extends the literature on consumer purchases across multiple categories to the context of durable technology products and addresses the unique challenges of doing so. 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. In §2 we present the framework for modeling consumer adoption and replacement of related technology products. Section 3 discusses the empirical application and estimation issues. Next, we describe the data used in the empirical application. This is followed by a section on our empirical results. Finally, we provide some concluding comments.

2. Modeling the Purchase Behavior of Related Technology Products

In this section, we present a framework for modeling consumer adoption and replacement of related technology products for a two-category case that accommodates multiple products within each category. In the following subsection, we discuss the implications of this general model for consumer purchase decisions. We subsequently discuss the data requirements to estimate the model. We then try to reconcile the discrepancies between the data we have and the data that are required, and discuss the restrictions that need to be imposed on the general model to estimate it with the data at hand. Finally, we discuss the specification of the restricted model that we estimate in our empirical analysis.

2.1. Overview of the Modeling Framework

We first consider the purchase of two related technology products by consumer i, $i = 1, 2, 3, \ldots, I$. Upon purchasing a product in 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 product in the category. This specification of the intrinsic valuation

(1) depends on the quality level at which the consumer purchases the product,[1]

(2) could depend on consumer-specific demographic and psychographic characteristics (sources of observed heterogeneity), and

(3) allows the intrinsic valuation to vary across consumers (because of unobserved heterogeneity).

Over her lifetime, the consumer receives a discounted infinite series of the per-period utility. An infinite horizon specification provides a natural way of accommodating replacement purchases and also appears to be more common in the literature on technology product purchases (see, for example, Song and Chintagunta 2003, Nair 2007, Gordon 2008).[2]

Upon purchasing products of quality q_{i1} from category 1 and q_{i2} from category 2, the consumer derives a lifetime of utilities from both categories plus an additional term that can take nonzero values if the two categories are related as complements or substitutes. Formally,

$$\bar{\alpha}_i(q_{i1}, q_{i2}) = \alpha_{i1}(q_{i1}) + \alpha_{i2}(q_{i2}) + \Gamma(q_{i1}, q_{i2}), \qquad (1)$$

where $\bar{\alpha}_i(q_{i1}, q_{i2})$ is the per-period utility that consumer i derives from products of quality q_{i1} in category 1 and q_{i2} in category 2. The term $\Gamma(q_{i1}, q_{i2})$ captures the additional per-period utility that the consumer derives from owning products from both categories. If the two categories are related as complements (substitutes), we would expect $\Gamma(q_{i1}, q_{i2})$ to be positive (negative), and for unrelated categories, $\Gamma(q_{i1}, q_{i2}) = 0$. The magnitude of complementarity (or substitutability) is a function of the quality levels of the products that the consumer owns in the two categories—as quality levels change over time, the perceived complementarity (or substitutability) between categories is also likely to change. An implication of Equation (1) is that the consumer derives the additional utility $\Gamma(q_{i1}, q_{i2})$ for every period from the time she adopts both products.

As in Gordon (2008), we aggregate the various products within a category into two variants—frontier (f) and nonfrontier (n) products. Therefore, during each period t, consumer i has three possible alternatives in *each* category—(1) no purchase in the category (ϕ), i.e., stay with the current product she owns if any; (2) purchase the frontier product (f); or (3) purchase the nonfrontier product (n). Thus, *across* the two categories, the consumer faces nine possible alternatives. If consumers make a purchase in a category they have not yet adopted, the purchase decision corresponds to adoption. A consumer who makes a purchase in a category she has already adopted is replacing an older product. The consumer decision problem comprises of choosing (1) the sequence of purchases across categories and the specific products within a category and (2) the timing of purchase in the two categories that maximizes her expected discounted stream of utilities.

As discussed earlier, a key characteristic of the market for technology products is that prices tend to decline over time while quality levels typically increase. Hence, consumers are likely to anticipate these future changes in price and quality levels and incorporate this information while making their purchase decisions. Because we do not observe actual expectations (as in Erdem et al. 2005), we assume, as in Song and Chintagunta (2003), that the consumers expect that the prices and quality levels of product a in category c follows a univariate Markov process as follows:

$$\ln(p^a_{c,\,t+1}) \mid \ln(p^a_{c,\,t}) \sim N(\ln(p^a_{c,\,t}) + \mu^p_{ac}, \sigma^{p^2}_{ac}),$$

[1] Note that the quality level at which the consumer purchases each category will depend on the time of purchase. Increasing quality over time implies that a consumer purchasing the product later would also purchase it at a higher quality level. Later, we discuss the effect of quality dynamics on consumer decision making.

[2] On the other hand, Erdem et al. (2005) use a finite horizon specification to model consumers' PC purchase decisions.

$$\ln(q^a_{c,\,t+1}) \mid \ln(q^a_{c,\,t}) \sim N(\ln(q^a_{c,\,t}) + \mu^q_{ac}, \sigma^{q^2}_{ac})$$
$$c = 1, 2,\ a \in \{f, n\},^3 \quad (2)$$

where $p^a_{c,\,t}$ and $q^a_{c,\,t}$ are the price and quality levels, respectively, of product a, $a \in \{f, n\}$, in category c in calendar time t. Declining prices and increasing quality would imply that $\mu^p_{ac} < 0$ and $\mu^q_{ac} > 0$. Moreover, the standard deviations, σ^p_{ac} and σ^q_{ac}, capture uncertainties in consumers' price and quality expectations, respectively.[4] For notational clarity, we would like to point out that $q^a_{c,\,t}$ refers to the quality of the product in the market at time t, and the term q_{ic} in Equation (1) refers to the quality of the product that consumer i owns. Thus, if consumer i purchases the frontier product in category c at time t, the quality of the product she would possess at the beginning of time $t+1$ is $q_{ic} = q^f_{ct}$.

2.2. The General Model with Replacement

Let $V^{a,\,b}_{it}(.)$, $a, b \in \{\phi, f, n\}$ be the observable component of the utility that consumer i derives from purchasing alternative a from category 1 and alternative b from category 2. The observable component of the utilities corresponding to the nine possible alternatives can be written as follows:

$$V^{a,\,b}_{it}(\Omega_t; q_{i1}, q_{i2}) = \alpha_{i1}(q^*_1) + \alpha_{i2}(q^*_2) + \Gamma(q^*_1, q^*_2) - \beta_i p^a_{1t} - \beta_i p^b_{2t} + \Delta_{it+1}(S_{it+1}), \quad (3)$$

where $\Omega_t = \{p^f_{1t}, p^n_{1t}, p^f_{2t}, p^n_{2t}, q^f_{1t}, q^n_{1t}, q^f_{2t}, q^n_{2t}\}$ is the set of observable state variables, $\{p^f_{1t}, p^n_{1t}, p^f_{2t}, p^n_{2t}\}$ is the set of prices of the frontier and nonfrontier products in the two categories at time t, and β_i is the marginal utility of income for consumer i. Furthermore, the prices p^a_{1t} and p^b_{2t} are the prices of the product that the consumer purchases in categories 1 and 2, respectively. Specifically, if the consumer purchases a frontier (nonfrontier) product in category 1, the corresponding price would be p^f_{1t} (p^n_{1t}). However, if she does not make a purchase in that category, she would not incur the cost; i.e., $p^\phi_{1t} = 0$. Similarly, q^*_1 and q^*_2 correspond to the quality levels of the products that would result as a consequence of the consumer's decision. If she purchases the frontier product in category c, then $q^*_c = q^f_{ct}$ (or $q^*_c = q^n_{ct}$ if she purchases the nonfrontier product). However, if she chooses not to make a purchase, she would continue with the product she currently owns in that category; i.e., $q^*_c = q_{ic}$, $c = 1, 2$.[5] $q^*_c = 0$ if the consumer has not yet adopted the category c. In Equation (3), $\alpha_{ic}(.) = 0$ if the consumer has not adopted category c, $c = 1, 2$; $\Gamma(.) = 0$ unless the customer has adopted both categories. The term $\Delta_{it+1}(S_{it+1})$ captures the option value that the consumer has in period $t+1$, i.e., the discounted expected value of the maximum of all the options that the consumer has in period $t+1$:

$$\begin{aligned}\Delta_{it+1}(S_{it+1}) &= \delta E[\max\{W^{\phi,\,\phi}_{it+1}(S_{it+1}), W^{f,\,\phi}_{it+1}(S_{it+1}), W^{n,\,\phi}_{it+1}(S_{it+1}),\\ &\quad W^{\phi,\,f}_{it+1}(S_{it+1}), W^{f,\,f}_{it+1}(S_{it+1}), W^{n,\,f}_{it+1}(S_{it+1}),\\ &\quad W^{\phi,\,n}_{it+1}(S_{it+1}), W^{f,\,n}_{it+1}(S_{it+1}), W^{n,\,n}_{it+1}(S_{it+1})\} \mid \Omega_t]. \quad (4)\end{aligned}$$

The terms $W^{a,\,b}_{it+1}(S_{it+1})$, $a, b \in \{\phi, f, n\}$ denote the total utility that the consumer would derive if she were to purchase product a (which includes no purchase) in category 1 and product b in category 2 in period $t+1$, and S_{it+1} is the corresponding set of state variables. We can express this utility that a consumer derives from such a purchase as the sum of two components—the component observed by the researcher, $V^{a,\,b}_{it}(\Omega_t; q_{i1,} q_{i2})$, and an unobserved error term. Hence, the total utility that the consumer derives from making such a purchase at time t can be written as

$$W^{a,\,b}_{it}(S_t) = V^{a,\,b}_{it}(\Omega_t; q_{i1}, q_{i2}) + e^{a,\,b}_{it}, \quad (5)$$

where $e^{a,\,b}_{it}$ is the unobserved component. Given the formulation above, $S_{it} = \{\Omega_t, q_{i1}, q_{i2}, e^{a,\,b}_{it}\}$ denotes the state variables for a consumer at time t. Note that the set of state variables consist of three components: (a) aggregate prices and quality levels, Ω_t, which are observed by both the consumer and the researcher; (b) quality levels of the products that consumer i owns at time t, q_{i1}, q_{i2}; and (c) $e^{a,\,b}_{it}$, which is observed by the consumer upon realization but not by the researcher. Note that the option value that consumer i faces at time $t+1$, $\Delta_{it+1}(S_{it+1})$, is affected by the quality level of the product she owns at time t. Therefore, a consumer who makes a purchase at time t would have a different option value, $\Delta_{it+1}(S_{it+1})$, than a consumer who does not; even if both of them started out with the same quality products at the beginning of time t.

If we assume that these unobserved state variables $e^{a,\,b}_{it}$ follow an IID type I extreme value distribution, the probability that consumer i chooses option a in category 1 and option b in category 2, $a, b \in \{\phi, f, n\}$, can be written as

$$h^{a,\,b}_{it} = \frac{\exp(V^{a,\,b}_{it}(\Omega_t; q_{i1}, q_{i2}))}{\sum_{a' \in \{\phi, f, n\}} \sum_{b' \in \{\phi, f, n\}} \exp(V^{a'b'}_{it}(\Omega_t; q_{i1}, q_{i2}))}. \quad (6)$$

Later, we discuss the implication of this assumption regarding the distribution of the error term on the

[3] One can generalize this equation and allow the price and quality processes to be correlated.

[4] In general, one could allow the processes in Equation (3) to be correlated across products and categories.

[5] Note that we have assumed that if the consumer replaces an existing product with a newer version, the salvage value for the replaced product is zero.

computation of the value functions, $V_{it}^{a,b}(.)$, $a, b \in \{\phi, f, n\}$.

The above model formulation can be readily extended to accommodate other features such as product depreciation over time and the availability of bundled options. These extensions are discussed in Technical Appendix A (an electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org) and are not presented here given space considerations.

2.2.1. Model Implications. In a single-category situation, the trade-off that the consumer faces is between (a) purchasing a product earlier and deriving utility over a longer period of time and (b) buying it later at a lower price or obtaining a higher quality product. Therefore, a consumer's replacement or adoption decision would depend on her anticipation of the future price and quality trajectories of the products in that category. In case of a replacement purchase, the decision would also depend on the difference between the quality of the product that a consumer owns and the quality of the products in the market at time t. If this difference is sufficiently large compared to the price, the consumer is likely to make the replacement decision.

When we extend the model to multiple categories, the relationship between categories because of product complementarity, $\Gamma(.)$, makes the analysis of purchase decisions more complicated. First, if the product complementarity, $\Gamma(.) = 0$, then the two categories would be unrelated. Under such a scenario, a consumer's purchase decision in one category would not be affected by her purchase decision in another category. On the other hand, if the products are complements, with $\Gamma(.) > 0$, purchase decisions in the two categories would no longer be independent. The impact of this complementarity would depend on how its magnitude varies as a function of the quality levels of the two categories that a consumer owns. First, consider the case wherein complementarity is invariant to the quality levels of the corresponding products; i.e., $\Gamma(.) = \Gamma$. Under such a scenario, a consumer who has adopted only one category will forego the additional utility she would derive from adopting or making a replacement purchase in the other category. Thus, she will have an incentive to accelerate adoption in the other category. As the magnitude of the complementarity effect between the two categories increases, the consumer will reduce the time interval between adoption of the two categories, i.e., adopt the two products in close succession or simultaneously.[6] However, once she has adopted products in both categories, the incentive to replace older products with newer ones would be driven largely by the higher intrinsic value (because of higher quality) she would derive from the category, i.e., higher $\alpha_{ic}(q_{ic})$. Therefore, the consumer's replacement decision would be similar to the case when the categories are unrelated.

Let us now consider the case when $\Gamma(.)$ is an increasing function of the quality levels of the two products that the consumer owns. This has three implications for purchase behavior.

1. Because the magnitude of complementarity would increase over time as quality levels increase, this is likely to have a time-varying effect on adoption decisions. As discussed above, complementarity provides an incentive for consumers to adopt products in close succession. With quality-dependent complementarity, this incentive would increase over time. Eventually, one would observe increased propensity amongst consumers to adopt products in these two categories in close succession.

2. When a consumer replaces an old product with a version with higher quality, the benefit would accrue from two sources—(1) higher $\alpha_{ic}(q_{ic})$ and (2) higher $\Gamma(.)$. Thus, the incentive to replace older products with newer ones would be greater than in the case when $\Gamma(.)$ is quality-invariant.

3. Building on the above implication, a consumer who has adopted only one category would derive the benefit from higher $\alpha_{ic}(q_{ic})$ when she makes a replacement purchase with a higher quality product. On the other hand, a consumer who has adopted both categories would derive the benefit of a higher $\alpha_{ic}(q_{ic})$ and also a higher $\Gamma(.)$. Thus, the latter consumer would have a relatively higher incentive to make a replacement purchase with a higher quality product in that category.

The above implications of the model could help in inferring how complementarity depends on the quality levels of the corresponding products.

When there are multiple-product offerings within each category (for example, frontier and nonfrontier products as discussed above), the model has some additional implications for the quality level of the product that a given consumer would purchase in each category. First, consider the case when there is no complementarity. If consumers differ in terms of their quality valuation, i.e., $\alpha_{ic}(q_{ic})$ differs in slope with respect to quality across consumers, consumers who derive greater marginal benefit with respect to

[6] If one considers single-category adoption decisions, the structural model can also be written out as a hazard rate model (see, for example, Song and Chintagunta 2003). With two categories, one can specify a reduced-form hazard rate model wherein the hazard rate for the second product depends on whether the consumer has already adopted the first category. However, such a reduced-form model treats the original purchase decision in the first category as exogenous.

quality (i.e., greater $\partial\alpha_{ic}(.)/\partial q_c$) are more likely to purchase the frontier version of the product. Extending this logic, conditional on the quality of the product they currently own, such consumers are also likely to make replacement purchases earlier.[7] If the product categories are related as complements and the magnitude of complementarity is invariant to quality, i.e., $\Gamma(.) = \Gamma$, it would not influence the choice between frontier and nonfrontier products, although as discussed above, it would affect the interpurchase time between categories. On the other hand, if the magnitude of complementarity depends on quality, the choice between frontier and nonfrontier products within each category would depend on the functional form of $\Gamma(.)$. If $\Gamma(.)$ is a convex function of the quality levels of the two categories, consumers would derive increasing returns from purchasing higher quality variants from the two categories. Thus, if a consumer owns a frontier product in one category, she would derive a much greater benefit from purchasing the frontier product in the second category. However, if consumers derive diminishing complementarity with quality, i.e., $\Gamma(.)$ is concave in quality, the benefit from owning frontier products might not exceed the cost for some consumers. Hence, we would observe fewer (more) consumers purchasing frontier products in both categories if $\Gamma(.)$ were concave (convex).[8] This implication of the model could help in inferring the functional form of complementarity from the data. At the same time, note that the S-shaped nature of the logit functional form in Equation (6) would imply that the marginal effect of the concave or convex functional from of $\Gamma(.)$ would be greater for consumers who do not have a very high or very low $\partial\alpha_{ic}(.)/\partial q_c$ in either category.[9]

2.2.2. Data Requirements for Estimating the General Model. To estimate the above model, we need a data set that possesses several features:

(a) Individual-level data on the sequence and timing of purchases across categories being considered;

(b) Data on whether each purchase is a first-time or replacement purchase in a category;

(c) Information on the specific product (or variant) purchased by these consumers within each category even if, as above, we focus only on the frontier and nonfrontier products; and

(d) Prices and quality levels of all the products over time.

Our data include information on the sequence and timing of purchases at the individual level across several categories (feature a). This information pertains to first-time purchases and not replacement (feature b). We also do not have information on the particular brand or variant that they bought (feature c); only the identity of the *category* being purchased. We also do not have information on the price and quality levels for different products over time (feature d); we only have this information at the category level. Recall that the general model allows us to (1) estimate complementarity between categories even in the absence of simultaneous purchases in these categories; (2) consider multiple products within each category; and (3) accommodate replacement purchase behavior. Below we discuss which of these features can be accommodated with the data on hand and the restrictions we will need to impose on the model in order to make it compatible with our data.

Estimating Complementarity in the Context of Durable Goods Purchases. Our data have the requisite information to infer complementarity. At the same time, the data only contain information on the timing of the first purchase in each category at the category level. As we discuss below, this restricts our ability to estimate the general form of complementarity described in the above model specification.

Allowing for Multiple Products Within Each Category. Allowing for multiple products within each category would realistically capture the nature of decisions that consumers make. Furthermore, the information on consumer purchases at different quality and price levels would provide us with variation to infer heterogeneity in their preference for quality versus price. Because consumers have the option of choosing between high- and low-quality alternatives at correspondingly high and low prices, consumers who value quality more (relative to price) are likely to choose the high-quality alternative, whereas consumers who value price more (relative to quality) are likely to choose the low-quality alternative. Our data do not contain individual-level information on frontier versus nonfrontier purchases by each consumer (feature (c) of the data described above) or prices and qualities of the various products within a category over time (feature (d) above). Regarding the latter issue concerning information on product-level prices and quality levels, syndicated sources of data that contain such information for various durable product

[7] Note that this assumes that consumers do not differ in terms of their price sensitivity, or if they do, consumers who have a greater quality sensitivity have a lower price sensitivity; i.e., they are negatively correlated. If, however, they are positively correlated, the greater benefit from higher quality will not always exceed the disadvantage of having to pay a higher price. Under such a scenario, consumers who value quality more need not always purchase the higher quality product.

[8] Note that this does not consider compatibility issues between different generations of related products.

[9] If consumers have a high (low) $\partial\alpha_{ic}(.)/\partial q_c$ in both categories, they are likely to have a very high (low) purchase probability for the frontier products in both categories. Hence, they would be on the flat portion of the S-shape where the marginal effects of the functional form of $\Gamma(.)$ are likely to be lower.

categories do exist. Nevertheless, given our focus on measuring complementarity it will still not be sufficient to estimate the model without information on which specific product each consumer purchased in each category. Hence, in our empirical application, we need to restrict our attention to category purchase decisions. Thus, a consumer faces only two alternatives (purchase versus no purchase) within each category; i.e., there are four possible alternatives that the consumer faces in a two-category situation.

Accommodating Replacement Purchases. In the previous paragraph we noted that availability of data at the product or variant level will enable us to uncover heterogeneity in quality or price sensitivity. An alternative way of getting to this heterogeneity would be if one observed replacement purchases by individual consumers (even in the absence of product-level data). Specifically, we would expect quality sensitive consumers (who derive more utility from higher quality products) to replace older products with more advanced versions. Therefore, based on their relative propensity to replace current product with advanced versions, we can infer which consumers are more responsive to quality (or price).[10] Our data contain information only on first-time purchases besides not having the product-level information noted above. Hence, we cannot accommodate replacement purchases in our empirical application and need to focus on the multicategory adoption decision. Furthermore, the absence of product-level data also prevents us from estimating the distribution of price or quality heterogeneity. With a focus on adoption decisions, a consumer exits the market for a category once she makes a purchase in the category. Therefore, the set of available alternatives she faces reduces as she adopts more and more categories. The specification of the value function corresponding to a purchase (or no purchase) decision, which depends on the set of alternatives that the consumer would possess subsequent to the decision, would vary with the set of categories the consumer has already adopted. For example, a consumer who has not adopted any category would have the full set of four alternatives. However, a consumer who has adopted one category would have only two options—purchasing or not purchasing the other category. A consumer who has purchased both categories would exit the market.

In sum, the above discussion highlights that the nature of our data would preclude us from estimating a model that allows for (1) multiple products within each category and (2) replacement purchases. An additional implication of not having such data is that we may not be able to identify the distribution of consumer heterogeneity in price and quality sensitivity parameters. Specifically, even if there are separate price and quality sensitive segments, we cannot infer them from the data used in our estimation. Below, we discuss if the data contain sufficient variation to identify the mean price and quality sensitivities, i.e., without heterogeneity.

Inferring Quality and Price Sensitivities. The general model allows for separate price and quality sensitivity parameters as well as the dependence of complementarity on the quality levels of the constituent products. Because we have category-level adoption data on consumers, estimation of such a model would require some independent variation in the category-level price and quality over time for each of the categories being analyzed. In other words, the data contain time periods when price (quality) remains unchanged while quality (price) increases (decreases). The relative extent to which purchases increase when quality (price) increases (decreases) will help in identifying the price sensitivity and quality sensitivity separately. Such instances of independent price and quality variation are more likely when we consider data at the individual product level or data at a higher frequency (e.g., weekly). However, as our data are at the category level and at an annual frequency, price and quality trajectories are likely to be highly collinear. 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 purchase decisions could be problematic. One can circumvent this problem by collecting consumer expectation data regarding the anticipated price trajectory in several waves of survey as in Erdem et al. (2005). In the context of our application, it would be infeasible to collect such data on price expectations retrospectively. Alternatively, 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.

2.2.3. Restrictions for the Empirical Application. In view of the above data limitations, we modify the general model in three ways.

First, to account for declining prices (p_{jt}) and for increasing quality levels (q_{jt}) to influence adoption decisions while dealing with the collinearity issue, we operationalize price as the quality-adjusted price (p_{jt}/q_{jt}) as in Song and Chintagunta (2003).

[10] Note that in Gordon's (2008) single-category case, no individual-level data are required—he uses a combination of aggregate sales data and aggregated data on product ownership—however, in our case the focus is on inferring complementarity. This necessitates consumer-level purchasing behavior across multiple categories.

Second, as a consequence of using quality-adjusted prices in lieu of prices, the intrinsic valuation of each category, $\alpha_{ic}(q_{ic})$, no longer depends upon the quality level at which a consumer adopts the category; i.e., $\alpha_{ic}(q_{ic}) = \alpha_{ic}$. Similarly, the pair-wise complementarity terms are independent of the quality levels at which the consumer adopts the two categories; i.e., $\Gamma^{cc'}(q_{ic}, q_{ic'}) = \Gamma^{cc'}$.[11] We do, however, retain the variation in the intrinsic valuation across consumers because of their observed and unobserved characteristics. The model thus implies that consumers who have similar observed and unobserved heterogeneity components would derive the same intrinsic valuations and complementarities from the categories irrespective of the quality level at which they adopt them. One can argue that this can be problematic for the types of product categories we consider. For example, although consumers might derive greater complementarity from purchasing a digital camera if they had a faster computer, our restricted model would not accommodate such a possibility.

Third, an additional implication of using quality-adjusted price is that the corresponding coefficients no longer reflect the marginal utility of income and we can no longer retain the same coefficient for price across all categories. In the subsequent discussion, we use "price" to refer to "quality-adjusted price."

2.3. The Restricted Model

Let $\{a, b\}$ denote a consumer's adoption in the two categories, where $a, b \in \{0, 1\}$ denotes either nonadoption (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 given 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—$\{1, 1\}$.

A consumer in adoption level 0 has the option of staying in level 0 or moving to level 1, level 2, or level 3; a consumer in adoption level 1 or level 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. We first start with the case when the consumer has adopted one of the product categories (levels 1 and 2) and then 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, $k = 1, 2$, $k \neq j$ and thus exiting the market. Such a consumer can (1) stay in level j or (2) move to level 3.

Moving from Level j to Level 3. A consumer who moves from level j to level 3 will derive an infinite stream of utilities from categories 1 and 2 as well as an infinite stream of the complementary effect and will pay a one-time price, p_{kt}, of category k to move to level 3 from level j. Hence, we have

$$W_{it}^{j3}(S_t^j) = V_{it}^{j3}(p_{kt}) + e_{it}^3, \tag{7a}$$

where

$$V_{it}^{j3}(p_{kt}) = \frac{\alpha_{i1}}{1-\delta} + \frac{\alpha_{i2}}{1-\delta} + \frac{\Gamma}{1-\delta} - \beta_k p_{kt}. \tag{7b}$$

In Equation (7a), $W_{it}^{j3}(.)$ 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 $\alpha_{i1}/(1-\delta) + \alpha_{i2}/(1-\delta) + \Gamma/(1-\delta)$ in Equation (7b) captures the infinite stream of utilities that the consumer would derive from adopting both. 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 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, $V_{it}^{jj}(p_{kt})$, comprises of two components: (1) the value of consuming category j in period t and (2) 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

$$\begin{aligned} &V_{it}^{jj}(p_{kt}) \\ &\quad = \alpha_{ij} + \delta E[\max\{W_{it+1}^{jj}(S_{t+1}^j), W_{it+1}^{j3}(S_{t+1}^j)\} \mid p_{kt}]. \end{aligned} \tag{8a}$$

Recall that the term α_{ij} captures the per-period utility that consumer i derives from category j. The term $W_{it+1}^{j3}(S_{t+1}^j)$ is defined as in Equation (7a) and captures the option value of moving to adoption level 3 in the next period. Along similar lines, the

[11] Recall that the inference of how the quality affects complementarity relies on (1) observing greater propensity to adopt the two categories simultaneously or in close succession as quality levels of the two categories increase and (2) greater propensity to replace products among consumers who have adopted both categories compared to those who have adopted only one. Because our data contain information only first time purchases, we have to rely solely on the first source of variation to identify the quality dependence of complementarity. However, as discussed later, our empirical analysis is based on six years of purchase history and does not contain sufficient temporal variation in the propensity to adopt the categories in close succession to infer this relationship.

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 (7a), 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 adoption level 2 at time t can be written as

$$W_{it}^{jj}(S_t^j) = V_{it}^{jj}(p_{kt}) + e_{it}^j, \quad (8b)$$

where $V_{it}^{jj}(p_{kt})$ 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, $S_t^j = \{p_{kt}, e_{it}^j, e_{it}^3\}$. Note that the set of state variables consist of two components: (1) $\Omega_t^j = \{p_{kt}\}$, which is observed by both the consumer and the researcher upon realization, and (2) $e_{it} = \{e_{it}^j, e_{it}^3\}$, 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: (1) stay in level 0, (2) move to level 1, (3) move to level 2, and (4) 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,

$$W_{it}^{03}(S_t^0) = V_{it}^{03}(p_{1t}, p_{2t}) + e_{it}^3, \quad (9a)$$

$$V_{it}^{03}(p_{1t}, p_{2t}) = \frac{\alpha_{i1}}{1-\delta} + \frac{\alpha_{i2}}{1-\delta} + \frac{\Gamma}{1-\delta} - \beta_1 p_{1t} - \beta_2 p_{2t}, \quad (9b)$$

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. 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

$$W_{it}^{0j}(S_t^0) = W_{it}^{jj}(S_t^j) - \beta_j p_{jt} = V_{it}^{jj}(p_{kt}) - \beta_j p_{jt} + e_{it}^j, \quad (10)$$

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. Note that the rationale behind Equation (10) 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 (8a) and (8b). However, the consumer has to pay a one-time price (of category j) to get to level j from level 0. Notice that Equation (10) implies that the consumer's decision to adopt category j not only depends on the price of that category, p_{jt}, but also on the anticipated price trajectory of category k, p_{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

$$V_t^{00}(p_{1t}, p_{2t}) = \delta E[\max\{W_{it+1}^{00}(S_{t+1}^0), W_{it+1}^{01}(S_{t+1}^0), W_{it+1}^{02}(S_{t+1}^0), W_{it+1}^{03}(S_{t+1}^0)\} \mid p_{1t}, p_{2t}], \quad (11a)$$

where $W_{it+1}^{01}(.)$ and $W_{it+1}^{02}(.)$ are defined as in Equation (6), and $W_{it+1}^{03}(.)$ is defined in Equation (11a). 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

$$W_{it}^{00}(S_t^0) = V_{it}^{00}(p_{1t}, p_{2t}) + e_{it}^0. \quad (11b)$$

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

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.

3. Empirical Application

In this section, we discuss the empirical application of the modeling framework presented in §2. First, we recast the model in our empirical context of three related categories. 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

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. With three categories, a consumer can exist in eight possible adoption levels at any point in time:

Adoption level 0: $\{0, 0, 0\}$
None of the three 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 3: $\{0, 0, 1\}$
Only a printer 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 6: $\{0, 1, 1\}$
Digital camera and printer are owned;
Adoption level 7: $\{1, 1, 1\}$
All three categories are owned.

In the above notation, the first, second, and third elements indicate whether the consumer has adopted categories 1, 2, and 3, respectively.

An interesting aspect of these categories is that the adoption of printers is contingent on adoption of the personal computer category; i.e., consumers would not purchase a printer in the absence of a personal computer. Nevertheless, there is no such restriction for the adoption of either personal computers or digital cameras.[12] In our framework, we can readily accommodate such contingent adoption by imposing constraints on the feasible adoption levels. Thus, the model with contingent adoption may be viewed as a constrained version of the general model. More specifically, we need to impose the restriction that a consumer cannot exist in level 3 (corresponding to $\{0, 0, 1\}$) or level 6 (corresponding to $\{0, 1, 1\}$).[13] An implication of consumers not being able to adopt a printer in the absence of a personal computer is that we cannot estimate the intrinsic preference for printers separately from the PC/printer complementarity. We discuss the intuition behind this subsequently.

[12] In §4, we present evidence for these claims.

[13] 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 §4, we do not observe any consumers adopting printers and digital cameras in the absence of a personal computer.

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 and digital camera	4, 7	p_{3t}
5	PC and printer	5, 7	p_{2t}

As in the two-category scenario discussed above, a consumer in adoption level 7 exits the market. Thus, the set of active adoption levels is $\Psi = \{0, 1, 2, 4, 5\}$. 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—levels 0 and 2. However, a consumer can adopt the digital camera category from three different adoption levels—levels 0, 1, and 5. Similarly, a consumer can adopt the printer from four different adoption levels—levels 0, 1, 2, and 4. In Appendix B, 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 complementarities. 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 printers.

3.2. Modeling Heterogeneity

In the model formulation, we 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:

$$\alpha_{cir} = \bar{\alpha}_{cr} + \chi_c d_i, \quad c = 1, 2, 3, \text{ and } r = 1, 2, \ldots, R, \quad (12)$$

where R is the total number of segments, $\bar{\alpha}_{cr}$ 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 Macready 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

$$\pi_{ir} = \frac{\exp(\lambda_r + \gamma_r z_i)}{1 + \sum_{r'=1}^{R-1} \exp(\lambda_{r'} + \gamma_{r'} z_i)}, \tag{13}$$

where z_i are the demographic characteristics of consumer i, and $\{\lambda_r, \gamma_r\}$ are parameters to be estimated. For identification, we set the parameters of the Rth segment to zero.

3.3. Estimation

As discussed earlier, 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, $l \in \Psi$, $\Psi = \{0, 1, 2, 4, 5\}$, will remain in the same adoption level or move 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

$$h_{irt}^{l,m} = \frac{\exp(V_{irt}^{lm}(\Omega_t^l))}{\sum_{m' \in \Xi_l} \exp(V_{irt}^{lm'}(\Omega_t^l))}. \tag{14}$$

Note that Equation (14) is a modified version of Equation (6) with the modification made to reflect the varying number of options in an adoption-based model. 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

$$\phi_{ir} = \prod_{t=1}^{T} \prod_{l \in \Psi} \prod_{m \in \Xi_l} (h_{cirt}^{l,m})^{d_{il,mt}}, \tag{15}$$

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

$$L(\Theta) = \prod_{i=1}^{I} \sum_{r=1}^{R} \pi_{ir} \phi_{ir}, \tag{16}$$

where π_{ir} corresponds to the probability that consumer i belongs to segment r, $r = 1, 2, \ldots, R$, 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) 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

$$V_{ir}^{ll}(\Omega_t^l) = \delta \int \ln\left[\sum_{m \in \Xi_l} \exp(V_{ir}^{lm}(\Omega_{t+1}^l))\right] dp(\Omega_{t+1}^l \mid \Omega_t^l). \tag{17}$$

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.[14] As discussed in the model section, 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 quality-adjusted prices.

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.[15] This high dimensionality of the state space along with the need to compute five different value functions significantly

[14] Please refer to Technical Appendix B (see the electronic companion) for the formulation of these utilities.

[15] 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 would have six dimensions.

complicates the estimation. Hence, traditional value function computation methods that use polynomial approximation turned out to be quite inefficient. To circumvent this problem, we used the randomized multigrid algorithm proposed by Rust (1996, 1997). Three features of this algorithm significantly ease the computational burden. First, Rust (1997) shows that using random grid points overcomes the need for an exponentially increasing number of grid points to compute the value function as the state space increases. Second, the randomized multigrid 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. Because the interpolation step is subject to the curse of dimensionality (Rust 1997), this significantly reduces the computational burden. Third, the multigrid 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 less time initially when we have less information about the value function. Further details of the estimation algorithm can be found in Technical Appendix C (see the electronic companion).

4. Data

We use a unique survey data set from 2002 that contains information on the time of first adoption of 2,005 respondents of laptop and desktop computers, computer printers, digital cameras, DVD players, personal digital assistants (PDAs), and global positioning systems (GPSs), etc. The survey was designed and conducted by a leading global manufacturer of technology products. The survey was sent to a representative national sample of 3,600 households by mail, yielding a response rate of 55.7%. In the survey, each respondent (the key decision maker in the household) is asked whether he or she owns each product, and if he or she does, the year his or her household first adopted the product. Hence, the data are similar in structure to a typical multicategory scanner panel data collected on an annual basis. The key difference, however, is that the household exits the market for 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. In our empirical application, we use three demographic variables—gender of the head of the household (Male HH $=1$, Female HH $=0$), whether they subscribe to magazines (Yes $=1$, No $=0$), and whether they subscribe to *Consumer Reports* (Yes $=1$, No $=0$). Recall that we allow the probability that a consumer belongs to each of the discrete segments to be a function of these demographic variables. Furthermore, as we discuss subsequently, we use each respondent's stated preference for technology products as a mechanism for identifying the complementarity effects separately from heterogeneity (see Harris and Keane 1999, Horsky et al. 2006, and Ching and Hayashi 2008 for examples of applications that use stated preference information). Specifically, in the survey each respondent was asked to state the extent to which they agreed (or disagreed) with several statements regarding their preference for technology products on a scale of 1 to 5. For our empirical application, we used responses to the statement, "I like gadgets and technical things." To economize on the state space, for the empirical application, we reclassified respondents into those with high and low technology preference based on a median split.

We focus on the adoption of three related product categories—personal computers (comprising of both laptop and desktop computers), digital cameras, and computer printers. Although 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. To ensure that our data are from a representative sample of consumers, we obtained correlations of 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 because information at the model or even the brand level is rarely available.

Because the survey 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 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*. As expected, these data reveal that the average prices for all three categories decrease significantly during the period of our analysis. Specifically, the personal computer, digital camera, and printer categories experienced an annual decrease in prices of 9.8%, 7.8%, and 13.8%, respectively.

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 Scorecard (http://www.cpuscorecard.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 the case of digital cameras, we used the maximum resolution (megapixels) of the digital cameras that were surveyed in the *Consumer Reports* during each year. Because the *Consumer Reports* typically carries 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 among the available attributes.[16] 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 (HP). We then collected several objective measures of printer quality such as speed in pages per minute in color and black and white as well as the internal memory of each printer from the corresponding product manuals from Hewlett-Packard's website. Based on *Consumer Reports* and 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 among 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. To ensure that the empirical application is consistent with the model, we need to restrict the data to the time period when all three 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.[17,18]

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 and digital camera	4	19	1.53
Own personal computer and printer	5	388	31.32
Own digital camera and printer	6	0	0.00
Own all three categories	7	84	6.78

After deleting respondents who purchased personal computers or printers prior to 1996, we ended up with a sample of 1,239 respondents.[19] For the printer category, the price levels differ significantly between the two common technologies available during this period—inkjet and laser printers. Because 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.[20]

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 at the end of the year 2001 across the various possible adoption levels in Table 2. Half the sample is in adoption level 0 as of 2001 and has not adopted either category. Among consumers who have adopted, the most populated adoption levels are levels 5 and 1. Hence, the 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.

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

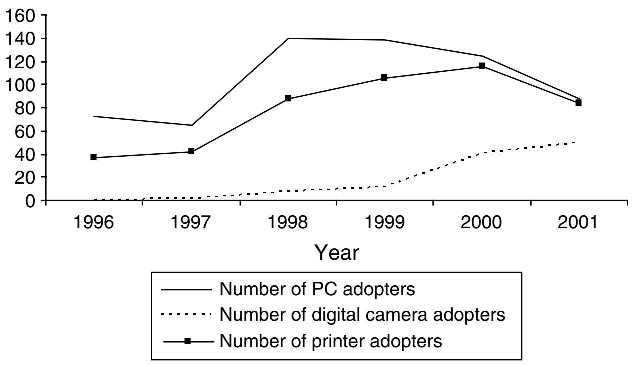
[17] Alternatively, if one were to use data prior to the period when digital cameras were available, we need to have different models for the period prior to and after digital camera availability (assuming that the other two technologies were available from the same year). For the period prior to the 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.

[18] 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. Although this is a strong assumption, it is necessitated by the lack of availability of data prior to 1996. However, we would like to note that the magnitudes of some parameters as well as the characteristics of the segments discussed in the results section are likely to be different if we were to explicitly consider nonpurchase prior to 1996.

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

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

Figure 1 Number of Adopters Over Time



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. Whereas 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 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. 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 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). However, a large 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.

Table 3 Sources of Adoption for the Three Categories

	Personal computer	Digital camera	Printer
Total no. of 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%	

As discussed in §2.2.3, we use quality-adjusted prices to capture the temporal variation in the attractiveness of the three categories. Furthermore, we assume that consumers have rational expectations about these quality-adjusted price processes. This implies that their belief about the price processes coincides with the actual process. As discussed in §3.3.1, we assume that the difference in the logarithm of the quality-adjusted price of each category ($\ln(p_{c,\,t+1}) - \ln(p_{ct})$) follows a normal distribution. In Table 4, we report the means and the standard deviations of these processes for the three categories. The mean values of the price processes imply that, on the average, the quality-adjusted prices decline annually by 44.5%, 35.1%, and 25.4% for the personal computer, digital camera, and printer categories, respectively.

Table 4 Parameters of the Price Process

Category	Mean	Std. dev.
PC	−0.588	0.117
Digital camera	−0.432	0.326
Printer	−0.293	0.250

Note that the quality-adjusted prices exhibit steeper declines than the corresponding raw prices because of increases in quality levels over time. The nonzero standard deviations in Table 4 imply that consumers are likely to perceive some uncertainty about future prices. A potential concern in obtaining the parameters of the price process is that we only have six observations to compute its mean and standard deviation. We note that this is a reflection on our data rather than on our modeling approach per se.

4.1. Identification

While addressing the data requirements for estimating the general model in §2, we provided some insights into the identification of the various components of the general model. In this subsection, we discuss the intuition behind the identification of model parameters for the model that we take to the data. Recall that our model requires estimation of three sets of parameters: (1) category-specific intercepts and complementarity effects, (2) price sensitivity, and (3) 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 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 complementarity. Moreover, because consumers may adopt multiple categories because of their intrinsic preferences rather than because of complementarity, the second issue is identifying consumer heterogeneity separately from complementarity.

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 (1) the intrinsic value of category 2 (category 1) and (2) 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.[21] Because printer adoption is contingent upon the adoption of personal computers, we do not observe consumers owning just a printer. Rather, we always observe them owning printers along with a personal computer. Thus, we cannot identify the PC/printer complementarity separately from the intrinsic preference for printers.

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, as stated earlier, our data set contains information of consumers' 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 the 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 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.[22] Furthermore, if there is no complementary relationship among the categories, the adoption behavior of the other category should remain unaffected. Hence,

[21] 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.

[22] 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.

the extent to which one observes higher adoption behavior for the second (first) category because of 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. In the absence of price variation, we may not be able to identify complementarity separately from heterogeneity. In such a situation, one may have to look for alternative variables that can provide the exclusion restriction.

To check if we can estimate complementarity with the price variation in our data, we performed a simulation exercise in the context of two categories. Specifically, we simulated the adoption decisions over 20 periods for 500 individuals belonging to one of the two segments that differed in their intrinsic preferences for these categories. In these simulations, we used the parameters of the price processes for the digital camera and printer categories as reported in Table 4 to simulate prices. We then estimated the model parameters using these data. Although not reported here, the results from the simulation revealed that all parameters could be recovered within two standard deviations of their true values. Hence, these results from the simulation exercise provide some confidence in the identification of complementarity in the context of our application.[23]

Our identification strategy for complementarity is, however, subject to the following caveat. In the categories that we study, it is common institutional practice to sell products in bundles, especially for personal computers and printers. Typically, the price of such a bundle would be lower than the sum of the prices of the individual components comprising the bundle. An extreme example of this bundling strategy is the practice of some manufacturers such as Dell to offer a free printer when a customer purchases a personal computer. Clearly, such bundled product offerings are likely to act as an incentive for customers to purchase these categories simultaneously even if they do not perceive any complementarity between them. Hence, if the data contain several simultaneous purchases for, say, two categories, and if some of those purchases were driven by the incentive of a bundled offering rather than complementarity (or substantially lower aggregate prices for both categories), our model is likely to overestimate the magnitude of complementarity.

[23] We would like to highlight the need to be careful about the identification of complementarity from heterogeneity in other contexts. If the underlying heterogeneity structure has a large number of consumer types, identification of complementarity from heterogeneity can become tenuous. We would like to thank an anonymous reviewer for pointing this out.

5. Results

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 Bayesian information criterion (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.

Before discussing the results from the proposed model, we show how the proposed model compares with some alternative models in terms of both in-sample and out-of-sample fit. Specifically, the two alternative models that we consider are (1) a myopic model where the discount factor δ is set to zero,[24] and (2) a model where there is no complementarity between categories ($\Gamma = 0$). To compare the fit of these alternative model specifications as well as the proposed model, we divide the sample of respondents into two groups. We calibrated the three models on the first group ($N = 632$) and used the second group ($N = 607$) to compute out of sample fit. To compute the fit statistics, we used the model estimates to predict the number of adopters for each category for each period. We then computed the sum of squared difference (across time periods and categories) between these predicted and actual number of adopters. We present the sum of squared errors in the number of adopters for the three models in Table 5. These results indicate that the proposed model performs better than the other two restricted models in predicting adoption behavior. In particular, models that account for complementarities between categories perform significantly better than the model that does not.

[24] Note that the myopic model differs from the models used to capture multicategory purchases in nondurable categories (see, for example, Gentzkow 2007). In the models of nondurable goods purchases, the purchase decision does not depend on what other categories the consumer has already adopted. However, the adoption decision of a category in our myopic model depends on what other categories the consumer has adopted (the current adoption level).

Table 5 **Sum of Squared Errors for Alternative Models**

Model	In sample	Out of sample
Myopic model	863.50	1,181.68
Forward-looking model without complementarity	925.38	1,272.37
Forward-looking model with complementarity (proposed model)	861.98	1,179.29

We present the results from the proposed model calibrated on the entire sample ($N = 1,239$) in Table 6. We present these results for two variants of the proposed model: with and without consumers' stated technology preference. Recall that we use the stated technology preference in the model to aid in the identification of the heterogeneity in preferences separately from complementarity. The results in Table 6 reveal that the log likelihood of the model that does not use the information on stated technology preference is lower than that of the full model. However, the estimates from the two models are comparable both in magnitude and direction, especially the complementarity effects that have approximately the same magnitude. These results demonstrate the robustness of the results to the model specification. Nevertheless, based on the stronger theoretical arguments for identification, we use the results from the full model with technology preference for the subsequent discussion.

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 categories 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 because of the contingent nature of printer adoption.

The intrinsic preferences for the categories exhibit significant variation across the three segments. 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

Table 6 **Estimates From the Model with Three Segments (Discount Factor = 0.9)**

		Model without technology preference		Model with technology preference	
	Parameter	Estimate	Std. error	Estimate	Std. error
PC	Price	−2.602	0.120	−2.350	0.849
	Segment 1 intercept	−0.602	0.085	−0.785	0.327
	Segment 2 intercept	1.369	0.063	1.210	0.574
	Segment 3 intercept	−2.059	0.082	−2.286	0.733
	Technology preference			−0.063	0.289
Digital camera	Price	−1.789	0.121	−1.793	0.618
	Segment 1 intercept	−1.300	0.059	−1.154	0.528
	Segment 2 intercept	−0.742	0.110	−0.794	0.390
	Segment 3 intercept	−1.060	0.005	−1.146	0.475
	Technology preference			0.069	0.042
Printer	Price	−0.043	0.105	−0.111	0.440
	Segment 1 intercept	−0.608	0.030	−0.613	3.497
	Segment 2 intercept	−0.208	0.036	−0.282	0.113
	Segment 3 intercept	3.697	0.417	3.582	1.861
	Technology preference			0.167	0.101
Complementarity effect	PC/digital camera	0.323	0.143	0.355	0.123
	Digital camera/printer	0.487	0.096	0.548	0.314
Segment 1 membership	Intercept	0.458	0.095	0.443	0.319
	Male HH	−0.249	0.142	−0.248	0.149
	Magazine	−0.265	0.146	−0.305	0.166
	Consumer Reports	−0.746	0.451	−0.746	0.368
Segment 2 membership	Intercept	−0.692	0.236	−0.690	0.348
	Male HH	0.081	0.104	0.081	0.237
	Magazine	0.220	0.341	0.238	0.294
	Consumer Reports	−0.117	0.969	−0.092	0.700
Log likelihood		−3,028.935		−3,012.490	

Table 7 Adoption Behavior Across the Three Segments

	Segment 1	Segment 2	Segment 3
No. of respondents	608	237	394
Percent of the sample	49.07	19.13	31.80
No. owning personal computer	0	235	394
No. owning digital camera	6	51	59
No. owning printer	0	78	394

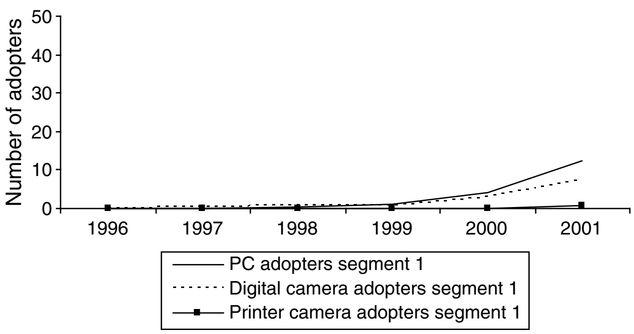
posterior segment membership probabilities. Specifically, we assign each respondent to the segment that has the highest posterior membership probability. We summarize the observed adoption behavior across these segments in Table 7. Segment 1 comprises about half the sample and is the single largest segment. From Table 6, 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 7 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. The observed adoption data suggest that 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. Because 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. Note that because we cannot separate out PC/printer complementarity from intrinsic preference for printers, an alternative interpretation is that consumers in segment 3 have a low preference for both PC and printer but perceive a high complementarity between these categories. In addition to 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 ($|T\text{-value}| = 0.216$).

The effect of the demographic variables on the segment membership probabilities in Table 6 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 implies that male households and households that subscribe to magazines or *Consumer 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. Because 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.

Whereas 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. To generate this temporal pattern, we use the model estimates in Table 6 to compute the probability of adopting each category at any given time conditional on not having adopted the category until 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.[25] In contrast to the adoption pattern for segment 1, the pattern for segment 2 reveals that personal 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

[25] Note that Figure 2 implies that there is 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 because the adoption behavior in Figure 2 is based on the conditional probability of adoption. As conditional probabilities implied by the model are strictly positive, the model predicts a nonzero 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 adoption behavior of the consumers belonging to each segment to trace the temporal pattern of adoption for each segment. However, because each consumer has a nonzero probability of belonging to each of the three segments, such a temporal pattern may not be very accurate.

Figure 2 Adoption Behavior in Segment 1



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. Because 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. An alternative explanation for the insignificant price coefficient for the printer category is that these two products are typically bundled together. Hence, a significant fraction of printer adopters could have purchased them as a part of a bundle. We would like to thank an anonymous reviewer for pointing this out.

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.

Figure 3 Adoption Behavior in Segment 2

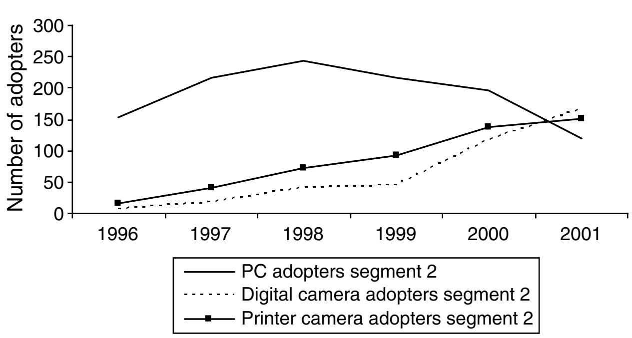
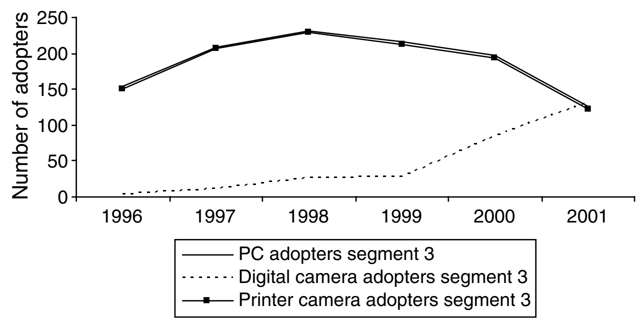


Figure 4 Adoption Behavior in Segment 3



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: (1) from level 0 when she has adopted none of the three categories, and (2) 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 (levels 0, 1, and 5) and the printer category from four different adoption levels (levels 0, 1, 2, and 4). 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 8, 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 6 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 in adoption level 0 has a 0.02 probability of adopting a digital camera. If she has already adopted the PC, this probability increases to 0.035 (75% higher), and if she has adopted both PC and printer the adoption probability increases to 0.069 (245% higher). Thus, although the percentage increases appear to be large, the actual probabilities are still small in magnitude.

5.1.1. Effect of Complementarity on Adoption Probabilities. To understand the extent to which the different complementarity effects contribute to this increase in the probability of adoption, we carried

Table 8 Change in Conditional Adoption Probabilities Because of 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 and digital camera	Avg. adoption probability after adopting PC and printer
PC	0.179		0.334		
Digital camera	0.020	0.035			0.069
Printer	0.115	0.367	0.244	0.457	

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: (1) complementarity between the personal computer and digital camera categories, and (2) 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. We present these results for the personal computer, digital camera, and printer categories in Tables 9, 10, and 11, respectively. Based on these results, we can draw three broad inferences. First, dropping the complementarity effect between any two categories (for example, complementarity between PC and digital camera) has a sizeable adverse effect on all three categories (including printers). For example, suppressing the complementarity between PC and digital camera not only has an adverse effect on the adoption probabilities of these two categories but also on that of the printer category. Second, a comparison of the effect of dropping complementarity on the purchase probabilities across the three categories (in percentage terms) reveals that the digital camera category is likely to be more adversely affected when the complementarity effects were shut off (effects vary between 67% and 87%). The effect on personal computer and printer categories is roughly of the same magnitude (effects vary between 3% and 41% depending on the adoption level and the complementarity being considered). The higher responsiveness of the digital camera adoption probabilities may be attributable to consumers having 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. Third, a comparison of these effects across the two complementarity effects suggests that dropping the complementarity between digital cameras and printers has a marginally greater effect compared to dropping the PC/digital camera complementarity. The only exception is the adoption probability for digital cameras among consumers who have already adopted the personal computer, where the magnitude of the effect is reversed. Note that the above discussion is based on the conditional probabilities of adoption, given that the consumer has not adopted the category yet and exists in a given adoption level. Because the absence of complementarity is also likely to affect the probability that a consumer would exist in each adoption level, the corresponding decrease in unconditional probabilities (and, hence, the number of purchases) is likely to be different.

5.2. Effect of a Change in Price Trajectory on Adoption Behavior

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 pertains 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 to begin

Table 9 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	Percent change due to dropping the complementarity	Avg. adoption probability after dropping the complementarity	Percent 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 10 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	Percent change due to dropping the complementarity	Avg. adoption probability after dropping the complementarity	Percent 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 and printer	0.069	0.021	69.31	0.009	87.17

with. 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. The second caveat is that the conditional probability analyses do not account for segment depletion. For example, our analysis of segment-level adoption behavior in Table 7 revealed that all consumers in segments 2 and 3 have adopted the personal computer. As a result, the unconditional probability of adoption for consumers belonging to these segments would decline as the number of remaining consumers in these segments decreases. However, the corresponding conditional probabilities discussed in the previous section are expected to increase as prices continue to decline.

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 policy change when the quality adjusted price trajectory of the personal computer category is flatter than the observed trajectory. Henceforth, we refer to the original price trajectory as scenario 1 and the modified price trajectory as scenario 2. The modification of the price trajectory is likely to have two effects on the adoption behavior of personal computers as well as the other two related categories. First, because we set the initial price level (i.e., period 1) for both price trajectories to be the same, the price levels for personal computers for the flatter price trajectory will be greater than the actual levels for all periods except the first. This is likely to deter adoption of personal computers and, consequently, the related categories. However, if consumers revise their expectation of the price process to match the flatter trajectory, they would have lesser incentive to postpone adoption. This would encourage earlier adoption. The total effect of the policy change is the net of these two opposing factors. Thus, it would be interesting to isolate the role played by these two factors in influencing adoption behavior. Accordingly, we performed an additional simulation wherein the price trajectory was less steep as above but consumers' expectation of the price process was at the original level. This implies that the only factor in play is the incentive to postpone purchases because of higher prices. Clearly, without the benefit of a flatter price expectation, this scenario is likely to yield the fewest number of adopters. We refer to this as scenario 3.

To understand the adoption behavior under these alternative scenarios beyond the period of our data, we perform these policy simulations for a total of 16 periods. Because we do not have the quality-adjusted prices for the three categories for the 16 years, we simulated these prices for all three scenarios based on the parameters of the price process reported in Table 4. We present the total number of adopters for the three categories at the end of 16 years under the three pricing scenarios in Table 12. As expected, the third scenario with flatter personal computer prices but the

Table 11 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	Percent change due to dropping the complementarity	Avg. adoption probability after dropping the complementarity	Percent 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 and digital camera	0.457	0.457	0.00	0.337	26.31

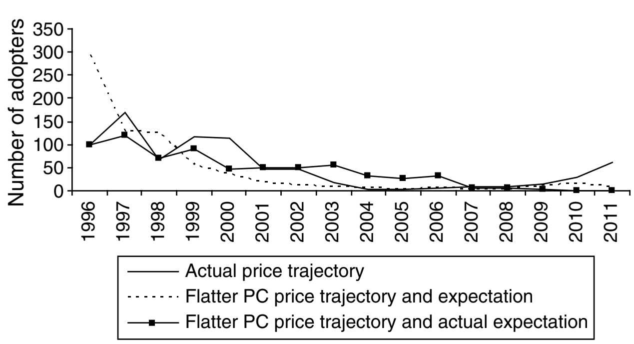
Table 12 Simulated Adoption Behavior Up to 2011 Under Alternative Scenarios

	No. of PC adopters	No. of digital camera adopters	No. of printer adopters
Forward-looking consumers			
Actual price trajectory	818	669	704
Flatter PC price trajectory and expectation	734	647	690
Flatter PC price trajectory and actual expectation	686	599	672
Actual PC price trajectory and flatter expectation	1,194	822	852
Myopic consumers			
Actual price trajectory	1,227	1,228	1,225
Flatter price trajectory	992	1,099	987

original price expectation yields the fewest number of adopters. Interestingly, across all three categories, the number of adopters is highest under the current price trajectory. Thus, when both factors, (1) higher prices because of flatter trajectory and (2) expectation of flatter prices, are in play, the negative effect of the former exceeds the positive effect of the latter. Note that if one were to extend the simulation well beyond the 16 years, all consumers would eventually have adopted the three categories under all three scenarios. Hence, these results only provide a snapshot of the number of adopters under alternative scenarios at the end of 16 years of simulation.

To understand the differences in the number of adopters across these alternative scenarios over time, we plot the adoption behavior for the personal computer category over the 16-year period in Figure 5. Note that because of complementarity, the differences in adoption behavior across the three scenarios for the other two categories are likely to be similar to that of the personal computer category. To understand the adoption behavior in Figure 5, it might be useful to consider the following. First, based on the characteristics of the three segments discussed earlier, we can

Figure 5 PC Adoption Under Alternative PC Price Trajectories



divide the market into two groups: (1) segments 2 and 3, in which consumers are likely to adopt the category early on; and (2) consumers in segment 1, who are likely to be late adopters. Hence, it would be useful to discuss the adoption pattern for these two groups separately. Second, because we begin at the same price levels in all three scenarios, the first and third scenarios where expectations of the price process are the same would yield the same number of adopters in the first period. However, under the second scenario in which consumers experience a flatter price trajectory for personal computers, consumers have less incentive to postpone their purchase of personal computers in the category. Consequently, we would expect a greater number of adopters for this category in the first period. Because the initial market comprises only of consumers in segments 2 and 3, this would leave fewer consumers for adoption in later periods under this scenario. This implies that we would observe a higher number of adopters under scenario 2 (compared to scenario 1) in the first period followed by a few number of adopters. On the other hand, consumers who face scenario 3 are likely to postpone adoption because of higher prices. This is the pattern we observe in the first half of Figure 5.

Towards the end of the simulation period, consumers in segment 1 begin to adopt personal computers. However, at this point, the price differential between the flatter and actual price processes would be greater than in the initial periods. Thus, the negative effect of higher prices overwhelms the incentive to purchase earlier because of flatter prices. This is likely to yield fewer adopters under scenario 2 than in scenario 1. However, consumers who face scenario 3 are likely to be the most reluctant to adopt this category. Clearly, this is the pattern we observe in the second half of Figure 5.

How do we explain the total number of adopters at the end of 16 years of simulation reported in Table 12? Note that consumers who adopt personal computers in the first half of simulation period are those in segments 2 and 3. However, all consumers in segments 2 and 3 would have adopted personal computers by the end of the simulation period. Hence, the difference in the total number of adopters at the end of 16 years of simulation reported in Table 12 should be attributable to consumers in segment 1. Hence, it is not surprising that the results in Table 12 mirror the pattern in the second half of Figure 5.

The above policy simulations illustrate the role of price trajectory and consumer expectation of this price trajectory in influencing adoption behavior. In technology product markets, where future price expectations are likely to play an important role in influencing purchase behavior, understanding the role of price levels as well as expectations in influencing purchases should be of interest to managers. However, in a myopic model, the adoption behavior would be driven solely by the price levels.

6. Conclusions

In this paper, we present a general framework for studying the purchase behavior of households across related categories of technology products. Households in the model are forward-looking in the sense that they trade off purchase today and the associated utility from the product with waiting until tomorrow with the current product(s) when the price of the product could be lower. Furthermore, these forward-looking consumers also base their purchase decision of the focal category on the anticipated time of purchase of other related categories. Although our empirical analysis is confined to a restricted version of the model that focuses on category-level adoption behavior, the empirical findings from this paper regarding the relationship in adoption across categories, as well as the implications of a price change in one category on the adoption behavior in related categories, could help managers in technology product firms such as HP, Dell, and IBM who manage such broad product lines.

We note that although our focus has been to understand the demand side and to characterize consumer purchase behavior, it will be interesting to investigate the optimal price trajectory or interrelease time (see, for example, Luan and Sudhir 2007) for related categories. In studying adoption and replacement behavior, we have assumed that the purchase decisions by a consumer are independent of purchase decisions by other consumers. In reality, it can be argued that expectations regarding when other consumers may adopt the product can influence a consumer's adoption decision. Incorporating such social interactions would thus be an interesting and useful extension. A key computational challenge in estimating adoption models across multiple categories is related to the number of value functions that need to be computed. More specifically, with C categories the estimation would require computation of $2^C - 1$ value functions. Coming up with a computational approach that can alleviate this problem would represent a methodological advance.

In sum, the paper seeks to make both methodological and substantive contributions to the extant literature on multicategory purchase behavior. We anticipate that future research will benefit and hopefully build on the approach presented in this paper.

7. Electronic Companion

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

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