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Abstract

New product introduction strategies are based primarily on analysis of potential market segments and the dynamics of these segments over the growth phase of the product. In aggregate, segment dynamics determine the market evolution of a new product. Adoption rate and overall market size are determined by growth of individual segments and changes to customers' perceptions of the new product's attributes. Despite the fundamental importance of these segment dynamics, the literature provides relatively little formalized knowledge about the market evolution for new products. Moreover, the two aspects of this evolution, changes in customer perceptions and changes in segment sizes, are not independent. For example, segmentation based on price elasticity may indicate a small size for the price sensitive segment early on but this becomes the major segment at a later point in the product life cycle. The objective of this paper is to propose a model that simultaneously captures: (1) within-segment perception dynamics and (2) segment size dynamics. To illustrate the benefits of the proposed model, we estimate the dynamics of internet shopping as an innovation over a nine-year period. This example illustrates the importance of distinguishing between growth due to changes in perceived attributes and those due to changes in the segment sizes.

Keywords: Segmentation, Innovation, Diffusion, Latent Class Models, Mixture Models

New product launch strategy is a critical set of marketing decisions, yet empirical evidence provides pessimistic views of marketers' ability to make these decisions optimally, as many if not most product launches fail (Schneider and Hall 2010). Strategy for introducing new products to markets is based in large part on two fundamental concepts: (1) market structure and (2) its evolution within the competitive context. The heterogeneity of consumers' response to innovations has been recognized in the literature as a primary determinant of the characteristic S-shaped adoption curve. Successful launch strategies should be based on a segmentation of potential adopters (Feder and O'Mara 1982, Jensen 1982, Chatterjee and Eliashberg 1990). Indeed, it is these various segments of customers with their different underlying preferences and behaviors that form the basis of the market structure. However, market segments evolve over time. Such evolution is especially the result of changes in consumer perceptions due to knowledge acquired about the product over time. The two concepts of market structure and market evolution are in fact intrinsically linked in a complex way (Soberman and Gatignon 2005). Hence, it is our ability to understand and to assess the evolution of the structure of new markets that will allow better launch decisions.

The evolution of a market is assessed in terms of two broad properties: market size growth and changes in customer perceptions of innovation attributes. While careful analysis of segments is typically made before launching a new product, this will have limited value after launch, as segments evolve throughout the growth phase, in terms of both size and characteristics. Currently, little is known about how perceptions of the innovation change within a segment over time and how those perception changes affect adoption behavior. Moreover, the evolution of perceptions and changes in segment size are not independent. For example, early adopters who tend to have higher incomes (Gatignon and Robertson 1985) may be price insensitive. Consequently, segmentation based on price elasticity that is performed early in a product's growth phase may indicate a small size for the price sensitive segment. However, this segment can become the major one as the product advances toward maturity. As a result, the mass market potential may be poorly estimated in the early stages of a product launch.

The objective of this paper is to propose a model to simultaneously capture market segment structure and the relevant aspects of segment dynamics. Specifically, we are able to capture (1) segment size dynamics and (2) within-segment perception dynamics. This model builds on the work of Brangule-Vlagsma, Pieters and Wedel (2002) and Paas, Vermunt and Bijmolt (2007). Brangule-Vlagsma, Pieters, and Wedel (2002) examine consumer values over a three-year period, and Paas, Vermunt and Bijmolt (2007) model household acquisitions of financial products. While we likewise fit a series of mixture models to investigate changes to segments over the period of study, our model differs from these previous models in two important respects. First, the previous models are fitted to repeated measurements from a panel, rather than to independent samples of a market. By analyzing market evolution from independent market samples, our model enables application to data that are more commonly available in practice. Second, they focus on changes to the latent Markov switching pattern. Instead, we focus on changes in perceptions as the main drivers of the changes to the segments. Other models using Markov switching between states or segments (Moon, Kamakura, and Ledolter 2007; Allenby, Leone, and Jen 1999; Netzer, Lattin, and Srinivasan 2008; Montgomery, Li, Srinivasan, and Liechty 2004) have been proposed, but in these models, the segments (or states) are assumed to remain constant over time. Even if Poulsen (1990) does account for changes to particular segments, he assumes static segment membership. Therefore, we start with data that are commonly collected by firms, i.e., that consist of a survey of consumers on their perceptions of an innovation's characteristics, repeated at different periods on a new sample of consumers. The model we propose provides information about the latent segmentation structure and the evolution of the perceptions by latent segment. To our knowledge, our model is the first to reflect our knowledge of new product introduction dynamics that simultaneously models changes to both segment membership and the segments themselves.

In the first section of this paper, we review the literature and provide a framework for analyzing segment dynamics over the growth of innovations. We then describe the data and present our model where both segment sizes and perceptions simultaneously evolve. We then present the results of our particular investigation of internet shopping and discuss the model benefits and implications. Besides serving as a guide that management can use to get better information about their specific innovation, the results of our specific investigation of internet shopping as an innovation provide new insights that can serve as a basis for further theorizing about new product adoption dynamics. In particular, these include propositions that (1) new product growth may depend on the evolution of a "middle" segment, that may never strongly favor nor strongly disfavor the innovation; (2) the segment of consumers “fearful” of an innovation may never go away although customers in that segment may still adopt the innovation in spite of significant reservations; (3) adoptions during early growth stages may be driven by changes in the sizes of the segments, but adoption later on is driven by more subtle, within-segment perception changes.

INNOVATION SEGMENTATION AND PERCEPTION DYNAMICS

Diffusion theory has long recognized the importance of market heterogeneity and has found key differences across innovators and late adopters, even if some of those differences are product category specific (Gatignon and Robertson 1985). Many recent models of diffusion formalize this heterogeneity with market segments and consider how this heterogeneity affects adoption dynamics. In the current article, we also examine heterogeneity through market segments, but instead of examining adoption dynamics, we focus on the dynamics of the evolution of the segments themselves. The framework shown in Figure 1 provides a guide to identify the factors involved in the evolution of market segments. The middle box of Figure 1 represents the two key dimensions of segment dynamics: the evolution of relative segment sizes and the evolution of perceptions. We discuss both segment dynamics and the evolution of consumers’ perceptions in the context of past literature.

[Insert Figure 1 about here]

Innovation Segmentation

Diffusion models have long been based on the idea of dual segments. The widely used Bass Model (1969) is based on the idea of two segments, innovators and imitators, which differ in the source of influence in adoption. Recent diffusion models have established the idea of more formally distinct segments, or dual markets, which appears to fit the observed diffusion curves better, as many such curves exhibit a saddle (Goldenberg, Libai, and Muller 2002). These dual-segment models focus on the social process of diffusion and the shape of the diffusion curve, rather than on the underlying rationale for the existence of these segments or their evolution. Segmentation in marketing research on innovations has not been limited to splitting the market in two groups of homogeneous consumers. Rogers’ (1962) innovation characteristics are often used to assess how consumers perceive an innovation and to distinguish among consumers according to their differences in perceptions of the innovation's benefits and risks. The technology acceptance model (Davis 1989) proposes another concept, perceived ease of use (Pavlou 2003, Davis, Bagozzi and Warshaw 1989), which is related to Rogers' factors and which can also serve to distinguish among groups of consumers. These characteristics are typically used to assess the market potential before the new product is launched or soon after its introduction, thus the dynamics of segments based on these characteristics has not received significant attention.

The relative size of the segments is often considered as a fixed market potential that does not evolve over time, in spite of a few exceptions that consider varying market potential (Mahajan, Muller, and Bass 1990). This is the case also in the dual-segment models. What varies is the rate of adoption within each of the two segments described earlier. However, a major practical issue is that the size of the segment may be difficult to predict at the introduction stage because we know little about how the size of the segments may evolve. For example, the conflict between Steve Jobs and John Sculley at Apple over the pricing strategy of the Macintosh illustrates their difference of opinions in the size of the expected mass market (Isaacson 2011). Even though the rate of adoption has been analyzed over time, this analysis is not performed at the segment level, as depicted on the right-hand side of Figure 1. One reason for the reliance on aggregate diffusion as opposed to segment dynamics is that the segmentation corresponds to an unobserved categorization of customers.

Perceptual Evolution of Innovations

The role of perceptions and perception dynamics in new product adoption has been treated quite differently across the literature. Research that focuses on adoption dynamics often ignores perceptions entirely, as their focus is on adoption, and not the underlying psychological drivers of that adoption (Mahajan, Muller, and Bass 1990). Other research has focused on consumer perceptions in an effort to identify the aspects of an innovation that lead to quick and successful diffusion (Rogers 1962). This research has typically assumed that the perceptions of each innovation were static. Still other research has examined the combined dynamics of perception change and adoption (Stoneman 1981, Jenssen 1982, Roberts and Urban 1988, Chatterjee and Eliashberg 1990), but this research treated perceptions as a uni-dimensional evaluation of the attractiveness of the new product. We take the view that perceptions are dynamic, are central to the adoption decision, and consist of multiple dimensions.

Customer exposure to information and learning are the key drivers of innovation diffusion (Gatignon and Robertson 1985). Because potential adopters do not learn everything about an innovation at once, every new piece of information obtained by a consumer has the potential to change his/her perceptions. Perceptions evolve as consumers learn more about the innovation, either through marketing materials from the company, through word-of-mouth, or through personal experience with the innovation. Most prior research assumes that perceptions of an innovation monotonically improve throughout the growth phase of a new product as information increases (Chatterjee and Eliashberg 1990). This is partially due to a selection bias. Diffusion studies typically focus on innovations that diffused successfully, thus perceptions improve as information increases, leading to increased adoption. However, perceptions need not improve monotonically during the growth stage of a new product. Perceptions of the iPhone 4 dipped when information about its antenna problems spread across the market (Apple, Inc. 2010).

Another source of perception change has been largely ignored in the literature—changes to the innovation itself. Most products change throughout their life cycle, and these changes can both improve and harm consumer perceptions of the innovation. While companies typically do not make changes that they expect will harm consumer perceptions, some changes often have this result, especially among select segments. For example, some of the changes in Final Cut that reflected the desire of Apple to serve the mass consumer market went against the professional market segment, many of whom moved from positive beliefs about Apple’s product to negative ones.

We focus in our study on the middle section of Figure 1 by developing a model that captures the two main characteristics of the evolving market discussed above: segment size evolution and perception evolution. We do not focus on the diffusion process per se (although it may be implicitly reflected by the parameter estimates of our model); instead, we focus on the dynamics of change in the perceptions that determine segments and on the changes in the relative size of these segments. The segments we examine are based on consumers’ perception of the innovation, which means segment membership is not fixed in time, as is assumed in the aforementioned diffusion models. Relaxing this assumption allows us to generate new insights regarding the evolution of market segments and consequently on the adoption of innovations by these segments. We now describe a model that analyzes these aspects of segment dynamics using data readily available to management.

DATA AND MODEL SPECIFICATION

In our study, we focus on consumer use of the internet for making purchases. We consider data that are typically collected over a period of time by manufacturing companies and market research organizations. Specifically, we analyze data from a decade-long study employing random samples of internet users in January of 2001, 2004, 2007, and 2010. Each sample was representative of the population of internet users at the time of each survey.[1] The survey asked participants to respond to a battery of 38 statements about their perceptions of internet shopping (these items are listed in Table 1), as well as several questions about their internet usage behavior. The perception statements provided a five-point Likert response scale with endpoints "Just like me" and "Not at all like me" (Swinyard and Smith 2003). Our interest is focused on the analysis of the behavioral consequences of changes in market structure and perceptions: whether the participants made purchases online during the previous holiday season. This binary response is an indicator of internet shopping adoption. Data were collected from 4501 respondents—1,942 from the 2001 sample, 1,385 from the 2004 sample, 500 from the 2007 sample, and 674 from the 2010 sample.

Because our four samples represent random samples of the market, and not repeated measures from a panel, we denote a given respondent's data as $X_{i(t)}$. The subscript t resides in parentheses to indicate that a given respondent is not sampled repeatedly at different times, but that his response is still time-dependent, because his response is generated from a market whose perceptions change over time. The market's perceptions are characterized by a mixture of normal distributions. Both the size of the segments and the means of those segments vary over time. In addition, the 38 measurement items are merely indicators of a smaller number of underlying perceptions that form the mixture of normal distributions. Hence, we utilize the following model:

$$\underset{p\mathrm{x}1}{X_{i(t)}} = \sum_{k=1}^{G} \underset{1\mathrm{x}1}{t_{kt}} \left(\underset{p\mathrm{x}J}{\mathrm{L}} \underset{J\mathrm{x}1}{x_{ikt}} + \underset{p\mathrm{x}1}{d_{i(t)}} \right) \tag{1}$$

where

$$E\left[\xi_{k(t)}\xi'_{k(t)}\right] = \Sigma_k; \quad E\left[\delta_{(t)}\delta'_{(t)}\right] = \Psi$$

The subscript k indexes the segment; τ_{kt} is the proportion of the sample belonging to segment k at time t. Respondent i's perceptions are represented by ξ_{ikt}, with dimensionality J <<p. A respondent's perceptions depend on the segment and time period of measurement. Following Higdon et al (2008), we identify Λ through a principal components decomposition of the data. That is, the underlying perceptions come from a traditional factor analysis of the response data. The $\delta_{i(t)}$ are the uniquenesses, or measurement errors, which do not vary systematically over time or across segments, implying that Ψ is a diagonal matrix common to time period and segment. Σ_k, on the other hand, is a fully estimated covariance matrix. The identification of G, the number of segments, and J, the number of common factors, will occur through model selection.

Consequently, the distribution of the 38 measurement items is entirely reflected by the joint distribution of the two parts: a set of common factors, F, and a set of uniquenesses, U, which can be considered measurement error (Rubin and Thayer 1982). The joint distribution of these two parts is given by

$$[F_{i(t)} \quad U_i] \cong \sum_{k=1}^{G} \tau_{kt} N([\mu_{kt} \quad \bar{0}], [\begin{matrix} \Sigma_k & 0 \\ 0 & \Psi \end{matrix}]) \tag{2}$$

Modeling the joint distribution of factors and uniquenesses instead of the data as given has a number of advantages. First, it enables a more precise characterization of the nature of each segment's perceptions, as it enables full estimation of the underlying covariance matrix, Σ_k. This would not be possible with the original data, as the covariance matrix would have length 38, requiring 741 degrees of freedom for estimation. In addition to this dimensionality reduction, this division converts discrete scale (observed) data into near continuous (latent) data, allowing use of the multivariate normal distribution rather than a more complex discrete analog. Note that identification of the model requires that the principal components decomposition remain constant over time. We later provide justification for this assumption, but we encourage future research to explore avenues to overcome this restriction.

As we mentioned above, we identify J, the number of common factors, through model selection. However, we now proceed out of order to provide insights into the factors extracted from the data. Table 1 presents the varimax-rotated factor loadings for the 38 measurement items. The 38 items that measure innovation perceptions are reflective of latent factors that fit the innovation adoption literature (Holak and Lehmann 1990): Relative advantage, perceived risk (which has been shown as particularly relevant for internet shopping by Kiely 1997 and Han and Noh 1999), a dimension that expresses the enjoyment in the sociality and atmosphere of brick and mortar shopping (a notion of compatibility with existing shopping habits), a dimension that reflects the difficulty to make online purchases (related to Rogers's complexity dimension and Davis's (1989) concept of ease of use), and a fifth dimension that is the antithesis of the first one in that it reflects the relative disadvantages of internet shopping. The segmentation is independent of the rotation performed on these latent factors. In fact, the rotation can be performed at any point before or after segmentation without affecting the segmentation results.

<Insert Table 1 about here>

The estimation of the model parameters requires that the researcher make several fundamental determinations. These concern the number of segments and the number of latent factors. The number of segments is typically defined using a metric on the amount of error contained in any given cluster solution. We tested mixtures of 6 and fewer distributions. To determine the superior model, we used BIC (rather than AIC), as it balances model fit with the degrees of freedom. Indeed, when the models vary widely in the number of parameters, and when the sample size is large, the two measures of model fit (BIC and AIC scores) diverge. BIC emphasizes identifying the correct underlying model, while AIC emphasizes prediction accuracy (Schwarz 1978). Given our goal to identify trend patterns, BIC is then the more suitable fit metric for model comparison purposes.

Regarding the determination of the number of factors or perceptions (J), a large number of methods exist for determining the number of underlying factors to extract from a factor analysis (Linn 1968; Montanelli and Montanelli 1975). Our methods allow us to determine the optimal number of factors by testing for differences in model fit with multiple levels of J.

Modeling Market Structure Dynamics

Beyond determining the number of segments and the number of factors, our model requires specification of market structure dynamics—namely, (1) how the mean of each segment will be allowed to change over time, and (2), how the changes in segment sizes will be specified. We discuss each in turn.

Modeling perception dynamics of means η_{kt}**.** Several hypotheses can be compared regarding the evolution of perceptions as reflected by the evolution of the means of the latent factors within each segment. At one extreme, no evolution means that the structure is constant in terms of means of the distributions. At the other extreme, each period can have a conditional, unconstrained mean. In between these two options, we can specify a basic linear drift or a curvilinear one.

Stable means. We start with the most basic assumption—that segment means do not change over time. This model specification does not imply that perceptions do not change at all, but merely that the average perception of a given segment does not change. Because segment sizes can change (which is considered in the next section), individual perceptions can indeed change, but the net effect of these changes is the growth or shrinkage of a segment rather than a change to the mean segment perceptions.

Linear drift. The average perception of a given segment can exhibit constant drift over time. This would reflect a process of perception change that is constant over time. For example, taking one of the fundamental characteristic of innovations, "Relative Advantage," a linear drift would indicate that a segment improves its perception of the relative advantage of internet shopping at a constant rate as time advances. Each perceptual dimension is modeled independently, thus the dimensions can move in different directions.

Curvilinear drift. Perceptions change over time, but not necessarily at a constant rate. For example, in a segment of late adopters, the perceived relative advantage may not change at all during the early stages of the internet's existence, as most members of the segment would not have adopted internet purchasing, and thus would continue to perceive it to have a low relative advantage. This perception might improve drastically in later stages of the measurement period, as late adopters experience internet shopping first-hand and improve their perception of its advantages. As with linear drift, we allow each perception to vary independently. We allow for curvilinear drift by adding a quadratic term to estimate mean shifts over time.

Unique means by time. In this specification, each segment's mean is unique to the time period—no restriction is made on the pattern of change. A segment's perception of relative advantage can increase, then decrease, and increase again over time. While it is difficult to venture an explanation for such irregular pattern of perception change, this corresponds to an unconstrained model specification against which we can compare the fit of the specific trends presented above.

Modeling variations on segment proportions t_{kt}**.** The parameter t_{kt} governs the relative size of each segment at each time period. When a constant panel provides repeated measures by the same panel members, a transition matrix typically governs probabilistic transitions between the segments. However, this is not the case in many instances where surveys are performed at different points in time on random samples of a marketplace. In such a case, no structural constraint can be imposed on the proportion changes. Consequently, we allow τ_{kt} to vary freely across the time periods and estimate these parameters for each time period.

Model Estimation

The research design required the fitting of 72 different mixture models, varying on (1) *G*, the number of segments (1 through 6), (2) J, the number of factors (4 through 6—isolated factor analyses indicated the need for five factors, so we fit one fewer and one greater to ensure that five factors did indeed yield superior models), and (3) the various dynamic segment mean changes (four variations).

The model specification presented above leads to the likelihood function expressed in Equation (3):

$$L = \prod_{i=1}^{n} \sum_{k=1}^{G} \tau_{kt} \frac{\exp(-\frac{1}{2}(x_{i(t)} - \mu_{k(t)})^{T} \Sigma_k^{-1} (x_{i(t)} - \mu_{k(t)}))}{(2\pi)^{p/2} |\Sigma_k|^{1/2}} \quad (3)$$

where each $x_{i(t)}$ is the extended vector of length 43. Each extended $\mu_{k(t)}$ is all 0 for the last 38 entries. Following Equation (2), the extended Σ_k are 0s everywhere except along the diagonal and the non-diagonal elements in the first five rows and columns.

To optimize the likelihood of each model, we utilized the expectation-maximization (EM) algorithm as given by Fraley and Raftery (2004). Consistent with the recommended method for fitting mixture distributions, we started the EM algorithm at the traditional k-means solution. To ensure that cluster identification would correspond across the four time periods, the k-means analysis was run on the pooled data. We ran the k-means analysis 50 times from random starting points and used the solution with the smallest error as the starting point for the EM algorithm.

In summary, the model presented in this section combines features of the Gaussian mixture models where each latent class corresponds to a cluster or segment (Fraley and Raftery 2004) and features of latent growth models where the latent variable parameters vary over time and panels of observations (MacCallum et al. 1997; Mehta and Neale 2005).

RESULTS

The models utilizing five factors consistently displayed significantly better fit than the models using four or six factors, so we display the BIC scores only from these 24 models in Table 2. We now present the results of the superior model.

<Insert Table 2 about here>

Shopper Segments

The model that best characterizes the data is one that includes three segments whose average perceptions move linearly over time. The BIC criterion is the smallest for that combination (BIC=468,587 in Table 2). Figure 2 depicts the snake plot of the three segment means at each time period. The first segment, which we call "Enthusiasts," expresses universal enthusiasm for internet shopping. They perceive its relative advantages to be high and its incompatibility, complexity, and relative disadvantages to be low. The second segment, the "Mainstream," does not have extreme views on any aspect of internet shopping. They view the risks as being relatively low, but do not perceive any of the other dimensions of internet shopping to be especially high or low. Finally, the "Fearful" segment perceives large risks with internet shopping and views it to be complex and incompatible with their regular shopping schema. They also do not perceive internet shopping to offer strong relative advantages.

<Insert Figure 2 about here>

Segmentation Dynamics

The best model specification indicates that the means of each segment are not constant but that they change over time. Over the nine-year period, each segment's perceptions changed gradually at a constant, linear rate. This should not be interpreted to mean that each individual's perceptions moved at a constant rate. Instead, it is the expected value of the latent factors that evolves linearly over time. Furthermore, on top of the linear movement in segment means, segment sizes also change over time. We begin by examining trends in the evolution of the segments' mean perceptions. Then, we present the results concerning the changes in segment sizes.

Evolution of segment perceptions. Regular learning about the innovation is reflected in the changes of segment perceptual means. The evolution in these segment means over time is highlighted in Figure 3. Interestingly, despite movement in all three segments, the relative character of the segments is maintained, as it does not change the nature of their interpretation. That is, the "Fearful" segment does not transform itself into the "Fearless" segment in 2010—it still has the highest perceived risk of the three segments in 2010 despite a significant drop in this perception. This provides evidence for the face validity of the results. Across the nine-year period of these four samples, the model is properly extracting the same underlying segments.

<Insert Figure 3 about here>

At the same time this gradual but constant change process occurs in perceptions, other changes occur within part of the population that explain changes in the size of each of these segments.

Evolution of segment sizes. Because our data are a series of market snapshots, and not repeated surveys from a panel, we cannot examine individual segment switching behavior. However, the overall growth and shrinkage of the segments that this switching produces is illuminating. Table 3 shows the percentage membership of each segment at each time period. We consider each segment in turn.

<Insert Table 3 about here>

The size of the "Fearful" segment decreases over time, from 55% of the sample in 2001 to only 26% of the sample in 2010. The "Fearful" segment's perceptions are defined by their low relative advantage and their high risk, incompatibility, complexity, and relative disadvantage, so this segment's decreasing size reflects a general shift of the market toward more positive perceptions of internet shopping over time. This is in line with the general pattern of perception change that would be expected from an innovation that offers benefits to the market. Consistent with the learning model of information exposure and integration, as information about the innovation spreads, the population increases their perceptions of relative advantage and compatibility while simultaneously decreasing their perceptions of risk and complexity. Note that the potential selection issues of our sampling method would only bias our results against this observed decrease. Because we sampled only internet users in 2001, the 55% Fearful membership is likely biased downward, if it is biased at all.

But the pattern of this decrease is different from what one might expect, and it leads to a novel insight into the pattern of innovation diffusion. The "Fearful" segment decreased from 55% to 29% between 2001 and 2004, but then remained at roughly this same size over the next six years. The decrease that occurred between 2001 and 2004 is consistent with an adoption-driven change in perceptions. Many who adopted internet shopping likely updated their perceptions based on this experience and henceforth joined the "Mainstream" or "Enthusiasts" segment. But membership in the "Fearful" segment stabilized in 2004. From 2004 to 2010, internet shopping continued to grow (Grau 2007, 2010), so it is somewhat puzzling that the "Fearful" segment did not continue to decrease in size during this time period.

We propose that it is because later adopters differ fundamentally in consumer characteristics from earlier adopters. Innovation researchers have identified a number of dimensions on which earlier adopters differ from later adopters. Early adopters are more cosmopolitan (Coleman, Katz, and Menzel 1966), less fatalistic (Bandura 1997), more educated (Rogers 1962), etc. These observations are consistent with the view that late adopters lag behind others because they shield themselves from new information and are more set in their ways. But one major difference between early and late adopters that has received less emphasis is that later adopters are simply less suited to the innovation. For example, they may consider brick and mortar shopping an important social outlet, or they may be high on Need for Touch (Peck and Childers 2003). As a result, later adopters, even after adopting the innovation, continue to hold their more negative perceptions of the innovation. When late-adopting members of the "Fearful" segment finally adopt internet shopping, they maintain their relatively low opinion of internet shopping instead of switching to a more favorable segment.

The “Enthusiasts” segment, with the most positive overall perception of internet shopping, grew from 2001 to 2004, but then decreased in relative size from 2004 to 2007. This is a surprising pattern. An underlying assumption of much innovation research is that adopters, as a result of adoption or as a precursor to adoption, change their perceptions to recognize the superiority of the innovation. Thus, one would expect the “Enthusiasts” segment to grow consistently over this time period. This surprising growth and subsequent shrinkage of the “Enthusiasts” segment requires future research, but we forward some speculation as to its cause. An innovation brings novel advantages. New adopters of such innovations become enthused by these novel advantages, thus many of them join the “Enthusiasts” segment. However, the reality is that these novel advantages also come with some disadvantages. The early enthusiasm about the novel advantages blinds early adopters to these disadvantages during early adoption, but as the excitement and novelty diminish, perceptions of the innovation become more realistic, and many “Enthusiasts” change their perceptions to be in line with those of the “Mainstream” segment. As argued earlier, the potential selection issues of our sampling method are not likely to drive this result: a selection bias might drive the decrease in the “Enthusiast” segment size, but not the observed increase from 2001 to 2004.

Only the “Mainstream” segment grows consistently across the sample period. This segment, rather than universally recognizing the superiority of internet shopping over brick and mortar shopping, has only neutral to moderately positive perceptions of internet shopping. Most of the “Fearful” consumers who changed their perceptions as a result of trial did not become “Enthusiasts.” Most became part of the “Mainstream” segment, with relatively neutral perceptions of internet shopping. A major driver of innovation diffusion is not always the recognition of the superiority of the innovation, but is often simply a perception that the innovation has some worthwhile characteristics.

Ultimately, we are interested in how the two types of changes in perception affect adoption behavior. Because we cannot track individuals, examining the connection between segment-switching perception change and adoption behavior is difficult, though still possible. The gradual, within-segment perception changes, on the other hand, naturally lend themselves to examination in connection with adoption behavior. Thus, we examine these perception changes in connection with adoption.

Segmentation Dynamics and Internet Purchasing Behavior

To relate internet usage to the segments, the percentage of users per segment must be estimated. The E-step of the EM algorithm calculates a segment membership weight, z_{ik}, of each observation based on that observation's value on each of the segment's normal pdf. The value of z_{ik} is given by the Equation:

$$z_{ik} = \frac{\tau_k f_k(x_i|\mu_k,\Sigma_k)}{\sum_{j=1}^{G} \tau_j f_j(x_i|\mu_j,\Sigma_j)} \tag{4}$$

Consequently, the number of people in each segment, n_k, is a summation of z_{ik} over all people. Since τ_k is just n_k/N, if y_i takes the value 1 if individual i has adopted (i.e., made at least one purchase through internet) and 0 otherwise, the percent of users per segment is given by:

$$\frac{\sum_{i=1}^{N} y_i z_{ik}}{n_k} \tag{5}$$

Table 4 shows the percentage of the members of each segment who reported having made an internet purchase during the previous holiday season. Across all four samples, "Fearful" consumers were least likely to have made an internet purchase, "Mainstream" consumers were more likely, and "Enthusiasts" were most likely to have made a purchase. More interesting than the between-segment pattern of purchase, however, is the within-segment purchase pattern over time. Almost all members of the "Enthusiasts" segment reported having made online purchases in 2007, but this dropped in 2010. We attribute this drop to the poor state of the U.S. economy during the 2009 holiday season. For both the "Mainstream" and "Fearful" segments, online purchasing increased consistently over time.

<Insert Table 4 about here>

Though we cannot establish the direct causality of the underlying perceptions on these adoption increases, it is nonetheless likely that the adoption patterns we observe are in part caused by changing perceptions. Hence, we examine the within-segment changes in perception to establish how these perception changes relate to adoption.

Surprisingly, relative advantage does not increase over time within any of the three segments. In fact, perceived relative advantage decreased within both the "Mainstream" and "Fearful" segments. This attests to the importance of measuring a full range of perceptions rather than simply one's overall positive or negative inclination toward an innovation. Relative advantage, despite being a central driver of adoption of many innovations, does not align with adoption patterns in this data. Adoption increased within both the "Mainstream" and "Fearful" segments, yet their perceived relative advantage decreased. To understand the connection between perception and adoption, one needs to measure more than just the perceived relative advantage, because several other dimensions of perception could be influencing the adoption decision.

This result also highlights an underappreciated driver of adoption behavior. Adoption need not always reflect an underlying perception of an innovation's superiority. Instead, it could simply reflect that the consumer perceives that the benefits of the innovation outweigh the costs for that particular purchase occasion. A consumer may maintain an overall negative perception of internet purchasing and still recognize that purchasing used books online, for example, is cheap and convenient enough to outweigh the risk and incompatibility of online shopping in general. To encourage adoption of their innovation, managers may not need to convince consumers of its general superiority, but to highlight a particular situation in which that innovation is advantageous.

The risk dimension of perception is one that prior research has shown to be influential in the adoption decision (Chatterjee and Eliashberg 1990). The within-segment perception change pattern supports this. Risk was the only perception that decreased for all three segments, and therefore the only perception that aligns with the general pattern of purchase increase of all three segments. This decrease in perceived risk was likely the result of both spreading information and changes to internet shopping itself, such as the standardization of secure purchasing portals. With the current data, it is impossible to determine which source contributed more to this decrease in perceived risk. Future research should investigate the relative importance of these two sources for reducing perceived risk, for they each provide different recommendations to managers as to the best course of action to drive adoption through perceived risk reduction.

Perceived incompatibility decreases in the "Fearful" segment and increases in the "Enthusiasts" segment. This provides some possible corroboration of our previous interpretation of the drop in size of the "Enthusiasts" segment. We proposed that the "Enthusiasts" segment decreased in size because the excitement over the novelty of internet shopping wore off after a while and made some "Enthusiasts" reconsider and temper their perceptions. The increase in perceived incompatibility is consistent with this interpretation. The early excitement over internet shopping perhaps caused some consumers to deny to themselves that they even had a desire to shop in brick and mortar stores. Over time, however, these “Enthusiasts” came to recognize that internet shopping was indeed incompatible for some shopping situations.

Complexity decreases for both the “Mainstream” and “Enthusiasts” segments, but the “Fearful” segment maintains a constant perceived complexity. The absence of decrease from the “Fearful” segment likely reflects the fact that this segment is the least practiced of the three. Because they have the lowest adoption, they have the least opportunity to become practiced in internet shopping procedures. The larger decrease in complexity perceptions from the “Mainstream” segment reflects their greater practice and greater room for improvement. The “Enthusiasts” have higher adoption, thus receive the greatest amount of practice, but because they already reported a low complexity in 2001, there was not much room for more additional decrease.

Perceived relative disadvantage increases for the “Enthusiasts” and “Fearful” segments. This increase from the “Enthusiasts” can also be explained by the same factor that we proposed to have caused the increase in perceived incompatibility. Early excitement over internet shopping perhaps prevented “Enthusiasts” from recognizing the real disadvantages that accompanied this shopping method. The increase in this perception from the “Fearful” segment again reiterates the need to measure various aspects of innovation perceptions to establish which perceptions are truly driving adoption. Adoption of internet shopping increased among “Fearfuls” despite this increase in perceived relative disadvantage.

Across the four samples, participants who reported having made internet purchases in the previous holiday season increased from 50.9% to 75.5%. Some of this increase occurred because purchasing within the segments increased. The rest of this increase occurred because people moved from segments that purchased less (“Fearful”) to segments that purchased more (“Mainstream”). Restated, adoption seems to be driven by both the smaller within-segment perception changes and the larger segment-switching perception changes. We can investigate the relative importance of these two causes of purchase increases by calculating the overall purchase incidence under two separate “as-if” conditions. First, we calculate the overall purchase incidence at each time period if the purchase propensity of each segment remained at the 2001 level (or in other words, that perceptions had not changed within each segment). That is, we assume that only 34.9% of the "Fearful" segment purchased during all four holiday seasons, only 66.9% of the "Mainstream" segment purchased online, etc. The second scenario holds membership constant across the four samples (or in other words, it imposes that no drastic perception changes occurred). That is, in 2004, 2007, and 2010, the "Fearful" segment still makes up 54.5% of the market, but their purchase propensity increases from 34.9% in 2001 to 55.8% in 2010, as observed.

Table 5 shows the overall purchase incidence that would have occurred under each of these two scenarios. If we assume no within-segment perception changes (we hold purchase propensity of each segment constant), purchasing increases from the 2001 level of 50.8% to 60.4%. Interestingly, this entire increase occurs between 2001 and 2004. From 2004 to 2010, the increases in internet purchasing were not caused by changes in segment membership. It seems that larger changes in perception reflective of being convinced about the superiority of an innovation only drive adoption in the early stages of the innovation. This influence dissipates drastically later on.

<Insert Table 5 about here>

Under our second "as-if" analysis, when we only allow for the gradual, within segment perception changes (we hold the size of each segment constant), overall purchasing increases to 68.0%, and the increase in purchasing is relatively constant across the three time gaps. For internet purchasing, the gradual, within-segment perception changes had a constant effect on adoption. Because drastic perception changes had most of their effect in the early period of internet shopping, later adoption is driven almost exclusively by small, gradual changes in perception. Overall, the small, gradual changes in perception drive twice the amount of adoption as do the large, drastic changes in perception over the nine years represented in our sample. During the later stages of a major innovations like internet shopping, managers should not try to convince consumers of the innovation's superiority, but merely that it is useful in specific situations. Adoptions during these later stages are not driven by a re-thinking of one's perception, but by a gradual realization of the innovation's usefulness on some dimension.

Understanding the Structure of Each Segment

Recall that the distribution of the latent factors is different for each segment, as reflected by each segment *k* having a unique covariance matrix Σ_k. Therefore, although the pooled perceptions are uncorrelated with unit variance by virtue of the factor analysis that produced the perceptions for identification purposes, the extent of the differences in the covariance structure across segment is an empirical question. We now provide evidence that the full covariance matrix provides better fit than a simple diagonal matrix. We fit another 24 models using only a diagonal matrix for each segment. That is, we fit solutions with one through six segments crossed by all four mean variations. In 20 of the 24 models, the BIC was higher than for the fully estimated covariance matrix (indicating inferior fit for these simpler models). The only exceptions were the four models that fit only one segment. Because the factor analysis creates factors that are uncorrelated, a diagonal matrix fits these one-segment solutions best. But even with only two segments, a fully estimated covariance matrix improves model fit. The small correlations we observe in the off-diagonal elements of each segment's matrix are meaningful.

Table 6 gives the upper triangle of the variance-correlation matrix for each segment. That is, on the main diagonal of each matrix we give the variance of each factor. The correlations between each pair of factors are displayed in the off-diagonals. Though none of the correlations are especially high, the fact that a diagonal covariance matrix leads to inferior fit establishes their importance. The correlations enable a more accurately specified distribution. The increased accuracy of the full specification is represented in the determinants of the covariance matrices of the segments. That is, we can calculate the determinant of each matrix with and without its off-diagonal elements to ascertain the impact these correlations have on the accuracy of the specification of each segment's underlying distribution. With the fully estimated covariance matrices, the determinant of the "Enthusiasts" segment is .0076; the determinant of the "Mainstream" segment is .145; the determinant of the "Fearful" segment is 1.15. Meanwhile, if we were to impose zeros on all the off-diagonal elements of these matrices, the determinants would increase to .0219, .198, and 1.43. Fitting a fully estimated covariance matrix for each segment decreases our model specification error for these segments by 65%, 27%, and 20%, respectively.

These parameters provide additional insights as to the heterogeneity of the segments. Complexity and relative disadvantage are relatively unique dimensions for the "Mainstream" and for the "Fearful" segments (correlations of -.11 and .01 respectively). However, complexity is strongly negatively related to relative disadvantage for the "Enthusiasts" segment. For these consumers, the complexity of an innovation may not be a negative factor. This is reinforced by the positive correlations of incompatibility and complexity with relative advantage in this segment (.39 and .34 respectively). Similarly, risk is negatively related to complexity for the "Enthusiasts" (-.45) so that consumers in that segment do not perceive that complexity is associated to higher risk; on the contrary, they appear to view complexity as a risk reduction potential. This same results holds, albeit to a lesser degree (with a correlation of .30) for the "Fearful" segment. This indicates that complexity may be an indication of better quality that results in less risk.

Focusing now on the variances (the diagonals in Table 6), apart from few exceptions, the "Enthusiasts" exhibit more cohesion with smaller variations in the factor perceptions across the group. For example, the variance of relative advantage for the "Enthusiasts" is only .32, less than half the distribution variance for the "Mainstream" and about three times smaller than the "Fearful" variance. The difference is even more striking for the complexity factor with variances of .15, .53 and 1.46 respectively for the "Enthusiasts," the "Mainstream" and the "Fearful" segments respectively. The variability of perceptions within each of the three segments is more similar, however, for the incompatibility and the relative disadvantage factors. These differences across segments in the distribution of the perceptions along the factors that characterize innovations indicate that the perceptual structures differ significantly across segments. These results allow management to better adapt the marketing of innovation to the targeted segments.

GENERAL DISCUSSION

The model and application we have presented provides insights both broad (market structure evolution) and focused (perceptual dimensions and their link to adoption). Our research makes a thorough examination of the structure and dynamics of perceptions while also enabling inference on the connection between perceptions and adoption. Managers attempting to influence the adoption decision of consumers need to know which dimensions of perceptions are most likely to encourage adoption, or conversely, which dimensions are likely to impede adoption.

Previous research has typically assumed adoption results from an improved perception of the product's advantages, but we find that a much larger percentage of adoptions results from a reduction in perceived risk rather than an increase in perceived advantage. Understanding the dimensions of perceptions and their links to adoption will aid managers in making strategic decisions for new products.

Simultaneously examining market structure and evolution provides insights that would be missed by evaluating market evolution in aggregate. For example, the "Mainstream" segment decreases in perceived complexity over time, while the "Fearful" segment's perception on this dimension remains constant. An examination of market evolution in aggregate would show a small decrease in the complexity dimension without showing that the "Fearful" segment is not receiving the aid needed to improve their perception on this dimension.

In examining market structure and evolution, we find a compelling pattern. Perceptual evolution can be characterized by two types of changes to the market structure: changes in segment size and changes in segment means. Perception changes that result in segment mean shifts are constant throughout the nine-year period of study. Perception changes that result in growth and shrinkage of segments are more prominent in the early phases of the product life cycle. This pattern is important because it speaks to the need to adjust new product strategy over time. Early adoptions are driven predominantly by large perception changes, thus early strategy should include a concentrated effort to flood the market with positive information about the product. In later stages, perceptions changes only slightly with new information, so messages should be focused on key dimensions known to influence adoption. This pattern would be missed by study of aggregate perceptions, again attesting to the value of our methodology.

We examined market evolution in terms of segment size changes and segment mean changes, but other options could be examined in future research. For example, the underlying structure of a given segment could change, or in other words, the covariance matrix of each segment's distribution could change over time. To examine this possibility, we ran models with four different variations in the evolution of the underlying covariance matrices of the segment distributions. None of these variations improved model fit (as measured by BIC). However, it is impossible to determine whether the underlying structure of segments is generally constant, or whether our particular application leads to constant segment structure. It is possible that in some markets, segments grow more or less homogeneous over time, or that specific perceptions grow more or less homogeneous within a segment, thereby changes the segment's shape. While these variations did not improve model fit in our application, other applications may find improved fit with these parameterizations.

Another aspect of evolution that future research could examine is the evolution of the underlying structure of perceptions. That is, perhaps the factor loadings change over time. This would be problematic for our study, as invariant factor loadings are a necessary assumption for the identification of our model, but exploring this assumption might be a fruitful area for future research. It is possible that the underlying dimensions of consumers' perceptions of a product or innovation change over time. Because the assumption of invariant factor loadings is important to our model, we sought to determine whether this assumption was reasonable for our application. We compared the model fit of two different confirmatory factor analysis models. In the first model, we used the same loadings (those found in Table 1) in all time periods. In the second model, we fit a different loading matrix at each time period. Model fit parameters (including RMSR, RMSEA, GFI, AGFI, CFI, etc.) were universally better (though only slightly so) in the first model, indicating that our assumption was at least reasonable.

To encourage consumers to adopt an innovation, managers must seek to change consumers' perceptions of the innovation. Consumers' perceptions change because of information they receive about the innovation or because the innovation itself is changed. Managers can influence both of these sources of perception change. They should seek to understand the best way to influence these perceptions, which perceptions ought to be most influenced, and the right time to pursue perception change, in order to maximize adoption.

References

Allenby, Greg M., Robert P. Leone, and Lichung Jen (1999), "A Dynamic Model of Purchase Timing With Application to Direct Marketing," *Journal of the American Statistical Association*, 94 (446), 365-374.

Apple, Inc. (2010, July 2). *Letter from Apple Regarding iPhone 4*. Retrieved 17 May 2011 from http://www.apple.com/pr/library/2010/07/02appleletter.html.

Bandura, Albert (1997), *Self-Efficacy: The Exercise of Control*, New York: Freeman.

Bass, Frank M. (1969), "A New Product Growth Model for Consumer Durables," *Management Science*, 15 (January), 215-27.

Brangule-Vlagsma, Kristine, Rik G.M. Pieters, and Michel Wedel (2002), "The Dynamics of Value Segments: Modeling Framework and Empirical Illustration," *International Journal of Research in Marketing*, 19, 267-285.

Chatterjee, Rabikar, and Jehoshua Eliashberg (1990), "The Innovation Diffusion Process in a Heterogeneous Population : A Micromodeling Approach," *Management Science*, 36(9), 1057-1079.

Coleman, James Samuel, Elihu Katz, and Herbert Menzel (1966), *Medical Innovation: A Diffusion Study*, New York, NY: Bobbs-Merrill Company.

Davis, Fred D. (1989), "Perceived Usefulness, Perceived Ease of Use , and User Acceptance of Information Technology," *MIS Quarterly*, 13(3 (September)), 319-340.

Davis, Fred D., Richard P. Bagozzi, and Paul R. Warshaw (1989), "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," *Management Science*, 35(8), 982-1003.

Feder, Gershon, and Gerald T. O'Mara (1982), "On Information and Innovation Diffusion: A Bayesian Approach," *American Journal of Agricultural Economics*, (February), 145-147.

Fraley, Chris, and Adrian E. Raftery (1998), "How Many Clusters? Which Clustering Method? Answers Via Model-Based Cluster Analysis," *The Computer Journal*, 41 (8), 1998.

Gatignon, Hubert, and Thomas S. Robertson (1985), "A Propositional Inventory for New Diffusion Research," *Journal of Consumer Research*, 11 (March), 849–867.

Goldenberg, Jacob, Barak Libai, and Eitan Muller (2002), "Riding the Saddle: How Cross-Market Communications Can Create a Major Slump in Sales," *Journal of Marketing*, 66(2), 1-16.

Grau, Jeffrey (2007), "Update: U.S. Retail E-Commerce," *eMarketer Report*, March 9, 2007.

Grau, Jeffrey (2010), "U.S. Retail E-Commerce Forecast: Room to Grow," *eMarketer Report*, March 30, 2010.

Han, Kyeong Seok and Mee Hyun Noh (1999), "Critical Failure Factors that Discourage the Growth of Electronic Commerce," *International Journal of Electronic Commerce*, 4 (2), 25-43.

Higdon, Dave, James Gattiker, Brian Williams, and Maria Rightley (2008), "*Computer Model Calibration Using High-Dimensional Output*," *Journal of the American Statistical Association*, 103 (482), 570-583.

Holak, Susan L. and Donald R. Lehmann (1990), "Purchase Intentions and the Dimensions of Innovation: An Exploratory Model," *Journal of Product Innovation Management*, 7 (1), 59-73.

Isaacson, Walter (2012), *Steve Jobs*, New York: Simon & Schuster.

Jensen, Richard (1982), "Adoption and Diffusion of an Innovation of Uncertain Profitability," *Journal of Economic Theory*, 27(1), 182-193.

Kiely, Thomas (1997), "The Internet: Fear and Shopping in Cyberspace," *Harvard Business Review*, 75 (4), 13-14.

Linn, Robert L. (1968), "A Monte Carlo Approach to the Number of Factors Problem," *Psychometrika*, 33 (1), 37–71.

MacCallum, Robert C., Cheongtag Kim, William B. Malarkey, and Janice K. Keicolt-Glaser (1997), "Studying multivariate change using multilevel models and latent curve models," *Multivariate Behavioral Research*, 32 (3), 215–253.

Mahajan, Vijay, Eitan Muller, and Frank M. Bass (1990), "New Product Diffusion Models in Marketing: A Review and Directions for Research," *Journal of Marketing*, 54(January), 1-26.

Mehta, Paras D., and Michael C. Neale (2005), "People Are Variables Too: Multilevel Structural Equations Modeling.," *Psychological Methods*, 10(3), 259-84.

Montanelli, Lloyd G. and Richard G. Montanelli, Jr. (1975), "An Investigation of the Parallel Analysis Criterion for Determining the Number of Common Factors," *Multivariate Behavioral Research*, 10 (2), 193-205.

Montgomery, Alan L., Shibo Li, Kannan Srinivasan, and John C. Liechty (2004), "Modeling Online Browsing and Path Analysis Using Clickstream Data," *Marketing Science*, 23 (4), 579 – 595.

Moon, Sangkil, Wagner Kamakura, and Johannes Ledolter (2007), "Estimating Promotion Response When Competitive Promotions are Unobservable," *Journal of Marketing Research*, 44 (August), 503-515.

Netzer, Oded (2008), "A Hidden Markov Model of Customer Relationship Dynamics," *Marketing Science*, 27 (2), 185-204.

Paas, Leonard J., Jeroen K. Vermunt, and Tammo H. A. Bijmolt (2007), "Discrete Time, Discrete State Latent Markov Modeling for Assessing and Predicting Household Acquisitions of Financial Products," *Journal of the Royal Statistical Society*, 170 (4), 955-974.

Pavlou, Paul A (2003), "Consumer Acceptance of Electronic Commerce : Integrating Trust and Risk with the Technology Acceptance Model," *International Journal of Electronic Commerce*, 7(3), 69-103.

Peck, Joann and Terry L. Childers (2003), “Individual Differences in Haptic Information Processing: The “Need for Touch” Scale,” *Journal of Consumer Research*, 30 (3), 430-442.

Poulsen, Carsten Stig (1990), “Mixed Markov and Latent Markov Modeling Applied to Brand Choice Behavior,” *International Journal of Research in Marketing*, 7 (1), 5-19.

Roberts, John H., and Glen L. Urban (1988), “Modeling Multiattribute Utility Risk, and Belief Dynamics for New Consumer Durable Brand Choice,” *Management Science*, 34(February), 167-185.

Rogers, Everett M. (1962), *Diffusion of Innovation*, New York: Free Press.

Rubin, Donald B. and Dorothy T. Thayer (1982), “EM Algorithms for ML Factor Analysis,” *Psychometrika* 47 (1), 69-76.

Schneider, Joan, and Julie Hall (2011), “Why Most Product Launches Fail,” *Harvard Business Review*, (April), 21–24.

Schwarz, Gideon E. (1978), “Estimating the Dimension of a Model,” *Annals of Statistics*, 6 (2), 461-464.

Soberman, David and Hubert Gatignon (2005), “Research Issues at the Boundary of Competitive Dynamics and Market Evolution,” *Marketing Science*, 24 (1), 165-174.

Stoneman, P. (1981), “Intra-firm Diffusion, Bayesian Learning and Profitability,” *The Economic Journal*, 91(June), 375-388.

Swinyard, William R. and Scott M. Smith (2003), “Why People (Don’t) Shop Online: A Lifestyle Study of the Internet Consumers,” *Psychology and Marketing*, 20 (7), 567-597.

Footnotes

[1] It is likely that the population of internet users itself changed over this period, thus potentially causing selection biases. In most cases, the selection bias does not change the insights gained from the model, as indicated in the section discussing the results.

Table 1
Rotated Principal Component Loadings

	Relative Advantage	Risk	Incompatibility	Complexity	Relative Disadvantage
I enjoy buying things on the Internet.	**.723**	-.332	-.189	-.220	-.058
I like having products delivered to me at home.	**.708**	-.129	-.210	-.140	-.023
I like that a car is unnecessary when shopping on the Internet.	**.701**	-.025	-.339	-.070	.007
I think on-line buying is (or would be) a novel, fun way to shop.	**.700**	-.296	-.127	-.163	-.047
I think Internet shopping would avoid the hassle of local shopping.	**.699**	-.116	-.356	-.063	-.067
I think Internet shopping offers better selection than local stores.	**.682**	-.117	-.162	-.095	-.190
I would like not having to leave home when shopping.	**.680**	-.007	-.467	-.021	-.032
I think Internet shopping offers better quality than local stores.	**.657**	-.035	-.097	.073	-.302
I often go to the Internet for product reviews or recommendations.	**.632**	-.038	.113	-.301	.147
I often go to the Internet to preview products.	**.606**	-.085	.134	-.341	.129
I think the Internet offers lower prices than local stores.	**.605**	-.032	-.078	-.082	-.278
I like browsing on the Internet.	**.558**	.057	.191	-.302	.099
I frequently worry about the security of credit card information that is stored by an online merchant.	-.101	**.769**	.131	.132	.181
Buying things on the Internet scares me.	-.240	**.728**	.163	.303	.091
I don't want to give out my credit card number to a merchant online.	-.267	**.722**	.155	.240	.110
I want my purchases to be absolutely private.	.175	**.590**	.052	.004	.118
I just don't trust Internet retailers.	-.289	**.579**	.142	.271	.281
I like the ''energy'' & fun of shopping at local retail stores.	-.243	.133	**.770**	.125	.169
I like to go shopping with my friends.	-.062	.161	**.736**	.100	.037
For me, shopping in stores is a hassle.	.479	.045	**-.614**	.061	-.042
I like the help and friendliness I can get at local stores.	-.107	.148	**.575**	.118	.119
I often buy using lay-away or store payment programs.	.034	.316	**.345**	.285	-.069
I'd have a hard time searching the Internet to find what I need.	-.166	.108	.103	**.741**	.184
I find the Internet ordering process is hard to understand & use.	-.171	.201	.143	**.701**	.141
I don't think Internet stores carry things I want.	-.200	.038	.144	**.643**	.295
I don't know much about using the Internet.	-.135	.282	.027	**.571**	-.133
None of my friends shop on the Internet.	-.085	.261	-.006	**.300**	.122
I often return items I have purchased.	-.026	.162	.234	**.282**	.154
I dislike the idea of shipping charges when buying on the Internet.	.036	.110	-.014	.017	**.676**
I would shop on the Internet (more) if the prices were lower.	.334	-.083	-.114	.040	**.558**
It's hard to judge the quality of merchandise on the Internet.	-.182	.405	.166	.128	**.537**
It would be a real hassle to return merchandise bought on-line.	-.175	.385	.107	.116	**.531**
I believe there are delivery problems and backorders when making Internet purchases.	-.145	.185	.102	.423	**.498**
Local stores have better prices and promotions than Internet stores.	-.238	.015	.244	.308	**.462**
I think local stores have better service policies than Internet stores.	-.236	.214	.318	.252	**.444**
I don't like having to wait for products to arrive in the mail.	-.191	.304	.179	.183	**.431**
I want to see things in person before I buy.	-.380	.306	.363	.165	**.380**
I always search for the lowest price in just about everything I buy.	.271	.156	.187	-.077	**.278**

Table 2

Model BIC Scores by Mean Form and by Number of Clusters

No. of Clusters	Identical Means	Linear Drift	Curvilinear Drift	Unique Means
1	469,770	469,380	469,340	469,352
2	468,802	468,737	468,779	468,829
3	468,616	**468,587**	468,668	468,755
4	468,615	468,639	468,744	468,852
5	468,675	468,722	468,848	469,012
6	468,735	468,839	469,065	469,161

Table 3

Segment Membership over Time

Membership	2001	2004	2007	2010
Segment 1				
Enthusiasts	8.8%	16.5%	9.7%	11.9%
Segment 2				
Mainstream	36.7%	54.9%	62.1%	62.0%
Segment 3				
Fearful	54.5%	28.6%	28.2%	26.1%

Table 4

Segment Purchasing over Time

Purchasing	2001	2004	2007	2010
Segment 1				
Enthusiasts	82.7%	82.1%	96.0%	86.4%
Segment 2				
Mainstream	66.9%	67.6%	77.4%	81.7%
Segment 3				
Fearful	34.9%	43.1%	47.4%	55.8%

Table 5

Comparing Adoption Under Two "As-If" Conditions

	% Buying	Only Drastic Perception Changes	Only Gradual Perception Changes
2001	50.9%	50.9%	50.9%
2004	63.0%	60.4%	55.5%
2007	70.8%	59.4%	62.7%
2010	75.5%	60.4%	68.0%
Change	24.6%	9.5%	17.2%

Table 6

Variance-Correlation Matrix: Segment 1

Enthusiasts

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1 Relative Advantage	**.32**	.07	.39	.34	-.28
Factor 2 Risk		**.67**	-.17	-.45	.09
Factor 3 Incompatibility			**.68**	.04	-.30
Factor 4 Complexity				**.15**	-.43
Factor 5 Relative Disadvantage					**1.03**

Variance-Correlation Matrix: Segment 2

Mainstream

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1 Relative Advantage	**.76**	.23	.14	.18	.08
Factor 2 Risk		**.64**	-.20	-.05	.06
Factor 3 Incompatibility			**.89**	-.24	-.03
Factor 4 Complexity				**.53**	-.11
Factor 5 Relative Disadvantage					**.85**

Variance-Correlation Matrix: Segment 3

Fearful

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1 Relative Advantage	**1.07**	.08	.07	.16	.13
Factor 2 Risk		**.83**	-.11	-.30	-.14
Factor 3 Incompatibility			**1.00**	-.06	.01
Factor 4 Complexity				**1.46**	.01
Factor 5 Relative Disadvantage					**1.10**

Figure 1 – Conceptual Framework

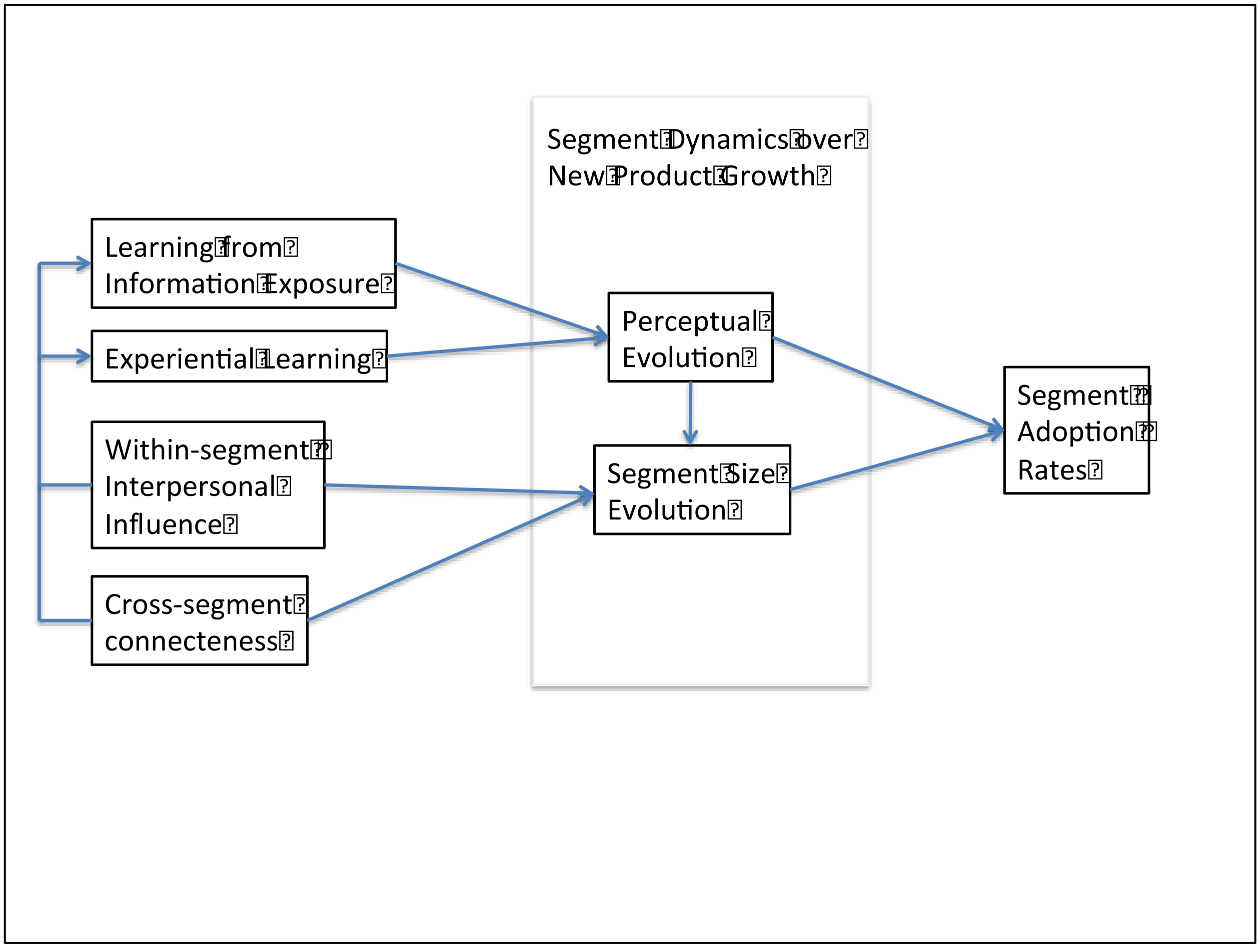
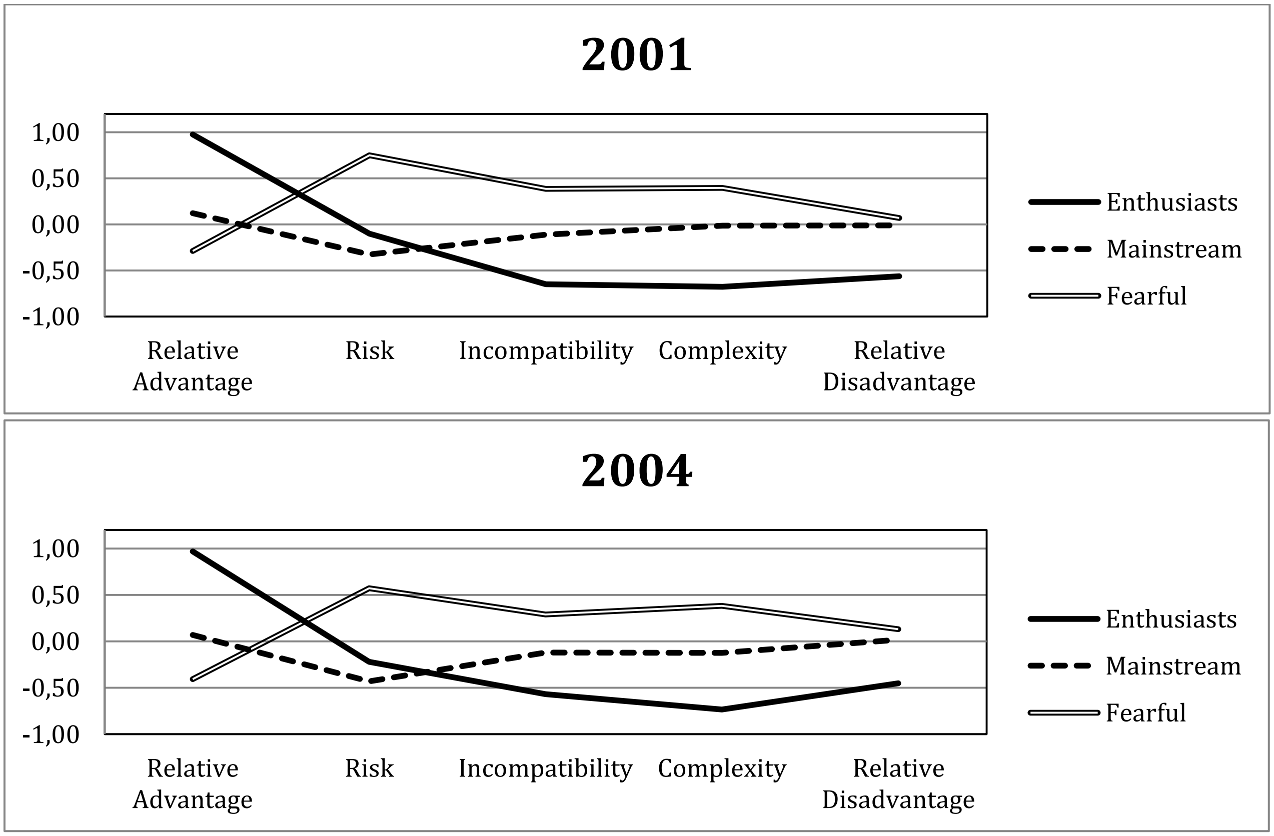


Figure 2 – Segment Means



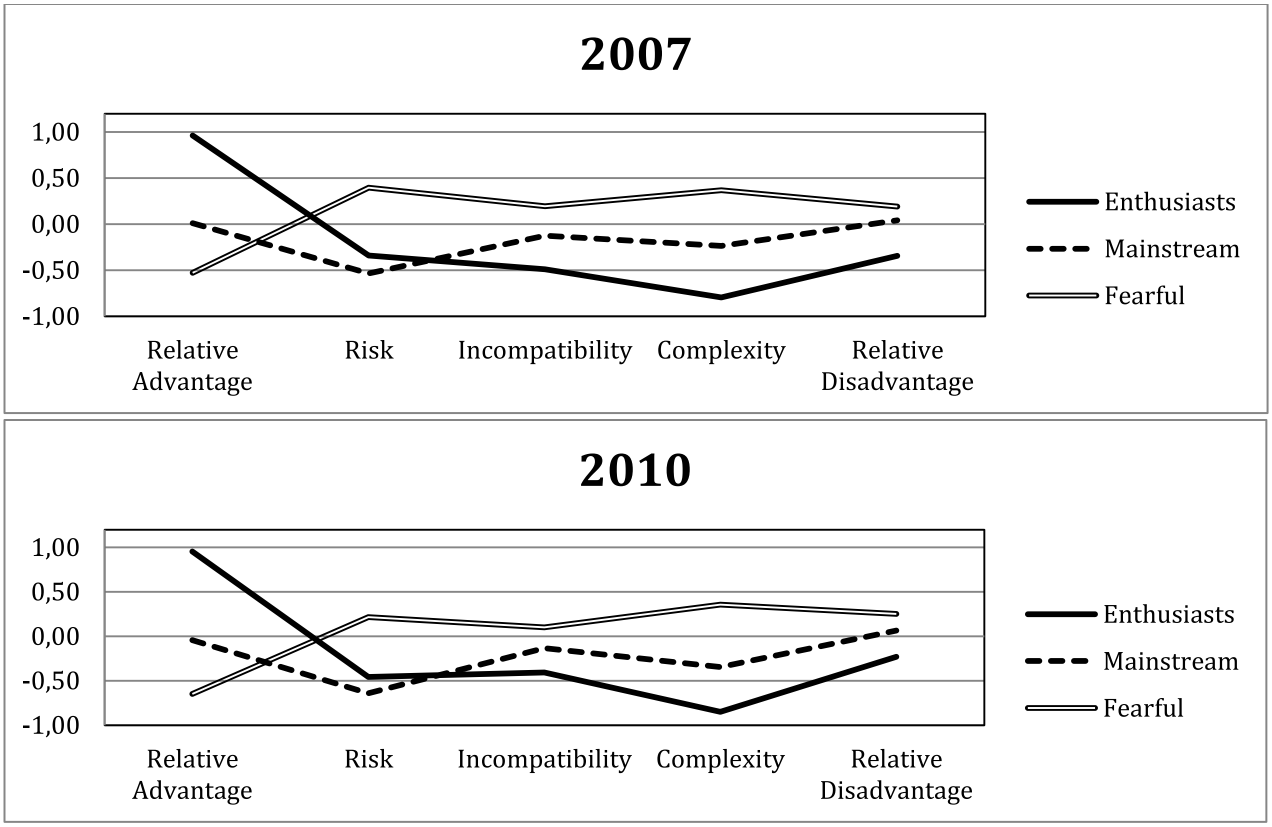
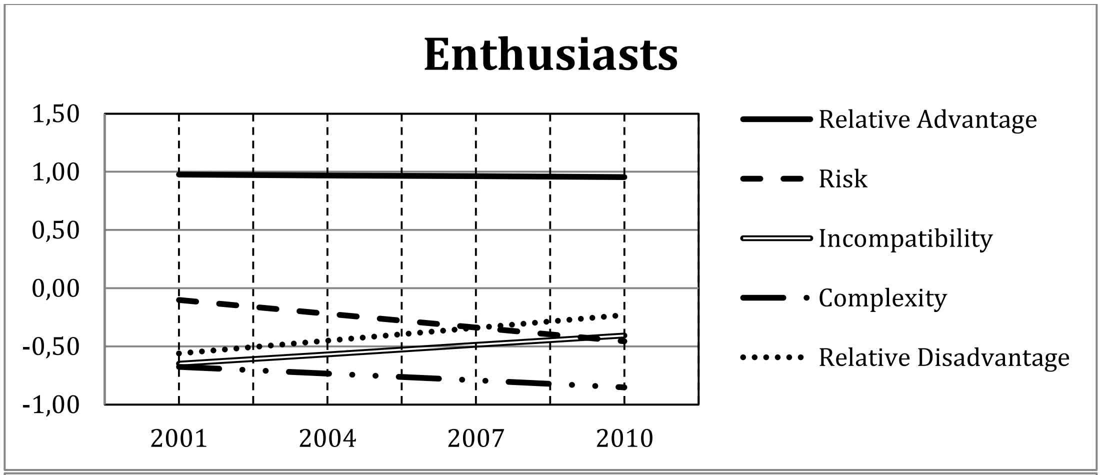
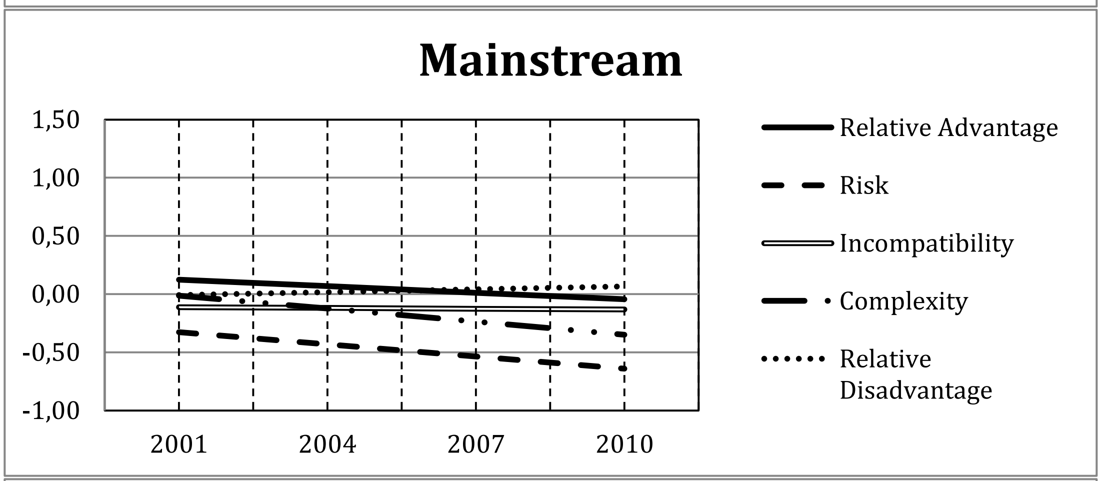
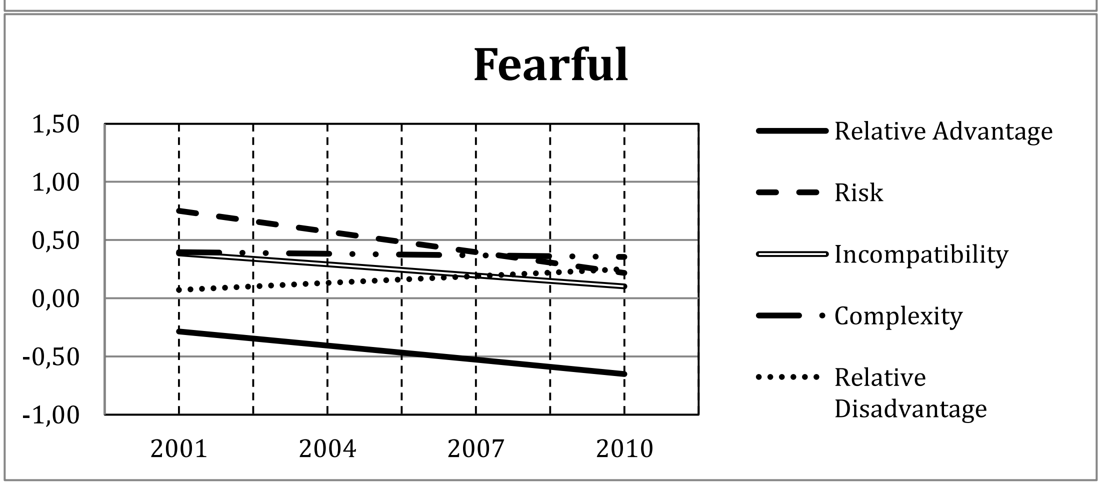


Figure 3 – Evolution of Segment Means over Time


Enthusiasts
1,50
1,00
0,50
0,00
-0,50
-1,00
2001
2004
2007
2010
Relative Advantage
Risk
Incompatibility
Complexity
Relative Disadvantage


Mainstream
1,50
1,00
0,50
0,00
-0,50
-1,00
2001
2004
2007
2010
Relative Advantage
Risk
Incompatibility
Complexity
Relative Disadvantage


Fearful
1,50
1,00
0,50
0,00
-0,50
-1,00
2001
2004
2007
2010
Relative Advantage
Risk
Incompatibility
Complexity
Relative Disadvantage

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