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GENERATION NEW PRODUCT ADOPTION

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THE EFFECT OF REPEAT ADOPTERS UPON SECOND  
GENERATION NEW PRODUCT ADOPTION

By

Kwong Chan

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# **ABSTRACT**

## **THE EFFECT OF REPEAT ADOPTERS UPON SECOND GENERATION NEW PRODUCT ADOPTION**

By

Kwong Chan

A second product generation is offered to two adopter populations: repeat adopters, who consist of innovative adopters that purchased the first generation product, and a larger market of imitative new-adopters that did not. New product adoption theory suggests that the first adopter population plays a key role in stimulating adoption behavior in the second imitative population. This importance stems from credibility gained from first generation product experience.

In this study, social connections between adopters are measured using a demographic similarity ratio, and piecewise Weibull regression used to analyze cross-generation product adoption. The analysis used a secondary survey dataset of new automobile owners.

The findings indicate purchase by new adopters of a second generation product is accelerated by repeat adopters and to a lesser extent, new adopters. Comparative analyses conducted on buyers of existing products indicate repeat buyers have no influence upon new buyers, but for some existing products new buyers stimulate other new buyers to early purchase.

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# **Chapter 1**

## **INTRODUCTION**

### **Word of Mouth Effects are Difficult to Capture in New Product Diffusion**

In new product diffusion, word of mouth describes communication between individuals in an adopting population. This communication occurs when individuals view product performance as uncertain and consequently utilize interpersonal contacts to gather relevant information. Widespread dissemination of information can accelerate adoption (Chatterjee and Eliashberg 1990), while a lack of such information flowing through interpersonal channels can lead to delayed market acceptance (Goldenberg, Libai and Muller 2002) and even market failure (Moore 1991). The importance of word of mouth is reflected in work that examines disproportionately influential individuals who may play a key role in catalyzing an adopting population to purchase (Rogers 1995; Feick and Price 1991).

Most diffusion models are able to account for word of mouth effects, and the majority of approaches are able to yield sales forecasts through the use of a mathematical functional form. The Bass Diffusion Model (Bass 1969) for example is defined by a market potential estimate, and coefficients of external and internal influence. The coefficient of internal influence captures the result of word of mouth effects, but this coefficient yields little insight into the mechanisms by which influence travels through a population. Purchase times are used as the basis for model estimation, however the times at which different individuals receive and transmit influence remain unknown. Diffusion models are thus

largely restricted to the realm of forecasting, and provide only limited guidance for marketing communications practice. An improved understanding of the processes that underlie the coefficient of internal influence would be invaluable to managers that wish to utilize interpersonal communication channels in marketing programs.

In contrast to diffusion studies, network models of diffusion focus primarily upon the mechanisms by which information flows through individuals. Forecasts of effect (such as sales rates), if possible, are mere by-products of network models. Relative to diffusion models, data requirements for network models are onerous. Relational models characterize the opinion leadership of an individual by consulting all other individuals in the network, structural models use patterns of present and absent ties to compare the network positions of network members (Valente 1995), while models of network spatial heterogeneity (Strang and Tuma 1993) require assessment of infectiousness, susceptibility, proximity and propensity at the individual level.

Clearly network models provide great insight into diffusion processes through individual-level relationships, behavior and characteristics. Equally clear is the comprehensive level of data needed to undertake network modeling. This greater data need alone has arguably resulted in a predominance of aggregate-level diffusion research that uses more accessible population-level sales data. This leaves a large middle-ground where data may be less rich than social network data, but more comprehensive than aggregate level sales data. Methods of broaching this gap such as through the use of demographic similarity

(De Bruyn and Lilien 2004) have begun to appear, although no benchmark approach currently exists.

## **Summary**

Past work has explored adoption patterns at a broad population level more suitable for sales forecasts than specific marketing policy, or at a network level where data requirements exceed those typically available in a new product diffusion context. There is a need to achieve greater insight at the individual level in a broader market level adoption context.

## **Demographic Similarity and Internal Influence**

This research examines internal influence in new product diffusion by using a social network rationale to apply demographic similarity as a proxy for internal influence, and link this proxy to adoption time. This measure assesses internal influence effects upon a potential adopter by determining the proportion of past adopters who have common demographic characteristics.

The importance of the social network perspective to new product diffusion is used to highlight the tradeoff between the need for empirical detail and difficulty in obtaining data of sufficient richness. An approach is proposed and tested that uses a demographic similarity ratio to link past and present adopters across and within two product generations. By examining the same individuals over two successive product generations, a method of identifying adopter influence is developed that examines the effects of “prior adopters” that have

already purchased, upon “current adopters” that have yet to. Prior adopters consist of both first-time adopters of a second generation product who are termed **prior New Adopters**; and more experienced adopters who have purchased both the first and second product generations and are termed **prior Repeat Adopters**. Current adopters have yet to purchase and may be potential first-time adopters who are termed **current New Adopters**, or potential repeat adopters who are termed **current Repeat Adopters**.

Specifically, this research uses a second successive automobile product generation context to identify the importance of prior New and Repeat Adopters in acceleration of second generation product adoption among current New and Repeat Adopters.

The research questions are:

- 1) Is purchase by current New Adopters accelerated by influence from both prior New Adopters and prior Repeat Adopters?
- 2) Is purchase by current Repeat Adopters accelerated by influence from both prior New Adopters and prior Repeat Adopters?

These questions are investigated through examination of repeat and new adopters over time. The results indicate that New Adopters do respond to both prior New and Repeat Adopters, whereas Repeat Adopters respond to neither.

## **Context of the Investigation**

Secondary data were obtained from a market research firm that collected national level survey response data for buyers of new automobiles for the period September 1998 to December 2004. The data contain information covering two successive generations of automobile purchase by an individual. This allows for the examination of repeat and new adopters as possible senders and receivers of influence in a product adoption context.

## **Chapter 2**

### **LITERATURE REVIEW**

*This chapter contrasts aggregate and network models of diffusion by examining how each investigates segments of adopters. The information rich, but relatively data intensive qualities of the network approach are highlighted, and a compromise approach suggested.*

This research aims to develop a cross-generational approach to describe how repeat and new adopter segments influence one another during adoption of a second product generation. To develop a conceptual model, prior work that links adopters across segments, and over time, is reviewed over three sections. The first section examines how the current state of cross-generational new product research views adopters of different generations as exerting influence upon one another; the second section examines how aggregate diffusion models and individual-level social network perspectives describe inter-adopter influence; and the third section proposes a means of linking adopter segments through the use of demographic similarity.

#### **Second Generation New Product Adoption**

The competitive significance of new products to firms has led to a desire to understand and predict new product adoption in the marketplace. However despite a general agreement that early market entry is advantageous (Bowman and Gatignon 1996; Symanski, Troy and Bharadwaj 1995; Kalyanaram and

Urban 1992), a successful initial first generation market entry alone does not guarantee long-term competitiveness or profitability (Boulding and Christen 2003; Bohlmann, Golder and Mitra 2002; Venkatesh, Carpenter and Krishnamurthi 1998). The problem of predicting the adoption of successive product generations has received less attention, but is no less important, as competitor entry and mass market acceptance often occur during adoption of the second, or later product generations (Christensen 1997). Furthermore, it is common for a second generation product launch to involve greater resource commitment because of the need to recoup fixed development costs, expand production capacity and broaden marketing effort.

Existing cross-generational product diffusion studies have focused upon market level adoption rather than the individual level communication processes that are theorized to underlie market acceptance of new products. The forecasting benefits of market level aggregate studies is clear, however it is the nature of the underlying word of mouth processes that is most informative for development of interpersonal influence theory and managerial action. Unfortunately it has proven far easier to observe the aggregate market result of such communication than identify individual-level behaviors that drive word of mouth influence.

The relatively few studies in multigenerational new product adoption have focused upon identification of differences in the diffusion patterns between product generations. Differences may be due to technological (Kim, Srivastava and Han 2001), marketing (Danaher, Hardie and Putsis 2001), related-product



category (Kim, Chang and Shocker 2000) or user-related cross-generational influence factors (Danaher, Hardie and Putsis 2001, Islam and Meade 1997).

Consideration of interpersonal influence has focused upon the role adopters of a newer generation play in both attracting completely new adopters of the product, and convincing adopters of prior generations to re-adopt the newer generation (Danaher, Hardie and Putsis 2001; Kim, Chang and Shocker 2000; Norton and Bass 1987), or the ability of the installed base of an earlier technology to enhance diffusion of a later technology generation (Kim, Chang and Shocker 2000; Islam and Meade 1997). These studies treat adopters of different generations as different adopter groups, and indicate influence can be described between adopters of succeeding and prior generations through distinct generational segments.

### **Influence between Adopter Categories**

Adopters may be categorized as “innovators” and “imitators”. Innovators make adoption decisions largely independent of others, while imitators are heavily influenced by other people (Bass 1969). Innovators rely proportionally more upon external sources of information such as advertising and critical reviews, have a lower risk threshold (Valente 1995), and are opinion leaders for following adopters (Rogers 1995). Imitators are a larger proportion of the market (Muller and Yogev 2005) and are thus critical to market success. In contrast to innovators, imitators pay great attention to those around them when making adoption decisions. While innovators are key in influencing following adopters,

their impact may vary according to different innovator types. Earlier innovators have personal and social characteristics that differ from later innovators, having lower risk adversity, more extreme behavior, and fewer social connections. Later innovators tend to be more socially connected, and may act as 'market mavens' who influence adoption among imitative adopters (Feick and Price 1987). A lack of influence between innovative and imitative segments may be responsible for the "chasm" in some diffusion curves that may indicate product failure (Moore 1991) or the "saddle" that is associated with delayed market acceptance (Goldenberg, Libai and Muller 2002). The importance of influence between innovative and imitative segments has led to investigations of diffusion dynamics across market segments.

### **Adopter Segments, Influence and Adoption**

The most utilized diffusion model in new product adoption is the Bass Diffusion Model (Bass 1969) that requires just three parameters for estimation: market potential, a coefficient of internal influence, and a coefficient of external influence. Internal influence is analogous to the word of mouth effect, while external influence is often interpreted as a measure of media effects. Each parameter may be interpreted as a summary result of underlying mechanisms. Differences in parameter coefficients indicate faster or slower adoption rates, but do not reveal whether differences are due to factors such as product features or characteristics of the adopting population. The desire to identify specific reasons

for different adoption rates has led to a stream of work that examines new product diffusion across contexts and time.

The use of diffusion models to investigate processes that generate the adoption curve have focused upon examination of model parameters across different market contexts, including product-markets (Talukdar, Sudhir and Ainslie 2002; Lenk and Rao 1990) and country-markets (Talukdar et al. 2002; Dekimpe, Parker and Sarvary 1998; Gatignon, Eliashberg and Robertson 1989). Talukdar et al. (2002) provide evidence internal influence varies according to ethnic diversity and experience of prior adopters that are found to be positively related to internal influence. This class of research provides evidence adopter characteristics are heterogeneous between adoption populations. Differences in internal influence have also been investigated in different populations over time.

The possibility that influence flows from earlier to later segments has been examined in the context of early and late adoption in different country markets. This so-called 'lead-lag' effect (Ganesh and Kumar 1996; Kalish, Mahajan, and Muller 1995; Takada 1991) varies according to factors such as social mixing and geographic proximity (Ganesh, Kumar and Subramaniam 1997; Putsis, Balasubramanian, Kaplan and Sen 1991), although it has proven difficult to consider lead-lag and mixing effects in the same framework. An exception is Kumar and Krishnan (2002) who applied the Generalized Bass Model (GBM) to simultaneously consider lead-lag and mixing effects, however a key limitation arising from the use of the GBM is the need for mixing to influence both early and late adopters identically, negating the possibility of testing for differences in

characteristics across adopter types. It is also difficult to examine detailed diffusion processes using country-based segments, as adopters in different countries may behave along dimensions that transcend political borders (Hofstede, Wedel and Steenkamp 2002).

These studies investigate influence *between* distinct populations rather than endogenous effects of earlier adopters upon later adopters *within* the same population. Such variation provides support for heterogeneous processes for internal influence across but not within market segments, because population-level diffusion models preclude examination of differences across individuals within the same segment (Strang and Tuma 1993). Despite these limitations, research across segments and over time has demonstrated the utility of considering adoption timing and inter-segment proximity as important determinants of new product adoption. In an effort to explicitly examine heterogeneous internal influence processes, social network models have been used to describe differences in the behavior of individuals during adoption of an innovation.

### **Social Network Models of Diffusion**

By allowing each individual adopter to have their own pattern of relationships, social network models of diffusion treat each individual as a distinct "market segment". Aggregation of these individuals yields collective behavior that may empirically resemble a diffusion curve (Strang and Tuma 1993). Two

perspectives to modeling social relationships are relational and structural networks (Valente 1995).

Diffusion effects can be explained from the relational network perspective that utilizes information concerning the nature of relations between people. Inward and outward communication to and from individuals can be mapped through nominations of alters (people other than the individual of focus) in the network with whom communication occurs (e.g. Rogers and Kincaid 1981; Coleman, Katz and Menzel 1966; Rogers and Beal 1958). Frequent nominations of an individual by network alters is indicative of strong influence, and early adoption of an innovation by individuals of this type can facilitate the linked alters to subsequently adopt. Nominations made by an individual toward others reflects connectedness to the network and suggests influence is received earlier, although empirical evidence here is mixed (Valente 1995:37). The relational network perspective thus emphasizes the role of an adopter's immediate personal network in explaining adoption behavior.

The structural network perspective is an alternative view that considers the architecture of relations across all adopters both immediate and distant in the network, and thus focuses upon the pattern and strength of relations rather than their nature (Valente 1995). Networks that are highly centralized feature groups of individuals who are densely connected within a group, but loosely connected to other groups. These networks are not conducive to rapid diffusion in a population because information remains confined in network cliques. In contrast, diffusion may be enhanced in a network when weak ties act as bridges that

connect relatively distant network groups (Granovetter 1983). The relational and structural views highlight in different ways, the role of micro-level adopter connections, and macro-level network features in diffusion.

The relationships that characterize each individual may be thought of as analogous to the covariates used in aggregate level diffusion research. At the aggregate level, covariates influence adoption, while at the individual level it is relationships with others that influence adoption. Social network models however do not capture the notion of path dependent influence over time. Relationships, and therefore influence, are assumed static in most social network diffusion studies, while in aggregate diffusion research, influence varies according to the number of individuals that have adopted at a given point in time. A unified longitudinal explanation for variation in relational effects attributed to inward and outward flows of information, and the network structure that facilitates these flows, is provided by heterogeneous diffusion models.

In a heterogeneous diffusion model, susceptibility, infectiousness, proximity, and propensity provide a rich description of the impact behavior in a social system has upon current individuals (Greve, Tuma and Strang 2001). Susceptibility is sensitivity to network influence, infectiousness refers to the ability to influence other network members, proximity describes the social closeness between a focal individual and network alters, and propensity is the intrinsic tendency to adopt independent of network influence. Formulated by Strang and Tuma (1993), the four dimensions of this approach capture both individual-specific and network-derived determinants of adoption. The contagion concepts

of susceptibility and infectiousness are analogous to the relational network concepts of 'connectedness' (nominations made), and 'opinion leadership' (nominations received) respectively, and proximity is analogous to the structural network concept of tie strength. Propensity is consistent with the concept of an individual's risk-return profile (e.g. Chatterjee and Eliashberg 1990), and also captures the influence of external sources such as media communication. While social network models view network connections as static, heterogeneous diffusion models incorporate temporal ordering and can model time varying network conditions on the basis of adoption behavior. Each adoption event alters network influence conditions that affect those that have yet to adopt.

The ability to monitor transmission of influence concurrent with these four contagion dimensions facilitates accurate attribution of cause and effect, but increases data collection requirements relative to aggregate level diffusion studies. Determination of inward network connections, outward connectedness, the strength of each of these, together with the risk-utility profile for every adopter can be difficult to achieve in a new product adoption context. This is reflected in the relatively small sample sizes used in social network research compared to market level diffusion studies. Three of the most famous studies in network diffusion: medical innovation (Coleman, Katz and Menzel 1966), Korean family planning (Rogers and Kincaid 1981) and Brazilian farmers (Rogers, Ascroft and Röling 1970), use sample sizes of 125, 1047 and 692 respectively (Valente 1995). The three population level products examined in Mahajan, Mason and Srinivasan (1986): room air conditioners, color televisions, and clothes dryers

have sample sizes of approximately 14.4 million, 32.3 million, and 12.5 million units respectively.

The heterogeneous diffusion model is a form of diffusion model that is able to incorporate social network features that aggregate population-level models generally do not. These enhancements allow for a more detailed attribution of effects than traditional diffusion studies that assume homogeneity of adopter characteristics. Nevertheless, data requirements make it difficult to apply to aggregate level studies that consider sample sizes several orders of magnitude greater than those normally used in social network research. An intermediate approach to measurement of network relationships is the use of common characteristics among adopting individuals.

### **Similarity as a Measure of Influence**

Network theory has been particularly informative in explaining the mechanics of diffusion, providing evidence that information travels through a population according to both the number and type of linkages between individuals in a social network (Valente 1995; Burt 1987; Granovetter 1973). According to models of diffusion, an individual's decision to adopt an innovation is based upon the behavior of others that are socially proximal and to which they have homophilous ties (Rogers 1995). These individuals may adopt according to the behavior of others for reasons of uncertainty reduction (Coleman, Katz and Menzel 1966) or status conformity (Burt 1987). While these two concepts deal with information collection and imitation respectively, both are based upon social



proximity. Individuals reduce their uncertainty toward a new product by consulting and gathering information from people that are socially close. Similarly, individuals aim to conform to people with whom they compare themselves - people that are also socially similar. Thus while uncertainty reduction relies upon consulting close contacts, and social conformity relies upon imitating one's social competitors (Dimaggio and Powell 1983), both rely upon influence from others that are socially proximal.

Common demographic attributes provide an avenue for measuring social proximity between members of a network. Organizations may imitate strategies of firms with similar resource endowments (Greve 1998), government institutions have been observed to act following prior actions by peer institutions of similar political orientation (Soule and Zylan 1997), and individuals may adopt a product upon observation of purchase by others with whom they identify. Mimicry of this kind occurs when an imitating party views the behavior of an acting party as similarly relevant to their own circumstance. This observation by potential adopters of prior adopters is an example of direct influence arising from homophily in social characteristics (Rogers 1983). Such similarity in social characteristics is also associated with *indirect* influence.

Influence by virtue of category membership can occur even when no direct relationships exist. "Cultural linkage" (Strang and Meyer 1993) or "nonrelational channels of diffusion" (McAdam and Rucht 1993) refer to avenues by which socially unconnected actors often behave similarly (Soule and Zylan 1997). Similar behavior across unconnected individuals can arise due to similar

circumstance dictating congruent needs. Organizations endowed with similar resources that face common competitive pressures may adopt familial strategies even in the absence of direct inter-organizational relationships. An explanation for such “mimetic adoption” (Greve 1998) is provided by the concept of structural equivalence across multiple individuals (Burt 1987), the presence of which facilitates diffusion amongst these structurally equivalent actors. Actors in similar network positions may adopt similar innovations, due to observance or path dependence. In observance, analysis of alters in similar network positions can substitute for an actor’s own grounded information search (Bikhchandani, Hirshleifer and Welch 1992). The behavior of a network alter may thus be imitated as a resource-saving action that reduces decision making time and effort. However path dependence requires no such observation as distinct actors with similar histories may independently innovate similar solutions to a problem – a phenomenon commonly cited by academics and artists as an alternative explanation to plagiarism when pieces of work asserted as different bear an uncanny resemblance to each another.

In the context of new product adoption, social proximity can be used to assess path dependence in the diffusion process. Every adopter’s decision is dependent upon the behavior of prior adopters, with socially close prior adopters having greater influence than more socially distant prior adopters. An absence of socially close prior adopters does not necessarily prevent adoption by subsequent adopters, but instead delays the decision to adopt while imitative

influences are transmitted through more heterophilous indirect social network channels.

There are therefore two reasons to consider common attributes of individuals in the investigation of diffusion mechanics: the known propensity for direct influence to travel directly between individuals with interpersonal connections that are often associated with similar demographic characteristics, and the tendency for unconnected parties to behave similarly due to common needs and resource endowments.

## **Summary**

Segments do not behave in isolation of one another. Diffusion studies capture this through population-level parameter variance, and social network studies capture this through atomistic relationships between individual adopters. Diffusion studies provide valuable forecasts of product adoption but offer limited insight into the mechanisms that underlie diffusion. Social network studies provide a detailed analysis of the diffusion process, but require highly detailed data that confines studies to small sample sizes and specific contexts. This data barrier has led to a presumption of a static network structure. The heterogeneous diffusion model incorporates dynamic social network relations into the traditional aggregate level diffusion approach, but at the cost of importing the need for detailed individual-level network data. An intermediate avenue for directly measuring social network relations is the use of common characteristics among adopting individuals to proxy for hypothesized direct and indirect

influence. The following section places inter-segment influence into a cross-generational context.

### **Adopter Segments for Different Product Generations**

Prior work has considered individuals who order prior to launch as innovative relative to post launch buyers (Moe and Fader 2002), and by extension it is also reasonable to view adopters of a first generation product as innovative, and adopters of a second generation product as imitative market segments. By definition the imitative segment is influenced by the innovative segment, and in general, innovative adopters are more influential in enhancing diffusion (Midgley, Morrison and Roberts 1992; Czepiel 1975), however some innovators such as “market mavens” (Feick and Price 1991) are more influential than others.

Heterogeneity in a second product generation market may be modeled through two populations: repeat adopters that have already purchased the previous first generation product, and new adopters that have not. These are referred to as generation 1 and generation 2 adopter populations respectively. It is useful to consider these two populations separately because their adoption behaviors are influenced by different factors, and the adoption behavior of each population can influence adoption behavior in the other differently. An understanding of these within- and between- population dynamics can inform us of how successive generations of a new product diffuse when some adopters have prior product experience and others do not.

Generation 2 adopters have no prior experience with the first generation product. These adopters may have been exposed to the first generation product through market or word-of-mouth information, but they did not purchase the first generation product. This lack of purchase is the key distinction between generation 1 and 2 adopter populations. Because they did not purchase the first product generation, generation 2 members are considered less innovative than generation 1 members. Their decision-making threshold is on average higher than that of generation 1 members, and their information comes from fewer external (media) and more internal (interpersonal) sources. Generation 2 adopters are more imitative than generation 1 adopters and their adoption decision is therefore more reliant upon consultation with others.

During adoption of the first product generation, generation 1 members follow a diffusion process for the same reasons generation 2 members follow a diffusion process. However when buying the second generation, generation 1 members differ in adoption behavior because they possess product knowledge gained from experience. For these veteran adopters of the second generation product, the decision to purchase is based less upon marketing information and behavioral imitation, and more upon marginal utility from comparisons of different product generations. Consistent with diffusion, adoption of the second generation product still follows a hazard process, however its form is dependent upon adoption decisions arising from judgments of marginal utility provided by the second generation product, rather than the network effects that influence the generation 2 population.

## **Development of Hypotheses**

Adopters of a second generation product are of two kinds: New Adopters who buy generation 2 but not generation 1, and Repeat Adopters who buy generation 2 and have also previously purchase generation 1. New Adopters rely upon prior adopters for advice more than Repeat Adopters, whose greater experiential knowledge lessens their need to seek information from the social network. Repeat Adopters are thus less susceptible to influence than New Adopters. The same experiential knowledge that makes Repeat Adopters less susceptible also makes them more influential. Experienced Repeat Adopters have greater knowledge-based credibility than New Adopters. Influence from Repeat Adopters is therefore stronger than influence from New Adopters, and Repeat Adopters may be said to be more infectious than New Adopters. These assertions are stated formally in Hypotheses 1 to 5:

- Hypothesis 1.        For second generation products, purchase by New Adopters is accelerated by social connection to prior New Adopters.
- Hypothesis 2.        For second generation products, purchase by New Adopters is accelerated by social connection to prior Repeat Adopters.
- Hypothesis 3.        For second generation products, purchase by New Adopters is accelerated more by social connection to prior Repeat Adopters, than social connection to prior New Adopters.

**Hypothesis 4.** For second generation products, purchase by Repeat Adopters is not accelerated by social connection to prior New Adopters.

**Hypothesis 5.** For second generation products, purchase by Repeat Adopters is not accelerated by social connection to prior Repeat Adopters.

## Chapter 3

### METHODOLOGY

*This chapter presents the hypotheses to be tested, data collection, product model generation selection, development of an influence measure, and the approach used for empirical estimation of the model.*

A cross-generational product context was used to examine differences in word of mouth influence and adoption time response between new and repeat adopters.

5 hypotheses were tested:

Hypothesis 1. For second generation products, purchase by New Adopters is accelerated by social connection to prior New Adopters.

Hypothesis 2. For second generation products, purchase by New Adopters is accelerated by social connection to prior Repeat Adopters.

Hypothesis 3. For second generation products, purchase by New Adopters is accelerated more by social connection to prior Repeat Adopters, than social connection to prior New Adopters.



**Hypothesis 4.** For second generation products, purchase by Repeat Adopters is not accelerated by social connection to prior New Adopters.

**Hypothesis 5.** For second generation products, purchase by Repeat Adopters is not accelerated by social connection to prior Repeat Adopters.

The methodology followed four phases: (1) data collection; (2) selection of product model generations; (3) definition of measures for the heterogeneous diffusion concepts of infectiousness, susceptibility, propensity, and proximity; and (4) empirical model estimation.

## **Data Collection**

A secondary new passenger car dataset was obtained from a market research firm. Passenger cars are a separate vehicle category from “light trucks”. This means vehicle types such as pickup trucks and many sports utility vehicles are not contained within the dataset. The distinction between passenger cars and light trucks has become less distinct in recent years. Sports utility vehicles for example are variously classified as passenger cars or light trucks. For future studies it is important to note this lack of discrimination is likely to increase as manufacturers expand hybridized models that include technical

features of both passenger cars and sports utility vehicles (and even pickup trucks).

This dataset consisted of survey response data gathered from individuals who purchased new passenger vehicles within the time period spanning September 1998 to December 2004. The market research firm compiled mailing lists from national-level vehicle registration data across all states of the United States. The protocol utilized stamped, self-addressed envelopes, and provided assurance that no sales solicitation would result from survey response. The survey instrument included questions concerning current and most recent vehicle ownership, and demographic information. The data were deemed suitable for this research because of respondent information concerning both current and previous automobile ownership allowing for cross-generational investigation. The subset of variables obtained from the data and used in the research are shown in Table 1.

**Table 1: Variables in the Dataset**

<b>Purchase Variables</b>	<b>Demographic Variables</b>
Calendar Date of Purchase	Household Income
Vehicle Make	Occupation
Vehicle Model Year	Level of Education
Vehicle Size Classification	Gender
Date new automobile purchased	Marital Status
Brand of automobile	Household Size
Automobile model year	Age
Size class of automobile	Race
Previously driven automobile model	Geographic State
Previously driven automobile model year	
Model and year of second household vehicle	
Model and year of third household vehicle	

The sampling strategy applied by the research firm used target sample size requirements. In general, more popular vehicle models were sampled more heavily than less popular models, although differences in target sample sizes are not proportional to market level differences in sales from year to year. While market level sales for an automobile model may vary over time, target sample sizes remain largely unchanged. Therefore, sample sizes from year to year do not reflect national level vehicle sales levels.

Surveys were administered on a quarterly basis and target samples for the first and second quarters of each year are double those of the third and fourth quarters. Samples were drawn randomly from the database. If a target sample size was not reached in a quarter, further random samples were drawn and additional surveys mailed until the target sample size for the quarter was approached. A breakdown of quarterly and annual sample distributions for each second generation automobile model used in the study are presented in Appendix A.

### **Selection of Product Model Generations**

Branding and manufacturing practices in the industry result in automobile models that are often related in content and lack technological distinction from one another. The same components may underlie mass-market and prestige versions of the same model. Such models are almost mechanically identical but for branding purposes they are targeted at different segments. For example the Ford Taurus and Mercury Sable are mainstream and prestige versions of

automobiles that have most of their technology in common. Consistent with the market segmentation intentions of manufacturers that design these models to appeal to different market segments, these models are treated as distinct automobiles for the purposes of this study.

A further complication arises from the practice of rebadging vehicles. For example the Geo Tracker, was also sold as the Chevrolet Tracker, and as the GMC Tracker, and in turn these models were re-branded from the original Suzuki Escudo vehicle model. Because customers may conceivably cross shop such automobile models within and between generations, these “twin” automobile models were excluded from this study if they were sold under different brand names. While such automobiles are not viewed by consumers as perfectly identical, consumers do perceive substantial similarity between rebadged automobiles (Sullivan 1998).

### **Generation Years versus Sale Years**

To investigate the complete adoption process, a subset of the data were used for motor vehicles whose most recent model generation began and finished within the 6 year window 1999-2004. The model year rather than the sales year of the vehicle was the basis for automobile model generation designation as model years reflect manufacturer changes in product content. Because a particular model year is usually available late in the prior calendar year (1999 model years for example are usually first sold in 1998), the number of sale years is often one year greater than the number of model generation years. Thus for

inclusion in the sample, individuals must have purchased a vehicle model whose model generation began and finished within the years 1999 to 2004. This distinction is necessary because while model years are used to designate a product as generation 1 or generation 2, it is the sales year of adoption that is the dependent variable.

Automobile model generations used in this research are defined by the manufacturer, and usually consist of substantial cosmetic and mechanical changes from a prior generation. Not all succeeding generations are 'all new' as most models between generations share components. Global manufacturing and product development means this is also often true between vehicle models and even between different manufacturers. Practices such as these led to the choice of using manufacturer definitions for model generations, rather than attempt to create an index of new technology content to distinguish between generations.

Within product generations, manufacturers usually incorporate minor technology content updates. Because continual feature incorporation is the benchmark practice in the industry, these updates can be viewed as maintenance of a product's quality and feature content rather than improvements or generational changes. This is consistent with consumer perception that vehicles from different model years are poor substitutes for one another (Copeland, Dunn and Hall 2005).

This research is concerned with second generation products. For these products, the first generation did not replace a prior vehicle generation of the

same or different brand name, and were built on vehicle platforms different from any related current or preceding model at the time of first generation product launch. Automobiles preceded by more than one generation are classified as existing products, and are not the focus of this study.

“G2” is the designation for models of the most recent generation. “G1” is the designation for models of the generation immediately prior. Based upon the requirement that the G2 sales period fall within 1999-2004 inclusively, 6 automobile models were isolated for use in this study.

This study calculates an influence ratio and uses the resultant measure together with additional propensity covariates in regression analyses. Because of missing values for some of these propensity covariates, some individuals could not be used in regression analyses, but were still retained for calculation of the influence ratio. Regression analyses thus utilize a sub-sample of individuals who have a complete set of propensity covariates.

The proposed measure of influence in this study (defined later in this chapter) is calculated from the number of similar and dissimilar prior adopters at yearly intervals. In the current sample repeat adopter sample size is always substantially lower than that of new adopters, and any micronumerosity sample size issues arise from repeat adopter restrictions. Because the proposed influence measure is a ratio of individuals, and adopters are classified dichotomously as either similar or dissimilar, the binomial procedure for determining the required sample size for evaluation of proportions in a population is used, given by:

$$n = pq*(Z_{\alpha}/E)^2$$

where:

n= required sample size

p= proportion in the population

q=(1-p)

Z=critical value from the normal distribution

$\alpha$ = desired confidence interval

E = margin for error

Note that the proportion of prior similar adopters is unknown. In the binomial distribution greatest variance and therefore the most conservative sample size estimate is provided if it is assumed the proportion of similar adopters is half (p=0.5). Choosing a 90% confidence interval (Z=1.65) and a 10% margin of error (E=0.1) for estimation of the proportion, the required sample size is calculated thus:

$$\begin{aligned} n &= (0.5)(0.5)*(1.65/0.1)^2 \\ &= 68.1 \end{aligned}$$

68 repeat adopters per year is therefore an upper bound on the desired sample size. It is unlikely half of all prior adopters will be similar to current adopters. A less conservative estimate is provided if it is assumed that 10% of all prior adopters are similar:

$$\begin{aligned} n &= (0.1)(0.9)*(1.65/0.1)^2 \\ &= 24.5 \end{aligned}$$

The value of 24.5 adopters provides an approximate lower bound for the required sample size. Based upon these sample size guidelines and the repeated yearly calculations of the influence ratio used in this study, an automobile model was only included in the study if the number of repeat adopters per sale year on

average was greater than or equal to 20. This excluded 2 of the 6 models.

These two models were the Honda Odyssey and Land Rover Discovery that had markedly lower numbers of repeat adopters per year than even the Mazda Miata which was the last automobile included. Automobile models retained and removed according to repeat adopter sample size are presented in Table 2.



**Table 2: Vehicle Models Retained and Removed According to Insufficient Repeat Adopter Sample Size**

<b>Model</b>	<b>G2 start</b>	<b>G2 end</b>	<b>G2 sale years</b>	<b>All Adopters</b>	<b>New Adopters</b>	<b>Repeat Adopters</b>	<b>New Sub-Sample</b>	<b>Repeat Sub-Sample</b>	<b>Repeat/G2 sale years</b>
<b>Retained</b>									
Dodge Neon	2000	2004	6	4516	1815	209	1138	152	34.8
Jeep Grand Cherokee	1999	2004	7	7951	1721	430	1144	318	61.4
Mazda Miata	1999	2004	7	2354	1185	153	836	128	21.9
Toyota Avalon	2000	2004	6	3854	1848	260	1083	152	43.3
<b>Removed</b>									
Honda Odyssey	1999	2004	7	3517	2323	49	1476	21	7.0
Land Rover Discovery I/II	1999	2004	7	1675	1246	97	949	80	13.9

The 4 retained automobile models belong to four different vehicle classes: compact sedan (Dodge Neon), sports utility vehicle (Jeep Grand Cherokee), convertible (Mazda Miata), and large sedan (Toyota Avalon). These four vehicles are therefore diverse in product characteristics.

### Sample Descriptive Statistics

Descriptive statistics presented for adopters in Tables 3 to 13 reveal several differences between the 4 automobile models and between New and Repeat Adopter groups.

**Table 3: Age Characteristics for New and Repeat Adopters**

		Dodge Neon	Jeep Grand Cherokee	Mazda Miata	Toyota Avalon
New Adopters	N	1,704	1,616	1,117	1,690
	Mean	40.69	45.94	49.22	60.57
	Std. Dev.	16.808	13.357	11.777	12.652
Repeat Adopters	N	200	415	146	241
	Mean	45.97	52.32	50.89	61.84
	Std. Dev.	17.231	11.390	11.344	11.663

For each automobile, Repeat Adopters always have a higher mean age than New Adopters. Distribution of household income by automobile and adopter group are displayed for New Adopters and Repeat Adopters in Table 4 and Table 5 respectively.

**Table 4: Household Income Characteristics for New Adopters**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
LESS THAN \$15000	85	4.7	4	0.2	3	0.3	10	0.5
\$15,000-\$24,999	212	11.7	28	1.6	12	1.0	32	1.7
\$25,000-\$34,999	289	15.9	70	4.1	38	3.2	84	4.5
\$35,000-\$44,999	258	14.2	96	5.6	77	6.5	103	5.6
\$45,000-\$59,999	231	12.7	179	10.4	106	8.9	141	7.6
\$60,000-\$74,999	214	11.8	217	12.6	115	9.7	179	9.7
\$75,000-\$99,999	142	7.8	295	17.1	204	17.2	239	12.9
\$100000-\$124999	85	4.7	202	11.7	164	13.8	202	10.9
\$125000-\$149999	25	1.4	125	7.3	95	8.0	101	5.5
\$150000-\$199999	8	0.4	102	5.9	90	7.6	94	5.1
\$200000-\$249999	6	0.3	43	2.5	37	3.1	38	2.1
\$250,000 OR MORE	5	0.3	64	3.7	44	3.7	38	2.1
Total	1,560	86.0	1,425	82.8	985	83.1	1,261	68.2
Missing	255	14.0	296	17.2	200	16.9	587	31.8
Total	1,815	100.0	1,721	100.0	1,185	100.0	1,848	100.0

The \$75,000-\$99,999 is the most prevalent category for all but the Dodge Neon whose lower income profile, likely reflects its economy vehicle status.

**Table 5: Household Income Characteristics for Repeat Adopters**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
LESS THAN \$15000	0	0	2	0.5	1	0.7	1	0.4
\$15,000- \$24,999	27	12.9	5	1.2	3	2.0	2	0.8
\$25,000- \$34,999	31	14.8	10	2.3	1	0.7	4	1.5
\$35,000- \$44,999	30	14.4	14	3.3	7	4.6	11	4.2
\$45,000- \$59,999	30	14.4	35	8.1	16	10.5	25	9.6
\$60,000- \$74,999	27	12.9	37	8.6	17	11.1	24	9.2
\$75,000- \$99,999	19	9.1	74	17.2	28	18.3	36	13.8
\$100000- \$124999	10	4.8	61	14.2	25	16.3	24	9.2
\$125000- \$149999	3	1.4	32	7.4	12	7.8	23	8.8
\$150000- \$199999	3	1.4	46	10.7	8	5.2	14	5.4
\$200000- \$249999	0	0.0	11	2.6	5	3.3	8	3.1
\$250,000 OR MORE	0	0.0	27	6.3	7	4.6	6	2.3
Total	180	86.1	354	82.3	130	85.0	178	68.5
Missing	29	13.9	76	17.7	23	15.0	82	31.5
Total	209	100.0	430	100.0	153	100.0	260	100.0

For Repeat Adopters the \$75,000-\$99,999 category is again the most prevalent except for the Dodge Neon. Categories of education are presented next in Table 6 and 7.

**Table 6: Education Categories for New Adopters**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
GRADE SCHOOL	25	1.4	14	0.8	8	0.7	16	0.9
HIGH SCHOOL	540	29.8	241	14.0	109	9.2	273	14.8
TRADE/VOCATIONAL	158	8.7	86	5.0	39	3.3	66	3.6
SOME COLLEGE	577	31.8	390	22.7	268	22.6	452	24.5
COLLEGE	335	18.5	592	34.4	378	31.9	499	27.0
GRADUATE								
POSTGRADUATE	135	7.4	350	20.3	360	30.4	478	25.9
COL								
Total	1,770	97.5	1,673	97.2	1,162	98.1	1,784	96.5
Missing	45	2.5	48	2.8	23	1.9	64	3.5
Total	1,815	100.0	1,721	100.0	1,185	100.0	1,848	100.0

Except for the Dodge Neon “College Graduate” is the most prevalent educational category.

**Table 7: Education Categories for Repeat Adopters**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
GRADE SCHOOL	2	1.0	0	0.0	0	0.0	1	0.4
HIGH SCHOOL	61	29.2	61	14.2	11	7.2	29	11.2
TRADE/VOCATIONAL	22	10.5	20	4.7	4	2.6	5	1.9
SOME COLLEGE	54	25.8	89	20.7	33	21.6	60	23.1
COLLEGE	46	22.0	146	34.0	47	30.7	82	31.5
GRADUATE								
POSTGRADUATE	19	9.1	110	25.6	54	35.3	79	30.4
COL								
Total	204	97.6	426	99.1	149	97.4	256	98.5
Missing	5	2.4	4	0.9	4	2.6	4	1.5
Total	209	100.0	430	100.0	153	100.0	260	100.0

A similar pattern is apparent for Repeat Adopters, except for the Dodge Neon whose more prevalent category is now “High School” instead of “Some College”. However there is evidence for all models that those at or around the college level have increased their level of education relative to New Adopters. Occupation categories are examined next in Tables 8 and 9.

**Table 8: Occupation Categories for New Adopters**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
TECH/SALES/ADMIN	265	14.6	231	13.4	181	15.3	152	8.2
MGR/PROFESSIONAL	428	23.6	731	42.5	576	48.6	501	27.1
CRAFT/REPAIR	61	3.4	40	2.3	18	1.5	19	1.0
OPERATOR/LABORER	177	9.8	52	3.0	18	1.5	15	0.8
SERVICE	159	8.8	64	3.7	49	4.1	68	3.7
FARM/FOREST/FISH	5	0.3	7	0.4	3	0.3	4	0.2
ARMED SERVICES	29	1.6	23	1.3	8	0.7	3	0.2
OTHER	332	18.3	188	10.9	83	7.0	122	6.6
Total	1,456	80.2	1,336	77.6	936	79.0	884	47.8
Missing	359	19.8	385	22.4	249	21.0	964	52.2
Total	1,815	100.0	1,721	100.0	1,185	100.0	1,848	100.0

Disregarding the occupation category “Other” the most common occupation category is always “Mgr/Profession” followed by the “Tech/Sales/Admin”. Respondents for the Toyota Avalon appear particularly reluctant to provide information concerning their occupation with over half of responses coded as ‘Missing’. This reluctance is possibly due to the mean age of Avalon respondents exceeding 60 years, meaning a substantial number of respondents are retired relative to buyers of the other automobiles.

**Table 9: Occupation Categories for Repeat Adopters**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
TECH/SALES/ADMIN	26	12.4	55	12.8	19	12.4	28	10.8
MGR/PROFESSIONAL	57	27.3	197	45.8	83	54.2	81	31.2
CRAFT/REPAIR	3	1.4	7	1.6	3	2.0	2	0.8
OPERATOR/LABORER	18	8.6	16	3.7	1	0.7	1	0.4
SERVICE	18	8.6	11	2.6	4	2.6	5	1.9
FARM/FOREST/FISH	0	0.0	0	0.0	0	0.0	2	0.8
ARMED SERVICES	3	1.4	5	1.2	1	0.7	0	0.0
OTHER	34	16.3	29	6.7	9	5.9	10	3.8
Total	159	76.1	320	74.4	120	78.4	129	49.6
Missing	50	23.9	110	25.6	33	21.6	131	50.4
Total	209	100.0	430	100.0	153	100.0	260	100.0

Results for Repeat Adopters show the same pattern of occupational category responses observed for New Adopters. Again more than half of respondents for the Toyota Avalon did not provide their occupational category. Gender characteristics are presented next in Tables 10 and 11.

**Table 10: New Adopter Gender Characteristics**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
MALE	718	39.6	860	50.0	679	57.3	982	53.1
FEMALE	1,017	56.0	790	45.9	486	41.0	778	42.1
Total	1,735	95.6	1,650	95.9	1,165	98.3	1,760	95.2
Missing	80	4.4	71	4.1	20	1.7	88	4.8
Total	1,815	100.0	1,721	100.0	1,185	100.0	1,848	100.0

Males are a higher proportion of adopters for all automobiles except the Dodge Neon.

**Table 11: Repeat Adopter Gender Characteristics**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
MALE	86	41.1	256	59.5	85	55.6	158	60.8
FEMALE	121	57.9	168	39.1	67	43.8	92	35.4
Total	207	99.0	424	98.6	152	99.3	250	96.2
Missing	2	1.0	6	1.4	1	0.7	10	3.8
Total	209	100.0	430	100.0	153	100.0	260	100.0

As for New Adopters, males are a higher proportion except for the Dodge Neon.

Race distribution characteristics are examined next in Tables 12 and 13.

**Table 12: New Adopter Race Characteristics**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
WHITE ONLY	1,435	79.1	1,451	84.3	1,020	86.1	1,539	83.3
HISPANIC+HISP-WH	101	5.6	60	3.5	36	3.0	29	1.6
ASIAN+ASIAN-WH	19	1.0	32	1.9	36	3.0	77	4.2
BLACK+BLACK-WH	113	6.2	49	2.8	11	0.9	61	3.3
NAT AM+NAT AM-WH	40	2.2	29	1.7	16	1.4	34	1.8
OTHER+OTHER-WH	30	1.7	23	1.3	10	0.8	14	0.8
ADDTL DUAL RACES	11	0.6	3	0.2	2	0.2	1	0.1
> 2 RACES	6	0.3	0	0	4	0.3	4	0.2
Total	1,755	96.7	1,647	95.7	1,135	95.8	1,759	95.2
Missing	60	3.3	74	4.3	50	4.2	89	4.8
Total	1,815	100.0	1,721	100.0	1,185	100.0	1,848	100.0

**Table 13: Repeat Adopter Race Characteristics**

	Dodge Neon		Jeep Grand Cherokee		Mazda Miata		Toyota Avalon	
	Freq	%	Freq	%	Freq	%	Freq	%
WHITE ONLY	176	84.2	395	91.9	136	88.9	233	89.6
HISPANIC+HISP-WH	7	3.3	5	1.2	1	0.7	2	0.8
ASIAN+ASIAN-WH	2	1.0	2	0.5	6	3.9	6	2.3
BLACK+BLACK-WH	6	2.9	9	2.1	1	0.7	3	1.2
NAT AM+NAT AM-WH	6	2.9	9	2.1	3	2.0	4	1.5
OTHER+OTHER-WH	3	1.4	2	0.5	1	0.7	0	0.0
ADDTL DUAL RACES	0	0.0	1	0.2	0	0.0	0	0.0
> 2 RACES	0	0.0	1	0.2	0	0.0	1	0.4
Total	200	95.7	424	98.6	148	96.7	249	95.8
Missing	9	4.3	6	1.4	5	3.3	11	4.2
Total	209	100.0	430	100.0	153	100.0	260	100.0

Race category distributions are quite consistent across New and Repeat Adopter groups. “White Only” is always the most common mode of race category. The dominant proportion of “White Only” respondents is lowest for the Dodge Neon in both New and Repeat Adopter groups.



## **Development of Measures**

Both individual characteristics and social effects can influence purchase over time. Individual characteristics are treated as unchanging over time, while social influence is a time varying construct. Following Strang and Tuma's (1993) interpretation of factors that affect the adoption decision, the concepts of infectiousness, susceptibility, propensity, and proximity are used to capture individual and network effects.

To capture these dynamics, a panel-type dataset was constructed as deemed suitable for infrequently purchased durables with new technology content (Kim, Srivastava and Han 2001; Hsiao 1986). Propensity factors remain constant over time for each individual. The status of an individual as susceptible and infectious are fixed according to New or Repeat Adopter status. The measure of proximity between susceptible and infectious adopters is calculated for each time period and is time varying. The dependent variable, measures of infectiousness, susceptibility and propensity, are defined before turning to development of the proximity measure.

### **Dependent Variable: Year of Purchase**

An individual's time to adoption is the dependent variable. Purchase timing in the dataset is measuring with calendar date precision, however sample size guidelines for estimation of proportions require independent time varying covariates to be assessed over 12 month intervals. To maintain parity between

dependent and independent variable time intervals, time to adoption was measured in years.

### **Adopter Groups: Susceptibility and Infectiousness**

Respondents were divided into one of two categories:

- **New Adopters:** An individual was classified as a new adopter if they purchased a vehicle model in G2 and did not own G1 of that model.
- **Repeat Adopters:** An individual was classified as a repeat adopter if they purchased both G1 and G2.

New Adopters represent an adopting population that is more **susceptible** to influence than Repeat Adopters. Prior Repeat Adopters represent a population that is more **infectious** than prior New Adopters.

### *Propensity*

**Propensity** is the likelihood of adoption by an individual, independent of network factors. Propensity is assumed to be constant and is measured by the age of the vehicle replaced, number of vehicles owned, and household income. As a durable good, the age of the vehicle currently owned, and the number of vehicles owned, clearly impact upon the need to purchase a replacement vehicle. Mechanical reliability of durable goods declines over time and the greater the number of alternative substitutes owned (number of vehicles), the lower the need for a replacement. Household income was measured because higher income

individuals are known to have higher tolerance for risk in risk-return utility functions and adopt more quickly.

*Proximity: the Demographic Similarity Ratio*

Determining whether two individuals are of identical character and social status is difficult. Studies of networks and diffusion have consequently utilized more visible qualities as proxy measures of similarity. Similarities consistent with structural network equivalence at the organizational level have been measured along geographic lines (Greve 1998; Davis and Greve 1997; Soule and Zylan 1997), organizational size (Davis and Greve 1997) and market size (Greve 1998). Indirect relationships in these studies were found to predict adoption of innovations where more similar organizations adopted similar innovations at similar times. De Bruyn and Lilien (2004) tracked direct relations at the individual level and found age, education, sex and occupational similarities provided avenues for word of mouth influence in a consumer decision making context.

To measure the influence of prior adopters upon current adopters an index of demographic similarity was constructed. This index assessed the proportion of prior adopters that are demographically similar to a current adopter. This time varying measure of **proximity** between individuals provides a means of linking past and present adopters.

The demographic characteristics used in this ratio calculation are:

- Household income (12 categories)
- Age (numeric)

- Race (8 categories)
- Level of education (6 categories)
- Occupation (8 categories)
- Gender (dichotomous)

Demographic factors were selected for likely time invariance. With the exception of “Age” all demographic characteristics were assumed to be constant for each individual. A tolerance range of plus or minus 5 years was used to account for change in age. Individuals were deemed similar along demographic lines if:

- they were of the same income class;
- they were within plus or minus 5 years in age;
- of the same race;
- of the same level of education;
- of the same occupation;
- of the same gender.

Variable properties for the 6 demographic characteristics are presented in Table 14.

**Table 14: Variable Properties for Demographic Characteristics**

Income	Occupation	Race	Education	Gender	Age
LESS THAN \$15000	TECH/SALES/ADMIN	WHITE ONLY	GRADE SCHOOL	MALE	NUMERIC
\$15,000-\$24,999	MGR/PROFESSIONAL	HISPANIC+HI SP-WH	HIGH SCHOOL	FEMALE	
\$25,000-\$34,999	CRAFT/REPAIR	ASIAN+ASIAN -WH	TRADE/VOCATIONAL		
\$35,000-\$44,999	OPERATOR/LABORER	BLACK+BLAC K-WH	SOME COLLEGE		
\$45,000-\$59,999	SERVICE	NAT AM+NAT AM-WH	COLLEGE GRADUATE		
\$60,000-\$74,999	FARM/FOREST/FISH	OTHER+OTH ER-WH	POSTGRADU ATE COL		
\$75,000-\$99,999	ARMED SERVICES	ADDTL DUAL RACES			
\$100000-\$124999	OTHER	> 2 RACES			
\$125000-\$149999					
\$150000-\$199999					
\$200000-\$249999					
\$250,000 OR MORE					

While degrees of similarity from 1 to 6 could potentially be examined, the nature of demographic measures such as race and gender mean almost no individuals have zero, or all 6 characteristics in common, and almost all individuals have one or two demographic features in common. This is because gender has only two categories, and for all car models the predominant race representation was 'white'. Therefore to establish the degree of similarity needed to informatively observe influence effects, three ratios with increasingly stringent similarity criteria were calculated:

- 3 or more demographic features in common;
- 4 or more demographic features in common;
- 5 or more demographic features in common;

These are referred to in the study as degree 3, 4, and 5 similarity respectively. Degree 3 similarity requires a past adopter to have 3 or more characteristics in common and thus includes individuals of degree 4 and 5 similarities. Degree 4 similarity requires 4 or more common characteristics and thus includes individuals of degree 5 similarity. The different similarity degrees are thus nested sets of individuals with more strict higher degrees consisting of subsets of individuals who also appear in less strict lower degrees. The algebraic expression used to calculate the demographic similarity ratio is developed next.

Let adopter  $j$  be fixed according to their year  $Y$ , of adoption given by:

$$Y(j);$$

All prior adopters are compared to  $j$ , given by:

$$Y(i) \quad \text{where } Y(i) < Y(j) ;$$

These prior adopters are denoted collectively as set members:

$$I(j) \quad \text{where } I(j) \{i=Y(i) < Y(j)\} ;$$

Individual  $Y(j)$  is compared to all prior adopters  $I(j)$  along 6 demographic dimensions according to the following decision rules:

$S_{ij}(\text{age})$	$= 1$	if $ \text{age}_j - \text{age}_i $	$\leq 5$ , 0 otherwise;
$S_{ij}(\text{inc})$	$= 1$	if $\text{inc}_j - \text{inc}_i$	$= 0$ , 0 otherwise;
$S_{ij}(\text{edu})$	$= 1$	if $\text{edu}_j - \text{edu}_i$	$= 0$ , 0 otherwise;
$S_{ij}(\text{gen})$	$= 1$	if $\text{gen}_j - \text{gen}_i$	$= 0$ , 0 otherwise;
$S_{ij}(\text{rac})$	$= 1$	if $\text{rac}_j - \text{rac}_i$	$= 0$ , 0 otherwise;
$S_{ij}(\text{occ})$	$= 1$	if $\text{occ}_j - \text{occ}_i$	$= 0$ , 0 otherwise;

where:

age = numeric age of adopter;  
inc = income level of adopter;  
edu = education level of adopter;  
gen = gender of adopter;  
rac = race category of adopter;  
occ = occupational category of adopter;

To sum the 6 dummy results:

$$\begin{aligned} \text{let } h &= [\text{age}, \text{inc}, \text{edu}, \text{gen}, \text{rac}, \text{occ}] \\ &= [1, \dots, 6] \end{aligned}$$

Adopter  $j$  is deemed similar to prior adopter  $i$  when  $\sum_h S_{ijh}$  is sufficiently high. To be sufficiently high, common characteristics must satisfy the 3, 4, or 5 degree cutoff. Similarity is thus dichotomous and is given by:

$$D_{cij} = 1 \quad \text{if } \sum_h S_{ijh} \geq c, i \in I(j);$$

where:

$c = 3, 4, 5$  cutoff points reflecting degree 3, 4, and 5 similarity

The proportion of similar prior adopters is the sum of similar prior adopters divided by the sum of all prior adopters. This ratio can be expressed thus:

$$\frac{\sum_{i \in I(j)} D_{cij}}{\sum_{i \in I(j)} 1}$$

For each ratio the numerator is the cumulative number of prior adopters with  $c$  or more demographic characteristics in common with the current adopter, and the denominator is the total number of prior adopters.

These ratios were calculated from all individuals that adopt in a prior calendar year to a current adopter. Consequently individuals who adopt in year

one have no demographic similarity ratio as no individuals adopt prior to their adoption year. An individual adopting in year 2 has a single demographic similarity ratio calculated from all individuals who adopted in year 1; an individual adopting in year 3 has two demographic similarity ratios based upon all prior adopters in year 1 and another based upon all prior adopters in both year 1 and year 2, and so on. These demographic similarity ratios are thus time-varying covariates with the ratio calculated repeatedly for each year prior to an adopter's purchase year.

Three forms of this ratio are calculated:

- a ratio for all prior adopters (new adopters and repeat adopters);
- a ratio for prior new adopters;
- a ratio for prior repeat adopters.

Respectively, these 3 forms assess overall prior effects, effects due to prior new adopters, and effects due to prior repeat adopters.

The ratio is calculated for each individual for every time period of exposure prior to purchase, from every prior adopter in the dataset. At each comparison, this involves comparison of the 6 demographic dimensions between individuals. Direct comparisons of demographic characteristics results were time consuming. Using the spreadsheet program Microsoft Excel, calculation times for a single year of exposure ranged between 2-8 hours depending upon sample size for the automobile model. To improve the efficiency of the comparison process a matrix for each individual was created to store the accumulation of similar prior individuals as each year was calculated. The PROCIML statement in SAS v9.1



was used to conduct the matrix algebra manipulations. The improvement in computation time was dramatic. Calculation time for all time periods for most automobile models took less than an hour. The cost of utilizing this cumulative approach is an inability to determine the source of similarity between individuals. Between current and prior adopters, it is not possible to determine which demographic characteristics are similar, only that a certain number (3, 4 or 5) are in common. Sensitivity simulation results partially compensate for this abstractness through stepwise removal of each of the 6 demographic characteristics. This involved repeating the dataset construction and regression analyses 6 times, once for each characteristic omitted.

### **The Demographic Similarity Ratio: Characteristics**

The demographic similarity ratio determines heterogeneous internal influence by taking a sample of adopters. The ratio differs from the internal influence parameter used in diffusion models, and is designed to assess network influence from a sub-sample of adopters. These two key points are discussed next.

The demographic similarity measure is a sampling ratio. The greater the proportion of prior adopters with demographic characteristics in common with a current adopter, the higher the ratio for that adopter. Lower ratios indicate prior adopters have fewer demographic characteristics in common. As a ratio of two cumulative functions, the demographic similarity ratio may increase or decrease at different points in time according to the number of connected versus

unconnected adopters. Each individual contributes equally to the ratio which is determined uniquely for each potential adopter until adoption occurs. This is similar in principle to diffusion models that interpret word of mouth through an influence parameter. For example the Bass Diffusion Model (Bass 1969) is of the form:

$$n(t) = p[m - N(t)] + (q/m) * N(t)[m - N(t)]$$

where:

$n(t)$  = number of adopters at time  $t$ ;  
 $N(t)$  = cumulative number of adopters;  
 $m$  = market potential;  
 $p$  = coefficient of innovation;  
 $q$  = coefficient of imitation.

Notably, the contribution of an adopter to  $N(t)$  declines as the cumulative number of adopters increase. Because  $N(t)$  is cumulative, it describes a monotonically increasing function, and as a consequence, each individual's proportional contribution to  $N(t)$  declines over time. At all times, each adopter makes an equal contribution to  $N(t)$  and therefore an equal contribution to the measure of internal influence,  $q$ . This means that all potential adopters receive influence equally.

It is stressed that the demographic similarity ratio measures the proportion of *connected* adopters, whereas internal influence in diffusion models generally assess all prior adopters and do not allow for heterogeneous influence between past and potential adopters. Like the Bass Model, the demographic similarity ratio weights all adopters equally, a key difference however is that a prior adopter only exerts influence when similar to a potential adopter, whereas a dissimilar

prior adopter lowers the ratio. However it would be incorrect to conclude from the ratio that adoption by an unconnected individual reduces influence in the network. Adopters may exert positive or no influence, but not negative influence. Although some adoption models have proposed modeling negative influence (Sharif and Ramanathan 1984; Midgely 1976), the similarity ratio does not. Because adoption data are not at the population level, it is not possible to simply accumulate all prior connected adopters. It is instead necessary to observe the available sample of adopters to measure if the proportion of connected to unconnected adopters changes over time, and apply this as an indicator of influence exerted by connected adopters at the population level. In the sample ratio, dissimilar individuals model lack of influence and not negative influence. It is thus important the sample provides a valid representation of influence.

The sampling assumption holds that the ratio measure is a reliable and valid indicator of influence from prior to current adopters. The data collection process randomly sampled a population level list of all new vehicle registrants. The classification of individuals into new and repeat categories, and choice of demographic characteristics as a measure of influence in the research are therefore unrelated to the process used to obtain data. It is therefore reasonable to assume the proportion of new and repeat adopters in the sample is similar to that in the population, provided the sample size is large enough to offset statistical fluctuations.

The data in this research are themselves a sample of the overall market for each automobile and to the extent this sample may not be representative of

the market, any derived ratios may also be non representative. This cannot be controlled for in the present study, however the problem of small samples was partially accounted for by ensuring that ratios for the smaller repeat adopter group (repeat adopters groups are always smaller than new adopter samples) are calculated from 20 or more adopters per calendar year. While this decision removed two second generation models from the study, partial vindication of this decision is provided by the observation that there is no consistent pattern in the results related to sample size of new or repeat adopters. 20 repeat adopters in a year is too small a number to be deemed representative of the market, but large enough to claim sufficient representation of the data in the sample.

### **Empirical Model Estimation: Piecewise Weibull versus Cox Regression**

Diffusion models assess the rate at which members of a susceptible population transition from a potential adopter to a past adopter state. The size of the susceptible population must be specified and the rate at which individuals transition from a potential adopter to adopter state defines the distribution of the adoption function. If the size of the potential adopting population is unknown, or the number of total adopters at all points in time is unknown, diffusion models cannot be used to describe new product adoption. The data in the research represent a subset of the market selected by event occurrence up to a target sample level, and therefore cannot be used to provide estimates of the potential market or the total number of adopters. Hazard rate models are more flexible

than diffusion models because it is not necessary to observe the entire population.

### *Hazard Rate Models*

Hazard rate models examine the probability of event occurrence over time. Parametric hazard rate models specify the distribution of the hazard (such as an exponential distribution) while semi-parametric models leave the distribution of the hazard unspecified (as in Cox Regression). Both parametric and semi-parametric models may be modeled as proportional hazards where differences in hazards over time between individuals remain constant. Consideration of factors where effects upon individual hazards vary over time, results in non-proportionality between the hazards of individuals. Incorporation of time-varying covariates in either parametric or semi-parametric hazard rate models is thus a means of modeling non-proportional hazard rates.

The choice of a parametric distribution is largely an empirical question determined by model fit. Even a strong a priori rationale for specification of a particular parametric distribution must be weighed against the possibility the underlying process that generates the hazard is less than fully understood. Importantly, incorrect specification can result in inaccurate estimation of covariate coefficients. This provides a strong argument for leaving the baseline hazard unspecified through the use of semi-parametric Cox regression.

The data in this research are known to have several sampling characteristics:

- 1) All individuals experience an event;

- 2) There are target sample sizes for each year that are not based upon market level sales;
- 3) Sample responses obtained in the first and second quarters are approximately twice the number of those in the third and fourth.

Respectively this means: (1) there are no right-censored data; (2) sample sizes are not representative of market sales levels; and (3) the distribution of events within model years is higher during the first half of the year. These sample characteristics preclude determination of the effect of time as a cause of purchase. In the context of consumer durables (in this case automobiles), product factors such as durability mean time undoubtedly has an influence upon time to the next vehicle adoption, however sample characteristics do not allow time to be tested in a causal manner. A hazard rate therefore cannot be specified with the aim of determining the effect of time upon event occurrence. The influence of covariates however may still be investigated if the effect of time (or more accurately, the distribution of events in the sample) is suitably accounted for.

The sampling strategy varies across quarters, but is consistent within a 12 month period. A piecewise approach to regression may therefore account for between year variations, and the choice of a suitable parametric distribution can account for within year variations. Because the distribution of events within a year is not constant (as first and second quarter samples sizes are twice that of third and fourth quarters) a piecewise exponential distribution is not appropriate.

By virtue of a more flexible specification, the piecewise Weibull is able to account for the non-constant event occurrence within each year. In addition, a piecewise approach is necessary to incorporate the time-varying covariates that are used to assess demographic similarity in this study. The piecewise Weibull model in hazard form is specified as:

$$h_i(t) = c_j \lambda_j t^{c_j-1}$$

$$\text{for } a_{j-1} \leq t < a_j$$

where:

$i$  = individual  $i$

$t$  = time

$c$  = shape parameter

$\lambda$  = rate parameter

$j$  = number of intervals

$a$  = cut point for the interval,  $a_0 = 0$ ,  $a_J = \infty$

Thus, the piecewise Weibull allows the hazard shape and scale parameters to vary for each interval  $j$  given by  $[a_{j-1}, a_j]$ , thereby accounting for within year sampling variation uniquely across different years. The non-piecewise form of the model does not partition by intervals, and does not incorporate the interval indicator  $j$ .

Alternatively, Cox regression allows for an unspecified baseline hazard, removing the need for selection of a parametric distribution. Events must still conform to a failure time process but the distribution of events over time need not be parametric in form. Purchase events for automobiles in the current sample are consistent with a failure time process that by reason of the data collection strategy, appear non-parametric in nature. The attraction of Cox regression can

be shown by contrasting the regression equations for Weibull regression versus Cox regression. Estimation of hazard rate models is typically undertaken in log form to ensure time remains positive as a dependent variable, and allow for an additive linear relationship among the variables. The Weibull model in log form is:

$$\log h_i(t) = \alpha \cdot \log t + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik}$$

where  $\alpha \cdot \log t$  represents the underlying time-based (Weibull) hazard distribution that must be estimated together with all covariates. The Cox model in log form can be represented as:

$$\log h_i(t) = \alpha(t) + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik}$$

where  $\alpha(t)$  represents any underlying hazard distribution that need not be specified due to the method of partial likelihood estimation used in Cox regression. Leaving the underlying hazard unspecified removes the possibility of modeling event distribution over time incorrectly, but reduces estimation efficiency for the covariates. Both piecewise Weibull and Cox regression were used in the research, and the results compared.

## **Regressions**

The time-varying demographic similarity ratios, and static propensity factors, were entered as explanatory variables in regressions upon the log of adoption time for separate New and Repeat Adopter groups. For each adopter group, 5



regressions were estimated to assess the effect of the demographic similarity ratios upon time to adoption:

1. A baseline regression with static covariates only;

$$\log(\text{time}_{jt}) = \alpha(t) + \beta_1(\text{inc}_j) + \beta_2(\text{veh}_j) + \beta_3(\text{vehage}_j) + u_{jt}$$

2. ALL prior adopters;

$$\log(\text{time}_{jt}) = \alpha(t) + \beta_1(\text{inc}_j) + \beta_2(\text{veh}_j) + \beta_3(\text{vehage}_j) + \beta_4(\text{ALL}_{jt}) + u_{jt}$$

3. Prior NEW adopters;

$$\log(\text{time}_{jt}) = \alpha(t) + \beta_1(\text{inc}_j) + \beta_2(\text{veh}_j) + \beta_3(\text{vehage}_j) + \beta_4(\text{NEW}_{jt}) + u_{jt}$$

4. Prior REPEAT adopters;

$$\log(\text{time}_{jt}) = \alpha(t) + \beta_1(\text{inc}_j) + \beta_2(\text{veh}_j) + \beta_3(\text{vehage}_j) + \beta_4(\text{REPEAT}_{jt}) + u_{jt}$$

5. Prior NEW adopters and prior REPEAT adopters.

$$\log(\text{time}_{jt}) = \alpha(t) + \beta_1(\text{inc}_j) + \beta_2(\text{veh}_j) + \beta_3(\text{vehage}_j) + \beta_4(\text{NEW}_{jt}) + \beta_5(\text{REPEAT}_{jt}) + u_{jt}$$

where:

time	= adoption time in years since year of product launch
j	= adopter j
t	= year of adoption, $1 < t \leq T$
inc	= income of adopter
veh	= number of vehicles owned by adopter
vehage	= calendar model year of vehicle previously driven
ALL	= demographic similarity ratio calculated from prior All Adopters
NEW	= demographic similarity ratio calculated from prior New Adopters
REPEAT	= demographic similarity ratio calculated from prior Repeat adopters

The time varying covariate ALL in regression form 2 is used to assist in hypothesis testing of simultaneous prior New and Repeat Adopters. Should NEW and REPEAT have similar effects in regression models 3 and 4, it is likely simultaneous consideration in model 5 would result in misleading conclusions. Inflated variance due to collinearity could result in one or both of NEW and REPEAT coefficients estimated as insignificant when in fact both groups are exerting significant influence. ALL is a demographic similarity ratio calculated from both NEW and REPEAT adopters collectively and is entered as a single regressor in regression 2, thus avoiding possible collinearity that could occur if NEW and REPEAT (with similar effects in regressions 3 and 4) were entered as distinct covariates in regression form 5, while still allowing for simultaneous consideration of New and Repeat Adopter influence effects.

Regression 2 may also be interpreted as a relaxation of the assumption prior adopters exert influence differentially according to New and Repeat status. This means if regressions 3 and 4 show similar effects for NEW and REPEAT, and the coefficient for ALL in regression 2 is consistent with NEW and REPEAT, effects cannot be separated by New and Repeat Adopter segments, as influence stems from a single prior adopter group rather than distinct New and Repeat groups. Substantively this would mean New and Repeat Adopters have equal infectiousness. Regression analyses 1 to 5 are represented in Table 15.

**Table 15: Analyses by Group and Covariate**

	Static Covariates	ALL	NEW	REPEAT
New Adopters	X			
	X	X		
	X		X	
	X			X
	X		X	X
Repeat Adopters	X			
	X	X		
	X		X	
	X			X
	X		X	X

To examine the prevalence of any influence effects, regressions were conducted for each of the 3, 4, and 5 degree demographic similarity ratios.

Relative to the baseline model with only static covariates, a log likelihood statistic was used to assess improvement in fit for models with time varying covariates. Statistical significance was assessed by comparing twice the difference in log likelihood statistics with 5% critical values of the Chi-square distribution. Log likelihood comparisons could be made within demographic similarity degrees but not between, as different degree similarity ratios are calculated from different sets of adopters. Regressions between degrees are thus non-nested.

### **Sensitivity Tests for the Demographic Similarity Covariates**

Robustness tests were conducted for each degree similarity measure through sequential removal of each demographic characteristic and recalculation

of the similarity covariate. Regressions were then repeated with the reduced set of covariates.

## **Chapter 4**

### **RESULTS**

#### **Piecewise Weibull Regression versus Cox Regression**

The piecewise Weibull distribution was chosen for its ability to model the distribution of the known sample fluctuations in purchase levels over time that were an inherent feature of the dataset. Cox regression utilizes partial likelihood estimation which leaves the baseline distribution for events over time unspecified. Since the piecewise Weibull was chosen to account for sample variation over time rather than estimate the effect of time upon purchase, Cox regression is a natural alternative to determine the suitability of the piecewise Weibull distribution. Support for the piecewise Weibull is provided if covariate effects upon purchase time for both methods are similar. The statistical software package SAS v9.1 was used to conduct all regression analyses.

Analyses were run for 3, 4, 5 and degree similarity. A 5% significance level was used for selection of coefficient significance. The results were highly congruent across piecewise Weibull and Cox regressions. As expected parametric estimation was more sensitive than semi-parametric estimation as some information is lost during partial likelihood estimation in Cox regression. The piecewise Weibull analyses yielded 169 significant static covariate and 108 significant time varying covariate coefficients across degree 3, 4, and 5 demographic similarity models. Cox regression results yielded 154 significant static and 80 significant time varying covariate coefficients. Of the 234 significant

coefficients identified during Cox regression, 225 were also identified by the piecewise Weibull technique for an overall overlap identification percentage of 96.2%. Because more significant coefficients were identified by the piecewise Weibull than the Cox regression method, Cox regression results overlapped less with piecewise Weibull results and commonly identified 81.6% of significant coefficients. The similarity of these results is consistent with the observation that Cox regression provides a reasonable approximation to parametric regression when covariates are uncorrelated (Kalbfleisch 1974). All commonly identified coefficients inferred the same direction of effect. The choice of the piecewise Weibull distribution to account for sampling fluctuations is therefore supported by the comparison results.

The choice was made to utilize piecewise Weibull estimation in preference to Cox regression because when the form of the underlying distribution is known, parametric estimation provides more efficient estimates than semi-parametric estimation in finite samples (Efron 1977). This greater efficiency is reflected in the comparison results where a greater number of significant effects were identified by piecewise Weibull regression. An additional advantage of using the piecewise Weibull is faster computation time. The Cox regression procedure in SAS v9.1 procedure requires recalculation of the dataset for every regression whereas the piecewise regression procedure does not.

In these analyses, piecewise Weibull estimation yields 3 kinds of covariates: static, time varying, and time-dependent. Normally time-dependent covariates assess how time affects purchase (i.e. the hazard of adoption over

time). However in this model time-dependent covariates have no substantive interpretation as the distribution of events over time is a result of target sample variations rather than market-level adoption dynamics. This means higher purchase levels indicate larger sample sizes instead of higher rates of market adoption.

In this study the purpose of the time-dependent covariates in the piecewise modeling approach is to partial out the effect of the longitudinal sampling frames used in data collection. Similarly, the scale and shape coefficients do not reflect the shape of the hazard distribution, but instead reflect changes in sampling levels in a given year. The Weibull scale and shape parameters, in conjunction with the Cox regression results, indicate the systematic non-uniform sample distributions within years are well accounted for by a Weibull function. Comparative analyses conducted against a piecewise exponential distribution (which assumes constant changes in sample distribution within years) using log likelihood statistic comparisons indicated the piecewise Weibull distribution provided markedly superior fit.

Abbreviated piecewise Weibull regression results for the 4 automotive models used in the study are shown in Tables 16 to 39. For clarity, only static and time varying coefficient results are presented. Coefficients for sales years, and Weibull scale and shape parameters are omitted. Chi-square results relative to the baseline model are shown for all models.

The dependent variable is log of adoption time, while all independent variables are regressed in their log forms. Positive coefficients indicate purchase

delay and negative coefficients indicate acceleration. Coefficient interpretation is achieved using the transformation:

$$100(e^{\beta} - 1)$$

which is a percentage point interpretation for static covariates and a percentage point change interpretation for time-varying influence covariates, because the time-varying demographic similarity ratio is a percentage. The result for the Dodge Neon “vehicle year” coefficient (0.020) for New Adopters is transformed thus:

$$100(e^{0.020} - 1) \\ = 2.02$$

Indicating a currently owned vehicle that is one year newer increases expected time to adoption by 2.02%. The result for the Dodge Neon degree 3 similarity for New Adopters and the REPEAT coefficient (-0.118) is transformed thus:

$$100(e^{-0.118} - 1) \\ = -11.1$$

Indicating a 1% change in the proportion of prior similar repeat adopters, decreases expected adoption time by 11.1%, measure in years. Caution should



be exercised in comparing coefficient magnitudes as the data are not capable of determining the precise effect of time upon purchase. Coefficient estimates assume the piecewise Weibull distribution sufficiently accounts for the quarterly sampling variation in the data. This assumption is supported by the comparisons with semi-parametric Cox regression, but it is possible the strength of the assumption varies across vehicles and adopter groups. It is stressed that emphasis should be placed upon polarity of effects rather than the absolute value of coefficients. This reduces the chance that incorrect specification of the piecewise Weibull distribution alters substantive conclusions regarding relative adoption times.

In log-likelihood regressions, nested models can be compared using log-likelihood ratio statistics. Twice the difference in log-likelihood ratio statistics between nested models are distribution Chi-square. Models, and accompanying model coefficients were only considered if the model Chi-square statistic indicated significantly better overall model fit than the baseline model at a 5% level of significance. For nested analyses, this same Chi-square statistic is used to select the model of best fit. The 5% critical Chi-square value is 3.84 for 1 degree of freedom, and 5.99 for 2 degrees of freedom. When analyses were repeated using a less conservative 10% level of significance for model selection, all newly significant models were consistent in coefficient effects with those identified using the 5% criteria, and the substantive conclusions remained the same. Complete static covariate and log likelihood statistic results are presented in Appendix B.

**Table 16: Dodge Neon Piecewise Weibull Regression Results, New Adopters Degree 5 Similarity**

New Adopters Years Obs.	Model	Log- likelihood		$\chi^2$ diff	Inc	veh	vehage	ALL	NEW	REPEAT
		$\beta$	s.d.							
6 3200	baseline	-1943.124			-0.006	<b>0.036*</b>	<b>0.020*</b>			
					0.005	0.011	0.002			
					0.287	0.001	<.0001			
		-1938.151	<b>9.946*</b>		-0.008	<b>0.036*</b>	<b>0.020*</b>	<b>-1.442*</b>		
1					0.006	0.011	0.002	0.445		
					0.134	0.001	<.0001	0.001		
		-1940.006	<b>6.237*</b>		-0.008	<b>0.036*</b>	<b>0.020</b>		<b>-1.067*</b>	
					0.006	0.011	0.002		0.416	
2					0.165	0.001	<.0001		0.010	
		-1938.780	<b>8.689*</b>		-0.007	<b>0.036*</b>	<b>0.020*</b>			<b>-0.752*</b>
					0.005	0.011	0.002			0.244
					0.200	0.001	<.0001			0.002
3		-1937.578	<b>11.092*</b>		-0.008	<b>0.035*</b>	<b>0.020*</b>		<b>-0.712</b>	<b>-0.603*</b>
					0.006	0.011	0.002		0.452	0.265
					0.145	0.001	<.0001		0.115	0.023
4										

$\chi^2$  diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 17: Dodge Neon Piecewise Weibull Regression Results, New Adopters Degree 4 Similarity**

New Adopters Years Obs.	Model	Log- likelihood	X <sup>2</sup> diff							
				inc	veh	vehage	ALL	NEW	REPEAT	
6 3200	baseline	-1943.124		$\beta$	-0.006	<b>0.036*</b>	<b>0.020*</b>			
				s.d.	0.005	0.011	0.002			
				p	0.287	0.001	<.0001			
				$\beta$	-0.008	<b>0.036*</b>	<b>0.020*</b>	<b>-0.385*</b>		
	1	-1939.302	<b>7.645*</b>	s.d.	0.006	0.011	0.002	0.138		
				p	0.142	0.001	<.0001	0.005		
				$\beta$	-0.008	<b>0.036*</b>	<b>0.020*</b>	<b>-0.316*</b>		
				s.d.	0.006	0.011	0.002	0.135		
	2	-1940.445	<b>5.358*</b>	p	0.158	0.001	<.0001	0.020		
				$\beta$	-0.007	<b>0.035*</b>	<b>0.020*</b>		<b>-0.276*</b>	
				s.d.	0.005	0.011	0.002		0.089	
				p	0.183	0.001	<.0001		0.002	
	3	-1938.505	<b>9.238*</b>	$\beta$	-0.008	<b>0.036*</b>	<b>0.020*</b>	-0.118	<b>-0.232*</b>	
				s.d.	0.006	0.011	0.002	0.165	0.109	
				p	0.158	0.001	<.0001	0.475	0.033	
	4	-1938.251	<b>9.747*</b>							

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 18: Dodge Neon Piecewise Weibull Regression Results, New Adopters Degree 3 Similarity**

New Adopters Years Obs.	Model	Log- likelihood	X <sup>2</sup> diff							
				inc	veh	vehage	ALL	NEW	REPEAT	
6 3200	baseline	-1943.124		$\beta$	-0.006	<b>0.036*</b>	<b>0.020*</b>			
				s.d.	0.005	0.011	0.002			
	1	-1939.950	<b>6.349*</b>	p	0.287	0.001	<.0001			
				$\beta$	-0.008	<b>0.036*</b>	<b>0.020*</b>	<b>-0.194*</b>		
	2	-1941.094	<b>4.060*</b>	s.d.	0.006	0.011	0.002	0.077		
				p	0.139	0.001	<.0001	0.012		
	3	-1940.962	<b>4.324*</b>	$\beta$	-0.008	<b>0.036*</b>	<b>0.020*</b>	<b>-0.153*</b>		
				s.d.	0.006	0.011	0.002	0.076		
	4	-1940.651	4.945	p	0.161	0.001	<.0001	0.045		
				$\beta$	-0.007	<b>0.036*</b>	<b>0.020*</b>		<b>-0.118*</b>	
				s.d.	0.006	0.011	0.002		0.057	
				p	0.196	0.001	<.0001		0.038	
				$\beta$	-0.008	<b>0.036*</b>	<b>0.020*</b>	-0.084	-0.074	
				s.d.	0.006	0.011	0.002	0.106	0.079	
				p	0.165	0.001	<.0001	0.429	0.349	

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 19: Dodge Neon Piecewise Weibull Regression Results, Repeat Adopters Degree 5 Similarity**

Repeat Adopters		Model	Log-likelihood	X <sup>2</sup> diff		inc	veh	vehage	ALL	NEW	REPEAT
Years	6	baseline	-246.427			$\beta$	0.026	0.058	0.032		
Obs.	387					s.d.	0.016	0.032	0.021		
		5	-242.531	7.794*		p	0.119	0.070	0.135		
						$\beta$	<b>0.033*</b>	<b>0.072*</b>	0.024	<b>4.078*</b>	
		6	-241.235	10.385*		s.d.	0.016	0.032	0.021	1.527	
						p	0.038	0.025	0.262	0.008	
		7	-245.814	1.226		$\beta$	<b>0.034*</b>	<b>0.071*</b>	0.024	<b>4.512*</b>	
						s.d.	0.016	0.032	0.021	1.482	
		8	-241.199	10.456*		p	0.034	0.027	0.266	0.002	
						$\beta$	<b>0.027*</b>	<b>0.065*</b>	0.030		0.771
						s.d.	0.016	0.033	0.022		0.716
						p	0.094	0.049	0.161		0.281
						$\beta$	<b>0.034*</b>	<b>0.072*</b>	0.024	<b>4.414*</b>	0.182
						s.d.	0.016	0.032	0.021	1.526	0.689
						p	0.033	0.026	0.266	0.004	0.792

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 20: Dodge Neon Piecewise Weibull Regression Results, Repeat Adopters Degree 4 Similarity**

Repeat Adopters Years Obs.	Model	Log-likelihood		X <sup>2</sup> diff	Inc	veh	vehage	ALL	NEW	REPEAT
6 387	baseline	-246.427	β	0.026	0.058	0.032				
			s.d.	0.016	0.032	0.021				
			p	0.119	0.070	0.135				
	5	-244.909	β	<b>0.032*</b>	<b>0.066*</b>	0.027	0.749			
			s.d.	0.016	0.032	0.022	0.432			
			p	0.047	0.039	0.214	0.083			
	6	-245.009	β	<b>0.032*</b>	<b>0.066*</b>	0.027		0.698		
			s.d.	0.016	0.032	0.022		0.417		
			p	0.050	0.039	0.212		0.094		
	7	-244.738	β	0.031	<b>0.067*</b>	0.028				0.465
			s.d.	0.016	0.032	0.022				0.263
			p	0.059	0.040	0.195				0.077
	8	-244.392	β	<b>0.033*</b>	<b>0.069*</b>	0.027		0.405		0.328
			s.d.	0.016	0.032	0.022		0.491		0.304
			p	0.044	0.033	0.218		0.410		0.282

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 21: Dodge Neon Piecewise Weibull Regression Results, Repeat Adopters Degree 3 Similarity**

Repeat Adopters Years Obs.	Model	Log- likelihood	X <sup>2</sup> diff							
				inc	veh	vehage	ALL	NEW	REPEAT	
6 387	baseline	-246.427		β	0.026	0.058	0.032			
				s.d.	0.016	0.032	0.021			
				p	0.119	0.070	0.135			
	5	-243.691	5.473*	β	<b>0.037*</b>	<b>0.069*</b>	0.028	<b>0.552*</b>		
				s.d.	0.016	0.032	0.021	0.228		
				p	0.025	0.032	0.185	0.016		
	6	-243.283	6.289*	β	<b>0.038*</b>	<b>0.071*</b>	0.028	<b>0.575*</b>		
				s.d.	0.016	0.032	0.021	0.223		
				p	0.020	0.029	0.183	0.010		
	7	-241.603	9.648*	β	<b>0.036*</b>	<b>0.067*</b>	0.026		<b>0.547**</b>	
				s.d.	0.016	0.032	0.021		0.171	
				p	0.023	0.035	0.226		0.001	
8		-241.548	9.759*	β	<b>0.037*</b>	<b>0.068*</b>	0.026	0.108	0.483	
				s.d.	0.016	0.032	0.021	0.324	0.256	
				p	0.022	0.033	0.224	0.740	0.059	

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 22: Jeep Grand Cherokee Piecewise Weibull Regression Results, New Adopters Degree 5 Similarity**

Model		Log-likelihood		X <sup>2</sup> diff	inc	veh	vehage	ALL	NEW	REPEAT	
New Adopters Years Obs.  7 4087	baseline		-2081.940	β	-0.023*	0.038*	0.027*				
				s.d.	0.005	0.010	0.002				
				p	<.0001	0.000	<.0001				
				β	-0.022*	0.037*	0.028*	-0.557*			
	1		-2079.852	4.177*	s.d.	0.005	0.010	0.002	0.269		
					p	<.0001	0.000	<.0001	0.038		
					β	-0.023*	0.037*	0.027*		-0.417	
					s.d.	0.005	0.010	0.002		0.248	
	2		-2080.588	2.705	p	<.0001	0.000	<.0001		0.093	
					β	-0.022*	0.038*	0.028*			-0.389*
					s.d.	0.005	0.010	0.002			0.194
					p	<.0001	0.000	<.0001			0.046
	3		-2080.003	3.875*	β	-0.021*	0.038*	0.028*		-0.234	
					s.d.	0.005	0.010	0.002		0.290	0.223
					p	<.0001	0.000	<.0001		0.420	0.176
					β	-0.022*	0.037*	0.027*			

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05



**Table 23: Jeep Grand Cherokee Piecewise Weibull Regression Results, New Adopters Degree 4 Similarity**

New Adopters Years Obs.	Model	Log- likelihood	X <sup>2</sup> diff							
				inc	veh	vehage	ALL	NEW	REPEAT	
7 4087	baseline	-2081.940		<b>-0.023*</b>	<b>0.038*</b>	<b>0.027*</b>				
				0.005	0.010	0.002				
				<.0001	0.000	<.0001				
				<b>-0.022*</b>	<b>0.038*</b>	<b>0.028*</b>	<b>-0.238*</b>			
	1	-2079.578	<b>4.724*</b>	0.005	0.010	0.002	0.109			
				<.0001	0.000	<.0001	0.029			
				<b>-0.023*</b>	<b>0.038*</b>	<b>0.027*</b>		-0.114		
				0.005	0.010	0.002		0.104		
	2	-2081.351	1.179*	<.0001	0.000	<.0001				
				<b>-0.021*</b>	<b>0.039*</b>	<b>0.028*</b>				
				0.005	0.010	0.002				
				<.0001	<.0001	<.0001				
	3	-2078.447	<b>6.987*</b>	<b>-0.021*</b>	<b>0.039*</b>	<b>0.028*</b>				
				0.005	0.010	0.002				
				<.0001	<.0001	<.0001				
				<b>-0.021*</b>	<b>0.040*</b>	<b>0.028*</b>				
	4	-2078.197	<b>7.486*</b>	0.005	0.010	0.002				
				<.0001	<.0001	<.0001				
				<b>-0.021*</b>	<b>0.040*</b>	<b>0.028*</b>				
				0.005	0.010	0.002				

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 24: Jeep Grand Cherokee Piecewise Weibull Regression Results, New Adopters Degree 3 Similarity**

New Adopters Years Obs.	Model	Log- likelihood		X <sup>2</sup> diff	Inc	totveh	vehyr	ALL	NEW	REPEAT
		baseline								
7 4087		-2081.940	$\beta$		<b>-0.023*</b>	<b>0.038*</b>	<b>0.027*</b>			
			s.d.		0.005	0.010	0.002			
			p		<.0001	0.000	<.0001			
	1	-2079.053	$\beta$	<b>5.775*</b>	<b>-0.022*</b>	<b>0.038*</b>	<b>0.028*</b>	<b>-0.170*</b>		
2			s.d.		0.005	0.010	0.002	0.071		
			p		<.0001	0.000	<.0001	0.017		
		-2080.220	$\beta$	3.440	<b>-0.023*</b>	<b>0.038*</b>	<b>0.028*</b>		-0.130	
			s.d.		0.005	0.010	0.002		0.070	
3			p		<.0001	0.000	<.0001		0.065	
			$\beta$	3.780	<b>-0.022*</b>	<b>0.038*</b>	<b>0.028*</b>			-0.108
		-2080.050	s.d.		0.005	0.010	0.002			0.056
			p		<.0001	0.000	<.0001			0.053
4			$\beta$	4.216	<b>-0.022*</b>	<b>0.038*</b>	<b>0.028*</b>		-0.067	-0.070
		-2079.832	s.d.		0.005	0.010	0.002		0.101	0.080
			p		<.0001	0.000	<.0001		0.507	0.382

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 25: Jeep Grand Cherokee Piecewise Weibull Regression Results, Repeat Adopters Degree 5 Similarity**

Repeat Adopters Years Obs.	Model	Log- likelihood		X <sup>2</sup> diff	Inc	veh	vehage	ALL	NEW	REPEAT
7 951	baseline		-647.295	$\beta$	-0.056*	0.041	0.059*			
				s.d.	0.013	0.028	0.017			
				p	<.0001	0.142	0.000			
	5		-647.292	$\beta$	-0.056*	0.041	0.059*	-0.054		
				s.d.	0.013	0.028	0.017	0.643		
				p	<.0001	0.147	0.000	0.933		
	6		-647.283	$\beta$	-0.056*	0.041	0.059*		-0.106	
				s.d.	0.013	0.028	0.017		0.683	
				p	<.0001	0.148	0.000		0.876	
	7		-647.192	$\beta$	-0.054*	0.040	0.059*			-0.170
				s.d.	0.013	0.028	0.017			0.371
				p	<.0001	0.160	0.000			0.647
	8		-647.180	$\beta$	-0.054*	0.040	0.059*		0.136	-0.216
				s.d.	0.013	0.028	0.017		0.866	0.469
				p	<.0001	0.159	0.000		0.875	0.646

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 26: Jeep Grand Cherokee Piecewise Weibull Regression Results, Repeat Adopters Degree 4 Similarity**

Repeat Adopters Years Obs.	Model	Log-likelihood		X <sup>2</sup> diff	Inc	veh	vehage	ALL	NEW	REPEAT
		Model	likelihood							
7 951	baseline	7	-647.295		$\beta$	-0.056*	0.041	0.059*		
					s.d.	0.013	0.028	0.017		
	5	5	-647.255	0.081	p	<.0001	0.142	0.000		
					$\beta$	-0.055*	0.041	0.059*	-0.074	
	6	6	-647.268	0.054	s.d.	0.013	0.028	0.017	0.261	
					p	<.0001	0.147	0.000	0.775	
	7	7	-647.294	0.003	$\beta$	-0.055*	0.041	0.059*	-0.063	
					s.d.	0.013	0.028	0.017	0.269	
	8	8	-647.252	0.087	p	<.0001	0.144	0.000	0.816	
					$\beta$	-0.056*	0.041	0.059*	-0.011	
					s.d.	0.013	0.028	0.017	0.198	
					p	<.0001	0.145	0.000	0.956	
					$\beta$	-0.056*	0.042	0.059*	-0.119	0.055
					s.d.	0.013	0.028	0.017	0.409	0.302
					p	<.0001	0.141	0.000	0.771	0.855

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 27: Jeep Grand Cherokee Piecewise Weibull Regression Results, Repeat Adopters Degree 3 Similarity**

Repeat Adopters Years Obs.	Model	Log-likelihood		X <sup>2</sup> diff	Inc	veh	vehage	ALL	NEW	REPEAT
7 951	baseline	-647.295	$\beta$	0.056*	0.041	0.028	0.017	0.042	0.039	0.029
			s.d.							
			p							
	5	-647.272	$\beta$	0.057*	0.041	0.028	0.017	0.042	0.039	0.029
			s.d.							
			p							
	6	-647.276	$\beta$	0.057*	0.041	0.028	0.017	0.042	0.039	0.029
			s.d.							
			p							
	7	-647.278	$\beta$	0.057*	0.042	0.028	0.017	0.042	0.025	0.015
			s.d.							
			p							
8		-647.274	$\beta$	0.013	0.028	0.042	0.017	0.060*	0.025	0.015
			s.d.							
			p							
			p							

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 28: Mazda Miata Piecewise Weibull Regression Results, New Adopters Degree 5 Similarity**

New Adopters Years Obs.	Model	Log-		Inc	veh	vehage	ALL	NEW	REPEAT
		likelihood	X <sup>2</sup> diff						
7 baseline 2895	1	-1497.639	8.855*	$\beta$	-0.006	<b>0.031*</b>	<b>0.019*</b>		
				s.d.	0.006	0.012	0.002		
				p	0.312	0.012	<.0001		
		-1493.212		$\beta$	-0.004	<b>0.034*</b>	<b>0.019*</b>	<b>-0.672*</b>	
2	2		8.049*	s.d.	0.006	0.013	0.002	0.216	
				p	0.521	0.007	<.0001	0.002	
		-1493.615		$\beta$	-0.003	<b>0.034*</b>	<b>0.019*</b>	<b>-0.661*</b>	
				s.d.	0.006	0.013	0.002	0.225	
3	3		19.529*	p	0.558	0.007	<.0001	0.003	
				$\beta$	-0.003	<b>0.033*</b>	<b>0.019*</b>	<b>-0.636*</b>	
		-1487.875		s.d.	0.006	0.012	0.002	0.137	
				p	0.599	0.008	<.0001	<.0001	
4	4		20.352*	$\beta$	-0.002	<b>0.034*</b>	<b>0.019*</b>	<b>-0.247</b>	<b>-0.569*</b>
				s.d.	0.006	0.013	0.002	0.269	0.157
		-1487.463		p	0.684	0.007	<.0001	0.358	0.000

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 29: Mazda Miata Piecewise Weibull Regression Results, New Adopters Degree 4 Similarity**

New Adopters Years Obs.	Model	Log- Likelihood		X <sup>2</sup> diff	Inc	veh	vehage	ALL	NEW	REPEAT
2895	7 baseline		-1497.639		$\beta$	-0.006	<b>0.031*</b>	<b>0.019*</b>		
					s.d.	0.006	0.012	0.002		
					p	0.312	0.012	<.0001		
					$\beta$	-0.004	<b>0.032*</b>	<b>0.019*</b>	-0.183	
	1		-1496.345	2.589	s.d.	0.006	0.013	0.002	0.113	
					p	0.491	0.011	<.0001	0.107	
					$\beta$	-0.004	<b>0.032*</b>	<b>0.019*</b>	-0.164	
					s.d.	0.006	0.013	0.002	0.113	
	2		-1496.591	2.097	p	0.477	0.011	<.0001	0.147	
					$\beta$	-0.003	<b>0.032*</b>	<b>0.019*</b>	-0.176*	
					s.d.	0.006	0.013	0.002	0.070	
					p	0.570	0.010	<.0001	0.012	
	3		-1494.562	<b>6.154*</b>	$\beta$	-0.003	<b>0.032*</b>	<b>0.019*</b>	-0.181*	
					s.d.	0.006	0.013	0.002	0.089	
					p	-0.003	<b>0.032*</b>	<b>0.019*</b>	0.014	
					$\beta$	0.006	0.013	0.002	0.144	
	4		-1494.557	<b>6.164*</b>	s.d.	0.564	0.010	<.0001	0.922	
					p				0.042	

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 30: Mazda Miata Piecewise Weibull Regression Results, New Adopters Degree 3 Similarity**

New Adopters Years Obs.	Model	Log-likelihood		X <sup>2</sup> diff	inc	veh	vehage	ALL	NEW	REPEAT
		baseline	7							
2895		-1497.639			-0.006	<b>0.031*</b>	<b>0.019*</b>			
					0.006	0.012	0.002			
					0.312	0.012	<.0001			
					-0.006	<b>0.031*</b>	<b>0.019*</b>	-0.028		
	1	-1497.585		0.109	0.006	0.013	0.002	0.084		
					0.345	0.012	<.0001	0.742		
					-0.005	<b>0.031*</b>	<b>0.019*</b>		-0.040	
	2	-1497.529		0.221	0.006	0.013	0.002		0.084	
					0.358	0.012	<.0001		0.639	
					-0.007	<b>0.031*</b>	<b>0.019*</b>			0.044
	3	-1497.333		0.612	0.006	0.012	0.002			0.056
					0.260	0.012	<.0001			0.433
					-0.006	<b>0.031*</b>	<b>0.019*</b>		-0.132	0.099
	4	-1496.574		2.130	0.006	0.012	0.002		0.107	0.071
					0.305	0.014	<.0001		0.217	0.165

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05



**Table 31: Mazda Miata Piecewise Weibull Regression Results, Repeat Adopters Degree 5 Similarity**

Repeat Adopters Years Obs.	Model	Log-		Inc	veh	vehage	ALL	NEW	REPEAT
		Model	likelihoood	X <sup>2</sup> diff					
7 399	baseline		-219.905	$\beta$	-0.026	<b>0.130*</b>	<b>-0.028*</b>		
				s.d.	0.013	0.033	0.013		
				p	0.055	<.0001	0.027		
				$\beta$	-0.025	<b>0.132*</b>	<b>-0.029*</b>	-0.298	
	5		-219.826	0.156	0.014	0.034	0.013	0.753	
				s.d.	0.064	<.0001	0.026	0.692	
				p	-0.024	<b>0.133*</b>	<b>-0.029*</b>	-0.622	
			-219.517	0.774	0.014	0.034	0.013	0.703	
	6			s.d.	0.075	<.0001	0.025	0.377	
				p	-0.025	<b>0.134*</b>	<b>-0.030*</b>	-0.540	
			-219.005	1.799	0.014	0.034	0.013	0.392	
				s.d.	0.071	<.0001	0.023	0.168	
	7			p	-0.025	<b>0.134*</b>	<b>-0.030*</b>	-0.183	
			-218.981	1.847	0.014	0.034	0.013	0.829	
				$\beta$	0.076	<.0001	0.023	0.826	
				s.d.				0.293	
	8			p					

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 32: Mazda Miata Piecewise Weibull Regression Results, Repeat Adopters Degree 4 Similarity**

Repeat Adopters Years Obs.	Model	Log- likelihood	X <sup>2</sup> diff						
				inc	veh	vehage	ALL	NEW	REPEAT
7 399	baseline	-219.905		$\beta$	<b>0.130*</b>	<b>-0.028*</b>			
				s.d.	0.033	0.013			
				p	<.0001	0.027			
	5	-219.888	0.032	$\beta$	<b>0.129*</b>	<b>-0.028*</b>	0.054		
				s.d.	0.033	0.013	0.298		
				p	0.053	0.027	0.857		
	6	-219.903	0.003	$\beta$	<b>0.130*</b>	<b>-0.029*</b>		-0.017	
				s.d.	0.033	0.013		0.294	
				p	0.059	0.027		0.954	
	7	-219.891	0.027	$\beta$	<b>0.130*</b>	<b>-0.028*</b>			-0.032
				s.d.	0.033	0.013			0.194
				p	<.0001	0.027			0.870
	8	-219.889	0.031	$\beta$	<b>0.130*</b>	<b>-0.028*</b>		0.024	-0.042
				s.d.	0.033	0.013		0.387	0.255
				p	0.059	0.028		0.950	0.869

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 33: Mazda Miata Piecewise Weibull Regression Results, Repeat Adopters Degree 3 Similarity**

	Model	Log-likelihood		X <sup>2</sup> diff	Inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters	7 baseline 399		-219.905		$\beta$	-0.026	<b>0.130*</b>	<b>-0.028*</b>		
Years					s.d.	0.013	0.033	0.013		
Obs.					p	0.055	<.0001	0.027		
	5		-219.898	0.014	$\beta$	-0.026	<b>0.130*</b>	<b>-0.028*</b>	-0.026	
					s.d.	0.014	0.033	0.013	0.216	
					p	0.061	0.000	0.028	0.906	
	6		-219.871	0.067	$\beta$	-0.025	<b>0.130*</b>	<b>-0.028*</b>	-0.056	
					s.d.	0.014	0.034	0.013	0.217	
					p	0.066	<.0001	0.028	0.796	
	7		-219.829	0.152	$\beta$	<b>-0.026*</b>	<b>0.129*</b>	<b>-0.028*</b>		0.058
					s.d.	0.013	0.033	0.013		0.147
					p	0.048	0.000	0.029		0.695
	8		-219.635	0.538	$\beta$	-0.025	<b>0.131*</b>	<b>-0.028*</b>	-0.166	0.126
					s.d.	0.014	0.034	0.013	0.267	0.181
					p	0.062	<.0001	0.033	0.534	0.486

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 34: Toyota Avalon Piecewise Weibull Regression Results, New Adopters Degree 5 Similarity**

New Adopters Years Obs.	Model	Log- likelihood		X <sup>2</sup> diff	inc	veh	vehage	ALL	NEW	REPEAT
6 3055	baseline		-1818.096		$\beta$	-0.012*	-0.014	0.018*		
					s.d.	0.005	0.013	0.002		
					p	0.010	0.257	<.0001		
	1		-1817.985	0.223	$\beta$	-0.012*	-0.013	0.018*	0.106	
					s.d.	0.005	0.013	0.002	0.225	
					p	0.011	0.302	<.0001	0.638	
	2		-1818.078	0.036	$\beta$	-0.012*	-0.015	0.018*	-0.041	
					s.d.	0.005	0.013	0.002	0.217	
					p	0.010	0.250	<.0001	0.850	
	3		-1814.651	6.889*	$\beta$	-0.012*	-0.009	0.018*		0.398*
					s.d.	0.005	0.013	0.002		0.154
					p	0.009	0.476	<.0001		0.010
	4		-1810.665	14.862*	$\beta$	-0.014*	-0.012	0.018*	-0.845*	0.811*
					s.d.	0.005	0.013	0.002	0.295	0.213
					p	0.003	0.333	<.0001	0.004	0.000

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 35: Toyota Avalon Piecewise Weibull Regression Results, New Adopters Degree 4 Similarity**

New Adopters Years Obs.	Model	Log-likelihood		X <sup>2</sup> diff		inc	veh	vehage	ALL	NEW	REPEAT
		Model	likelihood								
6 3055	baseline		-1818.096		$\beta$	-0.012*	-0.014	0.018*			
					s.d.	0.005	0.013	0.002			
					p	0.010	0.257	<.0001			
					$\beta$	-0.012*	-0.015	0.018*	-0.030		
	1		-1818.051	0.090	s.d.	0.005	0.013	0.002	0.099		
					p	0.010	0.242	<.0001	0.765		
					$\beta$	-0.012*	-0.016	0.018*		-0.066	
					s.d.	0.005	0.013	0.002		0.095	
	2		-1817.855	0.481	p	0.009	0.212	<.0001		0.488	
					$\beta$	-0.012*	-0.013	0.018*			0.036
					s.d.	0.005	0.013	0.002			0.073
					p	0.010	0.308	<.0001			0.622
	3		-1817.975	0.243	$\beta$	-0.013*	-0.015	0.018*		-0.239	0.174
					s.d.	0.005	0.013	0.002		0.145	0.111
					p	0.005	0.013	0.002		0.100	0.118
					$\beta$	0.005	0.251	<.0001			
	4		-1816.633	2.926	s.d.	0.005	0.013	0.002			
					p	0.005	0.251	<.0001			

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

**Table 36: Toyota Avalon Piecewise Weibull Regression Results, New Adopters Degree 3 Similarity**

New Adopters Years Obs.	Model	Log- likelihood	X <sup>2</sup> diff							
				Inc	veh	vehage	ALL	NEW	REPEAT	
6 3055	baseline	-1818.096		$\beta$	-0.012*	0.014	0.018*			
				s.d.	0.005	0.013	0.002			
				p	0.010	0.257	<.0001			
				$\beta$	-0.012*	-0.014	0.018*	-0.001		
	1	-1818.096	0.000	s.d.	0.005	0.013	0.002	0.073		
				p	0.010	0.264	<.0001	0.985		
				$\beta$	-0.012*	-0.014	0.018*	0.002		
				s.d.	0.005	0.013	0.002	0.071		
	2	-1818.096	0.000	p	0.010	0.268	<.0001	0.984		
				$\beta$	-0.012*	-0.016	0.018*			-0.046
				s.d.	0.005	0.013	0.002			0.058
				p	0.012	0.208	<.0001			0.424
	3	-1817.775	0.641	$\beta$	-0.011*	-0.015	0.018*	0.112		-0.115
				s.d.	0.005	0.013	0.002	0.112		0.090
				p	0.017	0.240	<.0001	0.320		0.203
	4	-1817.279	1.633	$\beta$						
				s.d.						
				p						

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 37: Toyota Avalon Piecewise Weibull Regression Results, Repeat Adopters Degree 5 Similarity**

Model		Log-likelihood	X <sup>2</sup> diff	inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters Years Obs.	6 436	baseline	-254.305	β	0.017	-0.014	0.079*		
				s.d.	0.013	0.042	0.021		
				p	0.198	0.744	0.000		
				β	0.027	-0.006	0.086*	1.361*	
	5		-252.341	s.d.	0.014	0.041	0.022	0.692	
				p	0.051	0.890	<.0001	0.049	
				β	0.028	-0.008	0.085*		1.171
				s.d.	0.014	0.041	0.022		0.655
	6		-252.678	p	0.051	0.837	<.0001		0.074
				β	0.023	-0.004	0.087*		1.138*
				s.d.	0.013	0.041	0.022		0.434
				p	0.081	0.931	<.0001		0.009
	7		-250.588	β	0.026	-0.002	0.089*	0.421	1.010*
				s.d.	0.014	0.041	0.022	0.711	0.484
				p	0.065	0.955	<.0001	0.554	0.037
	8		-250.410	β					
				s.d.					
				p					

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05

**Table 38: Toyota Avalon Piecewise Weibull Regression Results, New Adopters Degree 4 Similarity**

Model		Log-likelihood	X <sup>2</sup> diff	inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters Years Obs.	6 436	baseline	-254.305	β	0.017	-0.014	0.079*		
				s.d.	0.013	0.042	0.021		
				p	0.198	0.744	0.000		
				β	0.024	-0.003	<b>0.083*</b>	0.555	
	5		-252.774	s.d.	0.014	0.041	0.022	0.315	
				p	0.073	0.939	0.000	0.078	
				β	0.024	-0.007	<b>0.081*</b>	0.394	
				s.d.	0.014	0.041	0.022	0.300	
	6		-253.449	p	0.089	0.858	0.000	0.189	
				β	0.019	-0.006	<b>0.083*</b>		0.351
				s.d.	0.013	0.041	0.022		0.212
				p	0.141	0.890	0.000		0.098
	7		-252.904	β	0.021	-0.005	<b>0.083*</b>	0.150	0.289
				s.d.	0.014	0.041	0.022	0.364	0.258
				p	0.129	0.909	0.000	0.681	0.263
	8		-252.819	β	0.021	-0.005	<b>0.083*</b>	0.150	0.289
				s.d.	0.014	0.041	0.022	0.364	0.258
				p	0.129	0.909	0.000	0.681	0.263

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at p ≤ 0.05



**Table 39: Toyota Avalon Piecewise Weibull Regression Results, New Adopters Degree 3 Similarity**

Repeat Adopters		Model	Log-likelihood	X <sup>2</sup> diff	inc	veh	vehage	ALL	NEW	REPEAT
Years	6	baseline	-254.305		$\beta$	0.017	-0.014	0.079*		
Obs.	436				s.d.	0.013	0.042	0.021		
					p	0.198	0.744	0.000		
		5	-253.936	0.739	$\beta$	0.020	-0.008	0.081*	0.211	
					s.d.	0.014	0.042	0.022	0.243	
					p	0.138	0.847	0.000	0.386	
		6	-252.798	3.014	$\beta$	0.024	-0.003	0.081*	0.392	
					s.d.	0.014	0.042	0.022	0.223	
					p	0.077	0.953	0.000	0.078	
		7	-253.879	0.852	$\beta$	0.018	-0.010	0.081*	0.171	
					s.d.	0.013	0.042	0.022	0.184	
					p	0.172	0.819	0.000	0.353	
		8	-252.634	3.342	$\beta$	0.026	-0.002	0.080*	0.543	-0.163
					s.d.	0.014	0.042	0.022	0.347	0.287
					p	0.065	0.956	0.000	0.118	0.570

X<sup>2</sup> diff = Chi-square difference statistic relative to the baseline model

\* significant at  $p \leq 0.05$

## **Comparing Between Degree Similarity Analyses, and Between Adopter Group Analyses**

The magnitude and significance of static covariates are virtually identical across 3, 4, and 5 degree similarity models. There is a greater prevalence of significant regression coefficients for new adopters than repeat adopters. For each automobile model, static covariate results are consistent across degree similarities. The time varying influence covariates show a wider variety of results as some models have significant coefficients across all degree similarities in new and repeat adopter groups (as with the Dodge Neon) while others vary across both degree similarity, and new and repeat adopter group analyses (such as for the Mazda Miata).

Significant results at lower degrees of similarity are generally accompanied by significant results at higher degrees of similarity although the reverse is not the case. When results are apparent across different degrees, coefficients increase in magnitude the higher the degree of similarity. In general, this indicates the more similar current adopters are to prior adopters, the stronger the effect.

## **Inferring New and Repeat Adopter Effects through Model Selection**

For regression results conducted on current New Adopter groups, models 2 and 3 are nested within model 4, and for regressions conducted on current Repeat Adopter groups models 6 and 7 are nested within model 8. These

models utilize influence covariates calculated from prior new and repeat adopter groups. Models 1 and 5 utilize influence calculated from all prior adopters and are non-nested with models 2, 3, and 4; and 6, 7 and 8 respectively.

For nested analyses, the model of best fit is determined by Chi-square significance tests. An unrestricted model (such as 4 or 8) has better fit than restricted models (against 2 or 4; or 6 or 7) when the improvement in Chi-square is significant. If the unrestricted model does not have better fit, a restricted model is chosen. For Mazda Miata New Adopter group degree 5 similarity results, model 4 fits significantly better than model 2 ( $20.352 - 8.049 = 12.303$ ,  $> 3.84$ , 1 d.f.), however model 4 does not fit significantly better than model 3 ( $20.352 - 19.529 = 0.823$ ,  $< 3.84$ , 1 d.f.). Thus model 3 is the best model and indicates purchase by New Adopters is accelerated by prior Repeat Adopters. The same comparisons and conclusions occur for Dodge Neon New Adopter degree 4 and 5 similarity results. For Jeep Grand Cherokee New Adopter degree 4 similarity results, model 3 has better fit than model 4, because model 4 does not fit significantly better, ( $7.486 - 6.987 = 0.499$ ,  $< 3.84$ , 1 d.f.). This same conclusion is reached for the Mazda Miata New Adopter degree 4 similarity results.

When both restricted models are significant, and the unrestricted model does not have better fit than either, there is no statistical basis for choosing between restricted models. If the coefficients for the restricted models are of the same sign, the most likely reason for lack of improved fit in the unrestricted model is collinearity between NEW and REPEAT. In this instance it is inappropriate to use the unrestricted analyses to test simultaneous effects of

NEW and REPEAT. An equivalent means of testing NEW and REPEAT when effects seem collinear is to combine them as a single group to assess demographic similarity. This is achieved in non-nested analyses 1 and 5 that are the correct model choice when restricted models indicate similar effects of NEW and REPEAT, and unrestricted analyses do not fit significantly better than restricted models.

This occurs for the Dodge Neon degree 3 similarity New Adopter group, where models 2 ( $X^2 = 4.060$ ,  $>3.84$  1 d.f.) and 3 ( $X^2 = 4.324$ ,  $>3.84$  1 d.f.) fit better than the baseline model, and model 4 does not fit significantly better than models 2 ( $4.945 - 4.060 = 0.885$ ,  $< 3.84$  1 d.f.) or 3 ( $4.945 - 4.324 = 0.621$ ,  $< 3.84$  1 d.f.). Non-nested model 1 is a better model than model 4 because its single demographic similarity ratio covariate ALL consists of aggregated new and repeat adopters instead of the two separate NEW and REPEAT ratios used in model 4. This eliminates the problem of collinearity that occurs in model 4. This inference is supported by the ALL coefficient for model 1 ( $\beta = -0.194$ ,  $p = 0.012$ ) that is consistent in sign with the model 2 NEW coefficient ( $\beta = -0.153$ ,  $p = 0.045$ ), and model 3 REPEAT coefficient ( $\beta = -0.118$ ,  $p = 0.038$ ). When model 1 instead of model 4 is chosen to examine simultaneous new and repeat effects, the simultaneous NEW and REPEAT adopter effects in models 2 and 3 are of the same polarity as ALL in model 1. The same comparison procedure for model selection is followed for Dodge Neon repeat adopter degree 3 analyses.

Table 40 presents the identified prior NEW and REPEAT effects upon current New and Repeat Adopters. Coefficients effects are summarized as faster (-) or slower (+) effects upon time to adoption.

**Table 40: Identified Prior New and Repeat Effects upon Current New and Repeat Adopter Adoption Time**

Adopter Group	Model	5 degree similarity		4 degree similarity		3 degree similarity	
		NEW	REPEAT	NEW	REPEAT	NEW	REPEAT
New	Dodge Neon		-		-	-	-
	Jeep Grand Cherokee		-		-		
	Mazda Miata		-		-		
	Toyota Avalon	-	+				
Repeat	Dodge Neon	+				+	+
	Jeep Grand Cherokee						
	Mazda Miata						
	Toyota Avalon		+				

( - ) indicates faster time to adoption  
 ( + ) indicates slower time to adoption

### *Static Covariates*

With one exception, significant coefficients for income always accelerate time to adoption (for Dodge Neon Repeat Adopters higher income delays adoption). As expected, the greater the number of household vehicles the longer the time to adoption. In line with expectations the more recent the model year of the vehicle driven previously, the longer the time to adoption. The Mazda Miata Repeat Adopter group is the only exception.

### *Time Varying Covariates*

Coefficients for the effects of prior adopters upon New Adopters were predominantly negative. The few coefficients for the effect of prior Adopters upon Repeat Adopters were consistently positive.

### *Effects upon Repeat Adopters*

For the Dodge Neon, later repeat adopters have demographic characteristics in common with prior new adopters. This implies that late repeat adopters, but not early repeat adopters, are similar to prior new adopters. No other consistent effects are apparent.

### **Sensitivity Tests**

To determine relative impact of the 6 demographic dimensions upon the influence covariate results, analyses for new and repeat adopters were repeated 6 times, each with one of the demographic dimensions absent. For calculation of the demographic similarity ratios, this means only 5 dimensions were available. Thus degree 5 similarity requires all of 5 dimensions to be similar, degree 4 similarity requires 4 of 5 dimensions to be similar, and degree 3 similarity requires 3 of 5 dimensions to be similar. The impact upon the prevalence of significant results when removing each demographic dimension from the influence covariate is presented in Tables 41 and 42 for New Adopters and Tables 43 and 44 for Repeat Adopters.

**Table 41: Demographic Degree Similarity Sensitivity Test Results for New Adopters, Dodge Neon and Jeep Grand Cherokee**

Model	Dimension Removed	5 degree similarity		4 degree similarity		3 degree similarity	
		NEW	REPEAT	NEW	REPEAT	NEW	REPEAT
Dodge Neon	none		-		-	-	-
	age	-	-		-		-
	education	-	-	-		-	-
	gender		-		-		
	income	-	-		-		-
	occupation				-	-	
	race		-				
Jeep Grand Cherokee	none		-		-		
	age				-		-
	education	-			-		-
	gender						
	income				-	-	-
	occupation	-			-		-
	race						

( - ) indicates faster time to adoption

( + ) indicates slower time to adoption

**Table 42: Demographic Degree Similarity Sensitivity Test Results for New Adopters, Mazda Miata and Toyota Avalon**

Model	Dimension Removed	5 degree similarity		4 degree similarity		3 degree similarity	
		NEW	REPEAT	NEW	REPEAT	NEW	REPEAT
Mazda Miata	none		-		-		
	age	-	-	-	-		
	education	-			-		
	gender	-			-		
	income		-		-		-
	occupation				-		
	race	-			-		
Toyota Avalon	none	-	+				
	age	-	+				
	education						
	gender		+		+		
	income			-	+	-	+
	occupation	-	+	-	+		-
	race		+		+	+	

( - ) indicates faster time to adoption

( + ) indicates slower time to adoption

**Table 43: Demographic Degree Similarity Sensitivity Test Results for Repeat Adopters, Dodge Neon and Jeep Grand Cherokee**

Model	Dimension Removed	5 degree similarity		4 degree similarity		3 degree similarity	
		NEW	REPEAT	NEW	REPEAT	NEW	REPEAT
Dodge Neon	none	+				+	+
	age				+	+	+
	education	+		+		+	+
	gender	+	+				+
	income	+		+			
	occupation	+				+	+
	race			+			+
Jeep Grand Cherokee	none						
	age						
	education						
	gender						
	income						
	occupation						
	race						

( - ) indicates faster time to adoption

( + ) indicates slower time to adoption

**Table 44: Demographic Degree Similarity Sensitivity Test Results for Repeat Adopters, Mazda Miata and Toyota Avalon**

Model	Dimension Removed	5 degree similarity		4 degree similarity		3 degree similarity	
		NEW	REPEAT	NEW	REPEAT	NEW	REPEAT
Mazda Miata	none						
	age						
	education	-					
	gender		-				
	income	-					
	occupation	-					
	race	-					
Toyota Avalon	none		+				
	age	+	+				
	education		+				
	gender		+	+	+	+	+
	income						+
	occupation						
	race				+		

( - ) indicates faster time to adoption

( + ) indicates slower time to adoption



## Hypothesis Testing

Hypothesis 1. For second generation products, purchase by New Adopters is accelerated by social connection to prior New Adopters.

The results presented in Table 40 provide partial support for Hypothesis 1. Significant negative effects upon time to adoption are observed for just one degree similarity for the Dodge Neon (degree 3) and Toyota Avalon (degree 5). The presence of only 2 accelerative effects of prior New Adopters upon current New Adopters provides **weak support for Hypothesis 1**.

Hypothesis 2. For second generation products, purchase by New Adopters is accelerated by social connection to prior Repeat Adopters.

Significant negative coefficients for REPEAT are present for the Dodge Neon (degrees 3, 4, and 5), Jeep Grand Cherokee (degrees 4 and 5), and Mazda Miata (degrees 4 and 5), but not the Toyota Avalon that shows a single positive coefficient (degree 5). This indicates purchase by current New Adopters is predominantly accelerated by prior Repeat Adopters. Three of the four second generation automobiles show this effect, providing **strong support for Hypothesis 2**.

Hypothesis 3. For second generation products, purchase by New Adopters is accelerated more by social connection to prior Repeat Adopters, than social connection to prior New Adopters.

For the Dodge Neon, Repeat Adopters accelerate time to adoption across degree 3, 4 and 5 similarities. NEW accelerates time to adoption for only degree 3. For both the Jeep Grand Cherokee and Mazda Miata, REPEAT accelerates purchase in New Adopters at degree 4 and 5 similarities, and no NEW effects are observed. For each of the three second generation products that show consistent effects of prior adopters, REPEAT effects are consistently more prevalent than NEW across different degrees of demographic similarity. This provides **strong support for Hypothesis 3.**

Hypothesis 4. For second generation products, purchase by Repeat Adopters is not accelerated by social connection to prior New Adopters.

The results displayed in Table 40 for current Repeat Adopters show positive coefficients for the Dodge Neon for NEW at degree similarities 3 and 5, and no negative coefficients for NEW. This indicates that purchase by Repeat Adopters is not accelerated by prior New Adopters, and the positive coefficients even suggest Repeat Adopters of the Dodge Neon lack social connections to prior New Adopters. This provides **strong support for Hypothesis 4.**

Hypothesis 5. For second generation products, purchase by Repeat Adopters is not accelerated by social connection to prior Repeat Adopters.

There are no negative coefficients to indicate purchase by Repeat Adopters is accelerated by prior Repeat Adopters. However there are positive REPEAT coefficients for the Dodge Neon at degree similarity 3, and for the Toyota Avalon at degree similarity 5, which provides preliminary evidence Repeat Adopters lack social connections to New Adopters. The complete lack of negative coefficients for prior Repeat Adopter effects upon current Repeat Adopters provides **strong support for Hypothesis 5**.

## **Chapter 5**

### **DISCUSSION**

*This chapter discusses the research results and conducts several post-hoc analyses to aid in explanation of the findings by relaxing the assumption that new and repeat adopters are different, and applying the method to existing products. Evidence is found the method may be of value for existing products.*

The results of the research can be summarized thus:

- For second generation products, new adopters are susceptible to influence from prior adopters, and repeat adopters are not.
- For second generation products, repeat adopters are more infectious than new adopters.

#### **New and Repeat Adopters**

New Adopters are susceptible to influence, and are clearly an imitative segment. Early purchase in this group is associated with prevalent connections to earlier adopters. This supports the assertion that later adopter categories such as the late majority and laggards have fewer social connections than earlier categories such as early adopters and the early majority (Rogers 1995:283).

A possible explanation for the lack of significant results for the Toyota Avalon is its relative lack of innovativeness as a new product. The first and second generation Toyota Avalon models were built on a modified stretched

platform version of the simultaneously available smaller Toyota Camry that was already in its third generation when the Avalon was launched. In addition, the Toyota Avalon engine was almost identical to that used in the Toyota Camry. Adopters of the Toyota Avalon may not have viewed product performance as uncertain, due to a strong positive brand image of the Toyota Camry which was (and remains) one of the highest selling passenger cars in the United States. A sufficient level of media information would make consultation of the social network unnecessary.

There is a clear lack of susceptibility for Repeat Adopters although the smaller sample size and corresponding lower statistical power for these tests prevents direct comparisons with New Adopter susceptibility results. This study thus provides prima facie evidence that adopters of a prior generation are effective in stimulating adoption for the next product generation, a finding consistent with Kim, Chang and Shocker (2000) and Islam and Meade (1997), although the results provide no evidence second generation adopters encourage first generation adopters to switch.

Repeat Adopters are more infectious than New Adopters, indicating innovative adopters have greater credibility gained from product experience with the first generation product. It is also possible that as an innovative segment, Repeat Adopters are more outwardly connected than New Adopters. The difference between outward and inward connections cannot be determined in this study because the similarity measure is symmetrical. A relational network approach to inward and outward network nominations could distinguish between

connection flows, but the data requirement is outside the scope of the data used in this investigation. In either case, the existence of strong influence between innovative and imitative groups means firms should target innovators in order to improve the chances of new product launch success (Mahajan and Muller 1998).

## **Propensity**

The variables used to capture an individual's propensity to adopt independent of social influence are predominantly in the expected direction with no discernible difference in effect by New versus Repeat Adopter groups. While prior work has found that innovators have inherently higher propensity, in this study there appears to be no difference in the role propensity plays in making the adoption decision by innovators versus imitators.

## **Sensitivity Results**

In sensitivity tests each of the six demographic variables were removed in sequence from the calculation of the demographic similarity ratio, and all regression and model selection procedures repeated. This placed a more strict constraint upon similarity requirements as individuals have one fewer dimension for comparison. Most results retain their significance in the face of demographic dimension removal. Some changes occur for persistence across similarity degrees. The single notable change in result for Repeat Adopters is the omission of gender for the Toyota Avalon that results in persistent positive

coefficients when all other analyses suggest a lack of consistent effects. Several differences are observed for New Adopters.

Omission of race causes the single biggest change for the Dodge Neon where accelerative effects of prior Repeat Adopters almost disappear. This same effect occurs for the Jeep Grand Cherokee when gender or race is omitted and for the Mazda Miata when occupation is omitted. These dimensions seem to be particularly important to the flow of influence between prior Repeat and current New Adopters. The interpretation for the Dodge Neon is that similarities of age, education, gender, income, and occupation are not effective in establishing influence without simultaneously considering race. Similarly, for the Jeep Grand Cherokee, past Repeat Adopters are connected to current New Adopters largely through gender and race, and the connection is largely through occupational similarity for the Mazda Miata. Consideration of these omitted factors alone would likely be insufficient to link demographic similarity and adoption time, but must be used in conjunction with additional demographic factors.

The results for the Toyota Avalon are in contrast with the others in that the incidence of significant coefficients increases rather than decreases with removal of gender, income, occupation, and race. Positive coefficients appear for prior Repeat Adopter effects indicating that early New Adopters are not similar to prior Repeat Adopters, while later New Adopters are. A possible explanation is the relative lack of innovativeness for the Toyota Avalon identified previously. This would result in low usage of the social network for product information collection,

meaning information may have to travel through indirect network ties. The negative coefficients when income and occupation are omitted also indicate that New Adopters may be linked to prior New Adopters. These negative coefficients indicate New Adopter similarity with earlier prior New Adopters, and the positive coefficients indicate relative New Adopter dissimilarity to the earlier Repeat Adopters. This suggests early New Adopters are a distinct market segment from early Repeat Adopters.

Sensitivity analyses provide evidence of hierarchical importance in the use of demographic characteristics to proxy for internal influence. Future use of demographic characteristics to measure influence should therefore assess relative importance of the demographic dimensions used.

## **Influence in Diffusion**

Aggregate level diffusion studies investigate internal influence mechanisms by examining the variance of diffusion parameters across adopting populations (e.g. Kumar and Krishnan 2002). This necessitates consideration of multiple adoption contexts at the population level. Network studies obtain detailed insights in just a single adoption context, but each individual's position in the network must be described by examining their specific social relations with others. The demographic similarity approach used in this research provides greater insight into the diffusion process compared to aggregate level diffusion studies, and uses individual level information more parsimonious than typically used in network studies of diffusion. This practice of inferring word of mouth



influence from demographic comparisons thus provides an intermediate means of modeling internal influence in an adopting population that is suitable for samples sizes between those normally used in aggregate and individual level studies. Indeed demographic level customer data (such as scanner or survey data) are quite common in marketing contexts, holding promise for more widespread application of the technique developed here.

This study modeled influence in a manner consistent with the influence factors used in the heterogeneous diffusion model proposed by Strang and Tuma (1993), whose most important feature is arguably the incorporation of time varying internal influence. However the approaches used here and by Strang and Tuma differ in their measurement of propensity, proximity, infectiousness and susceptibility, and in addition the heterogeneous model assumes population level data rather than samples of the kind used in this study. Nevertheless, the current demographic similarity results indicate the factors proposed as key to capturing adoption behavior by Strang and Tuma have explanatory power beyond population level samples and individual level relationship data.

While other studies have also utilized an imitation rationale to infer influence by virtue of similarity (e.g. Greve 1998; Soule and Zylan 1997), further validation for the use of demographic similarity as a proxy measure for internal influence can be provided through use of simultaneous relation and demographic assessment of the kind applied by De Bruyn and Lilien (2004), who utilized online referrals to determine the role of network actors in influencing others of varying demographic similarity and social proximity; thus allowing for simultaneous

assessment of network relations and individual demographic characteristics. A useful starting point would be analysis of existing social network diffusion data that customarily include extensive information concerning relationships, demographics and adoption timing. Common incidence of relationship and demographics may then be first ascertained before incorporation of a demographic similarity index in a longitudinal context

### Comparison with an All Adopter Group

A naïve set of regression analyses were conducted for a single adopter group to determine the value of treating individuals as distinct new and repeat adopters. In these models current adopters are not treated as two distinct new and repeat groups, but as a single “all adopter” group. Table 45 presents the identified effects for prior ALL adopters upon current All Adopters. To aid in understanding of these naïve regression results, additional expanded analyses were also conducted that incorporated distinct prior NEW and REPEAT covariates. These results are presented in Table 46.

**Table 45: Naïve Analyses, Identified ALL Effects upon All Adopter Adoption Time**

<b>Model</b>	<b>5 degree similarity All</b>	<b>4 degree similarity All</b>	<b>3 degree similarity All</b>
Dodge Neon			
Jeep Grand Cherokee	-		
Mazda Miata		-	
Toyota Avalon			

( - ) indicates faster time to adoption  
( + ) indicates slower time to adoption

**Table 46: Expanded Naïve Analyses, Identified NEW and REPEAT Effects upon All Adopter Adoption Time**

Model	5 degree similarity		4 degree similarity		3 degree similarity	
	NEW	REPEAT	NEW	REPEAT	NEW	REPEAT
Dodge Neon						
Jeep Grand Cherokee	-	-		-		-
Mazda Miata	-		-	-	-	
Toyota Avalon						

( - ) indicates faster time to adoption  
 ( + ) indicates slower time to adoption

### Comparing All Adopters versus New and Repeat Adopter Groups

Naïve analyses for All Adopters treat New and Repeat Adopters as a single group, thereby assuming that all potential adopters are equally susceptible. Table 45 presents the simplest class of naïve results. This analysis yields only two results, negative coefficients for the Jeep Grand Cherokee for degree 5 and the Mazda Miata for degree 4. These are suggestive of word of mouth effects but are not prevalent across similarity degrees. Expanding the naïve analyses to include distinct prior New and Repeat adopter effects upon All Adopters is more informative.

Expanded naïve analyses reveal more prevalent effects across similarity degrees. Diffusion effects, or the absence of, are identified correctly for the Jeep Grand Cherokee, Mazda Miata and Toyota Avalon; but are incorrectly absent for the Dodge Neon. This incorrect result is likely due to the opposite effects found in the separate New and Repeat Adopter analyses for the Dodge Neon that have offset each other in the All Adopter analyses. The diffusion effects from prior New and Repeat groups for the Jeep Grand Cherokee are consistent with the

New Adopter group findings, but results in misattribution of effect for the Mazda Miata where influence now appears to stem largely from New rather than Repeat Adopters.

Conclusions based upon All Adopter analyses are substantially different compared to 2 of 4 New Adopter analyses, and 3 of 4 Repeat Adopter analyses; however when viewed as a complementary analysis, the results for All Adopters complement the separate New and Repeat analyses. Absent All Adopter results can be due to contrasting New and Repeat effects, or absent New and Repeat effects. These are apparent for the Dodge Neon and Toyota Avalon respectively. The Jeep Grand Cherokee expanded all adopter analyses (Table 46), are largely consistent with New Adopter results, but not with Repeat Adopter results (Table 40). This indicates Repeat Adopters are quite infectious, with effects pervasive over New and All Adopter analyses. For the Mazda Miata, All Adopter analyses would attribute influence largely to prior New Adopters, but separate analyses identify influence as stemming from Repeat Adopters. The All Adopter analyses therefore mask the infectious effect of Repeat Adopters.

While All Adopter analyses can potentially reveal the presence of diffusion effects, they do not reveal the relative susceptibility of New Adopters, and relative infectiousness of Repeat Adopters. Thus All Adopter analyses provide additional insight and support the findings of the New and Repeat analyses, but in isolation do not accurately reveal attribution of word of mouth effects.

## **Comparison with Existing Products**

What happens when the demographic similarity ratio is applied to buyers of existing products instead of adopters of new products? This is a natural question to ask as the marketplace for existing products is information rich compared to that for new products, and interpersonal word of mouth effects are hypothetically absent when there is little need to seek information from the social network. Compared to new products, buyers of existing products can assess likely product performance with greater confidence from available media and do not need to rely upon inter-personal information. Social connections between buyers are not used to exchange information regarding product performance. This makes the purchase decision insensitive to the actions of prior buyers. This is true for both first-time and loyal buyers of existing products who represent inexperienced and experienced market segments. Thus the presence of interpersonal influence for adopters of new products, and its absence for buyers of existing products would provide a means of distinguishing between new product “adopter segments” and existing product “market segments”.

The same procedure was followed to test for evidence of internal influence between early and later buyers of existing products. 18 automobile models were identified with complete generation sales years within 1999-2004, of these 8 satisfied the sample size requirements. The piecewise Weibull procedure again overlapped substantially with Cox regression results indicating sampling variation

was suitably accounted for. Vehicle details and abbreviated analyses are shown in Tables 47 and 48.

**Table 47: Existing Automobile Models Analyzed**

<b>Model</b>	<b>G2 start</b>	<b>G2 end</b>	<b>G2 sale years</b>	<b>All</b>	<b>New</b>	<b>Repeat</b>	<b>New Sub- Sample</b>	<b>Repeat Sub- Sample</b>
Buick LeSabre	2000	2004	6	7003	1964	983	804	522
Chevrolet Monte Carlo	2000	2004	6	4295	1737	336	1136	241
Ford Mustang	1999	2004	7	5521	1788	211	1202	152
Ford Taurus	2000	2004	6	5050	1032	272	572	191
Mercury Sable	2000	2004	6	3114	1287	264	793	165
Pontiac Bonneville	2000	2004	6	4414	1286	627	766	429
Pontiac Grand Am	1999	2004	7	7381	2005	372	1287	266
Subaru Legacy	2000	2004	6	6340	3337	641	2179	439

There are three types of results of the prior New Buyer covariate upon current adopters of non-new automobiles. The first effect is observed among a group that includes the Mercury Sable, Pontiac Grand Am and Subaru Legacy where there are negative coefficients for the 'new' component of NEW and REPEAT. The effect is consistent across all degree similarities, and suggests current New Adopters are similar to prior New Adopters. The second effect is observed in a group that includes the Chevrolet Monte Carlo, Ford Taurus, and Pontiac Bonneville that show positive coefficients for NEW for degree similarity 5, and as part of ALL in degree similarity 4. A significant positive NEW coefficient is also present for the Pontiac Bonneville at degree similarity 3. These positive coefficients indicate current New Buyers are dissimilar to prior New Adopters for these models. The third type of result is a lack of significant effect upon the Buick LeSabre and Ford Mustang where there are no consistently significant

coefficients across degree similarities, and no demographic similarities are apparent.

**Table 48: Existing Products: Identified Prior New and Repeat Effects upon Current New and Repeat Adopter Adoption Time**

	Model	5 degree similarity		4 degree similarity		3 degree similarity	
		NEW	REPEAT	NEW	REPEAT	NEW	REPEAT
New	Buick LeSabre	-		-	+		
	Ford Mustang						
	Mercury Sable	-	+	-	+	-	+
	Pontiac Grand Am	-	+	-	+	-	+
	Subaru Legacy	-	+	-	+	-	+
	Chevrolet Monte Carlo	+		+	+		+
	Ford Taurus	+		+	+		+
	Pontiac Bonneville	+		+	+	+	
Repeat	Buick LeSabre						
	Ford Mustang						
	Mercury Sable						
	Pontiac Grand Am		-				
	Subaru Legacy	-	+	-	+	-	+
	Chevrolet Monte Carlo		-				
	Ford Taurus	+					
	Pontiac Bonneville					+	

( - ) indicates faster time to adoption

( + ) indicates slower time to adoption

Significant coefficients for REPEAT are always positive. Present for the Mercury Sable, Pontiac Grand Am, Subaru Legacy, Chevrolet Monte Carlo, Ford Taurus and Pontiac Bonneville, this dissimilarity of prior Repeat Adopters to current New Adopters is observed across 6 of the 8 non-new automobiles.

A persistent positive coefficient for the effect of prior Repeat Buyers upon current New Buyer time to adoption indicates New Buyers are not influenced to purchase early by Repeat Buyers. This implies that early new and early repeat buyers are distinct market segments that have few demographic connections. However later New Buyers have demographic qualities in common with Repeat

Buyers, but these common characteristics do not result in accelerated adoption. This can indicate that later New Buyers are influenced by prior Repeat Buyers whereas earlier New Buyers are not, in which case any influence that may flow to later New Buyers is delayed while influence is transmitted through indirect network channels; or that later New Buyers make similar decisions to prior repeat buyers (but later in time) due to similar resource sets and circumstances. If similar demographics can be used to proxy for similar resources, the implication is that given similar resource sets, new buyers take longer to reach a decision and thus have a higher threshold than repeat buyers due to greater risk adversity and a need to accumulate more information.

Early New Buyers are thus always different from Repeat Buyers. This is consistent with the market segmentation view that buyers of varying loyalty are driven by different factors and exhibit different purchase behavior (Yim and Kannan 1999; Blattberg, Buesing and Sen 1980; Starr and Robinson 1978). The results here indicate this is true even if there are common demographic qualities.

These results for existing products provide insight into the findings for the Toyota Avalon, where the lack of significant results in initial analyses, together with the significant results found during sensitivity analyses, reveal the Toyota Avalon bears strong resemblance to existing products, thereby supporting the previously offered explanation that its use of an existing modified platform and engine led to its perception as a less innovative product. The results for second generation and existing products can be summarized as contrasting influence



effects from prior New and Repeat Adopters, upon current New Adopters. These contrasting effects are presented in Table 49.

**Table 49: Demographic Similarity Coefficient Effects of Prior Adopters upon New Adopter Time to Adoption**

<b>Product</b>	<b>Prior New Adopter</b>	<b>Prior Repeat Adopter</b>
<b>Second Generation</b>		
Dodge Neon		-
Jeep Grand Cherokee		-
Mazda Miata		-
<b>Existing 1</b>		
Mercury Sable	-	+
Pontiac Grand Am	-	+
Subaru Legacy	-	+
<b>Existing 2</b>		
Chevrolet Monte Carlo	+	+
Ford Taurus	+	+
Pontiac Bonneville	+	+

### **Positive Influence Coefficients**

Negative coefficients for demographic similarity influence variables indicate accelerated purchase, and a lack of significance indicates no accelerative effects. Interpretation of positive coefficients is somewhat more complex. The presence of positive coefficients indicates social connection to prior adopters is associated with later adoption. This means either information travels slowly through the social network, or that early and later buyers have similar resources (indicated through similar demographic characteristics) but different decision making thresholds. Positive coefficients occur most often for Repeat Adopters and Repeat Buyers and both of these groups have little reason

to utilize social contacts for information collection. Positive coefficients therefore indicate differences in decision making thresholds among adopters with similar resource endowments.

### **Demographic Similarity as a Classification Tool**

In a longitudinal purchase context, there appears to be value in considering demographics as a proxy for channels of influence. If word of mouth effects are expected during the process of product adoption, there is value in placing emphasis on demographic characteristics when forming market segments. The demographic similarity ratio used in this study was found to differentiate between second generation versus existing products, and between 2 different kinds of existing product buyer groups.

In forming adopter categories, Rogers (1995:280) only requires groups to be exhaustive, mutually exclusive, and classified upon a clear principle. In determining the utility of market segments: identifiability, substantiality, accessibility, stability, responsiveness, and actionability are often used (Wedel and Kamakura 2000:4). Rogers' three criteria, and the first two market segment criteria aid in conceptual distinction of groups, but do not assist in efforts to communicate with individuals within these groups. Accessibility, stability, responsiveness and actionability reflect the managerial desire to inform, and measure the response to potential buyers in a population. By identifying distinct effects exerted by infectious Repeat Adopters of a second generation product, future investigations now have an additional basis for forming market segments.

Together with the ability to specify the more important demographic dimensions of the similarity ratio, consideration of New and Repeat groups can improve the ability of researchers and managers to identify key customers.

### **Value to Managers**

Marketing data are typically rich in demographic information that has primarily been used to form market segments with the goal of predicting behavioral response. The time varying effects of the demographic similarity ratio upon adoption time in this study suggest a customer's demographic information can be used to predict not only their own response, but the responses of other individuals.

For second generation products, Repeat Adopters are an identifiable segment that can be marketed to. Their relatively small segment size enables more efficient marketing communication compared to targeting the entire adopting population. Demographic information can be used to both target Repeat Adopters for repurchase, and to stimulate influence in a potential New Adopting population. Care should be exercised in determining that a product is perceived by the market as new. The results for the Toyota Avalon in this study indicate some new products are not viewed as innovative by consumers and therefore do not stimulate word of mouth effects involving Repeat Adopters.

Some existing products are amenable to word of mouth marketing, but this is only the case for the effect of prior new buyers upon current new buyers. Consequently it is important that marketers track in real time the demographic

profiles of first time buyers of existing products. If demographic similarity reveals accelerated purchase among first time buyers, mechanisms may be implemented to encourage these recently identified buyers to share their purchase experience.

Repeat Adopters and Buyers are loyal consumers whose main barrier to early purchase is their decision making threshold. These individuals would be difficult to reach through word of mouth communication but should be receptive to resource-related firm actions such as financial incentives.

### **Study Limitations**

The data in the investigation are only a sample of the adopting population. This means network information is incomplete and influence can only be inferred rather than modeled explicitly. There is potential for misattribution of effect when data are incomplete (Greve, Strang and Tuma 2001), where infectiousness, susceptibility, proximity and propensity are mistaken for one another.

Due to smaller sample size and thus lower statistical power, the results for Repeat Adopters are a weaker test than for New Adopters. Conclusions drawn regarding the difference in the susceptibility of New versus Repeat groups are therefore less certain. Bootstrap sampling or investigation of product contexts where new and repeat adopters are more equally distributed would improve confidence in susceptibility findings.

The study considered data for automobiles which is a highly specific product context. The diffusion of automobiles as a technological innovation started more than a century ago in the United States around the year 1900 when

ownership penetration was at a low 1 per 1000 Americans, and reached saturation point sometime in the 1960s (Fischer and Carroll 1988). It is during this diffusion phase that automobiles may be reasonably described as a “new to the world” innovative product (Garcia and Calantone 2002). Automobiles are currently best described as a durable consumer good in a mature stage of the product life cycle where purchase is driven primarily by replacement. Despite the maturity of automobiles as a technological innovation, their high expense and relationship to social status (Fredrick 1971) suggest that purchase is highly dependent upon information concerning product performance and comparisons with choices made by others. The assertion that new automobile introductions generate word of mouth is supported by the incorporation of word of mouth into forecast models of new automobile acceptance (Urban, Hauser and Roberts 1990).

The moderate innovativeness of new automobiles mean this investigation has presented only a conservative test of the theory. Replications for products of higher innovativeness may reasonably be expected to yield stronger results, as word of mouth influence should play an even greater role in the adoption decisions of individuals.

### **Future Research Extensions**

The modeling approach used in this research identified the presence of demographic links between past and present individuals, but did not provide substantial detail on the nature of these links. The programming approach used

to calculate demographic similarity was able to determine similarity degree, but not the specific demographic dimensions of similarity or their relative strengths.

The means of establishing similarity treated demographic dimensions as qualitative, prevented consideration of varied levels of similarity for each demographic dimension. For example individuals are judged dissimilar if their incomes are not of the same category but there is no allowance for the degree of difference between adopters along the 12 income categories. Weighting of similarity by the level of difference for ordered demographic dimensions such as income and education, would provide a more detailed assessment of similarity, potentially improving the power of the demographic similarity ratio. The lack of weighting in this study reduced the capacity to detect more subtle influence effects. This approach was adopted to conserve computation time. To improve understanding of influence and managerial usefulness, specific demographic dimensions should be ranked in importance of influence using distance weights within dimensions, and relative weights across dimensions.

While results for existing products were consistent with market segmentation theory that distinguishes between new and repeat adopters; for 3 automobile models new buyers appear to respond to the actions of earlier new buyers, implying that actions by members of one segment alter membership in another. Should this latent change (Wedel and Kamakura 2000) finding be more than a methodological artifact, this has implications for market segmentation research that may need to entertain the possibility that latent change is an assumption for some products rather than the exception (Böckenholt and

Langeheine 1996; Farley, Lehmann and Winer 1987; Calantone and Sawyer 1978).

## **Conclusion**

Demographic similarity as a measure of internal influence is able to distinguish between New and Repeat Adopters of second generation products. Repeat Adopters accelerate purchase by New Adopters and represent an actionable market segment that is of use to managers due to their relatively small size. Together with a method of decomposing demographic similarity influence effects, Repeat Adopters may provide an efficient means of stimulating adoption in a New Adopter segment. There is a promising avenue for the use of demographic similarity to capture word of mouth effects generated by New Adopters of existing products.

## **APPENDICES**



## **APPENDIX A**

### **Second Generation Automobiles Model Quarterly and Annual Sample Size Distributions**

**Table 50: Dodge Neon New Adopter Sample Size by Survey Quarter and Calendar Year**

		Quarter				Total
		1	2	3	4	
Survey Year	1,999	0	0	55	50	105
	2,000	97	115	45	62	319
	2,001	121	120	51	76	368
	2,002	121	125	50	41	337
	2,003	137	146	63	51	397
	2,004	87	97	51	54	289
Total		563	603	315	334	1,815

**Table 51: Dodge Neon Repeat Adopter Sample Size by Survey Quarter and Calendar Year**

		Quarter				Total
		1	2	3	4	
Survey Year	1,999	0	0	9	2	11
	2,000	14	14	4	8	40
	2,001	16	12	6	12	46
	2,002	26	21	10	5	62
	2,003	6	13	4	6	29
	2,004	9	7	2	3	21
Total		71	67	35	36	209

**Table 52: Jeep Grand Cherokee New Adopter Sample Size by Survey Quarter and Calendar Year**

		Quarter				Total
		1	2	3	4	
Survey Year	1,999	131	113	39	108	391
	2,000	35	76	32	27	170
	2,001	90	74	27	40	231
	2,002	66	82	40	70	258
	2,003	88	118	107	140	453
	2,004	87	70	29	32	218
Total		497	533	274	417	1,721

**Table 53: Jeep Grand Cherokee Repeat Adopter Sample Size by Survey Quarter and Calendar Year**

		Quarter				Total
		1	2	3	4	
Survey Year	1,999	28	44	11	32	115
	2,000	14	26	9	9	58
	2,001	37	26	4	10	77
	2,002	21	14	8	10	53
	2,003	16	20	28	16	80
	2,004	18	14	7	8	47
Total		134	144	67	85	430

**Table 54: Mazda Miata New Adopter Sample Size by Survey Quarter and Calendar Year**

		Quarter				Total
		1	2	3	4	
Survey Year	1,999	42	56	22	31	151
	2,000	4	60	28	20	112
	2,001	99	89	49	51	288
	2,002	83	109	49	43	284
	2,003	0	114	66	52	232
	2,004	6	28	44	40	118
Total		234	456	258	237	1,185

**Table 55: Mazda Miata Repeat Adopter Sample Size by Survey Quarter and Calendar Year**

		Quarter				Total
		1	2	3	4	
Survey Year	1,999	0	6	4	2	12
	2,000	2	17	1	6	26
	2,001	14	14	7	7	42
	2,002	19	11	2	9	41
	2,003	0	8	3	6	17
	2,004	0	1	7	7	15
Total		35	57	24	37	153

**Table 56: Toyota Avalon Legacy New Adopter Sample Size by Survey Quarter and Calendar Year**

		Quarter				Total
		1	2	3	4	
Survey Year	2,000	90	132	49	52	323
	2,001	109	108	51	54	322
	2,002	116	145	59	184	504
	2,003	110	139	79	59	387
	2,004	116	102	46	48	312
Total		541	626	284	397	1,848

**Table 57: Toyota Avalon Repeat Adopter Sample Size by Survey Quarter and Calendar Year**

		Quarter				Total
		1	2	3	4	
Survey Year	2,000	20	24	6	6	56
	2,001	19	12	4	7	42
	2,002	20	16	3	19	58
	2,003	12	20	8	8	48
	2,004	23	17	6	10	56
Total		94	89	27	50	260

## **APPENDIX B**

### **Complete Second Generation Automobile Results for Piecewise Weibull Regressions**

**Table 58: Dodge Neon Piecewise Weibull Regression for Degree Similarity 5 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
New Adopters			1	-1943.124		-37.861	-0.006	<b>0.036</b>	<b>0.020</b>			
Years	6	s.d.				3.648	0.005	0.011	0.002			
Obs.	3200	p				<.0001	0.287	0.001	<.0001			
			2	-1938.151	<b>9.946</b>	-38.521	-0.008	<b>0.036</b>	<b>0.020</b>	<b>-1.442</b>		
		s.d.				3.643	0.006	0.011	0.002	0.445		
		p				<.0001	0.134	0.001	<.0001	0.001		
			3	-1940.006	<b>6.237</b>	-38.338	-0.008	<b>0.036</b>	<b>0.020</b>		<b>-1.067</b>	
		s.d.				3.646	0.006	0.011	0.002		0.416	
		p				<.0001	0.165	0.001	<.0001		0.010	
			4	-1938.780	<b>8.689</b>	-38.342	-0.007	<b>0.036</b>	<b>0.020</b>			<b>-0.752</b>
		s.d.				3.640	0.005	0.011	0.002			0.244
		p				<.0001	0.200	0.001	<.0001			0.002
			5	-1937.578	<b>11.092</b>	-38.610	-0.008	<b>0.035</b>	<b>0.020</b>		<b>-0.712</b>	<b>-0.603</b>
		s.d.				3.643	0.006	0.011	0.002		0.452	0.265
		p				<.0001	0.145	0.001	<.0001		0.115	0.023

**Table 58: (cont'd).**

[illegible]

**Table 58: (cont'd).**

			Model	loglikelihood	X <sup>2</sup> diff	Int	inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters		$\beta$	6	-246.427		-62.310	0.026	0.058	0.032			
Years	6	s.d.				42.723	0.016	0.032	0.021			
Obs.	387	p				0.145	0.119	0.070	0.135			
		$\beta$	7	-242.531	<b>7.794</b>	-46.492	<b>0.033</b>	<b>0.072</b>	<b>0.024</b>	<b>4.078</b>		
		s.d.				42.638	0.016	0.032	0.021	1.527		
		p				0.276	0.038	0.025	0.262	0.008		
		$\beta$	8	-241.235	<b>10.385</b>	-45.654	<b>0.034</b>	<b>0.071</b>	0.024		<b>4.512</b>	
		s.d.				42.276	0.016	0.032	0.021		1.482	
		p				0.280	0.034	0.027	0.266		0.002	
		$\beta$	9	-245.814	1.226	-58.778	<b>0.027</b>	<b>0.065</b>	0.030			0.771
		s.d.				43.002	0.016	0.033	0.022			0.716
		p				0.172	0.094	0.049	0.161			0.281
		$\beta$	10	-241.199	<b>10.456</b>	-45.678	<b>0.034</b>	<b>0.072</b>	<b>0.024</b>		<b>4.414</b>	0.182
		s.d.				42.326	0.016	0.032	0.021		1.526	0.689
		p				0.281	0.033	0.026	0.266		0.004	0.792





**Table 59: Dodge Neon Piecewise Weibull Regression for Degree Similarity 4 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
New Adopters			1									
Years	6	$\beta$										
Obs.	3200	s.d.										
		p	2									
		$\beta$		-1939.302	7.645	-38.597	-0.008	0.036	0.020	-0.385		
		s.d.				3.660	0.006	0.011	0.002	0.138		
		p	3			<.0001	0.142	0.001	<.0001	0.005		
		$\beta$		-1940.445	5.358	-38.536	-0.008	0.036	0.020		-0.316	
		s.d.				3.665	0.006	0.011	0.002		0.135	
		p	4			<.0001	0.158	0.001	<.0001		0.020	
		$\beta$		-1938.505	9.238	-38.583	-0.007	0.035	0.020			-0.276
		s.d.				3.641	0.005	0.011	0.002			0.089
		p	5			<.0001	0.183	0.001	<.0001			0.002
		$\beta$		-1938.251	9.747	-38.730	-0.008	0.036	0.020		-0.118	-0.232
		s.d.				3.652	0.006	0.011	0.002		0.165	0.109
		p				<.0001	0.158	0.001	<.0001		0.475	0.033



**Table 59: (cont'd).**

				Model	loglikelihood	X <sup>2</sup> diff	int	inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters				6									
Years	6		$\beta$										
Obs.	387		s.d.										
			p	7									
			$\beta$		-244.909	3.038	-51.873	<b>0.032</b>	<b>0.066</b>	0.027	0.749		
			s.d.				42.878	0.016	0.032	0.022	0.432		
			p	8			0.226	0.047	0.039	0.214	0.083		
			$\beta$		-245.009	2.837	-52.136	<b>0.032</b>	<b>0.066</b>	0.027		0.698	
			s.d.				42.846	0.016	0.032	0.022		0.417	
			p	9			0.224	0.050	0.039	0.212		0.094	
			$\beta$		-244.738	3.380	-54.314	0.031	<b>0.067</b>	0.028			0.465
			s.d.				42.933	0.016	0.032	0.022			0.263
			p	10			0.206	0.059	0.040	0.195			0.077
			$\beta$		-244.392	4.071	-51.550	<b>0.033</b>	<b>0.069</b>	0.027		0.405	0.328
			s.d.				42.902	0.016	0.032	0.022		0.491	0.304
			p				0.230	0.044	0.033	0.218		0.410	0.282

**Table 59: (cont'd).**

			Model	2	3	4	5	6	scale	shape
Repeat Adopters		$\beta$								
Years	6	s.d.	6							
Obs.	387	p								
		$\beta$		0.124	0.030	0.052	-0.012	0.000	0.348	2.872
		s.d.	7	0.135	0.131	0.133	0.135	.	0.025	0.206
		p		0.360	0.821	0.694	0.929	.		
		$\beta$		0.127	0.034	0.053	-0.011	0.000	0.349	2.870
		s.d.	8	0.135	0.131	0.133	0.135	.	0.025	0.206
		p		0.347	0.794	0.690	0.937	.		
		$\beta$		0.213	0.099	0.136	0.056	0.000	0.349	2.863
		s.d.	9	0.142	0.135	0.139	0.138	.	0.025	0.205
		p		0.134	0.466	0.327	0.684	.		
		$\beta$		0.186	0.081	0.111	0.033	0.000	0.348	2.872
		s.d.	10	0.145	0.137	0.142	0.141	.	0.025	0.206
		p		0.200	0.554	0.434	0.815	.		

**Table 60: Dodge Neon Piecewise Weibull Regression for Degree Similarity 3 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
New Adopters			1									
Years	6	$\beta$										
Obs.	3200	s.d.										
		p	2									
		$\beta$		-1939.950	<b>6.349</b>	-38.429	-0.008	<b>0.036</b>	<b>0.020</b>	<b>-0.194</b>		
		s.d.				3.656	0.006	0.011	0.002	0.077		
		p	3			<.0001	0.139	0.001	<.0001	0.012		
		$\beta$		-1941.094	<b>4.060</b>	-38.318	-0.008	<b>0.036</b>	<b>0.020</b>		<b>-0.153</b>	
		s.d.				3.658	0.006	0.011	0.002		0.076	
		p	4			<.0001	0.161	0.001	<.0001		0.045	
		$\beta$		-1940.962	<b>4.324</b>	-38.170	-0.007	<b>0.036</b>	<b>0.020</b>			<b>-0.118</b>
		s.d.				3.641	0.006	0.011	0.002			0.057
		p	5			<.0001	0.196	0.001	<.0001			0.038
		$\beta$		-1940.651	<b>4.945</b>	-38.318	-0.008	<b>0.036</b>	<b>0.020</b>		<b>-0.084</b>	<b>-0.074</b>
		s.d.				3.652	0.006	0.011	0.002		0.106	0.079
		p				<.0001	0.165	0.001	<.0001		0.429	0.349

**Table 60: (cont'd).**

			Model	2	3	4	5	6	scale	shape
New Adopters		$\beta$	1							
Years	6	s.d.								
Obs.	3200	p								
		$\beta$	2	0.227	0.179	0.152	0.067	0.000	0.356	2.812
		s.d.		0.040	0.039	0.038	0.038	.	0.009	0.075
		p		<.0001	<.0001	<.0001	0.078	.		
		$\beta$	3	0.226	0.178	0.152	0.066	0.000	0.356	2.812
		s.d.		0.040	0.039	0.038	0.038	.	0.009	0.075
		p		<.0001	<.0001	<.0001	0.082	.		
		$\beta$	4	0.225	0.181	0.149	0.071	0.000	0.356	2.812
		s.d.		0.040	0.039	0.038	0.038	.	0.009	0.075
		p		<.0001	<.0001	<.0001	0.063	.		
		$\beta$	5	0.226	0.180	0.151	0.070	0.000	0.356	2.812
		s.d.		0.040	0.039	0.038	0.038	.	0.009	0.075
		p		<.0001	<.0001	<.0001	0.067	.		

Table 60: (cont'd).

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters		$\beta$	6									
Years	6	s.d.										
Obs.	387	p										
		$\beta$	7	-243.691	5.473	-55.204	0.037	0.069	0.028	0.552		
		s.d.				42.533	0.016	0.032	0.021	0.228		
		p				0.194	0.025	0.032	0.185	0.016		
		$\beta$	8	-243.283	6.289	-55.261	0.038	0.071	0.028		0.575	
		s.d.				42.428	0.016	0.032	0.021		0.223	
		p				0.193	0.020	0.029	0.183		0.010	
		$\beta$	9	-241.603	9.648	-50.205	0.036	0.067	0.026			0.547
		s.d.				42.458	0.016	0.032	0.021			0.171
		p				0.237	0.023	0.035	0.226			0.001
		$\beta$	10	-241.548	9.759	-50.403	0.037	0.068	0.026		0.108	0.483
		s.d.				42.442	0.016	0.032	0.021		0.324	0.256
		p				0.235	0.022	0.033	0.224		0.740	0.059



**Table 60: (cont'd).**

			Model	2	3	4	5	6	scale	shape
Repeat Adopters		$\beta$	6							
Years	6	s.d.								
Obs.	387	p								
		$\beta$	7	0.131	0.033	0.058	-0.011	0.000	0.346	2.889
		s.d.		0.135	0.130	0.132	0.134	.	0.025	0.208
		p		0.331	0.802	0.661	0.933	.		
		$\beta$	8	0.147	0.054	0.069	0.002	0.000	0.346	2.893
		s.d.		0.135	0.130	0.132	0.134	.	0.025	0.208
		p		0.275	0.681	0.603	0.988	.		
		$\beta$	9	0.178	0.054	0.104	0.003	0.000	0.345	2.900
		s.d.		0.135	0.129	0.132	0.133	.	0.025	0.208
		p		0.187	0.675	0.431	0.984	.		
		$\beta$	10	0.177	0.057	0.102	0.004	0.000	0.345	2.902
		s.d.		0.135	0.130	0.132	0.133	.	0.025	0.208
		p		0.191	0.658	0.440	0.978	.		

**Table 61: Jeep Grand Cherokee Piecewise Weibull Regression for Degree Similarity 5 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
New Adopters		$\beta$	1	-2081.940		-51.979	-0.023	0.038	0.027			
Years	7	s.d.				4.210	0.005	0.010	0.002			
Obs.	4087	p				<.0001	<.0001	0.000	<.0001			
		$\beta$	2	-2079.852	4.177	-53.007	-0.022	0.037	0.028	-0.557		
		s.d.				4.258	0.005	0.010	0.002	0.269		
		p				<.0001	<.0001	0.000	<.0001	0.038		
		$\beta$	3	-2080.588	2.705	-52.648	-0.023	0.037	0.027		-0.417	
		s.d.				4.244	0.005	0.010	0.002		0.248	
		p				<.0001	<.0001	0.000	<.0001		0.093	
		$\beta$	4	-2080.003	3.875	-53.023	-0.022	0.038	0.028			-0.389
		s.d.				4.255	0.005	0.010	0.002			0.194
		p				<.0001	<.0001	0.000	<.0001			0.046
		$\beta$	5	-2079.685	4.510	-53.171	-0.021	0.038	0.028		-0.234	-0.302
		s.d.				4.265	0.005	0.010	0.002		0.290	0.223
		p				<.0001	<.0001	0.000	<.0001		0.420	0.176

[illegible]

**Table 61: (cont'd).**

				Model	loglikelihood	X <sup>2</sup> diff	Int	inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters				6	-647.295		-116.359	-0.056	0.041	0.059			
Years	7	$\beta$	s.d.				33.305	0.013	0.028	0.017			
Obs.	951	p					0.001	<.0001	0.142	0.000			
				7	-647.292	0.007	-116.147	-0.056	0.041	0.059	-0.054		
		$\beta$					33.395	0.013	0.028	0.017	0.643		
		s.d.					0.001	<.0001	0.147	0.000	0.933		
		p		8	-647.283	0.024	-115.946	-0.056	0.041	0.059		-0.106	
		$\beta$					33.402	0.013	0.028	0.017		0.683	
		s.d.					0.001	<.0001	0.148	0.000		0.876	
		p		9	-647.192	0.206	-115.341	-0.054	0.040	0.059			-0.170
		$\beta$					33.373	0.013	0.028	0.017			0.371
		s.d.					0.001	<.0001	0.160	0.000			0.647
		p		10	-647.180	0.230	-115.582	-0.054	0.040	0.059		0.136	-0.216
		$\beta$					33.418	0.013	0.028	0.017		0.866	0.469
		s.d.					0.001	<.0001	0.159	0.000		0.875	0.646
		p											

**Table 61: (cont'd).**

				Model	2	3	4	5	6	7	scale	shape
Repeat Adopters				$\beta$	0.164	0.301	0.406	0.440	0.078	0.000	0.450	2.221
Years	7			s.d.	0.104	0.110	0.116	0.121	0.106		0.023	0.112
Obs.	951			p	0.114	0.006	0.001	0.000	0.461			
				$\beta$	0.165	0.302	0.406	0.440	0.078	0.000	0.450	2.221
				s.d.	0.104	0.110	0.116	0.121	0.106		0.023	0.112
				p	0.114	0.006	0.001	0.000	0.461			
				$\beta$	0.165	0.302	0.406	0.440	0.078	0.000	0.450	2.221
				s.d.	0.104	0.110	0.116	0.121	0.106		0.023	0.112
				p	0.113	0.006	0.001	0.000	0.461			
				$\beta$	0.165	0.303	0.408	0.444	0.077	0.000	0.450	2.221
				s.d.	0.104	0.110	0.116	0.121	0.106		0.023	0.112
				p	0.114	0.006	0.000	0.000	0.468			
				$\beta$	0.164	0.303	0.408	0.444	0.076	0.000	0.450	2.221
				s.d.	0.104	0.110	0.116	0.121	0.106		0.023	0.112
				p	0.116	0.006	0.000	0.000	0.471			

**Table 62: Jeep Grand Cherokee Piecewise Weibull Regression for Degree Similarity 4 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
New Adopters												
Years	7	$\beta$	1									
Obs.	4087	s.d.										
		p										
		$\beta$	2	-2079.578	4.724	-53.362	-0.022	0.038	0.028	-0.238		
		s.d.				4.279	0.005	0.010	0.002	0.109		
		p				<.0001	<.0001	0.000	<.0001	0.029		
		$\beta$	3	-2081.351	1.179	-52.665	-0.023	0.038	0.027		-0.114	
		s.d.				4.269	0.005	0.010	0.002		0.104	
		p				<.0001	<.0001	0.000	<.0001		0.275	
		$\beta$	4	-2078.447	6.987	-53.300	-0.021	0.039	0.028			-0.203
		s.d.				4.257	0.005	0.010	0.002			0.076
		p				<.0001	<.0001	<.0001	<.0001			0.007
		$\beta$	5	-2078.197	7.486	-52.992	-0.021	0.040	0.028		0.097	-0.246
		s.d.				4.273	0.005	0.010	0.002		0.138	0.097
		p				<.0001	<.0001	<.0001	<.0001		0.483	0.011

**Table 62: (cont'd).**

				Model	2	3	4	5	6	7	scale	shape
New Adopters			$\beta$	1								
Years	7		s.d.									
Obs.	4087		p									
			$\beta$	2	0.339	0.361	0.388	0.215	-0.019	0.000	0.344	2.910
			s.d.		0.047	0.047	0.048	0.044	0.040	.	0.009	0.079
			p		<.0001	<.0001	<.0001	<.0001	0.629	.		
			$\beta$	3	0.339	0.359	0.387	0.215	-0.019	0.000	0.344	2.908
			s.d.		0.047	0.047	0.048	0.044	0.040	.	0.009	0.079
			p		<.0001	<.0001	<.0001	<.0001	0.633	.		
			$\beta$	4	0.339	0.366	0.396	0.221	-0.024	0.000	0.344	2.910
			s.d.		0.047	0.047	0.048	0.044	0.040	.	0.009	0.079
			p		<.0001	<.0001	<.0001	<.0001	0.555	.		
			$\beta$	5	0.336	0.366	0.396	0.221	-0.027	0.000	0.344	2.910
			s.d.		0.047	0.047	0.048	0.044	0.041	.	0.009	0.079
			p		<.0001	<.0001	<.0001	<.0001	0.501	.		

**Table 62: (cont'd).**

			Model	loglikelihood	X <sup>2</sup> diff	Int	inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters		$\beta$	6									
Years	7	s.d.										
Obs.	951	p										
		$\beta$	7	-647.255	0.081	-115.634	-0.055	0.041	0.059	-0.074		
		s.d.				33.399	0.013	0.028	0.017	0.261		
		p				0.001	<.0001	0.147	0.000	0.775		
		$\beta$	8	-647.268	0.054	-115.722	-0.055	0.041	0.059		-0.063	
		s.d.				33.417	0.013	0.028	0.017		0.269	
		p				0.001	<.0001	0.144	0.000		0.816	
		$\beta$	9	-647.294	0.003	-116.221	-0.056	0.041	0.059			-0.011
		s.d.				33.398	0.013	0.028	0.017			0.198
		p				0.001	<.0001	0.145	0.000			0.956
		$\beta$	10	-647.252	0.087	-115.837	-0.056	0.042	0.059		-0.119	0.055
		s.d.				33.422	0.013	0.028	0.017		0.409	0.302
		p				0.001	<.0001	0.141	0.000		0.771	0.855



				Model	2	3	4	5	6	7	scale	shape	
Repeat Adopters Years				6									
		$\beta$											
	7	s.d.											
Obs.		951	p										
			$\beta$	7	0.165	0.302	0.406	0.439	0.077	0.000	0.450	2.221	
			s.d.		0.104	0.110	0.116	0.121	0.106	.	.0023	0.112	
			p		0.113	0.006	0.001	0.000	0.466	.	.		
			$\beta$	8	0.165	0.302	0.406	0.439	0.078	0.000	0.450	2.221	
			s.d.		0.104	0.110	0.116	0.121	0.106	.	.0023	0.112	
			p		0.113	0.006	0.001	0.000	0.462	.	.		
			$\beta$	9	0.165	0.302	0.406	0.440	0.078	0.000	0.450	2.221	
			s.d.		0.104	0.110	0.117	0.121	0.106	.	.0023	0.112	
			p		0.114	0.006	0.001	0.000	0.462	.	.		
			$\beta$	10	0.164	0.299	0.402	0.436	0.078	0.000	0.450	2.221	
			s.d.		0.104	0.111	0.117	0.122	0.106	.	.0023	0.112	
			p		0.115	0.007	0.001	0.000	0.460				

**Table 63: Jeep Grand Cherokee Piecewise Weibull Regression for Degree Similarity 3 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
New Adopters			1									
Years	7	$\beta$										
Obs.	4087	s.d.										
		p	2									
		$\beta$		-2079.053	5.775	-54.057	-0.022	0.038	0.028	-0.170		
		s.d.				4.328	0.005	0.010	0.002	0.071		
		p	3			<.0001	<.0001	0.000	<.0001	0.017		
		$\beta$		-2080.220	3.440	-53.668	-0.023	0.038	0.028		-0.130	
		s.d.				4.332	0.005	0.010	0.002		0.070	
		p	4			<.0001	<.0001	0.000	<.0001		0.065	
		$\beta$		-2080.050	3.780	-53.266	-0.022	0.038	0.028			-0.108
		s.d.				4.278	0.005	0.010	0.002			0.056
		p	5			<.0001	<.0001	0.000	<.0001			0.053
		$\beta$		-2079.832	4.216	-53.678	-0.022	0.038	0.028		-0.067	-0.070
		s.d.				4.330	0.005	0.010	0.002		0.101	0.080
		p				<.0001	<.0001	0.000	<.0001		0.507	0.382

**Table 63: (cont'd).**

			Model	2	3	4	5	6	7	scale	shape
New Adopters		$\beta$	1								
Years	7	s.d.									
Obs.	4087	p									
		$\beta$	2	0.343	0.363	0.390	0.217	-0.017	0.000	0.344	2.911
		s.d.		0.047	0.047	0.048	0.044	0.040	.	0.009	0.079
		p		<.0001	<.0001	<.0001	<.0001	0.674	.		
		$\beta$	3	0.344	0.363	0.390	0.218	-0.015	0.000	0.344	2.910
		s.d.		0.047	0.047	0.048	0.044	0.040	.	0.009	0.079
		p		<.0001	<.0001	<.0001	<.0001	0.706	.		
		$\beta$	4	0.340	0.365	0.394	0.221	-0.022	0.000	0.344	2.909
		s.d.		0.047	0.047	0.048	0.044	0.040	.	0.009	0.079
		p		<.0001	<.0001	<.0001	<.0001	0.578	.		
		$\beta$	5	0.343	0.365	0.394	0.221	-0.019	0.000	0.344	2.910
		s.d.		0.047	0.047	0.048	0.044	0.041	.	0.009	0.079
		p		<.0001	<.0001	<.0001	<.0001	0.649	.		

**Table 63: (cont'd).**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters		$\beta$	6									
Years	7	s.d.										
Obs.	951	p										
		$\beta$	7	-647.272	0.045	-117.135	-0.057	0.041	0.060	0.042		
		s.d.				33.509	0.013	0.028	0.017	0.197		
		p				0.001	<.0001	0.141	0.000	0.831		
		$\beta$	8	-647.276	0.038	-117.076	-0.057	0.041	0.060		0.039	
		s.d.				33.510	0.013	0.028	0.017		0.198	
		p				0.001	<.0001	0.141	0.000		0.845	
		$\beta$	9	-647.278	0.035	-116.985	-0.057	0.042	0.060			0.029
		s.d.				33.466	0.013	0.028	0.017			0.154
		p				0.001	<.0001	0.140	0.000			0.851
		$\beta$	10	-647.274	0.043	-117.139	-0.057	0.042	0.060		0.025	0.015
		s.d.				33.520	0.013	0.028	0.017		0.292	0.226
		p				0.001	<.0001	0.141	0.000		0.932	0.948

**Table 63: (cont'd).**

			Model	2	3	4	5	6	7	scale	shape
Repeat Adopters			6								
Years	7	$\beta$									
Obs.	951	s.d.									
		p	7								
		$\beta$		0.163	0.300	0.405	0.440	0.078	0.000	0.450	2.221
		s.d.		0.104	0.110	0.116	0.121	0.106	.	0.023	0.112
		p	8	0.116	0.006	0.001	0.000	0.461	.		
		$\beta$		0.163	0.301	0.405	0.439	0.078	0.000	0.450	2.221
		s.d.		0.104	0.110	0.116	0.121	0.106	.	0.023	0.112
		p	9	0.118	0.006	0.001	0.000	0.464	.		
		$\beta$		0.163	0.299	0.403	0.438	0.078	0.000	0.450	2.221
		s.d.		0.104	0.111	0.117	0.121	0.106	.	0.023	0.112
		p	10	0.119	0.007	0.001	0.000	0.459	.		
		$\beta$		0.163	0.300	0.404	0.438	0.078	0.000	0.450	2.221
		s.d.		0.104	0.111	0.118	0.121	0.106	.	0.023	0.112
		p		0.119	0.007	0.001	0.000	0.462	.		

**Table 64: Mazda Miata Piecewise Weibull Regression for Degree Similarity 5 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	inc	veh	vehage	ALL	NEW	REPEAT
New Adopters			1	-1497.639		-36.121	-0.006	<b>0.031</b>	<b>0.019</b>			
Years	7	s.d.				3.782	0.006	0.012	0.002			
Obs.	2895	p				<.0001	0.312	0.012	<.0001			
			2	-1493.212	<b>8.855</b>	-36.714	-0.004	<b>0.034</b>	<b>0.019</b>	<b>-0.672</b>		
		$\beta$				3.796	0.006	0.013	0.002	0.216		
		s.d.				<.0001	0.521	0.007	<.0001	0.002		
		p										
			3	-1493.615	<b>8.049</b>	-36.728	-0.003	<b>0.034</b>	<b>0.019</b>		<b>-0.661</b>	
		$\beta$				3.795	0.006	0.013	0.002		0.225	
		s.d.				<.0001	0.558	0.007	<.0001		0.003	
		p										
			4	-1487.875	<b>19.529</b>	-36.544	-0.003	<b>0.033</b>	<b>0.019</b>			<b>-0.636</b>
		$\beta$				3.797	0.006	0.012	0.002			0.137
		s.d.				<.0001	0.599	0.008	<.0001			<.0001
		p										
			5	-1487.463	<b>20.352</b>	-36.723	-0.002	<b>0.034</b>	<b>0.019</b>		<b>-0.247</b>	<b>-0.569</b>
		$\beta$				3.804	0.006	0.013	0.002		0.269	0.157
		s.d.				<.0001	0.684	0.007	<.0001		0.358	0.000
		p										

**Table 64: (cont'd).**

			Model	2	3	4	5	6	7	scale	shape
New Adopters			$\beta$	0.468	0.243	0.129	0.217	0.053	0.000	0.342	2.923
Years	7		s.d.	0.058	0.049	0.046	0.050	0.047	.	0.011	0.091
Obs.	2895		p	<.0001	<.0001	0.005	<.0001	0.255	.		
			$\beta$	0.466	0.239	0.126	0.213	0.047	0.000	0.341	2.931
			s.d.	0.058	0.049	0.046	0.050	0.047	.	0.011	0.091
			p	<.0001	<.0001	0.006	<.0001	0.320	.		
			$\beta$	0.468	0.244	0.130	0.217	0.051	0.000	0.341	2.931
			s.d.	0.058	0.049	0.046	0.049	0.047	.	0.011	0.091
			p	<.0001	<.0001	0.005	<.0001	0.278	.		
			$\beta$	0.482	0.244	0.136	0.216	0.059	0.000	0.341	2.935
			s.d.	0.058	0.049	0.046	0.049	0.047	.	0.011	0.091
			p	<.0001	<.0001	0.003	<.0001	0.208	.		
			$\beta$	0.483	0.246	0.137	0.218	0.058	0.000	0.341	2.937
			s.d.	0.058	0.049	0.046	0.049	0.047	.	0.011	0.091
			p	<.0001	<.0001	0.003	<.0001	0.209	.		

**Table 64: (cont'd).**

				Model	loglikelihood	X <sup>2</sup> diff	Int	inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters				6	-219.905		58.370	-0.026	<b>0.130</b>	<b>-0.028</b>			
Years	7	s.d.					25.643	0.013	0.033	0.013			
Obs.	399	p					0.023	0.055	<.0001	0.027			
				7	-219.826	0.156	59.043	-0.025	<b>0.132</b>	<b>-0.029</b>	-0.298		
		s.d.					25.804	0.014	0.034	0.013	0.753		
		p					0.022	0.064	<.0001	0.026	0.692		
				8	-219.517	0.774	60.005	-0.024	<b>0.133</b>	<b>-0.029</b>		-0.622	
		s.d.					25.906	0.014	0.034	0.013		0.703	
		p					0.021	0.075	<.0001	0.025		0.377	
				9	-219.005	1.799	60.974	-0.025	<b>0.134</b>	<b>-0.030</b>			-0.540
		s.d.					25.970	0.014	0.034	0.013			0.392
		p					0.019	0.071	<.0001	0.023			0.168
				10	-218.981	1.847	61.186	-0.025	<b>0.134</b>	<b>-0.030</b>		-0.183	-0.486
		s.d.					26.021	0.014	0.034	0.013		0.829	0.462
		p					0.019	0.076	<.0001	0.023		0.826	0.293



[illegible]

**Table 65: Mazda Miata Piecewise Weibull Regression for Degree Similarity 4 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	inc	veh	vehage	ALL	NEW	REPEAT
New Adopters		$\beta$	1									
Years	7	s.d.										
Obs.	2895	p										
		$\beta$	2	-1496.345	2.589	-36.612	-0.004	<b>0.032</b>	<b>0.019</b>	-0.183		
		s.d.				3.803	0.006	0.013	0.002	0.113		
		p				<.0001	0.491	0.011	<.0001	0.107		
		$\beta$	3	-1496.591	2.097	-36.510	-0.004	<b>0.032</b>	<b>0.019</b>		-0.164	
		s.d.				3.798	0.006	0.013	0.002		0.113	
		p				<.0001	0.477	0.011	<.0001		0.147	
		$\beta$	4	-1494.562	<b>6.154</b>	-36.835	-0.003	<b>0.032</b>	<b>0.019</b>			<b>-0.176</b>
		s.d.				3.808	0.006	0.013	0.002			0.070
		p				<.0001	0.570	0.010	<.0001			0.012
		$\beta$	5	-1494.557	<b>6.164</b>	-36.824	-0.003	<b>0.032</b>	<b>0.019</b>		0.014	<b>-0.181</b>
		s.d.				3.810	0.006	0.013	0.002		0.144	0.089
		p				<.0001	0.564	0.010	<.0001		0.922	0.042



**Table 65: (cont'd).**

			Model	loglikelihood	$\chi^2$ diff	int	inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters		$\beta$	6									
Years	7	s.d.										
Obs.	399	p										
		$\beta$	7	-219.888	0.032	58.224	-0.026	<b>0.129</b>	<b>-0.028</b>	0.054		
		s.d.				25.611	0.013	0.033	0.013	0.298		
		p				0.023	0.053	0.000	0.027	0.857		
		$\beta$	8	-219.903	0.003	58.438	-0.026	<b>0.130</b>	<b>-0.029</b>		-0.017	
		s.d.				25.683	0.014	0.033	0.013		0.294	
		p				0.023	0.059	0.000	0.027		0.954	
		$\beta$	9	-219.891	0.027	58.440	-0.026	<b>0.130</b>	<b>-0.028</b>			-0.032
		s.d.				25.674	0.014	0.033	0.013			0.194
		p				0.023	0.059	<.0001	0.027			0.870
		$\beta$	10	-219.889	0.031	58.363	-0.026	<b>0.130</b>	<b>-0.028</b>		0.024	-0.042
		s.d.				25.692	0.014	0.033	0.013		0.387	0.255
		p				0.023	0.059	0.000	0.028		0.950	0.869

			Model	2	3	4	5	6	7	scale	shape	
Repeat Adopters Years			6									
		$\beta$										
	Obs.	399		p								
			7	0.455	0.146	0.038	0.228	0.197	0.000	0.357	2.805	
		s.d.		0.157	0.130	0.125	0.142	0.148			0.027	0.216
		p		0.004	0.264	0.761	0.108	0.185				
			8	0.457	0.145	0.037	0.229	0.195	0.000	0.357	2.801	
		s.d.		0.157	0.131	0.125	0.142	0.148			0.028	0.216
		p		0.004	0.268	0.765	0.107	0.188				
			9	0.457	0.142	0.036	0.227	0.195	0.000	0.357	2.800	
		s.d.		0.157	0.132	0.125	0.142	0.149			0.027	0.215
		p		0.004	0.280	0.775	0.111	0.190				
			10	0.457	0.142	0.035	0.226	0.194	0.000	0.357	2.801	
		s.d.		0.157	0.132	0.126	0.144	0.149			0.028	0.215
		p		0.004	0.283	0.778	0.116	0.191				

**Table 66: Mazda Miata Piecewise Weibull Regression for Degree Similarity 3 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	inc	veh	vehage	ALL	NEW	REPEAT
New Adopters		$\beta$	1									
Years	7	s.d.										
Obs.	2895	p										
		$\beta$	2	-1497.585	0.109	-36.205	-0.006	<b>0.031</b>	<b>0.019</b>	-0.028		
		s.d.				3.793	0.006	0.013	0.002	0.084		
		p				<.0001	0.345	0.012	<.0001	0.742		
		$\beta$	3	-1497.529	0.221	-36.228	-0.005	<b>0.031</b>	<b>0.019</b>		-0.040	
		s.d.				3.792	0.006	0.013	0.002		0.084	
		p				<.0001	0.358	0.012	<.0001		0.639	
		$\beta$	4	-1497.333	0.612	-35.852	-0.007	<b>0.031</b>	<b>0.019</b>			0.044
		s.d.				3.790	0.006	0.012	0.002			0.056
		p				<.0001	0.260	0.012	<.0001			0.433
		$\beta$	5	-1496.574	2.130	-35.874	-0.006	<b>0.031</b>	<b>0.019</b>		-0.132	0.099
		s.d.				3.790	0.006	0.012	0.002		0.107	0.071
		p				<.0001	0.305	0.014	<.0001		0.217	0.165

Table 66: (cont'd).

			Model	2	3	4	5	6	7	scale	shape
New Adopters		$\beta$	1								
Years	7	s.d.									
Obs.	2895	p									
		$\beta$	2	0.469	0.242	0.129	0.217	0.053	0.000	0.342	2.923
		s.d.		0.058	0.049	0.046	0.050	0.047	.	0.011	0.091
		p		<.0001	<.0001	0.005	<.0001	0.257	.		
		$\beta$	3	0.469	0.243	0.129	0.218	0.053	0.000	0.342	2.923
		s.d.		0.058	0.049	0.046	0.050	0.047	.	0.011	0.091
		p		<.0001	<.0001	0.005	<.0001	0.255	.		
		$\beta$	4	0.463	0.240	0.125	0.216	0.051	0.000	0.342	2.923
		s.d.		0.059	0.049	0.047	0.050	0.047	.	0.011	0.091
		p		<.0001	<.0001	0.007	<.0001	0.273	.		
		$\beta$	5	0.458	0.237	0.121	0.219	0.048	0.000	0.342	2.925
		s.d.		0.059	0.050	0.047	0.050	0.047	.	0.011	0.091
		p		<.0001	<.0001	0.010	<.0001	0.304	.		

			Model	loglikelihood	X <sup>2</sup> diff	int	inc	veh	vehave	ALL	NEW	REPEAT
Repeat Adopters			<b>6</b>									
Years	7	$\beta$										
Obs.	399	p										
		$\beta$	<b>7</b>	-219.898	0.014	58.305	-0.026	<b>0.130</b>	<b>-0.028</b>	-0.026		
		s.d.				25.663	0.014	0.033	0.013	0.216		
		p				0.023	0.061	0.000	0.028	0.906		
		$\beta$	<b>8</b>	-219.871	0.067	58.294	-0.025	<b>0.130</b>	<b>-0.028</b>		-0.056	
		s.d.				25.675	0.014	0.034	0.013		0.217	
		p				0.023	0.066	<.0001	0.028		0.796	
		$\beta$	<b>9</b>	-219.829	0.152	57.724	<b>-0.026</b>	<b>0.129</b>	<b>-0.028</b>			0.058
		s.d.				25.624	0.013	0.033	0.013			0.147
		p				0.024	0.048	0.000	0.029			0.695
		$\beta$	<b>10</b>	-219.635	0.538	56.507	-0.025	<b>0.131</b>	<b>-0.028</b>		-0.166	0.126
		s.d.				25.720	0.014	0.034	0.013		0.267	0.181
		p				0.028	0.062	<.0001	0.033		0.534	0.486



**Table 66: (cont'd).**

			Model	2	3	4	5	6	7	scale	shape
Repeat Adopters		$\beta$	6								
Years	7	s.d.									
Obs.	399	p									
		$\beta$	7	0.456	0.143	0.036	0.228	0.194	0.000	0.357	2.800
		s.d.		0.157	0.132	0.126	0.142	0.149	.	0.028	0.215
		p		0.004	0.278	0.775	0.109	0.191	.		
		$\beta$	8	0.455	0.141	0.035	0.228	0.194	0.000	0.357	2.799
		s.d.		0.157	0.131	0.125	0.142	0.149	.	0.028	0.215
		p		0.004	0.281	0.781	0.108	0.192	.		
		$\beta$	9	0.456	0.149	0.039	0.233	0.197	0.000	0.356	2.807
		s.d.		0.157	0.131	0.125	0.142	0.148	.	0.027	0.216
		p		0.004	0.254	0.756	0.101	0.184	.		
		$\beta$	10	0.449	0.143	0.031	0.235	0.191	0.000	0.357	2.804
		s.d.		0.157	0.131	0.126	0.142	0.148	.	0.027	0.216
		p		0.004	0.277	0.808	0.099	0.197	.		

**Table 67: Toyota Avalon Piecewise Weibull Regression for Degree Similarity 5 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
New Adopters			1	-1818.096		-34.407	-0.012	-0.014	0.018			
Years	6	s.d.				4.165	0.005	0.013	0.002			
Obs.	3055	p				<.0001	0.010	0.257	<.0001			
			2	-1817.985	0.223	-34.312	-0.012	-0.013	0.018	0.106		
		s.d.				4.167	0.005	0.013	0.002	0.225		
		p				<.0001	0.011	0.302	<.0001	0.638		
			3	-1818.078	0.036	-34.443	-0.012	-0.015	0.018		-0.041	
		s.d.				4.171	0.005	0.013	0.002		0.217	
		p				<.0001	0.010	0.250	<.0001		0.850	
			4	-1814.651	6.889	-34.111	-0.012	-0.009	0.018			0.398
		s.d.				4.152	0.005	0.013	0.002			0.154
		p				<.0001	0.009	0.476	<.0001			0.010
			5	-1810.665	14.862	-34.619	-0.014	-0.012	0.018		-0.845	0.811
		s.d.				4.163	0.005	0.013	0.002		0.295	0.213
		p				<.0001	0.003	0.333	<.0001		0.004	0.000

**Table 67: (cont'd).**

				Model	2	3	4	5	6	scale	shape
New Adopters				1	0.194	0.214	0.052	0.044	0.000	0.348	2.873
Years	6		$\beta$		0.041	0.041	0.038	0.039	.	0.010	0.078
Obs.	3055		p		<.0001	<.0001	0.170	0.267	.		
			$\beta$	2	0.194	0.214	0.052	0.044	0.000	0.348	2.873
			s.d.		0.041	0.041	0.038	0.039	.	0.010	0.078
			p		<.0001	<.0001	0.167	0.269	.		
			$\beta$	3	0.194	0.214	0.051	0.044	0.000	0.348	2.873
			s.d.		0.041	0.041	0.038	0.039	.	0.010	0.078
			p		<.0001	<.0001	0.176	0.269	.		
			$\beta$	4	0.190	0.212	0.046	0.047	0.000	0.348	2.877
			s.d.		0.041	0.041	0.038	0.039	.	0.009	0.078
			p		<.0001	<.0001	0.227	0.236	.		
			$\beta$	5	0.177	0.199	0.026	0.045	0.000	0.347	2.882
			s.d.		0.041	0.042	0.038	0.039	.	0.009	0.078
			p		<.0001	<.0001	0.503	0.256	.		

**Table 67: (cont'd).**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters		$\beta$		-254.305		-156.463	0.017	-0.014	<b>0.079</b>			
Years	6	s.d.	6			42.767	0.013	0.042	0.021			
Obs.	436	p				0.000	0.198	0.744	0.000			
		$\beta$		-252.341	<b>3.927</b>	-170.033	0.027	-0.006	<b>0.086</b>	<b>1.361</b>		
		s.d.	7			43.463	0.014	0.041	0.022	0.692		
		p				<.0001	0.051	0.890	<.0001	0.049		
		$\beta$		-252.678	3.254	-167.720	0.028	-0.008	<b>0.085</b>		1.171	
		s.d.	8			43.333	0.014	0.041	0.022		0.655	
		p				0.000	0.051	0.837	<.0001		0.074	
		$\beta$		-250.588	<b>7.435</b>	-172.941	0.023	-0.004	<b>0.087</b>			<b>1.138</b>
		s.d.	9			43.105	0.013	0.041	0.022			0.434
		p				<.0001	0.081	0.931	<.0001			0.009
		$\beta$		-250.410	<b>7.790</b>	-175.972	0.026	-0.002	<b>0.089</b>		0.421	<b>1.010</b>
		s.d.	10			43.516	0.014	0.041	0.022		0.711	0.484
		p				<.0001	0.065	0.955	<.0001		0.554	0.037

**Table 67: (cont'd).**

			Model	2	3	4	5	6	scale	shape
Repeat Adopters		$\beta$	6	0.193	0.274	0.156	0.001	0.000	0.345	2.900
Years	6	s.d.		0.109	0.115	0.107	0.102	.	0.025	0.213
Obs.	436	p		0.078	0.018	0.147	0.995	.		
		$\beta$	7	0.203	0.285	0.173	0.010	0.000	0.342	2.921
		s.d.		0.109	0.115	0.107	0.101	.	0.025	0.214
		p		0.064	0.013	0.108	0.925	.		
		$\beta$	8	0.204	0.287	0.176	0.010	0.000	0.342	2.921
		s.d.		0.109	0.115	0.108	0.101	.	0.025	0.215
		p		0.063	0.013	0.102	0.921	.		
		$\beta$	9	0.219	0.301	0.168	0.042	0.000	0.342	2.925
		s.d.		0.109	0.115	0.107	0.102	.	0.025	0.214
		p		0.045	0.009	0.116	0.679	.		
		$\beta$	10	0.224	0.306	0.178	0.044	0.000	0.341	2.929
		s.d.		0.110	0.116	0.108	0.102	.	0.025	0.215
		p		0.041	0.008	0.100	0.667	.		

**Table 68: Toyota Avalon Piecewise Weibull Regression for Degree Similarity 4 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
New Adopters												
Years	6	$\beta$	1									
Obs.	3055	s.d.										
		p										
			2	-1818.051	0.090	-34.504	-0.012	-0.015	0.018	-0.030		
		$\beta$				4.179	0.005	0.013	0.002	0.099		
		s.d.				<.0001	0.010	0.242	<.0001	0.765		
		p										
			3	-1817.855	0.481	-34.624	-0.012	-0.016	0.018		-0.066	
		$\beta$				4.181	0.005	0.013	0.002		0.095	
		s.d.				<.0001	0.009	0.212	<.0001		0.488	
		p										
			4	-1817.975	0.243	-34.241	-0.012	-0.013	0.018			0.036
		$\beta$				4.177	0.005	0.013	0.002			0.073
		s.d.				<.0001	0.010	0.308	<.0001			0.622
		p										
			5	-1816.633	2.926	-34.404	-0.013	-0.015	0.018		-0.239	0.174
		$\beta$				4.181	0.005	0.013	0.002		0.145	0.111
		s.d.				<.0001	0.005	0.251	<.0001		0.100	0.118
		p										

**Table 68: (cont'd).**

			Model	2	3	4	5	6	scale	shape
New Adopters		$\beta$	1							
Years	6	s.d.								
Obs.	3055	p								
		$\beta$	2	0.194	0.214	0.051	0.044	0.000	0.348	2.873
		s.d.		0.041	0.041	0.038	0.039	.	0.010	0.078
		p		<.0001	<.0001	0.174	0.267	.		
		$\beta$	3	0.192	0.212	0.049	0.043	0.000	0.348	2.873
		s.d.		0.041	0.042	0.038	0.039	.	0.010	0.078
		p		<.0001	<.0001	0.194	0.278	.		
		$\beta$	4	0.193	0.213	0.050	0.044	0.000	0.348	2.873
		s.d.		0.041	0.041	0.038	0.039	.	0.010	0.078
		p		<.0001	<.0001	0.187	0.261	.		
		$\beta$	5	0.182	0.202	0.034	0.042	0.000	0.348	2.874
		s.d.		0.042	0.042	0.039	0.039	.	0.009	0.078
		p		<.0001	<.0001	0.392	0.281	.		

**Table 68: (cont'd).**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters												
Years	6	$\beta$	6									
Obs.	436	s.d.										
		p										
		$\beta$	7	-252.774	3.062	-163.862	0.024	-0.003	<b>0.083</b>	0.555		
		s.d.				43.141	0.014	0.041	0.022	0.315		
		p				0.000	0.073	0.939	0.000	0.078		
		$\beta$	8	-253.449	1.713	-160.629	0.024	-0.007	<b>0.081</b>		0.394	
		s.d.				43.024	0.014	0.041	0.022		0.300	
		p				0.000	0.089	0.858	0.000		0.189	
		$\beta$	9	-252.904	2.802	-163.552	0.019	-0.006	<b>0.083</b>			0.351
		s.d.				42.946	0.013	0.041	0.022			0.212
		p				0.000	0.141	0.890	0.000			0.098
		$\beta$	10	-252.819	2.972	-163.899	0.021	-0.005	<b>0.083</b>		0.150	0.289
		s.d.				43.023	0.014	0.041	0.022		0.364	0.258
		p				0.000	0.129	0.909	0.000		0.681	0.263



**Table 68: (cont'd).**

			Model	2	3	4	5	6	scale	shape
Repeat Adopters		$\beta$	6							
Years	6	s.d.								
Obs.	436	p								
		$\beta$	7	0.193	0.274	0.165	0.006	0.000	0.343	2.914
		s.d.		0.109	0.115	0.107	0.101	.	0.025	0.214
		p		0.076	0.017	0.125	0.955	.		
		$\beta$	8	0.194	0.274	0.164	0.006	0.000	0.344	2.910
		s.d.		0.109	0.115	0.107	0.102	.	0.025	0.214
		p		0.076	0.017	0.127	0.955	.		
		$\beta$	9	0.183	0.267	0.141	0.008	0.000	0.344	2.908
		s.d.		0.109	0.115	0.107	0.102	.	0.025	0.213
		p		0.094	0.020	0.189	0.940	.		
		$\beta$	10	0.187	0.270	0.148	0.009	0.000	0.344	2.910
		s.d.		0.109	0.115	0.109	0.102	.	0.025	0.214
		p		0.088	0.019	0.172	0.926	.		

**Table 69: Toyota Avalon Piecewise Weibull Regression for Degree Similarity 3 Covariates**

			Model	loglikelihood	X <sup>2</sup> diff	Int	inc	veh	vehage	ALL	NEW	REPEAT
New Adopters												
Years	6	$\beta$	1									
Obs.	3055	s.d.										
		p										
		$\beta$	2	-1818.096	0.000	-34.416	-0.012	-0.014	0.018	-0.001		
		s.d.				4.192	0.005	0.013	0.002	0.073		
		p				<.0001	0.010	0.264	<.0001	0.985		
		$\beta$	3	-1818.096	0.000	-34.398	-0.012	-0.014	0.018		0.002	
		s.d.				4.187	0.005	0.013	0.002		0.071	
		p				<.0001	0.010	0.268	<.0001		0.984	
		$\beta$	4	-1817.775	0.641	-34.756	-0.012	-0.016	0.018			-0.046
		s.d.				4.191	0.005	0.013	0.002			0.058
		p				<.0001	0.012	0.208	<.0001			0.424
		$\beta$	5	-1817.279	1.633	-34.621	-0.011	-0.015	0.018		0.112	-0.115
		s.d.				4.192	0.005	0.013	0.002		0.112	0.090
		p				<.0001	0.017	0.240	<.0001		0.320	0.203

**Table 69: (cont'd).**

			Model	2	3	4	5	6	scale	shape
New Adopters		$\beta$	1							
Years	6	s.d.								
Obs.	3055	p								
		$\beta$	2	0.194	0.214	0.052	0.044	0.000	0.348	2.873
		s.d.		0.041	0.041	0.038	0.039	.	0.010	0.078
		p		<.0001	<.0001	0.171	0.267	.		
		$\beta$	3	0.194	0.214	0.052	0.044	0.000	0.348	2.873
		s.d.		0.041	0.041	0.038	0.039	.	0.010	0.078
		p		<.0001	<.0001	0.171	0.267	.		
		$\beta$	4	0.197	0.217	0.056	0.044	0.000	0.348	2.874
		s.d.		0.041	0.042	0.038	0.039	.	0.010	0.078
		p		<.0001	<.0001	0.143	0.263	.		
		$\beta$	5	0.203	0.224	0.066	0.046	0.000	0.348	2.875
		s.d.		0.041	0.042	0.039	0.039	.	0.009	0.078
		p		<.0001	<.0001	0.095	0.238	.		

**Table 69: (cont'd).**

			Model	loglikelihood	X <sup>2</sup> diff	Int	Inc	veh	vehage	ALL	NEW	REPEAT
Repeat Adopters		$\beta$	6									
Years	6	s.d.										
Obs.	436	p										
		$\beta$	7	-253.936	0.739	-159.911	0.020	-0.008	<b>0.081</b>	0.211		
		s.d.				43.160	0.014	0.042	0.022	0.243		
		p				0.000	0.138	0.847	0.000	0.386		
		$\beta$	8	-252.798	3.014	-160.689	0.024	-0.003	<b>0.081</b>		0.392	
		s.d.				43.228	0.014	0.042	0.022		0.223	
		p				0.000	0.077	0.953	0.000		0.078	
		$\beta$	9	-253.879	0.852	-160.071	0.018	-0.010	<b>0.081</b>			0.171
		s.d.				43.194	0.013	0.042	0.022			0.184
		p				0.000	0.172	0.819	0.000			0.353
		$\beta$	10	-252.634	3.342	-158.909	0.026	-0.002	<b>0.080</b>		0.543	-0.163
		s.d.				43.234	0.014	0.042	0.022		0.347	0.287
		p				0.000	0.065	0.956	0.000		0.118	0.570

**Table 69: (cont'd).**

			Model	2	3	4	5	6	scale	shape
Repeat Adopters		$\beta$	6							
Years	6	s.d.								
Obs.	436	p								
		$\beta$	7	0.198	0.279	0.164	0.007	0.000	0.344	2.903
		s.d.		0.110	0.115	0.108	0.102	.	0.025	0.213
		p		0.070	0.016	0.128	0.947	.		
		$\beta$	8	0.195	0.276	0.163	0.005	0.000	0.344	2.909
		s.d.		0.109	0.115	0.107	0.102	.	0.025	0.214
		p		0.074	0.017	0.128	0.961	.		
		$\beta$	9	0.205	0.284	0.163	0.022	0.000	0.345	2.902
		s.d.		0.110	0.116	0.108	0.104	.	0.025	0.213
		p		0.064	0.014	0.130	0.836	.		
		$\beta$	10	0.182	0.265	0.157	-0.015	0.000	0.343	2.913
		s.d.		0.111	0.116	0.108	0.107	.	0.025	0.214
		p		0.101	0.023	0.146	0.888	.		

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