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Park Aid Systems: Factors That Affect Consumer Purchase Decisions

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PARK AID SYSTEMS: FACTORS THAT AFFECT CONSUMER PURCHASE DECISIONS

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DECISIONS

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Thesis Advisor: Dr. Jonathan Rubin

An Abstract of the Thesis Presented
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Backover crashes in the United States result in at least 300 fatalities and 17,000 injuries every year. Backover crashes occur when a non-occupant of a vehicle is struck by a vehicle moving in reverse. Children are particularly vulnerable. Of the 300 fatalities, at least 100 deaths are children under the age of five. Limited visibility is one factor behind these deaths. The deaths are especially tragic, since the availability of a simple park aid device can expand a driver's field of vision during a reversal maneuver. Park aid devices include a rearview camera or a sensory system.

This project is undertaken to determine the factors which influence a consumer's willingness to pay for a vehicle with an already installed park aid system. We determine that these factors include consumer demographics (income and age), vehicle attributes (including drive type, width, height, mileage, make), vehicle operating costs (annual expenditure on fuel, gas price), and locational variables (an urban/rural setting, town population). We set up a binary

choice model to capture the impact of these variables. For the analysis, we rely on several datasets to build two regression models. The first model combines vehicle registration data from the Maine Bureau of Motor Vehicles with data from the 2010 US Census. The second regression model uses survey results from the 2009 National Household Travel Survey. The results show that older, more affluent consumers are more likely to purchase these vehicles. Additionally, park aid devices are usually found in luxury vehicle models or vehicles with a higher retail price. Furthermore, these devices are more likely to be included in family vehicles such as minivans, or larger vehicles such as vans and SUVs. Finally, a simple forecast shows that the number of vehicles with a park aid system will continue to grow. A Bass model and a Gompertz model are used for forecasting purposes.

The data used for this study has several limitations. We could only include vehicles with a pre-installed park aid device. We could not measure customers who chose an optional vehicle package solely based on the reason that they wanted the technology. Furthermore, we cannot include customers who chose to install an aftermarket park aid option. We believe that these factors will have a significant impact on our results. Once consumers who chose the optional package or the aftermarket installation are taken into account, it can greatly increase the stock of vehicles with a park aid device. An aftermarket device costs less than $100 and is more affordable.

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CHAPTER 1

INTRODUCTION

On March 20, 2013, Nathan Capponi, 6, was riding his scooter in the driveway of his home in Greene, Maine, when his father, Kevin, accidentally backed into him with his plow truck. Nathan was taken to Central Maine Medical Center and pronounced dead (Hoey, 2013). On May 26, 2013, another father backed his truck over his 5-year-old son, Trent, crushing him to death at their home in Charlotte, Maine. The boy was rushed to Calais Regional Hospital but was pronounced dead on arrival (Moran, 2013).

Both children died from backover crashes. Backover crashes occur when a non-occupant of a vehicle is struck by a vehicle moving in reverse (NHTSA, 2010). Often times, a parent, friend, or another family member will fail to see the child through the back windshield or in the rearview mirror and will continue to reverse. Due to limited visibility, children are particularly vulnerable. In a 2010 report, NHTSA (National Highway Traffic Safety Administration) estimates that backover crashes result in around 300 fatalities and 17,000 injuries annually (2010, p. i). Table 1 provides a breakdown of fatalities by the age of the victim. According to research by the advocacy web site, www.kidsandcars.org, back up collisions were the leading cause (34%) for U.S. non-traffic fatalities of children under 15 from 2006 to 2010 (KidsAndCars.org, 2011). The U.S. Center for Disease Control reported that from 2001 to 2003, an estimated 7,475 children (2,492 per year) under the age of 15 were treated for vehicle backover incidents (Center for Disease Control, 2005). There are no certain records of the number of total crashes since most occur on a private driveway. Crashes may involve minor or major property damage but can also result in death.

Table 1. A breakdown of backover fatalities by the age of the victim

Age of victim	Fatalities
Under 5	103
5-10	13
10-19	4
20-59	69
60-69	28
70+	76
Total	292

Note*:* A breakdown of backover fatalities by the age of the victim. Adapted from "Backover crash avoidance technologies" by the National Highway Traffic Safety Administration, 2010, p. III-2.

Over the past few years, these accidents have gained interest from the government and local media stations, mainly because the availability of a simple park-aid device, such as a sensor or a camera, could have certainly prevented many of these incidents. Several park aid systems are available in today's market. First, a sensor system works by emitting a beeping noise that becomes louder and more insistent the closer a vehicle moves towards a certain object. Second, a camera works by providing the driver with a picture scan of the environment behind the vehicle. Cameras with coverage of 160, 180 or 360 degrees are available. Some manufacturers equip their vehicles with only a camera or only a sensor. Finally, some systems have an auto park system which will park the vehicle for the driver. The driver is still responsible for shifting the gears and placing the appropriate pressure on the accelerator and brake pedals.

1.1 Objective

We undertook this study to estimate how consumers have responded to park aid systems. Our goal is to capture the characteristics of consumers who are willing to purchase a vehicle with an already installed park aid system. A second objective is to predict and capture the adoption of these park aid systems. This study will focus on camera and sensor systems. Even though the technology for an auto park system has been available for some time, it is a fairly new feature and was not available (either at the time of manufacture or as an optional feature) in the vehicle models that were used for this study.

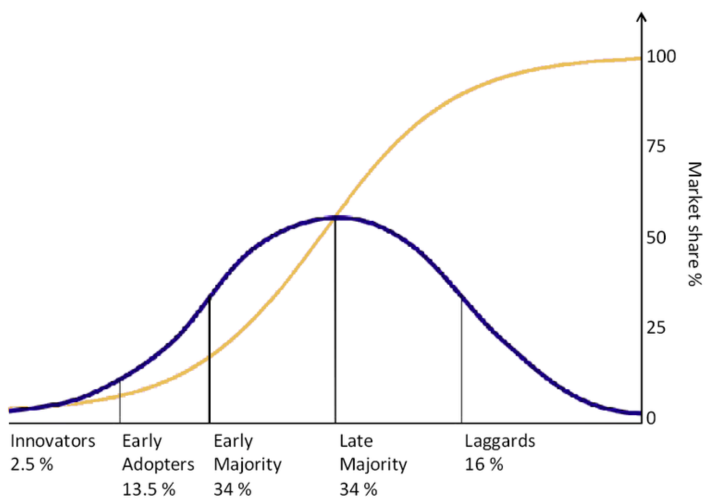
CHAPTER 2

LITERATURE REVIEW

2.1 General Description of Diffusion

Rogers (1962) defines diffusion as the speed with which members of a population will adopt a certain technology. The adoption of park aid systems can be represented using an S-curve. In an S-curve, the diffusion will begin at a steady rate, adoption will increase at the 'take-off' point, and the curve will slow down and flatten out once satiation (or saturation) is reached (Geroski, 2000, p. 604). Rogers (1962) shows the cumulative (all adopters) and period-by-period adoption using two graphs. Period-by-period adopters are represented by the bell-shaped curve, and cumulative adopters are depicted by the S-shaped curve. While the graph shows that 100 percent saturation has been reached, this is not usually the case.

Figure 1. The cumulative and period-by-period adoption of a product



Note: The cumulative and period-by-period adoption of a product. Adapted from *Diffusion of Innovations* by E. Rogers, 1962, New York: Free Press.

2.1.1 Characteristics which Influence Diffusion

When park aid systems were first introduced, consumers had the choice to purchase a vehicle with that technology. A park aid system can be viewed as a private good, and the benefits obtained from this technology are usually for one's own benefit.

The consumer choice to adopt the new technology is made more complex by the introduction of other external influences. First, the adoption of the new technology can be encouraged by society or mandated by the government. For instance, NHTSA is considering a proposal to mandate the inclusion of a park aid system in all new vehicles. Even though a decision was to have been finalized in early 2011, the passage of the bill has been postponed several times. Second, the decision to adopt the technology may no longer be a two option choice. Users can choose from different levels of the product, including a sensor, camera or auto park system. Finally, the adoption of the technology may be influenced by network externalities. A single person's use of the technology is dependent upon the number of other users. Network effects or social connectedness play two important roles in the adoption of the technology. In other words, the success of the new technology may depend on the number of people who are using the new product (Hall, 2004, p. 6). These social feedback effects may encourage the adoption of the new product.

The uptake of the product can be encouraged through advertisements. Initially, word of the new product will spread through a central source (Geroski, 2000, p. 604). Geroski (2000) uses alpha to measure the spread of information. A higher alpha shows a faster spread of information regarding the new product. If alpha is equal to one, the knowledge will reach all individuals. Later, word of mouth can be used to spread information (2000, p. 606). Geroski (2000) uses the variable beta to measure this. The higher beta is, the higher the diffusion rate.

2.1.2 Characteristics of the Supplier

When there are many suppliers of the same product, an early advantage for one supplier may influence the adoption pattern in the industry, for example, the VCR player. Upon purchasing a new VCR player, the consumer wanted a range of tapes to play on the new device. At the time, tapes were available as either VHS or Beta. Since VHS had an advantage in the length of the program that could be recorded, VHS became the industry standard over time (Hall, 2004, p. 14). Furthermore, in industries with very few suppliers, there will be a higher price to purchase the technology, slowing the adoption rate (2004, p. 21). Finally, information regarding the new product can be gained through advertising and experience with the technology (2004, p. 19). Suppliers will try to override the competition by offering free training, reimbursing the sunk cost of the previous technology and quoting a more competitive price to the owners of a rival product (2004, p. 18).

2.1.3 Characteristics of the Buyer

The diffusion of a park aid system is influenced by the benefits received, the cost of the technology, factors related to the social environment, uncertainty, and information problems (Hall, 2004, p. 12).

Early adopters will play a significant role in the success of a technology. First, a larger population of early adopters will encourage others to imitate. Second, change agents with dominant personalities can be introduced to promote the new technology (Fichman, 1992, p. 2). Meade and Islam (2006) determine early adopters (or change agents) tend to be more literate, have a higher social status, and are richer compared to later adopters. Finally, if there are many different brands of the same product available, adopter decision will depend on preference, attitude, and acquaintance with another adopter (Fichman, 1992, p. 13). At the same time, research shows that adoption rate is slower than expected when there are multiple systems available and when the spread of information is taken into account. This may be due to limited knowledge. Even though a product is advertised thoroughly, it may not be adopted. The users may not know which system best meets their needs. Perhaps the user may not know how to properly use the system. In this instance, a trial period is necessary.

While the new product will have an increasing rate of adoption following introduction, this rate will slow down and reach the satiation point. Later adopters may feel that they have no personal gain and prove increasingly resistant to adopt the new product (Geroski, 2000, p. 608). However, if the technology is modified to suit the needs of at least some of these resistant members, they may adopt the product and influence adoption rate again.

Geroski (2000) determines technological expectations will increase the cost of adoption. If adopters believe that the price of the technology will fall or that an improved and better model will be available in the future, then the cost of adoption (at this time period) will rise. Finally, if adopters believe the technology will be used by the masses, there is added pressure to purchase the new feature, leading to a self-fulfilling prophecy.

2.1.4 Other Characteristics

Hall (2000) states the adoption of technology will be influenced by the number of close substitutes. For example, the radio and the automatic clothes washer were introduced at the same time (in the early 1920s). However, the radio was more successful than the washing machine because there were no close substitutes for the product at that time.

Another variable which affects the adoption rate is the user-friendliness of the technology. In the example of software, user-friendliness can be divided into two categories: Type I and Type II. Type I software are easy to learn, user-friendly, and have high adoption rates. On the other hand, Type II software are characterized by a knowledge barrier or some sort (Fichman, 1992, p. 8). Therefore, Type I software will have a higher diffusion rate.

The decision to switch to the new software may not depend on the individual's discretion. The decision may be influenced by external and social conditions, such as advertisements, social pressure, or mandated by the government. Furthermore, if there are no costs (either monetary or otherwise) involved with upgrading from older software to a newer version, the switch will occur.

Finally, a standard may influence adoption. Benefits of a standard include successful communication between two products and ease of consumer learning. One example of a standard is a CD and a CD player.

2.2 Relevant Studies on Diffusion

There are several sources of literature that we considered for the study. This includes studies which look at characteristics that influence diffusion, the diffusion of niche vehicles, and the adoption of safety features.

2.2.1 Diffusion of Vehicle Features

Stephen Zoepf (2011) looks at the diffusion of vehicle features over time and across different vehicle makes. He states that when a new feature is introduced, it is usually made available in limited quantities and in high-end products (Zoepf, 2011, p. 55). For instance, park aid systems were first introduced in luxury vehicle models. However, Zoepf (2011) believes the developmental lag time of features has decreased overtime. Currently, the time between a feature's initial introduction and its uptake by the mainstream market has decreased to about ten years (2011, p. 76). Zoepf (2011) believes that exposure to new products through media, and communication between adopters and potential adopters may have decreased the lag time.

To study the adoption rates of different vehicle features, Zoepf (2011) relies on several data sources. This includes the Wards Factory Installed databases. A second source is the availability of the feature in top-selling vehicles for the year 2010 and the year each feature is introduced (Zoepf, 2011, p. 32). The potential market is the percentage of the new car fleet equipped with a given feature (2011, p. 51). Vehicle features have been divided into three categories, not included, optional, or available at the time of manufacture (2011, p. 26). While he acknowledges that NHTSA has not mandated many optional features, including rearview cameras (2011, p. 28), he admits that features later regulated by the government had already had a high adoption rate in the beginning (2011, p. 69). Safety features (versus comfort, convenience and powertrain features) have the fastest deployment rate and range from 4.5 to 23.9 percent per year (2011, p. 55). For example, there was a deployment rate of 17 percent per year for fuel injection in light-duty vehicles. Zoepf (2011) concludes there is no clear relationship between regulatory requirements and a technology's widespread adoption (2011, p. 76). Furthermore, Zoepf (2011) believes 100 percent saturation cannot be achieved. It is impeded by limited appeal, significant trade-off, and competing technology. For example, some customers may not want a rearview camera, or because rearview cameras are included as a package option, it may be cheaper to install the feature after purchase.

2.2.2 Purchase of a Hybrid Vehicle

The availability of a subsidy may have affected the purchase of a hybrid vehicle. Since the value of the subsidy decreased over time, there were periods of significant 'bunching' as well-informed customers chose to maximize the monetary allowance before it decreased significantly. Gallagher and Muehlegger (2011) determine that sales tax waivers, membership in an environmental advocacy group, and gasoline prices has a significant and positive impact on the purchase of hybrid vehicles. Poorly informed consumers preferred the less generous state sales tax waiver to the more generous income tax waiver (2011, p. 2). Ozaki and Sevastyanova (2011) use a Likert scale-based survey to determine that reduced fuel costs and overall costs are the main reason consumers will purchase a hybrid vehicle (2011, p. 2223).

To model the adoption of hybrid electric vehicles (HEVs), Lamberson (2009) uses a historical comparison approach. The adoption of HEVs may be similar to minivans and a niche market, which caters to a select number of consumers (Lamberson, 2009, p. 5). Lamberson uses US monthly vehicle registration data to forecast sales data through a Bass model and Gompertz model. Using US monthly registration data from 2001 to 2007, the Gompertz model predicts the sale of 25.7 million HEVs in the year 2015, whereas the Bass model shows that HEV sales would peak in the year 2008 and then decline overtime (2009, p. 10). A more detailed explanation of the Bass model and the Gompertz model can be found in section 3.2.

2.2.3 A Consumer's Willingness to a Pay (WTP) for a Vehicle Safety Device

Johannesson, Johansson, and O'Conor (1996) survey a group of 2000 individuals to determine the WTP for a public safety device versus a private safety device. In this instance, a private safety device is purchased by an individual, and its benefits will only be realized by the individual, whereas a public safety device is an investment made by a state authority, and the benefits from that are available to all in the community. The survey group is divided into two subsamples. The first subsample responds to survey questions on the WTP for a private device. The second subsample responds to survey questions on the WTP for a public device. The survey response is of a binary yes/no format. To avoid overestimation of the WTP amount, twelve surveys were designed with different bid amounts (or different WTP figures). Results show that for private safety devices, 82 percent of the participants agree to pay the lowest bid of $1,320, and 9 percent are willing to pay the highest bid of $132,000. For the public safety devices, the percentages decrease to 66 percent and 1 percent respectively. The mean WTP for a private device is $712 and $591 for a public safety device. The WTP increases with the perceived risk level.

Boulding and Purohit (1996) use a log-linear hedonic model to determine if individuals who earn a higher salary are WTP to pay a higher price for their safety. The price of safety is divided into two categories: preventive and crisis safety (1996, p. 12). Preventive safety measures a consumer's WTP to avoid a harmful incident, for example, antilock brakes. Crisis safety determines a consumer's WTP to mitigate the effects of a harmful incident, for example, air bags. The dependent variable is the retail price of the vehicle. This is used as proxy for income, building on the theory that individuals with a higher salary are able to afford a higher priced vehicle. The independent variables which have a significant and positive affect on the price (or which raise the price of a vehicle) are the availability of a driver's side airbag, antilock brakes, automatic transmission, horsepower, weight, length, and width. This shows that the availability of both preventative and crisis safety measures (airbags and antilock brakes) increases the retail price of the vehicle.

Mannering and Winston (1995) use a multinomial logistic model to determine the consumer WTP for the inclusion of air bags in a vehicle. The dependent variable is the consumer choice of which new vehicle to purchase. The independent variables with a significant effect include vehicle attributes (retail price, weight, and horsepower) and demographic variables (number of friends who own cars with air bags, hours spent watching television per day, consumer age, and consumer income). In 1990, the WTP is an average of $331 and in 1993, the WTP increases to an average of $512 (1995, p. 274). While the adoption of air bags has increased steadily during the early 1990s, the results show that there is no trend in the adoption rate. Instead, a rise in the popularity of air bags, promoted through actual experience, friends, and the media, shows an increasing WTP from consumers (1995, p. 275).

2.2.4 The Income and Diffusion Effect

Greenman (1996) develops several models to determine how income influences the purchase of a first vehicle and other secondary vehicles. The study is based in the UK, and the data is obtained from the UK's Family Expenditure Survey. By plotting income versus the number of vehicles per household, Greenman (1996) shows that income has a positive effect on the number of vehicles per household. Greenman (1996) does not use quantitative analysis methods in the first part of his paper. However, in the second part of his paper, Greenman (1996) separates the income and diffusion effects to determine which is more dominant and has a greater effect on a consumer's purchase decision. He shows that from 1965-1970, the two effects are equal or comparable. Within the middle period, the diffusion effect begins to dominate, but by the early 1990s, the income effect plays a more principal role (1996, p. 119).

2.2.5 The Income Effect

In a similar paper by Dargay and Gately (1998), the growth of the car/population ratio (car ownership) is modeled as a function of per capita income. While Greenman (1996) focus on the UK and Japan, Dargay and Gately (1998) focus on both the OECD and the developing world. In the OECD the annual rate of growth of vehicles was 1.8 percent. In the developing world, the figure is 4 percent. A second objective is to project the uptake of vehicles to the year 2015. Data was collected for twenty six different countries.

Dargay and Gately (1998) surmise that the relationship between vehicle ownership and income can be modeled using a logistic, logarithmic logistic, cumulative normal or a Gompertz function (1999, p. 110). Ultimately, the Gompertz model was chosen over a logistic function since its form allows for curvature at low and high income levels. In the final model, an adjustment is included for lags. These lags account for consumers who save up for a vehicle, changes in housing patterns and land use, and a shift in demographics as elderly users rely less on their vehicles and as young drivers begin to drive. Following calculations, the authors estimate that overall saturations levels are 0.62 for cars and 0.85 for vehicles per capita (1999, p. 116).

Future car uptakes in 2015 are projected using population projection data from UN statistics and GDP growth rates from the World Bank (1999, p. 118). While the study was conducted in 1998, the authors were able to accurately calculate many current economic conditions, including the growth of the Tiger Economies, and a 9 percent GDP growth rate in

China. At the same time, Dargay and Gately (1999) admit the model may be too simple. If an expansion were to be considered, it would look at:

1) Cost: the fixed cost of ownership, variable costs of operation,

2) Demographic variables: age, change over time, the adult to population ratio, the percentages of the population that are of driving age and own a car.

2.2.6 Initial Market Share

A more recent paper by Heutel and Muehlegger (2009) models the diffusion of hybrid vehicles. With the use of a discrete choice model, the authors' aim is to determine how different models of hybrid vehicles will diffuse among consumers and how initial diffusion patterns will affect later buyers (2009, p. 6). The dependent variable is the utility obtained from purchasing the vehicle. The independent variables are the utility from a hybrid vehicle, a dummy variable to indicate if the vehicle is a hybrid or not, and price (included as a negative variable). An additional variable is introduced to capture imperfect learning or consumer bias (2009, p. 7).

In an agent-based model, consumers interact with initial hybrid owners and obtain information regarding the quality of the vehicle. The probability of interacting with a specific vehicle owner is equal to the share of that hybrid in the total hybrid market (2009, p. 9). By interacting with the owner of a specific vehicle, the consumer can determine if it is something they are willing to purchase. The larger the initial share of the market, the greater the flow of information regarding its quality, and the higher the chance of a purchase, given the vehicle is of a good quality and the owner will recommend it to their friend (2009, p. 11).

Heutel and Muehlegger (2009) calculated that the elasticity of hybrid sales with respect to market penetration for the Toyota Prius was between 0.4 and 0.8, whereas the elasticity for the Honda Insight was placed at -0.06 and -0.03. This shows that the Prius sent a 'good' signal about quality, whereas the Insight sent a ‘bad’ signal. It might be that initial negative reviews may have had a strong impact on a consumer’s decision to purchase the Honda Insight.

The superior performance of one hybrid vehicle may lead the consumer to believe that other hybrid technology will perform at the same standard, prompting them to invest in a model of their choice (2009, p. 14). The opposite is also true. If the hybrid vehicle (with the largest market share) performs poorly, the overall adoption of hybrid vehicles will decrease.

The study shows that a poor review of the Insight’s performance may have dampened initial sales (2009, p. 21). At the same, the Toyota Prius’s performance may have influenced sales of other Toyota vehicles. The study also shows that the decrease in Insight sales increased the Prius’s initial sales.

CHAPTER 3

THEORETICAL MODEL

3.1 An Overview of the Decision Making Process

When a consumer is in the market to purchase a vehicle, he or she has a choice between several vehicle models. Ultimately, the consumer will purchase the vehicle which will provide him or her with the maximum utility. The utility that is obtained from the purchase of a vehicle depends on several factors, including vehicle attributes (such as mileage), available amenities (such as the inclusion of a rearview camera), price, and income.

The benefit obtained from an added park aid system can be shown using a consumer's indirect utility function (Train, 1986, p. 137).

$$Vm_n = f(Y, R_k, Xm_{cn}) \qquad (1)$$

Here, V is the indirect utility that is obtained by the consumer when he or she purchases a vehicle. m_n is the make/model of the n^{th} vehicle available in the market. Y represents income. R_k is a variable for the inclusion of a park aid system. The subscript k determines if the installed system is a sensor or a camera. Xm_{cn} is a vector of other observed and unobserved variables.

The individual's objective is to choose vehicle i where the utility obtained from vehicle i is greater than the utility obtained from vehicle j (Train, 1986, p. 137).

$$Vm_{ni} > Vm_{nj} \qquad \text{where } i \neq j \qquad (2)$$

Then the probability that the household will choose vehicle i is represented by:

$$P_{ni} = \frac{e^{V_{mni}}}{\sum_{j \in J_n} e^{V_{mnj}}} \qquad \text{for all i in } J_{n.} \qquad (3)$$

Where J_n is the total number of vehicle choices.

3.2 Guidance from Previous Literature

There are several models which can be used to depict an S-curve.

3.2.1 The Bass Model (Logistic Regression)

The Bass (1969) model was developed for consumer goods but has been used for telecom services, medical products, and other technology-based features. The Bass model assumes mass media are important during the early years of the product release, but interpersonal communication is far more important during the later years (Hall, 2004, p. 8). The Bass model reduces to a logistic function. In the logistic model, the diffusion curve is symmetric and has a fixed inflection point at 50% market penetration.

In a recent paper by Heutel & Muehlegger (2009), the authors hypothesize that interacting with an early adopter will influence a second person's decision to purchase the item. The results from an agent-based model show that high quality products with a larger, initial market share will be more successful (Heutel & Muehlegger, 2009, p. 11).

3.2.2 The Gompertz Model

The Gompertz model is used for products which have a slow uptake during the initial and final periods. The Gompertz model has been used to project the uptake of hybrid vehicles and the growth of future car stocks. Lescaroux (2007) uses the Gompertz function to project the future growth of car stocks (2007, p. 7). The non-linear model uses income and consumer spending as dependent variables. To simplify the model, Lescaroux (2007) assumes that income and income growth will stay constant until the year 2030 (2007, p. 15). Dargay & Gately (1998) use the Gompertz model to determine the relationship between vehicle ownership and income, stating the function allows for curvature at low and high levels of income.

The Gompertz model is asymmetric and the inflection point occurs at 37 percent (or 1/e) market penetration. In these models, the dependent variables are the binary adoption or non-adoption option, the time of adoption, and frequency of use (Fichman, 1992, p. 7).

A consumer will have the choice to purchase a vehicle with a park aid system. The choice can be represented through a binary choice model. Reverse sensor systems have been around for some time, but they are not readily available in most vehicles. From the vehicle models that were considered for this study, most had just the sensory system included at manufacture. Therefore, a binary model was chosen as the most suitable.

CHAPTER 4

DATA

To conduct the study, we need data on vehicle attributes and consumer demographics. There are two data sets that will be used for the study. The following sections will be divided into three parts to reflect these aims.

In the first part, Maine vehicle registration data from 2011 through March 2013 will be used to calculate a regression. In the second part, data from the 2009 National Household Travel Survey (NHTS) will be used to estimate the regression model. Finally, in the third section, the Maine vehicle registration dataset will be used to predict the uptake of vehicles with rearview systems.

4.1 Maine Vehicle Registration Data

We obtained a dataset of motor vehicle registrations from 2011 through March 2013 through Maine's Bureau of Motor Vehicles. Each vehicle registration (or each observation) is only included once, even if the vehicle had been registered several times the over the years. Vehicle Identification Number (VIN) decoding is used to identify the attributes relevant to each vehicle model. The VIN numbers are decoded by ESP Data Solutions Inc. of Lawrence, Massachusetts. The vehicle attributes include engine type, drive type, fuel type, horsepower, curb weight, and wheel base. We combine this dataset with 2010 US Census data at the town level to include demographic details.

Previous literature has suggested that income may have a significant effect on the purchase of a specific vehicle model. The reasoning follows that individuals with higher salaries can afford a higher priced vehicle. However, demographic information is not collected during a vehicle registration. Therefore, the dataset will be combined with town-level demographic data from the US Census. There are 433 towns in the State of Maine; this allows for significant variations between observations. While the variables are a proxy, they tend to represent an accurate picture of the individuals who live in that specific town. Aggregate data may provide different conclusions compared to disaggregate data (Garrett, 2002). The RSS (residual sum of squares) is less in aggregate data compared to disaggregate data. This means that coefficients from an aggregated regression will be statistically significant compared to identical coefficients from a less aggregated regression (Garrett, 2002).

4.1.2 Obtaining Consumer Demographic Data for the First Data Set

Income

We obtain income data from the 2010 US Census at the town level. The data includes the median and mean income for each town. Using the Consumer Price Index (CPI), the data are adjusted to reflect inflation for each year included in the observation set.

The following calculation is used to estimate the CPI-adjusted income for each township:

$$Y_{\text{current year}} = \frac{CPI\ current\ year}{CPI\ base\ year} \times Y_{\text{base year}} \tag{4}$$

4.1.3 Limitations and Advantages of the First Dataset

This dataset contains the most recent data. It has vehicle registration data from 2011 through 2013. However, the dataset has several drawbacks. First, it is limited to the State of Maine. Therefore, diffusion estimates can only be calculated for the State of Maine and not the entire United States. Compared to the rest of the United States, Maine residents tend to be older, less affluent and may drive vehicles which are more suitable for winter conditions.

Second, the dataset only contains information on the vehicle and its attributes. It has a very limited availability of consumer data. The only information available at the individual level is the registrant’s age. All other characteristics, including income, must be estimated at the town level.

Even with the VIN decoding, we did not identify a specific trim level for several vehicle types. For example, the trim levels for the Nissan Murano, S; SL; LE, were all included as a possibility. The ‘S’ and ‘SL’ trim levels did not include a reverse sensing system at manufacture. However, the trim level ‘LE’ did. These instances were few and rare. For the majority of the VIN decoded data, a specific trim level could be identified.

The following steps outline the process:

1) First, we will select vehicle models manufactured during 2009 through 2013. Park aid systems are a fairly new feature, and they are most likely to be available in the newer models.

2) Records which did not suit the purpose of this study are removed. This included records where the vehicle was listed as non-passenger, homemade, or commercial. Furthermore, records with incomplete information will also be removed.

3) Outlier records will be removed. These include observations where the registrant’s age is below 16 years age. Furthermore, outlier vehicle retail prices will be removed. This includes a vehicle with a retail price of over $28,000,000.

4) We will add vehicle attribute information to each individual vehicle registration. This will be done using the decoded VIN numbers provided by ESP Data Solutions Inc.

5) We obtain a count of vehicles by model, trim level and year. Then the website www.cars.com is used to obtain information on the availability of a park aid system.

6) Income data and population data are obtained from the 2010 US Census. Census data calculates the median and mean income for each town. Income is adjusted to reflect each year's inflation using the CPI. Income is represented in 1000 dollars in the regressions. Similarly, retail price is represented in 1000 dollars.

7) Time variables are added to the data. One time variable is the vehicle model year. The second time variable is the percentage of vehicles with a park aid system (over all vehicles on the road) for a particular month during the time period 2011 to the 2013. Registration expiration dates are used to obtain this information.

8) Using MS Excel and the statistical package SPSS, demographic information and vehicle attribute data are combined to form one datasheet.

4.2 2009 National Household Travel Survey

The National Household Travel Survey (NHTS) collects data on household transportation and travel behavior. The latest survey available is from the year 2009. The survey collects information from a specific household and the individuals who reside within it. Household level information includes annual income, the number of vehicles owned by the household, and the make, model and model year of each vehicle. Individual level data includes age, race, and education. While the data may not be the most recent, its main asset is that the demographic data is at the individual or household level.

4.2.1 Obtaining Vehicle Attribute Information for the Second Dataset

For every household that has at least one vehicle, the 2009 NHTS asks the survey respondents to list the make, model and model year of the vehicle. We use this information to capture vehicle attribute information. The one drawback is that the trim level is not included for each listed vehicle. Vehicle attribute information was available through a dataset purchased through Ward's Automotive. This includes passenger car and light truck information for vehicles manufactured during the time period 2004 through 2011. Since the trim level is not included in the NTHS dataset (and to be conservative), we combine each record with the most basic trim level (available in the Ward's Auto dataset). Park aid systems are not available in the basic trim level for most vehicle models, so there is no way to capture an accurate representation.

4.2.2 Limitations and Advantages of the Second Dataset

The 2009 NHTS has several limitations. First, since the trim level for each listed vehicle is not available, the NHTS survey information could not be accurately combined with the Ward's Automotive data. Second, even if the household is listed as having three or more vehicle models, information for just one vehicle was listed. Finally, since the survey was conducted sometime in the middle of 2009, there are limited observations from that year.

The following steps outline the data manipulation process:

1) Households that did not own a vehicle are removed. Out of the 7945 records that are eliminated, 5738 are listed as living in an urban location.

2) All commercial vehicles, recreation vehicles, vehicles with an unknown, unspecified or suppressed makes are removed. All motorbikes are likewise removed.

3) Only newer vehicle models (those manufactured from 2006 to 2009) are selected.

4) Retail price is represented in 1000 dollars.

5) From a household with more than one individual, the personal details of the first listed individual or person '1' are selected, based on the assumption that that individual is the head of the household.

4.3 The Dummy Dependent Variable

We used MS Excel to obtain the count for each vehicle by vehicle model, trim level, and year. We used the website www.cars.com to determine if a park aid system of some type was offered within a specific vehicle make and model. It identifies if a park aid system was included at manufacture, optional (with the price for that optional package), or was not available at all. The website identifies the features available within a specific trim level for a given vehicle. This information is used to create the dummy dependent variable, where the value ‘1’ is specified if a given vehicle has a park aid system of some sort already included. One limitation is that the website does not identify if the park aid is a sensor, a camera or if both features are available.

CHAPTER 5

EMPIRICAL MODELLING

We developed several models to determine the characteristics of a consumer willing to purchase a vehicle with an already installed park aid system. While the diffusion of many durable goods has already been modeled, such as hybrid vehicles, telecommunication systems, and household electronics, park aid systems have thus far been a fairly untouched area of research. In order to develop the model, we use several sources of literature. These include previous studies on the diffusion of durable consumer goods. Other sources consulted include studies on the diffusion of vehicle technology, including HEVs and airbags.

The empirical model uses the following classes of explanatory variables:

$$\text{DDV} = \beta_0 + \Sigma_{i=1}^{k}\Psi_i\text{DEM} + \Sigma_{i=1}^{k}\eta_i\text{VEH} + \Sigma_{i=1}^{k}\gamma_i\text{TRAVEL} + \Sigma_{i=1}^{k}\delta_i\text{GEO} \tag{5}$$

where DEM includes demographic variables, VEH includes vehicle attributes, TRAVEL includes vehicle operating costs, and GEO includes geographic variables.

There are several variable categories that are considered in the model. Demographic variables are (DEM) included to account for the characteristics of the vehicle buyer. Previous studies have recommended the inclusion of variables such as age, race, household size, the number of vehicles per household, income, and education.

When it comes to purchasing a vehicle, most vehicle buyers will be influenced by the presence of vehicle characteristics in addition to the inclusion of a park-aid system(Bacani, 2008, p. 18). As previously acknowledged, park aid systems are more common in luxury vehicles or vehicles with a high engine capacity. Vehicle attributes (VEH) are introduced to account for any correlation between the inclusion of a park-aid system and other vehicle attributes.

The third category of variables, vehicle operating costs (TRAVEL), are introduced to account for varying vehicle usage among consumers. TRAVEL includes variables for the annual operation cost, gas cost, and odometer readings. Consumers who use their vehicle more often may purchase a model with a lower operating cost and a higher mileage. This category of variables is used to capture any correlation between the cost of operating a vehicle and vehicle attributes.

The fourth variable category geographical variables (GEO) are a set of dummy variables which will account for spatial differences among households. This will measure population per square mile. Seven dummy variables are used to classify the population density of the respective city or town.

The dummy dependent variable, DDV, measures if a park aid system is included in a specific vehicle. The variable is binary and can only take the values of ‘0’ or ‘1.’ The value ‘1’ is specified if a given vehicle has a park aid system of some sort already included.

5.1 Variables used in Regression One (Using the Maine Vehicle Registration Data)

Table 2. Variables used in regression one. The table includes a list of the variables from the Maine vehicle registration dataset.

Type	Variable	Description	Included Categories	Base Dummy
DDV	Rear	If a park aid system is included at manufacture		
VEH	Drive type		RWD (rear wheel); AWD (all wheel); T4WD (four wheel); T2WD (two wheel)	FWD (front wheel drive)
	CITYMPG	Mileage in the city		
	HWYMPG	Mileage on the highway		
	CMBMPG	Combined mileage		
	Wheelbase	Distance between center of front and rear wheels		
	Vehicle type		Car; Minivan; SUV	Pickup/Truck
	Vehicle make	Make of the vehicle	All vehicle makes	Volvo
	Luxury	Vehicle is a luxury model		
	Retail	Retail price		
	Excise	Excise Tax		
	PerMonRear	Percent of vehicles with a rearview system added every month		
	Year	Vehicle model year	Y2010; Y2011; Y2012; Y2013	Y2009
DEM	Age	Registering person’s age		
	AgeSQ	Age squared		
	AgeCB	Age cubed		
	MeanIncome	Mean income of town		
	MedIncome	Median income of town		
	Pop	Population of town		

The dummy variables are shaded.

The final dataset is compiled following the removal of any observation with missing data. From the 105,387 observations that are included in the model, 8,090 had a park aid system included at manufacture. This shows that 7 percent of the observations have a value of '1' for the dependent variable. This may lead to some problems. If a large set of independent variables are included, many of these variables may show up as insignificant. Furthermore, when it comes to multi-category dummy variables, there can be instances where the data are concentrated in just one option. With the use of contingency tables, we can determine the number of observations which fall into each categorical slot. The coefficient of association, phi, is used to determine if there is association between the dependent variable and the independent variable. With the use of the feature CrossTabs on the statistical software SPSS, all of the categorical variables are included in a contingency table. Only variables with significant phi values are considered for the model.

Table 3. Significant variables following a crosstab reference. The variables are from the Maine vehicle registration data.

Variable	Phi	P-value
Minivan	0.273	0.000***
Car	-0.147	0.000***
FWD	-0.133	0.000***
AWD	0.163	0.000***
T4WD	0.018	0.000***
Luxury	0.044	0.000***
Vehicle make	0.302	0.000***

*** Significant at the 1%; ** Significant at the 5%; *Significant at the 10% level

Several continuous variables were evaluated using the crosstab feature. Figure 2 shows that older consumers are more likely to purchase a car with a park aid system included. The numbers peak between 41 and 75 years of age.

Figure 2. Registering person's age and vehicles with a park aid system. This graph uses Maine vehicle registration data.

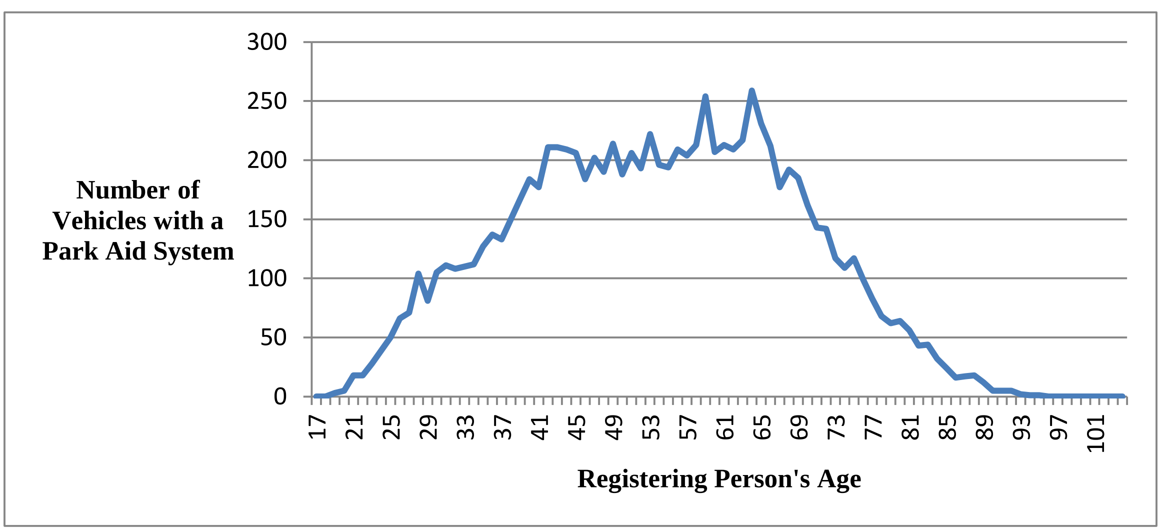


Figure 3 shows that consumers with a higher income are more likely to purchase a car with the park aid system. The data is in a histogram format and has been binned into 5000 range categories. However, this is not true for consumers at the extreme right. While this is counter-intuitive, one possible explanation is that some of the higher end luxury and sport vehicles may not include a rear sensory system. These vehicles are not marketed for safety but for leisure and societal status.

Figure 3. Income and vehicles with a park aid system. This graph uses Maine vehicle registration data.

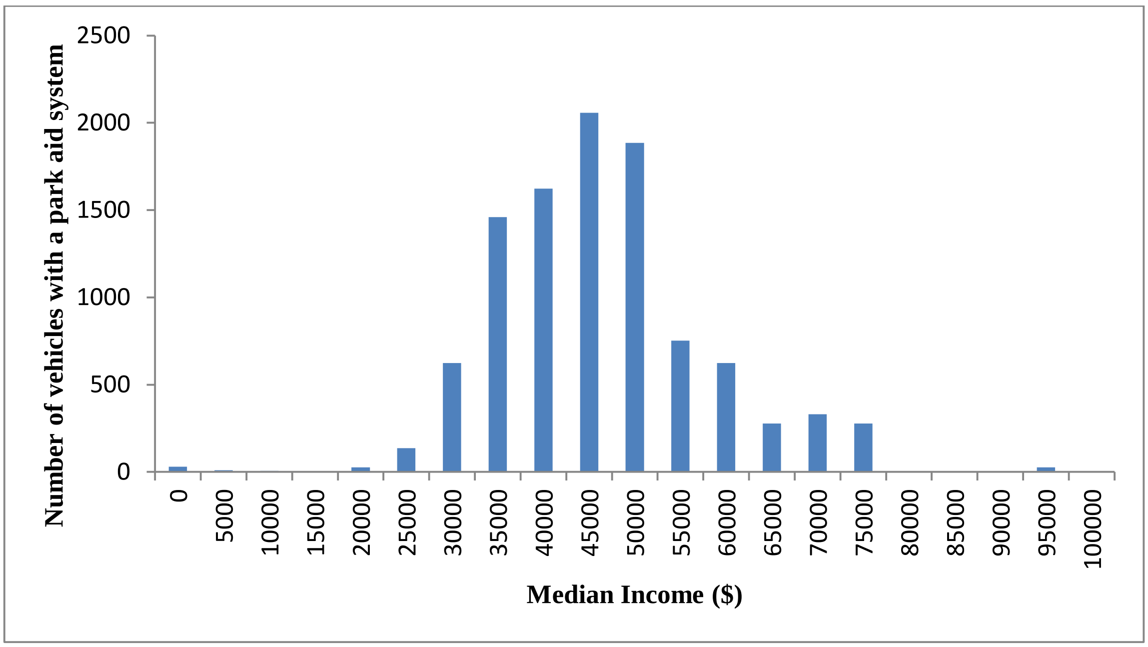
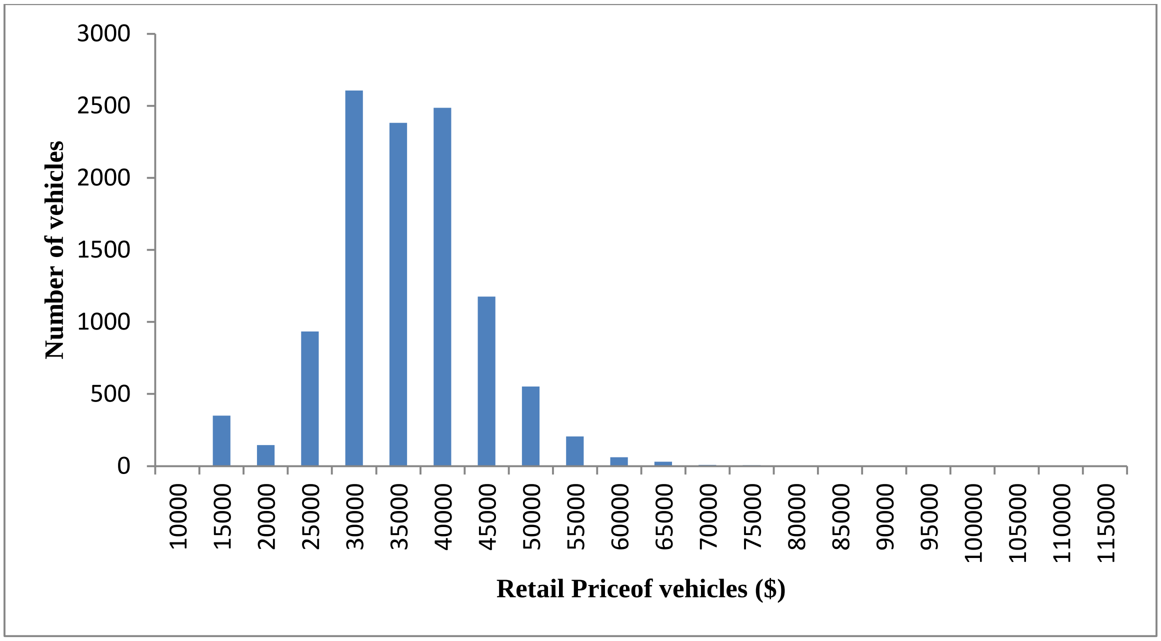


Figure 4. Retail Price of vehicles. This graph shows the retail price of vehicles with an already installed park aid system for Maine registration data.



Using MS Excel, a table was drawn to take a count of all available vehicles with a park aid system. The table is divided by model year. Each unique vehicle is included only once, depending on the year it was first registered.

Table 4. Availability of a park aid system. This tables shows the number of vehicle models with or without a park aid system.

	Number of vehicles without a park aid						Number of vehicles with a park aid					
Model/Year	**2009**	**2010**	**2011**	**2012**	**2013**	**Total**	**2009**	**2010**	**2011**	**2012**	**2013**	**Total**
Acura	-	-	-	10	-	10	-	-	-	2	-	2
BMW	134	14	89	39	-	276	-	7	-	13	-	20
Buick	272	123	407	47	-	849	-	108	248	212	-	568
Cadillac	39	8	-	-	-	47	-	23	33	-	9	65
Chevrolet	4385	3560	5709	3295	321	17270	40	834	510	557	48	1989
Chrysler	348	650	306	166	17	1487	-	379	1	441	-	821
Dodge	737	2409	1058	1062	-	5266	-	-	23	-	-	23
Ford	2877	5859	3358	5041	857	17992	163	297	832	340	414	2046
GMC	473	119	261	164	50	1067	-	127	295	573	-	995
Honda	3182	3053	2337	2176	-	10748	112	151	313	1237	351	2164
Infiniti	76	7	-	-	-	83	-	-	18	-	-	18
Jeep	374	1537	1748	1621	122	5402	-	45	64	133	-	242
Kia	768	301	196	178	-	1443	230	188	88	38	48	592
Mazda	153	690	227	418	-	1488	-	-	-	-	-	-
Mercury	78	282	-	-	-	360	-	11	-	-	-	11
MINI	-	48	-	7	-	55	-	-	-	-	-	-
Mitsubishi	-	-	174	47	-	221	-	31	-	27	-	58
Nissan	1576	2055	2231	2355	221	8438	-	-	-	-	-	-
Pontiac	36	-	-	-	-	36	-	-	-	-	-	-
Ram	-	-	-	658	-	658	-	-	-	-	-	-
Saturn	96	-	-	-	-	96	-	-	-	-	-	-
Scion	129	93	27	91	-	340	-	-	-	-	-	-
Smart	69	-	-	-	-	69	-	-	-	-	-	-
Suzuki	200	-	77	-	-	277	-	-	-	-	-	-
Toyota	7873	9666	6582	5868	773	30762	62	404	422	565	-	1453
Volkswagon	759	548	705	1058	165	3235	-	-	-	-	-	-
Volvo	109	80	63	90	33	375	-	-	64	-	-	64
Grand Total	**24743**	**31102**	**25555**	**24391**	**2559**	**108350**	**607**	**2605**	**2911**	**4138**	**870**	**11131**

5.2 Variables used in Regression Two (Using the 2009 NHTSA data)

Table 5. Variables used in regression two**.** This table includes a list of the variables that were used for the regression estimated using 2009 NHTS data

Type	Variable	Description	Included Categories	Base Dummy
DDV	Rear	If a park aid system is included		
VEH	Drive type		RWD (rear wheel); AWD (all wheel); T4WD (four wheel); T2WD (two wheel)	FWD (front wheel drive)
	Length	Length of the vehicle (measured in inches)		
	Width	Width (measured in inches)		
	Height	Height (measured in inches)		
	CC	Cubic centimeters of		
	CTY	Fuel economy (miles per gallon in the city)		
	HWY	Miles per gallon on the highway		
	Retail	Retail price		
	Vehicle type		Car; Van; SUV	Pickup/Truck
	Vehicle	Make of the vehicle	All vehicle makes	
	Luxury	Vehicle is a luxury		
	Fuel type		Diesel, Electricity, Motor Gasoline	Natural gas
	Hybrid	Is the vehicle hybrid		
	Model year		Y2007; Y2008; Y2009	Y2006
DEM	Race	Race of household occupants	HH_HIS (Hispanic); HH_WHT (Caucasian); HH_AFAM (African American:	HH_Other (Other race)

Table 5 contd.

	Income		HH25to50 (income between $25-$50,000); HH50to75 (income between $50-$75,000)	HHL25 (income less than $25,000)
	INCRETAIL	An interaction variable between retail price and income greater than $50,000		
	INCOP	An interaction variable between operating costs and income greater than $50,000		
	Household size		HHONE (one individual); HHTWO (two); HHTHREE (three)	HHFOPLUS (four or more individuals)
	Number of vehicles		VEHONE (one); VEHTWO (two); VEHTHE(three)	VEHFOPLUS (four or more vehicles)
	Education		HIGH (completed high school); SOME (some college); BACH (bachelor's degree); GRAD (graduate degree)	LHIGH (no high school)
	AGE	Respondent's age		
	AGE_SQ	Age squared		
	AGE_CB	Age cubed		
	Male	Respondent's gender is male		

Table 5 contd.

GEO	HBPPOPDN (Population per square mile)		L100TO499 (Pop per square mile between 100 and 499); L500TO999 (between 500 and 999); L1000TO1999 (between 1,000 to 1,999); L2000TO3999 (between 2,000 and 3,999); L4000TO9999 (between 4,000 and 9,999); L10TO24999 (between 10,000 and 24,999); L25TO999999 (between 25,000 and 999,999)	L0TO99 (population per square mile between 0 and 99)
Travel	OD_Read	The odometer reading as of the survey date		
	BESTMILE	Total annual miles		
	GSTOTCOST	Total cost of gasoline		

The dummy variables are shaded.

From the 3025 observations that are used for this regression, 2912 observations did not include a park aid system at manufacture. This shows that just 4 percent of the observations have a park aid system included or only a small number of observations have the value ‘1’ for the dependent variable. Again, contingency tables are used to determine the variables that would be included in the model. The following shows the phi values for all categorical variables. Some continuous variables such as respondent age and retail value are included to identify any trends within the dataset.

Table 6. Phi value for the variables following a crosstab reference. This tables uses data from the 2009 NHTS

Variable	Phi	p-value
Drive Type	0.111	0.000***
Vehicle Type	0.158	0.000***
Hybrid	-0.040	0.016**
Race	0.056	0.118
Income	0.087	.076*
Household Size	0.039	0.850
Number of Vehicles	0.021	0.998
Education	0.023	0.743
HBPPOPDN	0.057	0.096*
Male	0.007	0.682
Retail	0.985	0.000***
R_Age	0.151	0.130
Vehicle make	0.609	0.000***
Luxury	0.325	0.000***

*** Significant at the 1%; ** Significant at the 5%; *Significant at the 10% level

Figure 5. Retail price of vehicles with a park aid system. This graph uses data from the 2009 NHTS.

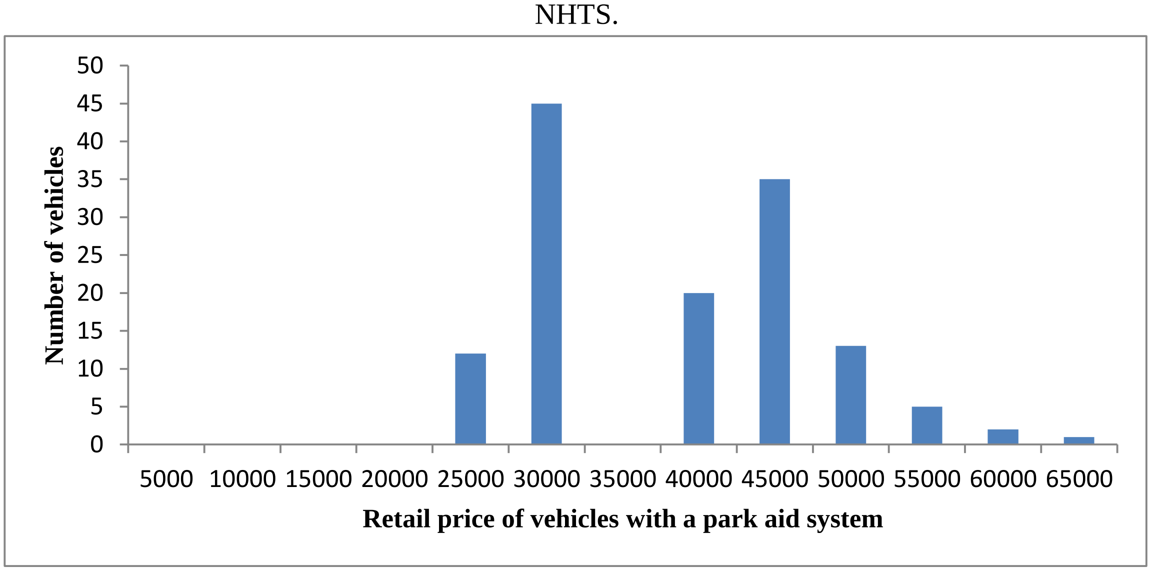


Table 7. Availability of a park aid system. This table uses data from the 2009 NHTS.

Number of vehicles with a park aid						Number of vehicles with no park aid				
Model/Year	2006	2007	2008	2009	Total	2006	2007	2008	2009	Total
ACURA	7	3	12	2	24	-	6	-	-	6
AM GENERAL	1	-	-	-	1	-	-	-	-	-
AUDI	1	4	5	-	10	-	-	-	-	-
BMW	1	4	5		10	3	-	-	-	3
BUICK	-	1	11	2	14	8	7	-	-	15
CADILLAC	11	5	-	-	16	13	16	10	1	40
CHEVROLET	160	188	135	8	491	-	-	-	-	-
CHRYSLER	41	31	19	2	93	-	-	-	-	-
DODGE	84	70	33	3	190	-	6	-	-	6
FORD	31	113	123	12	279	-	-	-	-	-
GMC	27	22	35	2	86	-	8	-	-	8
HONDA	157	210	184	23	574	-	-	-	-	-
HYUNDAI	51	52	33	10	146	-	-	2	-	2
INFINITI	6	14	-	-	20	2	2	-	-	4
JAGUAR	-	-	-	-	-	3	1	-	-	4
JEEP	19	21	31	-	71	2	4	2	-	8
KIA	40	35	23	-	98	-	-	-	-	-
LEXUS	4	-	4	-	8	-	-	-	-	-
LINCOLN	8	6	-	-	14	5	2	3	-	10
MAZDA	7	15	20	2	44	-	-	-	-	-
MERCURY	12	7	10	-	29	-	5	-	-	5
MITSUBISHI	8	6	2	1	17	-	-	-	-	-
NISSAN	88	63	79	14	244	-	22	-	-	22
PONTIAC	24	19	15	5	63	-	-	-	-	-
PORSCHE	-	1	2	-	3	-	-	-	-	-
SATURN	27	35	19	2	83	-	-	-	-	-
SMART	-	-	3	-	3	-	-	-	-	-
SUBARU	21	23	17	4	65	-	-	-	-	-
SUZUKI	4	2	-	-	6	-	-	-	-	-
TOYOTA	238	300	209	70	817	-	-	-	-	-
VOLKSWAGEN	20	12	10	3	45	-	-	-	-	-
VOLVO	-	4	3	-	7	-	-	-	-	-
Grand Total	1098	1266	1042	165	3571	36	79	17	1	133

The study models consumer characteristics which influence the purchase of a vehicle with a rearview system. Therefore, vehicle attributes are included to control for other characteristics which may influence the purchase. Demographic variables (from the 2010 US Census) are included to account for the consumer's characteristics. There are several initial hypothesis that were made before the model was run. Based on past literature, we hypothesize that a park aid system will be found in newer, higher priced, and larger vehicles. Similarly, consumers who purchase these vehicles will have a higher formal education and a higher income. In addition to the features that are included in the vehicles, gas prices and operating costs will have an influence in the purchase of a vehicle. For instance, if gas prices spike, consumers may want to purchase a vehicle with lower operating costs. Since park aid systems are more likely to be included in luxury models, a spike in gas prices will decrease the sale of these vehicles. Finally, a multi-category variable will be included to determine if location has any influence in the purchase of a park aid. It can be argued that a park aid is essential in an urban setting where there is higher traffic. At the same time, affluent, retired individuals will tend to live in suburban locations.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 Results from the Regression using the Maine Vehicle Registration Data

Two equations are generated from the Maine vehicle registration data. The first equation contains a time element. The time element includes the vehicle model year and the percentage of vehicles with a rearview system on the road. The time element is used to forecast the future diffusion of park aid systems.

The first regression model used is:

$$(\pi(x)) = \beta_0 + \eta_1 HWYMPG + \eta_2 CMBMPG + \eta_3 WHEELBASE + \eta_4 MINIVAN + \eta_5 CAR + \eta_6 SUV + \eta_7 FWD + \eta_8 AWD + \eta_9 T4WD + \eta_{10} PERMONREAR + \eta_{11} Y2010 + \eta_{12} Y2011 + \eta_{13} Y2012 + \eta_{14} Y2013 + \eta_{15} BUICK + \eta_{16} CADILLAC + \Psi_1 AGE + \Psi_2 AGESQ + \Psi_3 AGECB + \Psi_4 LUXURY*MEDINCOME + \varepsilon \quad (6)$$

Table 8. Maine registration data with time variables.

Type	Beta	Beta	S.E.	Wald	Significance	Exp(B)
	Intercept	-8.004	0.403	394.247	0.000***	0
VEH	HWYMPG	0.084	0.007	149.592	0.000***	1.087
	CMBMPG	-0.067	0.006	121.525	0.000***	0.935
	WheelBase	0.008	0.001	125.738	0.000***	1.008
	MINIVAN	4.314	0.149	838.994	0.000***	74.708
	CAR	2.198	0.154	204.594	0.000***	9.003
	SUV	3.789	0.165	526.756	0.000***	44.207
	FWD	-2.59	0.102	641.363	0.000***	0.075
	AWD	-2.173	0.108	403.283	0.000***	0.114
	T4WD	-2.457	0.108	514.842	0.000***	0.086
	PERMONREAR	0.045	0.006	66.453	0.000***	1.046
	Y2010	1.239	0.051	594.136	0.000***	3.454
	Y2011	1.207	0.052	532.521	0.000***	3.345
	Y2012	1.786	0.059	928.549	0.000***	5.967
	Y2013	2.167	0.076	802.87	0.000***	8.733
	BUICK	3.484	0.115	916.037	0.000***	32.598
	CADILLAC	5.173	0.259	397.523	0.000***	176.44
DEM	AGE	0.122	0.022	31.411	0.000***	1.13
	AGESQ	-0.002	0.000	30.134	0.000***	0.998
	AGECB	0.000	0.000	26.929	0.000***	1
	LUXURY* MEDINCOME1000	-0.019	0.002	90.945	0.000***	0.981

*** Significant at the 1%; **Significant at the 5% level; *Significant at the 10%

Summary statistics for the variables can be found in Appendix I.

The chi-square statistic for the model fit is 12167. With 20 degrees of freedom and a p-value of 0.0000, the chi-square test strongly rejects the null hypothesis of no explanatory power from the included variables.

The demographic values that are included are the registrant's age and the median income of the registrant's town. Median income is measured in 1000 dollars. As expected, the probability of purchasing a vehicle increases with age and then decreases (shown by AGESQ variable). This result is shown graphically in section 5.1. An interaction term between LUXURY*MEDINCOME shows that as median income increases, consumers are less likely to buy a luxury vehicle with a park aid. One possible explanation is that some of the higher end luxury and sport vehicles may not include a rearview system, since these vehicles are not marketed for safety but for leisure and societal status.

An included park aid system is less likely to be found in vehicles that are of the following drive types: front wheel, all wheel, or four wheel drive. They are more likely to be included in family vehicles such as minivans, cars, SUVs (as compared to pickups) and in vehicles with a greater wheelbase and vehicles with better highway mileage. They are also found in two luxury vehicles, Cadillac and Buick. Finally, the time variables show that newer models are more likely to have a rearview system, and that the percentage of vehicles with the system (PERMONREAR) increases every month.

The second regression model used is:

$$(\pi(x)) = \beta_0 + \eta_1\text{CITYMPG} + \eta_2\text{HWYMPG} + \eta_3\text{CMBMPG} + \eta_4\text{WHEELBASE} + \eta_5\text{MINIVAN} + \eta_6\text{CAR} + \eta_7\text{SUV} + \eta_8\text{FWD} + \eta_9\text{AWD} + \eta_{10}\text{T4WD} + \eta_{11}\text{RETAILPRICE1000} + \eta_{12}\text{MEANINCOME1000} + \eta_{13}\text{BUICK} + \eta_{14}\text{CADILLAC} + \eta_{15}\text{CHEVROLET} + \eta_{16}\text{CHRYSLER} + \eta_{17}\text{DODGE} + \eta_{18}\text{FORD} + \eta_{19}\text{GMC} + \eta_{20}\text{HONDA} + \eta_{21}\text{JEEP} + \eta_{22}\text{KIA} + \eta_{23}\text{MERCURY} + \eta_{24}\text{MITSUBISHI} + \eta_{25}\text{TOYOTA} + \eta_{26}\text{VOLVO} + \Psi_1\,\text{AGE*LUXURY} + \varepsilon \qquad (7)$$

Table 9. Maine registration data without time variables.

Type	Variable	Beta	S.E.	Wald	Significance	Exp(B)
	CONSTANT	-34.411	0.714	2323.787	0.000***	0
VEH	CITYMPG	-0.172	0.018	94.029	0.000***	0.842
	HWYMPG	0.308	0.014	464.855	0.000***	1.361
	CMBMPG	0.089	0.024	13.593	0.000***	1.093
	WheelBase	0.037	0.001	1229.121	0.000***	1.037
	MINIVAN	6.318	0.184	1173.852	0.000***	554.51
	CAR	3.187	0.207	237.14	0.000***	24.222
	SUV	1.608	0.221	52.872	0.000***	4.995
	FWD	-2.694	0.163	272.798	0.000***	0.068
	AWD	-1.658	0.171	94.496	0.000***	0.191
	T4WD	-3.208	0.18	315.934	0.000***	0.04
	RETAILPRICE1000	0.36	0.005	5434.101	0.000***	1.433
	MEANINCOME1000	-0.003	0.001	10.832	0.001***	0.997
	BUICK	11.145	0.373	892.177	0.000***	69245.88
	CADILLAC	7.579	0.439	297.841	0.000***	1956.723
	CHEVROLET	12.679	0.517	601.795	0.000***	321017.2
	CHRYSLER	17.118	0.538	1011.229	0.000***	27172839
	DODGE	10.184	0.57	319.531	0.000***	26468.32
	FORD	12.16	0.516	555.689	0.000***	191025.9
	GMC	15.077	0.539	783.903	0.000***	3531854
	HONDA	13.417	0.519	668.722	0.000***	671110.6
	JEEP	10.142	0.52	381.14	0.000***	25393.05
	KIA	16.914	0.532	1009.068	0.000***	22166785
	MERCURY	10.418	0.665	245.338	0.000***	33449.34
	MITSUBISHI	12.78	0.554	531.543	0.000***	355021.2
	TOYOTA	11.724	0.516	516.024	0.000***	123494.1
	VOLVO	7.065	0.374	356.313	0.000***	1170.605
DEM	AGE*LUXURY	0.024	0.007	11.917	0.001***	1.024

*** Significant at the 1%; **Significant at the 5% level; *Significant at the 10%

Summary statistics for the variables can be found in Appendix I.

The chi-square statistic for the model fit is 30521. With 27 degrees of freedom and a p-value of 0.0000, the chi-square test strongly rejects the null hypothesis of no explanatory power from the included variables.

The one demographic variable is an interaction term between LUXURY*AGE. The term shows that the probability of purchasing a luxury vehicle with a park aid system increases with age.

RETAILPRICE1000 shows that higher priced vehicles are more likely to include a park aid system. The variable measures the retail price of a vehicle in 1000 dollars. An included park aid system is less likely to be found in vehicles that are of the following drive types: front wheel, four wheel and all-wheel drive. Similar to the first regression, park aid systems are more likely to be included in family vehicles such minivans, cars, SUVS (as compared to pickups) and in vehicles with a greater wheelbase. They are more likely to be found in vehicles with better miles per gallon.

When the time variables are dropped, it is shown that a park aid system is more likely to be found in the following vehicle makes: Buick, Cadillac, Chevrolet, Chrysler, Dodge, Ford, GMC, Honda, Jeep, Kia, Mercury, Mitsubishi, Toyota, and Volvo. However, as Table 4 shows, these are the makes which offer at least one vehicle with an already included park aid system. The results do not provide much information except to state that there is a greater chance of finding a park aid system in one of the above mentioned makes.

6.2 Model Robustness

The park aid system is offered as standard or not included at all in several vehicle makes. Since it is already installed or not installed at all, it does not indicate the availability of choice, and the observations do not have much variance. All observations are removed for the following vehicle makes, including Lincoln, Subaru, LandRover, Mercedes, Hyundai, Lexus, Mazda, and Scion.

To ensure model robustness, each model is run using the complete dataset and several mined sampled datasets. The results from the sampled sets show that the variables Acura, Audi, and BMW are insignificant. They are removed from the final regressions.

6.3 Results from the Regression using the 2009 NHTS data

The regression model (with time variables) is shown below:

$$(\pi(x)) = \beta_0 + \eta_1 VAN + \eta_2 SUV + \eta_3 RWD + \eta_4 T2WD + \eta_5 CC + \eta_6 CITYMPG + \eta_7 BMW + \eta_8 CADILLAC + \eta_9 DODGE + \eta_{10} GMC + \eta_{11} INFINITI + \eta_{12} JEEP + \eta_{13} LINCOLN + \eta_{14} MERCURY + \eta_{15} NISSAN + \eta_{14} Y2007 + \Psi_1 LUXURY{*}AGE + \varepsilon \quad (8)$$

Table 10. 2009 NHTS data with time variables.

Type	Variable	B	S.E.	Wald	Significance	Exp(B)
	Intercept	-31.361	4.597	46.541	0.000***	0
VEH	VAN	6.623	1.256	27.801	0.000***	752.147
	SUV	6.758	1.078	39.319	0.000***	860.935
	RWD	-1.487	0.485	9.393	0.002***	0.226
	T2WD	2.745	1.009	7.393	0.007***	15.562
	CC	0.003	0.001	34.685	0.000***	1.003
	CITYMPG	0.267	0.124	4.669	0.031**	1.306
	BMW	1.478	0.944	2.45	0.118	4.384
	CADILLAC	6.531	1.206	29.309	0.000***	686.372
	DODGE	4.557	0.985	21.426	0.000***	95.343
	GMC	5.276	0.948	30.968	0.000***	195.657
	INIFINITI	4.778	1.15	17.269	0.000***	118.921
	JEEP	6.209	1.015	37.395	0.000***	497.161
	LINCOLN	4.076	1.661	6.018	0.014**	58.888
	MERCURY	9.652	1.298	55.323	0.000***	15545.35
	NISSAN	7.002	0.929	56.758	0.000***	1098.328
	Y2007	2.326	0.369	39.732	0.000***	10.24
DEM	LUXURY*AGE	0.132	0.017	63.193	0.000***	1.141

*** Significant at the 1%; **Significant at the 5% level; *Significant at the 10%
Summary statistics are included in Appendix I.

The chi-square statistic for the model fit is 835. With 17 degrees of freedom and a p-value of 0.0000, the chi-square test strongly rejects the null hypothesis of no explanatory power from the included variables.

One demographic variable is included in the model. LUXURY*AGE shows that the probability of purchasing a luxury vehicle increases with age. This makes sense since older individuals are more likely to earn a higher salary. It also shows that luxury vehicles (higher priced vehicles) are more likely to include a park aid.

Park aid systems are more likely to be included within certain vehicle categories, mainly SUVs and vans – family vehicles. The variables engine capacity and miles per gallon in the city are shown to have a positive effect, whereas the variable, rear wheel drive, has a negative effect. They are more likely to be included in the following vehicle types: BMW, Cadillac, Dodge, GMC, Infiniti, Jeep, Lincoln, Mercury, and Nissan.

The results show that vehicles manufactured in the year 2007 are most likely to include a park aid system (the years 2008 and 2009 show up as insignificant). One possible explanation is that before the 2008 recession, the demand for luxury vehicles was at an all-time high.

The regression model (without time variables) is shown below:

$$(\pi(x)) = \beta_0 + \eta_1 \text{VAN} + \eta_2 \text{SUV} + \eta_3 \text{T2WD} + \eta_4 \text{WIDTH} + \eta_5 \text{CC} + \eta_6 \text{CITYMPG} + \eta_7 \text{LUXURY} + \eta_8 \text{CADILLAC} + \eta_9 \text{GMC} + \eta_{10} \text{INFINITI} + \eta_{11} \text{JEEP} + \eta_{12} \text{MERCURY} + \eta_{13} \text{NISSAN} + \Psi_1 \text{AGE} * \text{LUXURY} + \varepsilon \quad (9)$$

Table 11. 2009 NHTS without time variables.

Type	Variable	B	S.E.	Wald	Significance	Exp(B)
	Intercept	-60.932	7.338	68.942	0.000***	0
VEH	VAN	5.215	1.149	20.604	0.000***	183.963
	SUV	6.152	1.057	33.843	0.000***	469.639
	T2WD	8.334	2.292	13.228	0.000***	4164.883
	WIDTH	0.393	0.069	32.091	0.000***	1.481
	CC	0.002	0	31.207	0.000***	1.002
	CITYMPG	0.443	0.072	38.146	0.000***	1.558
	LUXURY	5.851	2.595	5.083	0.024**	347.544
	CADILLAC	6.324	1.164	29.54	0.000***	557.687
	GMC	6.003	2.161	7.721	0.005***	404.776
	INIFINITI	3.61	1.416	6.497	0.011**	36.98
	JEEP	6.911	2.296	9.062	0.003***	1003.234
	MERCURY	11.32	2.295	24.324	0.000***	82421.69
	NISSAN	8.896	2.146	17.182	0.000***	7303.14
DEM	AGE *LUXURY	0.063	0.022	8.277	0.004***	1.065

***Significant at the 1%; **Significant at the 5%; *Significant at the 10% level
Summary statistics are included in Appendix I.

The chi-square statistic for the model fit is 807. With 14 degrees of freedom and a p-value of 0.0000, the chi-square test strongly rejects the null hypothesis of no explanatory power from the included variables.

One demographic variable is included in the model. AGE*LUXURY shows that the probability of purchasing a luxury vehicle increases with age.

Park aid systems are more likely to be included within certain vehicle categories, luxury and mainly SUVs and vans – family vehicles. They are more likely to be included in vehicles with a higher engine capacity, more miles per gallon in the city, and vehicles with a greater width.

They are more likely to be included in the following vehicle types: Cadillac, GMC, Infiniti, Jeep, Mercury, and Nissan. Again, these results do not provide much information except to state that there is a greater chance of finding a park aid system in one of the above mentioned makes. This is shown in table 7.

6.4 Model Robustness

As with the models which use Maine registration data, one variable, JAGUAR, is removed from the model. Park aid systems are a standard feature in Jaguar models. The feature is available in all Jaguar models in the NHTS dataset, and since it does not allow for choice and variation, the beta values for JAGUAR are high. The observations which included a Jaguar are removed from the dataset.

As before, each model is run using the complete dataset and several random sample datasets. The results from the sampled sets show that the variable Lincoln is insignificant. It is removed from the final regressions.

6.5 Conclusions

The overall results indicate that certain consumer groups are more likely to purchase a vehicle with a park aid system. This includes older and more affluent individuals. AGE *LUXURY shows a positive effect, meaning the probability of purchasing a luxury vehicle increases with age. The variable LUXURY*MEDINCOME shows a negative effect. As stated before, some of the higher end luxury vehicles, such as sports cars, may not include a park aid system since they are marketed for leisure and not safety.

Vehicles with two wheel drive are more likely to have a park aid system. These systems are more likely to be included in family vehicles such as minivans, cars, and SUVs. They are more likely to be included in luxury models, vehicles with a greater wheelbase, and vehicles with better highway and city mileage.

A park aid system is standard in several vehicle models with higher miles per gallon. This included the Toyota Prius. Even if a variant of miles per gallon is positive and significant in the regressions, it may be picking up on these few and select vehicle models.

CHAPTER 7

PREDICTING THE FUTURE DIFFUSION OF PARK AID SYSTEMS

We use three methods to forecast the future uptake of park aid systems. The first method is to extrapolate the data. In the second and third methods, we use a predefined set of parameters to obtain vehicle stock levels using the Bass and Gompertz models.

There is reason to believe that the stock level of vehicles with park aid systems will increase. Cao and Mokhtrain (2002) state that as different alternative fuel vehicles (AFV) models become available, consumers will be able to select from a more diverse choice set (2002, p. 54). This reasoning shows that as the number of models with park aid systems increase, the chance that each model will meet consumer requirements will follow suit. Additionally, customers who feel a certain brand loyalty may wait until their preferred brand manufactures a vehicle that will meet their needs.

7.1 Extrapolation

We can use a graphical approach to identify any trends within the vehicles. We use two datasets for this purpose. The first dataset contains Maine vehicle registration data for the years 2011 through March 2013. We use this dataset to run the first regressions for this study. The second dataset contains Maine vehicle registration data from 2006 through 2007. This dataset has been used for two previous studies by Siriwardena (2010) and Bacani (2008).

The following steps outline the process:

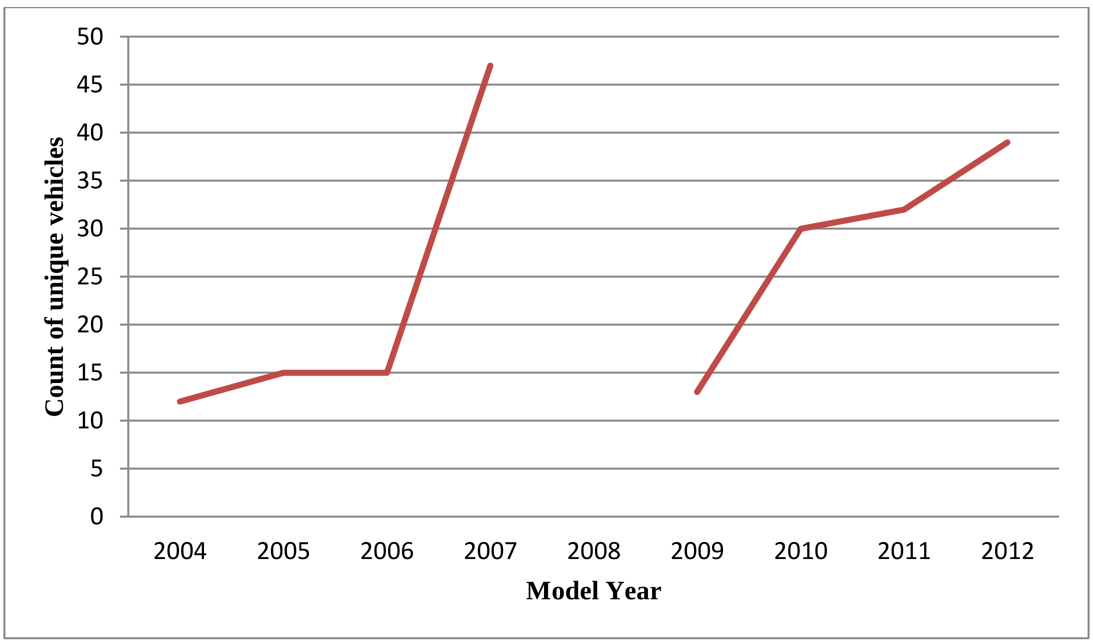
1) Using the advanced filter option available on MS Excel, unique vehicle records are selected by make, model, model year, and the availability of a park aid system. By selecting just the unique records, both datasets are standardized to determine the number of offered vehicle models with a park aid system.

2) We use the feature Pivot Tables on MS Excel to obtain a count of vehicle models with a park aid system.

Table 12. Number of models with a park aid system

Model Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Count	12	15	15	47	n/a	13	30	32	39	(too few observations)

Figure 6: Number of models with a park aid system



This graph provides several interesting results. Following a slow initial uptake, the number of models with a park aid system increase from a meager 15 to 47 between the years 2006 and 2007. The number plummets significantly by the year 2009. In 2009, there are only 13 models with a park aid system available. From the period 2009 to 2012, the number of vehicles is on the rise, even if the increase is not as steep.

There are several conclusions that can be drawn from this graph. Following the 2008 recession, the number of vehicles with park aid systems declined rapidly. It shows that a sudden economic change may have drastic influences on adoption patterns. The graph also shows that consumers are more cautious following recovery from a recession. While there is a rapid increase in the number of vehicles (with park aid systems) from 2006 to 2007, the increase from 2010 to 2012 is more gradual.

A second option is to calculate the percentage of vehicles with a park aid system over all vehicles registered for that particular year.

The following steps outline the process:

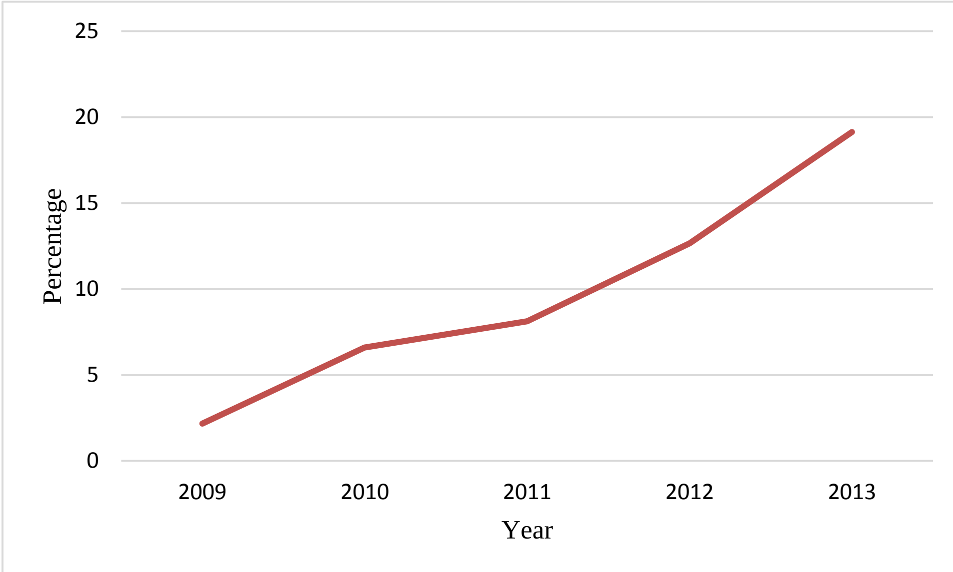
1) We use MS Excel to obtain a count of vehicles with a park aid system and a count of all vehicles registered in the State of Maine.

2) We calculate the percentage of vehicles with a park aid over all vehicles.

Table 13. Percentage of new vehicles with a park aid

Year	2009	2010	2011	2012	2013
Percentage	2.17	6.60	8.13	12.66	19.14

Figure 7. Percentage of new vehicles with a park aid system



During the period 2009 through 2013, the percentage increases steadily.

The above graphs show that the number of vehicles with a park aid is on the rise. The data can be extrapolated on a month by month basis to capture any trends. By subdividing the data into months, we will have more data points. Putsis (1996) (as cited in Cao and Mokhtarian (2002)) recommends that the number of data points should be increased to reduce bias within the observations.

The following steps outline our methods:

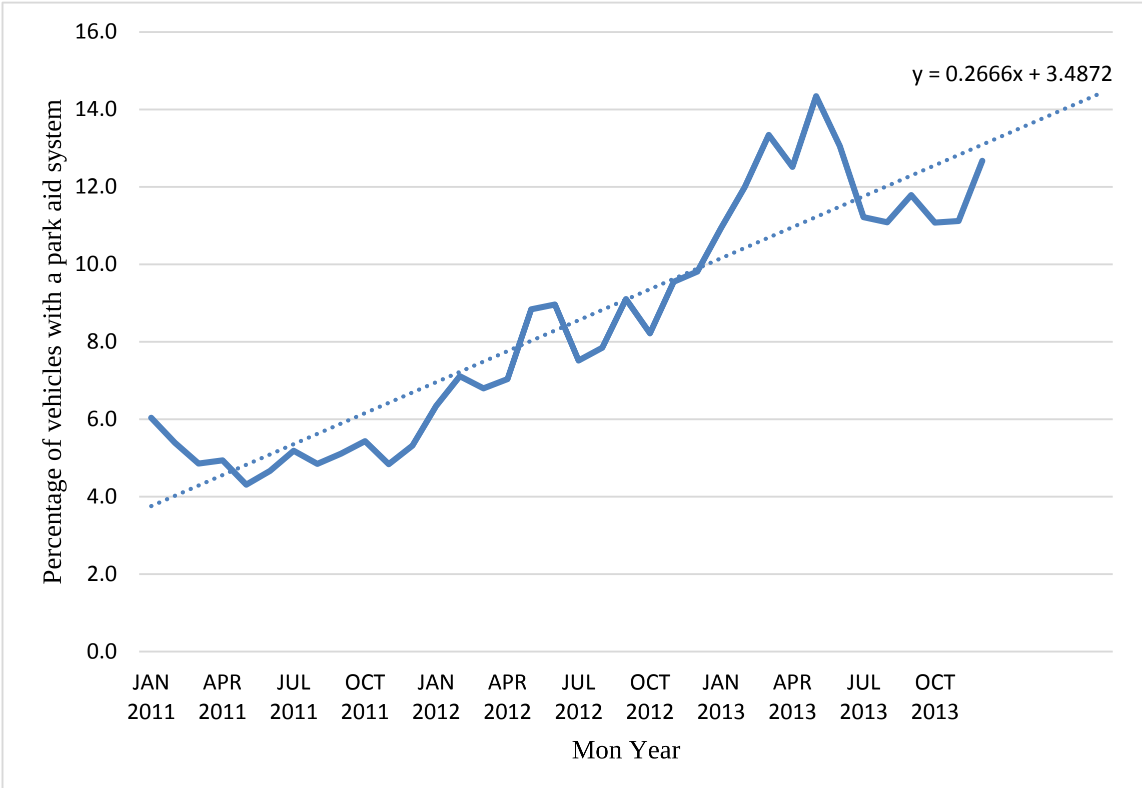
1) The vehicle registration data from the Maine BMV will be categorized by month based on the month and the year of the registration expiry date. The older dataset containing registration information for years 2006 through 2007 does not include registration expiration data and is excluded.

2) We will calculate the percentage of vehicles with a park aid system divided by all available vehicles. This percentage is calculated on a monthly basis.

Table 14. Percentage of vehicles with park aid system from Jan 2011 through Dec 2013.

Registration Expiration	Vehicles with Park Aids	All vehicles	% of vehicles with park aid
JAN 2011	76	1260	6.0
FEB 2011	163	3025	5.4
MAR 2011	247	5093	4.8
APR 2011	315	6380	4.9
MAY 2011	306	7104	4.3
JUN 2011	314	6729	4.7
JUL 2011	323	6236	5.2
AUG 2011	351	7241	4.8
SEP 2011	311	6088	5.1
OCT 2011	308	5669	5.4
NOV 2011	234	4840	4.8
DEC 2011	257	4835	5.3
JAN 2012	289	4561	6.3
FEB 2012	217	3054	7.1
MAR 2012	276	4064	6.8
APR 2012	287	4079	7.0
MAY 2012	397	4491	8.8
JUN 2012	376	4196	9.0
JUL 2012	251	3342	7.5
AUG 2012	262	3340	7.8
SEP 2012	292	3209	9.1
OCT 2012	244	2970	8.2
NOV 2012	264	2765	9.5
DEC 2012	245	2498	9.8
JAN 2013	315	2881	10.9
FEB 2013	398	3318	12.0
MAR 2013	568	4259	13.3
APR 2013	545	4356	12.5
MAY 2013	639	4455	14.3
JUN 2013	556	4261	13.0
JUL 2013	384	3424	11.2
AUG 2013	360	3249	11.1
SEP 2013	322	2731	11.8
OCT 2013	256	2311	11.1
NOV 2013	215	1934	11.1
DEC 2013	193	1523	12.7

Figure 8. Percentage of vehicles with a park aid system.



Both the table and graph show that park aid systems are increasingly available as a standard feature in newer vehicle models. A linear trend line with the equation y = 0.266x + 3.472 supports the observed data. The proposed mandate by NHTSA may have spurred vehicle manufacturers to include the system as standard.

7.2 The Bass Model

Our goal is to derive the estimates of the Bass diffusion model for park aid systems. For more information about the Bass model, see section 3.2.1. The discrete form of the Bass model is shown in equation (10).

$$S(t) = N(t) - N(t-1) = p[m - N(t-1)] + q\frac{N(t-1)}{m}[m - N(t-1)] \tag{10}$$

where S(t) is the number of adopters during time t, N(t) is the cumulative adopters during time period t, N(t-1) is the cumulative adopters during time period t-1, m is the market potential, p is the coefficient of innovation, and q is the coefficient of imitation.

To simplify the estimation, substitute parameters can be introduced in place of the more complex terms.

$$S(t) = pm + (q - p)N(t - 1) - \frac{q}{m}N^2(t - 1) + \varepsilon(t) \tag{11}$$

where β_1 = pm, β_2 = q-p, and β_3 = -q/m

$$S(t) = \beta_1 + \beta_2 N(t - 1) + \beta_3 N^2(t - 1) + \varepsilon(t) \tag{12}$$

There are three methods that can be used to estimate the parameters of a Bass Model: ordinary least squares (OLS), maximum likelihood estimation (MLE), and non-linear least squares (NLS). There are drawbacks to using each approach. Mahajan and Sharma (1986) summarize that the drawbacks from OLS include unstable parameters or parameters with the wrong sign, no standard errors provided for each of the parameter terms, and a time-interval bias since a continuous model is being estimated with discrete data.

MLE and NLS are superior estimation methods compared to OLS. MLE and NLS use an iterative procedure to converge to a global maximum. The one major drawback is that they both require starting values. Sirinivasen and Mason (1986) (as cited in Cao and Mokhtarian (2002)) believe an NLS approach will provide better results since MLE does not account for omitted variables or model misspecifications.

As stated, NLS will need starting parameter values to converge to the global maximum. There are two approaches that can be used to generate starting values. First, the estimates from the OLS technique can provide initial numbers. Mahajan and Sharma (1986) caution against this approach saying that sometimes the wrong parameter signs may be estimated. A second approach is to use the parameter estimates from a diffusion model for a similar product. Cao and Mokhtarian (2002) study the future demand for alternative fuel passenger (AFV) vehicles. Lamberson (2009) develops parameter estimates for the diffusion of hybrid electric vehicles (HEV). McManus and Senter (2009) develop estimates for plug-in hybrid electric vehicles (PHEV). The estimates that were calculated in these papers can be used as input values. This approach can be supported since the studies focus on passenger vehicles and are studying the diffusion rate of a new feature or standard.

The following steps outline the methods that are used:

1) The final parameter values from Cao and Mokhtarian (2002), Lamberson (2009), and McManus and Senter (2009) will be used as starting points.

2) The vehicle data obtained from the Maine BMV will be categorized by month based on the month and the year of the registration expiry date.

3) Using the values from these three studies as initial values, vehicle stock level estimates will be calculated from the discrete Bass model.

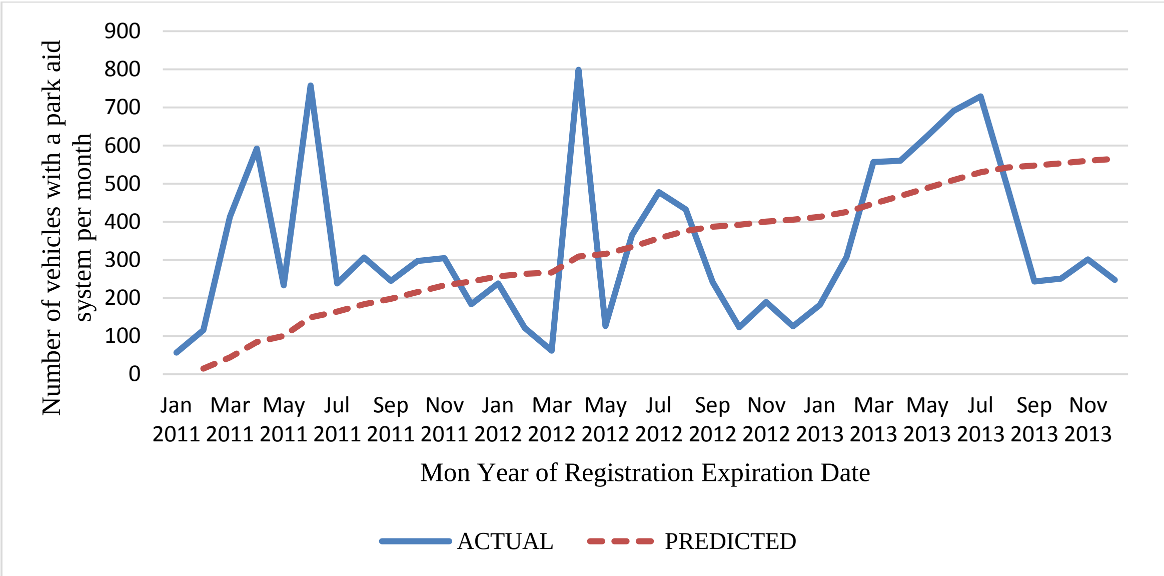
4) Results show that the p and q values calculated by Lamberson (2009) best fit the model. In his model, p, the coefficient of innovation, is 0.000055, and q, the coefficient of imitation is 0.0728. M, the market potential, is the number of new vehicles that are registered in Maine. 900,000 vehicles have been registered in Maine during the past 27 months. The value of m per month is 900000/27.

Table 15. Results from the Bass model.

EXPIRATION MON YEAR	ACTUAL	PREDICTED
Jan 2011	56	
Feb 2011	115	14
Mar 2011	413	44
Apr 2011	592	84
May 2011	233	100
Jun 2011	758	149
Jul 2011	238	164
Aug 2011	306	183
Sep 2011	245	198
Oct 2011	297	215
Nov 2011	304	233
Dec 2011	183	243
Jan 2012	238	257
Feb 2012	121	263
Mar 2012	61	267
Apr 2012	799	309
May 2012	126	315
Jun 2012	365	333
Jul 2012	478	356
Aug 2012	432	376
Sep 2012	241	387
Oct 2012	123	392
Nov 2012	189	400
Dec 2012	125	406
Jan 2013	182	413
Feb 2013	307	426
Mar 2013	557	447
Apr 2013	560	467
May 2013	625	488
Jun 2013	691	510
Jul 2013	729	530
Aug 2013	489	542
Sep 2013	243	548
Oct 2013	251	553
Nov 2013	301	560
Dec 2013	247	565

The column, Actual, provides real registration data on a month by month basis, and the column, Predicted, provides results from the Bass model.

Figure 9. Diffusion of park aid systems as predicted by the Bass model.



The predicted results follow a bell-shaped curve. The results show that vehicles with a park aid system are on the rise but have not yet peaked.

7.3 The Gompertz Model

Our final goal is to estimate the parameters of the Gompertz curve. Details about the Gompertz model can be found in section 3.2.2.The Gompertz curve is defined by equation 13.

$$N(t) = m * e^{-a(e^{-bt})} \tag{13}$$

where m is the market potential, a is a slope parameter, and b is the year to peak sales.

The estimation technique for the Gompertz model is similar to the Bass diffusion model. Of the three available techniques, NLS is again recommended.

The following are the steps that we took to estimate the parameters:

1) Lamberson (2009) and McManus and Senter (2009) develop estimates for a Gompertz model in their two studies.

2) Using the values from these two studies as initial values, vehicle stock level estimates will be calculated using an MS Excel worksheet

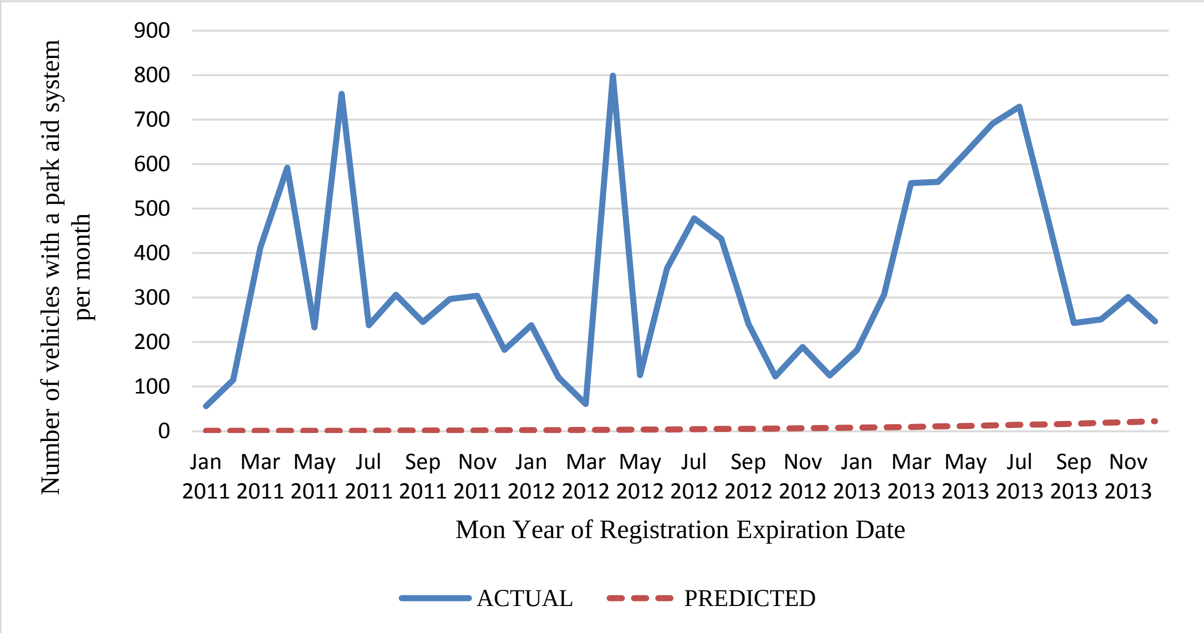
3) Again, results show that the values calculated by Lamberson (2009) best fit the model. In his model, a is 11.2 and b is 0.0118. M, the market potential, is the number of new vehicles that are registered in Maine. 900,000 vehicles have been registered in Maine during the past 27 months. The value of m per month is 900000/27.

Table 16. Results from the Gompertz model.

EXPIRATION MON YEAR	ACTUAL	PREDICTED
Jan 2011	56	1
Feb 2011	115	1
Mar 2011	413	1
Apr 2011	592	1
May 2011	233	1
Jun 2011	758	1
Jul 2011	238	1
Aug 2011	306	1
Sep 2011	245	1
Oct 2011	297	2
Nov 2011	304	2
Dec 2011	183	2
Jan 2012	238	2
Feb 2012	121	3
Mar 2012	61	3
Apr 2012	799	3
May 2012	126	3
Jun 2012	365	4
Jul 2012	478	4
Aug 2012	432	5
Sep 2012	241	5
Oct 2012	123	6
Nov 2012	189	7
Dec 2012	125	7
Jan 2013	182	8
Feb 2013	307	9
Mar 2013	557	10
Apr 2013	560	11
May 2013	625	12
Jun 2013	691	13
Jul 2013	729	14
Aug 2013	489	15
Sep 2013	243	17
Oct 2013	251	18
Nov 2013	301	20
Dec 2013	247	22

The column, Actual, provides real registration data on a month by month basis, and the column, Predicted, provides results from the Gompertz model.

Figure 10. Diffusion of park aid systems as predicted by the Gompertz model.



The graph plots an increasing trend for the number of vehicles with a park aid system. The Gompertz model follows an exponential growth trend, and the graph shows that the number of vehicles with park aid systems is starting to rise. Compared to the Bass model – which shows that the number of vehicles with a park aid system is approaching a peak – the Gompertz model predicts a rising increase. The results are similar to what Lamberson (2009) obtained. In his model, the Bass fit peaks sooner than the Gompertz model.

CHAPTER 8

A BENEFIT COST ANALYSIS OF PARK AID SYSTEMS

8.1 Introduction

In a November 2010 report, the Office of Regulatory Analysis and Evaluation at the National Center for Statistics and Analysis calculates the benefits and costs of a park aid system. The report is part of the Cameron Gulbransen Kids Transportation Safety Act of 2007, which requires NHTSA to enact regulations that will reduce child casualties inside or outside a passenger vehicle (NHTSA, 2010, I-1). In this study, we use the figures from the cost benefit analysis (BCA) to provide a final recommendation for the inclusion of park aid systems in all new vehicles.

There are two types of park aid systems that can be installed: rearview camera or sensory systems. Rearview camera systems are available to provide a video feed of the ground next to the rear bumper of a vehicle. The video feed covers an area of approximately 15 feet, except for the 8 to 12 inch field below the rear bumper (NHTSA, 2010, II-2).

Sensor systems have been available for over 15 years as an aftermarket product, but it was only recently that they were included as standard equipment in vehicles (2010, I-3). Tests conducted by NHTSA show that sensory systems are not very effective. The sensory systems provide inconsistent feedback, meaning the system would detect pedestrians only some of the time. Pedestrian size effected performance, and adults have a better detection rate compared to children between the ages of 1 and 3. However, if sensory systems are improved to detect the presence of children, their overall performance may increase (NHTSA, 2010, II-8).

8.2 Benefit Cost Analysis (BCA)

Several onsite experiments are conducted by NHTSA to evaluate the effectiveness of the camera and sensory systems. In the first series of experiments, NHTSA evaluates each system’s ability to detect a pedestrian and provide warning within a sufficient amount of time. Several camera types (including a 130 and 180 degree) and several sensory systems (including radar and ultrasonic) are used to conduct the preliminary tests.

One test was to place an unexpected obstacle behind the driver and evaluate both the system's performance and the driver's reaction. Results show that participants who made use of the camera feed (more than once) managed to avoid the crash (NHTSA, 2010, II-7). Results also indicate that the camera system was statistically significant in reducing 28 percent of crashes (with unexpected obstacles) compared to a vehicle with no camera system. Even though it was not statistically significant, drivers with both systems installed in their vehicles crashed more frequently (85 percent crashed) compared to those with only the camera system (58 percent crashed).

The true value of a rearview video or sensory system cannot be evaluated without determining driver response and use of each system (NHTSA, 2010, II-5). In order to prevent a collision, the video or sensory system must detect pedestrians and provide warning within a sufficient amount of time. Based on the experiments that were conducted, NHTSA notes that many drivers did not have enough time to react appropriately even if they were operating the vehicle at a slow speed. Furthermore, driver perceptions and expectations had a significant impact on their reaction to the warning. In some cases, even if a warning had been provided, some drivers had continued to back their vehicle. When questioned about their actions, the drivers stated they had searched for the object and failing to notice anything, continued to reverse the vehicle.

In the BCA, a value of $6.1 million was used as the cost per statistical life. The figure includes the lost quality of life, lost productivity, and factors such as medical care, emergency services, and other insurance, workplace, and legal costs (NHTSA, 2010, VII-10).

Table 17. Benefit Cost Analysis for a Park Aid system. Equivalent lives saved, net cost, and cost per equivalent life saved for backover systems at the 3 percent and 7 percent discount rate.

3 Percent Discount Rate				
	Equivalent Lives Saved	Installation Costs (in $M)	Lifetime Costs (incl. property damage only crashes) (in $M)	Net Costs/ EQ Life Saved (in $M)
130 Rearview Mirror	127.4	$2275.3	$1861.3	14.6
130 in Dash Display	127.4	$1919.2	$1501.1	11.8
180 Mirror	150.8	$2673.1	$2296.9	15.2
180 Dash	150.8	$2316.9	$1940.7	12.9
Ultrasonic Sensor	7.6	$685.8	$730.4	95.5
Radar Sensor	8.4	$1228.8	$1302.1	154.5
7 Percent Discount Rate				
	Equivalent Lives Saved	Installation Costs (in $M)	Lifetime Costs (incl. property damage only crashes) (in $M)	Net Costs/ EQ Life Saved (in $M)
130 Rearview Mirror	101.3	$2275.3	$1933.3	19.1
130 in Dash Display	101.3	$1919.2	$1577.2	15.6
180 Mirror	120.0	$2673.1	$2362.4	19.7
180 Dash	120.0	$2316.9	$2006.2	16.7
Ultrasonic Sensor	6.1	$685.8	$722.6	118.8
Radar Sensor	6.7	$1228.8	$1289.4	192.3

Note: Equivalent lives saved, net cost, and cost per equivalent life saved for backover systems at the 3 percent and 7 percent discount rate. Adapted from “Backover crash avoidance technologies” by the National Highway Traffic Safety Administration, 2010, p. VII-8. Adapted with permission.

The above table shows the calculated BCA figures per individual life saved. The calculations show that none of the systems are cost effective. The lowest estimated cost is at $11.8 million from the 130 degree dash display and at a 3 percent discount rate. The highest estimated cost is $192.3 million from the radar sensor and at a 7 percent discount rate. All figures were calculated at a value of $6.1 million per statistical life. However, the figure does not include costs for the emotional well-being of the affected individual as well as family members, friends, and those associated with the victim (NHTSA, 2010, V-16). Since these costs cannot be quantified, NHTSA did not include them in the BCA. If the emotional and psychological costs are included, the final figures will change considerably.

Furthermore, NHTSA believes that the proposed mandate will not have a have significant impact on vehicle manufacturers, including smaller companies (NHTSA, 2010, VIII-2). Even if the mandate will increase manufacturing costs, NHTSA believes that it will not affect have an effect on competition since all vehicle manufacturers must adhere to the standards. Finally, economies of scale and technological developments have allowed companies to manufacture rearview cameras and sensory systems at a reduced cost. In 2005, it cost $326[1] to install a camera system, whereas in 2010, NHTSA estimates that the cost totals between $173 and $203 (NHTSA, 2010, VI-2).

The 2009 NHTS is representative of the United States while the registration data focus only on the State of Maine. Even though two very dissimilar datasets are used for this study, they produce very similar results. Regressions from both datasets show that park aid systems are more likely to be included in higher end luxury vehicles. This includes family vehicles such as minivans, cars, and SUVs. Park aid systems are more likely to be found in larger vehicles, and vehicles which obtain better miles per gallon. Finally, these vehicles tend to be purchased by older and more affluent customers, depicted by the variable, AGE, which shows up as positive and significant in all four regressions.

Vehicles with park aid systems tend to be priced higher and are purchased by more affluent consumers. Data from the website www.cars.com show that a park aid system ranged

[1] Preliminary Regulatory Evaluation, FMVSS No.111, NPRM to Require a Rear Detection System for Single-Unit Trucks, August 2005, (Docket No. 19239-2).

from $250 to $2055. If a park aid is offered as an optional feature, the price is set so that a few, select customers will make the purchase. This may be a form of price discrimination since the costs exceeds the aftermarket cost of a similar system.

The results from the regressions and the diffusion models show a clear upward trend for park aid systems, meaning that more vehicles with this system will be available for purchase in the future. Based on the upward trends and the impending government mandate, we believe that the number of vehicles with park aid systems will increase.

However, we feel that these results should be accepted with caution. First, limitations within the dataset prevent us from drawing a clear conclusion. We use two methods, econometric analysis and adoption analysis, to determine the future diffusion of park aid systems. When econometric analysis is used, there is the chance that relevant variables will be left out of the model specification. This includes factors such as uncertainty, sunk costs, network effects, and complimentary products that are available in the market. While we have quantitative data readily available for the analyses, we did not have qualitative data regarding consumers and their decision to purchase a park aid system. Second, a very limited number of studies have been done on park aid systems. Even though the technology has been around for some time, park aid systems are a fairly untouched area of research.

Based on past observations, we believe that the number of vehicles with park aid systems will increase, even if a government regulation is not in place. For instance, a study published by NHTSA in 2006 estimates that the availability of electronic stability control (ESC) will reduce all single vehicle fatalities by 1,536 – 2,211 and injuries by 50,594 – 69,630 (NHTSA, 2006). Following this study, automakers began to offer the feature in most vehicles, and by the year 2010, ESC was offered in at least 85 percent of all vehicles manufactured in that year (Cars.com, 2012). By model year 2012, the Federal Motor Vehicle Safety Standards passed a standard which requires ESC in all new passenger vehicles.

The BCA shows that the systems are not cost effective, but these figures are conservative, and the benefits have been underestimated. This study concludes by stating that a park aid system is a valuable feature in any vehicle. It is a useful preventative safety measure.

CHAPTER 9

LIMITATIONS

An ideal data set would include consumers who chose the optional package solely based a desire for the park aid technology. However, through this data set, we can only estimate the characteristics of a consumer who purchased a car with a park aid system.

The decision to purchase a vehicle may be based on a number of factors. This includes the reputations of the brand, price, mileage, and safety ratings. If a park aid system is not offered, a consumer can still purchase the vehicle and install an aftermarket option. While an aftermarket option will need to be manually installed, it is often cheaper, and the consumer can choose from a range of similar items. Even if a rearview system is offered as optional, the consumer may still choose the aftermarket option simply because it is cheaper. Park aid systems are an example of third degree price discrimination. By offering the optional package at an over-priced option, dealers are able to differentiate between consumers who are willing to pay that amount versus consumers who will opt for the cheaper, after-market option. For instance, in the data collected from www.cars.com, the optional packages which included a rearview system ranged from $250 to $2055.

Finally, it may be difficult to forecast the diffusion of a park aid systems with the use of an economic model. Train (1986) believes that it will be difficult to create a model which includes the forecast for all vehicle makes and models. The sheer number of vehicle makes and models and the different features that are offered in each model will complicate any needed computations.

In addition to the large selection of different vehicle makes and models, there are a number of other factors which may affect the model. First, the model will need to include other external influences, making the prediction subject to significant uncertainty. Additionally, the model will need to incorporate changing consumer demands and preferences.

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APPENDIX. Summary Statistics for Each Independent Variable

Table 18. Summary statistics from Maine data with time variables.

Variable	Minimum	Maximum	Mean	Std. Deviation
REAR	0	1	0.09	0.291
HWYMPG	15	48	28.34	6.812
CMBMPG	2	50	23.77	6.881
WheelBase	74	186	113.72	14.948
PERMONREAR	4.31	14.34	7.89	3.13
AGE	17	112	53.46	15.503
MEDINCOME1000	0	92	43.67	10.974

Table 19. Summary statistics from Maine data without time variables.

Variable	Minimu	Maximum	Mean	Std. Deviation
REAR	0	1	0.09	0.28
CITYMPG	13	53	21.34	6.721
HWYMPG	15	48	28.34	6.812
CMBMPG	2	50	23.77	6.881
WheelBase	74	186	113.41	14.81
MSRP	7710	333930	24808.73	7333.412
AGE	17	112	53.45	15.492
MEANINCOME1000	19	283	64.91	19.438
RETAILPRICE1000	1	334	24.92	7.336

Table 20. Summary statistics from 2009 NHTS.

Variable	Minimum	Maximum	Mean	Std. Deviation
Width	0	89	72.695	4.2304
Height	49	81.2	63.25	6.7397
CC	999	6599	2874.98	927.381
CITYMPG	12	60	22.12	7.276
Retail	9995	230705	22256.92	11445.08
AGE	18	92	55.57	14.308

Table 21. Summary statistics from 2009 NHTS without time variables.

Variable	Minimum	Maximum	Mean	Std. Deviation
Width	0	89	72.695	4.2304
Height	49	81.2	63.25	6.7397
CC	999	6599	2874.98	927.381
CITYMPG	12	60	22.12	7.276
AGE	18	92	55.57	14.308

BIOGRAPHY OF THE AUTHOR

Nadeesha Thewarapperuma was born in Peradeniya, Sri Lanka. She earned her secondary education at Gateway International School, Kandy, Sri Lanka. In 2011, she graduated cum laude from the University of Wisconsin Oshkosh with a B.S. in Economics and Environmental Studies. In August 2011, Nadeesha began studying at the University of Maine's Resource Economics and Policy program. After receiving her degree, she plans on pursuing a PhD in Economics at the University of New Hampshire. Nadeesha is a candidate for the Master of Science degree in Resource Economics and Policy from The University of Maine in August 2013.