Steffens, P. R. and Balasubramanian, S. (1998), “A Study of the Time Varying Mean Replacement Age of Consumer Durables”, *Marketing Science Conference*, 10-13 July, 1998, Fontainbleau, France.

Title: An Aggregate Sales Model for Consumer Durables Incorporating a Time Varying Mean Replacement Age

Author: Dr Paul R Steffens

Lecturer

Graduate School of Management

The University of Queensland

Brisbane QLD 4072

AUSTRALIA

Phone: + 61 7 3365 6610

FAX: + 61 7 3365 6988

Key Words: Diffusion; Forecasting; Sales Models.

Word Count: 4402 (Main Body)

Author's Biographical Note.

Dr Paul Steffens is a lecturer in marketing at the Graduate School of Management, University of Queensland, Australia. His research interests are sales modelling and new product development.

An Aggregate Sales Model for Consumer Durables Incorporating a Time Varying Mean Replacement Age

Abstract

Forecasting category or industry sales is a vital component of a company's planning and control activities. Sales for most mature durable product categories are dominated by replacement purchases. Previous sales models which explicitly incorporate a component of sales due to replacement assume there is an age distribution for replacements of existing units which remains constant over time. However, there is evidence that changes in factors such as product reliability/durability, price, repair costs, scrapping values, styling and economic conditions will result in changes in the mean replacement age of units. This paper develops a model for such time varying replacement behaviour and empirically tests it in the Australian automotive industry. Both longitudinal census data and the empirical analysis of the replacement sales model confirm that there has been a substantial increase in the average aggregate replacement age for motor vehicles over the past twenty years. Further, much of this variation could be explained by real price increases and a linear temporal trend. Consequently, the time varying model significantly outperformed previous models both in terms of fitting and forecasting the sales data.

Sales of durable goods can be disaggregated into sales due to first purchases, replacements of existing units and purchases of multiple (additional) units. In most mature product categories sales are dominated by replacement purchases meaning that variations in replacement purchase patterns primarily govern sales trends. To models of the replacement component of sales have been under researched within the diffusion paradigm. Existing models assume that the replacement distribution does not vary over time. This paper develops a model which incorporates a time varying replacement distribution.

Two relevant streams of modelling literature can be identified. First, diffusion models largely from the marketing literature have incorporated aggregate replacement of durables when the original unit is taken out of service. Alternatively, economic models of scrapping behaviour consider the almost identical issue of scrapping of durables from an economic perspective. However, neither stream properly addresses the issue of aggregate replacement (or scrapping) substantively changing over time.

Diffusion models were popularised in the marketing literature with the seminal article by Bass (1969). Many variations and extensions have been proposed such as different functional forms (see review by Mahajan and Peterson, 1985), incorporating marketing mix variables (see review by Kalish and Sen, 1986), non-uniform influence (Easingwood et. al., 1983) and multistage diffusion (e.g. Midgley, 1976). From the perspective of durable products, these models are useful for describing first purchase sales. It can be noted that the non-uniform influence model and many of the models incorporating marketing mix variables, essentially result in an adaptation of the Bass model in which the original parameters vary over time. It is such an extension of the replacement models (discussed below) that this paper considers.

Due to their aggregate nature, the traditional and primary use of diffusion models is sales forecasting. While the models might also be used for descriptive or normative purposes (Mahajan, Muller and Bass, 1990), these applications are far less common. In any event, normative applications require forecasting accuracy as a pre-requisite condition. Unfortunately, forecasting applications of traditional first purchase diffusion models have met with only limited success (Mahajan et. al., 1990).

More recently, aggregate sales modelling has paid some attention to incorporating repeat purchases thereby increasing the time period for which the models are applicable. This essentially allows the models to be adequately estimated using early sales data, and subsequently forecast a reasonable period of the product's life. Most of the earlier efforts in this regard are directed towards models appropriate for frequently purchased products where repeat purchase sales at any time are approximately proportional to the number of consumers currently using the product. Contributions include Dodson and Muller (1978), Lilien et. al. (1981) and Mahajan et. al (1983). Others have studied replacements of durable products using a distribution of replacement ages approach. A number of different specifications of the replacement distribution have been suggested. Midgley (1981) uses an unspecified distribution, Lawrence and Lawton (1981) employ a constant age approach, Olson and Choi (1985) the Rayleigh distribution, Kamakura and Balasubramanian (1987) the truncated normal distribution and, finally, Bayus et. al. (1989) uses the Weibull distribution.

It is evident that much attention has focused on identifying the most appropriate distribution to represent the replacement component of sales. However, a far more important issue from a sales forecasting perspective, is whether this distribution changes over time. In particular, significant changes in the mean replacement age over time will have a pronounced impact on sales. All modelling efforts to date have assumed that this distribution remains constant over time. While some studies have investigated factors which might influence such variations (e.g. Bayus, 1988, Raymond et. al., 1993), these have not yet been included in aggregate sales models.

A stream of economic literature examines the closely related issue of aggregate scrappage, particularly that of motor vehicles. The economic literature has largely confined its attention to the logistic model of aggregate age distribution of scrappage (Walker 1968, Green and Chen, 1981) or empirically determined distributions (De Pelsmacker, 1990; Jorgensen and Wentzel-Larsen, 1990). While both Walker and De Pelsmacker assume aggregate scrappage might vary over time as a function of fluctuating economic factors, the models assume the scrappage distribution does not vary over time.

In summary, aggregate sales models have not incorporated temporal variations in the aggregate replacement distribution or the factors which might influence such variations. Such changes are of significant managerial importance for two reasons. First, temporal variations of the replacement distribution will naturally impact on medium to long term sales forecasts. Second, understanding the causes of these variations will give managers improved control over sales and profits. This paper first examines the literature which examines replacement timing for consumer durable products. An aggregate sales model incorporating a varying mean replacement age is then developed and empirically tested in the Australian automotive industry. The first purchase component of sales is not considered since the current model makes no contribution in this area. The paper concludes with a discussion of managerial implications and future directions.

Time Varying Replacement of Durable Products

Empirical Studies

The available evidence is mixed on the question of whether the mean replacement age for consumer durables changes significantly over time. Table 1 summarises the results of three similar studies. This shows that for most household products studied, the service life has remained largely unchanged over the 16-year period from 1957 to 1973. However, a number of studies seemingly contradict this finding. A study sponsored by MIT (1976) reveals that the technology for home appliances has advanced over time and product reliability has increased. Anecdotal evidence and increases in warranty periods for a wide range of products indicates that this trend has continued. While this ignores the attractiveness of repairing failed units, it tends to indicate that the average product age when a replacement is forced is increasing for the majority of durable products. Similarly, Greene and Chen (1981) show that the average scrapping age for both domestic and imported passenger cars and light trucks increased significantly between the time periods 1966-72 and 1973-77.

Finally, as discussed below, a number of other studies have identified both causal factors and individual (or household) characteristics which contribute to variations in replacement timing at an individual (or household) level. If these causal factors or the aggregate characteristics of the population change over time, it will result in a change in aggregate.

Durable Product Replacements

The distinction developed by Bayus (1988) between forced replacements (replacement of a failed unit) and unforced replacements (discretionary replacements of a working unit) provides a useful starting point for the discussion of durable product replacements. The drivers of each type of replacement are likely to be considerably different. A further important distinction is between replacement and scrapping. Some unforced replacements may result in a second hand transaction. In this case, the timing of the replacement of the unit by the original purchaser and the ultimate scrapping of the unit are clearly different. It is also noted that on occasion, a unit might be scrapped and not replaced. In this paper, the focus is aggregate sales forecasts. Hence, the complications of the second hand market are avoided by considering only aggregate replacements (replacements of vehicles retired from service) rather than individual replacements (replacements of a vehicles no longer used by the incumbent owner).

Numerous articles have posited that unforced replacements can be influenced by several factors such as price, advertising, promotion, residential moves, product features, product styling and colours and newer technologies (see Bayus 1988, 1991). Since many of these factors change over time it is reasonable to assume that aggregate replacement also varies. However, this has not been examined empirically. Nevertheless, a number of empirical cross sectional studies have investigated closely related issues such as variations in the timing of replacements across brands or product type and the impact of individual characteristics on individual replacement timing. These studies are discussed below.

Hoffer and Reilly (1984) examine the relationship between automobile sales growth and styling changes. They find that styling changes are significant in explaining variations in sales growth between various categories of cars. Though they do not explicitly examine forced replacements, rate of styling change is unlikely to have a strong influence on either forced replacements or first time buyers. Hence, the reported relationship is likely to be due to unforced replacements. Bayus (1988) explicitly measures forced and unforced replacement ages for colour televisions. Using a survey methodology, he establishes that the mean replacement age for unforced replacements to be less than that of forced replacements. He further shows that variations of the mean replacement age for different brands is influenced by the price and advertising level of the brand. While the above studies indicate variations in the mean replacement age at a brand (or product type), the aggregate nature of this relationship is unresolved. That is, it is unclear whether the mean replacement age for all units in the product category vary as the aggregate price, advertising, styling change (etc.) varies, or whether these factors primarily influence brand choice (and hence market shares) for consumers replacing working units.

Studies by Bayus (1991) and Raymond et. al. (1993) investigate cross sectional variations in the timing of household durable product replacements. Bayus uses a survey methodology to demonstrate differences between early and late replacers of automobiles in terms of income, education, occupation and response to styling, image and costs. Using survey data and a hazard function approach, Raymond et. al. demonstrate that individual household replacement of space heaters is influenced by factors such as age of household head, energy usage and natural gas availability. Hence, the results of the above studies indicate that the replacement timing decision for a product category of individual households is influenced by household characteristics, which in turn vary over time. However, their study does not explicitly look at aggregate (the entire population) changes over time.

A key driver of replacement sales of durable products is clearly the scrappage decision. Since many durable products represent significant expenditure, a considerable amount of work has examined the scrappage decision from an economic perspective. Walker (1968), in the context of automobiles, confirmed that aggregate scrappage rates are influenced by the rate of turnover of automobile ownership and the ratio of used car prices to the costs of car repairs. This notion is extended by Parks (1977) who develops a theoretical model of scrappage based on used car prices, repair costs, scrap values and probability of failure. Parks, Manski and Goldin (1983) and Berkovec (1985) all provide some indirect empirical support for this model by cross sectional analysis of the scrappage rates of different models of car. Of course, the used car prices are in turn determined in a complex way by the interaction of the new and used car market and other economic influences. However, the nature of these interactions is well beyond the scope of this paper.

Aggregate Replacement Models

Diffusion models of adoption are most commonly extended to include replacement purchases for durable products by modelling replacement times as a standard distribution function. Olson and Choi (1985) use the Rayleigh distribution, Kamakura and Balasubramanian (1987) introduce the truncated normal distribution and Bayus et. al. (1989) use the Weibull distribution. The discrete, deterministic form of this approach may be written as:

$$R_t = \sum_{i=1}^{t-1} S_i \left[F(t-i) - F(t-i-1) \right] \qquad (1)$$

where,

S_t = Total sales in year t

R_t = Replacement sales in year t

$F(t)$ = Cumulative replacement distribution.

Bayus (1988) compare the Rayleigh, truncated normal and Weibull distributions against empirical actuarial data for major household products. He demonstrates that the truncated normal and Weibull distributions fitted the data slightly better than the Rayleigh distribution.

The approaches above assume that the replacement of products remains static over time. Two efforts to extend this approach to dynamic models of aggregate replacement behaviour have appeared in the literature. Walker (1968) proposed an econometric model of automobile scrappage. While he assumes the replacement (or scrappage) distribution to be constant over time, he develops an econometric formulation which accounts for the annual variation around this trend. Using the logistic function as the scrappage distribution, he proposes the following model:

$$R_t = \alpha \bar{R}_t Z_t^{\varsigma} P_t^{\eta} \text{ ,and,}$$

$$\bar{R}_t = \sum_{i=1}^{t-1} S_i \left[G(t-i;a,b,k) - G(t-i-1;a,b,k) \right]$$

$$G(t;a,b,k) = \frac{1}{a + b\,e^{kt}} \tag{2}$$

where,

Z_t = rate of turnover of car ownership, approximated by the ratio of new car registrations to total car registrations in year t.

P_t = index of used car prices divided by index of car maintenance and repair prices in year t.

Walker found that the model explained 64% of the annual variation from the trend which assumed a constant replacement distribution. More generally, this econometric approach is useful for describing annual fluctuations about a trend, but is not appropriate if there is a sustained shift in the replacement distribution. This is true because the model is structurally inaccurate such that the remaining stock of cars will, over time, become increasingly inaccurate if there is a persistent trend in the replacement distribution.

Similarly, Bayus et. al. (1989) use a constant scrappage distribution with an econometric formulation to model variations in replacement sales for colour televisions. Their focus, however, is to explain variations between the number of units scrapped and those which are replaced. Using a linear difference formulation, they model replacements as a function of scrappage and real disposable income. Again, while useful for its intended purpose and suitable for annual fluctuations, the model is unable to adequately capture a trend in the replacement or scrappage distribution.

Model Development

A model of aggregate replacements is developed within the diffusion paradigm. Aggregate replacements are defined as sales to replace units retired from use within the entire population (rather than an individual household). A more formal definition is offered below. The use of aggregate replacements rather than household replacements is motivated by a focus on aggregate sales and the recognition that for many durable products there is a substantial second hand market. In this instance, an individual who replaces a functioning unit with a new unit and sells the old unit may cannibalise another potential sale, resulting in no net additional sale for the market. Traditional aggregate sales models incorporating durable product replacements at an individual of household level implicitly assume that a second hand market does not exist.

The model is developed in which the aggregate replacement distribution varies over time. More specifically, the mean aggregate replacement age is modelled to change over time. Total sales over a given period, S_t, are divided into two components. The first component is equal to the increase (if any) in number of units in service within the entire population. We term this component aggregate new purchases, N_t, as it equals the net number of new purchase sales. A second component termed aggregate replacement sales, R_t, is equal to all scrapped units over the given period. Note that since we are considering the population as a whole and not individual behaviour, this is a definition rather than an assumption that all scrapped units are replaced.

Thus, by definition,

$$S_t = N_t + R_t \tag{3}$$

Let $F(a,t)$ be the cumulative aggregate replacement distribution function at time t. That is, at time t, $F(a,t)$ represents the unconditional probability that a unit of age, a ,would have been taken out of service by this age. More specifically, following the comparison of distributions by Kamakura and Balasubramanian (1987) and Bayus (1988), we choose the truncated normal distribution as the functional form of the distribution. At any given time, $F(a,t)$ is assumed to follow the Truncated normal distribution with mean replacement age, L ,and shape parameter, h. However, we assume that the mean replacement age, L, may vary over time such that:

$$F(a,t) = \frac{\Phi(wa / L(t) - h)}{\Phi(-h)} \tag{4}$$

where,

$$w = h + \phi(-h) / \Phi(-h),$$

$\phi(\cdot)$ denotes the standard normal pdf, and $\Phi(x) = \int_{z=x}^{\infty} \phi(z)dz$. We note that $F(a,x+a)$ must be monotonically increasing in a. This requires that $L(t)$ must not increase too quickly. This condition is analysed in Appendix A.

Further, by treating the cumulative probability as a proportion of the aggregate population (see Kamakura and Balasubramanian, 1987), the replacement purchases may be determined by:

$$R_t = \sum_{i=1}^{t-1} S_i \left[F(t-i,t) - F(t-i-1,t-1)\right] \tag{5}$$

Variations in replacement behaviour over time is now represented by the time varying nature of $L(t)$. In turn, it is proposed that $L(t)$ will be influenced by a number of factors identified in previous research related to aggregate replacement (or scrappage), such as used product prices, scrappage values, repair costs, advertising, styling and feature changes and product reliability. However, given the lack of previous research into these relationships, no general mathematical specification is proposed.

Empirical Application

The model is tested within the context of the Australian passenger vehicle market. First, trends in the mean replacement age are directly investigated. Census data is available at 8 time periods between 1971 and 1993 that allow a replacement distribution to be empirically determined. Second, the sales model that incorporates a mean replacement age is empirically tested.

Replacement Trends

A number of data sources are utilised, though all are compiled by the Australian Bureau of Statistics (ABS). The first task is to establish whether or not the mean aggregate replacement age $L(t)$ is in fact changing over time. Two data sources are utilised for this purpose. The first is monthly registrations of new passenger vehicles as a representation of total new sales (annual data only 1930-1960). The second is 8 censuses of motor vehicles on register conducted by the ABS between 1971 and 1993. Part of the data collected by the censuses is the year of manufacture of each vehicle. For each census year, a service life distribution can then be established via actuarial tables (Ruffin and Tippett, 1975). However, a number of small adjustments to the data are necessary. First, since year of manufacture and year of registration do not necessarily coincide, an adjustment is made to the registration data. On the advice of industry sources, a shift of three months (considered about average) is used. The other adjustments are necessary due to vehicle classification changes made by the ABS in terms of the data collected over this period. First, in 1982 Commonwealth Government vehicles are included for the first time. Later in 1991, VIN numbers are used by the ABS for the first time for better vehicle type identification. Data prior to these changes are simply scaled by the amount that these changes affected registration figures of new passenger vehicles at the time of their introduction. Finally, for vehicles more than approximately five year old, the census data is presented in terms of groupings of years of manufacture. In these cases, the mean age of the grouping is used.

Empirical data for the replacement distribution is available for the 8 motor vehicle census years. Table 2 shows the results of fitting the truncated normal distribution to the aggregate replacement distribution data. Clearly the fits are very good, and there is a distinct upward trend in terms of mean aggregate replacement age. Note, however, there is no trend evident in terms of the shape parameter, nor any apparent relationship with the mean aggregate replacement age. There is no theoretical or empirical evidence to suggest it will vary, and previous experience shows it falls within a small range (Kamakura and Balasubramanian, 1987). Since it is not possible to reliably estimate both L and h from sales data alone, in the time varying model the parameter h, is constrained to be constant over time. To test the impact of this constraint, the truncated normal distribution is fitted to the same data with the shape parameter constrained to equal the mean value for the unconstrained fits ($h = 2.48$). The results are also displayed in Table 2. Clearly, the R squared results are still very satisfactory under this constraint.

Model Test

Having established that the mean aggregate replacement age, $L(t)$, is changing over time, we now investigate its impact on sales trends and model some of the factors which might influence this behaviour. Clearly, since the census data is available in only 8 time periods, this is not sufficient to systematically examine such influences. Hence, rather than directly estimating the replacement distributions from the census data, the entire model of replacement sales is estimated using sales data. Previous research has jointly estimated the first purchase diffusion model and replacement model using total sales data (Olson and Choi , 1985 and Kamakura and Balasubramanian, 1987). Since data for the aggregate replacement component are available in this application, it is possible to estimate the replacement model independently. Results of fitting standard diffusion models to the aggregate first purchase component of sales are not reported as no contribution to the existing literature is made.

A number of factors are expected to influence the aggregate replacement trends. Data for new car prices (price index) are again available from the ABS. Unfortunately, data for some of the other factors suggested by previous research, such as styling changes, advertising, used car prices and scrapping values are unavailable over the time periods concerned (1970 - 1986). Time is used as a proxy for a number of possible factors, such as reliability improvements, rate of styling changes and advertising expenditures, which anecdotally have been increasing over this time period.

The model is fitted to annual aggregate replacement sales from 1970 to 1986. The data is truncated to 1986, as in 1987, the Australian Federal Government introduced a Fringe Benefit Tax which applied to company owned vehicles utilized for private purposes. This had a dramatic impact on both car ownership and replacement for a number of years, causing a discontinuity in the data series. It is beyond the scope of this paper to model the impact of this tax.

One further source of data is utilised to test the model, namely, annual number of registered passenger vehicles in Australia. Differencing this time series gives the annual increase in vehicles, N_t. The annual number of replacement vehicles, R_t, can then calculated from Equation (3) since we already have S_t. In the year 1982 the above data could not be differenced to give N_t due to the changes in the ABS vehicle classification systems mentioned above.

The functional form chosen for the variation of L_t for this application is:

$$L_t = \alpha + \beta (t - 1971) + \gamma (P_t - P_{1971}) + \delta (P_{t-1} - P_{1971}) \tag{6}$$

where, P_t is the new car price index in year t, and α, β, γ and δ are all parameters of the model. A linear form of the model is chosen since previous research has shown these variables have a multiplicative impact on aggregate replacement. Since L_t itself has a mutiplicitative type impact on aggregate replacement, a linear relationship is then chosen for Equation (6). Nonlinear regression is used to fit the model, Equations (5) and (6), to the annual aggregate replacement data (1970 to 1986).

It is recognised that used car prices , rather than new car prices, would be a more appropriate variable. Unfortunately, no source of used car prices over the period of analysis could be identified. However, current and lagged new car prices are used as a proxy variable. A possible lagged relationship exists as a result of the complex interaction of the new car market which “feeds” the used car market.

To compare the model with existing stationary replacement models, the Kamakura and Balasubramanian, 1987 (K&B) model is also estimated:

$$L_t = \alpha \tag{7}$$

Finally, to compare with the econometric models given the available data, the following model is estimated.

$$R_t = \overline{R}t \ (t / 1971)^{\beta} \ (P_t / P_{1971})^{\gamma} \ (P_{t-1} / P_{1971})^{\delta} \tag{8}$$

Fitting results for the dynamic model (6), the econometric model (8) and the stationary K&B model (7) are given in Table 3 (note that standard errors are given in parenthesis). The estimated replacement sales are plotted against the data in Figure 1. It is noted that all 3 parameters of the logistic distribution used with the econometric model, could not be stably estimated by this one stage fitting method (as with the 2 parameters of the truncated normal distribution for the K&B or new dynamic model). Hence, the parameters b and k were held constant at values of 500 and 0.5 respectively, and only the parameter a estimated. These values were determined by fitting the logistic curve to the 8 empirical service life distributions from the censuses described above. It is clear that while the K&B model is inadequate in terms of explaining the replacement sales, both the econometric and dynamic model provide an excellent fit to the replacement data.

Finally, the forecasting ability of the models are compared. Both short term and medium term forecasting are investigated. First, the models are fitted to data up to each year from 1979 to 1985. To test short term forecasting, the estimated models are then used to forecast replacement sales in the following year. The mean of the absolute errors, squared errors and absolute percentage errors of these forecasts are listed in Table 4 as One Step Ahead Forecasts. To test the medium term forecasting ability of the models, where possible 5 or more year ahead forecasts are calculated. For all these forecasts, it is assumed that the actual price data is known. The arithmetic mean of the absolute errors, squared errors and absolute percentage relative errors of these forecast are again listed in Table 4.

Examination of Table 4 reveals that the dynamic model outperforms the K&B replacement model by almost an order of magnitude in terms of both short and medium term forecasting. Comparing the new dynamic model with the econometric model we find that while the dynamic model performs only marginally better at short term forecasting, it performs markedly better in terms of medium term forecasting.

These results are as expected, given the upward trend in mean aggregate replacement age empirically verified in the earlier part of this analysis. The dynamic model proposed is structurally designed to accommodate such trends, and in this application is able to both fit and forecast such a trend accurately. The econometric models are designed to model variations in aggregate replacement around a “mean aggregate replacement distribution”. Hence, they are able to fit a consistent trend in mean replacement age quite well since this is, in fact, just a variation around the mid value (albeit a consistent rather than fluctuating variation). However, these models are unable to adequately forecast such a trend since they do not structurally incorporate these trends by properly accounting for the resultant variations in remaining stock. Hence, when attempting to forecast an upward trend in mean aggregate replacement age, they underestimate the “mean aggregate replacement distribution” over the extended forecast period.

Summary & Discussion

Existing models of replacement and /or scrappage for durable products are extended to include a time varying aggregate replacement distribution. The new model is consistent with previous research which suggests that replacement behaviour is affected by a number of influences (such as prices, repair costs, reliability, styling changes etc.) which themselves vary over time.

Longitudinal census data for the car industry in Australia confirmed that there has been a substantial change in replacement behaviour (rising average aggregate replacement age) over the past twenty years. A model for the car industry is developed in which this time varying replacement distribution is related to price variations and a linear trend over time. When fitted to aggregate replacement sales data, this model significantly outperformed previous models, particularly in terms of its ability to forecast replacement sales. The model demonstrated that there has been a significant increase in average aggregate replacement age of motor vehicles in Australia over the last 20 years. This trend has considerably depressed motor vehicle sales. The model further demonstrated that average new car prices have a significant, though lagged, impact on replacement behaviour.

The model developed therefore has several important managerial implications. First, the model demonstrates the potential to offer significant improvements in medium- to long-term forecasts of industry or product category level sales. Such forecasts are essential for a company to be able to plan and control its operations, including production, promotion and product planning. This is particularly true for durable products, where significant investments in product specific production equipment and supply networks are required. Specifically, for the application discussed, a continuing trend of rising aggregate replacement age can be expected to depress automobile sales in the short to medium term. In the longer term, however, the extent to which the ultimate durability of motor vehicles might constrain this increase in aggregate replacement age is a topic warranting further investigation.

Price was found to be a significant explanatory variable of this increase in aggregate replacement age. As such, also allows companies some ability to control aggregate replacement sales and profits. Though it is acknowledged that no one firm controls the industry price, knowledge of the price demand relationship will enable more informed formulation of pricing policies.

The application highlights some important policy issues for the Australian government. The increasing aggregate replacement age is problematic for two reasons. First, older vehicles generally pose a larger safety risk. Perhaps more importantly, emissions from older vehicles are more environmentally damaging, especially from vehicles which use leaded petrol. In fact, the Australian government already provides an economic disincentive to use leaded petrol through a wholesale tax. An increasing aggregate replacement age will clearly slow the transition to lead free vehicles. A more direct measure would be a positive incentive for scrapping leaded petrol vehicles.

While the results presented are very encouraging, they are also preliminary in nature. Many avenues for further research in this area remain. The impact of many of the variables for which data is not currently available, such as rate of styling changes, advertising, reliability and durability, remains an open question. Anecdotally, these factors have increased over the past twenty years which is consistent with the observed linear trend. Additionally, the utility of the model in other durable goods industries has not yet been investigated.

References

Australian Bureau of Statistics, "Motor Vehicle Census: Australia," Catalogue No. 9309.0, Various Years.

Australian Bureau of Statistics, "Motor Vehicle Registrations: Australia," Catalogue No. 9303.0, Various Years.

Bass, F. M., “A new product growth model for consumer durables,” Management Science, **15** (1969), 215-227.

Bayus, B. L., “Accelerating the Durable Replacement Cycle with Marketing Mix Variables,” Journal of Product Innovative Management, **5** (1988), 216-226.

Bayus, B. L., "The Consumer Durable Replacement Buyer," Journal of Marketing, **55:1** (1991), 42-51.

Bayus, B. L., Hong, S. and Labe, R. P. Jr., “Developing and Using Forecasting Models of Consumer Durables,” Journal of Product Innovative Management, **6** (1989), 5-19.

Berkovec, J., “New Car Sales and Used Car Stocks: A Model of the Automobile Market,” Rand Journal of Economics, **16** (1985), 195-214.

De Pelsmacker, P., “A Structural model of the Demand for New cars in Belgium,” Applied Economics, **22** (1990), 669-686.

Dodson, J. A., and Muller, E. (1978), “Models of New Product Diffusion Through Advertising and Word-of-Mouth,” Management Science, **24** (1978), 1568-1578.

Easingwood, C. J., Mahajan, V. and Muller, E., "A Nonuniform Influence Innovation Model of New Product Acceptance," Marketing Science, **2** (1983), 273-295.

Greene, D.L. and Chen, C.K.E., “Scrappage and Survival Rates of Passenger Cars and Light Trucks in The U.S., 1966-77”, Transportation Research, **15A:5** (1981), 383-389.

Hoffer, G. and Reilly, R., “Automobile styling as a shift variable: An investigation by firm and by industry,” Applied Economics, **16** (1984), 291-297.

Jorgensen, F. and Wentzel-Larsen, T., “Forecasting Car Holding, Scrappage and New Car Purchase in Norway,” Journal of Transport Economics and Policy, **24** (1990); 139-156.

Kalish, S. and Sen, S. K., “Diffusion Models and the Marketing Mix for Single Products”, in Innovation Diffusion Models of New Product Acceptance, V. Mahajan and Y. Wind (eds), Cambridge, MA: Ballinger Publishing Co, 1986.

Kamakura, W. and Balasubramanian, S., “Long term forecasting with innovation diffusion models: the impact of replacement purchases,” Journal of Forecasting, **6** (1987),1-19.

Lawrence, K. D. and Lawton, W. H., “Applications of Diffusion Models: Some Empirical Results”, in New Product Forecasting, Y. Wind, V. Mahajan and R.C. Cardozo (eds), Lexington, MA: Lexington Books, 1981.

Lilien, G. L., Rao, A.G. and Kalish, S., “Bayesian Estimation and Control of Detailing Effort in a Repeat Purchase Diffusion Environment,” Management Science, **27** (1981), 493-506.

Lund, R., “Making Products Live Longer,” Technology Review, **79** (1977), 49-55.

Mahajan, V., Muller, E. and Bass, F. M., “New Product Diffusion Models in Marketing: A Review and Directions for Research,” Journal of Marketing, **54**(1990), 1-26.

Mahajan, V. and Peterson, R. A., Models for Innovation Diffusion. Beverly Hills, CA: Sage, 1985.

Mahajan, V., Wind, Y. and Sharma, S., “An approach to Repeat Purchase Diffusion Models,” Proceedings of the American Marketing Educators Conference, Chicago: American Marketing Association, 1983, 442-446.

Manski, C.F. and Goldin, E., “An Econometric Analysis of Automobile Scrappage,” Transportation Science, **17:4** (1983), 365-375.

Massachusetts Institute of Technology, “Consumer Appliances: The real cost,” A report issued by the Center for Policy Alternatives, 1976.

Midgley, D., “A Simple Mathematical Theory of Innovative Behaviour,” Journal of Consumer Research, **3** (1976), 31-41.

Midgley, D., “Toward a Theory of the Product Life Cycle: Explaining Diversity," Journal of Marketing, **45** (1981), 109-115.

Olson, J. and Choi, S., “A product diffusion model incorporating repeat purchases,” Technological Forecasting and Social Change, **27** (1985), 385-397.

Parks, R.W. (1977), “Determinants of Scrapping Rates for Postwar Vintage Automobiles,” Econometrica, 45(5), 1099-1115.

Pennock, J. and Jaeger, C., “Household service life of durable goods,” Journal of Home Economics, **56** (1964), 21-26.

Ruffin, M. and Tippett, K., “Service-life expectancy of household appliances: New estimates from the USDA,” Home Economics Research Journal, **3** (1975), 159-170

Raymond, J. E., Beard, R. T. and Gropper, D. M., "Modelling the consumer's decision to replace durable goods: a hazard function approach," Applied Economics **25:10** (1993), 1287-1292.

Walker, F.V., “Determinants of Auto Scrappage,” Review of Economic Statistics, **50** (1968), 503-506.

Table 1: Mean Replacement Ages of Durables

Appliance	Dept. of Agric. 1957-1961[a]	Mfrs. 1970[b]	Dept. of Agric. 1973[c]
Room Air Conditioner	-	12	-
Electric Range	16	16	12
Gas Range	-	16	113
Freezer	15	18	20
Refrigerator	16	15	15
Dishwasher	-	10	11
Clothes Washer	10-11	10	11
Electric Clothes Dryer	14	12	14
Gas Clothes Dryer	-	12	13
B&W TV	11	-	11
Colour TV	-	-	12

[a] *Source*: Pennock and Jaeger (1964).
[b] *Source*: Lund (1977).
[C] *Source*: Ruffin and Tippett (1975).

Table 2: Fitting Results for Aggregate Replacement Age Distribution
Australian Passenger Vehicles

	Shape Parameter Unconstrained			Shape Parameter Constrained (h = 2.48)	
Census Year	Mean Aggregate Replacement Age (L)	Shape Parameter (h)	R Squared	Mean Aggregate Replacement Age (L)	R Squared
1971	12.3	2.25	0.999	12.2	0.997
1976	13.0	2.85	0.996	13.2	0.992
1979	13.5	3.03	0.995	13.9	0.986
1982	14.2	2.98	0.988	14.6	0.970
1985	14.7	3.09	0.988	15.3	0.978
1988	16.2	2.55	0.996	16.2	0.996
1991	16.7	2.60	0.993	16.7	0.993
1993	17.4	3.24	0.996	17.6	0.992

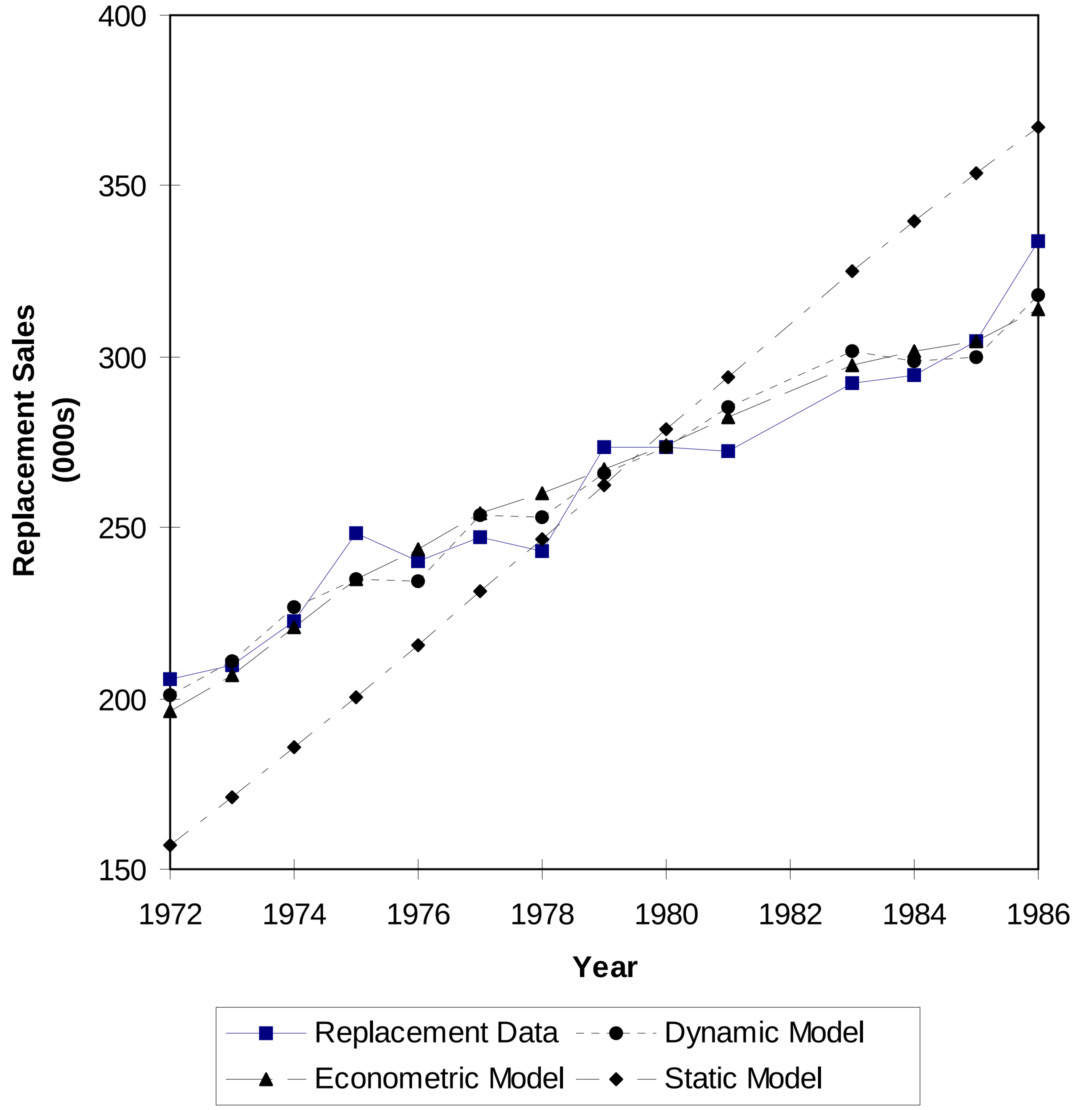
Table 3: Fitting Results for Replacement Sales Models

Model	Parameter Estimates				Mean Sqd. Error (10^7)	Adjusted R Squared
	α / a	β	γ	δ		
K&B Model	16.6 (.31)	-	-	-	111.7	0.129
Econometric	18.6 (.44)	-9.18 (2.3)	0 (at limit)	-0.158 (.13)	8.91	0.931
Dynamic	9.12 (.28)	.259 (.008)	0 (at limit)	.545 (.14)	7.14	0.944

Table 4: Forecasting Results for Replacement Sales Models

Model	One Step Ahead Forecasts: Mean Squared Error (10^8)	One Step Ahead Forecasts: Mean Absolute Error (10^3)	One Step Ahead Forecasts: Mean Absolute Percentage Error	5+ Year Ahead Forecasts: Mean Squared Error (10^8)	5+ Year Ahead Forecasts: Mean Absolute Error (10^3)	5+ Year Ahead Forecasts: Mean Absolute Percentage Error
K&B Model	23.9	48.1	16.4%	42.7	64.6	20.6%
Econometric	1.7	10.1	3.3%	9.9	29.1	9.0%
Dynamic	1.4	7.7	2.5%	2.6	13.5	4.1%

Figure 1: Models Fitted to Passenger Vehicle Replacement Sales Data



Appendix A

For a product purchased at a given time, x, its cumulative scrapping distribution F(a,t) must be constrained to be monotonically increasing with the age of the product. This condition may be expressed as:

$$\frac{dF(a, x + a)}{da} \geq 0$$

Hence, the following restriction on the rate of increase of L(t) may be derived:

$$\frac{d}{da}\left[\frac{\Phi(wa / L(x+a) \ - \ h)}{\Phi(-h)}\right] \geq 0$$

$$\frac{d}{da}\ \Phi\left(\frac{wa}{L(x+a)} \ - \ h\right) \geq 0$$

$$\frac{d\Phi(a)}{da} \bullet \frac{d}{da}\left(\frac{wa}{L(x+a)} \ - \ h\right) \geq 0$$

$$\Phi(a) \bullet \left[\frac{w}{L(x+a)} \ - \ \frac{d}{da}L(x+a)\ \frac{wa}{L(x+a)^2} \ - \ 0\right] \geq 0$$

$$\frac{w}{L(t)} \ - \ \frac{d}{dt}L(t)\ \frac{wa}{L(t)^2} \geq 0$$

$$\frac{d}{dt}L(t) \leq \frac{L(t)}{a}$$

where time, t = x + a.