25th Australasian Transport Research Forum
Incorporating the BTRE Transport Policy Colloquium
Canberra 2-4 October 2002

A study of Australian commercial vehicle scrappage rates

David Mitchell
Bureau of Transport & Regional Economics

Abstract

The paper provides estimates of fleet average vehicle survival functions for three separate classes of Australian commercial vehicles. A number of symmetric and non-symmetric logistic growth functions were estimated in order to test for the best functional form. The estimated survival functions were used to impute conditional vehicle scrappage rates, which are used in *TRUCKMOD*—the Bureau of Transport and Regional Economics' (BTRE) forecasting model of commercial vehicle use and emissions.

We are grateful for comments of an anonymous referee. All errors remain the responsibility of the author.

Contact author

David Mitchell
Bureau of Transport & Regional Economics
GPO Box 501
Canberra ACT 2601
David.Mitchell@dotars.gov.au

GO BACK TO START SCREEN GO BACK TO INDEX

Introduction

In 1995, as part of its research into the cost of policies aimed at reducing greenhouse gas emissions, the then Bureau of Transport Economics constructed a forecasting model of Australian commercial vehicle use, fuel consumption and emissions—*TRUCKMOD*. The scrappage rates of commercial vehicles are a key component of *TRUCKMOD*, as they determine the longevity of vehicles within the fleet and influence the number of new vehicles entering the fleet each year, ultimately affecting emissions.

As part of more recent work undertaken by the BTRE, to update projections of greenhouse gas emissions from the transport sector, *TRUCKMOD* was revised and updated. A key part of the revision work included re-estimating the commercial vehicle scrappage rates, and this paper outlines the methods and the data used in re-estimating those scrappage rates. The estimation results presented in this paper are a significant improvement on the original estimates of commercial vehicle scrappage rates (BTE 1996b, c), for two reasons: (i) the quality and quantity of the available vehicle fleet data has improved since the early 1990's; and (ii) we have tested a range of more general functional forms and used more efficient estimation procedures than used in BTE (1996b). In particular, with the benefit of additional data, it appears that during significant downturns in economic activity there has been a reasonable number of commercial vehicles *mothballed*, i.e. temporarily removed from use and subsequently re-entered into the vehicle fleet at a later date. One of these periods appears to occur around 1991, which was close to the last available observation when the estimates in BTE (1996b) were produced, and this may have adversely affected those results. As we are principally interested in the underlying scrappage rate, undistorted by mothballing, we attempt to allow for mothballing by including a proxy variable for road freight activity.

The paper is structured as follows: Section 2 briefly reviews previous empirical studies of vehicle scrappage and discusses the theory of commercial vehicle use and scrappage. There are two ways of measuring the rate of vehicle scrappage, either directly by the number of vehicle scrapped each period or indirectly from the proportion of vehicles surviving each period. In this paper, we have estimated vehicle survival curves and imputed scrappage rates therefrom. There are pros and cons of each approach and these are also discussed in section 2, along with the empirical model and the Australian commercial vehicle fleet and sales data. The empirical results are outlined in section 3 and some concluding remarks are provided in section 4.

Theory

There have been a number of published studies of vehicle scrappage. Most studies have focussed on passenger vehicle scrappage and most have been based in the U.S. There appear to have been few published studies that have estimated scrappage rates for commercial vehicles, and especially heavy commercial vehicles.

Among the more notable empirical studies of vehicle scrappage are Parks (1977), Manski & Goldin (1983), Miaou (1992) and Greene & Chen (1981).

Parks (1977) presented a model of passenger vehicle scrappage decisions. In his model, Parks relates the probability of vehicle scrappage to the probability of failure and the cost of repair. A vehicle is scrapped when the cost of repair exceeds the present value of the future stream of benefits derived from vehicle use less the current scrap value of the vehicle. Parks posited that the scrapping probability is expected to increase with age, fall as the price of the used cars relative to the price of repairs increases, and rise as the scrap price relative to the price of repairs rises. Parks estimated the scrappage rate for a range of different US passenger car models using a logistic function of vehicle age, vehicle durability, and the price of operating and scrapping vehicles relative to the cost of repairs.

Greene & Chen (1981) and Miaou (1992) also estimated logistic scrappage functions for the vehicle fleet. Greene & Chen estimated separate scrappage rate functions, for domestic and imported US passenger cars and light trucks, solely as a function of vehicle age. Miaou included new car prices, real disposable income, unemployment rates, used car prices, new car loans and motor vehicle accidents as covariates in a logistic function of vehicle age. Manski (1983) estimated make-model-vintage specific scrappage rates, for passenger cars in Israel, and found a significant relationship between a vehicle's price, which would reflect its discounted present value in use net of costs, and the probability of the vehicle being scrapped.

Other empirical studies of vehicle scrappage rates, include Walker (1968) and Hahn (1995), which also focused primarily on the passenger vehicle scrappage decision.

Vehicle acquisition, use and scrappage

The factors influencing vehicle ownership, use and scrappage for commercial vehicles are only slightly different to those affecting private passenger vehicles. Unlike most private passenger cars, commercial vehicles are purchased to provide commercial transport services and will only be purchased if the discounted return on use of the vehicle exceeds the purchase cost. The optimal level of vehicle use in any period is such that the current rents attributable to the vehicle are just equal to the diminution in the present value of future net receipts. It is optimal to scrap the vehicle if the present value of expected future earnings, net of operating costs, is less than the current scrap value. Vehicle owners have an additional option, which is to temporarily suspend use of the vehicle, i.e. to mothball the vehicle. When would it be optimal to mothball a commercial vehicle? If the current (short-run) operating costs exceed (short-run) revenue, but the present value of the expected future revenue less operating costs exceeds the value of the vehicle as scrap, then it would be economic to mothball the vehicle until revenues again exceed costs.

What factors are likely to influence the optimal use and scrappage decision? For freight vehicles, the main factors influencing the optimal level of vehicle use include the underlying demand for road freight services, freight transport input costs—such as fuel and maintenance—and new vehicle prices. The optimal time to scrap will depend on all these factors and the value of the vehicle as scrap. In general, the higher the level of underlying demand for road freight services the greater the overall level of vehicle use and the larger the optimal size of the vehicle fleet. The optimal level of vehicle use for any single freight vehicle will depend on freight rates and that vehicle's operating costs. Higher new vehicle prices would, all else equal, lead to a smaller commercial vehicle fleet, higher freight rates and possibly a higher average utilisation over the life of the vehicle. Any unexpected change in these factors will affect the rate of scrappage in the short-run as capital owners adjust to maximise the return on their asset.

Having outlined the economic factors that one would include in a model of commercial vehicle use and scrappage, the empirical models of vehicle scrappage estimated in this paper are primarily functions of vehicle age. However, vehicle age is a reasonable proxy for aggregate vehicle scrappage. Vehicle operating costs generally tend to increase with increasing vehicle use, due to increasing maintenance requirements. Continuing technological improvement, further increases the cost disadvantage of older vehicles relative to newer ones, so that the likelihood of a vehicle being scrapped tends to increase with vehicle age. Further, *TRUCKMOD* is a long-term forecasting model that tracks vehicles by vehicle vintage. The purpose of the scrappage function within the model is to determine the rate of turnover by vehicle age. Consequently, we are interested in estimating vehicle scrappage primarily as a function of vehicle age.

For *TRUCKMOD*, we also wish to exclude the effect of any mothballing. There are periods during which it appears, from the data, that mothballing of commercial vehicles may be significant, particularly in 1982 and 1991—both periods during which economic activity contracted. Since mothballing reflects a short-run surplus of capital, it is likely to be principally a function of unanticipated downturns in the demand for road freight services, largely driven by economic activity. In the empirical model, we have included the rate of economic growth in an attempt to capture mothballing.

Formally then, the number of vehicles on register at the end of period t+1 (V_{t+1}) is equal to the number of vehicles registered at time t (V_t), plus the number of new vehicles registered during the period t+1 (N_{t+1}), less the number vehicles scrapped (A_{t+1}) and the net number of vehicles mothballed during period t+1 (M_{t+1}):

$$V_{t+1} = V_t + N_{t+1} - A_{t+1} - \Delta M_{t+1} \tag{1}$$

Equation (1) may also be applied to the dynamics of any particular vehicle vintage, h:

$$V_{t+1}^h = V_t^h + N_{t+1}^h - A_{t+1}^h - \Delta M_{t+1}^h \tag{2}$$

Equation (2) describes the dynamics of the stock of vehicles, of vintage *h*, on register at any time. The specification allows for the possibility that new vehicles, of a particular vintage, may enter the fleet over a number of years. This specification corresponds with the Australian vehicle stock data, which is discussed later in the paper. If, for simplicity, we assume that all vehicles of vintage *h* enter the fleet during time period *h*, then the number of vehicles on register at any time thereafter is equal to the total number of new vehicles less the cumulative number of vehicles scrapped, less the net change in the number of mothballed vehicles (equation).

$$V^h_{t=h+1} = V^h_{t=h} - A^h_{t=h+1} - \Delta M^h_{t=h+1} \qquad (3)$$

The fraction of vehicles of vintage *h* surviving for at least *k* periods, the *survival* rate, $s^h_{t=h+k} = V_{t,h+k} / V_{t,h}$, must lie in a range between 1 and 0.

Over the long-run, the number of mothballed vehicles of any particular vintage *h* will tend to zero—either vehicle operating costs will be greater than potential revenues less the value as scrap, dictating that the vehicle be scrapped, or returns to the commercial vehicle rise sufficiently to cover operating costs and the vehicle is re-registered.

Model specification

We assume that the survival rate, for vehicles of vintage *h*, is a function of vehicle age. The survival rate is bound between 0 and 1, and is likely to have a ‘logistic’ shape when graphed against vehicle age. There are a large range of candidate functions for modelling such a relationship, such as the Gompertz function and members of the general logistic function family. Previous BTE research (BTE 1996a,b) used a simple linear logistic function to model the vehicle survival rate. The linear logistic function has the functional form:

$$y_t = \frac{k}{1 + e^{-(a+bt)}} \qquad (4)$$

where *k* is the saturation level, and *a* and *ß* are parameters.

The logistic function, however, restricts the distribution of y_t to be symmetric about the point *y*=*k*/2. Vehicle survival rates, however, may not be symmetric.

Miaou (1992) and Green & Chen (1981) assumed that the scrappage rate follows a linear logistic function, which implies a four-parameter survival function of the form:

$$y_t = \frac{1}{ag}\left[gt - \ln\left(a + \exp\left(b + gt\right)\right)\right] + C \qquad (5)$$

More general S-shaped functions, such as the Bass model (Bass 1969), the Gompertz curve and the flexible logistic model (FLOG) (Bewley & Fiebig 1988), permit asymmetric response. Mahajan, Muller & Bass (1990) reviewed a range of more flexible ‘logistic type’ models that have been utilised in empirical product diffusion research. The Gompertz function has the general form:

$$y_t = ke^{-e^{-(a+bt)}} \tag{6}$$

The Gompertz function, however, is also 'too rigid' in a sense—although it is non-symmetric, the point of inflection of the Gompertz is fixed at y=0.37k.

The flexible logistic (FLOG) function (Bewley & Fiebig 1988), permits more flexible response by allowing the point of inflection to be determined by the data. Moreover, Bewley & Fiebig show that the FLOG model can approximate a range of different logistic type functions including the linear logistic and the Gompertz functions. The general form of the FLOG function is:

$$y_t = \frac{1}{1+e^{-a+bt(m,k)}}, \quad \mathit{for} \quad m=0, k=0 \tag{7}$$

where

$$t(m,k) = \begin{cases} \left\{\left[(1+kt)^{(1/k)}\right]^m - 1\right\} / m, & m \neq 0, k \neq 0 \\ (1/k)\log(1+kt), & m = 0, k \neq 0 \\ (e^{mt} - 1)/m, & m \neq 0, k = 0 \\ t, & m = 0, k = 0 \end{cases} \tag{8}$$

Before completing the empirical specification we briefly review the data.

Data

The two principal sources of data on motor vehicle registrations in Australia are the Australian Bureau of Statistics' New Motor Vehicle Registrations (NMVR) (ABS 2001) and Motor Vehicle Census (MVC) (ABS 2000, and earlier issues) collections. The data used in this analysis is sourced from the MVC's undertaken in 1971, 1976, 1979, 1982, 1985, 1988, 1991, 1993, 1995, 1997, 1998 and 1999, and proxy annual sales of new motor vehicles (NMVR) since 1970. All data used in the analysis is available from the author upon request.

The NMVR collection records the number of new vehicles registered by State and Territory motor registries. It has been conducted since the mid-1950's, although detailed statistics on commercial vehicles are only available from the early 1970's. A new vehicle registration is recorded for each vehicle appearing on the motor vehicle registry's database for the first time. It is assumed that all vehicles newly appearing in the vehicle registry database were manufactured within the last 12 to 18 months for passenger cars, and slightly longer for commercial vehicles (pers. comm. ABS (Peter Willis), 16 March 2001). (The ABS NMVR collection ceased in December 2001. The principal source of new vehicle sales data is now the Federal Chamber of Automotive Industry's VFACTS database.)

The MVC has been conducted irregularly since 1963, more or less triennially between 1971 and 1995, and annually since then. It records the number of vehicles on register by vehicle type, make, size and year of manufacture, amongst other variables. The year of manufacture provides an indication of the age structure of the vehicle fleet, and is the closest available proxy for the on-road age of vehicles. To be included as a registered vehicle in the MVC a vehicle must either be registered for a period covering the date of the census or its registration must have expired less than one month prior to that date.

Both the MVC and NMVR separate commercial vehicles into four distinct vehicle classes: light commercial vehicles (LCVs), rigid trucks, articulated trucks and non-freight carrying vehicles. Since 1971 there have been two major changes to the vehicle classification, and some minor changes in the definition of those vehicles considered as within scope for the MVC. For commercial vehicles, the major changes in vehicle classification occurred in the 1976 and 1991 censuses. In both cases, the net impact of the re-classification was a transfer of vehicles from the rigid truck category to the LCV category. As the data used for estimation begins in 1976, we only need to allow for the 1991 change. The articulated truck definition has remained reasonably consistent since 1971.

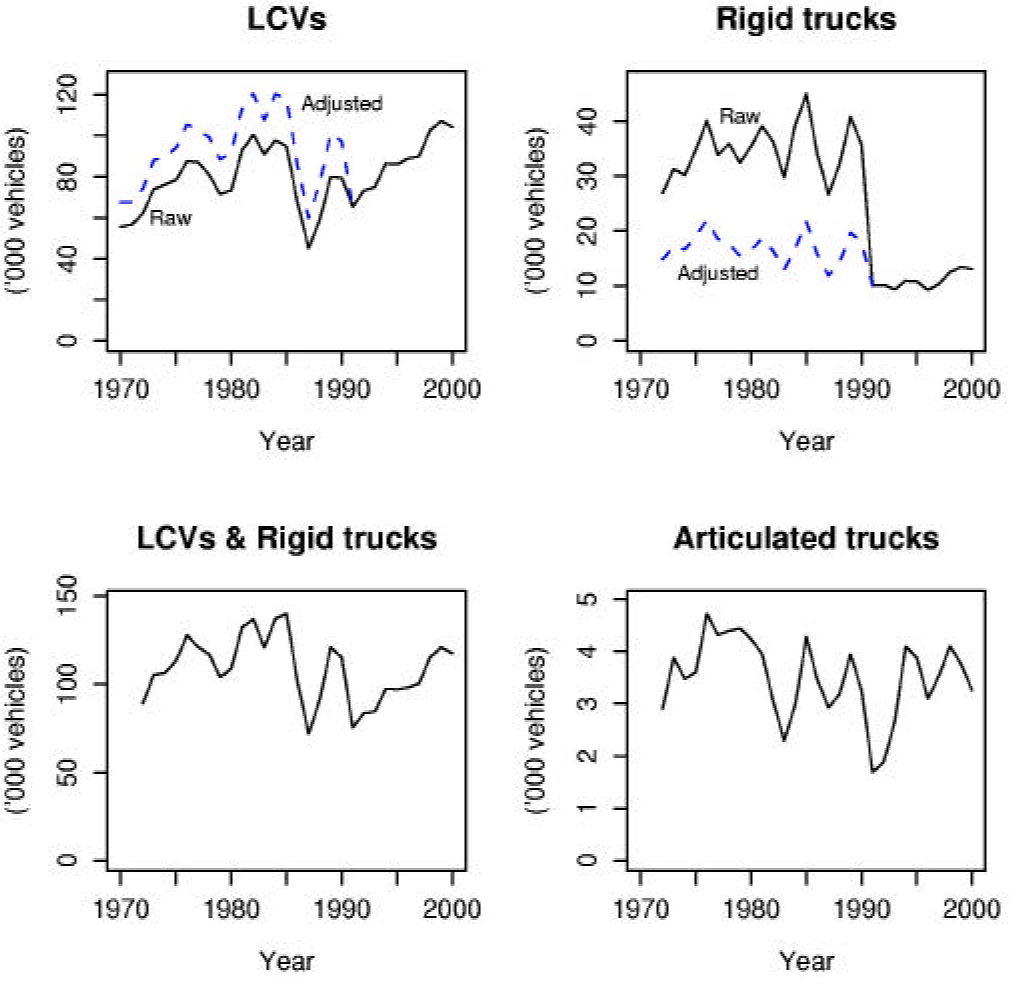
Adjusting for changes in vehicle classification

In 1991, the definition of LCVs was changed to include all commercial vehicles up to 3.5 tonnes gross vehicle mass (GVM). Prior to 1991 all commercial vehicles over 1.0 tonne GVM had been classified as rigid trucks. The change in vehicle classification had a major effect on the estimated stock of rigid trucks and LCVs, with a significant number of formerly rigid trucks re-classified as LCVs. To estimate the fraction of pre-1991 vintage rigid trucks surviving in the fleet beyond 1991 requires adjusting the pre-1991 NMVR data. Fortunately, the published NMVR data (ABS 1995, and earlier issues) included estimates of the number of new rigid truck registrations for vehicles under 4.0 tonnes GVM, as far back as September 1976. We have used this information to estimate pre-1991 rigid truck and LCV sales on the basis of the post-1991 vehicle classification, and used the adjusted LCV and rigid truck sales estimates to calculate vehicle survival rates, for pre-1991 vintage vehicles, after 1991. The methods used to adjust the vehicle sales data are available from the author upon request. Figure 1 shows annual new commercial vehicle sales in Australia between 1970 and 2000, and the adjusted LCV and rigid truck sales estimates accounting for the 1991 change in vehicle classification.

Calculating vehicle survival rates

Because new vehicle registrations are measured by year of *first registration* whereas the stock of vehicles is measured by year of *manufacture*, we can only approximate the proportion of vehicles surviving in the fleet. Based on the MVC, it appears that only 70 to 80 per cent of vehicles are sold within the same calendar year as their year of manufacture, with the remainder entering the fleet over the next one to two years. Over an extended period, however, differences in timing of new vehicle manufacture and registration will tend to even out, and the aggregate number of new registrations measured by year of first registration and year of manufacture tend to converge.

Figure 1 New commercial vehicle sales



The differences in definition between the NMVR data and MVC data place constraints on the number of valid observations. As previously mentioned, the MVC data show that only 70 to 80 per cent of vehicles are registered within the year of manufacture, with the remainder entering the fleet over the next one to two years. Further, the MVC collection cycle does not coincide with the calendar year—the MVC collections have been undertaken anywhere between May and October. For these reasons, the survival functions were estimated using data only for vehicles 3 years and older. By year 3, there are practically no additional new vehicle registrations of that vintage.

Empirical specification

The brief review of the motor vehicle stock and sales data, above, shows that the actual survival rate, s_t^h, of commercial vehicles is not known with certainty. The observed fraction of vehicles of vintage *h* remaining in the fleet at time *t*, $s{*}_t^h$, equals the true fraction of vehicles surviving, s_t^h, plus a disturbance term,

e_t^h.

$$s*_t^h = s_t^h + e_t^h \qquad (9)$$

Before completing the empirical specification we consider the placement of the disturbance term. Bewley & Fiebig (1988) discussed the appropriate error structure for estimating logistic type models. They canvassed three alternative locations for the disturbance term: (i) additive; (ii) multiplicative; or (iii) within the exponential term of the logistic function. They argued in favour of specification (iii)—within the exponential term—because only such a specification preserves the boundedness of the dependent variable. In our case, however, data deficiencies mean the observed survival rate may lie outside the range [0,1], and it is therefore more appropriate for the disturbance term to lie outside the logistic function—implying an additive disturbance term.

The full empirical models used to estimate commercial vehicle survival rates were:

$$\text{FLOG: } s*_t^h = \left(1+\exp\left(-\left(a+\left(b+gy_t\right)t\left(m,k\right)\right)\right)\right)^{-1} + e_t^h \qquad (10)$$

$$\text{Gompertz: } s*_t^h = k\exp\left(-\exp\left(-\left(a+\left(b+gy_t\right)t\right)\right)\right) + e_t^h \qquad (11)$$

where t = vehicle age, y_t = GDP growth, modelled as a covariate with vehicle age, and $e_t^h \sim \left(0, s_{e^h}^2\right)$).

Empirical results

Separate survival curves were estimated for each of LCVs, rigid trucks and articulated trucks. Because of the major vehicle re-classification that occurred in 1991, we also estimated a vehicle survival curve for LCVs and rigid trucks combined. All estimates were derived using the non-linear maximum likelihood estimation algorithm in R[1]. Six different functional forms were estimated, five variants of the FLOG specification—the linear logistic, inverse power transform (IPT), logarithmic inverse power transform (LIPT), Box-Cox, and the exponential logistic (ELOG)—and the Gompertz function.

Estimation of all functional forms was generally straightforward in all cases but the most general FLOG specification. In most cases, a convergent solution was achieved when the parameter estimates from linear logistic model were used as the initial values. Estimation of the general FLOG specification, however, was problematic. The FLOG function proved to be very sensitive to initial conditions—convergence was achieved only by judicious choice of appropriate starting values[2]. In all cases, the FLOG model failed to outperform one or more of the restricted FLOG variants, suggesting that the results did not

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1 R is the open-source statistical and data analysis package (See Ihaka & Gentleman 1996). R employs a Newton-type algorithm for non-linear estimation.

2 The ELOG specification parameter estimates worked in almost all cases. Removing any restrictions on the step length and including an estimated optimised function value 1 per cent better than the best alternative model result improved the chances of achieving a global maximum.

converge to a global maximum. Consequently, the FLOG estimates are not reported here. We also attempted to estimate the four-parameter logistic type function, specified in equation (5), but were unable to find a set of starting values that produced a convergent solution for any vehicle class.

Table 1 presents likelihood ratio (LR) test statistics comparing the statistical performance of the linear logistic model against the other variants of the FLOG model. Based on the assumed distribution of the disturbances, the likelihood ratio is asymptotically distributed as $c^{2}(m)$ under the null hypothesis, where m is the number of restrictions under the null hypothesis (Harvey 1981). At the 95 per cent significance level, $c^{2}(1)$ = 3.84 and $c^{2}(2)$ = 5.99. In almost all cases, the variants of the less restrictive FLOG specification produced a fit that was statistically significantly better the simple linear logistic function.

Table 1 Log-likelihood values – Commercial vehicle survival functions

	Vehicle type			
Model	LCVs	Rigid trucks	LCVs & rigid trucks	Articulated trucks
Linear	174.95	125.48	153.35	182.62
Gompertz	178.49	113.39	158.08	184.26
IPT	180.17	128.06	158.51	189.05
LIPT	179.20	127.17	156.99	188.34
Box-Cox	180.02	128.07	158.18	188.92
ELOG	178.78	127.46	156.33	188.21

As the FLOG and Gompertz functions are different functional forms, it is not possible to compare the statistical performance of the FLOG and the Gompertz specifications using a nested LR-test. A comparison of the log-likelihood values, however, shows that there is at least one variant of the general FLOG function that has a higher value for the log-likelihood function than the Gompertz function, for each commercial vehicle class. For articulated trucks, there appears to be very little difference between the Gompertz and all other variants of the FLOG model. The IPT specification (obtained by setting μ=1 in the general FLOG function) was preferred on the basis that it produced the highest log-likelihood value. For rigid trucks, the IPT and Box-Cox model specifications gave a slightly better fit than the other FLOG variants; the IPT specification was chosen as the preferred specification. For LCVs (and the combined LCV and rigid truck class) the IPT again produced a slightly higher log-likelihood value and so again it was chosen as the preferred empirical specification. Table 2 presents the preferred estimation results for each vehicle type.

Table 2 Preferred model parameter estimates

	Vehicle type			
	LCVs	Rigid trucks	LCVs & rigid trucks	Articulated trucks
Model	IPT	IPT	IPT	IPT
a	3.802	2.53	3.698	3.185
	(6.88)	(9.87)	(5.31)	(8.86)
b	–6.417	–0.0589	–0.7427	–0.4017
	(–3.14)	(–2.86)	(–2.59)	(–3.74)
m	na	na	na	na
k	1.667	0.6239	1.798	1.362
	(7.04)	(9.56)	(5.53)	(8.97)
g	0.0048	0.0026	0.01300	0.0045
	(2.41)	(2.81)	(3.55)	(3.07)
s_e^2	0.0056	0.0111	0.0075	0.0050
	(8.47)	(8.58)	(8.54)	(8.42)
Log–L	180.17	128.06	158.51	189.05

Note t-statistics given in parentheses.

Commercial vehicle scrappage rates and economic activity

The empirical model of vehicle scrappage contains little direct economic content, apart from the GDP growth term—scrappage rates are linked largely to vehicle age. The GDP growth term is intended to capture the impact of economic activity on the underlying vehicle scrappage rates.

In all cases, the GDP growth variable was small but statistically significant. The parameter estimate of the impact of GDP growth on vehicle survival rates was 0.0045 for articulated trucks, 0.0026 for rigid trucks and 0.0048 for LCVs. The elasticity of vehicle survival with respect to changes in GDP is $E_{s,y} = (1-s)g\,yt(m,k)$. So an increase in GDP increases the proportion of vehicles surviving in the vehicle fleet, with a proportionately greater effect on the survival of older vehicles than newer vehicles (due to the 1-*s* term). For example, an additional percentage point of economic growth, on an average rate of 3.5 per cent per annum, would increase the proportion of 4 year old articulated trucks surviving by 0.1 per cent while the same GDP increase would increase the proportion of 15 year old articulated trucks surviving by 1.8 per cent. The impact on the survival rate of LCVs and rigid trucks can be derived in a similar fashion.

A story that supports these results is that when economic activity is strong, demand for transport services is higher bidding up prices, increasing the returns to vehicles. Older vehicles may be retained in the fleet for longer as the higher rates of return cover the higher avoidable operating costs. In periods of economic slowdown, both mothballing and vehicle scrappage increases in response to lower freight demand.

Estimated vehicle survival rates and scrappage functions

Age specific fleet commercial vehicle scrappage rates are equal to the marginal change in the estimated vehicle survival functions. The scrappage rate a_k for vehicles of age k is equal to the proportionate change in the number of vehicle surviving each period: a_k=1-s_k/s_{k-1}. The preferred model-based commercial vehicle scrappage rates, and associated survival rates, for each commercial vehicle class, are listed in table 3.

Obviously, the survival rate should be close to 100 per cent for vehicles at age 0[3]. The estimated vehicle survival rates are slightly below 100 per cent at age 0, around 98 per cent for LCVs and articulated trucks and 97 per cent for rigid trucks. It seems unlikely that 2 per cent of new vehicles would be scrapped in the first year of operation. Part of the difference may be due to the fact that vehicle survival rates could not be estimated with certainty. For example, the empirical estimates for rigid trucks are heavily dependent on the adjusted rigid truck sales data, and the estimates may reflect deficiencies in the adjustment process. However, even if vehicle sales were known with certainty, it is possible that the estimated survival fraction might be less than one at age 0, unless the estimation process were constrained to meet this criterion. How should the analyst use these results? There are two ways to use these results, either the scrappage rates may be imputed directly from the estimated survival functions, which would have the effect that the underlying survival curve would be shifted upwards by the distance of the estimated survival curve from 100 at age 0, or the analyst could use the imputed scrappage rates, but adjust the first few years to meet the estimated survival curve from age 5 or so.

Figure 2 shows the observed commercial vehicle survival rates, by age of vehicle, the predicted survival rate functions and the implied scrappage rate for LCV's, rigid and articulated trucks. The empirical results suggest that the average time taken till 50 per cent of vehicles of a particular vintage are retired is 18 years for LCVs, 22 years for rigid trucks and 17 years for articulated trucks.

The data variation around the line of best fit, shown in figure 2, probably highlight both the uncertainty induced by having to estimate the number of new vehicles of a particular vintage and variations in the rate of scrappage across different vehicle vintages. This is especially so for articulated and rigid trucks where the observed fraction of vehicles surviving among older vintages, as indicated by the observations of vehicles around 25 years of age, suggest that survival rates may be lower among older vintage vehicles.

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[3] This ignores any significant forced scrappage of new vehicles due accidents. Unfortunately, there was not time to investigate the significance of new vehicle write-offs.

Concluding Remarks

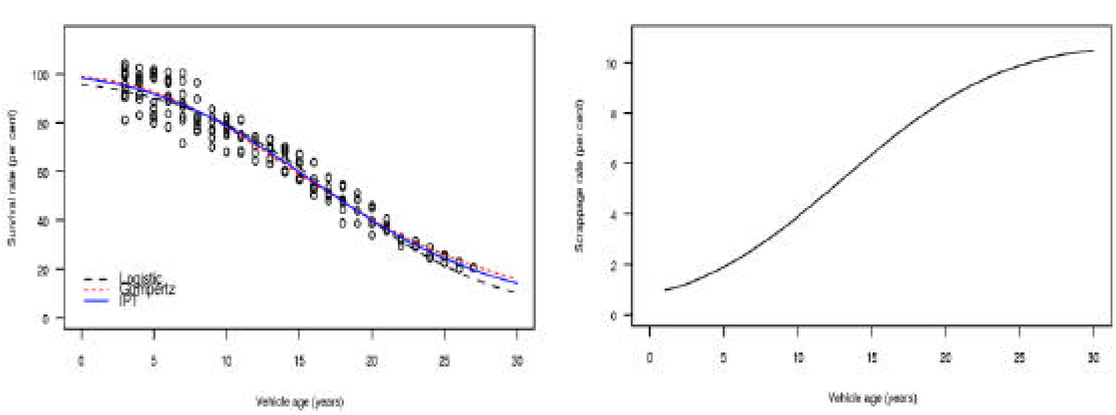
This paper has described the methods used to estimate the commercial vehicle scrappage rates used in the BTRE's forecasting model of commercial vehicle use and emissions—*TRUCKMOD*. The scrappage rates used in the model were based on age-based empirical survival functions estimated using a range of 'flexible' logistic functions. The empirical estimates show that the simple logistic model is too restrictive, and that more flexible functional forms, such as the Gompertz and FLOG models provide statistically superior fits to the data.

Table 3 Estimated commercial vehicle survival and scrappage rates

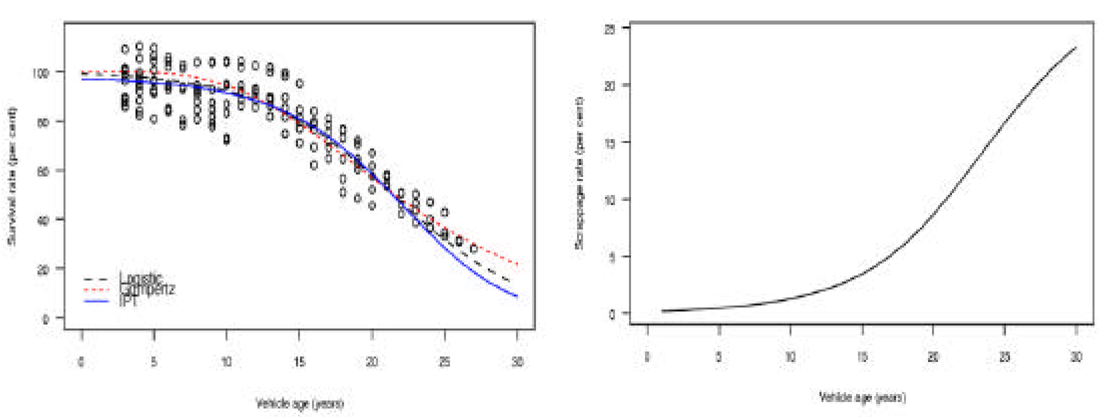
(per cent)

	LCVs		Rigid trucks		Articulated trucks	
Vehicle age	Survival rate	Scrappage rate	Survival rate	Scrappage rate	Survival rate	Scrappage rate
0	98.49		97.01		98.21	
1	97.53	0.97	96.84	0.18	96.97	1.26
2	96.43	1.13	96.61	0.24	95.58	1.43
3	95.13	1.35	96.31	0.31	93.97	1.68
4	93.60	1.61	95.94	0.38	92.12	1.97
5	91.82	1.91	95.49	0.47	90.00	2.30
6	89.76	2.24	94.94	0.58	87.61	2.66
7	87.42	2.61	94.27	0.70	84.95	3.04
8	84.79	3.01	93.47	0.86	82.03	3.44
9	81.88	3.44	92.49	1.04	78.86	3.86
10	78.69	3.89	91.32	1.27	75.47	4.29
11	75.25	4.37	89.90	1.55	71.90	4.73
12	71.59	4.86	88.20	1.89	68.18	5.18
13	67.76	5.36	86.16	2.31	64.35	5.62
14	63.79	5.86	83.72	2.82	60.46	6.04
15	59.74	6.35	80.84	3.44	56.56	6.46
16	55.65	6.83	77.46	4.19	52.68	6.85
17	51.59	7.30	73.53	5.07	48.88	7.22
18	47.61	7.73	69.04	6.10	45.19	7.56
19	43.73	8.14	64.00	7.29	41.63	7.87
20	40.01	8.52	58.48	8.64	38.23	8.16
21	36.46	8.86	52.56	10.11	35.02	8.41
22	33.12	9.17	46.41	11.70	31.99	8.64
23	29.99	9.44	40.22	13.35	29.17	8.83
24	27.09	9.68	34.18	15.01	26.54	9.00
25	24.41	9.88	28.49	16.65	24.12	9.14

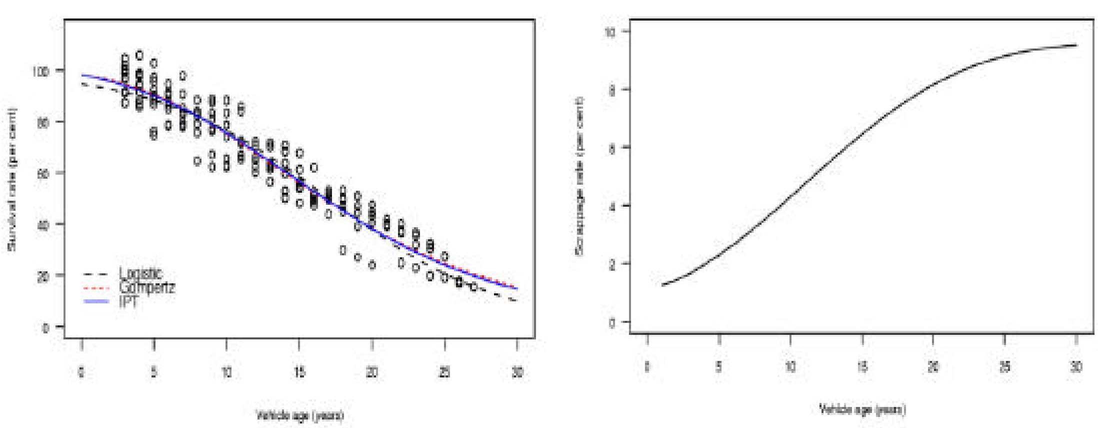
Figure 2 Actual and estimated commercial vehicle survival rates and implied scrappage rates



(a) LCVs



(b) Rigid trucks



(c) Articulated trucks

The paper also provides an estimate of the impact of economic activity on the aggregate rate of commercial vehicle retirement. The empirical analysis implies that increased economic activity has a statistically significant and positive effect on the survival rate of commercial vehicles, reducing the scrappage rate.

Further areas for research would include estimating vintage specific scrappage functions for commercial vehicles and testing whether the rate of scrappage had changed across different vintages. The ABS now undertakes the Motor Vehicle Census on an annual basis. As the number of annual collections increases, providing a longer time-series, estimating separate vintage specific scrappage functions will become more feasible. Availability of more vintage specific stock data on the number of older vehicles will facilitate reliable estimation of scrappage functions directly, as opposed to estimating the survival function and imputing the scrappage function. Incorporating more specific economic data affecting the commercial vehicle scrappage decision, such as new vehicle prices and freight activity, may explain more of the variation in vehicle survival rates observed for vehicles of similar ages across different vehicle vintages.

References

ABS (1995), *New Motor Vehicle Registrations, Australia, December 1994*, Cat. no. 9303.0, Australian Bureau of Statistics, Canberra.

ABS (2000), *Motor Vehicle Census: Australia, 31 October 1999*, Cat. no. 9309.0, Australian Bureau of Statistics, Canberra.

ABS (2001), *New Motor Vehicle Registrations, Australia: Preliminary, March 2001*, Cat. no. 9301.0, Australian Bureau of Statistics, Canberra.

Bass, F. (1969), ‘A new product growth model for consumer durables’, *Management Science* **15**(5), 215–227.

Bewley, R. & Fiebig, D. (1988), ‘A flexible logistic growth model with applications in telecommunications’, *International Journal of Forecasting* **4**(2), 177–192.

BTE (1996*a*), *Costs of Reducing Greenhouse Gas Emissions From Australian Cars: An Application of the BTCE CARMOD Model*, Working Paper 24, BTE, Canberra.

BTE (1996*b*), *Costs of Reducing Greenhouse Gas Emissions From Australian Road Freight Vehicles: An Application of the BTCE TRUCKMOD Model*, Working Paper 22, BTE, Canberra.

BTE (1996*c*), *Transport and Greenhouse: Costs and Options for Reducing Emissions*, Report 94, AGPS, Canberra.

Greene, D. & Chen, C. (1981), 'Scrappage and survival rates of passenger cars and light trucks in the U.S., 1966–1977', *Transportation Research, Part A* **15A**(5), 383–389.

Hahn, R. (1995), 'An economic analysis of scrappage', *RAND Journal of Economics* **26**(2), 222–242.

Harvey, A. (1981), *The Econometric Analysis of Time Series*, Phillip Allan Publishers Limited, Oxford.

Ihaka, R. & Gentleman, R. (1996), 'R: A language for data analysis and graphics', *Journal of Computational and Graphical Statistics* **5**(3), 299–314.

Mahajan, V., Muller, E. & Bass, F. (1990), 'New product diffusion models in marketing: A review and directions for research', *Journal of Marketing* **54**(1), 1–26.

Manski, C. & Goldin, E. (1983), 'An econometric analysis of automobile scrappage', *Transportation Science* **17**(4), 365–375.

Miaou, S. (1992), 'Factors associated with aggregate car scrappage rate in the United States: 1966–1992', *Transportation Research Record* **1475**, 3–9.

Parks, R. W. (1977), 'Determinants of scrapping rate for postwar vintage automobiles', *Econometrica* **45**(5), 1099–1116.

Walker, F. (1968), 'Determinants of auto scrappage', *Review of Economic Studies* **50**, 503–506.