Probability based estimation of human productivity losses from road fatalities

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1 Introduction

The human capital approach used by the Bureau of Infrastructure, Transport and Regional Economics (BITRE) to estimate road crash costs in Australia requires rigorous analysis of national road crash data. Such analysis is necessary to determine the internal factors that influence crash variability both spatially and temporally, and the external factors (such as the quality of data) that cause similar variability. The internal factors influencing road crashes relate directly to road users, roads, vehicles and their innumerable interactions.

Data analysis to duly recognise the influence of internal factors on the number, severity and probability of occurrence of road crashes is important to those endeavouring to formulate programs and policies to save life and limb.

This paper aims to explore trends and probabilities of crash fatalities, hence human productivity and other losses with a view to better inform those formulating road safety programs and policies.

2 Background

The human capital approach is an accounting procedure currently adopted by BITRE to estimate the human cost of a road crash fatality or what the practitioners would like to call it, the value of statistical life (VOL). It requires adding together the human productivity and other quantifiable losses due to all premature road crash fatalities in a year and dividing total by the number of fatalities in that year (see for instance BTE 2000, Risbey *et al*. 2007).

In the past, the Bureau used this averaging procedure for a single year (see BTE 2000, BTE 2003). Determining VOL using data for a single year has many deficiencies, in particular:

It bears an inconsistent relationship[1] with the number of fatalities per year (e.g. in some years, VOL increases as the number of fatalities decrease).

- It generates a VOL that does not capture significant trends in the change in the number of fatalities due to factors such as the impact of safety programs and/or other developments that alter fatality risk.
- It is overly sensitive to the average age of fatalities, because loss of contribution to economic productivity is higher if lives are lost at early stages of economic contribution. BTRE (2006) demonstrated that the total cost of $2.17 million attributable to a fatality (VOL) would fall by 15 per cent to a value of $1.9 million if the average age of a fatality rises from 35 to 42 years.
- The estimated VOL is unstable over future years, even in the short run, hence requiring revisions to the value at regular intervals.

[1] The observed aberration is due to a combination of factors, some explanation is in another section of the paper.

It is assumed that these and other deficiencies of the basic single-year approach to valuing losses can be effectively rectified through due recognition of trends and probabilities of fatal crash occurrences. Such estimation requires:

(i) detailed time series crash data of sufficient duration to estimate (a) expected probability of fatality risks within a year and (b) change in annual fatality trend over several years; and

(ii) a suitable standardisation procedure to capture expected probabilities of road fatalities that are both age- and gender-specific.

2.1 Human capital approach

The first column of Table 1 shows various cost elements that are added up to estimate VOL using the human capital approach to valuing life and limb. It includes two measures of human productivity losses forgone by the victim's family, friends and relatives and the society due to premature death and other economic and non-economic losses. The second column shows how the age at which a fatality occurs and its gender are recognised in the measurement of costs. This is to enable the reader to appreciate the conceptual and empirical principles underlying human capital approach to valuation of life. Accordingly, an 'early premature death' results in discounted productivity losses over a longer period than the corresponding losses for a 'late premature death'.

To enable direct comparison of estimates made in 1996 with different approaches proposed in this paper, (a) the cost components used in this study are identical to those used in the 1996/2000 study (see BTE 2000), (b) the costs are expressed in 1996 prices and (c) discounted at 4 per cent – the lowest discount rate used in 1996.

Table 1 – Breakdown of human costs included in the estimation

Cost elements		*How costs are measured*
Productivity losses		
1.	Labour in the workplace	Discounting age and gender specific lost earnings
2.	Labour in the household	As above
Associated costs		
3.	Quality of life – family & relatives	Linear extrapolation of cost per capita
4.	Medical/ambulance	Discounting age and gender specific lost earnings
5.	Legal	As above
6.	Correctional services	As above
7.	Workplace disruption	As above
8.	Premature funerals	Discounting age specific costs
9.	Coroner	Linear extrapolation of cost per capita
10.	Other associated costs	As above

Source: Based on Risbey et al. (2007)

2.2 Structure of the paper

The paper is structured as follows:

- Section 3 of this paper outlines common approaches to account for probabilities specific to road crashes when estimating VOL. It justifies selecting an econometric approach as in this paper to get meaningful estimates of the losses due to fatalities.
- Section 4 presents the econometric approach and the empirical results based on detailed data from 1996 to 2007 from the Australian Transport Safety Bureau (ATSB).
- Section 5 compares results of different approaches of accounting for probabilities in the estimation of fatality costs.
- Main concluding observations made during the research and analysis undertaken for this paper are in Section 6.

3 Accounting for probability of road fatality risks

In any given year, the productivity losses due to road fatalities are influenced directly by factors like age, gender, the geographic area in which the fatalities occur etc. Several road crash studies have reported historical time series data showing the association of these factors with the probability of occurrence of road fatalities (Barnard, 1989, BTE 2000, ATSB 2007). Such historical data can be used to determine the expected/future numbers of road fatalities by age and gender. Table 2 shows the expected occurrence of road fatalities for the age group of 17 to 25 year-olds and for all ages - for the period 1996 to 2004. Here, the term ‘expected occurrence’ refers to the probability weighted average number of fatalities - and have been calculated by expressing the number of road fatalities in a certain age group per 100,000 persons of that age group. The use of probability based estimates yield more meaningful estimates (DFA, 2006) of the future fatalities and in turn fatality costs of road crashes — an important input in the design of safety projects and programs.

Table 2 – Expected occurrence of fatalities by age group, gender and by year

Year	*Probability weighted average of*			
	17-25 year old male fatalities per 100,000 persons of that age group	*male fatalities at any age per 100,000 persons*	*17-25 year old female fatalities per 100,000 persons of that age group*	*female fatalities at any age per 100,000 persons*
1996	35.60	15.40	8.90	6.10
1997	30.80	13.10	11.30	6.00
1998	29.50	13.30	8.80	5.50
1999	30.20	12.90	9.70	5.70
2000	30.50	13.60	10.50	5.40
2001	30.50	13.10	7.00	4.80
2002	27.40	12.80	9.20	4.80
2003	25.90	11.70	7.30	4.70
2004	25.10	11.30	9.00	4.50

Source: ATSB (2007)

Preliminary analysis showed that the average age of road fatalities remained stable within the age band of 17 to 25 years and the relative proportion of male fatalities remained consistently high over the years (se also Table 2). Capturing the influence of these cost drivers that are characteristic of road crash fatalities in Australia (and in most developed countries) in the estimation of road crash costs is important – in particular to enable road investments conceptually and empirically more focused. In view of this, does the use of traditional methods to estimate road crash costs such as the use of data for a single year effectively capture the characteristic features? The answer to this question rests largely on comprehensive analysis of road crash data using traditional approaches and comparing those with the approaches that have been in wider usage for the last two decades (see Traub, 1994; DFA, 2006).

Therefore the aim of this section is to show some common approaches to analyse crash data and to estimate losses due to road crash fatalities and how they relate to the probabilities of road fatalities by age and gender. For purposes of comparison, this section first presents the approach adopted by the Bureau in the 1990s.

3.1 Single period of estimates

In early to mid 1990s the Bureau used data for a single year to estimate age and gender specific productivity and other associated losses due to premature transport-related deaths. These estimates were then pooled and an average VOL per transport mode was estimated by dividing it by the respective number of fatalities. BTE (2000) provides details of the estimation for road crash fatalities and BTE (2003) for rail accident fatalities.

The use of a single year has a number of disadvantages. It assumes implicitly that the number and the age and gender distribution of fatalities in the chosen year is representative of other years, both past and future. This method provides a good measure of central tendency. Nevertheless given the left skewed distribution of road crash fatality data, the use of this method has the tendency to generate a VOL that ignores the observed age-specific distribution of fatalities.

3.2 Trend-based smoothing of fatalities

The aim of smoothing of fatality data is to develop a fatality function which is stable against factors that cause variability in fatality numbers. ATSB data in Table 1 shows that the probability of a fatality at a given age varies for males and females over the years. Therefore smoothing age and gender specific fatality functions for yearly variations is essential to estimate a stable VOL. The estimated VOL is expected to be less sensitive to variations in fatality numbers. This assumption is tested in Section 4.

A key criticism of the trend-based smoothing is its tendency to conceal important information in the basic data. For example, smoothing the number of fatalities against a single factor such as age would fail to capture the influence of gender on fatality numbers. Such smoothing could also conceal important information about yearly variation in fatality numbers and/or the age and gender specific distribution of fatalities. Figure 1 supports this argument, showing the scatter of fatality numbers by age for a ten year period. The smoothing line in the figure explained over 90 per cent of the variability of data. Nevertheless the smoothed line fails to make a balanced representation of the annual variation.

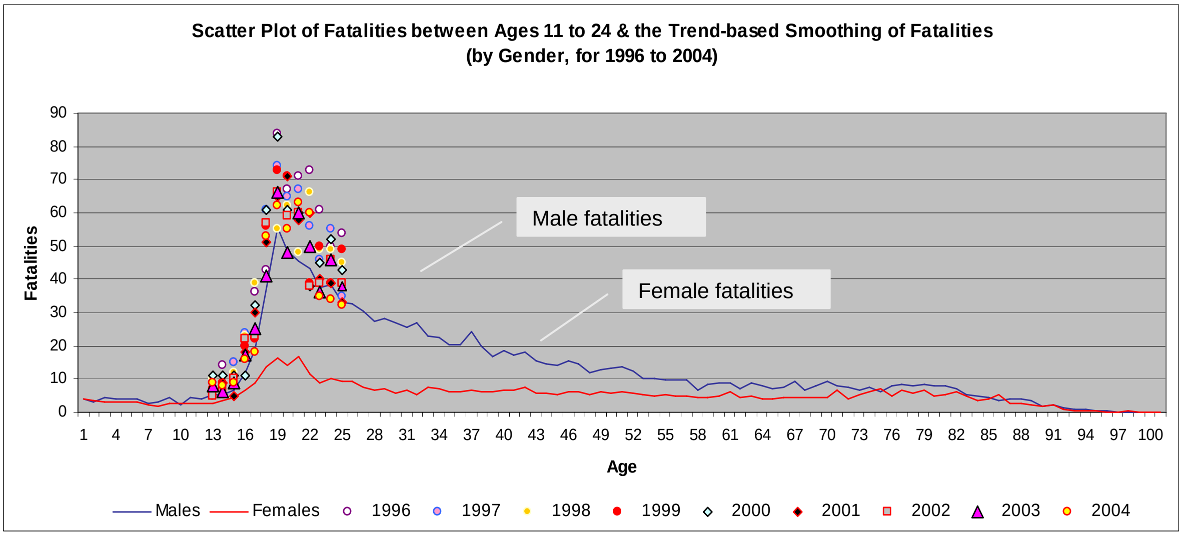


Figure 1 – Scatter plots and the smoothed trend line of fatality data for 1996 to 2004

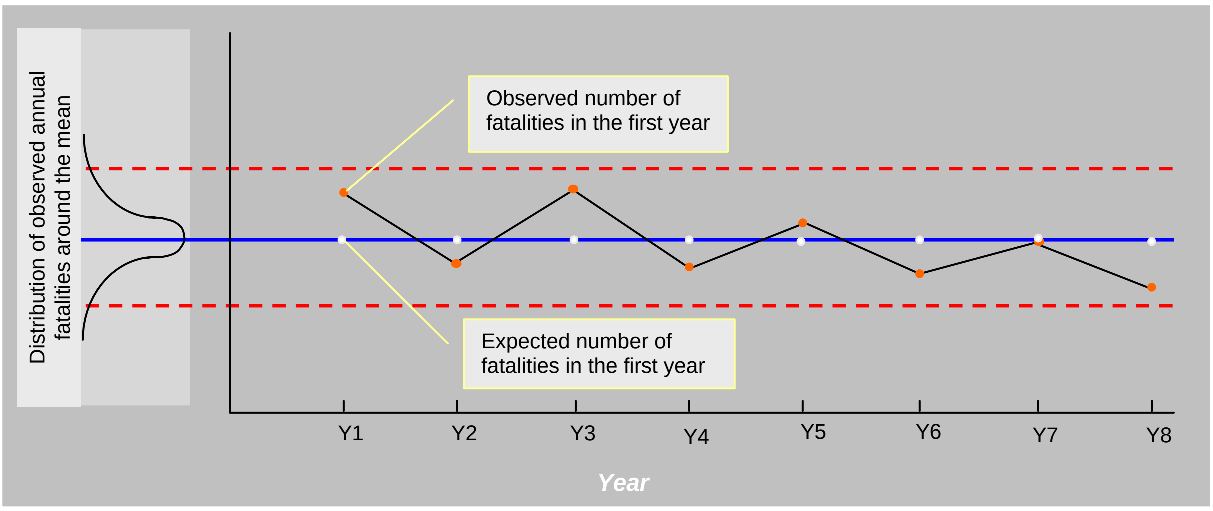
3.3 Weighted averaging

This method requires VOL estimates for a number of years. It has limited use in situations where detailed time series data are not available for sufficiently long periods.

Weighted averaging can be used in conjunction with other methods as discussed in Section 4.

3.4 Expected probability approach

The expected values are derived via a probability analysis of crash fatalities. This method requires data for a number of years and can be effectively used in conjunction with econometric modelling. The advantage of this method is that it captures the vital trends in the data and leaves out disordered fluctuations that could distort the final results. Using 8 hypothetical data points, Figure 2 shows what could be the expected number of fatalities if the observed fatality numbers are normally distributed.



Source: Based on Mundorff (2005)

Figure 2 – What the expected probability approach aims to achieve

4 Modelling road crash fatalities

Using age, gender and year (trend) as explanatory variables, a conceptual model was specified to explain the variability in road crash fatalities, both within a year and between years (Equation 1).

$$Road\,crash\,fatalities\,in\,a\,year = f(Age, Gender, Year) \quad [1]$$

The variables required to transform the conceptual model to an empirical model are identified below. Variable specification involved preliminary analysis of time-series data on road crashes and drawing inferences about the behaviour of the three independent variables in the conceptual model. The inferences that were drawn from the preliminary analysis were:

- The peaks in the distribution of fatality numbers for both males and females were skewed towards the left, suggesting a higher probability of occurrence of fatalities in age groups represented by younger drivers;
- Fatalities rates for males are higher than the rates for females;
- The fatality rates for males and females showed a gradual logarithmic decline over the ten years (1995 to 2004);
- For males, a notable change in the trend of age-specific fatality numbers occurred at age 18 and for females, such a change occurred at age 16; and
- Trends in the rate of increase in fatalities towards the peak and the rate of decline in fatalities from the peak were non-linear.

Listed in Table 3 are the explanatory variables that accorded with the inferences drawn from preliminary analysis and what the regression experiments drew out as statistically viable.

Table 3 – Explanatory variables

deaths	The dependant variable. The number of road fatalities (e.g. 0, 1, 2, …n);
gender	A binary dummy variable where 0 = female and 1 = male;
age	The age, in years, of the fatality at the time of the crash;
age_3	The age at which crash fatality occurs raised to the power 3;
age18_m	A binary dummy variable where 1 is for males aged 18 or older, 0 otherwise;
age16	An age specific indicator variable 0 = 15 or younger and 1 = 16 or older
ln_year	A time-trend variable ranging from 1 to 11 (e.g. 1995 represented by ln(1));
age16_in_a	Interaction term between age 16 (and above), gender and inverse of age
age16_ln_a	Interaction term between age 16 (and above), gender and the logarithm of age
age16_sq_a	Interaction term between age 16 (and above), gender and the square root of age
age16_a2	Interaction term between age 16 (and above), gender and age squared
age16_a3	Interaction term between age 16 (and above), gender and age cubed
age16_a4	Interaction term between age 16 (and above), gender and age to the fourth power
age18m_in_a	Interaction between age 18 (and above), gender and the inverse of age
age18m_ln_a	Interaction between age 18 (and above), gender and the logarithm of age
age18m_sq_a	Interaction between age 18 (and above), gender and the square root of age
age18m_a2	Interaction between age 18 (and above), gender and the square of age
age18m_a3	Interaction between age 18 (and above), gender and age to the third power
age18m_a4	Interaction between age 18 (and above), gender and age to the fourth power
_cons	Constant term

Almost all the variables in the empirical model are transformations of the main variable and their interactions with other variables as well as binary forms of the resulting variables. In some instances it became necessary to transform the explanatory variable to the log scale to meet the behavioural properties of those variables and the statistical properties of the Generalised Linear Model (Poisson GLM) that was used in the analysis. For example the long-term trend of road fatalities was captured by (ln_year).

As the number of fatalities by age varied considerably over the 10 years, a number of variables were included to capture this variability and their interaction with the trend variables.

The model also contains a number of binary variables. These were included principally to capture the distinct deflection points in the age-specific distribution of fatalities.

This model is designed to find what would be an expected total amount of deaths in a year by considering data for several years. For example if total deaths had been decreasing by 2 per cent every year for 10 years and then suddenly increased by 1 per cent without a known explanation, the model would standardise the amount of all deaths so that the new year's total would be approximately 2 per cent less than the year before as the trend suggested.

The variable specification of the model also enables it to treat gender-specific standardisation in a similar way. There it controls randomness in the amount of males relative to females who are killed each year. This can also affect the total productivity losses, hence the average VOL.

As preliminary analysis suggested significant differences in the distribution of male and female fatalities, explanatory variables for gender and their interactions with age were included. The empirical model specified above was analysed using road fatality data for 10 years from 1995 to 2004.[2] The analysis was carried out using the generalised linear model programs in STATA *Version 9*.

4.1 Model results

The model explained over 65 per cent of the variability in data. It also performed well against a number of standard diagnostic tests and tests specific to Poison GLMs.

The explanatory variables used were all significant at the 0.05 per cent level of probability. Comparison of the chosen model with several alternative models that were tested showed that it faired better than the alternatives. The comparisons were done using the likelihood ratio tests and Akaike information criterion.

The estimated coefficients were reliable as suggested by their smaller standard errors. The Z values for all independent variables were significant at 1 per cent level of probability, indicating that the variables retained in the model are statistically significant. Tests for over-dispersion of predictability did not show significant over-dispersion of expected fatalities.

Table 4 shows the model results. The first column gives the names of the independent variable and in the second column are the values of the model coefficients. The statistics used for testing the viability of coefficients are in the remaining columns.

[2] Data for the 10 year period was from the road crash data published by the Australian Bureau of Transport Safety.

4.2 Forecasting ability of the model

Using data from ATSB (2007) for 2005 to 2007, the model's ability to forecast future fatalities was tested. The difference between the predicted and observed was about one per cent. To forecast the expected values from 2005 to 2007, the trend variable (see Table 2) was assigned values from 12 to 14, where 12 represented the year 2005.

Table 4 – Variables used in the regression model and the model results

Variable	*Coefficient*	*Standard Error*	*Z value*
male	0.6138	0.0452	13.5800
age	–0.0950	0.0149	–6.3700
age_3	0.0006	0.0001	10.1400
age18_m	–1370.9580	257.9439	–5.3100
age16	2149.9910	180.9397	11.8800
log_year	–0.0920	0.0105	–8.7400
age16_in_a	–6814.1050	576.6280	–11.8200
age16_ln_a	–1354.5800	113.1318	–11.9700
age16_sq_a	521.1346	43.2622	12.0500
age16_a2	–0.2582	0.0211	–12.2300
age16_a3	0.0017	0.0002	8.6300
age16_a4	0.0000	0.0000	–12.7400
age18m_in_a	4420.7390	832.2006	5.3100
age18m_ln_a	838.6638	158.9202	5.2800
age18m_sq_a	–314.3570	60.1038	–5.2300
age18m_a2	0.1428	0.0286	4.9900
age18m_a3	–0.0012	0.0002	–4.8200
age18m_a4	0.0000	0.0000	4.6500
_cons	1.2388	0.0763	16.2400

Source: BITRE

4.3 Using the estimated model for standardisation

The model coefficients shown in Table 2 of the preceding section was used with raw data for the nine years from 1996 to 2004 to estimate the expected number of male and female fatalities for those years. In the predictions, the time trend variable was given values ranging from 1 to 10, where 1 represented year 1995.

For purposes of modelling, this paper used data for 10 years from 1995 to 2004. As the model has a good forecasting ability (see Section 4.2) and if the downward trend in road crash fatalities continues, the model would be able to make efficient forecasts of expected fatality numbers for a number of future years.

Figure 3 shows the total observed and expected number of fatalities for the ten years by age. The gap between the observed and the expected fatality numbers show the variability that cannot be explained by the factors considered in the model.

Table 5 provides a comparison of the observed and expected fatalities by gender for each of the 10 years. It shows that the positive differences between the observed and expected for some years are offset by negative differences for the other years. On average, the positive and negative differences between the predicted or expected values were about 3.5 per cent. The difference for 1997 was the highest. In that year, the expected fatalities for males exceeded the observed by about 8 per cent.

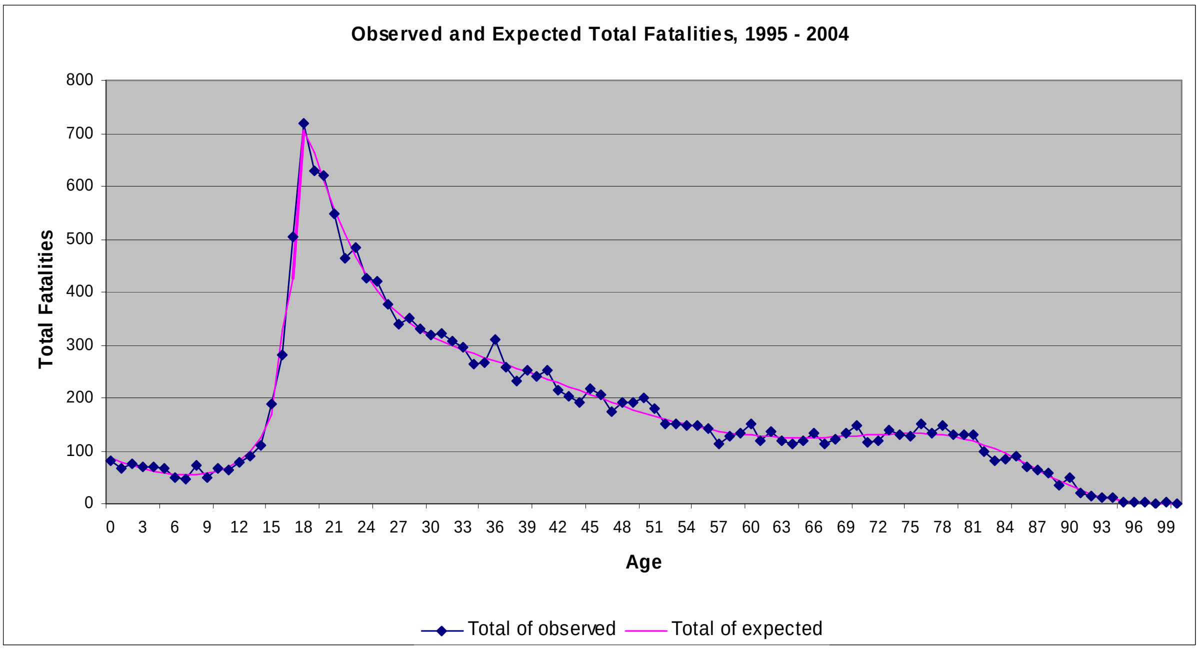


Figure 3 – Observed and expected total fatalities for the ten-year period 1995 – 2004

Table 5 – Comparison of expected and observed fatalities by gender, 1995 – 2004

	Male			*Female*			*Persons*		
Year	*Observed*	*Expected*	*Δ*	*Observed*	*Expected*	*Δ*	*Observed*	*Expected*	*Δ*
1995	1 411	1 436	-1.8%	602	593	+1.5%	2 013	2 029	-0.8%
1996	1 404	1 347	+4.0%	563	556	+1.2%	1 967	1 904	+3.2%
1997	1 198	1 298	-8.4%	558	536	+3.9%	1 756	1 834	-4.5%
1998	1 225	1 264	-3.2%	517	522	-1.0%	1 742	1 786	-2.5%
1999	1 209	1.239	-2.4%	546	511	+6.3%	1 755	1 750	+0.3%
2000	1 296	1 218	+6.0%	521	503	+3.5%	1 817	1 721	+5.3%
2001	1 265	1 201	+5.1%	471	496	-5.3%	1 736	1 697	2.3%
2002	1 243	1 186	+4.6%	470	490	-4.2%	1 713	1 676	+2.2%
2003	1 147	1 173	-2.3%	469	485	-3.3%	1 616	1 658	-2.6%
2004	1 127	1 162	-3.1%	455	480	-5.5%	1 582	1 642	-3.8%
All years	**12 525**	**12 525**	**0.0%**	**5 172**	**5 172**	**0.0%**	**17 697**	**17 697**	**0.0%**

Source: BITRE

5 Discussion of results

Empirical results for the four methods proposed in Section 3 are presented in this section.

5.1 Single period estimates

Fatality of a younger person results in a higher productivity loss than for an older person. Because of the differences in the average per capita incomes between genders, the productivity losses due to a male fatality would be higher than the losses for a female fatality of the same age.

As shown in Table 6, the number of young male fatalities decreased relative to fatalities in other ages. Consequently, the average age of male fatalities increased since 1996. Compared to males, the average age of female fatalities decreased over the years, while at the same time showing considerable decrease in the fatality numbers. Detailed analysis showed that the opposing and non-negating influences between the productivities of males and females were characteristic of any single year from 1996 to 2004.

Table 6, Figure 4 and Figure 5 show the overall influence of the opposing trends in the average age and fatality numbers on the productivity. For males the trend in productivity increased over the years, while it decreased for females.

Table 6 – Trends in the average age and the number of fatalities 1996 – 2004

Year	*Total male fatalities*	*Average age of male fatalities*	*Total female fatalities*	*Average age of female fatalities*
1996	1404	36.5	563	42.5
1998	1225	37.0	517	43.9
2000	1296	37.2	521	41.2
2002	1243	37.2	470	42.8
2004	1127	38.5	455	42.7

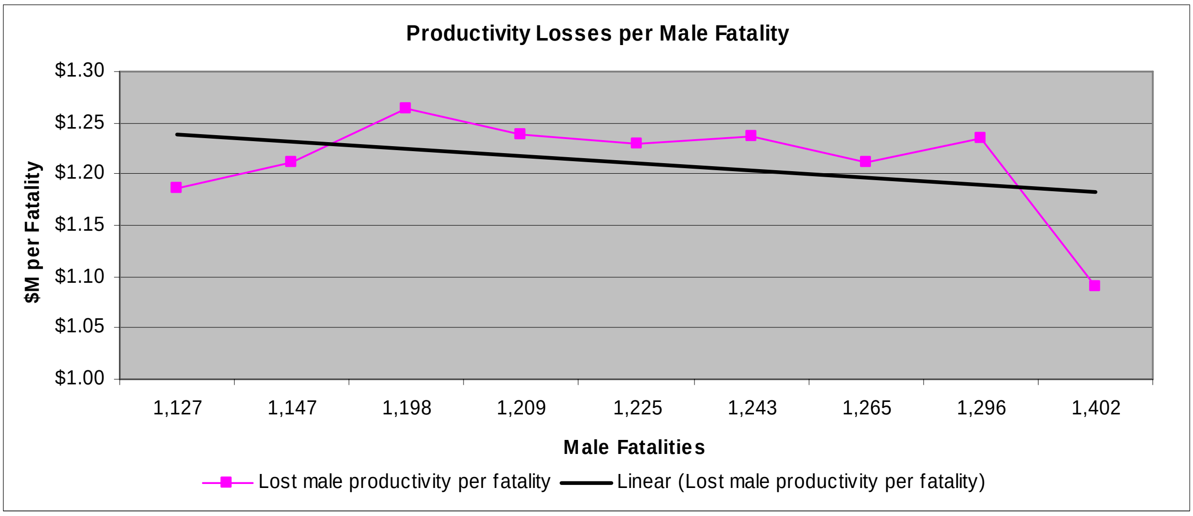


Figure 4 – Relationship of productivity loss per male fatality and the total male fatalities

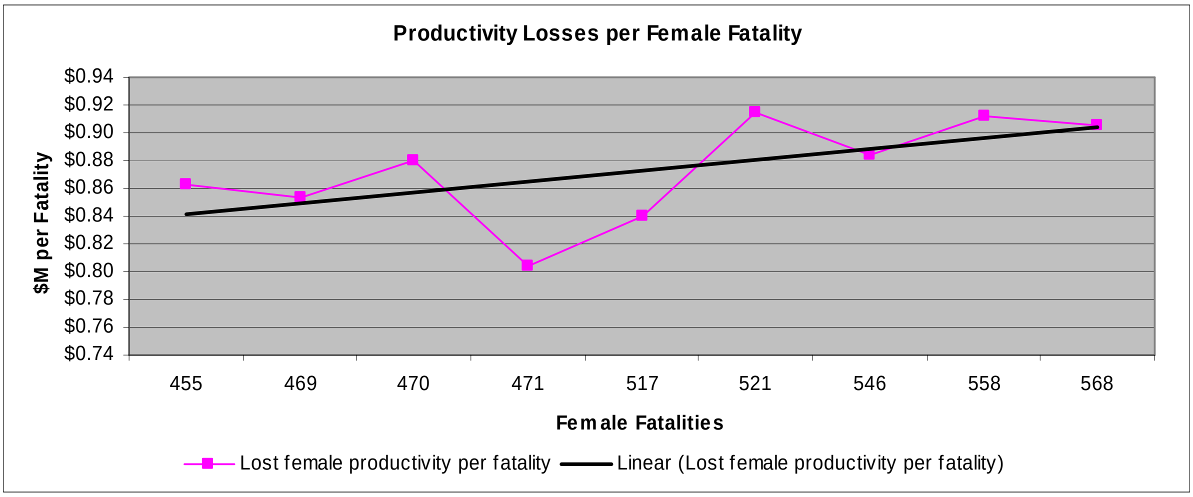


Figure 5 – Relationship of productivity loss per female fatality and the total female fatalities

These suggest that the main disadvantage of the single year/period estimates is that it is not representative of productivity losses of any past year, perhaps of any future year as well.

This anomaly could be rectified effectively by using age-specific fatality data for a number of years to calculate the weighted average of productivity, hence the VOL. Estimating weighted averages for males and females separately and combining those may improve the estimates.

5.2 Trend-based smoothing of fatalities

Trend-based estimates showed some improvement in the stability of the estimated VOL. The stability improved as the number of years that were combined to estimate the trend.

5.3 Weighted averaging

This method involves determining VOL weighted by the number of fatalities. As shown in last column of Table 7, the weighted averages of VOL calculated by expected values and the VOL for any year using that method are virtually the same. This is not true for methods involving a single year of data (see column 5).

Table 7 – Relationship between the number of fatalities and VOL estimates

Year	*Total male fatalities*	*Total female fatalities*	*Total fatalities*	*Value of life using observed fatalities*	*Value of life using expected fatalities*
1996	1,347	556	1,904	$1,483,179	$1,574,925
1997	1,298	536	1,834	$1,598,903	$1,574,917
1998	1,264	522	1,786	$1,560,834	$1,574,917
1999	1,239	511	1,750	$1,575,139	$1,574,917
2000	1,218	503	1,721	$1,589,304	$1,574,917
2001	1,201	496	1,697	$1,547,950	$1,574,917
2002	1,186	490	1,676	$1,585,631	$1,574,917
2003	1,173	485	1,658	$1,553,800	$1,574,917
2004	1,162	480	1,642	$1,539,685	$1,574,917
			Weighted average	**$1,558,666**	**$1,574,918**

Source: BITRE estimates based on ATSB data

Note: 1996 dollars

5.4 Expected probability approach

Probability based estimation of the human costs of road crashes enables us to recognise factors posing higher fatality risks (e.g. relationship between road fatality and age), to identify if any persistent trends are present and extract other useful information to implement measures to reduce those risks in the future. Such estimates can be regarded as more amenable to cost-benefit analysis of programs and projects aimed at improving safety.

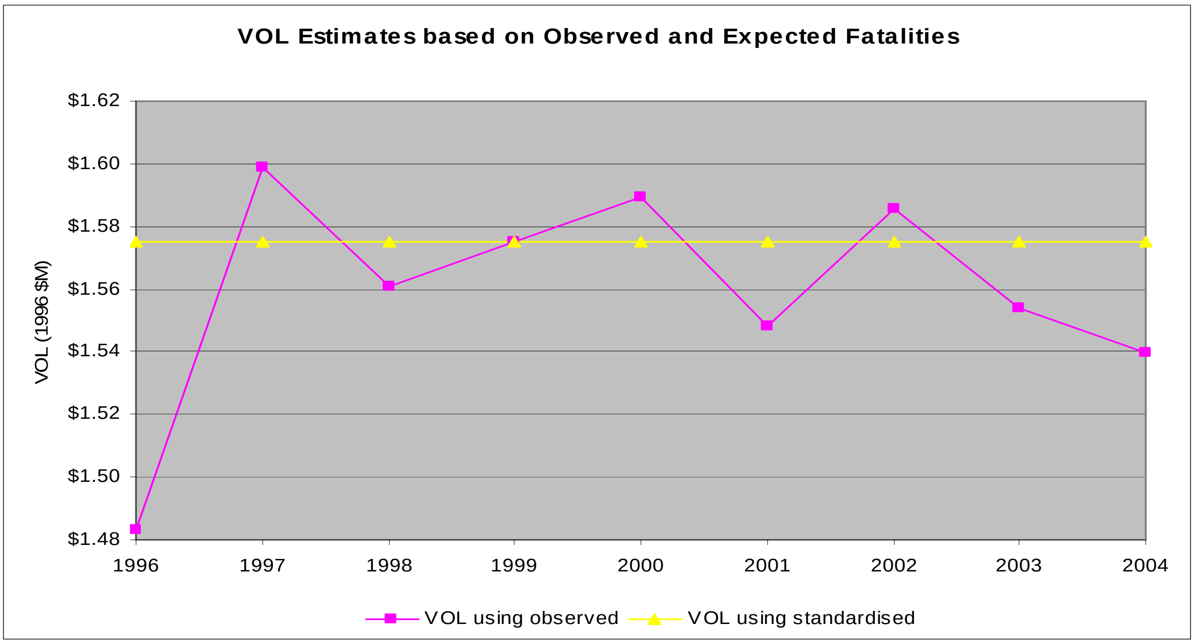


Figure 6 – Yearly differences in the Value of Life estimates using single period and expected value approaches

6 Concluding observations

The Bureau in its forthcoming 2008 publication of road crash costs will be using the human capital approach to value productivity and other losses due to premature death (VOL), but with considerable improvements as proposed in an earlier paper (see Risbey, de Silva and Tong, 2007). This paper discusses one of the improvements proposed there, that is the proposition to use data for a number of years, but in recognition of age groups with a relatively high probability of crash fatalities.

The Bureau in the 1990s estimated VOL using data for a single year. This paper shows that using a single year is not ideal, because the estimated VOL varies with the number of fatalities in a year. The year chosen by the Bureau in its previous estimate of road crash costs viz 1996 provided a lower VOL estimate than the corresponding values for any of the following years. This paper argues that methods that recognise probability of occurrence of fatalities at varying ages are better because those methods (a) recognise expected number of fatalities by age, hence reflect that explicitly in the VOL estimates and (b) that the VOL estimates are relatively more stable over the years than when other methods are used.

The analysis in this paper showed a relatively stable annual pattern in the determinants of human productivity losses. In particular, the average age of fatalities and the percentage of male and female fatalities showed stability over the years. Consequently, the values of life measured using a single year and that measured using the expected value approach differed marginally. Such a stable annual pattern in the human productivity losses is not common to most other transport modes. Therefore the expected value approach would have much higher potential benefits in those situations.

As noted in a recent publication on cost-benefit analysis, it is advisable to use expected values rather than arithmetic means[3] (DFA, 2006) in all instances where data for a reasonable time-series is available.

Using only the age and gender out of a host of variables that affect VOL, the paper discusses the strengths and weaknesses of the simple arithmetic averaging and expected value methods, and concludes that the latter approach has the ability to best inform policy.

Acknowledgements

The authors wish to thank Dr Mark Harvey of the Bureau of Infrastructure, Transport and Regional Economics for useful comments during the preparation of this paper.

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[3] The expected value of a set of observations differs from its arithmetic mean. The latter is calculated by adding all observations and dividing by the number of observations, "whereas the former is derived using the probability distribution" (Traub, 1994:p7) of those observations.