MACQUARIE UNIVERSITY
FACULTY OF BUSINESS AND ECONOMICS

Centre for Financial Risk

A matter of time – an analysis of decision making using estimates for the frequency and severity of bushfire risk

Thomas Longden, Supriya Mathew, Stefan Trück

Working Paper 15-01

The Centre for Financial Risk brings together Macquarie University's researchers on uncertainty in capital markets to investigate the nature and management of financial risks faced by institutions and households.

Research conducted by members of the centre straddles international and domestic issues relevant to all levels of the economy, including regulation, banking, insurance, superannuation and the wider corporate sector, along with utility and energy providers, governments and individuals.

The nature and management of financial risks across these diverse sectors are analysed and investigated by a team of leading researchers with expertise in economics, econometrics and innovative modelling approaches.

A matter of time – an analysis of decision making using estimates for the frequency and severity of bushfire risk

Thomas Longden[1], Supriya Mathew[2], Stefan Trück[1,#]

[1]Faculty of Business and Economics, Macquarie University
[2]Northern Institute, Charles Darwin University

Abstract

The term 'a matter of time' is often used for infrequent and severe extreme events, such as earthquakes or bushfires. Risk assessments of the likely damage associated with extreme events should focus on an appropriate time horizon that is consistent with the frequency of the event as a short term view may disproportionally deflate the risk involved. As there is often a lack of information at the local level on the frequency and/or severity of rare catastrophic or climate impacted hazards, this paper employs expert elicitation to derive distribution parameters for the frequency and severity of extreme events. Following this, the so-called loss distribution approach (LDA) in combination with discounting is used to produce present value estimates of cumulated losses. With a focus on the risk of bushfires in a local area in Sydney, Australia; this paper reviews how sensitive the cumulative loss estimates are to the time horizon used in the decision making process. The decision maker or analyst is assumed to be affiliated with a local government and has been assigned to conduct a risk assessment or cost benefit analysis. The importance of a suitable time horizon, understanding the consequences of risk-adjusted decisions and using an appropriate discount rate are also reviewed in the paper.

Keywords: Catastrophic Risks, Climate Impacted Hazards, Decision Making, Expert Opinions, Local Level, Loss Distribution Approach

---

[#]Corresponding Author: Stefan Trück, Address: Department of Applied Finance and Actuarial Studies, Faculty of Business and Economics, Macquarie University, North Ryde, NSW 2109.
Email: stefan.trueck@mq.edu.au, Ph: +61- 2 9850 8483.
This work was supported by funds from the National Climate Change Research Facility (NCCARF) through grant no. EM11 03.

1) Introduction

At the national level bushfires are a relatively common phenomenon with the annual probability of a non-zero property loss for Australia during the 20th Century falling between 48% and 57% (McAneney et al. 2009). In contrast, the Ku-ring-gai region and surrounding areas of Sydney, which includes areas that are subject to high bushfire risk, have had six major fires since 1976 with approximately 28 houses lost. In accordance, it has been estimated that there are usually one or two significant bushfires that impact the region every ten years (Ku-ring-gai Council 2012). Unsurprisingly, the regularity of bushfires at the national or regional level is not consistent with the frequency of severe events at the local level. Disaggregating data from a large region is likely to be inappropriate as the risk of bushfire tends to be location specific. And while historical observations on losses from bushfires do exist for the local region of Ku-ring-gai, the data is insufficient to build a distribution that can be used to forecast property losses over a given period. An alternative for estimating parameter values of distributions is to engage local experts to solicit their opinions (Schröter et al. 2005; Næss et al. 2006). With a focus on local decision making, this paper uses expert opinions to obtain values for distribution parameters that are used to provide estimates of property losses related to significant bushfire events.

In addition to providing these estimates, this paper will review important issues around the specification of costs that a local government decision maker needs to understand upon using these property loss estimates within a cost benefit analysis. These include: the importance of using an appropriate time horizon for the review of infrequent and severe extreme events, such as bushfires; assessing the impact of risk aversion on the assessment of probabilistic estimates of costs; and the importance of adaptation when considering an increase in the frequency of bushfires due to climatic change.

Extreme events are rare, however, over a long period of time decision makers will have to confront the possibility of extreme losses and this infers that performing risk assessment is important. In this study we prescribe an approach that uses expert elicitation for determining estimates of the frequency and severity of an extreme event. The procedure is based on the loss distribution approach (LDA) and results in inter-temporal probabilistic estimates of property losses. These estimates can then be used in decision making on issues around the management of bushfire risk and deciding whether to employ risk reduction techniques, such as, for example, controlled burning. Within this paper we assume that the decision maker conducting or evaluating the analysis is affiliated with a local government council, possibly as an analyst or elected official. The analysis focuses on developing estimates of the property losses from bushfires that can be used in a cost benefit analysis, once risk reduction measures have been identified. In this paper we will not perform a cost benefit analysis as the focus is on establishing estimates of the cost of bushfire damage.

Assessing the damage from extreme events over multiple periods of time introduces other parameters that are not related to the severity or frequency of events and whose appropriate value is a matter of uncertainty. This includes the discount rate and growth rate applied within the model. Another crucial component of the analysis is the time horizon that is applied. Upon discussing extreme events and discount rates, Ermoliev et al. 2008 raised the importance of assessing the appropriateness of the time horizon being reviewed within a cost benefit analysis. The authors focus upon the appropriate specification of the discount rate and the ‘stopping time horizon’ that the use of a discount rate implies. And while the stopping time horizon is an important factor within this paper, the discussion will also focus upon the appropriate 'starting time horizon' for an assessment of an infrequent, but highly damaging extreme event.

The analysis of the time dependency of risk assessments of extreme events is conducted, using a case study of bushfires in the Ku-ring-gai local government area in Sydney, Australia. Figure 1 presents the location of Ku-ring-gai in comparison to the surrounding Sydney area. Amongst other considerations, the Ku-ring-gai area has been chosen as the basis for the analysis as it has a high risk of bushfire due to the prevalence of 18,000 hectares of bushland and 89 kilometres of urban/bushland interface (Taplin et al. 2010). In addition, the area has 13,000 homes (equivalent to 36% of the total) with a high risk rating for property damage (Chen 2005). Consistent with Ku-ring-gai Council 2012, the expert who participated in the study specified that under current conditions, a severe bushfire is expected to happen approximately once every ten years, with only one in five of these fires damaging houses.

With bushfires expected to occur once every ten years, the appropriate starting time horizon is expected to be greater than ten years, and the effectiveness of extending a long term view past forty years is constrained by the stopping time horizon that is influenced by the discount rate applied. As a prelude to the results of the paper, we can note that upon applying a discount rate of 4%, moving from a ten year to a twenty year time horizon leads to a notably different present value estimate for property losses due to bushfires in Ku-ring-gai (i.e. an estimate that is inflated by 74%). In contrast, moving from fifty years to one hundred years results in a relatively moderate increase in the estimate for property losses due to bushfires in Ku-ring-gai (i.e. an estimate that is inflated by 24%). The disparity between these two examples highlights the importance of decision makers having an understanding of the concepts of a 'starting time horizon' and a 'stopping time horizon' when evaluating the appropriate time horizon for assessing an intertemporal stream of benefits or costs. We contend that a suitable time horizon for project assessment will be between the 'starting time horizon' and the 'stopping time horizon'. The actual number of years will be dependent upon the frequency of events, the project lifetime and the discount rate.

With a focus on the issue of time and bushfire risk, the remainder of the article is set up as follows. Section 2 reviews the framework used to specify the accumulated losses from bushfires for the Ku-ring-gai area. Section 3 presents the results of the empirical analysis. We start with a base case scenario and illustrate the issue of risk-adjusted analysis as reflected in differences between the mean estimate and the higher percentiles of the loss distribution. We also review the issue of how different discount rates will impact on the present value of accumulated losses and consider multiple scenarios where the time horizon is modified to replicate a change in a decision maker's outlook. With scenarios spanning from five years to one hundred years, the relevance of near sightedness is discussed with notable changes in the estimates occurring with a shift from a ten year to twenty year outlook. Finally, we review scenarios that assess how the impact of climate change increases the estimates of property losses. Section 4 concludes the paper with a discussion of the major insights gained from this study.

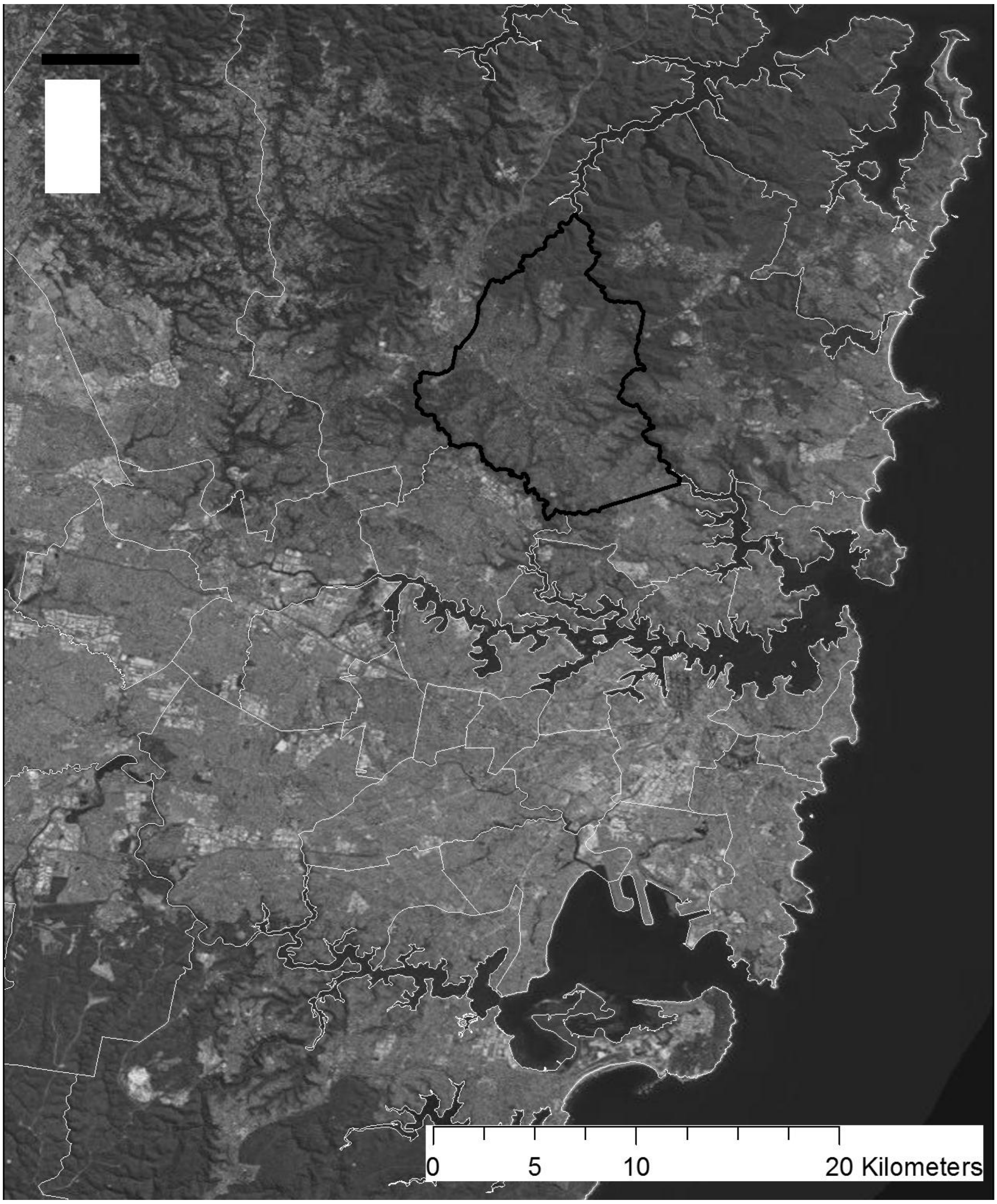

Figure 1: Location of Ku-ring-gai within Sydney (ABS 2011)

2) Modelling bushfire risk over time

In this section, we illustrate how a local decision maker or analyst can create an aggregate loss distribution for extreme events using the loss distribution approach (LDA), which has gained popularity in the financial sector for modelling insurance claims or losses arising from operational and credit risks within the banking industry (Klugman, et al. 1998; Basel Committee on Banking Supervision 2001). The LDA is a statistical approach that generates an aggregate loss distribution built upon underlying frequency and severity distributions. While the discussion in this paper will outline the core details of our model of bushfire risk, Keighley et al. 2014 provide a more detailed explanation that includes the derivation of key parameter values for a range of severity distributions. In the following, we focus on the most common approach for modelling the severity of extreme losses, the Lognormal distribution. We illustrate how to specify the loss distribution approach using the frequency and severity of events, describe the simulation of aggregate losses and extend the framework for use across multiple time periods.

2.1 The loss distribution approach (LDA)

Our model of bushfire risk uses the loss distribution approach (LDA) to generate an aggregate loss distribution for extreme events. In this framework, the cumulative loss *G* is defined as

$$G = \sum_{i=1}^{N} X_i \qquad (1)$$

where *N* is the number of events over a considered time period (usually one year) that is typically modelled as a random variable from a discrete distribution[2]. In addition, $X_i, i = 1,..., N$ denotes the severities of the events modelled as independent random variables from a continuous distribution. Note that in the LDA, the frequency distribution and severity distribution are assumed to be independent and as a result the distributions can be modelled separately. This becomes important in the empirical analysis, where we adjust the frequency and severity of bushfires in multiple ways to build a range of scenarios.

One advantage of the LDA over just using a point estimate of the expected catastrophic losses, is that the approach allows for a computation of the expected loss at any given confidence level α. Typically, Monte Carlo simulation is used to generate the aggregate loss distribution and compute the expected (or mean) loss or higher percentiles for the event over a given time horizon.

As the frequency of events is modelled by a Poisson distribution all that is required is an estimate of the parameter λ of the distribution, which is the expected number of events per year. For our empirical analysis, we assume that an expert will be able to provide an appropriate estimate for the expected number of events.[3] Usually expert elicitation is conducted using multiple experts; however, in cases where the focus is on the local level, it may be difficult to engage with more than one suitably qualified person. The expert specified that under current conditions, a severe bushfire is expected to happen approximately once every ten years such that the parameter of the Poisson distribution is estimated as $\lambda = 0.1$. In the Ku-ring-gai case study it has been possible to validate the expert's estimate for the frequency of bushfire using historical data. Nevertheless, we recommend that an analysis of the sensitivity of results to the central parameters should be conducted.

2.2 Estimating severity using quantiles

In addition to requesting that the expert provide an estimate of the frequency of an extreme event, the approach we utilise involves the elicitation of an estimate for the values of two

[2] Within this paper the annual frequency of the extreme event *N* is modelled using a Poisson probability distribution. Alternatives include, for example, the Binomial, Negative Binomial or Geometric distributions.
[3] While we focus on determining frequency and severity distributions from a single expert, refer to Shevchenko and Wüthrich 2006, Mathew et al. 2011 or Mathew et al. 2012 for applications of combining expert estimates with the empirically observed frequency of events using Bayesian analysis.

quantiles for the severity of the losses i.e. $P(X < x_1) = p_1$ and $P(X < x_2) = p_2$. These estimates are then used to calculate the parameters of the probability distribution. We suggest to use the median of the distribution, $p_1=0.5$, and a more extreme outcome for the distribution, the 95th percentile $p_2=0.95$, during the expert elicitation. As we are using a heavy tailed distribution for the severity of events, i.e. the lognormal distribution[4], it should be noted that the value for the 95th percentile will be as important as the value for the median as both of these values will be used to derive the parameters of the severity distribution.

Figure 2 presents a probability density function (PDF) for the Lognormal distribution, where the parameters $\mu = 3.40$ and $\sigma = 1.15$ were calculated based on the expert specifying (i) the median to be equal to 30, i.e. $P(X < 30) = 0.5$, and, (ii) the 95th percentile of the distribution to be equal to 200, i.e. $P(X < 200) = 0.95$. The black area between 0 and 30 to the left of the specified median illustrates that there is a 50% probability for the loss to be less than or equal to 30. On the other hand, the black area to the right of 200 is equal to 0.05, indicating that there is only a 5% probability of observing losses that are greater than 200. Figure 2 also illustrates that the mean of the distribution, *E(X)=58.37*, is clearly greater than the median which is indicative of the heavy-tailed nature of the Lognormal distribution.

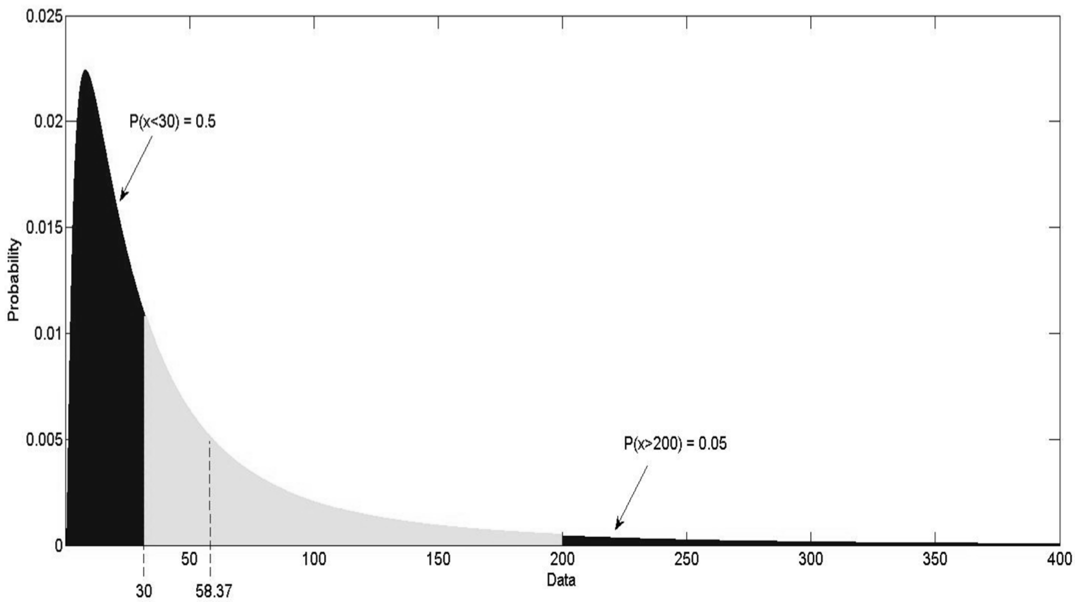

Figure 2: Probability density function (PDF) for a Lognormal distribution, with parameters $\mu = 3.40$ and $\sigma = 1.15$. The distribution exactly matches the conditions (i) P(X < 30) = 0.5, and, (ii) P(X < 200) = 0.95.

2.3 Simulation of Aggregate Losses

Having defined the specification of the frequency and severity distributions, this section outlines how these functions are combined into estimates for the aggregate losses, see, e.g., Klugman et al. 1998, for further details. With the utilisation of Monte Carlo simulation one can generate a compound loss distribution using a simple simulation algorithm with the following steps:

[4] For applications of other types of heavy tailed distributions refer to Keighley et al. 2014.

1. Take a random draw from the frequency distribution with the values defined as N events per year.
2. Take N random draws from the severity distribution with the values defined as simulated losses $X_1, X_2, \ldots, X_N$.
3. Sum the N simulated losses to obtain the simulated annual loss G.
4. Return to Step 1, and repeat the process k times. As a result the process produces $G_1, G_2, \ldots, G_k$ annual losses and this enables the derivation of a distribution of the aggregate losses. As noted in section 2.1, the value of k should be sufficiently high so as to build a robust distribution for analysis.

The accuracy of the estimation depends on the adequacy of the parameter estimates but also on the number of simulations in the Monte Carlo approach (k); refer to Fishman 1996 for an explanation. As a result, it is prudent to run a high number of simulations and we use 100,000 simulations during the computation of each separate scenario.

2.4 Considering long time horizons - discounting and the impact of climate change

To extend the analysis of the total loss across a number of years discounting needs to be employed to convert the future losses into present value estimates. The discounted present value of the cumulative loss (*DPVL)* over a considered time horizon T can then be calculated using simulated annual aggregate losses G_t (for $t=1,\ldots T$) as well as an applied growth rate g, and discount rate d, using the following formula:

$$DPVL = \sum_{t=1}^{T} \frac{G_t (1+g)^t}{(1+d)^t} \qquad (2)$$

The level of the discount rate d is important and will impact upon the results of this paper as it converts future values into present values. A higher rate reduces the influence of future values and this effect means that the discount rate has been referred to as a ‘killing rate’ (Haurie 2003: 122), refer to section 3.2 and 3.3 for further details. The growth rate g represents economic growth and can capture the rising costs for the replacement of property and/or infrastructure. It may also represent an increased exposure to risk or an increase in economic damage over the time horizon considered. For example, the increase in damage may be due to new properties being built in areas exposed to risk. In addition, the approach can be adapted to produce forecasts that take into account the change in frequency (through adjusting the parameter λ) and severity (through adjustment of the distribution for the losses X_i) of the extreme event due to climatic change.

3) Empirical Results

In the following section, we provide estimates of the total losses from bushfires in the Ku-ring-gai area for a range of time horizons. These estimates are based on the derived probability distributions for the number of houses destroyed for a range of scenarios that focus upon changes in the discount rate and the time horizon applied, as well as the incorporation of changes that are consistent with the impact of climate change. To calculate the total losses the following data has been used. The mean cost of reconstruction per house is 422,000 AUD. The current risk prone property value is approximated by the property construction cost, which is obtained by subtracting the average land value per property from the average property sale price. The regional land value is estimated by the NSW Valuer General (DOL 2009) and the regional average property sales price is obtained from Hatzvi and Otto 2008.

As mentioned in the introduction, the frequency of bushfires for the Ku-ring-gai area was specified by an expert to be λ=0.1. This corresponds to one fire every ten years. Due to the efforts of fire brigades and other existing resources, the expert clarified that the number of severe bushfires that would actually lead to property damage would be one out of five events, i.e. only 20% of the bushfires are associated with property loss. The expert also specified that total losses would not exceed 1000 properties even under a maximum loss scenario. This means that we needed to adjust the process prescribed in Section 2 so that the frequency of events (i.e. the Poisson distribution) interacts with an additional Bernoulli variable that accounts for the actual occurrence of lost houses per event. In addition, we have imposed a restriction so that the upper bound of losses is equal to 1000 properties. As mentioned in the discussion of Figure 2, the expert also specified that the median of the severity distribution be set to 30 houses, i.e. $P(X < 30) = 0.5$, and the 95^{th} percentile to 200 houses, i.e. $P(X < 200) = 0.95$.

In the following, we will examine loss scenarios and their relevance for the decision-making process. In particular we will compare mean and worst-case estimates of catastrophic losses and illustrate the sensitivity of the estimates to the applied discount rate, time horizon and to the impacts of climate change.

3.1 Mean losses versus Worst-Case Scenarios

Table 1 reviews a range of scenarios that have been developed to highlight the sensitivity of the results to key factors. We ground our analysis by comparing the simulated losses to a base-case scenario with a time horizon of 40 years and an applied discount rate of 4% that is also highlighted in Table 1. Considering mean estimates and higher percentiles of the loss distribution will be important as it provides the decision-maker with an idea about losses under a worst-case scenario. Typically risk management strategies in the financial and insurance industry are not based on the mean or expected loss, but rather on the unexpected loss, i.e. the 95^{th} or 99^{th} percentile of the loss distribution that is often referred to as the Value-at-Risk, see e.g. Jorion 2006. Clearly, decisions that also consider worst-case scenarios will be more consistent with the idea of risk aversion of a decision-maker. As we are dealing with extreme events, moving to the right-hand tail of the distribution results in significantly increased losses. The extent to which this occurs can be seen in a comparison of the mean and median for the base case scenario, 8.6 Million AUD and 1.43 Million AUD, respectively. The mean estimate accounts for the tails of the distribution and it is important to keep in mind that the applied Lognormal distribution is highly skewed to the right and will exhibit a heavy tail. As a result of the skewed shape of the distribution, the mean is also influenced by extreme values of the distribution and is significantly greater than the median. The level of risk aversion that is applied within the decision making process is an important factor that will impact on the evaluation of the same set of results. In accordance, it should be noted that a move away from evaluating the average loss estimate to the worst-case loss estimate is consistent with increases in the estimates of 350% for the 95^{th} percentile and over 900% for the 99^{th} percentile.

Table 1 – Simulated discounted present values (NPV) of the cumulative losses from bushfires for the Ku-ring-gai area in Millions of Australian Dollars ($M). Different scenarios for the applied time horizon (5, 10, 20, 40, 50 and 100 years) and for the discount rate (4%, 1.35%) are being considered. The base case scenario (40 year time horizon, 4% discount rate) is highlighted in bold.

Time Horizon (years)	Discount Rate	Mean	Percentiles				
			25	50	75	95	99
5	4%	1.69	0	0	0	8.70	39.14
	1.35%	1.81	0	0	0	9.03	41.92
10	4%	3.12	0	0	0	18.28	56.28
	1.35%	3.69	0	0	0	21.32	65.94
20	4%	5.42	0	0	3.68	28.74	72.16
	1.35%	7.19	0	0	5.04	38.24	96.48
40	**4%**	**8.60**	**0**	**1.43**	**9.42**	**38.83**	**87.42**
	1.35%	13.77	0	2.54	15.88	61.79	136.62
50	4%	9.58	0	2.71	11.13	40.83	89.54
	1.35%	16.87	0	5.38	20.84	70.65	146.87
100	4%	11.85	1.26	5.36	14.35	44.81	93.64
	1.35%	31.22	5.38	18.26	41.34	107.11	197.20

Upon discussing the percentile estimates, it should be noted that the 25th percentile estimate for the NPV of property damage in Millions of Australian Dollars ($M) is zero across all but one of the scenarios due to the low frequency of severe bushfire events (λ=0.1) and only one out of five of these events generating a loss of property. Given these specifications, we would expect to observe a severe bushfire in the Ku-ring-gai area on average approximately every ten years, however, 80% of these events would not damage any houses. Therefore, upon considering a 40 year time horizon, for a relatively high percentage of the simulation runs (i.e. more than 25%), there will be no losses during these 40 years, and this explains the 25th percentile of the cumulative loss distribution being equal to zero.

3.2 Discount rate

Discounting is important for analysing options that involve long-term time horizons. Dasgupta 2008 highlights the importance of discounting using an example based on a comparison of the impact of a 4.3% and a 1.4% discount rate for a 100 year time horizon. In this example, using the higher discount rate leads to a present-value estimate that is 17 times lower than that when the lower rate is applied. The choice of an appropriate discount rate is important as the results of an economic analysis will be sensitive to the value chosen. While the debate on the appropriate level of a discount rate remains beyond the likely local government focus on climate adaptation, an extended time horizon does mean that the sensitivity of different discount rates needs to be understood. The discount rate is an important factor and when there is not a clear agreement on the choice of the discount rate to be used in the analysis, sensitivity tests that include a variation of the discount rate will assist in the understanding of its effect on the final result and the level of risk exposure.

The derivation of the appropriate social discount rate depends upon the so-called elasticity of the marginal felicity[5], the time discount rate, and the growth rate of consumption applied. The rates used in the example provided by Dasgupta 2008 are based on the discount rates used by Stern 2006, i.e. 1.4%, and Nordhaus 2008, i.e. 4%. We follow a similar approach and consider a base-case discount rate of 4% and a significantly lower social discount rate of 1.35%[6]. The difference between the base case and the low discount rate scenario, i.e. the low rate from Garnaut 2008, is due to the elasticity of marginal felicity and growth rate of consumption assumed.

For the 40-year base case scenario, the low discount rate scenario is consistent with a 60% increase in the mean and 95th percentile estimates and significantly raises the expected loss from 8.60 Million AUD to 13.77 Million AUD. Table 1 also illustrates that the impact of using a lower discount rate becomes far more significant when longer time horizons are examined. Scenarios considered include a shorter decision making horizon of 5 years, 10 years and 20 years, in comparison to the 40 years used in the base case. A longer decision making horizon of 50 years and 100 years are also included.

For a 10-year time horizon, moving from the base-case to the lower social discount rate increases the mean loss estimate by only 18%, for a 20-year time horizon, the estimated mean loss is increased by approximately 33% and for a 100-year time horizon the difference in the estimated mean loss is greater than 160%. Therefore, a decision-maker has to be aware of the fact that the longer the time-horizon considered in the analysis, the more significant will be the impact of the chosen discount rate on the results.

3.3 Time dimension

In the following we will further examine the importance of the applied time-horizon for the decision-making process. Across these scenarios the accumulated losses differ greatly due to the frequency of bushfires and the regularity of damage that was specified by the expert. The prevalence of zero losses reflects this with a 5 year and 10 year time horizon having zero losses for all of the percentiles reported, except for the 95th and 99th estimates. As a result, due to the tail of the distribution the mean estimate of losses for the 5 year and 10 year scenario are non-zero and numerically significant at 1.50 Million AUD and 3.12 Million AUD, respectively (for a 4% discount rate).

Figure 3 reviews additional time horizon scenario results using the two levels of discount rates and a higher incidence of damage (HID) to provide comparative examples. In terms of changing the time dimension of the analysis, the largest change (in terms of projected cumulative losses) occurs for shorter time horizons, i.e. with a move from, e.g., a five year outlook to a ten year outlook or a ten year to a 20 year time horizon. This holds regardless of the level of risk considered with both the mean estimate and the 95th percentile estimate showing far more significant relative increases for shorter time horizons. Moving from a

[5] The elasticity of marginal felicity has been defined in Dasgupta 2008 as “the elasticity of the social weight that ought to be awarded to a small increase in an individual’s consumption level”. (Dasgupta, 2008: 144)
[6] For a more detailed description on the derivation of these rates we refer to Garnaut 2008, IPCC 2014 and Keighley et al. 2014.

five year to a ten year outlook will inflate the mean loss estimate by 85%, moving from a ten year to a 20 year outlook increases the estimate by 74%, while moving from a 40 to a 50 year outlook only increases the estimate by approximately 11%. Even increasing the considered time horizon from a 50 to a 100 year window will only increase the estimated mean loss by 24%. These results show that the effect of gaining a longer term view is quelled as the number of years increases and that there is greater sensitivity in the more immediate time period. Of course, the reduction over time is mainly an effect of discounting future losses to report the cumulative loss in present value figures.

The quelled impact of moving to a greater outlook, i.e. moving from five years to ten years in comparison to moving from ten years to twenty years, reduces when a lower discount rate is applied. The impact of discounting can be seen with a comparison of the 4% and 1.35% scenarios as the cumulative losses in the base case flattens and plateaus after 30 to 40 years. This shows that with a discount rate of 4%, the time horizon for decision making matters and that moving from a short time horizon to a time horizon of ten to twenty years emphasises the risk of an extreme event that is infrequent, but highly damaging. In addition, there is a moderate impact of gaining a longer term view once the discount rate becomes a factor. As noted previously, this is reflected in the example of moving from five years to ten years (i.e. an increase of 84%) in comparison to moving from ten years to twenty years (i.e. an increase of 74%) and can be reviewed graphically in Figure 3. With a notable discount rate applied, extending a decision makers outlook to forty years in comparison to twenty years (i.e. an increase of 59%) or to one hundred years in comparison to fifty years (i.e. an increase of 24%) results in smaller increases in losses from extreme events.

Upon reviewing different time horizons, Haurie 2003 define the discount rate as a 'killing rate' and note that a discount rate of 5% corresponds to "a random life duration with (an) expected value (of) 1/0.05 = 20 years" (Haurie 2003: 122). This killing rate implies that the life expectancy of an infinitely living agent is equal to 1 + 1/r years. Upon discussing the strong impact of discounting on cost benefit analysis associated with climate change Ermoliev et al. 2008 refer to the same concept as the 'stopping time horizon'. Another example used in Ermoliev et al. 2008 is that of society's assessment of the risks related to a 300-year flood and this raises the issue of the appropriateness of market interest rates to extremely infrequent events. With a discount rate of 4%, the killing rate implies a life value of 25 years. In contrast, a discount rate of 1.35% has a life value of 74 years. These life values are suitable for the assessment of bushfire risk in Ku-ring-gai as the expert stated that bushfires are likely to occur once every ten years. In accordance, the evaluation of the extent of bushfire risk will depend upon the discount rate applied and the time horizon focused upon, as well as the frequency and severity of extreme events.

The influence of a 'starting time horizon' and a 'stopping time horizon' upon estimates of the impact of extreme events means that decision makers need to understand these factors when quantifying the potential benefits of risk reduction measures in a cost benefit analysis. The assessment of whether to take action or to do nothing in response to the risk of an extreme event will depend upon the appropriateness of the time horizon to the frequency of the events and the discounting of future costs/benefits of an adaptation measure. It should be noted that this paper focuses upon an analysis of the costs of bushfires within a risk assessment; however a decision maker will generally need to also assess alternative risk reduction measures using cost benefit analysis. The analysis of potential risk abatement measures will be left for future research as the approach used in this paper has the potential to be modified to incorporate risk reductions associated with adaptation measures. Nevertheless, it should be noted that Ku-ring-gai Council have reviewed risk abatement measures, such as establishing new community fire units, provide rebates for fire resilient installations in homes and constructing new fire trails (Ku-ring-gai Council 2010).

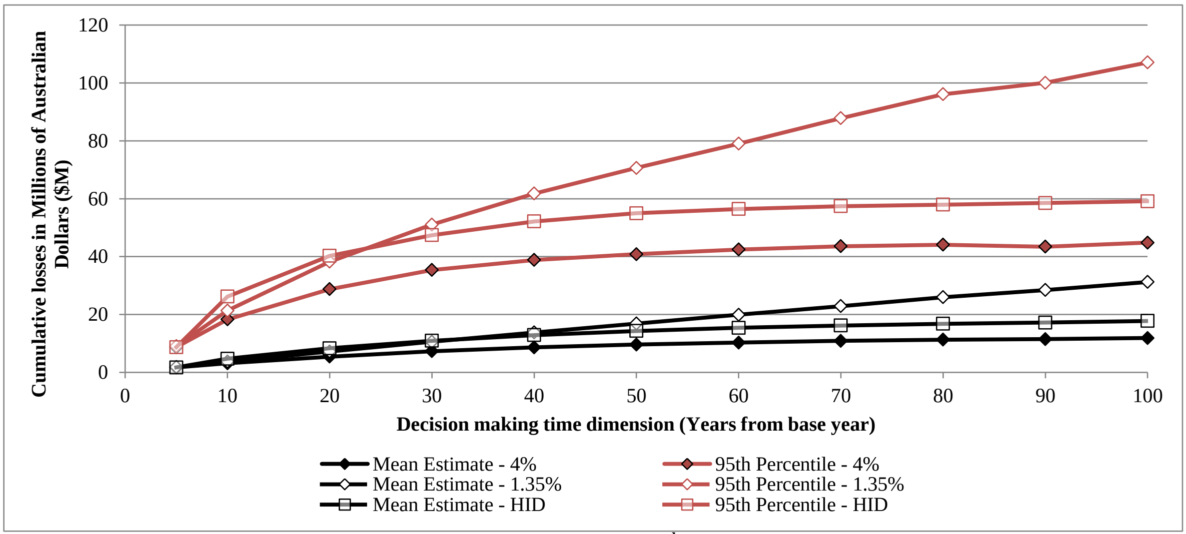

Figure 3: Cumulative mean loss estimate and 95th percentile of estimated losses across different decision making time horizons (from five years up to 100 years) and different discount rates of 4% and 1.35%.

3.4 Climate change impacts

Table 2 reviews scenarios that capture changes in the estimates due to the impact of climate change. Lucas et al. 2007 propose that climate change can impact the occurrence of fires in two ways; the first is an exacerbation of the fire-weather risk for any given day that leads to increased frequency or intensity of extreme fire weather days. This is captured within this analysis by a change in the frequency of fires over a 40 year time horizon in the ‘climate change with adaptation’ scenario. Hennessy et al. 2006 note that for southeast Australia the frequency of very high and extreme fire danger days is expected to rise 15 to 70% by 2050. As a result our scenarios include a moderate increase in frequency (i.e. an increase of 30%) and a strong increase in frequency (i.e. an increase of 100%) over the 40 year time horizon considered. An increase in the accumulated fire risk over a year may also occur due to a longer fire season and a reduction in the number of days suitable for controlled burning. This is captured in a second set of scenarios that have a change in the frequency of fires, but also assumes that changes in weather cause an immediate reduction in controlled burning and this is captured in the median estimate of property losses rising from 30 to 40 houses.

With adaptation (or no change in the amount of controlled burning) the impact of climate change results in an increase of the mean estimate by 12% or 38%, in comparison to the base case, depending upon the intensity of the change in the frequency of bushfire events. With a decrease in the amount of controlled burning, the scenarios show an increase in the mean estimate of 24% or 55%, in comparison to the base case, respectively. Increases in the extremes of the distribution are more moderate, but in the order of millions of dollars. Nevertheless, reviewing the worst case scenarios, as presented in the 95th percentile estimates, results in costs that are around four times the size of the mean. The decrease in the amount of controlled burning, modelled as an increase in the median to 40 properties lost, increases the average loss by approximately 11-12%. The importance of adaptation is reflected in this result and the long-life time of greenhouse gases implies that it is only a matter of time until local government decision making will need to manage risks related to climate change.

Table 2 – Simulated discounted present values (NPV) of the cumulative losses from bushfires for the Ku-ring-gai area in Millions of Australian Dollars ($M). The climate change impact scenarios assume a linear increase in the frequency of bushfires. The strong scenario increases the frequency from $\lambda=0.1$ in year 0, to $\lambda=0.1025$ in year 1,…., $\lambda=0.2$ in year 40, i.e. an increase by 100% over the considered time horizon. The moderate scenario increases the frequency by 30% over the considered time horizon, i.e. to $\lambda=0.13$ in year 40. The second set of climate change scenarios assumes that on top of an increase in the frequency, bushfires become more severe such that the median estimate for property losses increases from 30 to 40.

Scenario	**Increase Lambda**	**Severity Increase**	**Disc Rate**	**Mean**	**Percentiles**				
					25	**50**	**75**	**95**	**99**
Base	-	-	4%	8.60	0	1.43	9.42	38.83	87.42
Moderate Frequency	30%	-	4%	9.62	0	2.34	11.07	42.27	92.59
Strong Frequency	100%	-	4%	11.89	0	4.46	14.67	48.12	99.37
Moderate Frequency & Severity	30%	33%	4%	10.70	0	3.51	13.84	44.58	86.71
Strong Frequency & Severity	100%	33%	4%	13.32	0	6.16	17.88	50.78	94.56

4) Conclusion

Local decision makers are faced with extreme events that are often hard to assess using the available historical data. As a result, this paper reviews a methodology that utilises the loss distribution approach and expert opinion to estimate the frequency and severity of bushfires to produce present value cumulated loss estimates for property losses. Such an analysis is important for performing risk assessments at a level that is suitable for a local government jurisdiction, such as Ku-ring-gai in Sydney, Australia. Upon using this methodology, decision makers need to be aware of key factors that influence the cost estimates. These include the importance of a suitable time horizon that accounts for the infrequency of extreme events and the impact of discounting. As the methodology produces probabilistic estimates, the implications of a risk-adjusted analysis and reviewing the worst case scenario was also discussed.

For a forty year period, the mean and median estimate of the present value of cumulative losses in Ku-ring-gai is 8.6 Million AUD and 1.43 Million AUD, respectively. As we have used a heavy tailed distribution for the severity of the events, i.e. a lognormal distribution, the mean estimate is notably larger than the median due to the extreme of the tail. This is reflected in the worst case scenario estimate, defined as the 95th percentile, which has a present value of cumulative loss of 38.83 Million AUD. The large difference between the expected loss and higher percentiles of the loss distribution play an increasing role when decisions-making is not based on the most likely outcome only, but takes a more risk-adjusted angle.

The interaction of discounting and the time horizon used for planning leads to notable changes in the estimates from the scenarios. Risk assessment using a short time period, such as five or ten years, corresponds with low estimates of the present value of cumulative losses due to the infrequency of extreme events. Moving from a five year to a ten year outlook provides the largest increase in the loss estimates for all of the time horizons reviewed irrespective of the level of risk aversion or the discount rate applied, since the effect of discounting is the smallest for such short time horizons. Also, a decision-maker has to be aware of the fact that the longer the time-horizon considered in the analysis, the more significant will be the impact of the chosen discount rate on the results. For example, in the case of a short time horizon, moving from a 4% to a lower social discount rate (1.35%) only marginally increases the loss estimates, while for a 100-year time horizon the estimated losses are more than doubled when a social discount rate is being applied.

As noted in this paper, this implies that there is a ‘starting time horizon’ for the assessment of infrequent and severe extreme events that should be considered when choosing a time horizon to focus upon. The suitability of the time horizon should be assessed with respect to both the short term and the long term. For example, the impact of the discount rate means that there is a ‘stopping time horizon’ where moving from an adequately long time horizon results in relative minor differences in the results of an intertemporal analysis.

An assessment of the potential impact of climate change is also conducted within this paper by modifying the frequency and/or the median estimate of the severity of bushfires. The moderate scenarios for increased bushfire risk due to climatic change reviewed in our analysis are consistent with a 12% or 24% increase in the mean estimate of cumulative losses, depending upon whether adaptation has occurred. It is important to note that the analysis within this paper is based on a risk assessment of the damage of bushfires and does not extend to incorporating the costs or net benefits of adaptation or risk reduction measures. Nevertheless, our results show that the assessment of adaptation measures will matter when reviewing the consequences of climate change impacts upon the risk of property losses from bushfires.

References

ABS 2011, ‘Australian Standard Geographical Classification (ASGC) Digital Boundaries, Australia 2011’ (cat. no. 1259.0.30.001), Australian Bureau of Statistics.

Basel Committee on Banking Supervision 2001, *Consultative document: operational risk*, Bank for International Settlements, viewed 29 January 2015, <https://www.bis.org/publ/bcbsca07.pdf>.

Chen, K 2005, ‘Counting bushfire-prone addresses in the greater Sydney region’ in *Symposium on planning for natural hazards–how can we mitigate the impacts*. University of Wollongong.

Dasgupta, P 2008, 'Discounting climate change', *Journal of Risk and Uncertainty*, vol. 37, no. 2-3, pp. 141-69.

Department of Land 2009, *Land values issued for Ku-ring-gai*, Office of the New South Wales Valuer General.

Ermoliev, Y, Ermolieva, T, Fischer, G, Makowski, M, Nilsson, S & Obersteiner, M 2008 ‘Discounting, catastrophic risks management and vulnerability modeling’, *Mathematics and Computers in Simulation*, vol. 79, pp. 917-924.

Ermoliev, Y, Ermolieva, T, Fischer, G, Makowski, M, Nilsson, S & Obersteiner, M 2008, 'Discounting, catastrophic risks management and vulnerability modeling', *Mathematics and Computers in Simulation*, vol. 79, no. 4, pp. 917-24.

Fishman, G. 1996, *Monte Carlo: concepts, algorithms and applications*, Springer Series in Operations Research, Springer, New York.

Garnaut, R 2008, *The Garnaut climate change review: final report*, Cambridge University Press, Port Melbourne, VIC.

Hatzvi, E & Otto, G 2008, 'Prices, Rents and Rational Speculative Bubbles in the Sydney Housing Market', *Economic Record*, vol. 84, no. 267, pp. 405-20.

Haurie, A 2003, 'Integrated assessment modeling for global climate change: an infinite horizon optimization viewpoint', Environmental Modeling & Assessment, vol. 8, no. 3, pp. 117-32.

Hennessy, K J, Lucas, C, Nicholls, N, Bathols, J M, Suppiah, R & Ricketts, J H 2005, *Climate change impacts on fire-weather in south-east Australia*, Commonwealth Scientific and Industrial Research Organisation (‘CSIRO’), Australia.

IPCC 2014, ‘Social, Economic and Ethical Concepts and Methods’, in *Climate Change 2014: Mitigation of Climate Change,* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jorion, P 2006, *Value at Risk*, McGraw-Hill, 3rd Edition.

Keighley, T, Longden, T, Mathew, S & Trück, S 2014, ‘Quantifying catastrophic and climate impacted hazards based on local expert opinions’, *FEEM Working Paper*, No. 093.2014.

Klugman, S, Panjer, H & Willmot, G 1998, *Loss Models: From Data to Decisions*, John Wiley, New York.

Ku-ring-gai Council 2010, *Climate Change Adaptation Strategy*, Ku-ring-gai Council, Sydney, Australia.

Ku-ring-gai Council 2012, *Managing Bushfire Risk, Now and into the Future: Ku-ring-gai Principal LEP Background Study*, Ku-ring-gai Council, Sydney, Australia.

Lucas, C, Hennessy, K, Mills, G & Bathols, J 2007, *Bushfire Weather in Southeast Australia: Recent Trends and Projected Climate Change Impacts*, Bushfire Cooperative Research Centre.

Mathew S, Henderson-Sellers, A & Taplin R 2011, ‘Prioritising climatic change adaptation investment at local government levels’ in Leal, W. (Ed.) *Social, Economic and Political Elements of Climate Change*, Springer, pp. 733-751.

Mathew, S, Truck, S & Henderson-Sellers, A 2012, 'Kochi, India case study of climate adaptation to floods: Ranking local government investment options', *Global Environmental Change*, vol. 22, no. 1, pp. 308-19.

McAneney, J, Chen, K, & Pitman, A 2009, ‘100-years of Australian bushfire property losses: Is the risk significant and is it increasing?’, *Journal of Environmental Management*, vol. 90, no. 8, pp. 2819-2822.

Naess, LO, Norland, IT, Lafferty, WM & Aall, C 2006, 'Data and processes linking vulnerability assessment to adaptation decision-making on climate change in Norway', *Global Environmental Change*, vol. 16, no. 2, pp. 221-33.

Nordhaus, W D 2008, *A Question of Balance: Economic Modeling of Global Warming*, Yale University Press, New Haven, CT.

Schröter, D, Polsky, C & Patt, AG 2005, 'Assessing vulnerabilities to the effects of global change: an eight step approach', *Mitigation and Adaptation Strategies for Global Change*, vol. 10, no. 4, pp. 573-95.

Shevchenko, PV & Wuthrich, MV 2006, 'The structural modelling of operational risk via Bayesian inference: Combining loss data with expert opinions', *The Journal of Operational Risk*, vol. 1, no. 3, pp. 3-26.

Stern, N 2007, *The economics of climate change: the Stern review*, Cambridge University press.

Taplin, R, Henderson-Sellers, A, Trück, S, Mathew, S, Weng, H, Street, M, Bradford, W, Scott, J, Davies, P & Hayward, L 2010, *Economic evaluation of climate change adaptation strategies for local government: Ku-ring-gai Council case study*, Ku-ring-gai Council, Sydney, Australia.