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It's not now or never: Implications of Investment Timing and Risk Aversion on Climate Adaptation to Extreme Events

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Abstract

Public investment into risk reduction infrastructure plays an important role in facilitating adaptation to climate impacted hazards and natural disasters. Evaluating risk reduction projects is a challenging exercise, complicated by the long life of the investment projects, the need to consider the impacts of climate change, and the difficulty of quantifying the risk at the local level. We propose an economic framework that allows to incorporate the value of investment deferral flexibility and insurance market risk preferences, when evaluating climate-related adaptation investments. The model is applied to a case study of managing the risks from bushfires. We find that optimal timing of the investment may significantly increase the net present value (NPV) of an adaptation project in comparison to immediate investment, while risk preferences also have an impact on the NPV. The optimal waiting time increases for lower levels of risk aversion, higher investment costs and higher discount rates, while assumptions about more serious climatic change will typically reduce the deferral of the investment.

Keywords: Climate change adaptation, Investment timing, Catastrophic risk, Risk aversion, Real option

1. Introduction

A major concern with global warming is that the climate system may become more energetic and the frequency and severity of catastrophic events may increase in the years

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to come. The rising number of natural disasters during the last two decades has put governments under increasing pressure to implement policies and investment projects to facilitate climate change mitigation and adaptation (Hochrainer-Stigler et al., 2014; Van Aalst, 2006). Mitigation requires time to yield impacts since greenhouse gases have long life and the global climate system takes time to cool down once being heated. The global temperature is going to increase before stabilizing, even if emission is substantially reduced (Solomon, 2007). Therefore, the risks related to catastrophic events are expected to increase regardless of existing and potential additional mitigation efforts, making climate adaptation an essential task.

Australia is well-known for bushfire, storm surge and flood disasters. Several studies suggested that these events would become more frequent in many regions of Australia and more attention should be paid to adaptation measures (Garnaut, 2011; Murphy and Timbal, 2008; Antón et al., 2013). Climate adaptation requires input from all levels of government and could be one of the most challenging tasks in environmental management. While it has often been argued that action is most effective at the local level, local government is confronted with the complex and difficult task of planning and implementing mitigation and adaptation actions within existing budget constraints. This requires an economic framework to evaluate potential climate adaptation options to facilitate decision making.

Although climate adaptation is required for many sectors and in many cases involves expensive investments, see e.g., Felgenhauer and Webster (2013), there are few empirical studies conducting cost benefit analysis for catastrophic risk reduction projects. Studies that evaluate catastrophic risk reduction projects include Kirshen et al. (2008a,b); Michael (2007); Symes et al. (2009); West et al. (2001) who examine storm surge risk in coastal areas and Brouwer and van Ek (2004); Waters et al. (2003); Zhu et al. (2007); Bouwer et al. (2010); Mathew et al. (2012) who examine flood risk in riverine regions. In these studies, except for Michael (2007), it is assumed that the benefits of a risk reduction project are equal to the expected avoided losses. This assumption holds when the potential losses are insured and the insurance premium is actuarially fair. However, in practice, it is often found that full insurace uptake is rare (Kunreuther, 1996) and insurance premiums in laissez-faire markets may not be actuarially fair, especially for extreme events. Insurers may charge unfairly high premiums when the risk cannot be accurately estimated, for example due to the uncertain impacts of climate change, to reduce their insolvency risk, or when risks are highly correlated (Kunreuther and Michel-Kerjan, 2007). Correlated risks require additional capital for insurers to protect themselves against large losses. Further, when spatially correlated losses occur, they may drain the capital of the insurance industry and put insurance firms under financial distress. Insurers may therefore require an additional premium to bear the risk of financial distress (Cummins and Trainar, 2009; Froot, 2007). Assuming risk neutrality when evaluating adaptation projects is likely to result in an underestimation of the project benefits.

Michael (2007) is the first study that estimates the cost of increased flood damage from storm surges under climate change based on insurance premiums. Flood damage in the study region depends on the elevation of properties and insurance premiums are determined based on properties' elevation. Under climate change, sea level rise reduces the elevation of all properties in a coastal region and increases insurance premiums accordingly. The cost of increased flood damage is found by aggregating additional discounted premiums required in future years. The method is argued to provide more reliable estimates of flood cost due to the detailed and accurate scheme of an insurance rate applied at the local level. Note that by using the current insurance rate scheme for future years, Michael (2007) assumes that the frequency and intensity of storms in future years do not change. Such an assumption is not required for the method we propose in this paper.

In addition to the risk neutrality assumption, most studies (with the exception of West et al. (2001) and Zhu et al. (2007)) use the NPV rule to determine the investment decision: a project is invested if its NPV is positive. However, investing (now) when the NPV is positive is not optimal if investing in a future time provides an even higher NPV. This occurs when the NPV of the project is increasing in investment time (see e.g. Firoozi and Merrifield (2003)), what may often be the case for projects that deal with risk reduction of climate impacted hazards. Annual benefits of such a project typically increase over time due to increasing catastrophic risk or growing potential losses, while annual costs such as interest expenses on the investment cost or project maintenance costs remain rather constant. Deferring (instantaneous) investment to a future period may then help to avoid the initial years' negative impact on the NPV, when annual benefits of the project are lower than the occurred costs. Overall, in such a situation a deferral of the investment would be expected to increase the NPV of the project. Therefore, in order to obtain the optimal investment decision, one also needs to determine the investment time that gives the highest NPV of a project.

West et al. (2001) and Zhu et al. (2007) departed from the NPV rule to examine the optimal time to invest. In Zhu et al. (2007), simulation techniques are used to compute the expected avoided losses. Time series of future climate variables for the studied region are simulated from a climate model, which are then used as inputs to a vulnerability model to generate losses. In contrast, West et al. (2001) derives the expected avoided losses using a statistic model called the Loss Distribution Approach (LDA)[1]. The simulation approach used in Zhu et al. (2007) is computationally intensive due to the time required to run complex climate simulation models and vulnerability models. The LDA, on the other hand, is tractable and can give rise to an analytical solution to the investment problem. In practice, the two approaches can be combined, with simulation results being used to estimate the parameters of the LDA, as suggested in our approach.

In this paper, we propose a general economic framework to determine optimal adaptation decisions at the local level. Different from previous studies, we evaluate the investment benefits based on optimal timing of the investment as well as the risk preference of representative agents in the insurance market. Our model is developed in a continuous time framework and provides a simple formula to determine the optimal time for adaptation investment. Using a case study of bushfire risk management, we illustrate that investing at the optimal time, determined by the model, has the potential to significantly increase the net present value (NPV) of the project, even though the project provides a positive NPV if invested immediately. Risk preference also has an important impact on the NPV of the project, but tends to be less important in comparison to the impact of investment

[1]The Loss Distribution Approach is a term commonly used in insurance analysis, see e.g. Klugman et al. (2008); Shevchenko and Wüthrich (2006). In this paper, it is used to refer to catastrophic risk modelling.

timing. Factors that significantly influence investment decisions and outcomes include climatic change scenarios, risk preferences, investment costs and the applied discount rate. We find that a more serious scenario of climate change and higher risk aversion increase the NPV of the project for any investment time and will reduce the optimal waiting time. The value added by the investment model compared to a simple NPV rule, i.e. invest immediately if the project provides a positive NPV, is lowered in these cases. In contrast, higher investment costs and higher discount rates increase the optimal waiting time and raise the value added by the investment model.

The remainder of the paper is organized as follows. Section 2 outlines and analyzes the developed modeling framework. Section 3 provides an application of the framework in a case study, using catastrophic risks from bushfires as an empirical example. The section also examines the impacts of optimal investment timing, risk preferences, investment costs and the applied discount rate on the results. Section 4 concludes and gives suggestions for future work.

2. Modeling framework

We adapt the standard LDA to quantify potential losses from extreme events and apply the Bühlmann (1980) framework to convert a loss distribution into insurance premiums. Then, a dynamic investment model is constructed to determine the optimal investment time.

2.1. Frequency and Severity of Climate Impacted Hazards

The LDA is commonly used to model catastrophic losses in the insurance and banking sector as well as losses arising from operational risks, see e.g. Klugman et al. (2008); Shevchenko and Wüthrich (2006). There are also a few applications of the framework to modeling losses related to natural or climate impacted hazards such as, e.g. storms, earthquakes and flooding (West et al., 2001; Härdle and López Cabrera, 2010; Mathew et al., 2012). With this approach, the total loss over a period $(0, t]$ is modeled as a compound Poisson process:

$$S_t = \sum_{n=1}^{N(t)} X_n, \tag{2.1}$$

where $N(t)$ is the number of catastrophic events occurring from time 0 up to time t, X_n is the loss caused by the n^{th} event. In this standard model, $N(t)$ is assumed to follow a homogeneous Poisson process with intensity $\lambda > 0$, X_n is assumed to be independently and identically distributed according to a distribution $H(X)$ and X_n is independent from $N(t)$. A realization of two catastrophes with severities x_1, x_2 over period $(0, t]$ corresponds to $\{N(t) = 2; X_1 = x_1, X_2 = x_2\}$.

The standard model (2.1) can be extended to allow for growing loss severity and frequency. We allow loss severity to grow over time by modeling the catastrophic loss X_n as a product of the catastrophic loss under zero growth X_0 and a growth component:

$$X_n = X_0 e^{\gamma \tau_n}. \tag{2.2}$$

In Equation (2.2), γ is the growth rate of the risk prone asset values, and τ_n is the random time when the n^{th} climate impacted event occurs, which is determined by the Poisson process. A growth in the value of risk prone assets may, for example, be due to increases in the number of properties in a region, investment in additional infrastructure, or due to improvements in a properties' or assets' condition as the economy grows.[2] The random variable X_0 is the catastrophic loss when the values of the assets at risk do not grow over time, which can also be interpreted as a measure of the destruction force of the catastrophe. It is assumed that X_0 is identically, independently distributed and X_0 is independent from $N(t)$ and therefore τ_n.

Increasingly frequent catastrophes can be modelled by allowing $N(t)$ to follow a non-homogeneous Poisson process with intensity $\lambda(t)$ increasing over time. Following previous studies on climate change (Garnaut et al., 2008; Quiggin et al., 2010), we assume that the climate changes over time but due to mitigation efforts, it will stabilize eventually. We also assume that the frequency of catastrophes is increasing in global temperature. As a result of these assumptions, the probability of a catastrophe occurring during a small

[2]The exponential growth of loss severity is consistent with the pattern of natural disaster losses observed in Australia, see, e.g., Crompton and McAneney (2008), Crompton et al. (2006), and the pattern of flood losses in Netherlands, see, e.g., Brouwer and van Ek (2004).

time interval grows over time, but converges to a limit as time becomes large:

$$\lambda(t) = \lambda(0)e^{-\alpha t} + \bar{\lambda}(1 - e^{-\alpha t}). \tag{2.3}$$

In Equation (2.3), t represents time that can take any value from 0 to infinity, $\lambda(0)$ is the Poisson intensity at time 0, $\bar{\lambda}$ is the Poisson intensity when the climate system stabilizes and α is the rate at which the Poisson intensity $\lambda(t)$ grows towards its limit (Figure 1)[3]. A higher Poisson intensity $\lambda(t)$ means a higher expected frequency of catastrophic events.

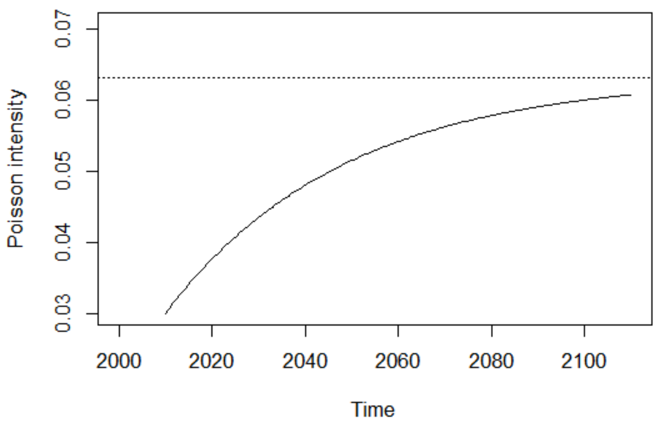

Figure 1: Time path of Poisson intensity. Poisson intensity drives the frequency of catastrophic events. We assume that Poisson intensity increases with global warming. It converges to a long run level corresponding to the new equilibrium of the climate system.

The function $\lambda(t)$ in Equation (2.3) is concave and is consistent with the projected global temperature provided by Nordhaus (2007) and many of IPCC emission scenarios, see e.g. Meehl et al. (2007)[4] In practice, estimates of the equilibrium level of global temperature and therefore $\bar{\lambda}$ are quite uncertain and we follow the literature in using sensitivity analysis to examine the impact of different estimates (West et al., 2001; Waters et al., 2003; Brouwer and van Ek, 2004; Zhu et al., 2007; Michael, 2007; Kirshen et al., 2008b,a; Symes et al., 2009).

[3]Note that since the functional form assumed in Equation (4) mirrors the projected global temperature change, it is appropriate for catastrophes whose frequency is increasing in global temperature. These include flood, drought, bushfire and storm surge, see e.g. Symes et al. (2009).

[4]Note that one could further extend the suggested approach, by modeling the frequency of catastrophic events using a doubly stochastic Poisson process (also called Cox process), where the time-dependent intensity $\lambda(t)$ is itself a stochastic process. See, e.g., Härdle and López Cabrera (2010) for an application of doubly stochastic Poisson processes to modeling the frequency of earthquakes.

2.2. Insurance Premium

To determine the value of the project, we need to determine the premium p_t that is paid at time $t = 0$ to insure loss $L_t = S_{t+dt} - S_t$ that occurs during a small time period $(t, t+dt]$. Insurance markets, however, do not exist for risk in the far future, and to overcome this incomplete market problem, we use the market equilibrium model proposed by Bühlmann (1980) to determine the risk premium. The Bühlmann model has been used widely to price insurance products (Aase, 1999; Christensen and Schmidli, 2000; Dassios and Jang, 2003; Muermann, 2008; Cox et al., 2010) as well as financial products (Embrechts, 2000; Gerber and Shiu, 2000). According to this model, assuming that the risk preferences of economic agents in the insurance market can be represented by exponential utilities, the premium p_t paid at time $t = 0$ to insure a loss L_t is given by:

$$p_t = e^{-rt} E\{\frac{e^{\theta L_t}}{E[e^{\theta L_t}]} L_t\}, \tag{2.4}$$

where θ is an aggregate measure of the risk aversion of economic agents in the market.[5] Note that the premium given in (2.4) depends only on the probability distribution of the loss and the risk aversion parameter. When insurers are uncertain about the estimation of the loss distribution and charge an additional premium to cover the uncertainty, such prudent action is reflected by an increase in the risk aversion parameter. A high risk aversion parameter may also reflect high transaction costs in the market, or it may reflect the additional premium required to compensate for financial distress caused by catastrophic events. The risk aversion parameter θ can be calibrated using data on observed premiums in the market.

Equation (2.4) is also known as the Esscher transform pricing rule which states that the premium required to insure a loss L_t is the discounted expected value of L_t under a transformed probability measure P_θ. In Equation (2.4), $\frac{e^{\theta L_t}}{E[e^{\theta L_t}]}$ is the state price density used to transform the original (or physical) measure P into P_θ. When $\theta = 0$, i.e. the representative agent is risk neutral, the transformed measure P_θ is the same as the physical

[5] The aggregate risk aversion, θ, is related to the risk aversion $\theta_1, ..., \theta_n$ of individual agents 1, ..., n via $\theta^{-1} = \sum_{i=1}^{n} \theta_i^{-1}$. As such, adding more agents to the market will reduce the aggregate risk aversion and makes the market less risk averse.

measure P and the risk premium is equal to the discounted expected loss under P.

The premium or the discounted expected value of L_t under P_θ is calculated using moment generating functions. As a result of (2.4), the moment generating function $M_{L,\theta}(u)$ of the loss L_t under the transformed measure P_θ can be expressed in terms of the moment generating function $M_L(u)$ of the loss L_t under the physical measure P:

$$M_{L,\theta}(u) = \frac{M_L(u+\theta)}{M_L(\theta)}. \tag{2.5}$$

If the project is not invested, the loss $L_t = S_{t+dt} - S_t$ that occurs during a small time period $(t, t+dt]$ follows a compound Poisson process with intensity $\lambda(t)dt$ and severity density h_t. The moment generating function of L_t under the measure P_θ can be written as

$$M_{L,\theta}(u) = \exp\{\lambda(t)dt \int [(e^{ux}) - 1] e^{\theta x} h_t(x)dx\}, \tag{2.6}$$

which shows that under the transformed measure, the density of loss size is changed from $h_t(x)$ to $e^{\theta x}h_t(x)$. Since $\theta \geq 0$, a higher probability is assigned to a larger loss size under the transformed measure. The adjustment in the loss size distribution usually leads to an adjustment of the Poisson intensity as well. For example, if h_t follows a normal distribution $N(\mu, \sigma)$, then under the transformed measure, it becomes $N(\mu + \theta\sigma^2, \sigma)$ and the Poisson intensity becomes $\lambda_t dt e^{\mu\theta + \frac{1}{2}\theta^2\sigma^2}$.

The effects of an Esscher transform for commonly used severity distributions are presented in Table 1. Note that other more flexible, but more complex distributions such as Variance Gamma, Generalized Hyperbolic, Meixner, or Carr-Geman-Madan-Yor distributions can also be used to model loss severities using the Esscher transform method. For details on these distributions, see e.g. López Cabrera et al. (2013); Dingeç and Hörmann (2012).

Table 1: Esscher transform for selected loss severity distributions

Severity distribution	Transformed severity	Transformed Poisson intensity
Normal, $N(\mu, \sigma)$	$N(\mu + \theta\sigma^2, \sigma)$	$\lambda_t dt e^{\theta\mu + \frac{1}{2}\theta^2\sigma^2}$
Gamma, $G(a, s)$	$G(a, s/(1-\theta))$	$\lambda_t dt(1-\theta)^a$
Normal-inverse Gamma, $NIG(\mu, \alpha, \beta, \delta)$	$NIG(\mu, \alpha, \beta + \theta, \delta)$	$\lambda_t dt e^{\theta\mu}$

Given the lack of data on losses, in this paper, we will use a Gamma distribution to model the loss severity. When X_0 follows a Gamma distribution with density $h_0(x) = \frac{1}{\Gamma(a)s^a} x^{a-1} e^{-x/s}$, the insurance premium p_t in (2.4) can be denoted by

$$p_t = e^{-rt}\lambda(t) dt sa e^{\gamma t}(1 - s e^{\gamma t}\theta)^{-a-1}. \tag{2.7}$$

2.3. Investments into Climate Change Adaptation

In the next step, the costs and benefits of investments into climate change adaptation are determined. We consider an investment project with investment cost I and maintenance cost flow C. As in other real option studies (Baranzini et al., 2003; Dixit and Pindyck, 1994; Fisher, 2000; Gollier and Treich, 2003; Pindyck, 2002), we assume that the project lasts infinitely and the investment cost is sunk once committed. In practice, an infinitely lasting project is constructed as a series of finite lifetime projects, where a new finite lifetime project is put in place whenever the previous project is fully depreciated.

Investment projects may reduce losses by reducing loss frequency or loss severity, depending on the type of catastrophes. For bushfires, where fire is contained if it is discovered and suppressed in time, the main impact of investment projects such as construction of fire trails or fire stations is to reduce the frequency of house damaging events. For flood and storm surges, dams and dykes weaken the destruction force, and losses are reduced through a reduction in loss severity. In investigating bushfire risk management strategies, we use a non-decreasing, linear function k of Poisson intensity $\lambda(t)$ to model the risk reduction impact of the project. With the project in place, bushfire events occur with Poisson intensity $k\lambda(t)$ and severity $X_0 e^{\gamma t}$. The model can be adjusted for uses in flood and storm surge risk management by assuming k as a piece-wise linear function of the destruction force X_0 as illustrated by Figure 2. Computation of the optimal investment time in this case would involve the simulation of the mitigated loss severity distributions. In the following, we present the model applied to bushfire management for which, no simulation is required.

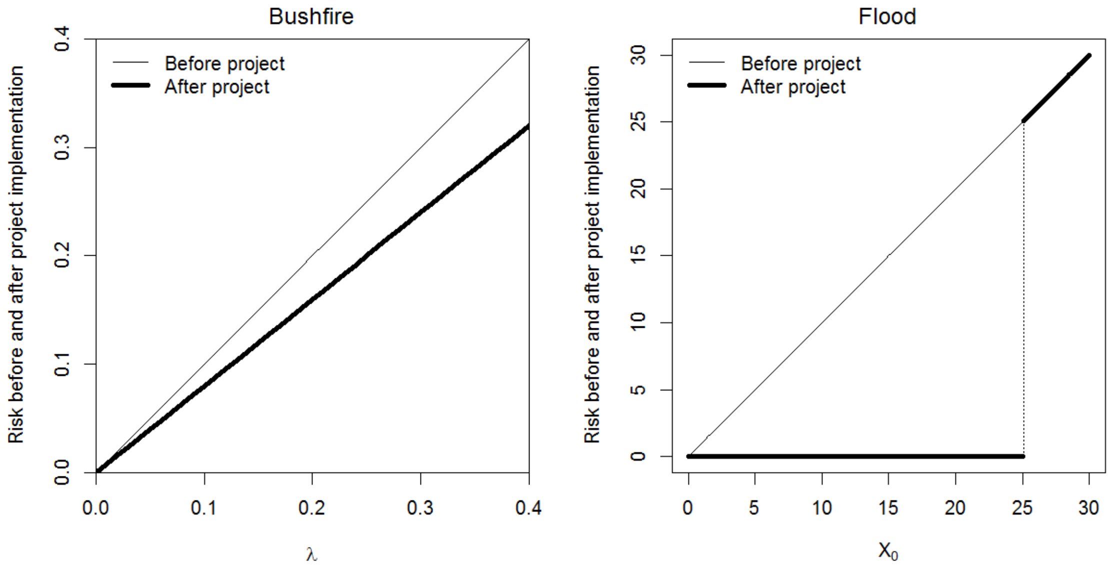

Figure 2: Examples of possible risk mitigation functions. The functional form of risk mitigation should depend on the type of risk considered. We assumed an increasing, linear risk mitigation function for the case of bushfire risk. In the case of flood, a piecewise linear function is more suitable.

The benefit of the investment project is the total discounted value of the reduction in the insurance premium due to the project. With the project in place, the Poisson intensity of the loss L_t (under measure P) is reduced to $k\lambda(t)dt$ and the premium is reduced to kp_t, where p_t is given in (2.7). The premium reduction due to the project over period $(t, t+dt]$ is therefore $(1-k)p_t$. Integrating this premium reduction from time T, when the project is invested, to infinity gives the benefit $B(T)$ of the project:

$$B(T) = \int_T^\infty (1-k)e^{-rt}\lambda(t)sae^{\gamma t}(1 - s\theta e^{\gamma t})^{-a-1}dt. \tag{2.8}$$

The NPV of the project invested at time T, $V(T)$, is obtained by subtracting the present value of the project's investment and maintenance costs from its benefits:

$$V(T) = \int_T^\infty (1-k)e^{-rt}\lambda(t)sae^{\gamma t}(1 - s\theta e^{\gamma t})^{-a-1}dt - e^{-rT}(I + C/r). \tag{2.9}$$

Equation (2.9) allows us to examine the optimal time for a considered investment into climate change adaptation. Clearly, the optimal time to invest is the time when $V(T)$ is maximized. It can be shown that the maximal value of $V(T)$ is obtained from the first order condition:

$$(1-k)\lambda(T)sae^{\gamma T}(1-s\theta e^{\gamma T})^{-a-1} = r(I + C/r). \tag{2.10}$$

The right hand side of Equation (2.10) is the marginal benefit of deferring the investment by a small time period dt, which is the interest expense on the investment cost and the maintenance cost of the project that would have incurred if the project was invested instantly. The left hand side is the marginal cost of investment deferral, which is the insurance premium that would be avoided should the project be in place. Intuition about the first order condition is provided in Figure 3, where at the current time, the marginal benefit of investment deferral is higher than the marginal cost and deferring investment by a small time period will increase the NPV of the project. Increasing deferral time continues to improve the NPV of the project until the point where the marginal cost is equal to the marginal benefit, while longer deferral beyond that point reduces the NPV of the project. The optimal deferral time or investment time is therefore attained when the marginal benefit of deferral is equal to the marginal cost. The optimal investment time can be found by solving Equation (2.10) numerically.

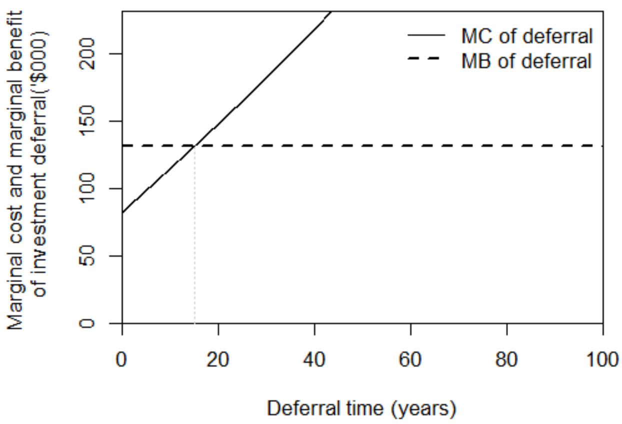

Figure 3: Marginal analysis of optimal investment time. Deferring investment by one period provides the marginal benefit in terms of saving on project maintenance and interest expense on investment cost. The marginal cost of investment deferral is the insurance premium that would be avoided should the project be in place. It is optimal to defer investment to a later time if at time T=0, the marginal benefit exceeds the marginal cost.

3. Case Study Results

In the following, the proposed model is applied to a case study of bushfire management in a local area (Ku-ring-gai) of Southeast Australia. Climate change seems to already show its impact as an upward trend in the historical records of Forest Fire Danger Index (FFDI)[6] in various areas in Southeast Australia (see Figure 4).

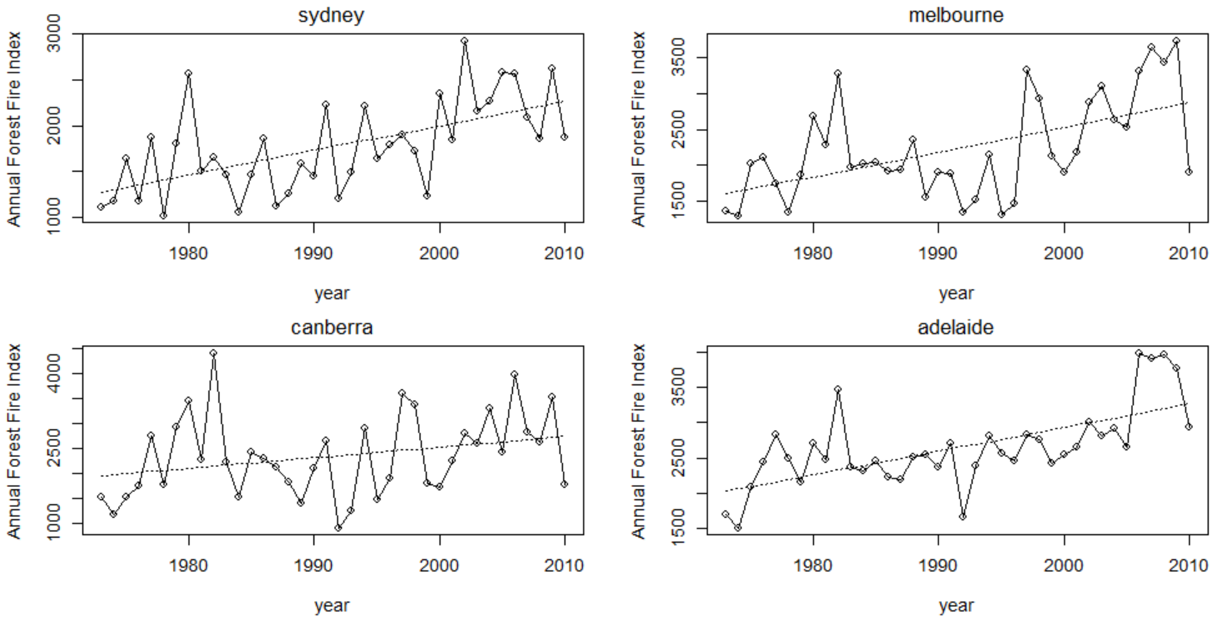

Figure 4: Time series plots of annually cummulated FFDI for Sydney, Melbourne, Canberra, Adelaide. Dotted lines present the linear trend. Data are obtained from Lucas (2010).

Ku-ring-gai is an urban area with residential properties surrounded by three National Parks. It has 89 kilometres of urban and bushland interface and ranks third in bushfire vulnerability among the 61 local government areas in the Greater Sydney region (Chen, 2005).[7] The community in Ku-ring-gai recognizes bushfire as the most concerning risk under climate change, followed by storm, water supply security and heat stress mortality risk (KC, 2010).

Adaptation to the increased bushfire risk can be done at various levels. The Federal and State governments can revise building codes and adjust funding for investment projects to

[6]FFDI is a an index created based on weather variables. It was proposed by an Australian CSIRO scientist A.G. McArthur in the 1960s. A higher index indicates a higher risk of bushfire

[7]Bushfire vulnerability is defined as the number of addresses within 130 meters of bushland.

reduce bushfire risk. Local governments can propose and implement investment projects and provide education programs to reduce the risk. Households can purchase insurance and upgrade their home to increase their resilience. However, adaptation at the local government level seems to be most feasible and effective. At the household level, insurance takeup is already high and improvement in fire resistance is costly in many cases.[8] The adaptation benefits of revising building codes at the Federal and State government are also limited, since revised building codes apply only to new or reconstructed houses.

A number of options has been identified by Ku-ring-gai Council to reduce the risks from bushfires. These include, among others, building new fire-trails, constructing new fire-stations and rezoning land, see KC (2010). Fire trails allow for controlled hazard reduction burning, break wild fire transition and potentially allow more time for fire brigades to respond to bushfires. Constructing more fire stations reduces the response time and, thus, may also significantly reduce the risk of a fire to become more severe. In the following, we will focus on evaluating an adaptation project that involves the construction of additional fire trails to illustrate the proposed framework and provide economic insights on the optimal timing of the investment.

3.1. Parameter Estimation

Information on the estimated and assumed parameter values for the considered investment project are provided in Table 1. The appropriate process for the Poisson intensity of the occurrence of bushfires in the area is derived in the following way. The current frequency of bushfires over a one year time horizon, $\lambda(0)$, is estimated from historical data, i.e. three bushfires with damage to houses over the last 100 years. To estimate the growth rate of the catastrophic intensity, we adopt the results of Hasson et al. (2009) who used 10 general circulation models together with a low (B1) and a high (A2) GHG emission scenario to study the changes in the frequency of extreme fire weather events in south-eastern Australia. The authors find that on average, the frequency of the extreme events increases from one event every two years during the 20^{th} century to one event per year by the end of the 21^{st} century, while results given by different models vary significantly.

[8]In NSW, the building code did not reflect bushfire risk until 1997 and houses that were constructed before 1997 may not be as fire resistant as they should be.

Assuming that the frequency of bushfires is proportional to the frequency of extreme fire weather events, the frequency of bushfire is therefore predicted to double by the end of the 21^{st} century. Equation (2.3) then becomes:

$$\lambda(0)e^{-90\alpha} + \bar{\lambda}(1 - e^{-90\alpha}) = 0.06 \tag{3.1}$$

Also, assume that the bushfire frequency in 2100 is close to the equilibrium frequency, i.e.

$$0.06 = 0.95\bar{\lambda}, \tag{3.2}$$

then $\bar{\lambda} = 0.0632$ and $\alpha = 0.026$.

The loss severity is the product of the number of damaged houses and the construction cost per house. We estimate the reconstruction cost per house by subtracting the average land value estimated by the NSW Valuer General (DOL, Department of Land (2009)) from the average property sales price in the region provided by Hatzvi and Otto (2008). This results in an estimated reconstruction cost per house of $422,000.
The number of damaged houses in a bushfire fire event is estimated using information provided by a local expert from the bushfire brigade. The expert suggests that for a severe bushfire, the average number of houses being damaged is 30 and the range for the average number of damaged houses is between 15 (the lower quartile) and 50 (the upper quartile) houses. These figures yield an expected loss of $12,660,000, while the 25th percentile for the severity of losses is $6,330,000 and the 75th percentile is $21,100,000. The corresponding parameters of the gamma distribution matching these loss estimates are $a = 8242.57$ and $s = 1535.93$.
The growth rate of loss severity (γ) is estimated based on disaster insurance claim data provided by Insurance Council Australia (ICA) and yields a growth rate of $\gamma = 0.01$.

Estimation of the risk aversion parameter θ requires information about the loss distribution and the corresponding risk premium. Without access to risk premium data for the study region, we follow Farrow and Scott (2013) to examine the impact of risk preference on the optimal investment decision for a range of possible risk aversion values, $\theta \in [2 \times 10^{-9}, 10^{-8}]$. We use the mid-point of the range, $\theta = 6 \times 10^{-9}$, for the baseline

Table 2: Information on estimated and assumed parameter values, including the current intensity of bushfires $\lambda(0)$, the intensity $\bar{\lambda}$ when the climate stabilizes, the growth rate for the intensity α, the location (a) and scale (s) parameter of the Gamma distribution for severity, the risk aversion parameter θ. The table also provides information on the estimated growth rate of the cost of reconstruction γ, the assumed impacts on risk mitigation of the project $1-k$, the lifetime of the project M, the investment cost per project I_M, project maintenance costs C and the applied discount rate r.

Parameters	Value
Current Poisson intensity ($\lambda(0)$)	0.03
Steady state Poisson intensity ($\bar{\lambda}$)	0.0632
Rate of Poisson intensity growth (α)	0.026
Location parameter of severity distribution (a)	8242.57
Scale parameter of severity distribution (s)	1535.93
Risk aversion parameter (θ)	6×10^{-9}
Growth rate of reconstruction cost (γ)	0.01
Risk mitigation by project (*1-k*)	20%
Lifetime of the project (M)	50 years
Investment cost per project (I_M)	\$1.5 million
Project maintenance cost (C)	\$50,000
Discount rate (r)	5%

case.

Other parameters relating to the investment project, including investment cost, loss mitigation effectiveness and project life, are estimated using expert elicitation. Expert elicitation method is an effective way to overcome data scarcity problems and has been used in many previous climate adaptation studies, see e.g. Baker and Solak (2011); Mathew et al. (2012). The expert specifies that the conducted project is expected to reduce the frequency of house damaging bushfire events by 20%. The estimated costs for a finite lifetime project can be used to calculate the investment cost of an infinite lifetime project as follows. First, we convert the investment cost I_M of a project that lasts M years into an annuity flow, A:

$$A = I_M \frac{1-\beta}{1-\beta^{M+1}},$$

where $\beta = 1/(1+r)$. The annuity A is then used to calculate the investment cost of an infinite life project:

$$I = A(1+r)/r. \tag{3.3}$$

Thus, at a 5% discount rate, the present value of building a bushfire trail every 50 years, each costing \$1.5 million to build is \$1.64 million.

3.2. Baseline Analysis

Figure 5 provides a plot for the NPV $V(T)$ of the considered project as a function of investment time T. Hereby, T ranges from immediate investment into the project ($T = 0$) up to an initial investment into the project in $T = 100$ years. We find that immediate investment into the project provides a positive NPV of \$401,152. However, deferring the investment to a later time can provide an even higher value for the conducted project. Based on our model, the optimal time to invest is in year $T = 15$ and investing according to this optimal rule will provide a NPV of \$701,887 for the project, a difference of \$300,735 in comparison to the value of the project for investment at $T = 0$. From $T = 15$ onwards, postponing the investment to a later point in time will decrease the NPV of the project. Overall, applying the developed framework to the case study, we find that the optimal timing of the investment will have a significant impact on the NPV of the investment. Clearly, if the project was invested at $T = 0$ based on a simple $NPV_0 > 0$ rule to guide the investment decision, ignoring the optimal timing would lead to a lower NPV.

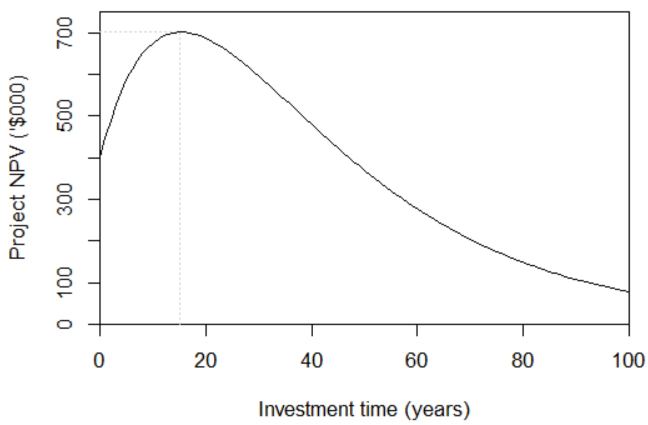

Figure 5: NPV of the considered project for different timing of the investment, starting from an immediate investment at time $T = 0$ up to an investment in $T = 100$ years.

3.3. Impact of risk aversion

The impact of risk aversion on the results is examined by comparing the baseline case with the case of risk neutrality ($\theta = 0$), see Figure 6. We also provide the plots for the case when risk aversion takes a higher value and the case when it takes a lower value (than in the baseline case) in Figure 6 to examine the sensitivity of the results to changes in risk aversion parameter.

Recall that the coefficient of risk aversion for the baseline case was estimated as $\theta = 6 \times 10^{-9}$. We find that risk aversion significantly changes the NPV of the project. For example, under risk neutrality, the NPV of the project invested at time $T = 0$ is below \$200,000, while under risk aversion, the NPV of the project invested at the same time is more than twice as large. Consequently, assuming risk neutrality may severely underestimate the NPV of climate change adaptation projects and will possibly allocate more public funding towards non-climate related investments where risk neutrality holds such as, e.g., road infrastructure.

A more risk averse preference, in fact, raises the NPV of the project in a way that causes the optimal investment to occur earlier. Assuming risk neutrality will lead to an optimal investment time in year $T = 19$, while assuming a higher degree of risk aversion in the market ($\theta = 10^{-8}$) will lead to an earlier optimal investment time ($T = 13$) than the baseline case ($T = 15$).

We find that immediate investment at time $T = 0$ will always result in a significantly lower NPV than investing at the optimal time, regardless of the coefficient of risk aversion. The loss in investment value is highest in the case of risk neutrality (\$397,265 or 81% of the investment value) and lowest in the case of high risk aversion (\$243,310 or 28% of the investment value). This result is not surprising given that more risk averse preferences will lead to an earlier investment, such that the difference between immediate and optimal timing of the investment are not as significant as for the risk neutral case.

3.4. Impact of climate change

The impact of climate change is examined by comparing the baseline scenario with the case where the frequency of bushfire triples (instead of doubles) by 2100, corresponding to $\bar{\lambda} = 0.0947$, and $\alpha = 0.029$, see Figure 7. We find that the more serious climate change scenario results in significant increases for the NPV of the project. For example, in the baseline case, the NPV of the project invested at time $T = 0$ is below \$500,000, while

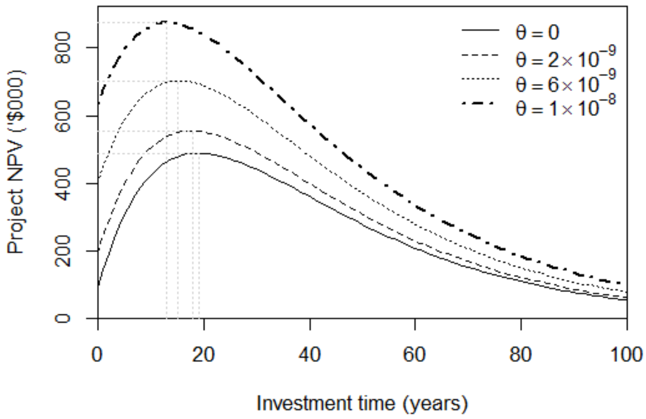

Figure 6: Impact of risk preference on the NPV of the examined investment. The baseline scenario corresponds to a coefficient of risk aversion of $\theta = 6 \times 10^{-9}$, while for the risk neutral case we set $\theta = 0$. We also consider the case of a lower ($\theta = 2 \times 10^{-9}$) and a higher ($\theta = 1 \times 10^{-9}$) coefficient of risk aversion. For all cases we plot the NPV of the project for different timing of the investment, starting from an immediate investment at time $T = 0$ up to an investment in $T = 100$ years.

under a more serious scenario for climatic change, the NPV of the project invested at the same time is about three times as large. In addition, the more serious climate change scenario also changes the relationship between timing of the investment and NPV of the project. Given that a faster increase in the frequency of bushfires, we would expect an earlier optimal time to invest than under the base scenario. Indeed, we find that the optimal investment time is reduced from $T = 15$ in the baseline case to $T = 8$ under the assumption of a more serious scenario for climatic change and the frequency of bushfires in the considered area. Therefore, we also find that investment in $T = 0$, based on a simple NPV rule, is much closer to the optimal timing of the investment under a more serious climate change scenario. The reduction in NPV due to an investment in $T = 0$ is smaller under the more serious scenario for climate change scenario ($182,322 compared to $300,735) than in the baseline case.

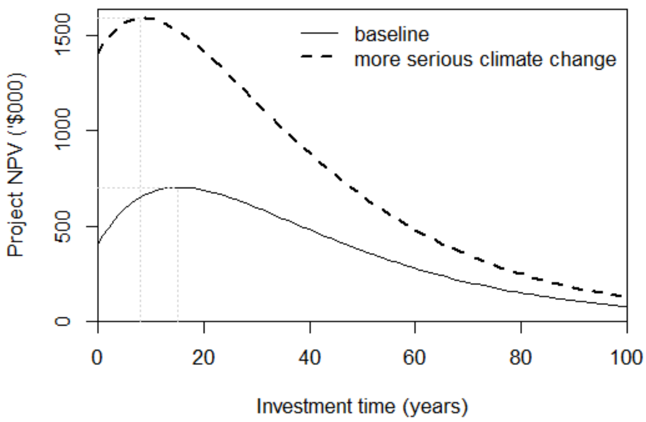

Figure 7: Impact of climate change scenarios. The baseline scenario corresponds to a Poisson intensity path given by $\lambda(0) = 0.03, \bar{\lambda} = 0.0632, \alpha = 0.026$ *(solid line)*, while the case of more serious climatic change corresponds to $\lambda(0) = 0.03, \bar{\lambda} = 0.0947, \alpha = 0.029$ *(dashed line)*. The Poisson intensity given by the latter is 3 times as large as the Poisson intensity given by the former in year 2100. For all cases we plot the NPV of the project for different timing of the investment, starting from an immediate investment at time $T = 0$ up to an investment in $T = 100$ years.

3.5. Impact of investment cost

The impact of investment cost on the results is examined by allowing investment costs to range between \$1 million and \$2 million. Figure 8 provides a plot that illustrates how the investment costs will impact on the NPV of the project. Hereby, for the entire range of possible investment costs from \$1 million - \$2 million, we plot the maximal possible NPV that is obtained when the project is conducted (i) under optimal timing of the investment, and (ii) the NPV for the project under immediate investment in $T = 0$. As expected investment cost has a significant impact on the NPV of the project. Interestingly, higher investment costs seem to decrease the NPV of the project under immediate investment in $T = 0$ even more than when the project is conducted under optimal timing. For example, an increase in investment cost by 10% (from \$1.5 million) reduces the NPV of the project under immediate investment by 41%, while it reduces the maximal NPV (under optimal timing) by only 10%. The Figure also illustrates that the difference between the NPV of the project under optimal timing and the NPV for immediate investment in $T = 0$ becomes larger for increasing investment costs.

Investment cost also has an impact on the optimal investment time. When investment cost increases by 10% from \$1.5 million to \$1.65 million, the optimal time to invest increases by 16% from $T = 15$ to approximately $T = 17$. On the other hand, for a lower investment cost of $1 million, the waiting time for optimal investment is reduced and to less than ten years. The higher the investment cost, the more important becomes the optimal timing of the investment, since it is more valuable to avoid the interest expense on the investment costs in the initial years, when the benefits of the project are still lower. Thus, when investment costs for the project increase, so does the waiting time for optimal timing of the investment.

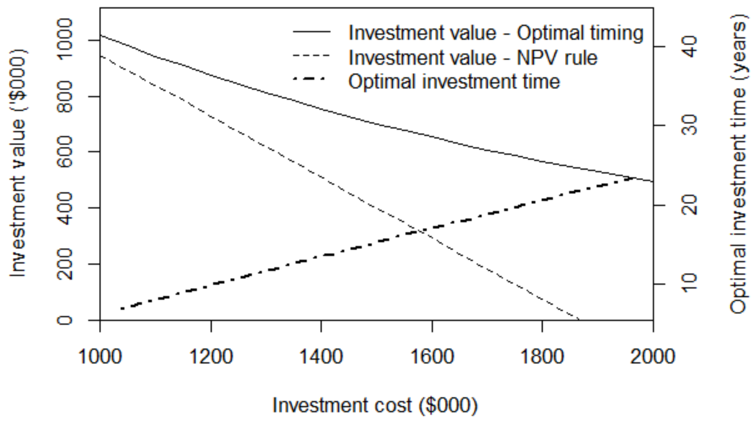

Figure 8: Impact of investment cost on NPV of the project. We provide a plot of the NPV of the project under optimal timing of the investment *(solid line)*, and, when the investment is conducted immediately in $T = 0$ *(dashed line)* for a range of investment costs between $1 million and $2 million. The difference between the NPV of the project under optimal timing T^* and the NPV for immediate investment in $T = 0$ becomes larger for increasing investment costs. The Figure also illustrates the positive relationship between investment cost and the optimal time to invest *(dotted line)*.

3.6. Impact of discount rate

The impact of discount rate on the results is examined by calculating the NPV under optimal timing of the investment and for immediate investment in $T = 0$ as well as the optimal investment time for different discount rates. Figure 9 provides the results for a range of discount rates between 3% and 9%.

We find that discount rate has a significant impact on the NPV of the project. Again, the impact on the NPV under immediate investment is more significant than when the project is conducted under optimal timing. For example, an increase in discount rate from 5% to 5.5% reduces the NPV of immediate investment by 71% while it reduced the NPV under optimal timing of the investment by 32% only. Also, the difference in the

NPV of the project under optimal timing and for immediate investment becomes more significant when the discount rate is higher.

Discount rate also has an important impact on the optimal investment time. We find a positive linear relationship between discount rate and the optimal time to invest. An increase in the discount rate by 10% results in an increase in the optimal investment time by 13%. This also illustrated that the optimal timing of the investment becomes more important for higher discount rates, since it is more valuable to avoid the interest expense in initial years when investment benefits are still low. With higher discount rates, the waiting time becomes longer and the difference between the NPV of the project for investment under optimal timing in comparison to investment at $T = 0$ becomes larger. We also find that for an assumed discount rate greater than 5.75%, immediate investment into the project will provide a negative NPV.

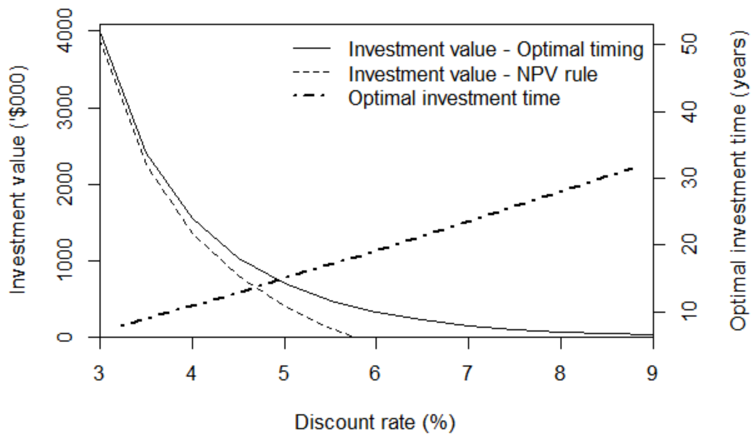

Figure 9: Impact of discount rate. We plot the value obtained when the project is invested at the optimal time, the value obtained when it is suboptimally invested according to the NPV rule and the optimal time of investment for a range of discount rate (3% - 9%).

4. Conclusion

In this paper, we have introduced a new modeling framework that allows to analyze the optimal investment time when evaluating climate change adaptation strategies. Investment into climate change adaptation is potentially one of the most important tasks in upcoming years and decades, given the imminent prospect of more frequent and severe extreme climate impacted events. With existing budget constraints and uncertainty about these events, adaptation requires a simple and applicable economic framework for decision-making, that includes various important aspects of investment into climate adaptation.

Our model is developed in a continuous time framework and allows for flexible timing of the initial investment into a climate change adaptation project. In particular, our approach provides a formula to determine the optimal timing for the adaptation investment. Using our framework, we illustrate that when the marginal benefit of a deferral of the investment is higher than the marginal costs, deferring the investment to a later point in time will increase the NPV of the project. Under these circumstances, deferring the investment continues to improve the NPV of the project until the marginal cost of the investment is equal to the marginal benefits. From this point onwards, longer deferral of the adaptation investment will reduce the NPV of the project such that the optimal investment time is attained when the marginal benefits are equal to the marginal costs. We illustrate the framework in a case study on managing catastrophic risks from bushfires and examine the impact of major factors such as timing of the investment, risk preference, climatic change, investment costs and discount rates on the net present value of the project. We find that optimal timing of the investment will significantly increase the net present value of the considered adaptation project, while immediate investment based on a simple positive $NPV > 0$ rule does not maximize the net benefits of the project. The difference between the NPV of the considered project under optimal timing of the investment and immediate investment further increases for higher discount rates, higher investment costs and for lower levels of risk aversion. However, the difference decreases for a more serious scenario of climatic change that is expected to increase the frequency of bushfires, what also yields greater benefits for early or immediate adaptation.

We also find that risk preference has a significant impact on the net present value of the considered adaptation project. The higher the assumed level of risk aversion among agents, the higher is the corresponding NPV of the considered adaptation investment. Assuming risk neutrality may therefore result in a significant underestimation of the actual economic net benefit of a project. However, the reduction in NPV of an adaptation project caused by ignoring optimal timing of the investment is potentially much larger than the loss caused by wrong assumptions about risk preference. These results are important for research prioritization and suggest that optimal timing of an adaptation investment is potentially more important than assumptions about risk preference.

We also found that climate change scenarios have an impact on investment decisions, under both the NPV rule and the model for optimal timing of the investment. Scientific knowledge improvement that helps reduce the uncertainty in climate change prediction can therefore make an important contribution towards increasing investment efficiency and values. When climate change prediction is significantly uncertain, the attitude of a decision maker towards uncertainty has significant impact on the investment decision. A decision maker who wants to maintain a reasonable level of risk under the extreme and less likely scenario of climate change will choose to invest in the project at an earlier time than a decision maker who considers the most likely scenario of climate change.

In applying the model, we have used expert opinions to estimate parameters of the loss severity distribution and the impacts of the investment project on catastrophic losses. These parameters could alternatively be estimated using models developed in previous studies, when feasible. For example, for the case of flooding, the simulated data on flood losses obtained from climate Models or vulnerability studies could be used for parameter estimation. As such, the proposed model can also be applied in a straightforward manner to enrich existing studies to examine the optimal timing of suggested adaptation measures.

Note that in our analysis we have assumed that the impact of climate change is known and, as a result, parameters of the assumed Poisson process are deterministic. Although the uncertainty about climatic change has been partially considered through sensitivity analysis, a better approach would be to incorporate the impacts of uncertainty directly in the modeling framework. Future studies could extend the framework to allow the catastrophic intensity to change stochastically over time and allow new observations on the climate or catastrophic events to be incorporated into investment decision making. According to the theory of investment under uncertainty, incorporating future information into decision making will enhance the value of investment timing. Therefore, when the model's parameters are uncertain, it is even more important to consider the value of investment timing into cost benefit analysis.

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