Climate change and the increased risk in the insurance industry

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Abstract

There has been no solid economic argument for taking action to prevent or amend the effects of climate change due to the uncertainty in its timing and the level of its impact. However, the rise in economic cost in recent years due to unpredictable variability in weather appears to be a potential longer term threat of catastrophic losses. After another summer of flooding and extreme weather volatility, Australia has been re-rated on the international insurance market (Insurance Council of Australia). Through the use of time series analysis, our study shows that growing levels of climate variability directly give rise to the variability in the level of damage to insured assets which will then incur a negative economic cost justifying an increase in insurance premiums. The result of the model then emphasises the fact that the recent year's rise in catastrophic claim cost does not follow a weather cycle. It is time for the insurance industry to consider this new climate variability risk.

Keywords: Climate change effects, adaptation, Insurance industry, Business opportunities, Australia.

Introduction

In the last decade, weather-related catastrophes have appeared to be a considerable challenge for the industry due to significant losses experienced by insurers worldwide. For instance, during the past 10 years, the United States suffered from two of the costliest hurricanes of all time namely Hurricane Katrina and Hurricane Sandy which incurred a cost of US$125 and US$68 billion respectively (Wikipedia, 2013). Asia also experienced considerable economic losses from weather-related catastrophes. Thailand experienced the worst flood in 50 years which incurred a huge economic loss of US445.7 billion (World Bank, 2011). In Australia, weather-related catastrophes have tripled in the last three decades. Summer floods and extreme weather phenomenon occurring repeatedly have caused Australia to be re-rated on the international reinsurance markets (Hannam, 2013). Overall the world has suffered from one of the costliest economic losses and specifically insured losses in history, with the all-time highest economic loss of US$380 billion and US$105 billion insured loss in 2011 (Munich, 2012). The extreme degree of losses highlights the increased risk exposure of modern society to climate extremes.

The Intergovernmental Panel on Climate Change (IPCC) has predicted that climate change will increase the regularity as well as the severity of weather-related catastrophes (Botzen, van den Bergh, & Bouwer, 2010). This has therefore increased the vulnerability of the whole societal economy towards weather extremes. Processing and anticipating this trend is especially crucial to the insurance industry as insurers and reinsurers bear a large portion of the economic loss caused by the unexpected severity of a weather-related catastrophe.

This paper examines the current correlation between climate change and the annual catastrophic insurance claims in Australia. The analysis will use a time series model to demonstrate how climate data relates to recent rises in catastrophic claim costs. Furthermore, the impacts of climate change on the insurance sector are assessed and proposed solutions and opportunities for the insurance sector in the time of climate change are investigated.

Description of the data:

Climate change data:

Graphs and data regarding climate change in the context of Australia are extracted from the Bureau of Meteorology of Australia website.

In the initial analysis all the variables of climate change comprises LAGS(Log_NormCost,1)of: Average Number of hot days, Average Number of Cold nights, Average Number of Cold days, Annual Sea Surface Temperature Anomaly, Average Number of hot nights, Rainfall, Annual Average Temperature Anomaly.

LAGS (Log_NormCost, 1) is the log of normalised cost from the year before the year we want to predict. Average Number of hot days, Average Number of Cold nights, Average Number of Cold days, Average Number of hot nights are defined according to the following table (Bureau of Meteorology, 2013).

Table 1. Definition of extreme temperature indices

Extreme Temperature indices	**Definition**
Hot nights	Annual count of nights with minimum temperature > 20°C
Hot days	Annual count of days with maximum temperature > 35°C
Cold nights	Annual count of nights with minimum temperature < 5°C

After performing time series analysis we realize that it is not necessary to include all predictors in the model. The only most significant predictor is the average sea surface temperature anomaly

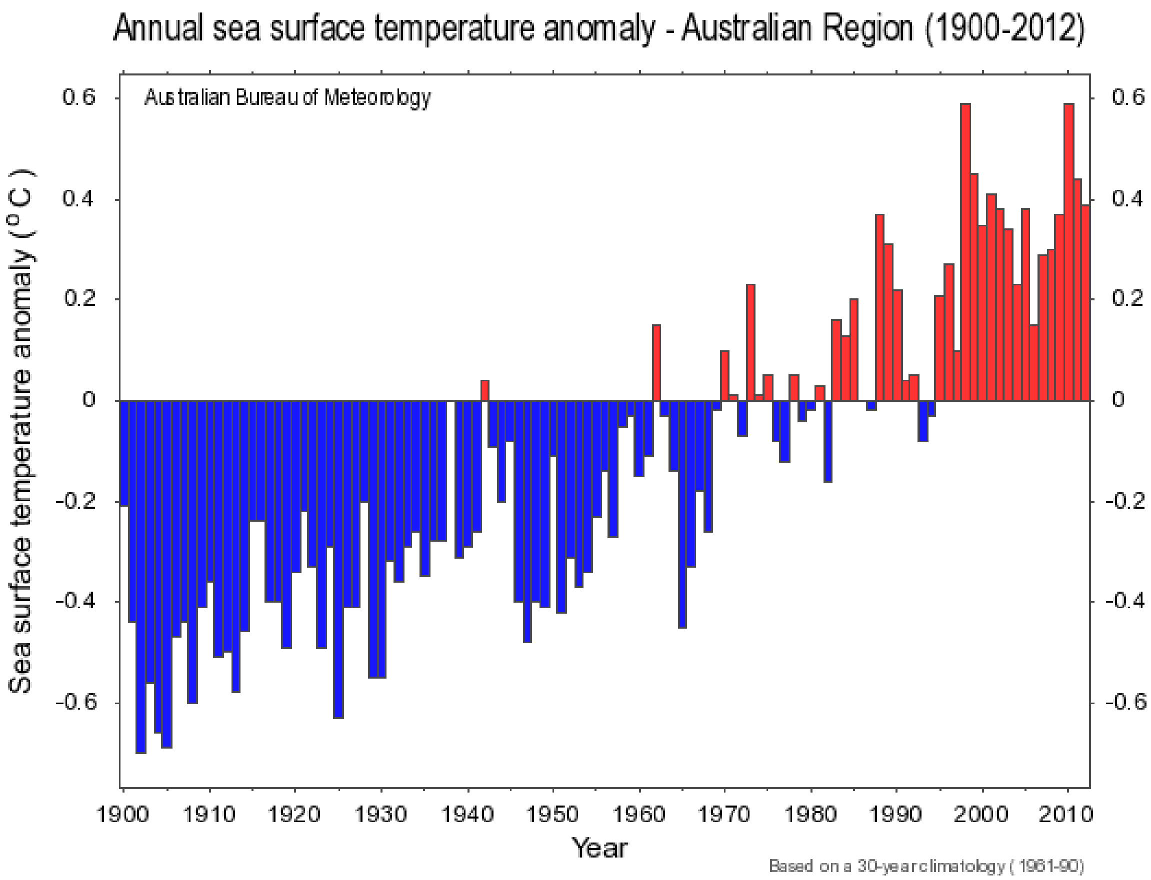


Figure 1: Sea surface temperature anomalies (CSIRO, 2012).

The data for 11-year average sea surface temperature anomalies represents the mean deviation of sea surface temperature from the normal sea surface temperature. This variable is regarded as the “Sea surface temperature anomalies” variable in the statistical analysis section. The data from 1970 - 2012 are extracted from this graph.

Claim cost data:

Claim cost due to weather-related catastrophe is obtained from the Insurance Council of Australia (2013).

The accumulated inflation factor is taken from the RBA website (Reserve Bank of Australia, 2013).

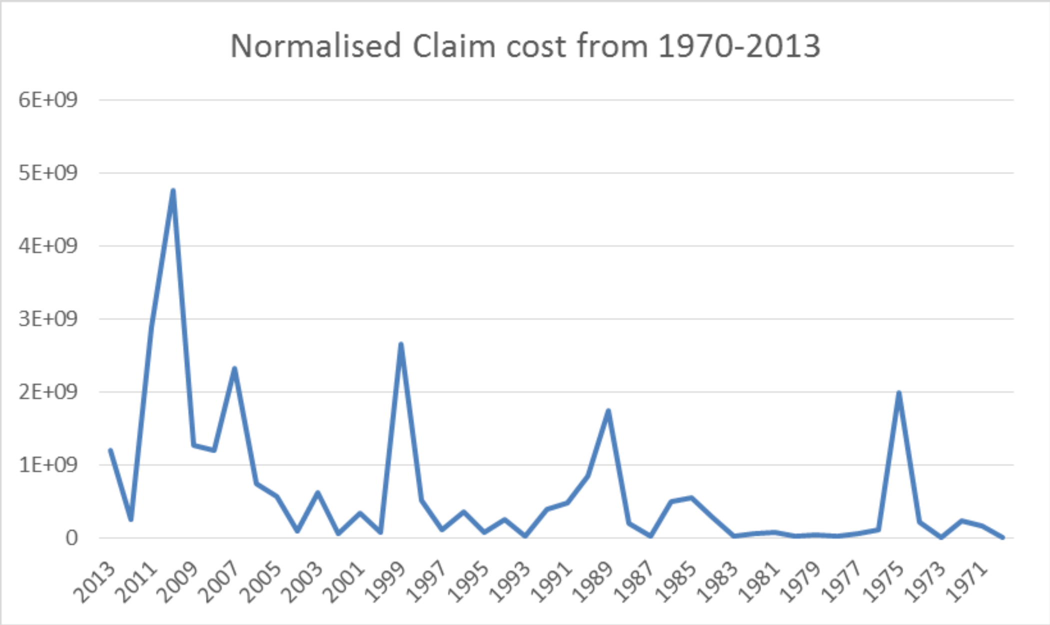


Figure 2: Normalise cost from 1970-2013

Statistical Analysis:

Choice of variables:

Actual nominal costs are normalised to the price of 2012 in order to evaluate the equivalent real impact of the cost to the insurance industry.

There are many variables regarding climate change such as Average Number of hot days, Average Number of Cold nights, Average Number of Cold days, Annual Sea Surface Temperature Anomaly, Average Number of hot nights, Rainfall, Annual Average

Temperature Anomaly etc. However, many of these variables are multicollinear as these predictor variables are highly correlated. Therefore it is not necessary to include all of them as one significant predictor that can represent all other multicollinear variables. In order to eliminate multicollinear variables without compromising the complexity of the model, the method of stepwise regression and backward selection is used. This method involves starting with all the predictor variables then eliminating step by step the most insignificant one to the model until we arrive at the most significant predictor variables for this time series analysis predicting the current claim cost. The most significant variable is sea surface temperature anomaly.

The tables which shows the collinear level of excluded variables and the reason why we removed it from the model can be found in Appendix 1. After removing all multicollinear variables, we arrive at the final most significant predictor: Annual sea surface anomaly.

Table2: Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	18.0537	20.9622	19.3578	.76035	43
Residual	-2.92697	2.54275	-.05827	1.26606	43
Std. Predicted Value	-1.707	2.079	-.009	.990	43
Std. Residual	-2.367	2.056	-.047	1.024	43

a. Dependent Variable: Log_NormCost

Statistical Model:

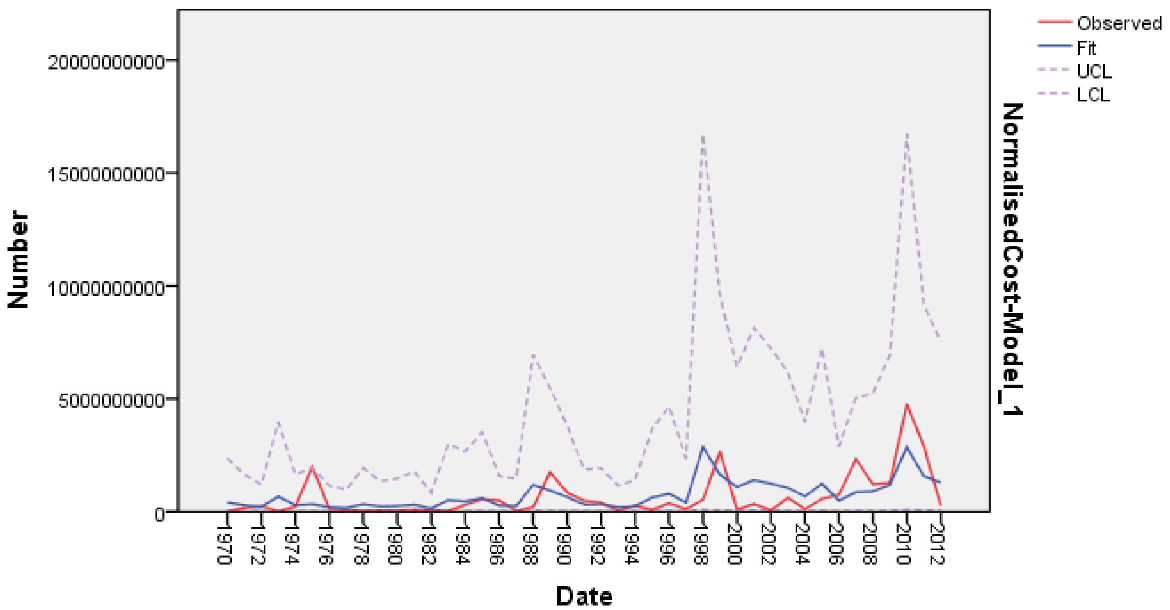
Table 3: Years: 1971-2013

Model	***Number of Predictors***	***Model Fit statistics***							
		Stationary R-squared	***R-squared***	***RMSE***	***MAPE***	***MAE***	***MaxAPE***	***MaxAE***	***Normalized BIC***
Normalised Cost	1	0.277	0.352	7.95E+08	429.718	5.47E+08	3927.707	2.33E+09	41.161

Ljung-Box Q(18)			***Number of Outliers***
Statistics	***DF***	***Sig.***	
18.368	18	0.432	0

Table 4: ARIMA Model Parameters

					Estimate	***SE***	***t***	***Sig.***
Normalised Cost Model	Normalised Cost	Natural Logarithm	Constant		18.595	0.264	70.402	0
	Annual Sea surface temperature Anomaly	No Transformation	Numerator	Lag 0	3.996	1.008	3.964	0



The model is created using SPSS statistics. The value of stationary R-squared is 0.352 suggesting that the model has explained 35.2% of the variability of the data.

All the Sig. (p-value) for all of the predictors variable are small ($\approx$0.000) suggested that the predictor contributing significant additional information to the model.

The graph visualises the observed value (red line) compared to the fit value (blue line) which is the expected value using the model, the UCL and LCL (dotted line) which are lower and upper points of 95% confidence interval for the fit.

Model is now given by:

$$log(N) = 18.595 + 3.996T + \varepsilon$$

Where: T is the Sea Surface temperature anomaly

ε is the error term of the model

Model Interpretation:

The CSIRO report *State of Climate* 2012 shows that there is clear evidence that climate change exists. The average temperature is increasing, there are more hot days and less cold days in the year and the weather has become more and more extreme. There is also an increasing trend in the claims cost for weather related events. The question now is how climate change affects the insurance claim cost and in what way.

According to the statistical model, normalised claim cost is positively correlated with sea surface temperature anomaly. This result suggests that hot temperature greatly contributes to claim cost as rising sea surface temperature means the Earth is getting warmer in general. This can be explained by the climate pattern of Australia, a hot temperature for a prolonged period, relative low humidity, high winds and lack of rain can contribute greatly to fire danger. Sunshine and temperatures rapidly dry timber and grass which serve as fuel to bush fires. It is estimated that hot air can lower the moisture content of forests and grasslands to around 5 per cent and in extreme cases 2-3 per cent, which greatly increases the intensity as well as the speed of fire (Bureau of Meteorology, 2013).

In addition, an increase in overall temperature also greatly increases the chance of an extreme heat wave. The heatwave affecting Australia in late December and early January 2013 brought extreme hot heat all over Australia for a prolonged period. With the record of 40^{o}C and 45^{o}C this extreme heatwave is perceived as unprecedented in both maximum temperature and duration. This not only greatly increases the chance of bushfire but also increases the casualties caused by heat wave since there is a clear relationship between environmental heat and mortality.

The hot climate and especially warm sea surface temperature is also acting as a crucial contributor to the intensity of tropical storms and flooding. As temperature continues to rise, more and more water vapour could evaporate into the air, and water vapour is known to fuel storms and flood (Prest, 2013). With the atmosphere loaded with humidity, any normal storm that has developed greatly increases its potential to become an intense storm. In addition, some scientists have speculated that a warmer climate which allows more intense storms to develop would also spawn more hurricanes (Riebeek, 2013). This is crucial to the insurance industry as these stronger storms can increase damage to human structures when they make landfall.

This analysis has proven that climate change has greatly increased the intensity as well as the frequency of natural hazards. This leads to the consequence that there will be more and more claim costs for the insurance industry due to natural catastrophe. The risk caused by climate change has become greater than ever.

Proposed solutions:

Response to increased risk:

These adaptation methods could certainly limit the increased risks. However, it is unlikely that risk reduction and adaptation will completely eliminate the increasing loss trends of natural hazards which are expected to increase more rapidly due to climate change. This is where we have to take our approach to the next level, to perceive climate change not only as risks but also profitable business opportunity.

Exploring Opportunities:

Traditional measures to counter climate risks are to limit risks that are raising premiums, transfer damage or damage control. The first two approaches can be effective but undesirable due to the fact that they limit the insurance availability (Tucker, 1997). This will then shift a considerable amount of risk to households, the public and the business sector and hence indirectly avoid corporate social responsibility (CSR). The insurance industry needs to take one more step forward, to perceive these new climate risks as opportunities (Mills, 2009). On one hand, insurers can cooperate with the government to promote emission reduction, climate change mitigation and adaptation measures. This method requires long term investment. However they can limit major climate risks while committing to their CSR, building a good public image by not limiting insurance availabilities. Furthermore, insurance companies can transform climate risk into profitable opportunities by stimulating the implementation of environmentally friendly products and efficient risk reduction measures by aligning their terms and conditions with respective risks, providing carbon services and crafting innovation insurance products (Mills, 2012). Ultimately, climate change not only imposes increased risks on the industry but also spawns new profitable business opportunities. Insurance companies need to actively search for ways to cover the insurable gap deriving from these opportunities.

Conclusion

According to the statistical analysis, the more the temperature rises, the more intensity and frequency of natural disasters. There is no doubt that climate change incurs negative economic losses on the insurance industry. This trend of increasing claim cost due to extreme weather patterns can be observed clearly in the last three decades. Socioeconomic developments such as economic growth and population expansion leading to a considerable amount of infrastructure developed in vulnerable areas also play a vital part in the claim increasing trend. The combination of societal developments and climate change are expected to fuel upward trends in claim cost due to weather-related events. This negative trend will have a significant effect on society and especially the insurance sector.

This paper has examined the relationship between climate change and catastrophe claim cost for the Australia insurance sector and identified some main factors that influence the rise of claim cost in recent years. Climate change risks are real and they are increasing at an alarming rate. This analysis offers a basis for future research which should center on quantifying and evaluating risk adaptation methods and the profitability of innovation products. These further innovative researches require insurance companies to work closely with the academic research community. Specifically, insurer should disclose detailed historical data on claims and economic loss caused by extreme weather. At the present time, this information is limited due to the competitive value of such data and climate change research is not considered as a top priority for insurance companies. This indifference towards an alarming matter needs to change to prevent further worsening of economic losses due to increasing exposure to climate change.

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Appendix 1:

Table 5: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.903	8	3.988	2.461	.033[b]
	Residual	53.479	33	1.621		
	Total	85.382	41			
2	Regression	31.902	7	4.557	2.897	.017[c]
	Residual	53.480	34	1.573		
	Total	85.382	41			
3	Regression	31.883	6	5.314	3.476	.008[d]
	Residual	53.499	35	1.529		
	Total	85.382	41			
4	Regression	31.669	5	6.334	4.245	.004[e]
	Residual	53.713	36	1.492		
	Total	85.382	41			
5	Regression	30.874	4	7.719	5.239	.002[f]
	Residual	54.508	37	1.473		
	Total	85.382	41			
6	Regression	30.355	3	10.118	6.988	.001[g]
	Residual	55.027	38	1.448		
	Total	85.382	41			
7	Regression	28.327	2	14.164	9.682	.000[h]
	Residual	57.055	39	1.463		
	Total	85.382	41			
8	Regression	24.192	1	24.192	15.814	.000[i]
	Residual	61.190	40	1.530		
	Total	85.382	41			

a. Dependent Variable: Log_NormCost

b. Predictors: (Constant), LAGS(Log_NormCost,1), Average Number of hot days, Average Number of Cold nights, Average Number of Cold days, Annual Sea Surface Temperature Anomaly, Average Number of hot nights, Rainfall, Annual Average Temperature Anomaly

c. Predictors: (Constant), LAGS(Log_NormCost,1), Average Number of hot days, Average Number of Cold nights, Average Number of Cold days, Annual Sea Surface Temperature Anomaly, Rainfall, Annual Average Temperature Anomaly

d. Predictors: (Constant), LAGS(Log_NormCost,1), Average Number of hot days, Average Number of Cold nights, Annual Sea Surface Temperature Anomaly, Rainfall, Annual Average Temperature Anomaly

e. Predictors: (Constant), LAGS(Log_NormCost,1), Average Number of hot days, Average Number of Cold nights, Annual Sea Surface Temperature Anomaly, Rainfall

f. Predictors: (Constant), LAGS(Log_NormCost,1), Average Number of hot days, Average Number of Cold nights, Annual Sea Surface Temperature Anomaly

g. Predictors: (Constant), LAGS(Log_NormCost,1), Average Number of Cold nights, Annual Sea Surface Temperature Anomaly
h. Predictors: (Constant), Average Number of Cold nights, Annual Sea Surface Temperature Anomaly
i. Predictors: (Constant), Annual Sea Surface Temperature Anomaly

As is seen from the table, the significance of the model increases (Sig. value decrease) as we remove variables from the model.

Table 6: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	16.347	5.340		3.061	.004
	Annual Average Temperature Anomaly	.434	1.363	.117	.318	.752
	Annual Sea Surface Temperature Anomaly	4.664	1.537	.640	3.035	.005
	Average Number of hot nights	-.001	.066	-.002	-.008	.993
	Average Number of hot days	-.057	.074	-.308	-.767	.448
	Average Number of Cold nights	.045	.054	.185	.837	.409
	Average Number of Cold days	-.004	.037	-.017	-.098	.922
	Rainfall	-.002	.005	-.167	-.533	.597
	LAGS(Log_NormCost,1)	.141	.152	.147	.928	.360
2	(Constant)	16.330	4.857		3.362	.002
	Annual Average Temperature Anomaly	.432	1.322	.117	.327	.746
	Annual Sea Surface Temperature Anomaly	4.662	1.501	.640	3.107	.004
	Average Number of hot days	-.057	.065	-.310	-.880	.385
	Average Number of Cold nights	.045	.053	.185	.850	.401

	Average Number of Cold days	-.004	.034	-.017	-.111	.912
	Rainfall	-.003	.004	-.168	-.653	.518
	LAGS(Log_NormCost,1)	.141	.148	.147	.953	.347
3	(Constant)	16.143	4.487		3.597	.001
	Annual Average Temperature Anomaly	.470	1.257	.127	.374	.711
	Annual Sea Surface Temperature Anomaly	4.707	1.425	.646	3.304	.002
	Average Number of hot days	-.058	.063	-.317	-.928	.360
	Average Number of Cold nights	.046	.052	.188	.886	.382
	Rainfall	-.003	.004	-.172	-.682	.500
	LAGS(Log_NormCost,1)	.141	.146	.148	.970	.339
4	(Constant)	15.809	4.345		3.638	.001
	Annual Sea Surface Temperature Anomaly	4.772	1.397	.655	3.416	.002
	Average Number of hot days	-.042	.045	-.229	-.936	.356
	Average Number of Cold nights	.035	.042	.142	.831	.411
	Rainfall	-.003	.004	-.181	-.730	.470
	LAGS(Log_NormCost,1)	.154	.140	.161	1.098	.279
5	(Constant)	13.866	3.412		4.064	.000
	Annual Sea Surface Temperature Anomaly	4.279	1.215	.587	3.523	.001
	Average Number of hot days	-.015	.025	-.082	-.594	.556
	Average Number of Cold nights	.046	.039	.189	1.201	.237
	LAGS(Log_NormCost,1)	.155	.139	.161	1.111	.274
6	(Constant)	12.816	2.893		4.431	.000
	Annual Sea Surface Temperature Anomaly	4.178	1.192	.573	3.504	.001
	Average Number of Cold nights	.050	.038	.204	1.319	.195
	LAGS(Log_NormCost,1)	.163	.137	.170	1.183	.244
7	(Constant)	15.219	2.071		7.350	.000
	Annual Sea Surface Temperature Anomaly	4.765	1.090	.654	4.372	.000

	Average Number of Cold nights	.062	.037	.252	1.681	.101
	(Constant)	18.674	.258		72.369	.000
8	Annual Sea Surface Temperature Anomaly	3.878	.975	.532	3.977	.000

a. Dependent Variable: Log_NormCost

Table 7: Excluded Variables[a]

Model		Beta In	T	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
2	Average Number of hot nights	-.002[b]	-.008	.993	-.001	.331
3	Average Number of hot nights	-.011[c]	-.049	.961	-.008	.384
	Average Number of Cold days	-.017[c]	-.111	.912	-.019	.751
4	Average Number of hot nights	-.005[d]	-.023	.982	-.004	.386
	Average Number of Cold days	-.031[d]	-.207	.838	-.035	.806
	Annual Average Temperature Anomaly	.127[d]	.374	.711	.063	.155
5	Average Number of hot nights	-.075[e]	-.418	.679	-.069	.552
	Average Number of Cold days	-.046[e]	-.313	.756	-.052	.824
	Annual Average Temperature Anomaly	.149[e]	.445	.659	.074	.156
	Rainfall	-.181[e]	-.730	.470	-.121	.284
6	Average Number of hot nights	-.101[f]	-.621	.538	-.102	.652
	Average Number of Cold days	-.025[f]	-.178	.859	-.029	.866
	Annual Average Temperature Anomaly	-.049[f]	-.301	.765	-.049	.666
	Rainfall	.010[f]	.073	.942	.012	.887
	Average Number of hot days	-.082[f]	-.594	.556	-.097	.910

7	Average Number of hot nights	-.084[g]	-.516	.609	-.083	.656
	Average Number of Cold days	-.036[g]	-.253	.801	-.041	.869
	Annual Average Temperature Anomaly	-.043[g]	-.263	.794	-.043	.666
	Rainfall	.022[g]	.159	.875	.026	.892
	Average Number of hot days	-.096[g]	-.701	.488	-.113	.919
	LAGS(Log_NormCost,1)	.170[g]	1.183	.244	.189	.825
8	Average Number of hot nights	-.150[h]	-.943	.352	-.149	.711
	Average Number of Cold days	-.040[h]	-.278	.782	-.044	.870
	Annual Average Temperature Anomaly	-.142[h]	-.967	.339	-.153	.833
	Rainfall	.002[h]	.014	.989	.002	.899
	Average Number of hot days	-.135[h]	-.980	.333	-.155	.951
	LAGS(Log_NormCost,1)	.219[h]	1.571	.124	.244	.886
	Average Number of Cold nights	.252[h]	1.681	.101	.260	.766

a. Dependent Variable: Log_NormCost

b. Predictors in the Model: (Constant), LAGS(Log_NormCost,1), Average Number of hot days, Average Number of Cold nights, Average Number of Cold days, Annual Sea Surface Temperature Anomaly, Rainfall, Annual Average Temperature Anomaly

c. Predictors in the Model: (Constant), LAGS(Log_NormCost,1), Average Number of hot days, Average Number of Cold nights, Annual Sea Surface Temperature Anomaly, Rainfall, Annual Average Temperature Anomaly

d. Predictors in the Model: (Constant), LAGS(Log_NormCost,1), Average Number of hot days, Average Number of Cold nights, Annual Sea Surface Temperature Anomaly, Rainfall

e. Predictors in the Model: (Constant), LAGS(Log_NormCost,1), Average Number of hot days, Average Number of Cold nights, Annual Sea Surface Temperature Anomaly

f. Predictors in the Model: (Constant), LAGS(Log_NormCost,1), Average Number of Cold nights, Annual Sea Surface Temperature Anomaly

g. Predictors in the Model: (Constant), Average Number of Cold nights, Annual Sea Surface Temperature Anomaly

h. Predictors in the Model: (Constant), Annual Sea Surface Temperature Anomaly