An Empirical Investigation of the Dependence between Catastrophe Events and the Performance of Various Asset Classes

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Abstract: For insurance and reinsurance companies primarily involved in the Catastrophe business, the dependence between losses from catastrophe events and the returns on their asset portfolio can significantly impact their risk capital calculation. This dependence is also of relevance to capital market investors involved in Insurance Linked Securities (ILS) funds. In this paper, we draw on more than 60 years of data to investigate the dependence between insured and economic losses from catastrophe events and the relative performance of several asset classes, commodities, and economic indices in the US. We also look at the association between catastrophes and equities for selected catastrophe prone countries around the world. For US equities, our investigation suggests two correlation effects: one corresponding to the lowest 80th percentile of catastrophe losses, and another corresponding to the highest 20th percentile.

Keywords: Enterprise Risk Management, Economic Capital Model, Dependence, Correlations, Assets, Catastrophes, Insurance Linked Securities

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1. INTRODUCTION

Within the realm of dynamic financial analysis, there is broad recognition of both the importance and the challenges of adequately representing the dependence between risk variables. Indeed, some have partially blamed the 2008 financial crisis on the failure of quantitative analysts across the financial industry to accurately model the dependence between complex financial instruments[1]. Those tasked with building capital models for P&C insurance and reinsurance entities need to account for the dependence between a number of risk variables across multiple dimensions. There is some consensus around modeling the dependence of risk variables that fall within the same risk categories, which, for general insurance companies, are generally defined as insurance, market, credit, and operational. For instance, many practitioners use normal correlation matrices to capture the dependence between the underwriting results for various classes of business (i.e. Marine, Property, Medical Malpractice), or between the performance of different asset classes (i.e. Equities, Mortgage Backed Securities, Treasuries). There is much less agreement around how to represent the dependence between risk variables that fall in different risk categories.

For insurance and reinsurance companies primarily involved in the Catastrophe business and capital market investors involved in Insurance Linked Securities (ILS) funds, the dependence between losses from catastrophe events and the returns on their asset portfolio are particularly relevant. In this paper, we investigate the dependence between insured and economic losses from catastrophe events and the relative performance of several asset classes, commodities, and economic indices in the US. We also investigate the dependence between economic losses from catastrophes and the performance of equities in Australia, Chile, Japan, the Philippines, and Thailand. In section 2, we provide a brief overview of our approach. We present our findings and offer commentary in sections 3 and 4, respectively. We describe the data underlying this study and provide data sources in Appendix A. In Appendix B, we describe the calculations of the P-values and provide the distributions from which they are derived. Finally, we show selected graphs in Appendix C.

2. OVERVIEW OF APPROACH

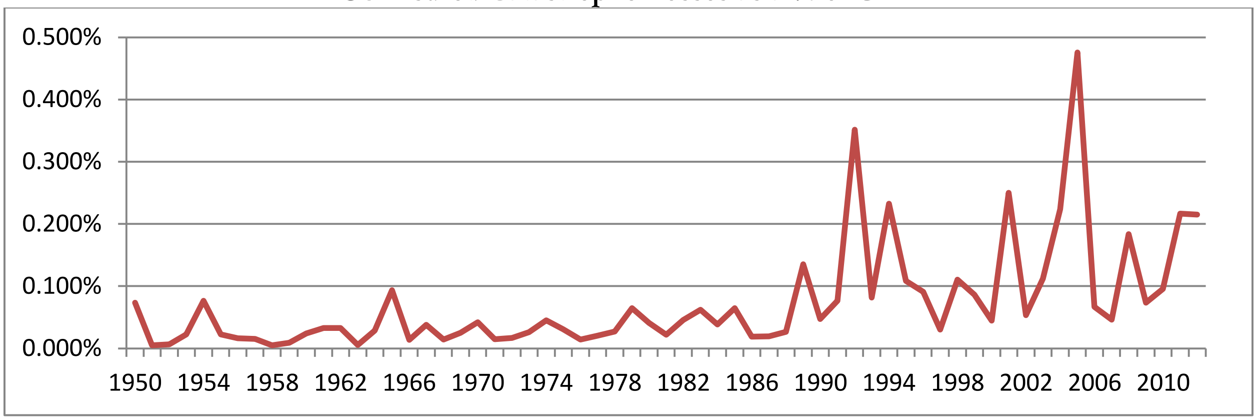
For the purpose of this study, we expressed aggregate catastrophe losses incurred in a calendar year as a percentage of Gross Domestic Product (GDP) in the same year. We believe this provides a more consistent measure of the relative importance of catastrophe losses across time but also across countries. Graph 2.1 below shows annual insured catastrophe losses as a percentage of GDP for the

[1] See Mackenzie, D. and Spears, T. (2012): "The Formula That Killed Wall Street"? (School of Social & Political Science, University of Edinburgh, Scotland) http://www.sps.ed.ac.uk/__data/assets/pdf_file/0003/84243/Gaussian14.pdf

US from 1950 to 2013. Throughout the remainder of this text, we will use the terms "catastrophe losses" and "catastrophe losses as a percentage of GDP" interchangeably. Annual catastrophe losses are compared to the percentage change in various financial and economic indices over the same calendar year. In the remainder of this text, we will sometimes use the term "return" when referring to the percentage change in the financial indices.

Graph 2.1

US Insured Catastrophe Losses as a % of GDP



Our investigation relies on the following tools:

a. Visual representations of the relationships through the use of percentile scatter plots – Each point on the plots represents the percentile value for each pair of observations within their respective sample. These scatter plots represent the empirical copula of each pair of variables. We reviewed these plots to search for trends and other patterns in the data. For brevity, we refer to the percentile scatter plots simply as scatter plots in the remainder of this document. Selected scatter plots are shown throughout the paper and in Appendix C.

b. Rank correlation measurements – We used the Kendall's Tau[2] and the Kendall's Partial Tau[3] statistics as non-parametric measures of rank correlation. We chose non-parametric measures as we did not want to make any assumptions about the distributions underlying the variables we were studying. As Graph 2.1 shows, US insured catastrophe losses show an upward trend over time even after being normalized for GDP. Without controlling for time, some of the correlations we observe may simply be driven by common time dependencies coming across the data for both catastrophes and the financial and economic indices. Hence, we used the Kendall's Partial Tau to provide a measure of correlation between any pair of variables that removes the effect of common time correlations. We assess significance by calculating the P-values associated with the Kendall's Tau and the Kendall's

[2] We reach virtually the same conclusions about the significance of the observed correlations using a Spearman Rho rather than a Kendall's Tau statistic. We prefer the latter statistic as it has a more intuitive interpretation than the Spearman Rho.

[3] Assume we have three variables, X, Y, and Z, the Kendall's Partial Tau correlation coefficient for X and Y after removing the effect of Z is given by: $\tau_{xy.z} = \frac{\tau_{xy} - \tau_{xz}\tau_{yz}}{\sqrt{1-\tau_{xz}^2}\sqrt{1-\tau_{yz}^2}}$ where $\tau_{xy}, \tau_{xz}, \tau_{yz}$ represent the Kendall's Tau correlation coefficients for the pairs XY, XZ, and YZ respectively. See Gibbons, J.D. (1993, p. 49) *Nonparametric measures of association* (Sage University Paper series on Quantitative Applications in the Social Sciences, series no. 07-091). Newbury Park, CA: Sage.

Partial Tau statistics. The calculations of the P-values, including the underlying null hypotheses, are described in Appendix B.

c. Difference in rank correlation measurements – We measured the differences between the Kendall's Tau and the Kendall's Partial Tau statistics wherever we had an indication that there was a shift in the correlation trends. We assess significance by calculating the P-values associated with the differences in the Kendall's Tau and Kendall's Partial Tau statistics. The calculations of the P-values are described in Appendix B.

d. We determine the significance of the Kendall's Tau, Kendall's Partial Tau, and of the differences in the Kendall's Tau and Kendall's Partial Tau values throughout this paper based on the interpretation of P-values shown in Table 2.1 below. This is perhaps the most subjective and also the most important table in this entire study. Different interpretations of the P-values will likely lead to different conclusions about the statistical significance of the observed correlations.

Table 2.1
P-Value Interpretation

One-Tailed P- value Ranges	Reject Null Hypothesis?
P-value ≤ .05	Yes
P-value > .05	No

3. FINDINGS

We present our key findings below:

a. We find two correlation trends between US annual catastrophe losses – either insured or economic – and annual changes in US equity prices. We observe a zero or a weak positive correlation when catastrophe losses as a percentage of GDP fall in the first 80th percentile and a negative correlation when they are at or above the 80th percentile. This is shown in Table 3.1.a below. This finding is unchanged when we remove the effect of time on the Kendall's Tau correlations as shown in Table 3.1.b. Tables 3.11.a and 3.11.b show the P-values for the differences in the Kendall's Tau and Kendall's Partial Tau values, respectively. We show the annual returns of the DJIA and DJCA against the highest 20th percentile of annual insured catastrophe losses in Table 3.2. We also show the annual returns of the DJIA against the highest 20th percentile of economic losses due to catastrophe in Table 3.3. Graph 3.1 shows a scatter plot of the annual DJIA returns against annual insured catastrophe losses. Graphs 3.1.a and 3.1.b show separate scatter plots corresponding to the lowest 80th percentile and the highest 20th percentile of annual insured catastrophe losses. We show the corresponding scatter plots for economic losses against the DJIA in Graphs 3.2, 3.2.a, and 3.2.b.

Table 3.1.a
Annual Catastrophe Losses against Annual Changes in Equities – US

Catastrophe Losses	Catastrophe Loss Percentile	Index	No. of Observations	Kendall's Tau	One Tailed P-value	Is Correlation Significant?
Insured	<.80	DJIA	51	17.3%	0.036	Yes
Insured	≥.80	DJIA	13	-53.8%	0.005	Yes
Insured	<.80	DJCA	51	14.5%	0.066	No
Insured	≥.80	DJCA	13	-41.0%	0.025	Yes
Insured	<.80	S&P 500	51	12.9%	0.090	No
Insured	≥.80	S&P 500	13	-46.2%	0.014	Yes
Economic	<.80	DJIA	56	18.8%	0.020	Yes
Economic	≥.80	DJIA	15	-48.6%	0.006	Yes

Table 3.1.b
Annual Catastrophe Losses against Annual Changes in Equities after Removing Effect of Time – US

Catastrophe Losses	Catastrophe Loss Percentile	Index	No. of Observations	Kendall's Partial Tau	One Tailed P-value	Is Correlation Significant?
Insured	<.80	DJIA	51	15.7%	0.054	No
Insured	≥.80	DJIA	13	-56.2%	0.003	Yes
Insured	<.80	DJCA	51	13.9%	0.078	No
Insured	≥.80	DJCA	13	-42.7%	0.021	Yes
Insured	<.80	S&P 500	51	12.8%	0.095	No
Insured	≥.80	S&P 500	13	-48.7%	0.009	Yes
Economic	<.80	DJIA	56	18.2%	0.025	Yes
Economic	≥.80	DJIA	15	-48.5%	0.006	Yes

Table 3.2
Highest 20th Percentile of Annual Insured Catastrophe Losses against Annual Equity Returns – US

Year	Insured Cat as % of GDP	Insured Cat[1] (USD MM)	DJIA Return	DJIA Rank [2]	DJCA Return	DJCA Rank [2]
2010	0.096%	14,315	11.0%	32	13.1%	29
1995	0.109%	8,325	33.5%	4	32.9%	3
1998	0.111%	10,070	16.1%	24	10.1%	34
2003	0.112%	12,885	25.3%	9	26.3%	7
1989	0.135%	7,642	27.0%	6	25.3%	10
2008	0.184%	27,045	-33.8%	64	-29.8%	64
2012	0.215%	34,960	7.3%	35	5.0%	41
2011	0.217%	33,640	5.5%	38	4.9%	42
2004	0.224%	27,490	3.1%	43	13.2%	28
1994	0.233%	17,010	2.1%	46	-7.7%	54
2001	0.250%	26,549	-7.1%	53	-12.8%	57
1992	0.351%	22,970	4.2%	42	4.1%	43
2005	0.476%	62,301	-0.6%	47	7.1%	38

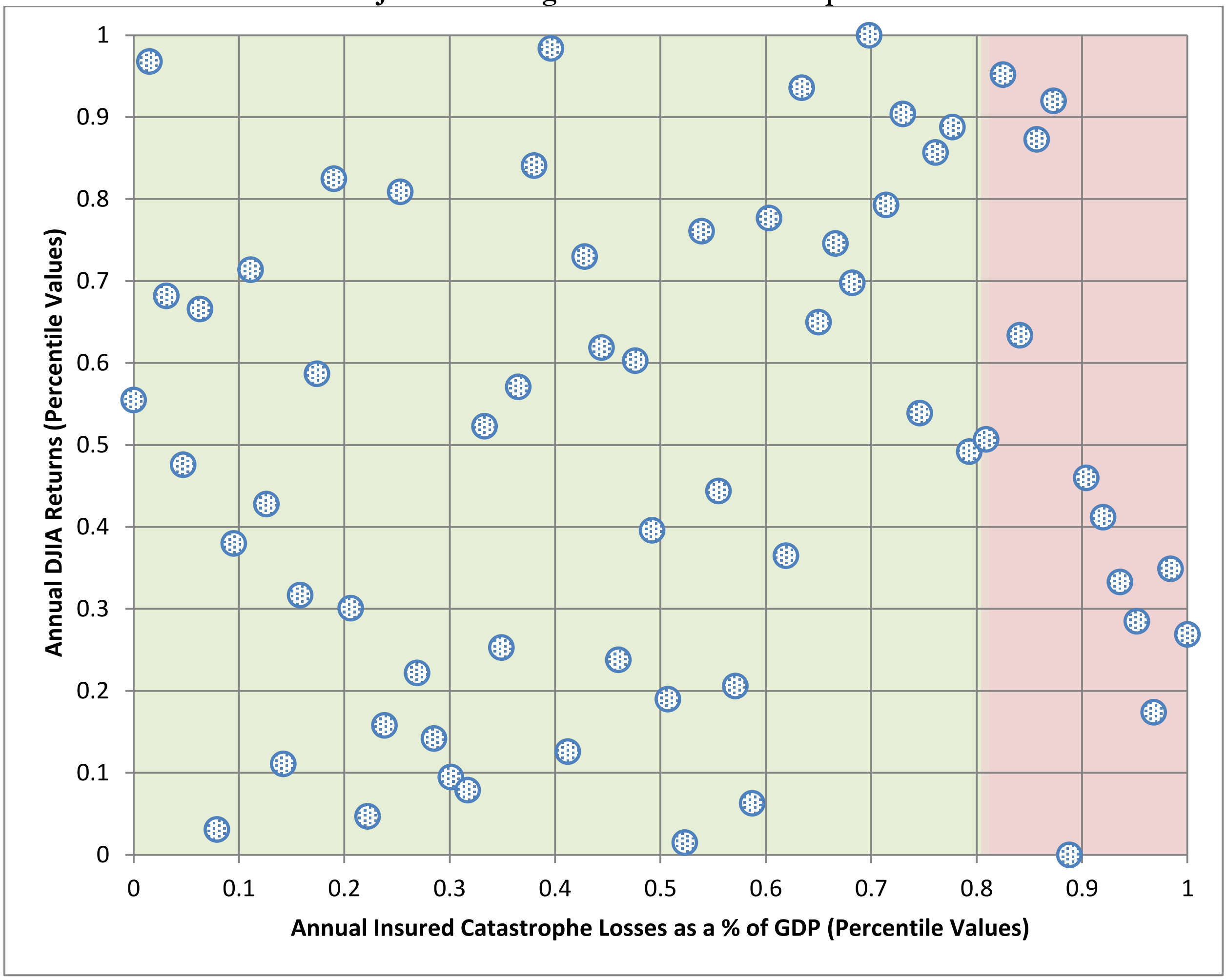
(1) Source: PCS
(2) Rank from best to worst out of 64

Table 3.3
Highest 20th Percentile of Annual Economic Losses due to Catastrophes against Annual Equity Returns – US

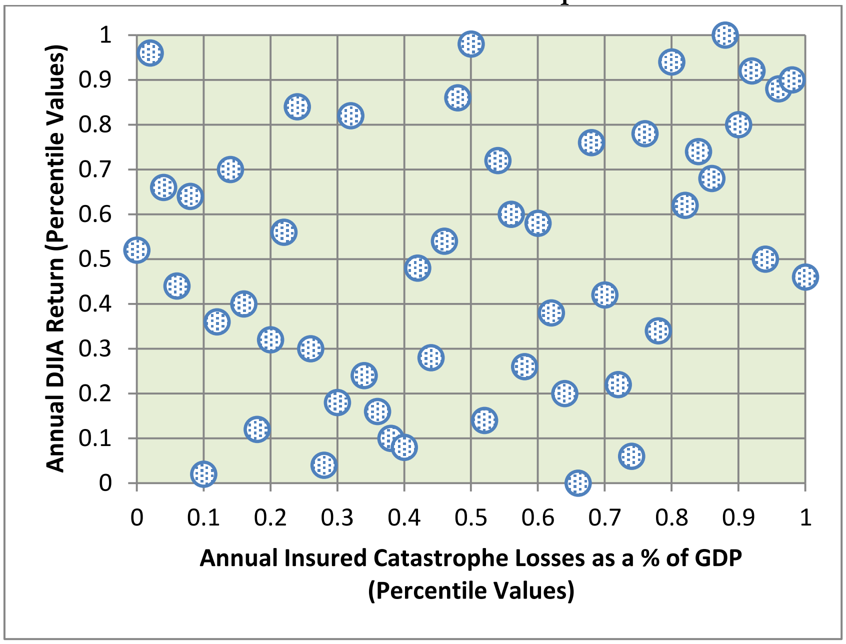
Year	Economic Losses Due to Cats as % of GDP	Economic Losses Due to Cats[1] (USD MM)	DJIA Return	DJIA Rank [2]
1995	0.220%	16,890	33.5%	5
1989	0.238%	13,480	27.0%	8
1993	0.268%	18,423	13.7%	33
1951	0.296%	1,029	14.4%	31
1964	0.305%	2,090	14.6%	30
2011	0.331%	51,433	5.5%	42
1938	0.350%	306	28.1%	6
2008	0.392%	57,762	-33.8%	71
1994	0.432%	31,554	2.1%	50
1943	0.443%	900	13.8%	32
2004	0.454%	55,692	3.1%	47
1937	0.471%	438	-32.8%	70
2012	0.483%	78,469	7.3%	39
1992	0.534%	34,950	4.2%	46
2005	1.215%	159,060	-0.6%	51

(1) Source: EM-Dat; Years with no losses are excluded
(2) Rank from best to worst out of 71

Graph 3.1
Scatter Plot of Annual DJIA Returns against Insured Catastrophe Losses as a % of GDP

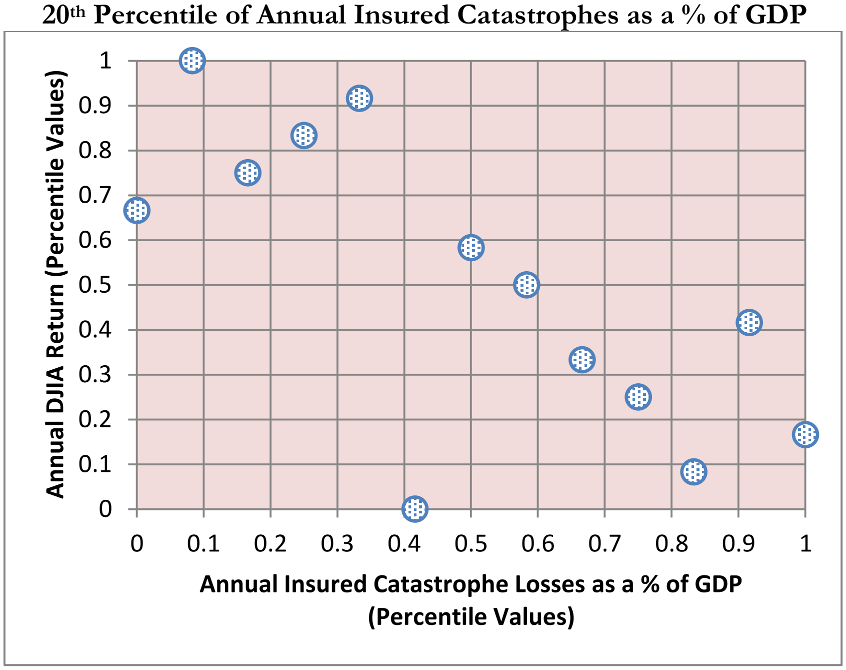


Graph 3.1.a
Scatter Plot of Annual DJIA Returns against Insured Catastrophe Losses as a % of GDP for lowest 80th Percentile of Annual Insured Catastrophes as a % of GDP



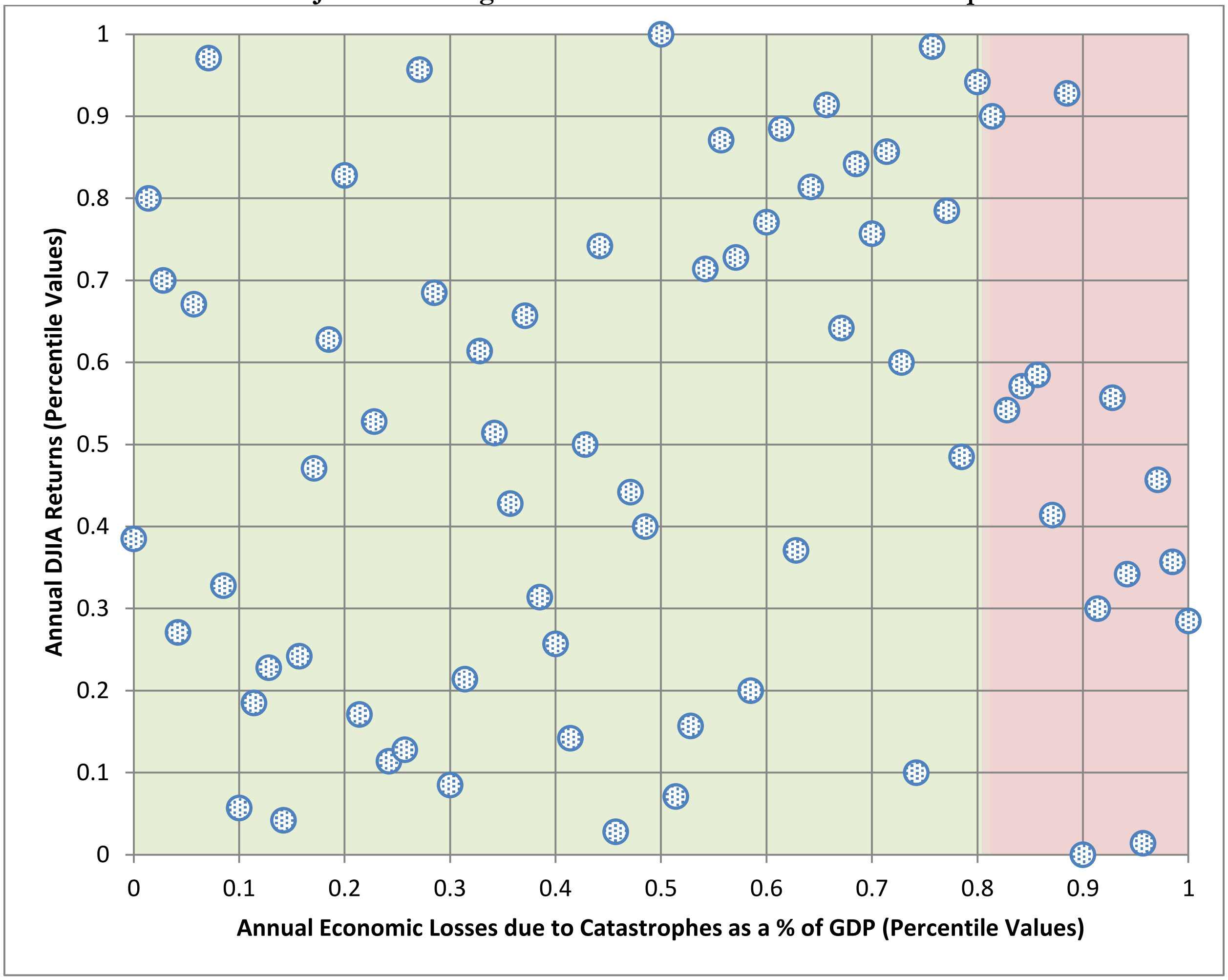
Please note that the percentiles in the above graph have been recalculated based on the relative rankings of the subset of points that fall in the lowest 80th percentile of annual insured catastrophe losses as a % of GDP. As such, these percentiles range from 0 to 1.

Graph 3.1.b
Scatter Plot of Annual DJIA Returns against Insured Catastrophe Losses as a % of GDP for highest 20th Percentile of Annual Insured Catastrophes as a % of GDP

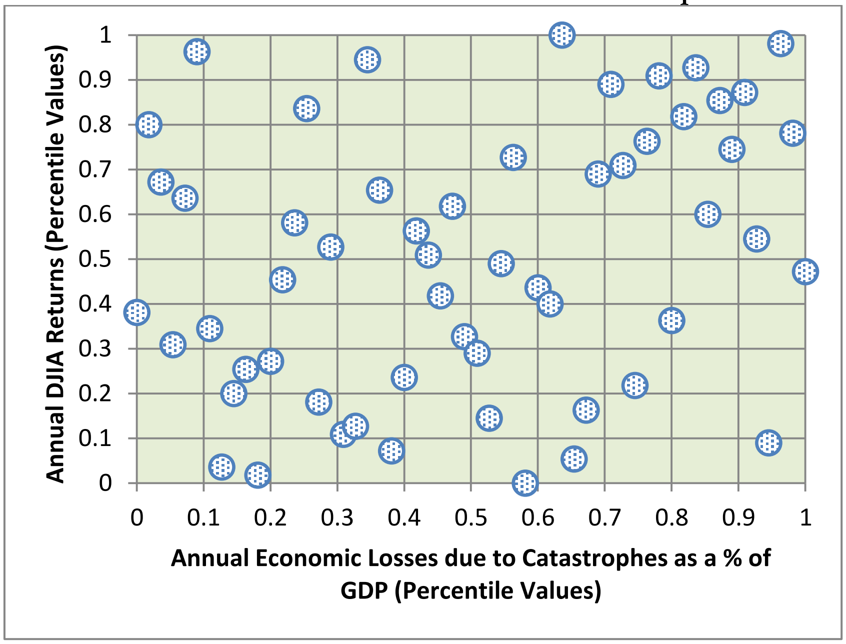


Please note that the percentiles in the above graph have been recalculated based on the relative rankings of the subset of points that fall in the highest 20th percentile of annual insured catastrophe losses as a % of GDP. As such, these percentiles range from 0 to 1.

Graph 3.2
Scatter Plot of Annual DJIA Returns against Economic Losses due to Catastrophes as a % of GDP

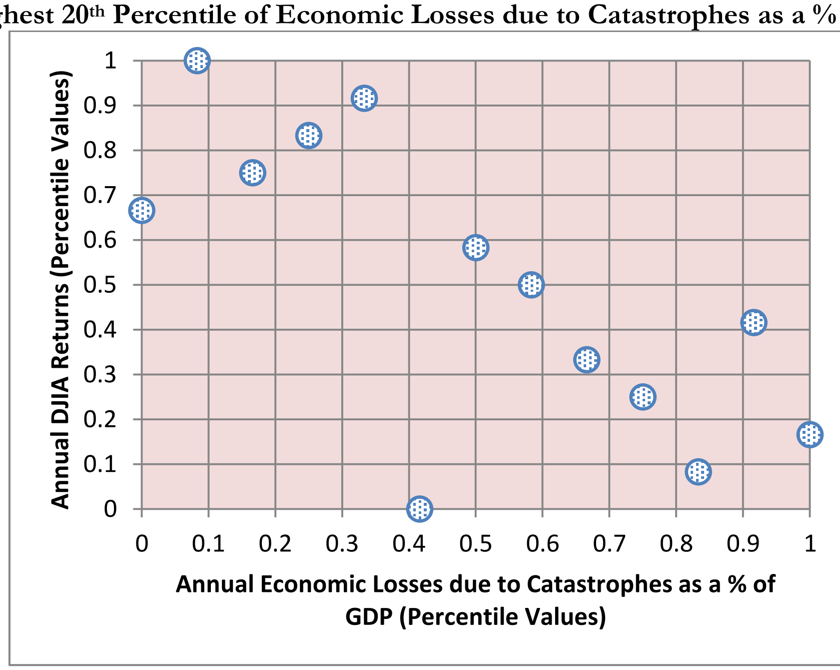


Graph 3.2.a
Scatter Plot of Annual DJIA Returns against Economic Losses due to Catastrophes as a % of GDP for lowest 80th Percentile of Economic Losses due to Catastrophes as a % of GDP



Please note that the percentiles in the above graph have been recalculated based on the relative rankings of the subset of points that fall in the lowest 80th percentile of annual insured catastrophe losses as a % of GDP. As such, these percentiles range from 0 to 1.

Graph 3.2.b
Scatter Plot of Annual DJIA Returns against Economic Losses due to Catastrophes as a % of GDP for highest 20th Percentile of Economic Losses due to Catastrophes as a % of GDP



Please note that the percentiles in the above graph have been recalculated based on the relative rankings of the subset of points that fall in the highest 20th percentile of annual insured catastrophe losses as a % of GDP. As such, these percentiles range from 0 to 1.

b. We find no significant correlation between catastrophe losses and changes in equity prices for Australia, Chile, Japan, and Thailand. We did not find any significant shift in correlation based on the relative size of catastrophe losses. This is shown in Table 3.4.a below. This finding is unchanged when we remove the effect of time on the Kendall's Tau correlations as shown in Table 3.4.b. Please note that we only have economic losses for these countries. Also, the data set for these countries is much sparser compared to the US.

Table 3.4.a
Annual Catastrophe Losses against Annual Changes in Equities – Australia, Japan, Chile, and Thailand

Catastrophe Losses	Index	No. of Observations	Kendall's Tau	One Tailed P-value	Is Correlation Significant?
Economic Losses	All Australia Shares	44	-11.2%	0.140	No
Economic Losses	Nikkei 225	38	1.3%	0.455	No
Economic Losses	IGPA	30	11.3%	0.191	No
Economic Losses	SET Index	22	4.8%	0.378	No

Table 3.4.b
Annual Catastrophe Losses against Annual Changes in Equities after Removing Effect of Time – Australia, Japan, Chile, and Thailand

Catastrophe Losses	Index	No. of Observations	Kendall's Partial Tau	One Tailed P-value	Is Correlation Significant?
Economic Losses	All Australia Shares	44	-11.2%	0.142	No
Economic Losses	Nikkei 225	38	0.4%	0.488	No
Economic Losses	IGPA	30	3.3%	0.401	No
Economic Losses	SET Index	22	3.9%	0.383	No

c. Similar to US equities, we find two correlation trends between annual catastrophe losses in the Philippines and annual changes in the main Philippines stock index, PSEi. We observe a zero correlation when catastrophe losses as a percentage of GDP fall in the first 70th percentile and a negative correlation when they are at or above the 70th percentile. This is shown in Table 3.5.a below. This finding is unchanged when we remove the effect of time on the Kendall's Tau correlations as shown in Table 3.5.b. Tables 3.11.a and 3.11.b show the P-values for the differences in the Kendall's Tau and Kendall's Partial Tau values. We show the annual returns of the PSEi index against the highest 30th percentile of annual economic losses due to catastrophes in Table 3.6. Please note that the number of observations is quite sparse compared to the US data. Graph 3.3 shows a scatter plot of the PSEi return against catastrophe losses. Graphs 3.3.a and 3.3.b show separate scatter plots corresponding to the lowest 70th percentile and the highest 30th percentile of catastrophe losses.

Table 3.5.a

Annual Catastrophe Losses against Annual Changes in Equities – Philippines

Catastrophe Losses	Catastrophe Loss Percentile	Index	No. of Observations	Kendall's Tau	One Tailed P-value	Is Correlation Significant?
Economic Losses	<.70	PSEi	18	3.3%	0.425	No
Economic Losses	≥.70	PSEi	8	-64.3%	0.013	Yes

Table 3.5.b
Annual Catastrophe Losses against Annual Changes in Equities after Removing Effect of Time – Philippines

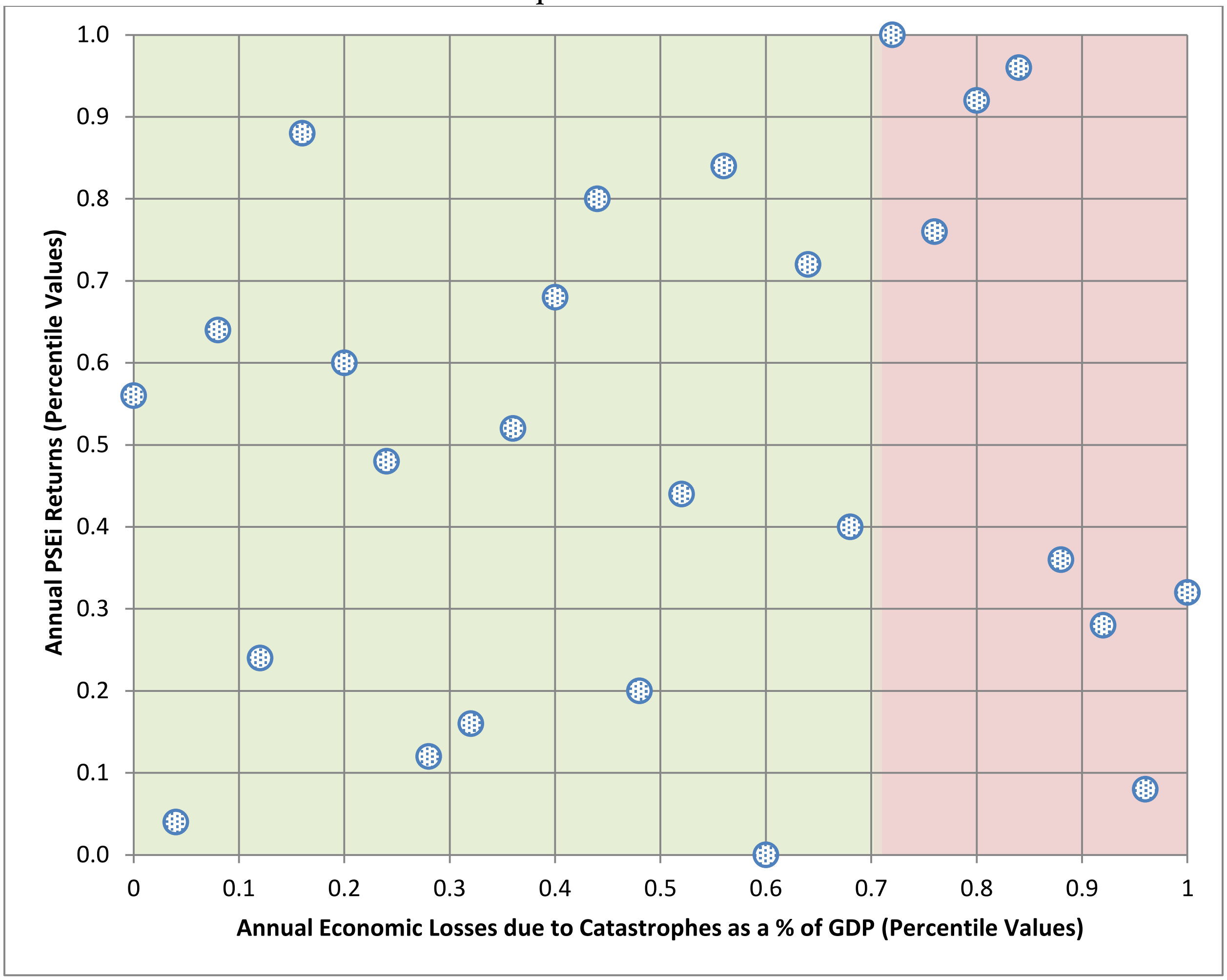
Catastrophe Losses	Catastrophe Loss Percentile	Index	No. of Observations	Kendall's Partial Tau	One Tailed P-value	Is Correlation Significant?
Economic Losses	<.70	PSEi	18	2.8%	0.439	No
Economic Losses	≥.70	PSEi	8	-64.5%	0.011	Yes

Table 3.6
Highest 30th Percentile of Annual Catastrophe Losses against PSEi Returns – Philippines

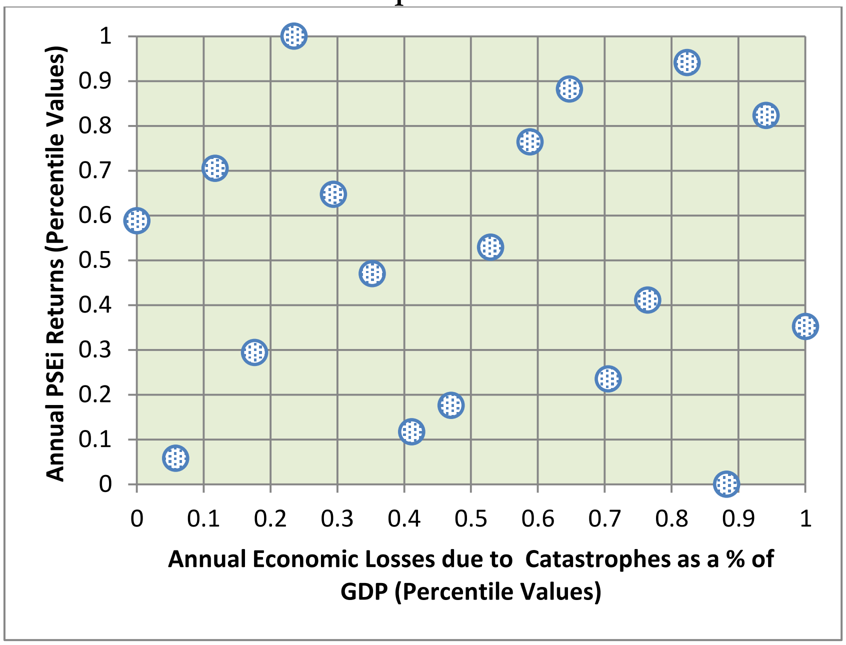
Year	Economic Losses Due to Cats as % of GDP	Economic Losses Due to Cats(1) (USD MM)	PSEi Return	PSEi Rank (2)
1993	0.209%	456	152.0%	1
2012	0.241%	855	33.6%	7
2009	0.295%	876	62.9%	3
1991	0.349%	699	76.7%	2
1988	0.400%	673	2.8%	17
1995	0.490%	1,305	-7.9%	19
1990	0.588%	1,134	-41.2%	24
2013	2.742%	10,413	1.3%	18

(1) Source: EM-Dat; Years with no losses are excluded
(2) Rank from best to worst out of 26

Graph 3.3
Scatter Plot of Annual PSEi (Philippines Stock Index) Returns against Economic Losses due to Catastrophes as a % of GDP

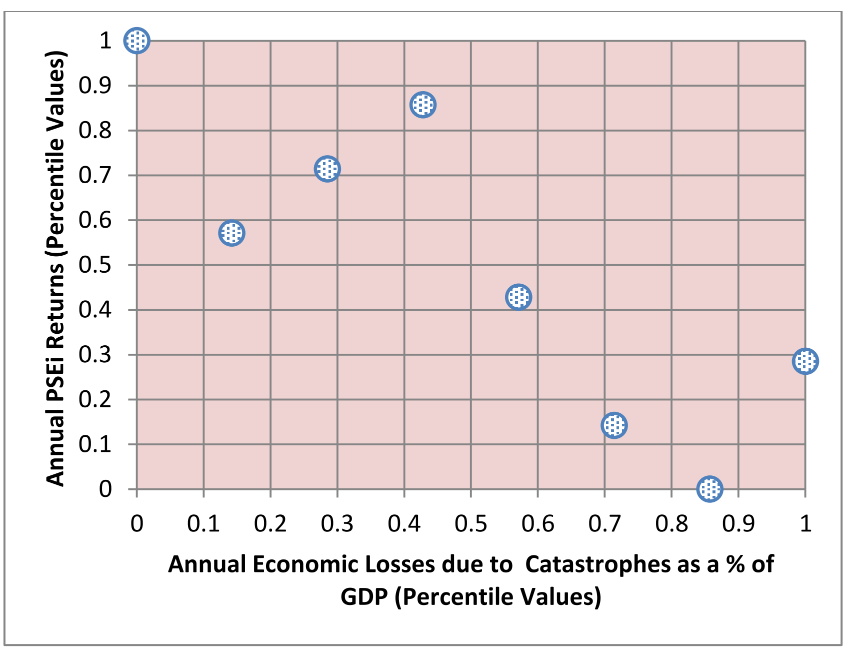


Graph 3.3.a
Scatter Plot of Annual PSEi (Philippines) Returns against Economic Losses due to Catastrophes as a % of GDP for lowest 70th Percentile of Economic Losses due to Catastrophes as a % of GDP



Please note that the percentiles in the above graph have been recalculated based on the relative rankings of the subset of points that fall in the lowest 70th percentile of annual insured catastrophe losses as a % of GDP. As such, these percentiles range from 0 to 1.

Graph 3.3.b
Scatter Plot of Annual PSEi (Philippines) Returns against Economic Losses due to Catastrophe Losses as a % of GDP for highest 30th Percentile of Economic Losses due to Catastrophes as a % of GDP



Please note that the percentiles in the above graph have been recalculated based on the relative rankings of the subset of points that fall in the highest 30th percentile of annual insured catastrophe losses as a % of GDP. As such, these percentiles range from 0 to 1.

d. We find no significant correlation between catastrophe losses and the returns on the Barclays Capital US bond indices shown below. We did not find any significant shift in correlation based on the relative size of catastrophe losses. This is shown in Table 3.7.a below. This finding is unchanged when we remove the effect of time on the Kendall's Tau correlations as shown in Table 3.7.b. Please note that the data for the Barclays Capital indices only goes back to 1973.

Table 3.7.a
Annual Catastrophe Losses against Annual Returns on US Treasury, Agency, and Corporate Bonds

Catastrophe Losses	Barclays Capital Index	No. of Observations	Kendall's Tau	One Tailed P-value	Is Correlation Significant?
Insured Losses	US Treasury	41	-9.8%	0.188	No
Insured Losses	US Intermediate Treasury	41	-16.6%	0.066	No
Insured Losses	US Long Treasury	41	3.9%	0.365	No
Insured Losses	US Credit	41	-6.6%	0.277	No
Insured Losses	US Intermediate Credit	41	-10.5%	0.172	No
Insured Losses	US Long Credit	41	-0.7%	0.479	No

Table 3.7.b
Annual Catastrophe Losses against Annual Returns on US Treasury, Agency, and Corporate Bonds after Removing Effect of Time

Catastrophe Losses	Barclays Capital Index	No. of Observations	Kendall's Partial Tau	One Tailed P-value	Is Correlation Significant?
Insured Losses	US Treasury	41	-4.06%	0.355	No
Insured Losses	US Intermediate Treasury	41	-8.10%	0.229	No
Insured Losses	US Long Treasury	41	4.02%	0.357	No
Insured Losses	US Credit	41	-4.39%	0.344	No
Insured Losses	US Intermediate Credit	41	-6.03%	0.291	No
Insured Losses	US Long Credit	41	-1.08%	0.462	No

e. We find no significant correlation between annual catastrophe losses and annual movements in crude oil prices as shown in Table 3.8.a below. We did not find any significant shift in correlation based on the relative size of catastrophe losses. This finding is unchanged when we remove the effect of time on the Kendall's Tau correlations as shown in Table 3.8.b.

Table 3.8.a
Annual Catastrophe Losses against Annual Changes in Crude Oil Price – US

Catastrophe Losses	Index	No. of Observations	Kendall's Tau	One Tailed P-value	Is Correlation Significant?
Insured Losses	Crude Oil	63	9.9%	0.126	No

Table 3.8.b

Annual Catastrophe Losses against Annual Changes in Crude Oil Price after Removing Effect of Time – US

Catastrophe Losses	Index	No. of Observations	Kendall's Partial Tau	One Tailed P-value	Is Correlation Significant?
Insured Losses	Crude Oil	63	6.8%	0.222	No

f. We find no significant correlation between annual catastrophe losses and annual movements in the US CPI as shown in Table 3.9.a below. We did not find any significant shift in correlation based on the relative size of catastrophe losses. This finding is unchanged when we remove the effect of time on the Kendall's Tau correlations as shown in Table 3.9.b.

Table 3.9.a
Annual Catastrophe Losses against Annual Changes in the US CPI

Catastrophe Losses	Index	No. of Observations	Kendall's Tau	One Tailed P-value	Is Correlation Significant?
Insured Losses	CPI	64	-6.0%	0.242	No

Table 3.9.b
Annual Catastrophe Losses against Annual Changes in the US CPI after Removing Effect of Time

Catastrophe Losses	Index	No. of Observations	Kendall's Partial Tau	One Tailed P-value	Is Correlation Significant?
Insured Losses	CPI	64	-8.6%	0.158	No

g. We find evidence of a negative correlation between annual catastrophe losses and annual changes in both nominal and real GDP as shown in Table 3.10.a below. We did not find any significant shift in correlation based on the relative size of catastrophe losses. However, when we remove the effect of time, the correlation between catastrophe losses and nominal GDP gets weaker while that between catastrophe losses and real GDP becomes statistically insignificant as shown in Table 3.10.b.

Table 3.10.a
Annual Catastrophe Losses against Annual Changes in US GDP

Catastrophe Losses	Index	No. of Observations	Kendall's Tau	One Tailed P-value	Is Correlation Significant?
Insured Losses	Nominal GDP	64	-25.6%	0.001	Yes
Insured Losses	Real GDP	64	-18.3%	0.017	Yes

Table 3.10.b
Annual Catastrophe Losses against Annual Changes in US GDP after Removing Effect of Time

Catastrophe Losses	Index	No. of Observations	Kendall's Partial Tau	One Tailed P-value	Is Correlation Significant?
Insured Losses	Nominal GDP	64	-15.0%	0.041	Yes
Insured Losses	Real GDP	64	-6.6%	0.226	No

Table 3.11.a
P-values for Difference in the Kendall's Tau Values

Catastrophe Losses	Index	Percentile / # obs	Kendall's τ	Percentile / # obs	Kendall's τ	Kendall's Diff δ	One Tailed P-value	Is Difference Significant?
Insured	DJIA	<.80/51	17.3%	≥.80/13	-53.8%	-71.2%	-	Yes
Insured	DJCA	<.80/51	14.5%	≥.80/13	-41.0%	-55.5%	0.007	Yes
Insured	S&P 500	<.80/51	12.9%	≥.80/13	-46.2%	-59.1%	0.004	Yes
Economic	DJIA	<.80/56	18.8%	≥.80/15	-48.6%	-67.4%	-	Yes
Economic	PSEi	<.7/18	3.3%	≥.7/8	-64.3%	-67.6%	0.021	Yes

Table 3.11.b
P-values for Difference in the Kendall's Partial Tau Values

Catastrophe Losses	Index	Percentile / # obs	Kendall's Partial τ	Percentile / # obs	Kendall's Partial τ	Kendall's Partial Diff δ	One Tailed P-value	Is Difference Significant?
Insured	DJIA	<.80/51	15.7%	≥.80/13	-56.2%	-71.9%	0.001	Yes
Insured	DJCA	<.80/51	13.9%	≥.80/13	-42.7%	-56.6%	0.007	Yes
Insured	S&P 500	<.80/51	12.8%	≥.80/13	-48.7%	-61.5%	0.004	Yes
Economic	DJIA	<.80/56	18.2%	≥.80/15	-48.5%	-66.7%	0.001	Yes
Economic	PSEi	<.70/18	2.8%	≥.70/8	-64.5%	-67.3%	0.023	Yes

4. COMMENTARY

There is a widely held view in the catastrophe insurance space that the capital markets are uncorrelated to catastrophe losses. This seems to hold true for fixed income securities in the US but not for equities according to our investigation. However, we can see how a casual evaluation of the data might tend to validate the conventional wisdom. Had we measured the Kendall's Tau and Kendall's Partial Tau statistics for US equities without taking into account the shifts in correlation, we might come to the conclusion that equities are indeed uncorrelated to catastrophes as shown in Tables 4.1.a and 4.1.b below.

Table 4.1.a
Annual Catastrophe Losses against Annual Changes in Equities – US

Country	Catastrophe Losses	Index	No. of Observations	Kendall's Tau	One Tailed P-value	Is Correlation Significant?
US	Insured Losses	DJCA	64	4.9%	0.285	No
US	Insured Losses	DJIA	64	6.8%	0.212	No
US	Insured Losses	S&P 500	64	6.3%	0.229	No
US	Economic Losses	DJIA	71	7.9%	0.164	No

Table 4.1.b
Annual Catastrophe Losses against Annual Changes in Equities after Removing Effect of Time – US

Country	Catastrophe Losses	Index	No. of Observations	Kendall's Partial Tau	One Tailed P-value	Is Correlation Significant?
US	Insured Losses	DJCA	64	5.5%	0.265	No
US	Insured Losses	DJIA	64	6.6%	0.226	No
US	Insured Losses	S&P 500	64	6.9%	0.215	No
US	Economic Losses	DJIA	71	8.0%	0.164	No

When thinking about the relationship between US catastrophe losses and equities, say in terms of 2014 dollars, it helps to split the annual insured losses into two ranges: one below $16.5B and one above that. Similarly, annual economic losses can be split into two ranges: one below $38B and one above that. These thresholds represent approximately .096% and .22% of projected 2014 GDP[4] and correspond to the 80th percentile of annual insured and economic catastrophe losses, respectively. Below these thresholds, the correlation is either neutral or slightly positive. Above, the correlation is negative indicating that equity returns tend to deteriorate as the size of catastrophe losses increases. This deterioration entails weaker but not necessarily negative equity returns. Also, just as importantly, the deterioration is only relative to the 13 to 15 data points that fall in the range of the highest 20th percentile of catastrophe losses. For some institutions, most of the coverage they sell is only triggered for large enough catastrophe events so the correlation in the highest 20th percentile is really the most relevant.

The Kendall's Tau and Kendall's Partial Tau values above the 80th percentile thresholds are approximately -50% as shown in Tables 3.1.a and 3.1.b. These values imply that, once catastrophe losses are above these thresholds, equity returns are approximately three times more likely to deteriorate as the size of catastrophe losses increases than they are to improve[5].

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[4] 2014 GDP is estimated at $17.3T by applying a growth rate of 2.8% to the 2013 GDP. This growth forecast is taken from the World Economic Outlook Update published on January 21, 2014 by the International Monetary Fund. http://www.imf.org/external/pubs/ft/weo/2014/update/01/pdf/0114.pdf

[5] The Kendall's Tau coefficient τ is equal to

$\frac{2(C-D)}{n(n-1)}$ where C and D represent the number of concordant and discordant pairs, respectively; $\frac{n(n-1)}{2}$

A discussion on how to model the dependence structure between assets and catastrophe losses is beyond the scope of this paper. Whatever the chosen modeling approach, it needs to be complemented by robust sensitivity and scenario testing.

There are many caveats and limitations to this study, some of which are discussed below:

a. Our findings only apply to calendar year data and should not be extrapolated to longer or shorter time periods. We did not necessarily observe the same degree of correlation when we studied some of the data for quarterly periods. A presentation of our findings based on quarterly data is beyond the scope of this paper.
b. This investigation neither demonstrates nor suggests any causation relationship between catastrophes and the various indices we evaluated even where the correlations are significant.
c. The percentages of GDP discussed in the preceding paragraphs are purely a function of the PCS and EM-Dat data sets. They should not be interpreted as some fixed, exact, or universal thresholds above which catastrophe losses and equity returns are negatively correlated.
d. The losses in the observation period are primarily from natural catastrophes with 9/11 being the most notable exception. We would not extrapolate the findings of this study to losses stemming from terrorist acts, especially those that involve nuclear, biological, chemical, or radioactive material.

We hope this paper provides but the beginnings of a robust discussion around the subject of dependence between catastrophes and assets. We have shared our data sources in Table A.1 of Appendix A hoping that others will take a critical look at the data in order to correct or augment our findings. We would be interested in expanding the analysis to more countries and to a broader set of financial and economic indices for the five countries we reviewed outside of the US. Finally, we would like to examine the sensitivity of our findings to the data on which we relied by looking into alternative data sources.

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represent the total number of pair combinations. τ can be interpreted as follows: $\tau = \pi_c - \pi_d$, where $\pi_c = \frac{C}{n(n-1)/2}$ and $\pi_d = \frac{D}{n(n-1)/2}$ represent the probability of concordant and discordant pairs C and D, respectively.

Solving for the following equations: $\begin{cases} \pi_c - \pi_d = -.5 \\ \pi_c + \pi_d = 1 \end{cases}$ yields $\pi_c = .25$ *and* $\pi_d = .75$. Hence $\pi_d = 3\pi_c$. For a definition of the Kendall's Tau coefficient, see Gibbons, J.D. (1993, p. 11) *Nonparametric measures of association* (Sage University Paper series on Quantitative Applications in the Social Sciences, series no. 07-091). Newbury Park, CA: Sage.

APPENDIX A

DATA

A.1. United States

Insured Losses

For insured losses in the United States, we relied on data from Verisk's PCS and their definition of catastrophe events. Losses are in actual dollars and not adjusted for price levels. The PCS insured loss catalog goes back to 1950. We understand that the threshold above which losses are captured in the PCS database has changed a few times since 1950. We are comfortable that the changes in these thresholds do not create any significant distortion in our analysis.

Economic Losses

For economic losses in the US, we relied on data from the International Disaster Database (EM-DAT) published by the Center for Research on the Epidemiology of Disasters of the Université Catholique de Louvain in Brussels, Belgium. As with PCS's insured losses, the economic losses are in nominal dollars and are not adjusted for inflation. We only considered catastrophe events associated with windstorm, wildfire, earthquake, and flood. The EM-DAT loss catalog goes back to 1900 and is available on an annual aggregate basis. However, there were a number of years for which the estimated losses from the EM-DAT catalog amount to zero. We think that the prevalence of years with no losses could distort the statistics we use to measure correlation. As such, we performed our analysis excluding years with no losses.

GDP

We used the historical GDP information available from the US Department of Commerce's Bureau of Economic Analysis. As noted above, we relied on the GDP in nominal (current) dollars unadjusted for price levels. The annual GDP information goes back to 1929.

Financial and Economic Indices

The following indicators of financial and economic performance were used for the US:

US Equities – We analyzed the percentage change in the value of the Dow Jones Composite Average (DJCA), the Dow Jones Industrial Average (DJIA), and the S&P 500 as a proxy for the performance of US equities. We made no attempt to factor in dividend yields. We obtained the value of the indices at the daily market close for both the DJCA and the DJIA from the FRED database, which start from 1/3/1949 and 5/26/1896 for the DJCA and DJIA, respectively. The S&P 500 data was obtained from proprietary sources but is widely available across a number of different sources.

US Treasury Bonds – We obtained the annual returns on the Barclays Capital US Treasury, US

Intermediate Treasury, and US Long Treasury indices. The return information spans 41 years dating back to 1973.

According to the website http://etfdb.com/, the Barclays Capital U.S. Treasury Index includes all publicly issued, U.S. Treasury securities that are rated investment grade, and have $250 million or more of outstanding face value. The Barclays Capital US Intermediate Treasury and US Long Treasury Indices have a remaining maturity of between 1 and 10 years, and 10 or more years, respectively.

US Corporate Bonds – We obtained the annual returns on the Barclays Capital US Credit, US Credit Intermediate, and US Credit Long indices. The return information spans 41 years dating back to 1973.

According to the website http://etfdb.com/, the Barclays Capital US Credit and US Intermediate Credit indices measure the performance of investment grade corporate debt and agency bonds that are dollar denominated and have a remaining maturity of greater than one year, and between more than one year and ten years, respectively. The Barclays Capital U.S. Long Credit Index measures the performance of the long term sector of the United States investment bond market, which as defined by the Long Credit Index includes investment grade corporate debt and sovereign, supranational, local authority and non-U.S. agency bonds that are dollar denominated and have a remaining maturity of greater than or equal to 10 years.

Oil – We analyzed the changes in the spot price for West Texas Intermediate crude oil. We obtained the information at quarterly intervals dating back to 1/1/1946 from the FRED database. This data series has been discontinued as of 7/1/2013.

GDP Growth – We analyzed the changes in both nominal and Gross GDP. The GDP information is obtained from the Bureau of Economic Analysis as explained above.

CPI – We used the annual average CPI for all urban consumers as published by the Minneapolis Fed. The data goes back to 1913.

Observation Frequency

We studied the correlation of data observed over annual periods. We paired the annual aggregate catastrophe losses with changes in the index value taken over the same period. For instance, annual losses incurred in 1969 are paired with the changes in asset prices observed from January 1 to December 31 of 1969.

A.2. Australia, Chile, Japan, Thailand, and the Philippines

Similar to the US data, we expressed annual economic losses incurred in a year as a percentage of Gross Domestic Product (GDP) in the same year. For Chile, Japan, Thailand, and the Philippines, both economic loss and GDP figures are adjusted to 2005 US price levels. For Australia, these figures are adjusted to 2011 US price levels.

Economic Losses

For all five countries, we relied exclusively on the economic loss data available from the International Disaster Database (EM-DAT) mentioned above. This loss information is originally provided in nominal US dollars. Because the corresponding GDP information we used for these countries is adjusted to 2011 and 2005 price levels for Australia and the remaining countries, respectively, we brought the economic losses to the price levels corresponding to the GDP using US CPI data obtained from the US Bureau of Labor Statistics. We only considered catastrophe events associated with windstorm, wildfire, earthquake, and flood for Chile and Japan. We also included industrial accidents for Australia, Thailand and the Philippines. The EM-DAT loss catalog goes back to 1900 and is only available on an annual aggregate basis. However, there were a number of years for which the estimated losses from the EM-DAT catalog amounted to zero. For many of those years, it appears that there were significant catastrophes for which the economic loss data was not recorded or not available. We think that the prevalence of years with no losses could distort the statistics we use to measure correlation. As such, we performed our analysis excluding years with no losses. Please note that the standards and sources used by EM-Dat to collect and measure economic losses due to catastrophes may vary significantly by country. Also, the EM-Dat data may not match corresponding statistics collected by other local and international agencies.

GDP

We used the historical GDP information available from a database established by the Economic Research Division of the Federal Reserve Bank of St. Louis's (FRED). As noted above, this information is already expressed in 2011 USD for Australia and in 2005 USD for the remaining four countries. The FRED GDP data only goes up to 2011 so we extrapolated the GDP figures for 2012 and 2013 for each country by applying to the 2011 GDP figure the GDP growth rates corresponding to 2012 and 2013 obtained from various sources. While this extrapolation is an oversimplification of the correct calculation of GDP in 2011 or 2005 US prices, we believe it is adequate for our purposes. We also extrapolated the 2005 level GDP for years prior to 1950 for Japan and prior to 1951 for Chile by using the growth rates corresponding to these prior years observed from information available from a database established by the Maddison Project.

Financial and Economic Indices

We only looked at equity performance for Australia, Chile, Japan, Thailand, and The Philippines.

Equities – We analyzed the price changes for all shares in Australia, for the Nikkei 225 (Japan), IGPA (Chile), SET (Thailand), and PSEi (Philippines) indices as a proxy for the performance of equities in those countries. Similar to US equities, we made no attempt to factor in dividend yields.

The total share prices for all shares for Australia was obtained at annual periods from the FRED database along with the daily market close for the Nikkei 225 index. The IGPA data was obtained from proprietary sources while the SET and PSEi historical data were obtained from Bloomberg.

Summary of Data Sources

Table A.1 below provides a comprehensive list of our data sources, most of which are available publicly. We hope that others will use this data to rectify or augment our findings.

Table A.1
Data Source List

Data	Source	Web Address
Insured Catastrophe Losses – US	PCS - Verisk	Subscription
Economic Catastrophe Losses – Australia, Chile, Japan, Philippines, Thailand, US	International Disaster Database	http://www.emdat.be/database
GDP – US	US Department of Commerce	http://www.bea.gov/
GDP – Australia, Chile, Japan, Philippines, Thailand	St Louis Fed	https://research.stlouisfed.org/
DJCA, DJIA, Nikkei 225, Australia Total Share Price Index	St Louis Fed	https://research.stlouisfed.org/
S&P 500	Proprietary	Subscription
IGPA (Chile Stock Index)	Proprietary	Subscription
SET: Index (Thailand), PSEi (Philippines)	Bloomberg	Subscription
Barclays Capital US Treasury and US Credit Indices	Barclays Capital	Subscription
West Texas Oil Spot Rate	St Louis Fed	https://research.stlouisfed.org/
US CPI	Minneapolis Fed	https://www.minneapolisfed.org/

APPENDIX B

CALCULATION OF P-VALUES

B.1 Kendall's Tau

We used the Kendall's Tau τ statistic to measure the correlations. For the null hypothesis, we posit that catastrophe losses and the performance of the financial and economic indices are independent. We used a simulation to generate the distributions, under the null hypothesis, of the Kendall's Tau corresponding to each specific number of observations. For instance, where we have 64 years of observations, we calculated the Kendall's Tau based on the simulation of 64 pairs of independent variables uniformly distributed on [0,1]. We derived the P-values from these distributions, which are summarized in Table B.1.a below for various observation counts. Alternatively, for a large enough number of observations, P-values can be determined by assuming the Kendall's Tau to be approximately normally distributed under the null hypothesis with a mean of zero and variance given by $\frac{2(2n+5)}{9n(n-1)}$.

B.2 Kendall's Partial Tau

We used the Kendall's Partial Tau τ statistic to measure the correlations after removing the effect of time. For the null hypothesis, we posit that catastrophe losses and the performance of the financial and economic indices are independent after removing the effect of time. We used a simulation to generate the distributions, under the null hypothesis, of the Kendall's Partial Tau corresponding to each specific number of observations. For instance, where we have 64 years of observations, we simulated 64 pairs, say X and Y, of independent variables uniformly distributed on [0,1] for each of the 64 years, say Z. We calculated the Kendall's Partial Tau based on the triplets (X,Y,Z) as described in the Overview of Approach in section 2 above[6]. We derived the P-values from these distributions, which are summarized in Table B.1.b below for various observation counts.

B.3 Difference in Kendall's Tau and Kendall's Partial Tau

We calculate the differences δ in the Kendall's Tau (Kendall's Partial Tau) statistics for the two different ranges of percentile value under consideration. For the null hypothesis, we posit that the Kendall's Tau (Kendall's Partial Tau) is zero across the entire range of percentile values. We used a simulation to generate the distributions, under the null hypothesis, of the differences in the Kendall's Tau (Kendall's Partial Tau) statistics for the two different ranges of percentile values. For instance, where we have 64 years of observations and want to compare the Kendall's Tau (Kendall's

[6] The P-values as calculated assume X, Y, and Z are mutually independent. Further work is needed to calculate the P-values when the assumption of independence is violated, as is the case for some of the variables we reviewed.

Partial Tau) for the first 80th percentile to the Kendall's Tau (Kendall's Partial Tau) for the last 20th percentile, we calculated the difference in the Kendall's Tau (Kendall's Partial Tau) for the lowest 51st observations ranked by size of catastrophe to the Kendall's Tau (Kendall's Partial Tau) for the highest 13 observations. We derived the P-values from the distributions of δ obtained through the simulations. Tables B.2.a and B.2.b show the distributions of δ for various observation counts.

Table B.1.a
Simulation-based Distribution of Kendall's Tau Statistic under Null Hypothesis by Number of Observations

Observations	8	13	15	18	22	30	38
Mean	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Std Dev	0.288	0.210	0.192	0.173	0.153	0.129	0.113
1.00%	(0.643)	(0.487)	(0.448)	(0.399)	(0.359)	(0.301)	(0.263)
5.00%	(0.500)	(0.359)	(0.314)	(0.281)	(0.255)	(0.214)	(0.186)
10.00%	(0.357)	(0.282)	(0.257)	(0.229)	(0.195)	(0.168)	(0.147)
15.00%	(0.286)	(0.231)	(0.200)	(0.176)	(0.160)	(0.136)	(0.118)
20.00%	(0.286)	(0.179)	(0.162)	(0.150)	(0.134)	(0.108)	(0.095)
25.00%	(0.214)	(0.154)	(0.124)	(0.124)	(0.108)	(0.090)	(0.078)
30.00%	(0.143)	(0.103)	(0.105)	(0.098)	(0.082)	(0.067)	(0.061)
35.00%	(0.143)	(0.077)	(0.067)	(0.072)	(0.056)	(0.053)	(0.044)
40.00%	(0.071)	(0.051)	(0.048)	(0.046)	(0.039)	(0.034)	(0.030)
45.00%	(0.071)	(0.026)	(0.029)	(0.020)	(0.022)	(0.016)	(0.016)
50.00%	-	-	(0.010)	(0.007)	(0.004)	(0.002)	(0.001)
55.00%	0.071	0.026	0.029	0.020	0.022	0.016	0.013
60.00%	0.071	0.051	0.048	0.046	0.039	0.034	0.030
65.00%	0.143	0.077	0.067	0.072	0.056	0.048	0.044
70.00%	0.143	0.103	0.105	0.085	0.082	0.067	0.058
75.00%	0.214	0.154	0.124	0.111	0.100	0.085	0.075
80.00%	0.214	0.179	0.162	0.150	0.126	0.108	0.095
85.00%	0.286	0.231	0.200	0.176	0.160	0.136	0.118
90.00%	0.357	0.282	0.238	0.216	0.195	0.163	0.144
95.00%	0.500	0.333	0.314	0.281	0.255	0.209	0.186
99.00%	0.643	0.487	0.448	0.399	0.351	0.297	0.260

Table B.1.a (continues)
Simulation-based Distribution of Kendall's Tau Statistic under Null Hypothesis by Number of Observations

Observations	41	44	51	56	63	64	71
Mean	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Std Dev	0.109	0.104	0.097	0.092	0.087	0.086	0.081
1.00%	(0.254)	(0.241)	(0.225)	(0.214)	(0.200)	(0.198)	(0.189)
5.00%	(0.180)	(0.173)	(0.159)	(0.152)	(0.142)	(0.142)	(0.134)
10.00%	(0.139)	(0.135)	(0.125)	(0.119)	(0.111)	(0.111)	(0.105)
15.00%	(0.112)	(0.108)	(0.101)	(0.096)	(0.091)	(0.089)	(0.085)
20.00%	(0.093)	(0.089)	(0.082)	(0.078)	(0.073)	(0.072)	(0.069)
25.00%	(0.073)	(0.072)	(0.067)	(0.062)	(0.059)	(0.058)	(0.055)
30.00%	(0.059)	(0.055)	(0.051)	(0.049)	(0.046)	(0.046)	(0.043)
35.00%	(0.041)	(0.040)	(0.038)	(0.035)	(0.033)	(0.034)	(0.031)
40.00%	(0.029)	(0.027)	(0.024)	(0.023)	(0.022)	(0.022)	(0.021)
45.00%	(0.015)	(0.013)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)
50.00%	-	-	(0.001)	-	(0.001)	-	0.000
55.00%	0.012	0.013	0.012	0.012	0.011	0.011	0.010
60.00%	0.027	0.025	0.024	0.023	0.022	0.022	0.021
65.00%	0.041	0.040	0.037	0.035	0.033	0.033	0.031
70.00%	0.056	0.055	0.051	0.048	0.046	0.045	0.042
75.00%	0.073	0.070	0.065	0.062	0.058	0.058	0.054
80.00%	0.090	0.087	0.081	0.077	0.072	0.071	0.068
85.00%	0.112	0.108	0.100	0.095	0.090	0.088	0.084
90.00%	0.139	0.133	0.123	0.118	0.111	0.109	0.104
95.00%	0.178	0.171	0.159	0.151	0.142	0.141	0.133
99.00%	0.251	0.241	0.225	0.214	0.201	0.199	0.190

Table B.1.b
Simulation-based Distribution of Kendall's Partial Tau Statistic under Null Hypothesis by Number of Observations

Observations	8	13	15	18	22	30	38
Mean	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Std Dev	0.292	0.211	0.193	0.173	0.154	0.129	0.113
1.00%	(0.645)	(0.485)	(0.443)	(0.399)	(0.356)	(0.299)	(0.264)
5.00%	(0.486)	(0.351)	(0.318)	(0.285)	(0.254)	(0.214)	(0.187)
10.00%	(0.382)	(0.275)	(0.249)	(0.223)	(0.198)	(0.166)	(0.147)
15.00%	(0.309)	(0.223)	(0.202)	(0.181)	(0.161)	(0.135)	(0.119)
20.00%	(0.253)	(0.180)	(0.165)	(0.147)	(0.131)	(0.110)	(0.097)
25.00%	(0.207)	(0.145)	(0.133)	(0.118)	(0.105)	(0.088)	(0.077)
30.00%	(0.162)	(0.113)	(0.104)	(0.092)	(0.082)	(0.069)	(0.061)
35.00%	(0.125)	(0.083)	(0.076)	(0.068)	(0.061)	(0.051)	(0.045)
40.00%	(0.076)	(0.055)	(0.050)	(0.045)	(0.040)	(0.034)	(0.030)
45.00%	(0.042)	(0.028)	(0.025)	(0.022)	(0.020)	(0.017)	(0.015)
50.00%	-	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
55.00%	0.042	0.026	0.025	0.021	0.019	0.016	0.014
60.00%	0.075	0.053	0.049	0.044	0.039	0.032	0.028
65.00%	0.125	0.082	0.075	0.067	0.059	0.049	0.044
70.00%	0.162	0.113	0.102	0.090	0.081	0.067	0.059
75.00%	0.207	0.146	0.132	0.117	0.104	0.087	0.077
80.00%	0.253	0.180	0.164	0.146	0.130	0.109	0.095
85.00%	0.309	0.221	0.200	0.180	0.160	0.134	0.117
90.00%	0.380	0.272	0.247	0.222	0.196	0.165	0.145
95.00%	0.486	0.346	0.316	0.286	0.252	0.211	0.185
99.00%	0.645	0.481	0.442	0.398	0.351	0.294	0.261

Table B.1.b (continues)
Simulation-based Distribution of Kendall's Partial Tau Statistic under Null Hypothesis by Number of Observations

Observations	41	44	51	56	63	64	71
Mean	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Std Dev	0.109	0.104	0.097	0.092	0.087	0.086	0.081
1.00%	(0.254)	(0.241)	(0.226)	(0.214)	(0.201)	(0.199)	(0.189)
5.00%	(0.180)	(0.173)	(0.160)	(0.152)	(0.143)	(0.142)	(0.134)
10.00%	(0.140)	(0.134)	(0.125)	(0.119)	(0.112)	(0.111)	(0.105)
15.00%	(0.113)	(0.109)	(0.101)	(0.096)	(0.090)	(0.089)	(0.085)
20.00%	(0.092)	(0.088)	(0.082)	(0.078)	(0.073)	(0.072)	(0.069)
25.00%	(0.074)	(0.071)	(0.066)	(0.063)	(0.058)	(0.058)	(0.055)
30.00%	(0.058)	(0.055)	(0.052)	(0.049)	(0.046)	(0.045)	(0.043)
35.00%	(0.043)	(0.041)	(0.038)	(0.036)	(0.034)	(0.033)	(0.031)
40.00%	(0.029)	(0.027)	(0.025)	(0.024)	(0.022)	(0.022)	(0.021)
45.00%	(0.014)	(0.014)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)
50.00%	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000
55.00%	0.013	0.013	0.012	0.011	0.011	0.011	0.010
60.00%	0.027	0.026	0.025	0.023	0.022	0.022	0.021
65.00%	0.042	0.039	0.037	0.035	0.033	0.033	0.031
70.00%	0.057	0.054	0.051	0.048	0.045	0.045	0.042
75.00%	0.073	0.070	0.065	0.062	0.058	0.058	0.054
80.00%	0.092	0.088	0.081	0.077	0.072	0.072	0.068
85.00%	0.113	0.108	0.100	0.095	0.089	0.089	0.084
90.00%	0.139	0.134	0.124	0.118	0.111	0.110	0.104
95.00%	0.178	0.172	0.159	0.151	0.142	0.141	0.133
99.00%	0.250	0.241	0.225	0.214	0.201	0.200	0.189

Table B.2.a
Simulation-based Distribution of Difference δ between Kendall's Tau Statistics under Null Hypothesis by Number of Observations

Observation Splits	18/8	51/13	56/15
Mean	(0.001)	0.000	0.000
Std Dev	0.336	0.231	0.213
1.00%	(0.769)	(0.530)	(0.491)
5.00%	(0.553)	(0.381)	(0.351)
10.00%	(0.436)	(0.298)	(0.275)
15.00%	(0.352)	(0.242)	(0.223)
20.00%	(0.287)	(0.197)	(0.181)
25.00%	(0.233)	(0.158)	(0.145)
30.00%	(0.182)	(0.123)	(0.113)
35.00%	(0.131)	(0.090)	(0.083)
40.00%	(0.089)	(0.059)	(0.054)
45.00%	(0.045)	(0.029)	(0.027)
50.00%	(0.000)	0.000	0.000
55.00%	0.040	0.030	0.028
60.00%	0.085	0.059	0.055
65.00%	0.130	0.090	0.084
70.00%	0.176	0.123	0.113
75.00%	0.228	0.158	0.145
80.00%	0.286	0.197	0.181
85.00%	0.352	0.242	0.223
90.00%	0.435	0.299	0.275
95.00%	0.553	0.381	0.351
99.00%	0.762	0.532	0.491

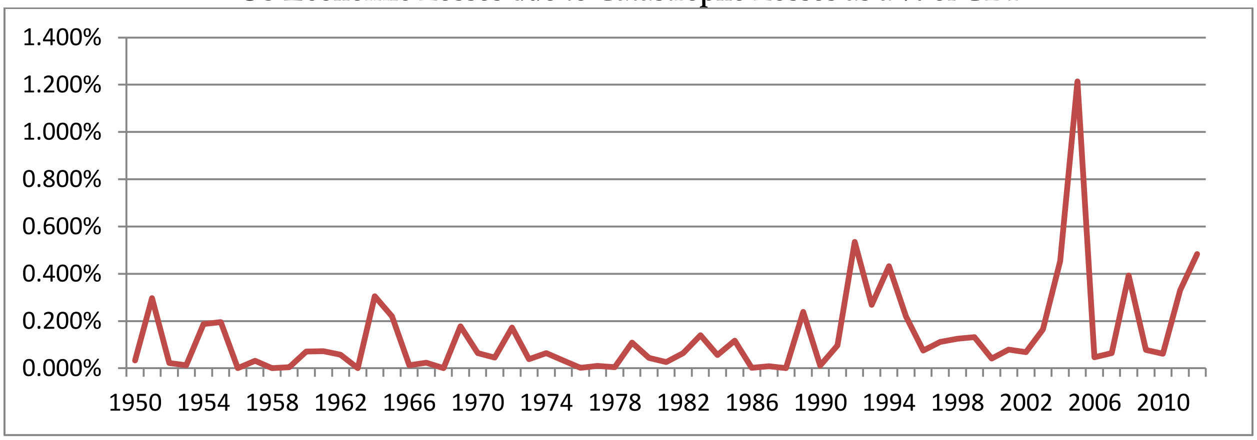
Table B.2.b
Simulation-based Distribution of Difference δ between Kendall's Partial Tau Statistics under Null Hypothesis by Number of Observations

Observation Splits	18/8	51/13	56/15
Mean	0.001	0.001	0.000
Std Dev	0.339	0.231	0.213
1.00%	(0.768)	(0.530)	(0.492)
5.00%	(0.559)	(0.380)	(0.351)
10.00%	(0.439)	(0.297)	(0.275)
15.00%	(0.357)	(0.241)	(0.222)
20.00%	(0.289)	(0.197)	(0.180)
25.00%	(0.233)	(0.159)	(0.145)
30.00%	(0.181)	(0.123)	(0.113)
35.00%	(0.132)	(0.090)	(0.083)
40.00%	(0.085)	(0.059)	(0.054)
45.00%	(0.040)	(0.028)	(0.027)
50.00%	0.003	0.001	0.001
55.00%	0.047	0.031	0.028
60.00%	0.091	0.061	0.056
65.00%	0.137	0.092	0.084
70.00%	0.186	0.125	0.114
75.00%	0.237	0.160	0.146
80.00%	0.293	0.198	0.181
85.00%	0.358	0.242	0.222
90.00%	0.438	0.298	0.275
95.00%	0.557	0.379	0.350
99.00%	0.769	0.528	0.488

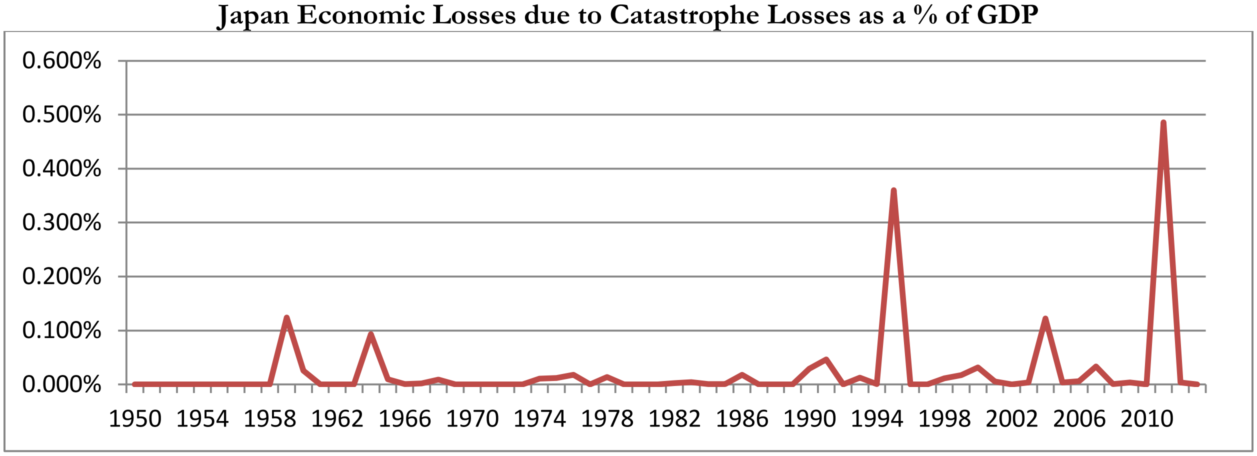
APPENDIX C

SELECTED GRAPHS

Graph C.1
US Economic Losses due to Catastrophe Losses as a % of GDP

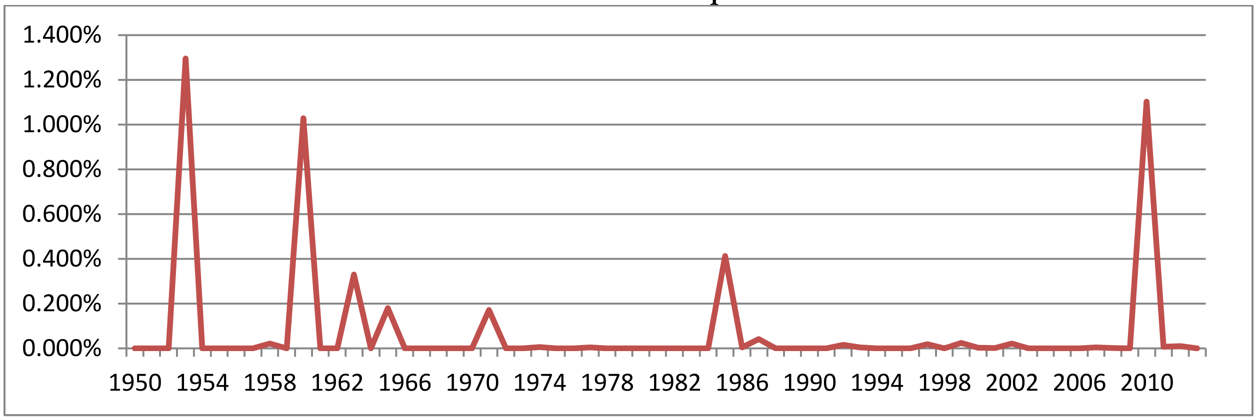


Graph C.2
Japan Economic Losses due to Catastrophe Losses as a % of GDP

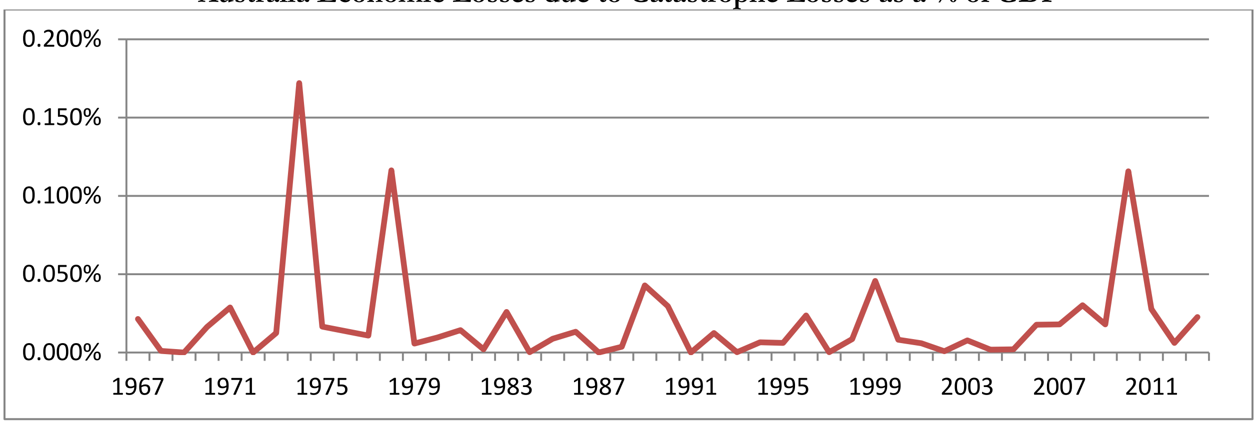


Note: When comparing graphs across countries, please note that the standards and sources used by EM-Dat to collect and measure economic losses due to catastrophes may vary significantly by country. The data may not match corresponding statistics collected by other local and international agencies.

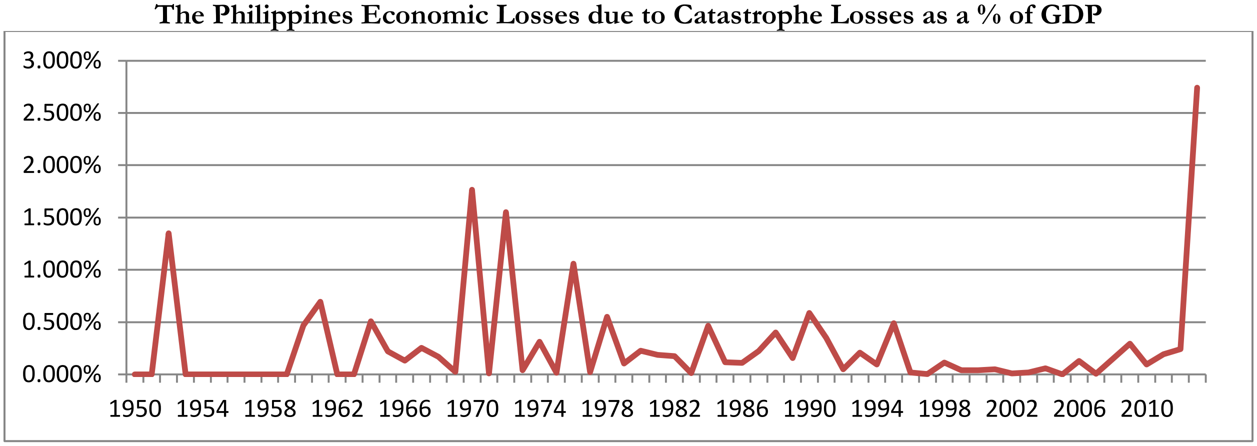
Graph C.3
Chile Economic Losses due to Catastrophe Losses as a % of GDP



Graph C.4
Australia Economic Losses due to Catastrophe Losses as a % of GDP

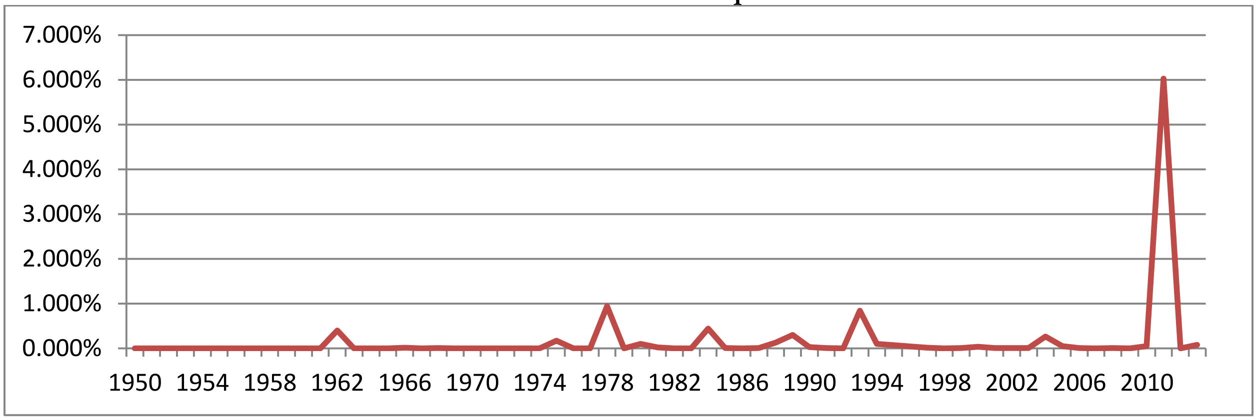


Graph C.5
The Philippines Economic Losses due to Catastrophe Losses as a % of GDP



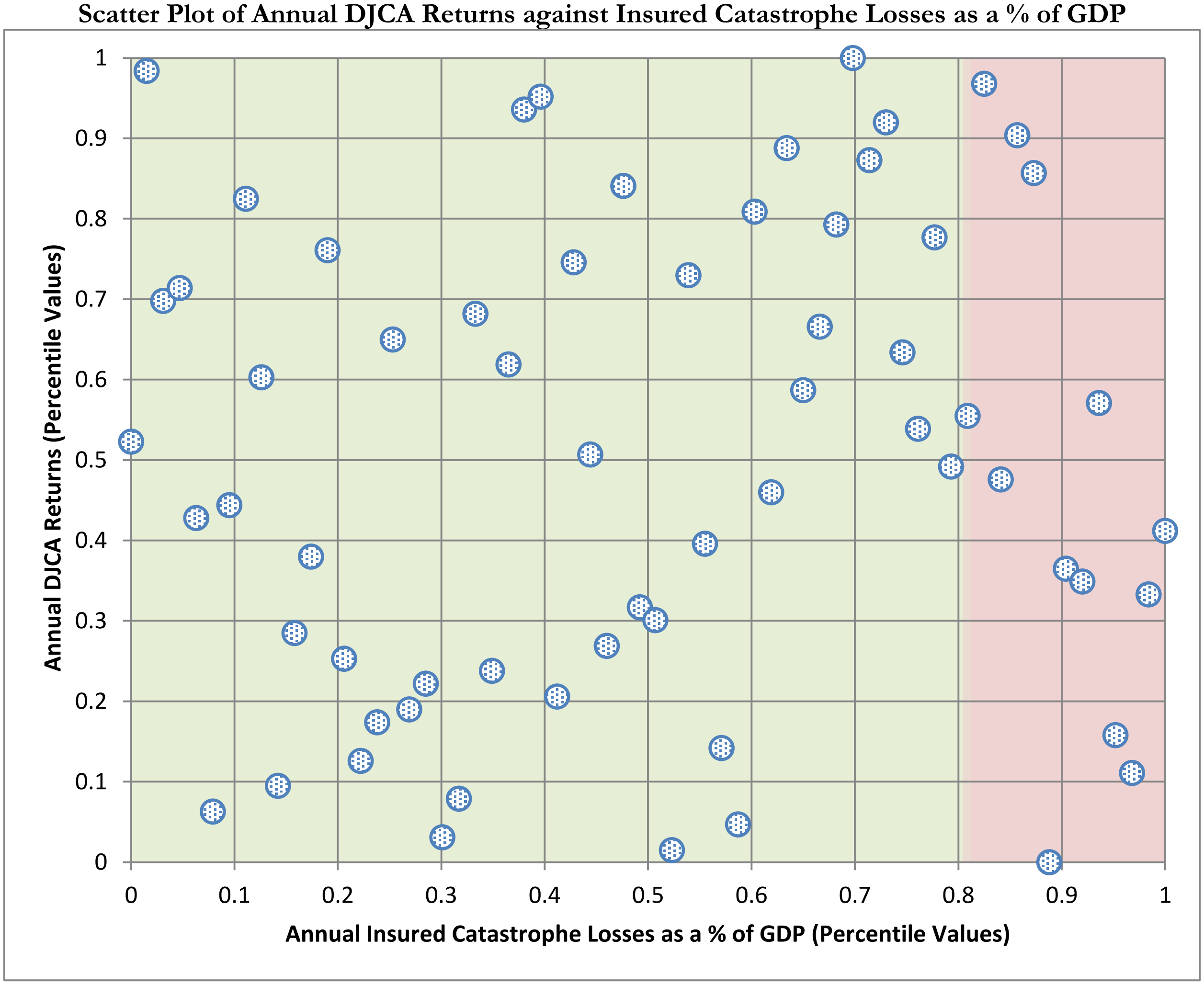
Note: When comparing graphs across countries, please note that the standards and sources used by EM-Dat to collect and measure economic losses due to catastrophes may vary significantly by country. The data may not match corresponding statistics collected by other local and international agencies.

Graph C.6
Thailand Economic Losses due to Catastrophe Losses as a % of GDP

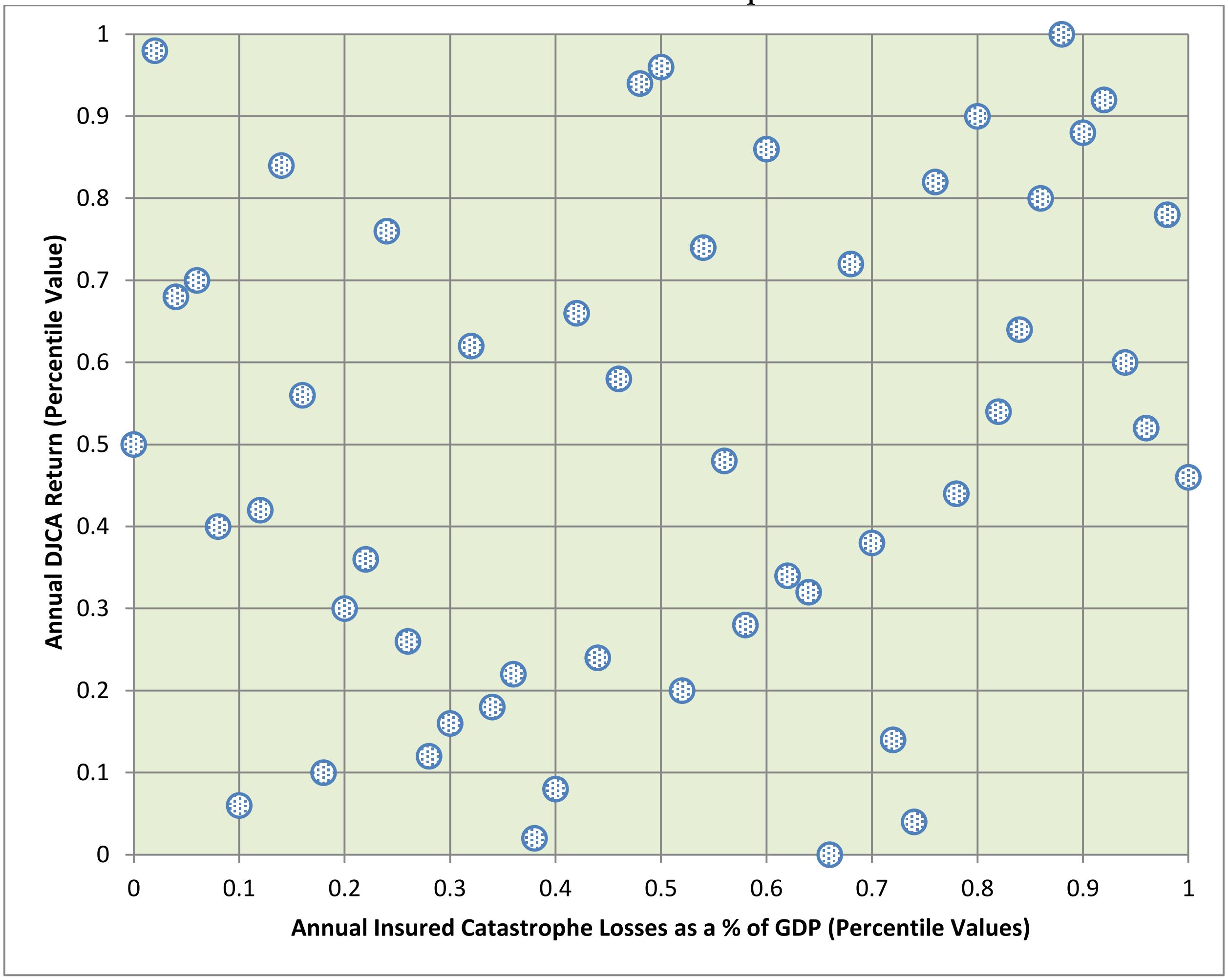


Note: When comparing graphs across countries, please note that the standards and sources used by EM-Dat to collect and measure economic losses due to catastrophes may vary significantly by country. The data may not match corresponding statistics collected by other local and international agencies.

Graph C.7
Scatter Plot of Annual DJCA Returns against Insured Catastrophe Losses as a % of GDP

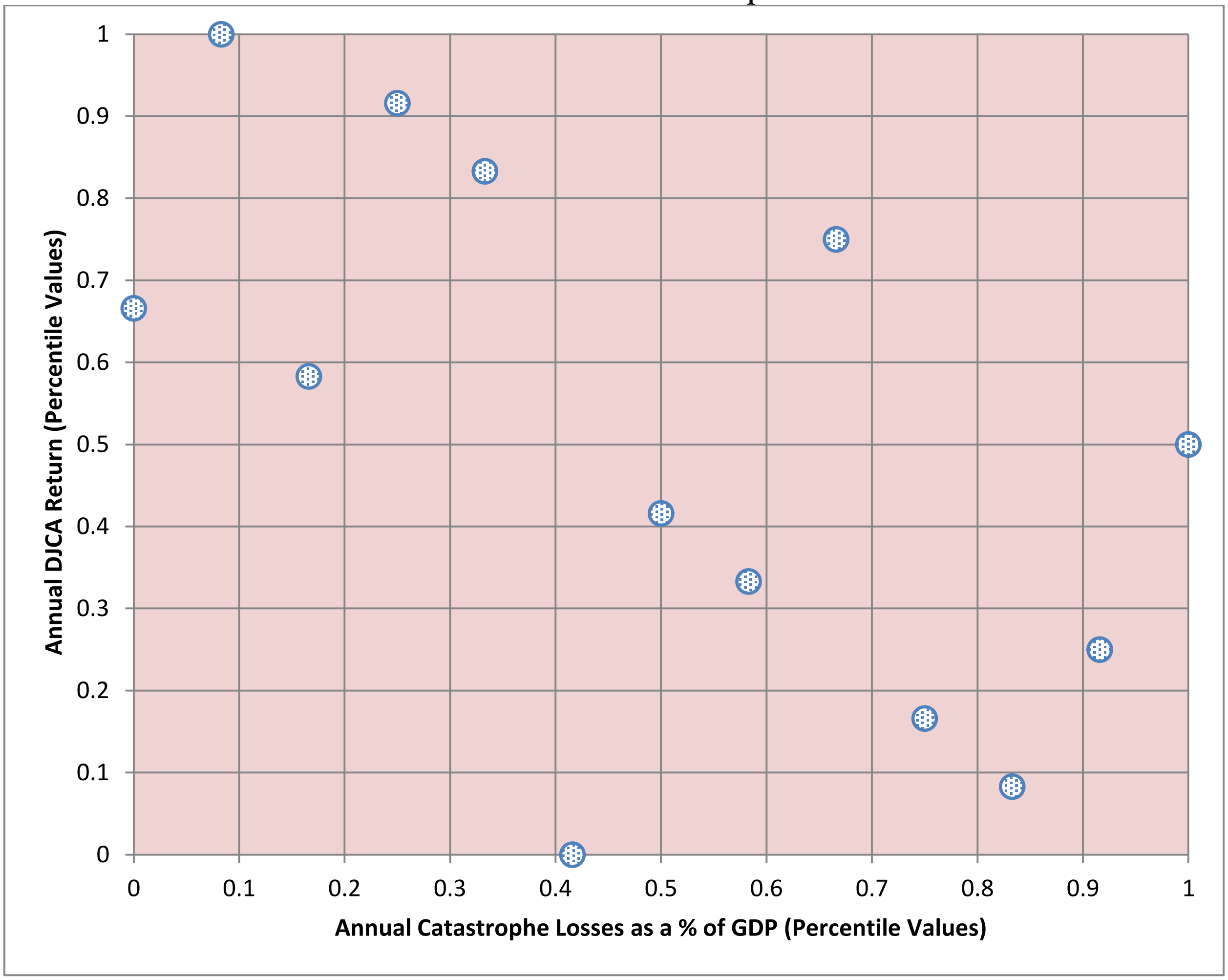


Graph C.7.a
Scatter Plot of Annual DJCA Returns against Insured Catastrophe Losses as a % of GDP for lowest 80th Percentile of Annual Insured Catastrophes as a % of GDP



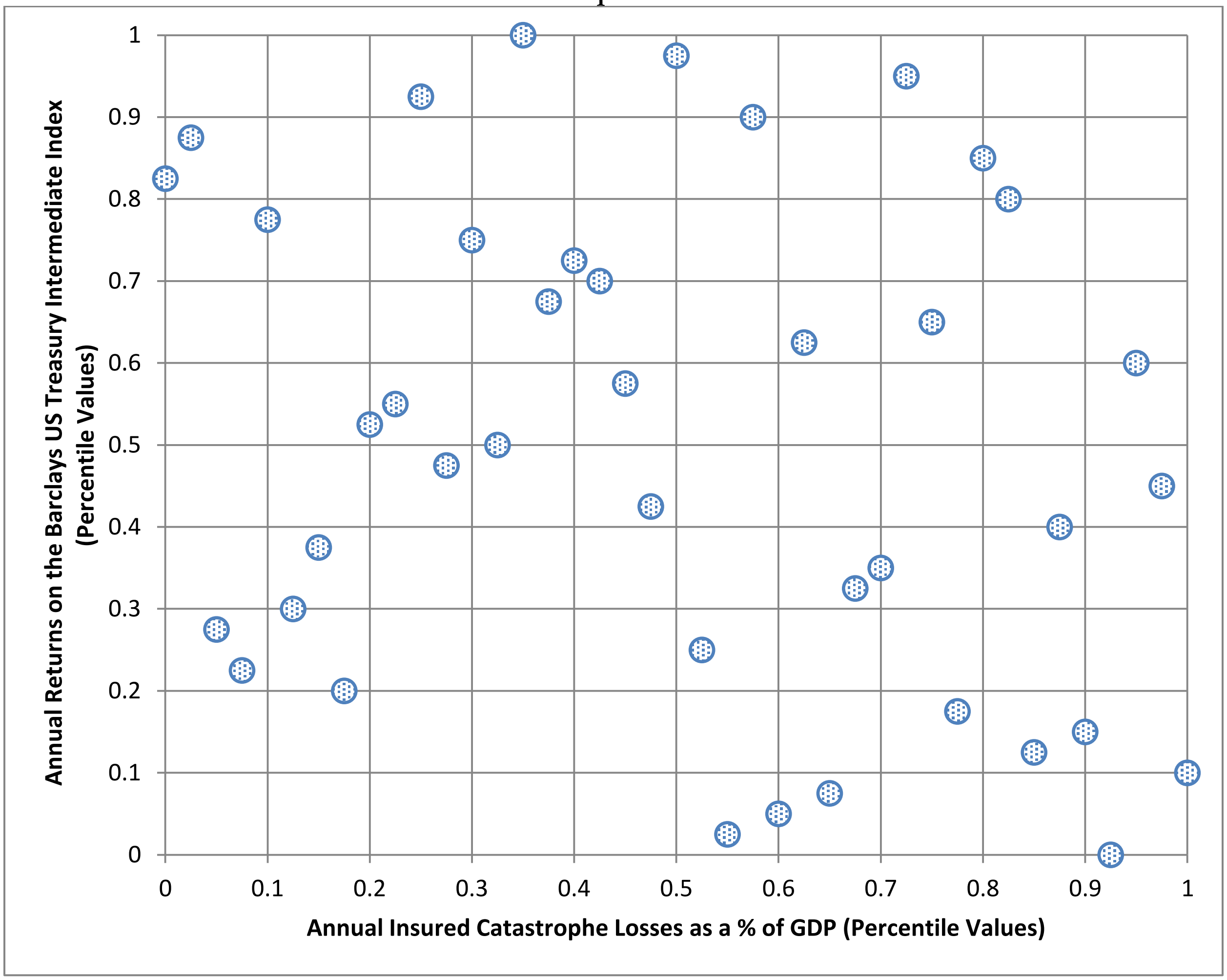
Please note that the percentiles in the above graph have been recalculated based on the relative rankings of the subset of points that fall in the lowest 80th percentile of annual insured catastrophe losses as a % of GDP. As such, these percentiles range from 0 to 1.

Graph C.7.b
Scatter Plot of Annual DJCA Returns against Insured Catastrophe Losses as a % of GDP for highest 20th Percentile of Annual Insured Catastrophes as a % of GDP

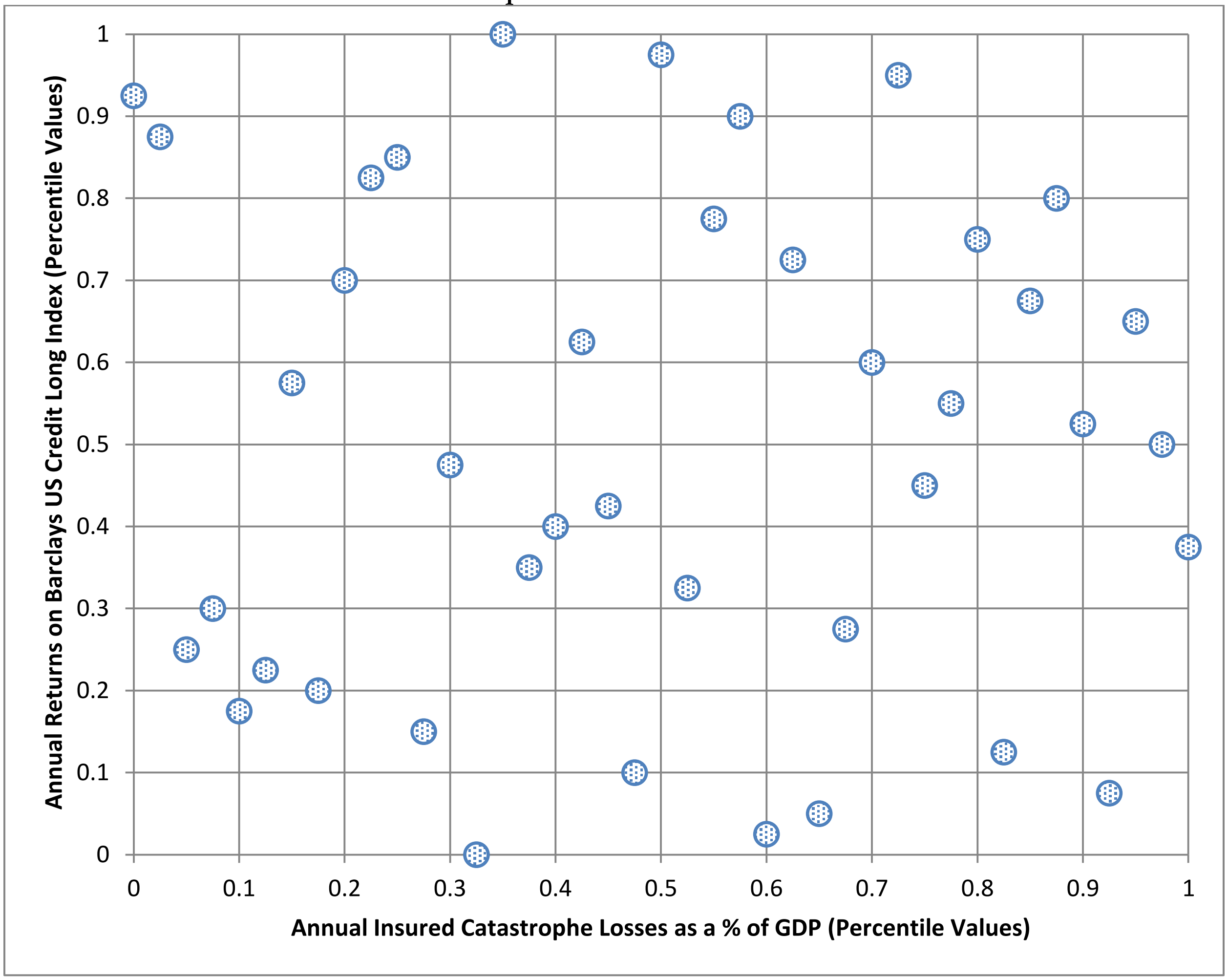


Please note that the percentiles in the above graph have been recalculated based on the relative rankings of the subset of points that fall in the highest 20th percentile of annual insured catastrophe losses as a % of GDP. As such, these percentiles range from 0 to 1.

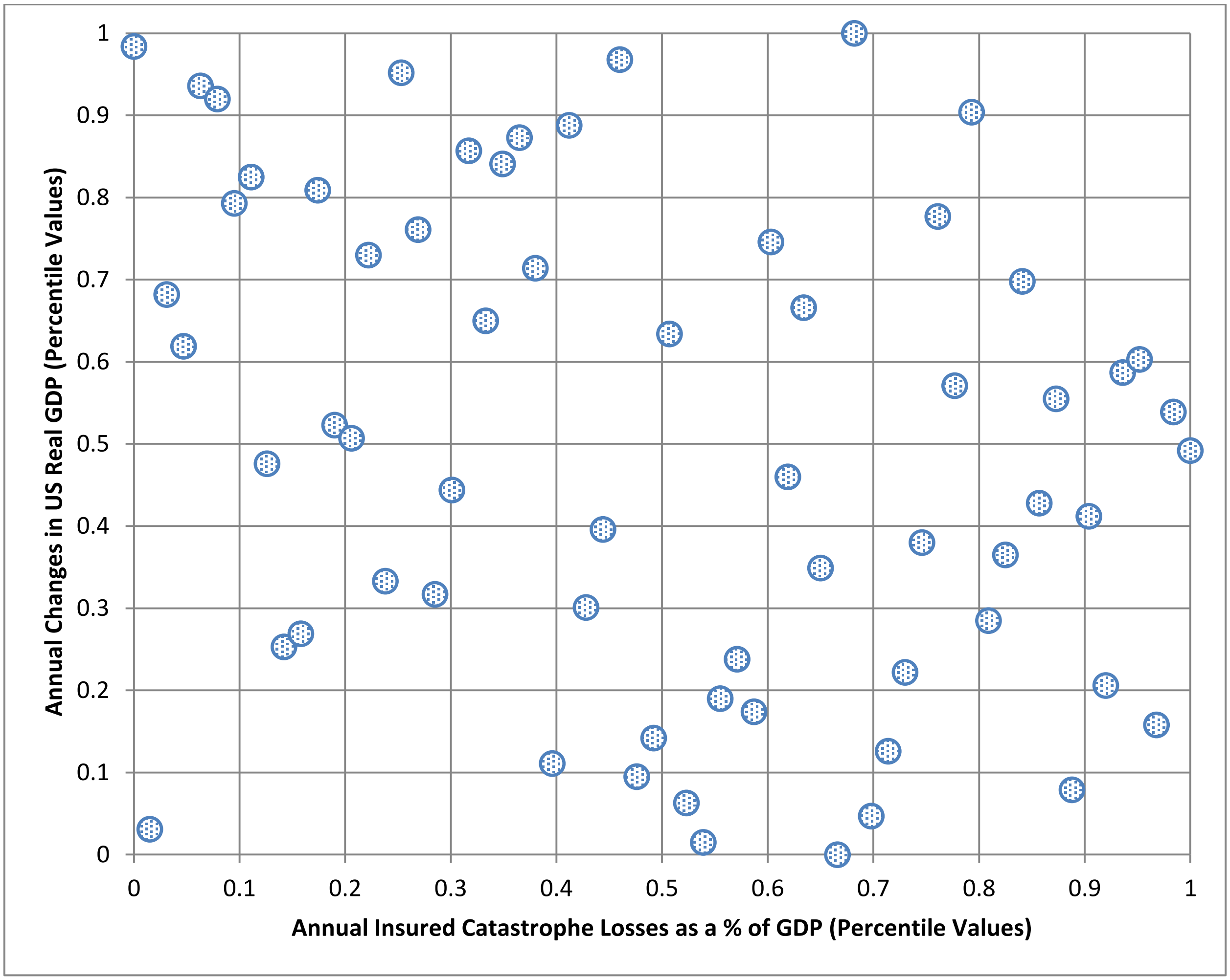
Graph C.8
Scatter Plot of Annual Returns on Barclays Capital US Treasury Intermediate Index against Insured Catastrophe Losses



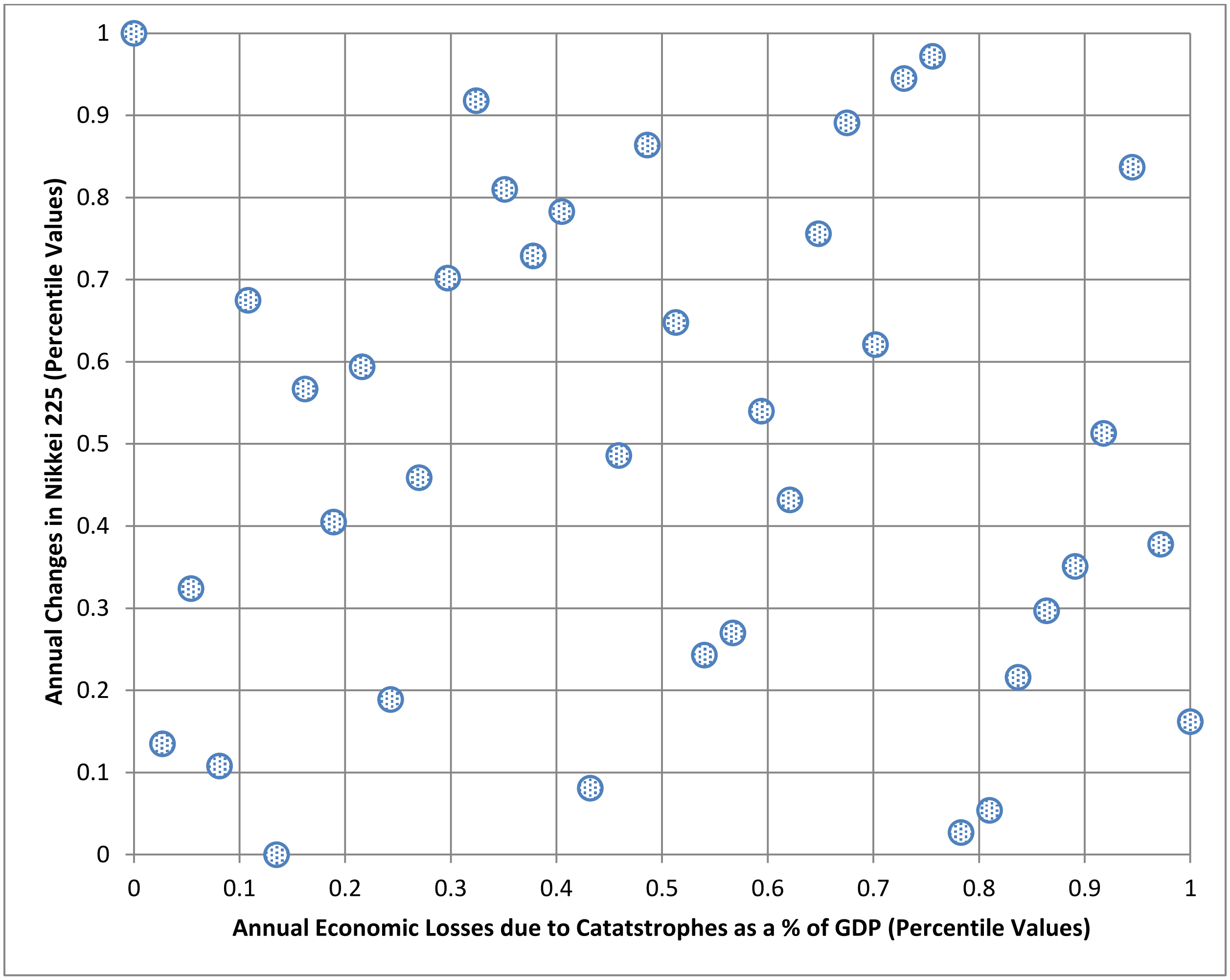
Graph C.9
Scatter Plot of Annual Returns on Barclays Capital US Credit Long Index against Insured Catastrophe Losses as a % of GDP



Graph C.10
Scatter Plot of Annual Changes in the US Real GDP against Insured Catastrophe Losses as a % of GDP



Graph C.11
Scatter Plot of Annual Changes in the Nikkei 225 against Economic Losses due to Catastrophes as a % of GDP



Graph C.12
Scatter Plot of Annual Changes in all Australia Shares against Economic Losses due to Catastrophe Losses as a % of GDP