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Featured Article

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Measuring U.S. Hurricane Risk Associated with Natural Climate Cycle and Global Warming Effects

Abstract: This paper develops a threshold function of the Atlantic Multidecadal Oscillation (AMO) index and allows the effect of AMO index changes over time due to global warming to yield improvements in the forecasts of U.S. hurricane activity. The influence of the threshold effect, the AMO effect, and the global warming effect on Value at Risk and expected shortfall of hurricane risk is also examined. The empirical results of a time-variant threshold Poisson regression model provide an excellent projection for which the forecasting error of average annual U.S. hurricane activity is less than one. We find that the threshold effect and global warming effect dominate the AMO effect. In particular, the global warming effect dominates the AMO effect in extreme hurricane events, and this domination increases over time.

Keywords: hurricane activity, AMO index, global warming, threshold poisson regression model, hurricane risk measurement

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1 Introduction

Fluctuations in U.S. hurricane frequency have significant effects on human life and on the economy. Table 1 lists the top 10 costliest and deadliest hurricanes from 1980 to 2011 in the U.S. (Lott et al., 2012). The loss of human life and the economic damage fluctuate because of variations in the frequency of hurricane events and in the damage from individual events. Thus, it is important to be able to statistically characterize the distribution of the frequency of U.S. hurricanes, especially if this frequency is increasing with time or if the intensity levels of hurricane activity are changing with the natural climate cycle. Historical hurricane data provide clues regarding the future frequency and intensity of

Table 1: The top 10 costliest and deadliest hurricanes from 1980 to 2011.

Rank	Hurricane	Economic cost (Billions of dollars)	Hurricane	Persons
1	Katrina (2005)	$ 145.0	Katrina (2005)	1,833
2	Andrew (1992)	$ 43.5	Rita (2005)	119
3	Ike (2008)	$ 28.4	Ike (2008)	112
4	Wilma (2005)	$ 18.6	Hugo (1989)	86
5	Rita (2005)	$ 18.6	Floyd (1999)	77
6	Charley (2004)	$ 17.9	Juan (1985)	63
7	Ivan (2004)	$ 16.7	Andrew (1992)	61
8	Hugo (1989)	$ 12.9	Ivan (2004)	57
9	Frances (2004)	$ 10.7	Isabel (2003)	55
10	Jeanne (2004)	$ 8.3	Gustav (2008)	53

hurricanes. Skillful annual forecasts of hurricane activity are important for emergency management and (re)insurance contracts. When a hurricane activity model is well forecasted, hurricane risk can be more accurately estimated.

Numerical models are now capable of simulating hurricane months in advance with some skill.[1] Elsner, Niu, and Tsonis (1998) first employ a time-series model based on a singular spectrum analysis for the examination of the annual North Atlantic hurricane counts. However, there are limitations to the model of Elsner, Niu, and Tsonis (1998). For example, (i) hurricane counts are directly used in building their model, and (ii) the model lacks covariate information. Recently, the Poisson regression model[2] has been used as the canonical

1 For example, Bayesian models have been applied in climate studies: Slow (1998), LeRoy (1998), Berliner et al. (2000), Wikle (2000), Katz (2002), Wikle and Anderson (2003), Chu and Zhao (2004), and Elsner and Jagger (2004, 2006). Daneshvaran and Haji (2012a) provide a prediction method for U.S. landfalling hurricanes and identify the differences between long term and warm phase of the atmosphere in terms of U.S. landfall occurrence by using hurricane origination points. Daneshvaran and Haji (2012b) further calculate the hurricane risk from loss point of view in the USA for both long-term and warm phase conditions using a simulation-based stochastic model. Daneshvaran and Haji (2013) use principal components analysis (PCA) to identify possible patterns in historical data based on six climate variables to discuss the relationship between the climate signals and Atlantic hurricane activity. The empirical results show that PCA-based approach provides better estimates compared to ARIMA model and Colorado State University's forecast.

2 This regressions model is based on the Poisson distribution, which is a discrete distribution that is defined based on nonnegative integers. The Poisson regression, a variant of the linear regression, is appropriate for modeling the influence of some set of independent variables (covariates) on the expected rate of a Poisson distributed random process.

model for hurricane count data (Elsner and Schmertmann 1993; Solow and Moore 2000; Elsner, Jagger, and Niu 2000; Elsner, Bossak, and Niu 2001, 2006; Jagger, Niu, and Elsner 2002; Elsner 2003; McDonnell and Holbrook 2004). The Poisson distribution is used to characterize North Atlantic hurricane counts, and the log-linear Poisson model is used to describe the influence of climate variables on various aspects of North Atlantic hurricane activity (Elsner and Schmertmann 1993; Elsner, Bossak, and Niu 2001, 2002; Elsner and Bossak 2004; Briggs 2008; Elsner et al. 2008).

In addition, for climate variables, recent studies (e.g. Lehmiller et al. 1997; Bove et al. 1998; Maloney and Hartmann 2000; Elsner, Jagger, and Niu 2000; Goldenberg et al. 2001; Landsea 2005; Sutton and Hodson 2005) have attributed Atlantic hurricane activity increases to a natural climate cycle, termed the Atlantic Multidecadal Oscillation (AMO), the El Nino-Southern Oscillation (ENSO), and the North Atlantic Oscillation (NAO). In recent decades, Geo Risks Research has undertaken hurricane frequency analyses that account for the AMO. The AMO index is a detrended (anomaly) measure of sea surface temperatures (SSTs) (e.g. Knight et al. 2005) and is believed to be capable of explaining the recently elevated levels of hurricane activity. Because it is a measure of SST anomalies, which are correlated with hurricane activity, the AMO index has been used to predict near-term hurricane activity. Therefore, warm phases in the AMO (positive AMO index) are theorized to lead to higher SSTs and above long-term average hurricane activity in the Atlantic. Conversely, cool phases in the AMO (negative AMO index) are theorized to lead to lower SSTs and below long-term average hurricane activity. One of the most important recent papers on this topic is the article by Elsner et al. (2008), who consider a time-series model to forecast the average hurricane-season Atlantic SST and then use a linear Poisson regression model to forecast North Atlantic hurricane intensity given the predicted coefficients of the Atlantic SST model.

However, some studies (Knutson and Tuleya 2004; Barnett et al. 2005; Emanuel 2005; Webster et al. 2005, 2006) indicate that global climate change (rather than natural climate cycles) may play the dominant role. In addition, the fourth status report of the Intergovernmental Panel on Climate Change (IPCC 2007) highlights the significant link between human-induced global warming and the greater frequency and intensity of unanticipated tropical cyclone events. Figure 1 clearly shows that the average number of destructive major hurricanes is significantly higher in the warm phases of the AMO than in the cold phases. This finding supports the theory that hurricanes form over warm sea surfaces. However, storm frequencies during the current warm phase (since 1995) have also been much higher than during the previous warm phases in the middle of the last century. The difference can no longer be explained by natural fluctuation; rather, this difference must be attributed to global warming. Based on these

opinions, the modeling of hurricane activity should have the ability to additionally capture the time trend of hurricane activity to illustrate the phenomenon that hurricane activity increases with time because of global warming. Therefore, we intend to provide a time-variant Poisson regression model that is associated with the AMO index and global warming to model U.S. hurricane activity. Furthermore, Figure 1 shows that the increasing effect of global warming may also result in a more significantly asymmetric effect of the AMO index on hurricane activity, indicating significantly higher hurricane activity in the warm phases of the AMO index than in the cold phases. Hence, the threshold Poisson regression model, in which the AMO index is considered as the threshold point, should be more appropriate than the linear Poisson regression model. To the best of our knowledge, no previous studies have considered both natural climate cycles and global warming in the models of hurricane activity based on whether these models are nonlinear Poisson regression.

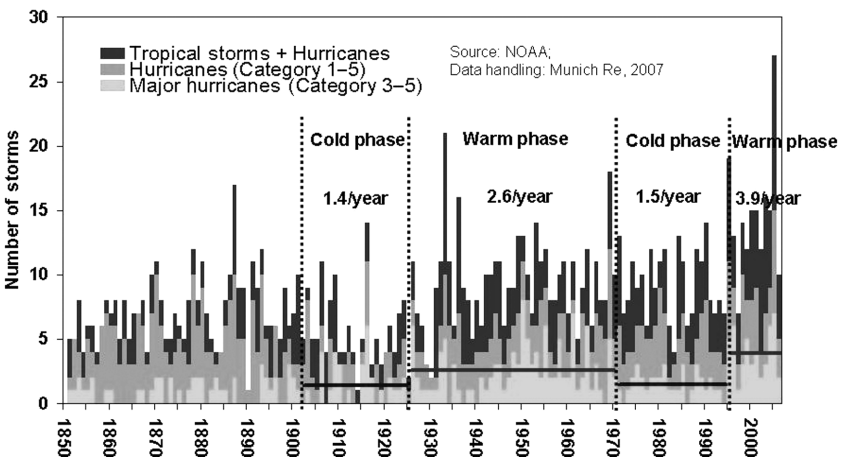

Figure 1: Annual number of tropical cyclones formed in the Atlantic Basin from 1851 to 2006. Source: NOAA

This study intends to contribute to the literature in three ways. First, using the AMO index and annual hurricane counts from 1960 through 2008 available from the National Oceanic and Atmospheric Administration (NOAA), we model hurricane activity (frequency and intensity) as a threshold (nonlinear) function of the AMO index and allow for the possibility that the AMO index changes over time as a result of global warming. In our threshold Poisson regression function, we hypothesize that the explanatory power of the threshold model can be improved

by using two-state hurricane intensity while using the AMO index as the threshold variable rather than the one-state hurricane intensity provided by Elsner et al. (2008). Another limitation to the Elsner et al. (2008) model is that the time-variant AMO index does not respond to global warming. Emanuel (2005) and Webster et al. (2005) note that because SSTs are influenced by global warming rather than by the natural variability of climate factors, the next lull in hurricane activity will not be as low as those in the past. Hence, the objective is to fit a time-series model of the AMO index and the time-variant threshold model of U.S. hurricane activity and then determine the threshold point responses to the AMO index. Second, given the actual/predicted values of the AMO index and global warming as covariate information combined with threshold point of the AMO index, we further forecast U.S. hurricane activity to show how forecasts can be improved. With both of these improvements, the skill and accuracy levels of U.S. hurricane activity projections are expected to increase. Third, using annual hurricane losses from 1960 through 2008 to fit the appropriate distribution of hurricane loss, we forecast the Value at Risk (VaR) and expected shortfall (ES) of the total hurricane loss from 2009 to 2012 based on four models, including the threshold Poisson regression model with the time-variant AMO index, the linear Poisson regression model with the time-variant AMO index, the linear Poisson regression model with the AMO index, and the linear Poisson regression model with a constant drift term. We intend to examine the influence of the threshold effect, the AMO index effect, and the global warming effect on VaR and ES.

The empirical results show that hurricane event activity increases when the AMO index is positive and when climate change occurs as a result of human-induced global warming. The threshold model produces a higher adjusted R-squared statistic than the linear model, and the AMO effect has an asymmetric effect on the activity of hurricane events. For the projection of hurricane frequency, we find that a threshold model with the AMO index and time-variant effects provides better projection than the linear model with the AMO index alone with respect to the prediction error criterion, which contributes to an additional 70% rate of improvement in hurricane projection. For the projection of hurricane intensity, the threshold Poisson regression model with the real AMO index (ARMA(3,2) AMO index) produces better prediction performance than the linear Poisson regression model, and the improvement rate is approximately 30–50% (24–40%). Furthermore, the time-variant threshold Poisson regression with the ARMA(3,2) AMO index is an excellent model for predicting U.S. hurricane activity. The mean absolute error (MAE) of this model is only 0.963, which indicates that the forecasting error number of annual U.S. hurricane activity is less than one. Finally, we find that the threshold effect and the global warming effect dominate the AMO effect. In particular, the global warming effect

dominates the AMO effect in extreme hurricane events, and this domination increases over time. Therefore, our finding is compatible with the opinions of Emanuel (2005) and Webster et al. (2005, 2006), who indicate that global climate change plays a dominant role in hurricane activity. In sum, the importance of the threshold effect and the global warming effect must be considered when modeling and forecasting hurricane activity and hurricane risk.

We begin in Section 2 by providing a preliminary analysis of the AMO and U.S. hurricanes and find a suitable autoregressive moving average (ARMA) model for the AMO. In Section 3, we employ a threshold Poisson regression model of hurricane intensity to discuss the goodness of fit of hurricane activity in the linear and threshold models. Furthermore, in consideration of the real AMO index and the predicted AMO index, we project the subsequent 3-year hurricane frequency and intensity. In Section 4, we provide the VaR and ES of hurricane risk. The final section provides the conclusion and further implications.

2 Preliminary analysis of the AMO index and hurricane frequency

2.1 Descriptive statistics

In this section, we use the AMO index and annual hurricane counts from 1960 through 2008. The data are extracted from the NOAA. The AMO index is computed by averaging SSTs between 0° and 60°N and 75° and 7.5°W; here, the monthly AMO was averaged from June through September.[3] Figure 2 shows the time series of the AMO index and the hurricane frequency from 1960 to 2008. The correlation coefficient of the AMO index and hurricane frequency is approximately 50%. Hence, the AMO index is positively related to hurricane frequency.

Next, Table 2 provides the descriptive statistics for the AMO index and hurricane frequency from 1960 to 2008. For the AMO index, the skewness is insignificantly different from zero, and the excess kurtosis is not significantly large. The Jarqur–Bera statistic of the AMO index is 1.134 and is not statistically significant at the 5% level; thus, we do not reject the assumption of normality.

3 These particular start and stop dates for the averaging points do not appear to be especially important to the following analysis (we also attempted to use several other monthly averages, all of which yielded nearly identical results).

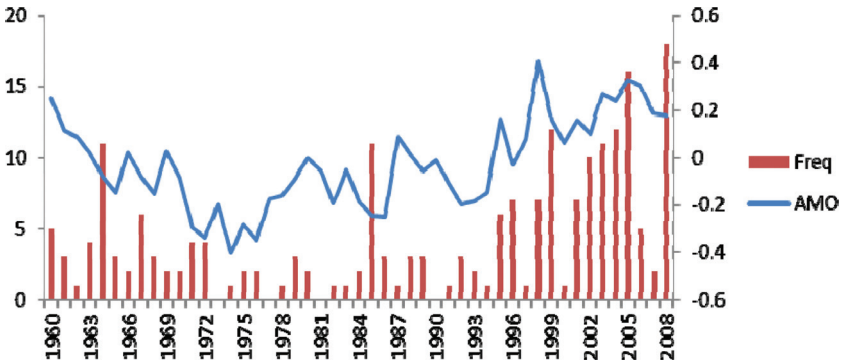

Figure 2: The time series of the AMO index and hurricane frequency.

Table 2: Descriptive statistics from 1960 to 2008.

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
Freq	4.245	3	18	0	4.289	1.489	4.544
AMO	−0.028	−0.053	0.403	−0.405	0.191	0.194	2.364

Furthermore, for the hurricane frequency, the chi-squared statistic of the goodness-of-fit test is 51.469, which is insignificant at the 5% level; thus, we cannot reject the assumption of the Poisson distribution. Therefore, we fit the ARMA model with the Gaussian innovations to the AMO index and use the Poisson distribution to fit and forecast the hurricane activity in the next section.

We employ standard tools of time-series analysis to assist us in modeling the AMO index. Our goal is a prediction model for the AMO values. Regardless of how well we understand the nature of the phenomenon behind the identified time-series patterns, we can extrapolate the patterns to predict future values if such patterns are properly modeled. The first step in developing a time-series model is to check for stationarity. The Phillips–Perron (PP) test (Phillips and Perron 1988) is used in the time-series analysis to test the null hypothesis that a time series is non-stationary with a unit root. The PP method estimates the non-augmented Dickey–Fuller test and modifies the t-ratio of the alpha coefficient, such that serial correlation does not affect the asymptotic distribution of the test statistic. In Table 3, we report the results of the unit root tests for hurricane frequency and for the AMO index. The PP test rejects the null hypothesis of the unit root; consequently, we directly use hurricane frequency and the AMO index for further analysis.

Table 3: PP unit root tests.

	Intercept	Trend and intercept	None
Freq	(4) −4.291***	(4) −5.085***	(3) −1.662*
AMO	(4) −2.751*	(3) −3.684**	(4) −2.711***

Notes: The numbers of optimal lag length are reported in parentheses. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Next, following Elsner et al. (2008), we employ univariate ARMA models for the purpose of hurricane projection. Using data for the period from 1960 to 2008, the ARMA(3,2) is determined to be the optimal model for the AMO index based on the Akaike information criterion (AIC) and the Hannan–Quinn information criterion. According to the Schwarz Bayesian information criterion values, the AR(1) model offers the best fit for the AMO index. As a result, we further compare these two models using the log likelihood and LR test and find that the log-likelihood values of ARMA(3,2) and AR(1) are 36.51984 and 31.32434, respectively, and that ARMA(3,2) is significantly superior to AR(1) at the 5% level. Consequently, we use ARMA(3,2) to model the AMO index and project future hurricane frequency and intensity. The estimated result is as follows:

$$\begin{aligned} \mathrm{AMO}_t = &- 0.00585 + 0.77858\mathrm{AMO}_{t-1} - 0.74852\mathrm{AMO}_{t-2} + 0.69472\mathrm{AMO}_{t-3} \\ &+ \varepsilon_t - 0.21412\varepsilon_{t-1} + 0.96864\varepsilon_{t-2} \end{aligned} \quad [1]$$

3 Modeling and results for hurricane frequency and intensity

Figure 2 indicates that hurricane activity is positively correlated with the AMO index.[4] In this section, we first use a simple linear model to capture the relationship between hurricane frequency and the AMO index, and we then use the linear model with time-variant effects to consider the effect of global climate change, which indicates increasing hurricane frequency over time. Furthermore, we use a threshold model with time-variant effects to capture the asymmetric effect of AMO index on variation in hurricane activity. For the modeling of

4 At least for the Atlantic, the year-to-year variation in hurricane activity is statistically linked (positively correlated) with the AMO index (Saunders and Harris 1997; Kimberlain and Elsner 1998; Goldenberg et al. 2001; Landsea 2005; Elsner et al. 2008).

hurricane intensity, we extend the linear Poisson regression model provided by Elsner et al. (2008) to develop the time-variant threshold Poisson regression model with an asymmetric effect of change on the AMO index. This modeling assists us in determining the overall structure of the prediction algorithm for annual hurricane frequency and intensity.

3.1 Modeling of hurricane frequency

First, based on the empirical studies of the relationship between hurricane frequency and the AMO index, we model hurricane frequency as a linear function of the AMO index in the *Basic model (FLM1)* as follows:

$$\text{Basic model (FLM1): } \text{Freq}_t = a_0 + a_1\text{AMO}_t + \varepsilon_t \quad [2]$$

where a_0 is the intercept and a_1 is the coefficient of the AMO index, and we expect that a_1 is significantly positive. ε_t is the error term in FLM1.

In addition to the natural variability of the climate factors, some studies suggest that global warming also plays a dominant role (Emanuel 2005; Webster et al. 2005). Moreover, the report of the Intergovernmental Panel on Climate Change (IPCC, 2007) indicates that future climate change could become increasingly serious because of human-induced global warming and could result in more unanticipated tropical cyclone events. Hence, global climate change is likely to cause a gradual shift in hurricane intensity over time. As shown in Figure 1, hurricane frequency appears to increase over time, particularly after 1995. Therefore, we further model hurricane frequency as a linear function of the AMO index with a time-variant model, *Time-variant model (FLM2)*, as follows:

$$\text{Time-variant model (FLM2): } \text{Freq}_t = b_0 + b_1\text{AMO}_t * \text{time} + \varepsilon_t \quad [3]$$

where b_0 is the intercept in FLM2 and b_1 is the coefficient of the AMO index with the time-variant effect. If b_1 is significantly positive, then the effect of the AMO index on hurricane frequency is assumed to increase over time because of human-induced global warming. ε_t is the error term of hurricane frequency in FLM2.

Figure 3 shows a recursive residual of the FLM1 model from 1960 to 2008. Clearly, some recursive residuals exceed the critical band of two standard errors; thus, this finding suggests that the linear model may not perfectly capture the influence of the climate factor on the frequency of hurricane events. This result implies two potential phenomena. First, the parameter of hurricane frequency

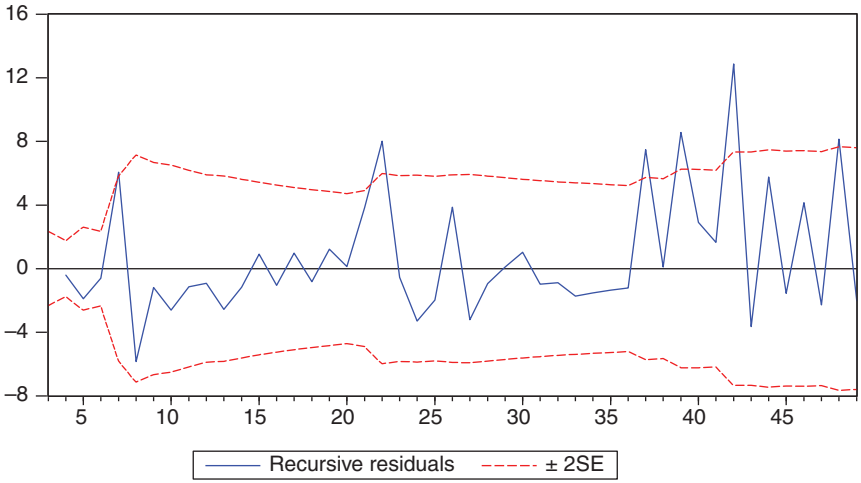

Figure 3: Recursive residuals of hurricane frequency from 1960 to 2008.

may be time-varying, thus supporting us to estimate the FLM2 model. Second, hurricane frequency may appear as structure changes, which may partly result from the increasing influences of human-induced global warming. To find a suitable nonlinear model, we sort the values of the AMO index and obtain their corresponding values with respect to hurricane frequency from 1960 to 2008, as shown in Figure 4. Of the 28 years that have a negative AMO index, only 2 years (7.14%) have hurricane frequencies that are higher than 8. However, of the 21 years with a positive AMO index, there are 6 years (28.57%) with hurricane frequencies above 8. Hence, we further employ alternative threshold models to capture the asymmetric effect of the AMO index on the frequency of hurricane events, as expressed in the following forms:

$$\text{Basic model (FTM1): } \text{Freq}_t = \begin{cases} a_0^{(1)} + a_1^{(1)}\text{AMO}_t + \varepsilon_t, & \text{if AMO}_t > r \\ a_0^{(2)} + a_1^{(2)}\text{AMO}_t + \varepsilon_t, & \text{if AMO}_t \leq r \end{cases} \quad [4]$$

$$\text{Time-variant model (FTM2): } \text{Freq}_t = \begin{cases} b_0^{(1)} + b_1^{(1)}\text{AMO}_t{}^* \text{ time} + \varepsilon_t, & \text{if AMO}_t > r \\ b_0^{(2)} + b_1^{(2)}\text{AMO}_t{}^* \text{ time} + \varepsilon_t, & \text{if AMO}_t \leq r \end{cases} \quad [5]$$

where $a_0^{(1)}(a_0^{(2)})$ is the intercept at state 1, that is, the warm phase (state 2, cool phase) in FTM1; $a_1^{(1)}(a_1^{(2)})$ is the coefficient at state 1 (state 2) in FTM1;

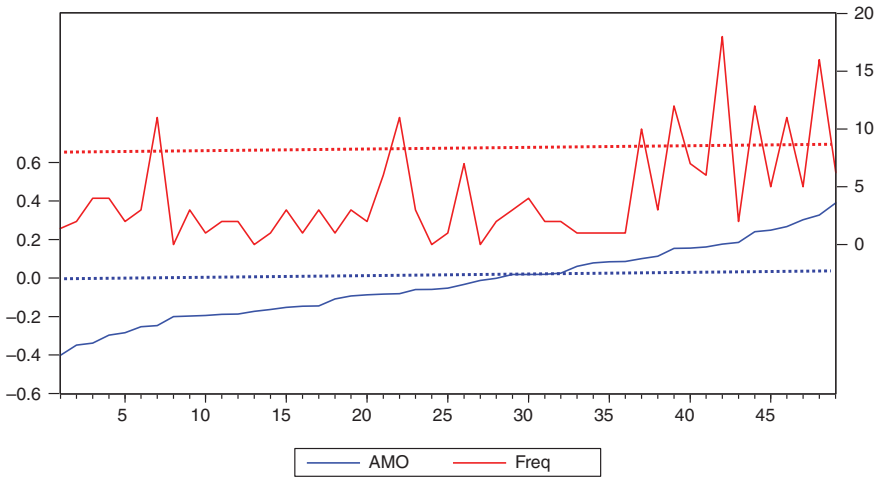

Figure 4: Sorting by AMO index values and corresponding values of hurricane fequency from 1960 to 2008.

$b_0^{(1)}(b_0^{(2)})$ is intercept of the AMO index with a time-variant effect at state 1 (state 2) in FTM2; $b_1^{(1)}(b_1^{(2)})$ is the coefficient of the AMO index with a time-variant effect at state 1 (state 2) in FTM2; and r is the threshold value.

With respect to Figure 3, which indicates that the recursive residual of the linear model is unstable, this subsection employs certain statistics to objectively test and select the optimal threshold. We first use the Chow breakpoint test for each possible point of structure change and then iDentify the point with the most significant F-statistic as the optimal structure breakpoint r. The idea behind the breakpoint Chow test is to fit the equation separately for each subsample and then to confirm whether there are significant differences in the estimated equations. A significant difference indicates a structural change in the relationship. The Chow breakpoint statistic can be evaluated using the F test and is defined as follows:

$$F = \frac{(\mathrm{SSR}_{\mathrm{all}} - \mathrm{SSR}_1 - \mathrm{SSR}_2)/(p+1)}{(\mathrm{SSR}_1 + \mathrm{SSR}_2)/(T-2p-2)} \sim F(p+1,\ T-2p-2)$$

where $\mathrm{SSR}_{\mathrm{all}}$ is the sum of the squared residuals from the linear model, SSR_1 and SSR_2 are the sum of squared residuals from two separating subsamples, T is the total number of observations, and $p+1$ is the number of parameters (including the constant) in the equation. We choose the point with the most significant F-statistic as the structure breakpoint. Accordingly, the F-statistic is 7.2224 with a

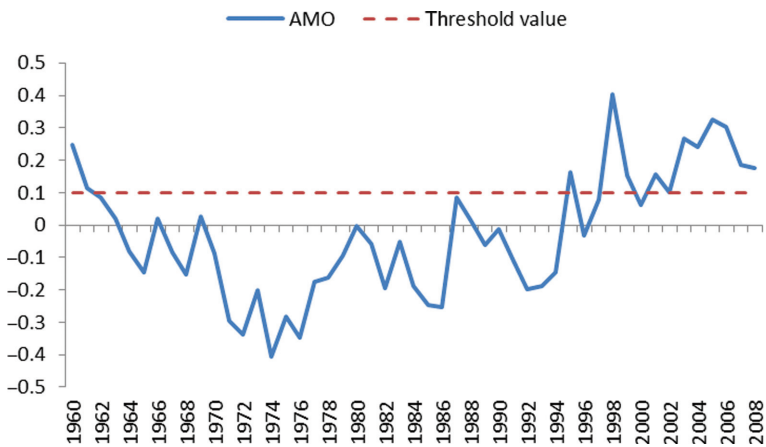

Figure 5: AMO index and threshold values.

p-value of 0.0019 and corresponds to the value of AMO index, which is approximately 0.1.[5] The relation between this threshold value and the AMO index is shown in Figure 5.

3.2 Modeling of hurricane intensity

We employ a recently developed and validated Poisson regression model to model hurricane intensity (Elsner and Schmertmann 1993; Solow and Moore 2000; Elsner, Bossak, and Niu 2001, 2008; Jagger, Niu, and Elsner 2002; Elsner 2003; McDonnell and Holbrook 2004). Based on the Poisson distribution, which is a discrete distribution defined on the nonnegative integers, the Poisson regression model is derived from the distribution of wait times between successive events. In this context, we use this model to model a set of basin-wide hurricane counts on the nonnegative integers for a set of observed years $t = 1, \ldots, T$. Elsner et al. (2008) provide a statistical algorithm to predict North Atlantic hurricane activity. The algorithm has two components: a time-series model to forecast the average hurricane-season Atlantic SST and a Poisson regression model to forecast the

5 For convenience, some studies (e.g. Goldenberg et al. 2001; Landsea 2005; Sutton and Hodson 2005) claim that there are different situations in which the AMO index is positive or negative (i.e. the threshold value is 0). We also consider this assumption, and its corresponding F-statistic of the Chow breakpoint test is 3.1657 with a p-value of 0.0517. Clearly, our objective estimating result is superior to such a convenient assumption.

hurricane intensity given the predicted SST value. We use a threshold Poisson regression model to forecast hurricane intensity given the estimated basic model (ITM1) or time-variant model (ITM2) and the real/predicted AMO index. Thus, the models of the threshold Poisson regressions are as follows:

$$\text{Freq}_t \sim \text{Poisson}\ (\lambda_t^i),\ i = \text{ITM1},\ \text{ITM2}$$

The models of hurricane intensity are as follows:

$$\text{Basic model (ITM1):}\ \lambda_t^{\text{ITM1}} = \begin{cases} \exp(\lambda_0^{(1)} + \lambda_1^{(1)} * \text{AMO}_t), & \text{if AMO}_t > 0.1 \\ \exp(\lambda_0^{(2)} + \lambda_1^{(2)} * \text{AMO}_t), & \text{if AMO}_t \leq 0.1 \end{cases} \quad [6]$$

$$\text{Time-variant model (ITM2):}\ \lambda_t^{\text{ITM2}} = \begin{cases} \exp(\lambda_0^{*(1)} + \lambda_1^{*(1)} * \text{AMO}_t * \text{time}), & \text{if AMO}_t > 0.1 \\ \exp(\lambda_0^{*(2)+} \lambda_1^{*(2)} * \text{AMO}_t * \text{time}), & \text{if AMO}_t \leq 0.1 \end{cases} \quad [7]$$

where $\lambda_t^i, i = \text{ITM1}, \text{ITM2}$ describe the mean (and variance) of the hurricane frequency, which is the hurricane intensity for year t. The symbol ~ refers to a stochastic relationship and indicates that the variable on the left-hand side is a random draw (sample) from the distribution that is specified on the right-hand side. The equal sign indicates a logical relationship with the variable on the left-hand side that is algebraically related to variables on the right-hand side. If $\lambda_0^{(1)} = \lambda_0^{(2)}$ and $\lambda_1^{(1)} = \lambda_1^{(2)}$, then the ITM1 model will reduce to linear Poisson regressions (ILM1). If $\lambda_0^{(1)} = \lambda_0^{(2)}$ and $\lambda_1^{(2)} = \lambda_1^{(2)} = 0$, then the ITM1 model will reduce to a linear constant model without the AMO index (CM). If $\lambda_0^{*(1)} = \lambda_0^{*(2)}$ and $\lambda_1^{*(1)} = \lambda_1^{*(2)}$, then the ITM2 model will reduce to time-variant linear Poisson regressions (ILM2).

3.3 In-sample goodness of fit

Once the structure breakpoint (threshold value), $r = 0.1$, is determined, we further estimate the parameters of the linear model with time-variant effects and the threshold model with time-variant effects. The empirical results pertaining to hurricane frequency are shown in Table 4.

Panel A of Table 4 represents $a_1 = 10.760$ and thus indicates that the frequency of hurricane events is significantly positively affected by the AMO

Table 4: Goodness of fit of hurricane frequency in linear and threshold models.

Panel A: basic model			
		Threshold model (FTM1)	
Explanatory variables	**Linear model (FLM1)**	**Low AMO index AMO ≦ 0.1**	**High AMO index AMO > 0.1**
Constant	4.546***	2.345***	7.480***
	(0.549)	(0.762)	(2.559)
AMO_t	10.760***	−2.276	5.913
	(2.868)	(4.397)	(10.922)
$\bar{R}^2$	0.214	0.379	
AIC	5.549	5.352	
SBC	5.626	5.507	

Panel B: time-variant model			
		Threshold model (FTM2)	
Explanatory variables	**Linear model (FLM2)**	**Low AMO index AMO ≦ 0.1**	**High AMO index AMO > 0.1**
Constant	4.002***	2.398***	6.020***
	(0.506)	(0.711)	(1.792)*
AMO_t * time	0.427***	−0.095	0.330
	(0.087)	(0.203)	(0.185)
$\bar{R}^2$	0.324	0.415	
AIC	5.398	5.292	
SBC	5.475	5.447	

Notes: Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

index in the FLM1 model. However, with respect to the nonlinear model, the FTM1 model produces a higher adjusted R-squared statistic ($\bar{R}^2$) than the FLM1 model ($\bar{R}^2$ increases from 0.214 to 0.379), but the coefficient of the AMO index is not significant at the 5% level in the FTM1 model. This result demonstrates that the purely linear influence of the AMO index would disappear when we consider the threshold effect. The FTM1 is reduced to a simple model with two static states: when the AMO index is less than 0.1, the expected hurricane frequency is 2.345 and when the AMO index is above 0.1, the expected hurricane frequency may be as high as 7.48. This result implies that in addition to the AMO index, other variables may influence hurricane frequency; thus, the relationship between the AMO index and hurricane frequency may be nonlinear rather than linear.

We further focus on the time-variant effect in the linear model (FLM2) and the threshold model (FTM2), and the results are shown in Panel B of Table 4. In the FLM2 model, the coefficient of the AMO index with time-variant effects is significantly positive ($b_1 = 0.427$). In addition, the FTM2 model produces a higher adjusted R-squared statistic ($\bar{R}^2$) than the FLM1 model ($\bar{R}^2$ increases from 0.214 to 0.324). This result implies that the effect of the AMO index on the frequency of hurricane events could increase with time. This result can be explained by the report of the Intergovernmental Panel on Climate Change (IPCC 2007), which indicates that future climate change could become more serious as a result of human-induced global warming and thus could lead to more unanticipated hurricane events. We further divide the sample into events with a low AMO index and those with a high AMO index to investigate whether the asymmetric effect of the AMO index on hurricane frequency exists. The result of the FTM2 model suggests that the coefficient of the AMO index with time-variant effects in the regime of a high AMO index is still significantly positive ($b_1^{(1)} = 0.330$), whereas the corresponding coefficient in the regime of a low AMO index is insignificant. This result implies that the effect of the AMO index on the frequency of hurricane events would increase with time in the context of a high AMO index. By contrast, when the AMO index is relatively low ($\leqq 0.1$), such a significant influence of the AMO index vanishes. Therefore, this result illustrates that the frequency of hurricane events would increase when the AMO index is positive and when the tendency of climate change resulting from human-induced global warming is considered.

Table 5 exhibits the results of the goodness of fit of hurricane intensity in the linear Poisson regressions and threshold Poisson regressions models. Similar to Table 4, we observe that the threshold Poisson regressions dominate the linear Poisson regressions, and the time-variant threshold Poisson regressions produce the highest adjusted R-squared statistic ($\overline{R}^2 = 0.36$). Consequently, we observe the asymmetric effect of the AMO index on both hurricane frequency and intensity. Hurricane frequency and intensity would increase when the AMO index is positive, and this effect would increase as a result of global warming.

3.4 Prediction of hurricane frequency and intensity

The empirical results from the previous section provide us with the background that is necessary to develop a prediction algorithm for hurricane frequency and intensity. Specifically, given eq. [3], the time-series model and the historical

Table 5: Goodness of fit of hurricane intensity in linear and threshold models.

Panel A: basic model			
		Threshold model (ITM1)	
Explanatory variables	**Linear model (ILM1)**	**Low AMO index AMO ≦ 0.1**	**High AMO index AMO > 0.1**
Constant	1.402***	0.853***	2.025***
	(0.042)	(0.112)	(0.1801)
AMO_t	2.486***	−0.859	0.664
	(0.214)	(0.652)	(0.793)
$\overline{R}^2$	0.254	0.309	
AIC	277.616	253.115	
SBC	281.400	257.412	

Panel B: time-variant model			
		Threshold model (ITM2)	
Explanatory variables	**Linear model (ILM2)**	**Low AMO index AMO ≦ 0.1**	**High AMO index AMO > 0.1**
Constant	1.272***	0.816***	2.113***
	(0.049)	(0.188)	(0.099)
AMO_t * time	0.081***	−0.144	0.0610*
	(0.006)	(0.111)	(0.034)
$\overline{R}^2$	0.339	0.360	
AIC	264.578	250.631	
SBC	268.361	254.928	

series of the AMO index produce the subsequent predicted AMO index. For example, using the AMO index over the 1960–2008 period, we obtain a predicted AMO index in 2004 according to the ARMA(3,2) model. Then, using the historical AMO index over the period from 1960 to 2008 (in-sample), we again obtain a predicted AMO index for the 2004–2008 period. Finally, given the predicted AMO index, each Poisson regression model produces the corresponding recursive hurricane intensity from 2004 to 2006, 2004 to 2007, and 2004 to 2008. To measure the predictive ability of the models, we employ MAE and the root mean square error (RMSE) methods to measure projection performance. Table 6 provides the predictions of annual hurricane frequency given the actual AMO index and the predicted AMO index with the ARMA (3,2) model. In Panel A of Table 6, we find that Model B produces better prediction performance than

Table 6: Prediction of annual hurricane frequency.

		Linear model	Threshold model	Improvement rate (%)
Panel A: actual AMO index				
Model A	MAE	4.353	2.468	43.306
	RMSE	4.456	2.655	40.425
Model B	MAE	2.304	1.189	48.418
	RMSE	2.488	1.305	47.549
Panel B: forecast of the ARMA (3,2) model				
Model A	MAE	4.551	2.478	45.538
	RMSE	4.657	2.665	42.772
Model B	MAE	2.729	1.364	50.027
	RMSE	2.913	1.601	45.032

Model A, which suggests that it is necessary to consider the time variance effect. Furthermore, in both Models A and B, the MAE and the RMSE in the threshold model are lower than those in the linear model. This result implies that the threshold model produces better prediction performance than the linear model, and the improvement rate is approximately 40–70%. For instance, comparing the linear model with the AMO index alone (Model A), we find that the threshold model with the AMO index and time-variant effects could reduce prediction errors by $(4.353-1.189) \div 4.353 = 72.269\%$. Furthermore, the minimum MAE in the linear model (threshold model) is 2.304 (1.189), and the improvement rate is $(2.304-1.189) \div 2.304 = 48.418\%$.

In Panel B of Table 6, rather than using the actual AMO index, we use the predicted AMO index with the ARMA(3,2) model to forecast hurricane frequency. The result is similar to Panel A of the table, and we again find that the threshold model could produce better prediction performance with an improvement rate of approximately 40–50%. Hence, when forecasting hurricane frequency, the use of the predicted AMO index with the ARMA(3,2) model could produce forecasts that are similar to the actual AMO index.

Table 7 reports the predictions of annual hurricane intensity given the actual AMO index and the predicted AMO index with the ARMA(3,2) model. In Panel A of Table, we find that the threshold model produces better prediction performance than the linear model, and the improvement rate is approximately 30–50%. For instance, comparing the linear model with the AMO index alone (Model A), we find that the threshold model with the AMO index and time-variant effects could reduce prediction errors by $(4.337-2.119) \div 4.337 = 51.14\%$.

Table 7: Prediction of annual hurricane intensity.

		Linear model	Threshold model	Improvement rate (%)
Panel A: actual AMO index				
Model A	MAE	4.337	2.885	33.484
	RMSE	4.675	3.259	30.281
Model B	MAE	3.175	2.119	33.263
	RMSE	4.097	2.633	35.751
Panel B: forecast of the ARMA (3,2) model				
Model A	MAE	1.581	1.201	24.025
	RMSE	2.031	1.394	31.380
Model B	MAE	1.312	0.963	26.562
	RMSE	1.592	1.065	33.104

Notes: Variable in Model A: AMO; Variable in Model B: AMO*time_trend.

In Panel B, the improvement rate from using the threshold model is approximately 24–40%. Furthermore, whether utilizing the linear model or the threshold model, the use of the predicted AMO index with the ARMA(3,2) model produces lower forecasting errors than the use of the actual AMO index. This finding implies that the time-variant threshold Poisson regression using the predicted AMO index with the ARMA(3,2) model is a better means of predicting U.S. hurricane activity. The minimum MAE of this model is only 0.963, which indicates that the forecasting error for the average annual U.S. hurricane activity is less than one.

4 Hurricane risk measurements: VaR and ES

This section measures the VaR and ES of hurricane risk from 2009 to 2012 based on the four models (the ITM2, ILM2, ILM1, and CM models). We examine the influence of the threshold effect, the AMO effect, and the global warming effect on VaR and ES. To compute the VaR and ES, we use a compound Poisson process to model the total hurricane losses. We use a maximum likelihood estimation to estimate the parameter values of a specific hurricane loss with several popular distributions, including exponential, gamma, Weibull, Pareto, and lognormal distributions. We observe that the gamma distribution exhibits the best goodness of fit with shape parameters = 0.144 and scale parameters = 117.941. The value of the negative log-likelihood function is 26.104.

4.1 VaR of hurricane risk

The value of VaR is obtained as follows:

1. Based on the compound Poisson process, a specific hurricane loss must be computed. In order to explain clearly the influence of the threshold effect, the AMO effect, and the global warming effect on the hurricane intensity, for simplification, we assume that each specific hurricane loss is equal to the mean of the gamma distribution $(0.144 * 117.941 = 16.990 \text{ billion})$.
2. We simulate 100,000 paths for the standard normal random variables to generate the AMO index with the ARMA(3,2) from 2009 to 2012. Given a 5% significance level, we can determine the value of the AMO index to compute the hurricane intensity of the ITM2 model, the ILM2 model, and the ILM1 model.
3. We multiply each specific hurricane loss by the hurricane intensity to obtain the VaR of hurricane risk at a 5% significance level based on the ITM2, ILM2, ILM1, and CM models.
4. We add the VaR of last year to obtain the cumulative VaR for each year.

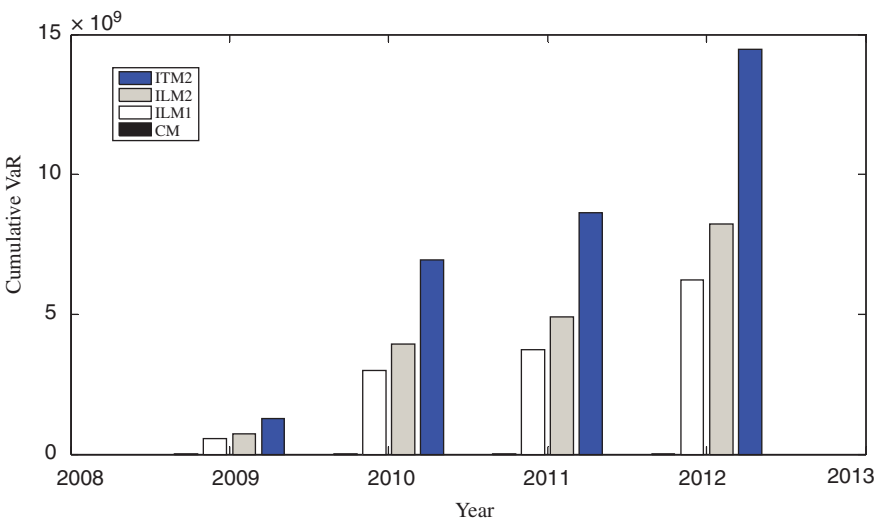

Figure 6: Cumulative VaR in linear and threshold models.

Figure 6 exhibits the cumulative VaR in the linear and threshold models. From this figure, we observe that the cumulative VaR in the ILM2, ILM1, and CM models is underestimated more significantly than in the ITM2 model when we do not consider the threshold effect, global warming effect, and AMO effect. Furthermore, this strength of underestimation appears to increase with time.

We further compare the ITM2, ILM2, ILM1, and CM models to provide more insight on how the threshold effect, the global warming effect, and the AMO effect influence the change in the cumulative VaR.

$$
\begin{aligned}
&\text{Let the change of the cumulative VaR } (\Delta \text{ Cumulative VaR}) \\
&\quad \equiv \text{VaR(ITM2 model)} - \text{VaR(CM model)} \\
&\quad = [\text{VaR(ITM2 model)} - \text{VaR(ILM2 model)}] + [\text{VaR(ITM2 model)} \\
&\qquad - \text{VaR(ILM1 model)}] + [\text{Var(ILM1 model)} - \text{Var(CM model)}] \\
&\quad = \text{change of cumulative VaR resulting from threshold effect} \\
&\qquad + \text{change of cumulative VaR resulting from global warming effect} \\
&\qquad + \text{change of cumulative VaR resulting from AMO effect} \\
&\quad \equiv \text{threshold effect} + \text{gobal warming effect} + \text{AMO effect} \\
&\quad \equiv \text{Total effect}
\end{aligned}
\tag{8}
$$

We use eq. [8] to compute the total effect, threshold effect, global warming effect, and AMO effect, and the results are shown in Figure 7. Figure 7 indicates that the total effect becomes stronger with time and that the threshold effect and global warming effect dominate the AMO effect in each year. This result indicates the importance of considering the threshold effect and the global warming effect when modeling and forecasting hurricane activity and hurricane risk.

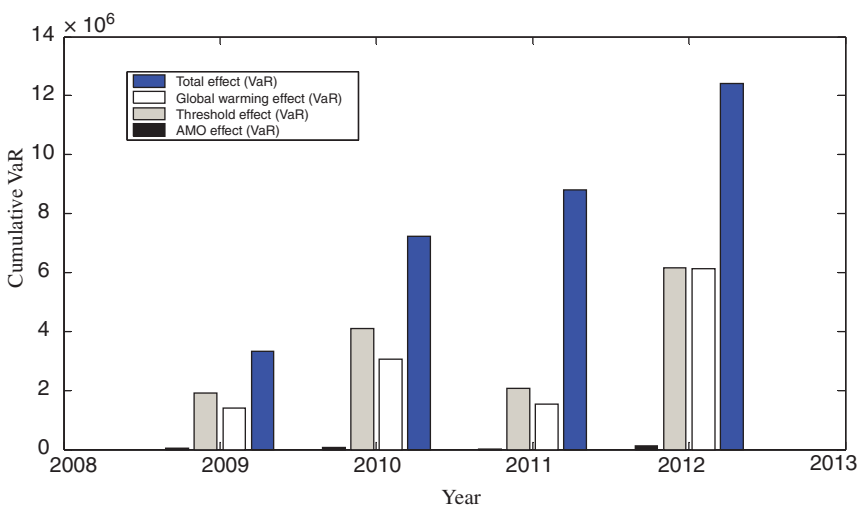

Figure 7: Total effect, threshold effect, global warming effect, and AMO effect with cumulative VaR.

4.2 ES of hurricane risk

Because hurricane losses have fat tails, the cumulative ES of hurricane risk must be provided. The computation of cumulative ES is similar to that of the cumulative VaR of hurricane risk. The simulation results are shown in Figures 8 and 9. Figure 8 shows that the ILM1 and CM models are significantly underestimated.

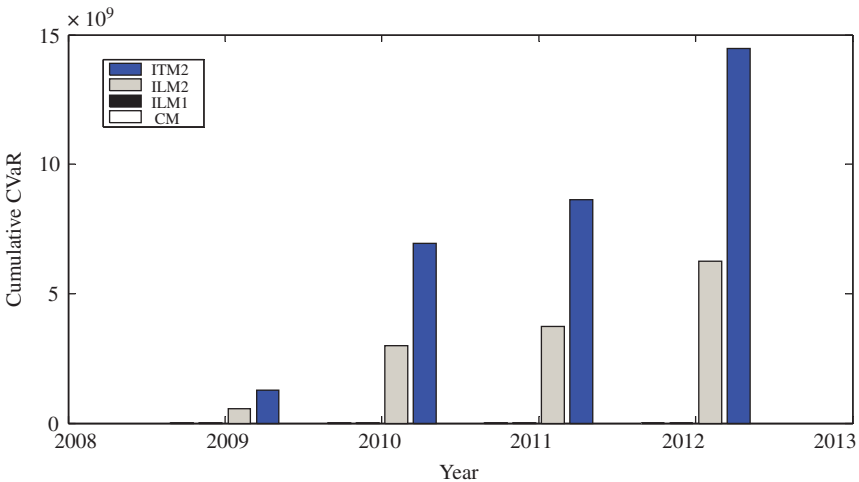

Figure 8: Cumulative ES in Linear and threshold models.

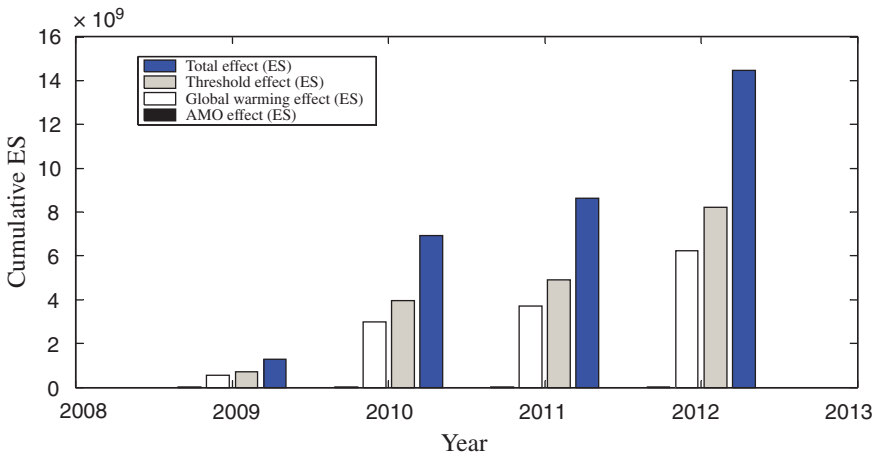

Figure 9: Total effect, threshold effect, global warming effect, and AMO effect with cumulative ES.

The cumulative ES in the ILM1 model is between 670,000 billion and 2,610,000 billion, whereas the cumulative ES in the CM model is only 1,190 billion. Furthermore, Figure 9 demonstrates that the threshold effect and global warming effect dominate the AMO effect more significantly and that the threshold effect and global warming effect strengthen over time. Comparing Figures 7 and 9, we find that the global warming effect dominates the AMO effect in extreme hurricane events and that this domination strengthens over time. Therefore, our result is consistent with the empirical findings of Emanuel (2005) and Webster et al. (2005, 2006), who indicate that global climate change (rather than natural climate cycles) may play a dominant role in hurricane activity.

5 Conclusions and implications

We model both hurricane frequency and intensity as a threshold function of the AMO index and allow for the possibility that the AMO index may change over time as a result of global warming to show how forecasts of U.S. hurricane activity can be improved. The empirical results show that the threshold model produces better prediction performance than the linear model and demonstrate the asymmetric effect of the AMO index on hurricane frequency and intensity. Furthermore, a time-variant threshold Poisson regression model using a predicted AMO index with the ARMA(3,2) model provides excellent projections of U.S. hurricane activity, as the MAE of this model is only 0.963, which indicates that the average forecasting error of annual U.S. hurricane activity is less than one. Finally, we also examine the influence of the threshold effect, AMO effect, and global warming effect on the VaR and ES of hurricane risk. We find that the threshold effect and the global warming effect dominate the AMO effect. Furthermore, the global warming effect dominates the AMO effect in extreme hurricane events, and this domination increases with time. Therefore, our findings are compatible with the assertions of Emanuel (2005) and Webster et al. (2005, 2006), who consider that the effect of global warming rather than the natural climate cycle plays the dominant role in hurricane activity. In sum, the importance of the threshold and global warming effects must be considered when modeling and forecasting hurricane activity and hurricane risk.

The results of hurricane frequency and intensity predictions have important implications for the catastrophic risk management of property-liability insurance companies. The worldwide financial crisis of 2008 prompted regulators to reexamine the amount of capital that is sufficient for the insurance industry. Insurance executives must determine how they will obtain adequate capital to comply with Solvency II capital requirements while continuing to manage

catastrophe risk and maintaining their capacity to absorb losses. According to a recent report issued by Guy Carpenter & Company, insured losses from global catastrophes outside of the United States reached USD$36 billion in 2010, compared with USD$27 billion in 2009. Natural hazards constituted the largest source of losses in 2010 at USD$31 billion. Therefore, the implications of our study could provide insurance companies with an appropriate model for predicting hurricane frequency and thus could enable them to obtain accurate estimations of future catastrophe losses to maintain Solvency II capital requirements. Given the increasing frequency of natural catastrophes, the demand for catastrophic risk instruments for (re)insurers with increasing catastrophic risk exposure is predicted to increase in the future.

These types of catastrophic risk instruments include hedging instruments (such as catastrophe options and catastrophe bonds) and financing instruments (such as contingent surplus notes issues and catastrophe equity put options). Hence, further research could focus on the (re)insurers' strategies for pricing the catastrophic risk instruments based on the results of our model. In addition, if an insurance company can accurately forecast catastrophe losses, then the values of these catastrophic risk instruments could be priced accurately. Well-predicted hurricane losses are clearly based on well-predicted hurricane frequency; hence, further researcher could attempt to combine these exacter forecasts of U.S. hurricane activity and provide insurance companies with a more precise valuation of catastrophic risk instruments. Finally, the proxies of climate variables are not only AMO index but also ENSO, NAO, and many others. Furthermore, in addition to time trend, other proxy variables can be used to describe the global warming effect. It may be of interest for future research to construct a forecasting model which simultaneously considers different climate variables and their interactions.

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