III
Epilogue: Beyond ENSO

10
Arctic Oscillation (AO)

If ENSO markets reach sustainable liquidity, then there is a host of similar climate anomalies that could follow it onto traded markets. The climate professional I interviewed, believe that the Arctic Oscillation (AO) will lead that second wave of teleconnections markets. Like ENSO, AO is closely watched by energy firms today.

This epilogue introduces AO and its promise as a traded index, including:

- a description of the AO as a climate phenomenon;
- a review of what current climate science tells us about its impacts;
- a discussion about how the underlying index is calculated; and,
- statistical analysis of the correspondence between the ENSO index and disaster impacts around the world.

Introduction to the Arctic Oscillation (AO)

The Arctic Oscillation (AO) (often called the Northern Annular Mode (NAM)) refers to changes in a wall of atmospheric pressure and wind that normally holds cold Arctic air in the polar region. During the northern hemisphere winters, when the index measuring AO is positive, the wall is particularly strong - a ring of air currents, blowing west to east (also called the Westerlies) keeps cold Arctic air trapped in the low pressure zone of the Arctic. This results in relatively warm wet winters in much of the United States east of the Rockies and Northern Eurasia, with an increase in European wind storms[1]. Positive anomalies are also associated with lower than average precipitation in the American west and Spain[2] [3].

In contrast, when the index is negative, the barrier holding cold air in the Arctic is weak and the atmospheric pressure at the North Pole is high. During negative AO anomalies, cold Arctic air penetrates into the *middle latitudes* - the region around 45 degrees North, which runs

[1] J.W. Hurrell, Y. Kushnir, G. Ottersen, and M. Visbeck. An overview of the North Atlantic Oscillation. *Geophysical Monograph Series*, 134: 1–36, 2003

[2] S.A. McAfee and J.L. Russell. Northern Annular Mode impact on spring climate in the western United States. *Geophysical Research Letters*, 35(L17701):10–1029, 2008

[3] C.C. Raible, U. Luksch, and K. Fraedrich. Precipitation and Northern Hemisphere regimes. *Atmospheric Science Letters*, 5(1-4):43–55, 2004

roughly through Montreal Canada, Bordeaux, France, the Northern tip of Sapporo Island, Japan and Portland, Oregon.

Negative anomalies in the AO are associated with winter storms. In February 2010 NOAA registered the largest negative anomaly in the Arctic Oscillation (a value of 4.266) in the agency's basic times series (beginning in 1950). That month there were three historic winter storms in the mid-Atlantic United States. The first two storms, arriving within days of one another, shut down Washington, DC and produced monthly snowfall records roughly 25 percent above previous historic highs for Baltimore and Washington DC. Klein et al. [2011] Oceanic and Administration [2010] and Seager et al. [2010] suggest that these extreme snowfalls, as well as higher than normal snowfall in northwestern Europe during 2009-2010, were indeed driven by the negative phase of the AO. Cohen et al. [2010] comes to similar conclusions. This coupling of extreme index values and high profile natural catastrophes with large economic impacts may be important for attracting hedgers to an AO market. Vivid examples of a hazard appear critical to prospective hedgers' perceptions of risk, especially in the context of extreme weather, where individuals may have difficulty estimating expected losses[4] [5] [6] [7] [8] [9].

Viewed in isolation, the index appears to be a random walk, flipping signs every few weeks. (Given this random-walk behavior, the AO is not a true oscillation, which explains why many scientists have switched from the more popular name, the Arctic Oscillation.) However, recent work including Baldwin et al. [2003], climate scientists have shown some mid-range predictive skill for the AO index, hints that the anomaly may show longer-term trends. This could be important for attracting speculators to an AO market, as it offers the possibility of profitably trading on private forecasts.

Over the past few decades the AO has tended towards higher index values. This tendency remains subtle. Winter index values reject non-stationarity with 95 percent confidence when subjected to the Augmented Dickey-Fuller test for the presence of a unit root. Nevertheless, climate experts have found this upward bias in repeated studies and believe that it likely reflects climate change associated with greenhouse gas emissions or changes in ozone layer [10]. This connection to global climate change means that a derivatives markets based on AO will provide an important leading indicator for global climate change, perhaps even better than ENSO, which has shown a similar upward bias. Whereas prices on existing climate markets (such as those for carbon dioxide emissions) are contingent on government regulation in response to climate change, prices on an AO market will respond to global climate change itself, insofar as it impacts the index.

AO is often associated to two other important climate indexes.

[4] M.J. Browne and R.E. Hoyt. The demand for flood insurance: Empirical evidence. *Journal of Risk and Uncertainty*, 20(3):291–306, 2000

[5] E.J. Johnson and A. Tversky. Affect, generalization, and the perception of risk. *Journal of Personality and Social Psychology*, 45(1):20, 1983

[6] H. Kunreuther, R. Ginsberg, L. Miller, P. Sagi, P. Slovic, B. Borkan, and N. Katz. *Disaster Insurance Protection: Public Policy Lessons*. Wiley New York, 1978

[7] H. Kunreuther and P. Slovic. Economics, psychology, and protective behavior. *The American Economic Review*, 68(2):64–69, 1978

[8] V. Denes-Raj and S. Epstein. Conflict between intuitive and rational processing: When people behave against their better judgment. *Journal of Personality and Social Psychology*, 66(5):819, 1994

[9] V. Denes-Raj and S. Epstein. Conflict between intuitive and rational processing: When people behave against their better judgment. *Journal of Personality and Social Psychology*, 66(5):819, 1994

[10] N.P. Gillett, M.R. Allen, R.E. McDonald, C.A. Senior, D.T. Shindell, and G.A. Schmidt. How linear is the Arctic Oscillation response to greenhouse gases? *Journal of Geophysical Research*, 107(10.1029):233–248, 2002; and D.T. Shindell, R.L. Miller, G.A. Schmidt, and L. Pandolfo. Simulation of recent northern winter climate trends by greenhouse-gas forcing. *Nature*, 399(6735):452–455, 1999

First the Antarctic Oscillation (AAO) (or Southern Annular Mode (SAM)) is a similar anomaly affecting the Southern Hemisphere. Only a handful of the world's southernmost countries peak into the zone impacted by AAO, so it has understandably received less research attention than its northern twin[11]. Second, some climate scientists consider the AO the parent of the North Atlantic Oscillation (NAO)[12]. I discuss neither the AAO nor the NAO in depth here.

[11] H.A. Bridgman and J.E. Oliver. *The Global Climate System: Patterns, Processes, and Teleconnections.* Cambridge University Press, 2006

[12] John M Wallace. North Atlantic Oscillation/Annular Mode: Two paradigms—one phenomenon. *Quarterly Journal of the Royal Meteorological Society*, 126(564):791–805, 2000

Index construction

NOAA's index tracking the AO is derived from atmospheric pressure patterns in the northern hemisphere measured between 20 degrees latitude (landmark cities roughly at this latitude include Mumbai, India and Mexico City, Mexico) and 90 degrees latitude (the North Pole). NOAA uses satellites to measure the height above the sea surface level (adjusted for the differing effects of gravity at difference places on earth) that gives an atmospheric pressure of 1000 hectopascals (hPa). The actual index is a statistical abstraction (the leading Empirical Orthogonal Function (EOF)) of the daily and monthly mean anomalies of those pressure measurements.

Empirical Orthogonal Function (EOF): reducing the multi-dimensional data into one number

It is difficult to synthesize a matrix of values taken at different times across many locations, even when the resulting matrix is projected onto a series of maps. Imagine looking at a matrix of daily temperatures for major cities across the globe. How can you say from that matrix that the earth, as a whole, is cold or hot? Even if know something about the spatial array of those cities, you can assign virtually any weight each city's contribution to the global temperature.

Climate scientists routinely face that problem. In the case of AO, they distill a single tractable index covering the atmospheric pressure across the AO zone using a statistical transformation called an Empirical Orthogonal Function (EOF). That transformation involves [13]:

[13] H. Bjornsson and SA Venegas. A manual for EOF and SVD analyses of climatic data. Technical Report 1, McGill University, 1997

1. Constructing a matrix of pressure measurements where each column represents a time series for a particular location and each row represents a series of point measures (a map) for a given time.

2. Adjusting the matrix values to reflect that they are coming from a rounded surface

3. Subtracting from those values the seasonally adjusted mean for

each location and scaling their values to produce a standard deviation of one for measurements between 1979 and 2000.

4. Finding the set of eigenvalues associated with the resulting matrix's covariance matrix

5. Identifying the largest eigenvalue in that set

This procedure obscures intuitive interpretations for non-experts, but it results in a single index that explains much of the variance in wind and pressure patterns in middle latitudes of the northern hemisphere and can be applied consistently over a relatively long geospatial time series. As I mentioned various times in this dissertation, the Case-Shiller home price index, which condenses repeat home sales data into a single value for a given geographic reason, provides a good precedent for trading based off of an index measure, developed in academia with the purpose of condensing an otherwise intractable panel dataset into a single value [14].

[14] K.E. Case Jr, R.J. Shiller, and A.N. Weiss. Index-based futures and options markets in real estate. *The Journal of Portfolio Management*, 19 (2):83–92, 1993

Statistical analysis of EM-DAT disasters

Relative to ENSO, AO is characterized by:

- a short lag time between high index values and subsequent catastrophic weather
- a relatively circumscribe group of countries with the most direct exposure to AO risk (those with territory above 45°N)
- a clear seasonal window in which the index is most influential on weather (Northern Hemisphere winter)

For these reasons I chose to benchmark NOAA's monthly AO index's[15] impacts on weather disaster losses by looking at monthly damages from my enhance EM-DAT database (see chapter 1) between December to March due to extreme temperatures and storms aggregated across the countries with territory above 45°N. This gave a sample of 526 individual disasters spread across 204 months. I divided each month's aggregate damage by its monthly median from 1960 to 2010 (see table 10.1). Figure 10.1 shows damages for the AO region for all disaster types.

[15] As of June 2013, NOAA's monthly AO index is available at http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/monthly.ao.index.b50.current.ascii.table.

month	median damage for all countries above 45°N
Dec	181.108
Jan	674.379
Feb	165.211
Mar	202.054

Table 10.1: Median damage (USD m) for countries with territory above 45°N between 1960 and 2010

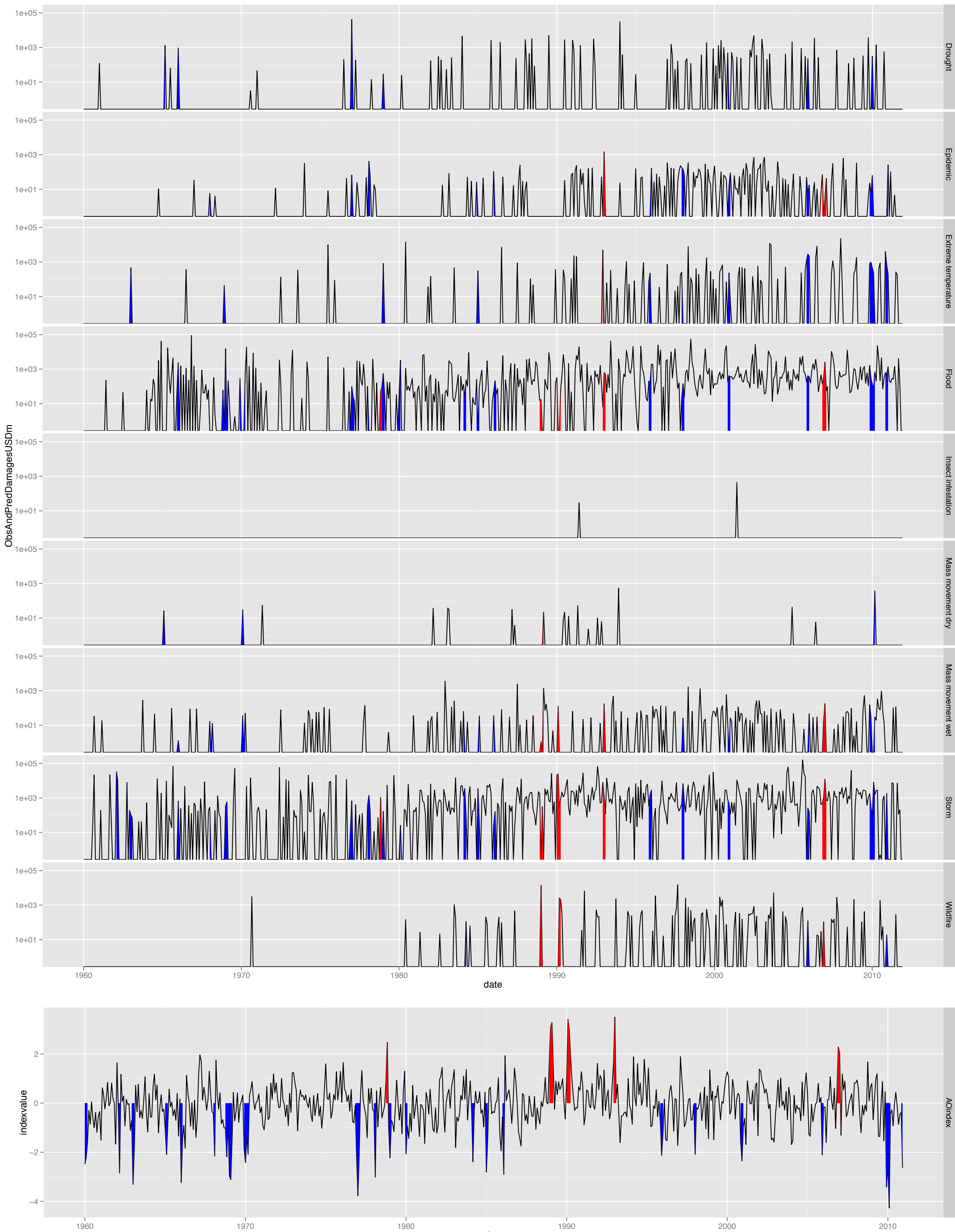

Figure 10.1: Disaster damage estimates by disaster type for countries with territory above 45 °N compared to AO index

I performed the Augmented Dickey-Fuller Test and the Phillips-Perron Unit Root Test on both the index time series and the damage as a percentage of monthly median time series. Both tests favored the alternative hypothesis of stationarity with greater than 95 percent confidence.

The damages series showed no significant autocorrelation using a standard autocorrelation function, indicating that there is only weak interaction between the damage values of one month and the next. However, the AO index showed significant autocorrelation up to two lags. I plan to control for this dynamic explicitly in further analysis.

I defined an anomaly in the AO index as a value outside the range of -1 to 1, and ran three separate regressions - one for a high anomaly, one for a low anomaly, and one for normal conditions. In this case, the climate literature suggests that AO's high and low anomalies may cause regression lines of damages to have opposing signs (negative for low anomalies, positive for high anomalies).

The equations for those regressions are in 10.1. I selected diffuse priors for all coefficients, although I centered the priors of each slope coefficient with a slight bias toward my expectation for the sign of the coefficient. I choose diffuse priors for my AO regressions because there is relatively little published economic work on the impacts of AO to inform my inference. However, I believe these priors can be materially improved by the addition of information from the climate literature, along the lines of chapter 2.

$$
\begin{aligned}
\log \text{monthly damage/median}_t &\sim \mathcal{N}(\hat{y}_i, \sigma_y^2) \\
\hat{y}_t &= a_{\text{AO phase}} \\
&\quad + b_{\text{AO phase}} * \\
&\quad \text{monthly damage/median} \\
a_{\text{low}} &\sim \mathcal{N}(1, 1000) \\
a_{\text{normal}} &\sim \mathcal{N}(1, 1000) \\
a_{\text{high}} &\sim \mathcal{N}(1, 1000) \\
b_{\text{low}} &\sim \mathcal{N}(-1, 1000) \\
b_{\text{normal}} &\sim \mathcal{N}(0, 1000) \\
b_{\text{high}} &\sim \mathcal{N}(1, 1000) \\
\sigma_y^2 &\sim \mathcal{U}(0, 100)
\end{aligned}
\tag{10.1}
$$

The output from those regressions in table 10.2, indicate that, with 95 percent probability, the slope on the low anomaly regression is negative. That means that more extreme AO index values in the negative range are indeed associated with increased disaster damages. 0 is within the 95 percent probability interval for the slopes for positive anomaly and normal seasons. That suggests a weak or non-existent relationship between disaster damages and AO index values outside

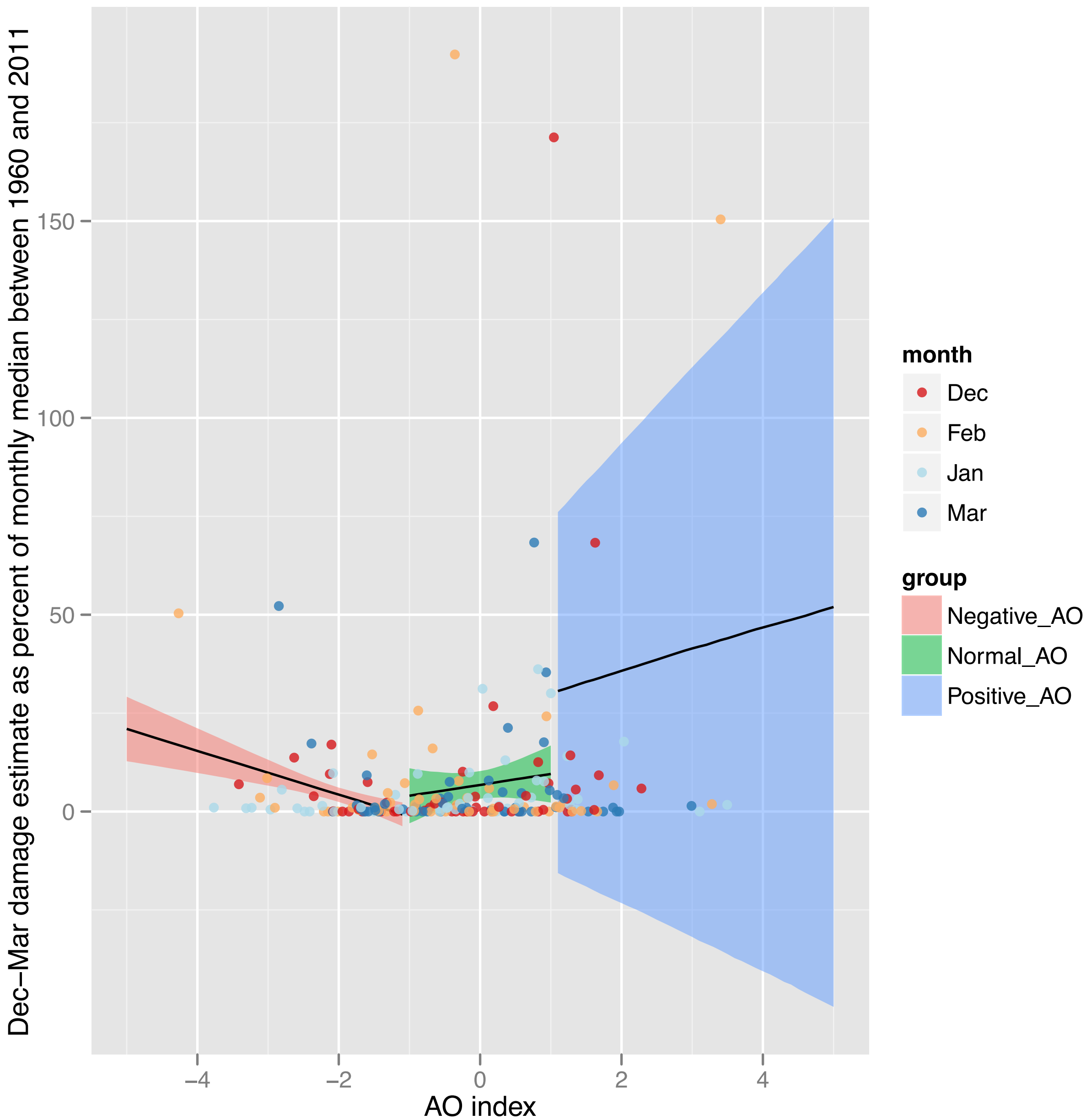

Figure 10.2: Bayesian regression analysis of damage estimates due from storms and extreme temperature during winter months predicted by AO index

positive anomaly	Observed winter months	39							
	mean	sd	2.50%	25.00%	50.00%	75.00%	97.50%	$\hat{R}$	n.eff
b[1]	24.114	18.839	-12.796	11.524	24.082	36.406	61.261	1.0016	2800
b[2]	5.239	8.690	-11.766	-0.521	5.218	10.978	22.332	1.0016	2900
sigma.y	38.441	4.659	30.786	35.125	37.963	41.265	48.909	1.0009	11000
neutral AO	Observed winter months	102							
	mean	sd	2.50%	25.00%	50.00%	75.00%	97.50%	$\hat{R}$	n.eff
b[1]	6.783	2.116	2.672	5.355	6.760	8.194	10.955	1.0015	3100
b[2]	2.833	3.770	-4.449	0.278	2.785	5.329	10.314	1.0013	4500
sigma.y	21.388	1.542	18.640	20.320	21.298	22.364	24.650	1.0009	11000
negative anomaly	Observed winter months	63							
	mean	sd	2.50%	25.00%	50.00%	75.00%	97.50%	$\hat{R}$	n.eff
b[1]	-6.854	3.375	-13.644	-9.099	-6.826	-4.620	-0.249	1.0012	6600
b[2]	-5.579	1.596	-8.730	-6.628	-5.570	-4.537	-2.403	1.0012	5800
sigma.y	8.982	0.843	7.531	8.382	8.924	9.509	10.839	1.0011	10000

Table 10.2: Diagnostics for Bayesian regression of economic damages, as a percent of the monthly median, from storms and extreme temperatures in countries with territory above 45°N from December to March on monthly AO index

the low anomaly range. While the 50 percent probability interval of the low anomaly is distinct from those of the other regressions, the 95 percent probability intervals of the slope coefficients on all three regressions have some overlap. So while low AO anomalies produce higher damages with high probability, the impacts of low anomalies are only distinct from those associated with normal conditions with 89 probability.

Pr(anomaly ≥ magnitude)	magnitude	DEC	JAN	FEB	MAR
13%	-2	779.49	2902.53	711.07	869.64
7%	-2.5	1284.69	4783.71	1171.93	1433.27
3.5%	-3	1789.89	6664.89	1632.78	1996.90
1%	-3.5	2295.09	8546.06	2093.64	2560.52

Table 10.3: Damage estimates from AO anomalies of various magnitudes and months in USD m

To simulate the expected losses associated with extreme low anomalies in the AO index across four months studied, I drew 10,000 simulated simulated parameter value sets from the output of the low anomaly regression and applied each to the historical record of AO index, aggregating damage estimates across each season (December of year t to March of year $t+1$). Across the 10,000 simulated replays of the historical record, the mean damage due to low AO values was USD 1.6 billion in any given season. Restricting the sample to the 19 seasons (out of 51 total) with monthly index values of -2 or below, the mean damage was USD 4.6 billion. Table 10.3 shows the inferred damage estimate when I applied the low anomaly mean parameters to anomalies of various sizes and months. The table also includes the probability of seeing an anomaly of each magnitude or greater in any given month (from the empirical CDF in 10.3 and 10.4). As you can see from that estimate, individual monthly anomalies can cause damages many time greater than the annual average.

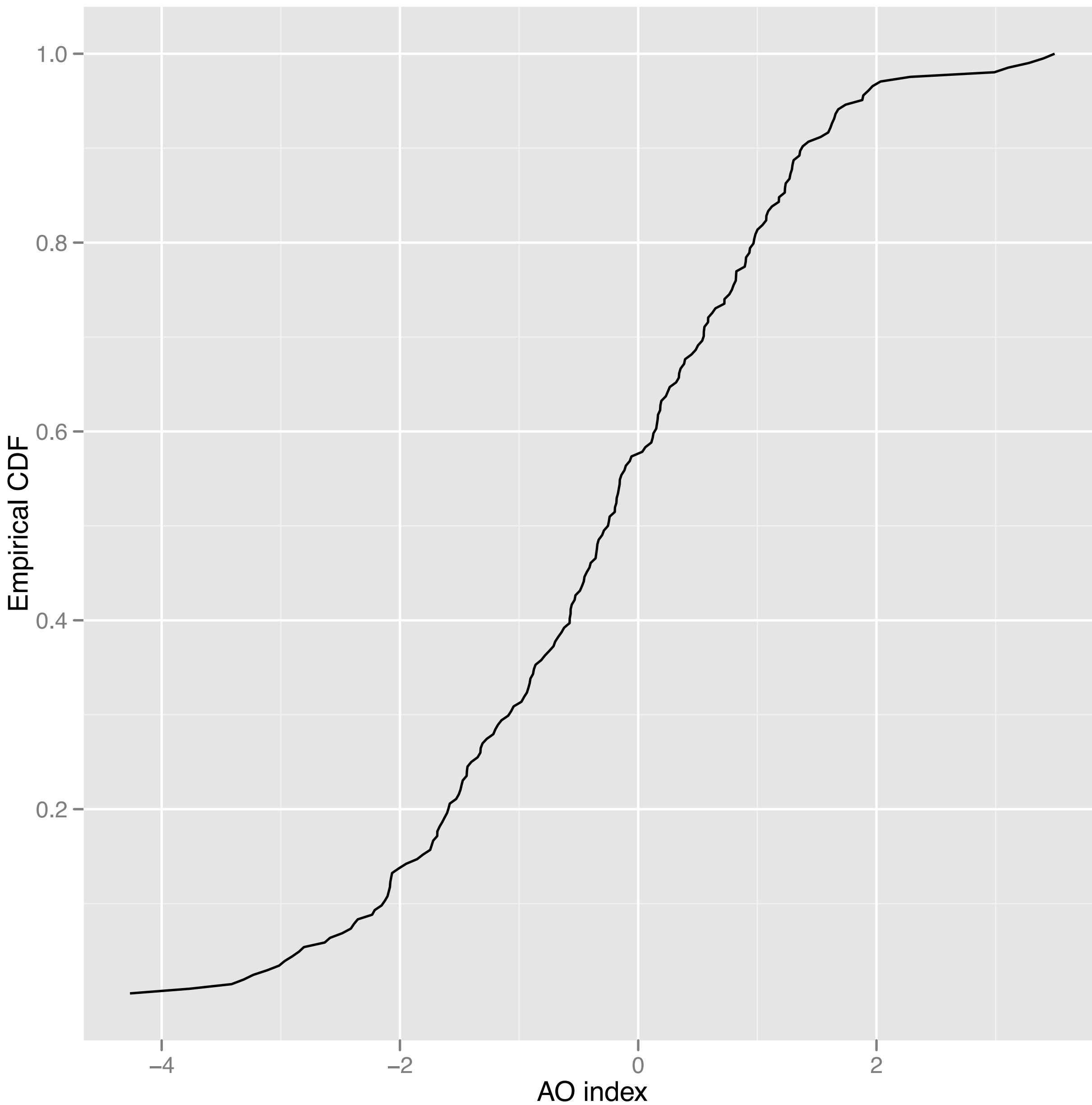

Figure 10.3: Empirical CDF of AO index during winter months 1960-2010

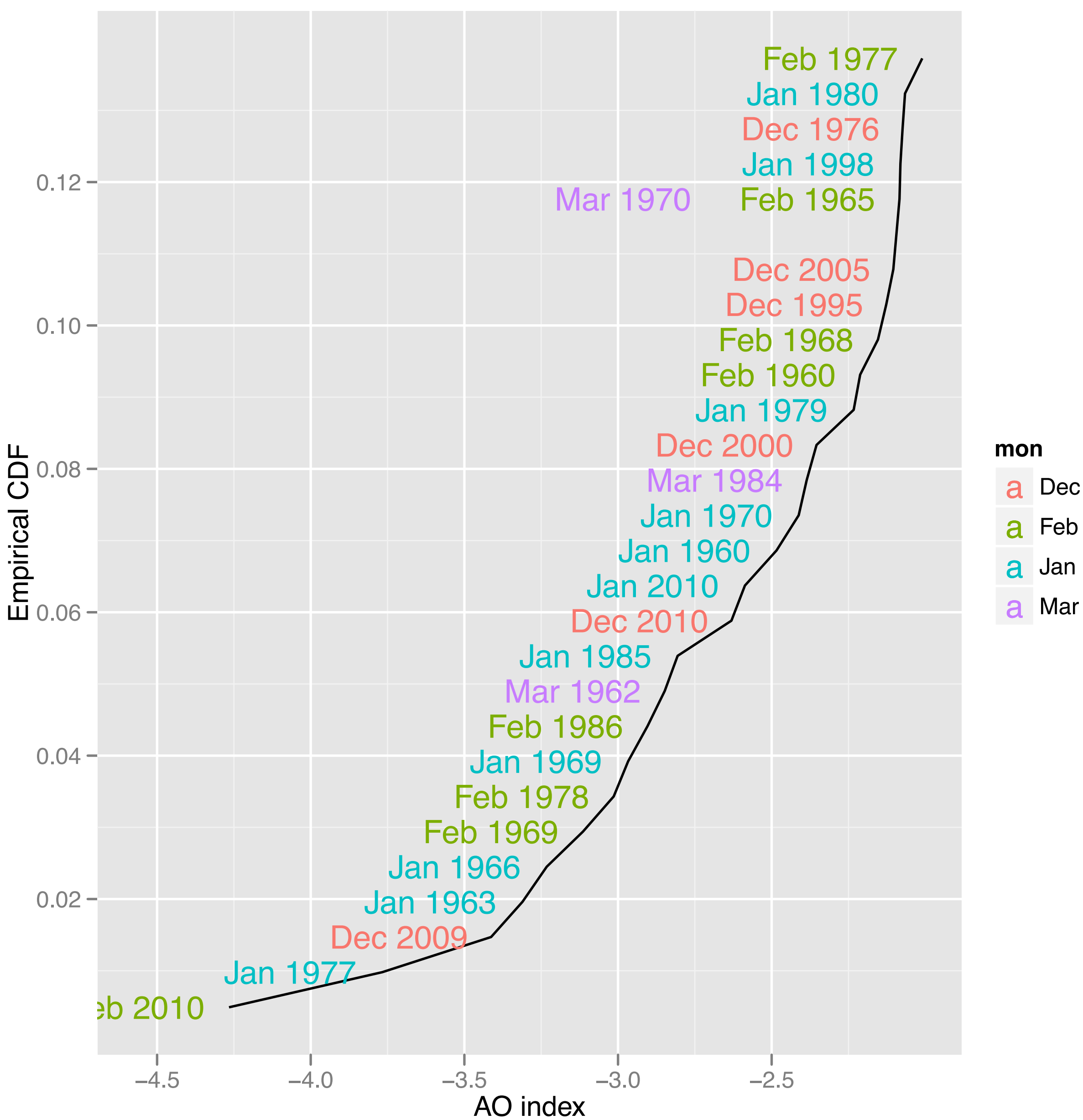

Figure 10.4: Empirical CDF of AO index during winter months 1960-2010: low anomalies

AO as a traded market

Based on those estimates, I believe that the expected hedging interest for exchange traded market on AO index risk is very large. It may in fact be larger than that for a comparable market in ENSO risk (estimated in chapter 2). Independent of specific AO conditions, the average estimated loss associated with AO is USD 1.6 billion, but the losses from a single month's anomaly can be many times that. Given the autocorrelation within the index, it is possible that over the course of an AO season, the hedging interest may growth rapidly as daily AO values climb.

Even with this clear potential hedging interest, In my opinion a few challenges set AO behind ENSO as a candidate for trading:

- The index itself remains highly unpredictable and markets generally favor semi-predictable risks. That link between modest predictability and liquidity was noticed as early as Working [1953]. Some degree of predictability offers hedgers and speculators alike, the possibility of profiting from predictive skill.
- The basis risk on AO remains high. While my regressions suggest that AO is a strong predictor of winter disaster damage aggregated across all countries with territory above 45°N, few hedgers worry about risks spread over such a large geographic area. Before AO can be linked to the losses of specific hedgers, it will need to be decomposed or augmented to reflect the experience across smaller regions.
- Most AO risk tends to concentrate on the low side of the index. This may complicate the search for hedgers to balance the market. Unlike ENSO, AO does not create offsetting pools of risk across the globe. While many industries undoubtedly benefit from negative AO anomalies (such as ski resorts) and there may be some large groups of hedgers who actively benefit from positive AO anomalies, it may be difficult to identify enough hedging interest to roughly balance out the positions of firms and institutions looking to protect themselves from low anomalies.

These factors favor reinsurance markets as a destination for AO.