## Quantifying the Impact of Non-Modeled Catastrophes on Homeowners Experience

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#### Abstract

Much has been done in recent years to quantify the impact of hurricanes and earthquakes on Homeowners loss experience, primarily through the construction of simulation models. Nonmodeled catastrophes, primarily Wind, have retained the standard catastrophe ratemaking methodology. This paper examines various different ways of improving that methodology via the incorporation of other states' data.

#### ACKNOWLEDGEMENT

Many thanks to Joel Atkins, Erik Bouvin, Dave Chernick, Fred Cripe, Kevin Dickson, Sara Drexler, Christopher Monsour, and Fei Zeng, and readers of the paper for valuable input and suggestions.

#### INTRODUCTION

The 1990's saw considerable attention paid by the actuarial community to natural catastrophes, that is: hurricanes and earthquakes. The impetus for this focus was the gargantuan losses incurred by these perils, most dramatically by Andrew and Northridge. The most significant pricing related development to evolve from this attention has been the creation of catastrophe models by various entities (insurance companies, consulting firms, and companies whose primary product are these models). To a large extent these catastrophe models are black box simulations, not typical actuarial models. They have, however, by now gained a wide measure of acceptance by all segments of the industry. And their use has been addressed by Actuarial Standard of Practice #38.

This paper will not deal with the aforementioned models, about which a considerable amount has been written.<sup>1</sup> It will rather focus on other natural catastrophes, of which the most significant peril, from an insured loss perspective, is (non-hurricane) wind and hail (which are lumped together and referred to as "wind" in the balance of the paper); though fire, water, and explosion, can cause substantial damage as well. To distinguish the catastrophe losses generated by these perils from hurricane and earthquake losses, they shall be referred to as "non-modeled catastrophes". The criteria for what constitutes a catastrophe vary by company. Typically there will be a dollar threshold (not increased nearly often enough) and

<sup>&</sup>lt;sup>1</sup> See for instance Burger, et. al. [1], Chernick [2], Walters and Morin [3]

some other criteria, such as more than one insured sustaining a loss. On an industrywide basis Property Claims Service (PCS) assigns catastrophe numbers to natural events based on its estimate of total damage.

In the last few years two phenomena have begun to focus attention on non-modeled catastrophes. The first is that by mere virtue of the fact that there exist models that quantify hurricane and earthquake catastrophe risk, the "remainder" has taken on an identity of its own, and become the subject of distinct analyses. From an operations perspective a similar process has occurred. Companies have mitigated their hurricane and earthquake exposures via reinsurance—private and governmental, higher mandatory deductibles, limiting writings in designated areas, etc.. Homeowners insurance, which has not in recent memory been significantly profitable, has had particularly poor results recently. For 1991 through 2000 the industry has run a 110.9 operating ratio (combined ratio after dividends and investment income); for only one of these years has the ratio been less than 100.<sup>2</sup> Non-modeled catastrophes, now separated from hurricanes and earthquakes, have drawn attention as a distinct and significant contributor to these poor losses.

The second phenomenon is that not only have the non-modeled losses begun to stand out in relief as a distinct peril (to use the term broadly) worthy of study, but the actual quantity of losses derived from these events have been rising, when measured over the long term (see for example Figure 1 and Exhibit 2). This is so whether one measures losses in absolute dollars, per dollar of premium, per house year or per amount of insurance year (these latter being the natural exposure bases).

#### 2. CURRENT METHODOLOGY

Prior to the creation of the hurricane and earthquake models, the most widely used method of quantifying catastrophe risk was the ISO excess wind methodology. While many of its faults were clearly understood, it nevertheless remained the best that could be done. As simulation models have gained popularity for the hurricane peril, the ISO methodology, or one of its many variants, has been the primary methodology for quantifying what's left over. (Note that sometimes this procedure is applied to non-hurricane catastrophe wind losses only, and sometimes to all non-hurricane, non-earthquake catastrophe losses. Thus the ISO excess wind methodology takes as excess losses all wind losses in excess of the long term historical median ratio of wind to non-wind losses, but only for years in which that wind/non-wind ratio is in excess of 1.5 times the historical median ratio. These excess losses are then spread to all years. Again, the basic concept, for this and the many variants, is to take a long-term ratio of catastrophe losses—however defined-- to non-catastrophe losses, and spread the losses across years (or equivalently load in the average).

There are many problems with these procedures. Some of them are.<sup>3</sup>

<sup>&</sup>lt;sup>2</sup> And 2001 has likewise been a poor year.

<sup>&</sup>lt;sup>3</sup> Some of the points are mentioned already in Hays and Farris[4], and McCarthy[5] and Chernick[2].

- The impact of distributional changes over time: in policy forms, geography, etc.. Changes over time in policy form, such as actual cash value vs. replacement cost, and coverages can affect the extent to which a natural event will yield covered losses. Even more significantly changes in exposure concentration over time will affect loss potential.
- The impact of changes in the definition and coding of catastrophes. PCS has gone from being in excess of 1 to 5 to 25 million as its definition of catastrophe. It is safe to conjecture that all major companies periodically change their definitions as well.
- Even what is considered long term (e.g. 30 years) for the calculation of the catastrophe factors, is not long enough, for a given state.
- Adjustments that are typically made to numbers in the rate analysis process, such as trend and loss development, should probably be done separately for the catastrophe and noncatastrophe components. This is not so much a problem as a suggested refinement. The impact of severity trends and development on "excess" losses (in for instance the excess wind procedure) call for individualized attention. Similarly, frequency of catastrophe events might possibly not track with the frequency of non-catastrophe events.
- Changes in premium adequacy over time, if the statistic one is using is loss ratio, should be adjusted for. A very poor loss ratio could be a function of very poor rates and not unusually large losses. Capping should not be a function of premium adequacy.
- The non-catastrophe losses that form the base for the excess ratio comprehend multiple perils. Trends in some of these perils, such as liability and crime, may have no correlation to catastrophes, and cause distortion in excess ratios. Thus if liability losses become a much greater proportion of all coverages, then the ratio of catastrophe to non-catastrophe losses will artificially appear to go down, all other things being equal.
- For those procedures that apply to excess wind only, there needs to be some adjustment for non-wind catastrophe such as fire, explosion, and water.

We shall stop at this summary description of the current methodology. Those wishing further details can see Chernick [2], Hays and Farris [4], and Homan [6]. Bradshaw and Homan [7] suggest a variation which incorporates the output of a simulation model. McCarthy [5] recommends a procedure, which develops the catastrophe load based on non-hurricane wind loss frequency. Dean, Hafling, Wegner and Wilson [8], suggest a variation wherein capping is done below as well as above. (This list is not necessarily comprehensive).

The primary focus of this paper will be on methods for analyzing a given state's nonmodeled catastrophe experience by incorporating other states' data. The lack of such external data is a deficiency in most currently used methods. We will not be discussing how to take the indicated non-modeled catastrophe damage ratio, and incorporate it into an overall (loss ratio or pure premium) rate indication methodology. (Damage ratio is defined as losses over AIY—amount of insurance years. This is the primary statistic we will be dealing with.) While there are details to be worked out, the overall procedure should be fairly straightforward. Exhibit 1 gives one such way.

Before discussing specific methods some general comments are in order. First, all the methods to be presented had, in their creation, various externally imposed requirements. 1) That the separate indicated state damage ratios sum to a reasonable countrywide damage ratio. 2) If credibility is used, states with very stable damage ratios over time, even if small, should have relatively high credibilities. (In many of these states we would have good reason to believe that the state' process variance is lower than average, to put it in these terms, based on external—e.g. meteorological—considerations.) 3) States which had (what appears to be) an extreme (once in a hundred year or greater, say) event, should not be unduly penalized for said event.

Most of the methods examined were constrained by the nature of the data available. An analysis with better or more restricted data can adjust the methods accordingly. The primary data used consisted of a summary, by state and calendar year, of various Allstate companies catastrophe losses and amount of insurance years from 1971 to 2000.<sup>4</sup> These losses are for Homeowners, Renters and Condo. In addition, for the years 1988 to 2000, data was available in some further detail. For these latter years thought was given to segregating other than wind (non-modeled) catastrophes, and perhaps having a separate load for these in selected states.<sup>5</sup>

Some of the methods to be presented below (e.g. the trended method) will likely strike the reader as having problems which make them less optimal than the other methods, since they yield results that are significantly unintuitive for specific states. For the remaining methods though, it is not obvious which one is best Aside from meeting the above externally imposed requirements there are three primary criteria by which a method is judged. The first is accuracy. This is the most important but most difficult to apply, since by their very nature, the existence or absence of catastrophes in a state in years subsequent to the predicted indication, do not necessarily bear directly on the accuracy of the indication. The second criterion is stability. This is easier to measure, and some exhibits will be presented below. The final is "sellability". Especially given the lack of a good test for accuracy, characteristics deemed unacceptable to either regulators or parts of one's internal organization, will count

<sup>&</sup>lt;sup>4</sup> Because these were calendar year one does get, in a few instances, odd results such as negative loss numbers. <sup>5</sup> This option was rejected since it did not seem to improve the results. Water catastrophe losses correlate with

wind catastrophe losses, and other catastrophe perils-with exceptions in a few states--are usually small.

heavily against a method. One instance of such a characteristic is having losses spread from one state to another.

Since it is unclear which of the methods to be presented is optimum, this paper should be viewed as providing ideas on how to improve the non-modeled catastrophe component of the rate indication process. For this reason, and to keep the number of permutations down, not every modification or refinement (e.g., of credibility) is presented for each method.

#### 4. SIMULATION MODELS

Since our goal is to improve on the current methodology, we briefly note a potential methodology, not discussed in detail, which--once fully developed--may be the most accurate. That method is to construct simulation models for the non-hurricane wind peril analogous to those developed for hurricanes. Such models are in fact actively being worked on by the various modeling firms, and some of the first (Beta) versions are being released.

The most glaring problem of other methods, including those to be presented below, is the omission from the analyses of change over time in exposure concentration, in areas that are likely to have windstorms or other natural disasters. No doubt increases in non-modeled catastrophe losses are to a significant extent driven by increases in these concentrations. To quantify the impact of increases in concentration we need the likelihood of natural events for each geographic area, where what constitutes a geographic area varies by the type of natural event. We need to understand how losses caused by different types of events are differentially impacted by the interaction of changes in exposure concentration and topography. In short, we need a simulation model that, in its very broad outline, is similar to hurricane models.

Why not then use the soon to be available commercial models? First one should never use a Beta version of anything. Secondly, hurricane models required quite a few iterations until they reached their present state. The non-hurricane wind models will be, it appears, even harder to get right than hurricane models because of the different sorts of events and the high level of resolution needed<sup>6</sup>. The combinations of types of event and topography are numerous, and the amount of historical data needed for accurate simulations great indeed. Nevertheless one can be (cautiously) optimistic that eventually we will have a workable model. In the meantime the methods presented below may be of some use.

<sup>&</sup>lt;sup>6</sup> Even restricting ourselves to windstorms there are hailstorms, tornadoes, and straight line windstorms; each of these have a wide range of intensities and interact differently to the geographical environment.

#### 5. TRENDED METHOD

The first method to be discussed is the "trended method". It might be conjectured that data going back as far as 1971 would be sufficient to calculate each state's own indicated damage ratio. One major problem (not discussed in the literature) is the calculation of trend factors for catastrophe data at the state level. Catastrophe losses are dramatically more volatile than non-catastrophe losses, and fitting trends to an individual state's catastrophe data does not give reliable results. Nor would applying a countrywide trend to each state's be appropriate, since the true trends (which are indiscernible with the data we have) will clearly vary by state. Credibility weighting trend (of which there are a few methods) might have been pursued, but without a good understanding of the drivers underlying these trends, would not likely result in reliable estimates: Methods of credibility weighting trend lines usually assign credibility as some function of the variability of the trend (parameter) estimate. Catastrophe experience at the state level would tend to be very variable, and one would like to be able to distinguish the noise from true trends. Typically the level of exposure in a state would be a factor in estimation variability. If, however, because of concentration impacts additional exposure does not yield less variability (and more credibility) to damage ratios—as would be typically assumed, then one should know what these increases in concentration are, and what their impact is, before assigning a credibility weight to a trend indication.<sup>7</sup>

One solution is as follows: first calculate a countrywide (linear) trend in damage ratios, weighted by amount of insurance years (AIY). Exhibit 2 gives the calculation of the countrywide trend. Note that the numbers are unadjusted (e.g., for development, change in threshold, etc.). The trend is projected out to the average loss date under consideration.

The ratio of this countrywide trended damage ratio to the countrywide arithmetic mean damage ratio is calculated. This ratio, 1.701 from line 10 of Exhibit 2, is then applied to the arithmetic mean damage ratio of each state, to produce the indicated non-modeled catastrophe damage ratio. This method applies a "trend" factor to state data, while mitigating many of the problems with a straightforward trend calculation. Thus, since it is only one of 30 years, any outlier in a given state will not significantly distort the state indication, as the direct application of trend to state data frequently does.

There do remain significant problems with the method. States which appear to have no trend, or much higher trend than countrywide, are multiplied by a seemingly inappropriate factor.<sup>8</sup> Further, distributional shifts alone could and do distort the indications. Thus there is about a five point difference between the countrywide trended damage ratio, and the sum of the state damage ratios derived by using the "trended" methodology, when weighted by 2000 AIY. A large part of this discrepancy is due to a distributional shift, caused by much higher growth than average in the most recent years in a state having particularly poor catastrophe experience. In short, while initially promising, there still remain problems with this method.

<sup>&</sup>lt;sup>7</sup> It must be admitted though, that further investigation along these lines—even with the data at hand—might prove fruitful.

<sup>&</sup>lt;sup>8</sup> Though one typically tends to hear complaints only when the factor was too high.

#### 6. REGIONWIDE METHODS

All of the subsequent methods—barring the last which skips the second step--begin with the same first two steps. Step one calculates a countrywide indicated damage ratio. Step two divides the country into "regions", i.e., collections of states, and then calculates an indicated damage ratio for each such region. These region-wide indications are rebalanced, based on the *most recent* year's AIY (which should take care of the problem of distributional shifts), to the overall countrywide indicated damage ratio. These rebalanced indicated regional damage ratios are the beginning points for all subsequent calculations. It should be noted that the actual method used here of calculating the indicated regional and countrywide damage ratios (as discussed immediately below), are not an essential component of the methodologies. One could, if so inclined, use more elaborate procedures. What is essential is that there be a countrywide indication and regional indications to be balanced back to it.

#### A. Countrywide Indication

The first step then is to calculate a countrywide indicated damage ratio, to be balanced back to. Figure 1 shows the raw countrywide damage ratios over time. The increases appear to come in steps and from 1990 on there appears to be no trend. As noted at the bottom of the graph the trend for each segment is very close to 0, and the means for each segment (the horizontal bars on the graph) are significantly different. Consequently the arithmetic mean of years 1990 on is used<sup>9</sup>. The mean is not weighted (by AIY), for the accuracy of each estimate (year) is, as far as can be told, independent of the size of that year. From the exhibit it is apparent that the 1990-2000 numbers already incorporate all the "trend" of prior years. Consequently the state indications, which ultimately balance back to the countrywide indication, are "trended" without the explicit application of trend on an individual state basis. Again, this is particularly significant given that data was not available on the previously mentioned drivers of these trends (on a countrywide or individual state basis) such as exposure concentration, or on the nature of data related distortions.

<sup>&</sup>lt;sup>9</sup> In practice a (somewhat arbitrary) load of 4% was tacked on to the countrywide damage ratio. This was done to recognize the fact that deviation is likely to be on the upside: I.e., it is much less likely that countrywide damage ratios will systematically start going down.



1990-1999

1990-2000

-0.019 -0.010

## FIGURE 1 <u>CW Cat damage ratios</u> including 2000

It will not have escaped the observant reader's attention that the endpoints on Figure 1 were selected so as to make the trends look flat and have discrete jumps, and could have been made to look dramatically otherwise had the endpoints been chosen differently. This is correct. The crucial point is that given countrywide data the best guess as to the following year's damage ratio is the average of the years since 1990, or so we would claim.<sup>10</sup>

There is one other minor point to be addressed. Given the above should one use 1990 forward for the countrywide indication, or take a rolling 10 years (1991-2000 currently) average. On the one hand we want to use all relevant points that have information. On the other hand, 10 years is a more standard choice (e.g. in a filing). And if there is in fact a trend in countrywide numbers going forward, a rolling average will pick it up better. There does not seem to be a clear-cut answer to this question.

#### B. State Groupings

The second step is to group the states into regions based on their catastrophe experience (historical damage ratios). Since we only have aggregated data by state and year, there is a limit to the analysis that can be done. Basically, contiguous states with similar damage ratios are grouped together. A few large states are standalone groupings. Where a state looks as if it might reasonably go into more than one region, historical correlations of damage ratios are used to decide the issue.<sup>11</sup>

Some more sophisticated method of grouping than above might conceivably produce better results, but with the data available it is doubtful. Grouping states will be problematic no matter how it is done, for natural catastrophes do not obey arbitrarily drawn political boundaries. Frequently, an appropriate meteorological territory will cross state lines, and there may be natural breaks within a state. (E.g., Colorado which is divided into mountain ranges and plains with very different weather patterns). Indeed one could argue for needing different regions for different catastrophe perils. Since wind is such a dominant component of the losses, in practice this is not an issue.

<sup>&</sup>lt;sup>10</sup> It is not that we have totally discounted the possibility of damage ratios trending up further: whether continuously or via a "jump"(see the previous footnote). But we should need evidence. Certainly over time one would think that a constant threshold and monetary inflation would, certure paribus, cause damage ratios to rise. But thresholds can be changed, and monetary inflation affects the denominator (AIYs) as well as the numerator (catastrophe losses)--though the effects on losses have historically been greater than on AIYs. More importantly, there are presumably more significant forces affecting the overall catastrophe damage ratios: Frequency and severity of natural events, changes in concentration (have our writings in concentrated areas remained relatively constant, or even gone down, over the last 10, 11 years, where it had been increasing previously?), and so on. The impact of these will clearly swamp the impact of, e.g., pure monetary inflation (especially in the current monetary environment). So given the data we have, the most rational assumption would be to take a recent average, until the evidence argues otherwise.

<sup>&</sup>lt;sup>11</sup> This procedure is due to Kevin Dickson (personal communication). I do not give additional details, since the actual grouping process is somewhat tangential to the main concerns.

Even when working within our constraint of using state and not topographic groupings what looks like an obvious grouping based on the data, may not be optimal.<sup>12</sup> In order to circumvent these problems and create more refined territories one would need to have both meteorological data and geographic exposure distributions: i.e., would be back to the simulation model data requirements.

Once the "regions" are constructed, indicated damage ratios are then calculated. Once again a straight arithmetic mean of the latest 10 or 11 years was chosen as the indicated damage ratio. These average damage ratios are rebalanced to the countrywide indication based on the most recent year's AIY distribution. Exhibit 3 provides state groupings and the rebalanced damage ratios for use in one of the methods below. Other equally reasonable groupings could have been chosen.

#### 7. DUAL CAPPING METHODOLOGY

The first method considered is a modification of one proposed by Dean et al [8]. Their method is a variation of the excess wind methodology, but with loss ratios censored below as well as above. In a given state non-modeled catastrophe loss ratios--catastrophe losses divided by total earned premium--are calculated for each year (of seventeen). These are ranked from low to high. A low and high loss ratio is chosen (corresponding to percentiles previously decided on). Any loss ratios below or above these two designated loss ratios are "capped" at the low and high loss ratios respectively. The net of losses excluded from above minus losses excluded from below are "excess" losses. These excess losses are summed and divided by the total earned premium for all seventeen years, to yield a load factor. In the overall rate indication calculation, wind losses are again capped above and below for each year at the chosen loss ratios, and the previously calculated load is factored in; these adjusted wind loss ratios are then added back to the loss ratios for all other perils.

While two sided censoring is certainly an improvement over the traditional method, there still remain problems. First the use of earned premium could distort the procedure if there are substantial differences in premium adequacy over the years. Changing to damage ratios, as we do below, addresses this issue. The next problem, and it is a large one, is that the losses ratios are either trended or they are not. (Their paper does not say, a reasonable guess is that they are.) At the state level, as discussed above, trending catastrophe losses is a problematic exercise: changes in catastrophe thresholds and definitions; changes in storm frequency and severity; changes in concentration of exposure, all need to be taken into account. If the numbers are not trended, then there is an inconsistency with the non-catastrophe indications, wherein the losses are standardly trended. Further the capping procedure itself will be

<sup>&</sup>lt;sup>12</sup> Two states may be close geographically, have approximately the same level of damage ratio, with a relatively consistent pattern over a short period of time, and still not in reality belong in the same group. One state may have, for example, an increase in its catastrophe damage ratio due primarily to a large increase in concentration of exposures, while the frequency of catastrophes remains constant; while a second state could have no or a negative increase in concentration, but have an increase (random or not) in the frequency of natural events causing catastrophes. Though their numbers make them look similar, they might be more appropriately slotted in different groupings. But without more detailed data there is no way to tell.

distorted: The most recent and oldest years will more likely be capped—from above and below, respectively—than the other years. Finally, as the authors recognize, seventeen years, while a considerable amount for most purposes, is not adequate for a catastrophe load in any one given state.

A synthesis of two-sided capping method with some of the components from above, neutralizes some of these problems. Rather than going back in time as far as possible, one gets more data points by using all the damage ratios from a region. For each state in such a region one takes the latest ten years damage ratios (so there will be 10 x the number of states, points). One then ranks these ratios irrespective of state. The two-sided capping procedure is then applied to the damage ratios within the region, so ranked. The method then proceeds as in the original paper with a load calculated and incorporated into the rate indication process. Exhibit 4 provides an example for one region of the calculation of an excess load factor which would be applied to the wind peril in a Homeowners indication calculation.

This modification has various benefits. First, since it uses damage ratios and not loss ratios, premium adequacy is not an issue. Secondly, it typically contains more points: in Exhibit 4 there are ninety versus seventeen in the original paper.<sup>13</sup> Finally, since we are assuming that trend is already incorporated into the most recent ten years, there is no trending problem.

There are some remaining problems. As discussed, there is no perfect grouping of states. Consequently, some states may seem out of place, having lower or higher damage ratios on average than the rest of the states in its region. (Percentiles should be chosen so that the capping procedure does not penalize or reward a particular state because of this phenomenon.) Further the procedure might have a difficult time gaining acceptance because it appears too much to just be spreading losses from one state to another.

#### 8. CREDIBILITY WEIGHTING STATE INDICATIONS

The remaining four methods all credibility weight individual state indications: the first two use actual damage ratios, the latter two relativities. The first three weight against the previously referenced "regional" (rebalanced) indications, the last directly against a countrywide indication.

The use of credibility in these methods proceeded in an extremely pragmatic and somewhat ad-hoc fashion (some would say alarmingly so). Given the external constraints listed above the rational for a given formula is often to a large extent teleological. Further, it is clear (see below) that the standard Buhlman-Straub formulation is not appropriate in the present context. Mahler [9] in a recent comprehensive paper, expounds--among many other things--on how one might adjust for different behavior for different size risks; for parameter shifts over time, for parameter uncertainty and for use of external state data. All these adjustments are potentially applicable, with modifications, to our case. However because of the summary nature of the data, credibilities so adjusted often can not be derived; and even where

<sup>&</sup>lt;sup>13</sup> And our working assumption is that the region consists of states with roughly similar catastrophe exposures; to the extent that this is true the points can be considered drawn from the same population.

quantities could be calculated, they would not be trustworthy since, once again, the primary drivers of the variance and covariance of the damage ratios, e.g. increases in concentration of exposure, <sup>14</sup> are not known.

For our purposes then our pragmatic approach, which is somewhat forced upon us, does not lose us much, especially since it has been shown<sup>15</sup> that within a wide range of values the use of any credibility weighting will be superior to none (even if it is not the best). Our adjustments were to the calculation of the process variance, and to the variance of the hypothetical means<sup>16</sup>. In the presentation of these methods various credibility adjustments have been made not because a particular adjustment is necessarily tied to the method in which it is presented, but simply as a way of presenting examples.

#### A. Credibility Weighting Damage Ratios with the Region As Complement

The first credibility method uses the latest 11 years of catastrophe damage ratios for each state, (circumventing trending problems). The unweighted mean damage ratios for each state, is credibility weighted against the average (unweighted) damage ratio for its region. The standard calculation of process variance, which weights by exposures (in this case AIY) would be inappropriate here, as it would also be in the next three methods. An assumption underlying the weighting is that the process variance (in this case of the damage ratio) is inversely proportional to the exposures; and that in turn assumes that exposures are (more or less) independent. With the catastrophe peril this is very often not the case: additional exposures, in an already concentrated area, are very much correlated. And one should not expect a proportional decrease in variance with additional exposures, in such a case.<sup>17</sup> Hence the credibility formula used here is z=y/(y+k) where y is the number of years, and k is the ratio of the exposure level. This is a case where, given the data we have, the decision not to use exposures as weights seems theoretically as well as pragmatically correct.<sup>18</sup>

Because some regions have what seems clearly to be different process variances by state, the first credibility method presented uses a weighting of each state's own calculated process variance with the average process variance (See exhibit 5); This might be thought of as a very crude attempt to capture some of the additional structure in the data.<sup>19</sup>

<sup>&</sup>lt;sup>14</sup> Even if an effort were made to gather data on the change in exposure concentration, there is not currently a clear conception of what the appropriate level of detail is: is it relevant how concentrated one's become in a state, a county, a zip, or a census track? The answer no doubt varies with topography.

<sup>&</sup>lt;sup>15</sup> See Loss Models [10] pp 451-454

<sup>&</sup>lt;sup>16</sup> There does not seem much point to making other refinements, such as using the credibility weighted overall mean as the complement of credibility.

<sup>&</sup>lt;sup>17</sup> There is some, admittedly weak, evidence for this. See table 2 below.

<sup>&</sup>lt;sup>18</sup> There are various empirical tests one could attempt to estimate the relationship between size and variance (See Mahler[9]). Because of the aggregated nature of the data, and more importantly because, as mentioned, the process variance is among other things a function of size and concentration—which we do not have—one would have to be very suspicious of any quantitative inferences about how the process variance should vary with exposure. Hence assuming no relationship seemed safest.

<sup>&</sup>lt;sup>19</sup> While in general using the average expected value of the process variance is mathematically less variable than the using each state's own estimated process variance, in the present case our adjustment will hopefully yield a

Three different estimates of the variance of the hypothetical means are calculated. 1) The variance of the state mean damage ratios; 2) The difference between the total variance and the average process variance; 3) The covariance of the sum of the first five years damage ratios and the second five years, across the states in the region. The covariance estimator has in other contexts proven to be quite good. In the present context it was not, yielding wide swings by region, including negative results. The other two calculations also yielded slightly negative numbers in some cases. The standard interpretation is that this entails that each state should get 0 credibility. This is a hard conclusion to accept, particularly given the somewhat arbitrary way some of the regions were put together. Consequently the bias adjustment from the estimate of the variance of the means (i.e. subtracting the process variance/number of years) was eliminated from the first estimate, and a floor of zero was put on the second; the average of the two was then taken, as can be seen in exhibit 5.<sup>20</sup>

Once the credibility weighted state damage ratios--with the complement being the regionwide (unweighted) average damage ratio—are calculated, they are adjusted to the chosen regional factor. First the damage ratio for each state is multiplied by its most recent year's AIY. These are summed and compared to the latest year's losses implied by the previously calculated regional factor (The regional latest year AIY x the indicated regional damage ratio). The difference between these two is spread back to each state on a flat percentage basis. Exhibit 5 provides details of this procedure for one region.

#### B. Including Non-Hurricane Wind Data

more accurate estimate.( About twenty years ago I asked Glenn Meyers why a particular ISO credibility procedure had settled on the average process variance for the expected process variance, rather than have each state (or class—I don't recall) use it's own calculated variance. His reply was—if memory serves me correctly—that ISO had indeed looked into that alternative, but the results were too variable.)

Our case might be thought similar to Mahler's cases of heterogeneity; his example is a large WC insured with several locations. These locations might share some risk characteristics, and be different on others. (His other example is commercial auto.) He derives formulas that give less credibility to heterogeneous risks by virtue of the variance of the hypothetical means increasing less slowly that as the square of the sizes of the risk (as it would in Buhlman credibility).

Let us take an auto example, where we have divided the populations into various classes based on some subjective criteria, and wherein each insured is assumed to have a Poisson distribution. Each class is certainly still heterogeneous to a certain extent, so if we could estimate the various parameters in Mahler's procedure we could apply that procedure. But it is difficult to estimate the parameters. Another possibility is to focus in on the classes themselves; think of them as indivisible entities, and assume, say, that they have Negative Binomial distributions—as is often done. In that case differences in heterogeneity will manifest themselves in different Negative binomial parameters for the classes and hence in different process variances. One way to accommodate these differences would be to take into account a class's own (sample) process variance as well as the average. This is what we have done above—where, by the way, it would be well nigh impossible to come up with an estimate of heterogeneity.

<sup>20</sup> This "adjustment" is indeed arbitrary. However, even though estimating the variance of the hypothetical means with the correction included, is an unbiased estimate, the consequent estimation of the credibility factor Z remains biased. (See Ventner[11] pp 440-446). Since it is reasonable that each state does have some credibility, my adjustments do not seem unreasonable.

The next regional method, is really not so much a change in method as a change in data. Rather than non-modeled catastrophes only, losses are taken for all non-hurricane wind plus all non-modeled catastrophes.<sup>21</sup> Combining the two might seem to run counter to the standard rational for a separate catastrophe analysis that catastrophe losses make indications too variable: that by analyzing the catastrophe losses separately we cap the underlying wind losses and hence provide more stable indications for that segment; while the catastrophe losses can then be grouped (across many years, many states, etc.). We loose refinement, but we gain stability.

While the above is true, there are various practical considerations arguing for combining nonhurricane wind with non-modeled catastrophe losses. First there are the standard coding problems that will misclassify catastrophe losses. Further, catastrophe thresholds and definitions typically vary over time and are not necessarily consistently applied across all states. Combining eliminates these potential, and frequently occurring, distortions,

Territorial indications, also become considerably more stable and reasonable when wind and catastrophe are combined. Finally because of the additional ballast provided by the wind numbers, the standard deviations and coefficients of variation for the indications are substantially reduced for the catastrophe portion of the indications(though not necessarily for the indication process in aggregate), as is presented in Table 1.

#### Table 1

	State	State	Year	Year
	SD	CV	SD	CV
Cat	0.61	1.21	0.12	0.25
Cat+wind	0.78	0.82	0.12	0.16

For this second method, the process variance is calculated slightly differently. It reflects the consideration that even a state which has been very stable could have a huge catastrophe; that there is an element of randomness in one particular state within a region having had the once in a hundred year event rather than the others (which is why they were grouped into the same region).<sup>22</sup> Therefore the expected process variance was calculated as a weighting of the average process variance with the maximum process variance of any state in the region.

Exhibits 6 presents the results of using the procedure on the combined non-hurricane wind and non-modeled catastrophe losses.

<sup>&</sup>lt;sup>21</sup> Again, we have an apples and oranges situation somewhat. The catastrophes contain perils other than wind. The justification for this is that the other peril catastrophes are too small to be analyzed on a standalone basis, and do not seem to distort the indications here. <sup>22</sup> Many regions had at least one state that had a huge catastrophe (10 times the median for that state as an

approximation)

#### C. Credibility Weighting Relativities with the Region As Complement

The final two methods use non-modeled catastrophe <sup>23</sup>damage ratio relativities rather than the damage ratios themselves. The motivation for using relativities is that though for a given state the damage ratios typically vary significantly over the long term, we might expect the relativities to be more stable: even if there is trend in the damage ratios we might hope for none in the relativities, thus allowing for a longer time period for each state's data; and indeed there is in general no significant trend as can be seen from the line labeled "linear trend," on exhibit 7,<sup>24</sup> which contains other descriptive statistics as well for examining the reasonableness of using relativities<sup>25</sup>.

While data is available from 1971 on, the early years are too sparse and variable even when using relativities (some years have 0 losses), as can be seen in table  $2^{26}$ . Therefore only 1981 and subsequent is used.

#### Table 2

Average state va	ariance of relativities
	Average
Years	Variance
1971-1980	11.07
1981-1990	1.87
1991-2000	4.24

The procedure proceeds, as can be seen on Exhibit 8, along the same lines as the first regional method, but uses relativities as the statistic. Once a credibility weighted relativity is calculated the estimated damage ratio is calculated by multiplying the estimated relativity factor by the indicated region-wide damage factor. They are then rebalanced as before.<sup>27</sup>

One additional detail which needs to be addressed when using relativities is the impact of distributional shifts in exposure between states. These can, and on occasion do, have significant impacts. This problem is addressed by adjusting all relativities to the 2000 AIY

<sup>&</sup>lt;sup>23</sup> Because of the greater number of years used, non-hurricane wind could not be included.

<sup>&</sup>lt;sup>24</sup> These relativities are to adjusted countrywide damage ratios; relativities to region-wide damage ratios should be even more stable.

<sup>&</sup>lt;sup>25</sup> The R-squared that goes along with the trend is given. Standard deviation and coefficients of variations of the relativities with which to measure the variability of relativities by state are given. The correlation of each states damage ratio (not relativity) to the countrywide (adjusted) damage ratios, is also given. All rows are labeled.
<sup>26</sup> One would conjecture that the variance has gone up in the most recent years due to increases in concentration. But the data is not available to test this hypothesis.

<sup>&</sup>lt;sup>27</sup> In the calculation of credibility the process variance was again calculated as a weighting of the maximum process variance for any state within the region with the average process variance of all states.

level. Thus let  $w_i$  be the 2000 AIY for state i; let  $d_{ij}$  be the damage ratio for state i in year j; then the adjusted region-wide damage ratio for year j is  $A_j = \Sigma_i (w_i \ge t_{ij})/\Sigma_i w_i$ . Relativities are then taken to this adjusted region-wide damage ratio; that is the relativity for state i and year j is  $d_{ij} / A_j$ . A similar adjustment is made to the relativities in the next method. For a simple numerical example assume there are 3 states in the region (or countrywide for the next case).

Year	State1	קרו	State 2	קרו	State 3	מח	Regionwide	Adjusted
1981	<u>AII</u> 10	.3	<u>AII</u> 10	.6	<u>AII</u> 10	<u>DR</u> .9	.6	.7
2000	20	.05	40	.1	60	.20	.142	.142

Here DR represents the damage ratio relativity. The 1981 regionwide adjusted relativity would be  $(20^{*}.3+40^{*}.6+60^{*}.9)/120 = .7$ . The relativity for State 1 in 1981 would be .3/.7.

The three previously referenced estimates of the variance of the hypothetical means come out to be quite close (for this and the next method) and the first estimate of the variance was used. Exhibit 8 gives the results of these calculations for one region.

#### D. Credibility Weighting Relativities with Countrywide As Complement

The final method calculates relativities in a year as each state's damage ratio divided by the countrywide adjusted damage ratio.<sup>28</sup> For the countrywide damage ratio (by which the final calculated state relativities are multiplied to obtain the final state indicated damage ratios) it was also necessary to use the mean of the adjusted countrywide averages, rather than the mean of the raw countrywide averages. This had the effect of changing the countrywide damage ratio to approximately .56 from approximately .52. Texas had tripled its AIY between 1990 and 2000 while all other states had on average approximately only doubled. This state had huge catastrophes in two of the last 10 years, and had significant impact on the countrywide average. Without readjusting to the 2000 AIY distribution the relativities as well as the countrywide average would have been distorted.

Using countrywide relativities has one major drawback. The complement is biased. That is, it is clear that many states have an expected relativity, while not known precisely, much different than 1. Indeed, a significant argument for using regional relativities, is that it eliminates (imperfectly) this problem. Exacerbating this problem is the desiderata that a given method should not overly penalize a state for a one in a hundred (or greater) year event.<sup>29</sup> For these extreme states one desires lower credibility than would otherwise be obtained given the wide spread of countrywide relativities.

<sup>&</sup>lt;sup>28</sup> With the same adjustment, but with the adjusted countrywide damage ratio replacing the regionwide damage ratio in the above explanation.

<sup>&</sup>lt;sup>29</sup> These losses could not simply be eliminated, since another desiderata was that on a countrywide level, they be accommodated.

This problem was resolved by having unusually large relativities capped and the off balance spread back to each state in proportion to the state's relativity standard deviation (after capping), as measured in 2000 expected losses. This method of rebalancing gives states with high average relativities (excluding the impact of once in a hundred year events) more load and those with lower relativities less, counterbalancing the impact of the biased complement. Further the loading back of these losses (a catastrophe load for catastrophe losses, if you will), is a function of the state's own characteristics. States with lower variance get less load and states smaller in absolute size (AIY) get less load, and vice versa. This procedure is intuitively appealing: smaller states, all else being equal, should get a commensurately smaller load, and less variable states, all else being equal, should get smaller loads. This characteristic should also make the capping and spreading more palatable to outside parties.

The capping procedure calls for some comment. Within each state, the standard deviation of the relativities before capping is calculated. If any relativity for that state is greater than the arithmetic mean relativity plus three standard deviations, that relativity is capped (between 1 and 2% of the points were capped). The relativity exceeding the cap is changed not to the mean plus 3 standard deviations, but to the highest actual relativity lower than the capalmost always the next lower actual relativity. To cap the losses more conventionally would not have accomplished much, since the standard deviation calculation included the extreme event, and the conventionally capped number would have been much higher than desired. Further, on an intuitive basis, this procedure replaces an extreme year with an estimate of a typical (once in 20) really bad year. While the proposed method does have the disadvantage that a state with a damage ratio slightly beneath the cap might easily have a higher indication than if it had come in slightly above the cap, this is not a major problem in practice.

The spreading back of losses is calculated as follow (references are to exhibit 9). The indicated damage ratio relativity for state i is  $d_i$  (line 7); expected 2000 losses for the state i (line 8) is the indicated damage ratio relativity times the countrywide chosen damage ratio times its 2000 AIY:  $d_i x CWD x AIY_i$ . One standard deviations worth of these losses are (line 9) line 8 x sd<sub>i</sub>. The off balance, calculated in a manner similar to previous methods, is spread back in proportion to line 9. The detailed steps for one state are given in Exhibit 9.

#### **10. CONCLUSION**

Various methods have been presented which use additional states' data to calculate nonmodeled catastrophe loads. Every one of these methods is an improvement over current methodology, and each has its own strengths and weaknesses. The trended and dual capping methods have problems (discussed previously) that the other methods do not. Of the remaining four, using relativities, for either the regional or countrywide method, would seem superior to using damage ratios since it allows for the inclusion of many more years without concern about adjusting the numbers for trend. On the other hand, in our case we can no longer include ground up wind experience in the data; if one does have wind data going back that far, then incorporating it into the relativity methods would be optimal. This leaves the regional and countrywide relativity methods, with wind data if one has it. Exhibit 11 gives a comparison of the results by state for these two methods as well as the trended method and the "Agg/Agg" method, which is simply a weighted average of all years of a state's (untrended) damage ratios. How do these two remaining methods compare on the criteria delineated at the beginning of the paper?

The first, and most important criteria is accuracy; as mentioned we unfortunately know of no way to measure this, even on a relative basis. While, as can be seen on Exhibit 10, there are some significant differences in estimates, especially for the larger damage ratio states, even had we the results of the next few years because of the nature of catastrophes we could not assess how well each method has done. The second criterion is stability. Exhibit 11 provides a test of the stability of the countrywide relativity method: i.e. the change in state indications between 1999 and 2000. The results are much more stable than the trended and Agg/Agg method to which it is compared. Similar results obtain for the regionwide method. And indeed the regionwide method is superior in this regard. Because of the capping process used in the countrywide method a capped year might become uncapped the next calendar year and vice versa. While this is not necessarily a drawback-our assessment of what is extreme will change with new information--it does cause less stable results. The third criterion is sellability. Here the countrywide method comes out ahead. Most audiences understand and are willing to accept the concept of a relativity to countrywide. However, somewhat paradoxically, once the relativity is to a region, there is, based on informal observation, more of a (negative) flavor of spreading losses. So there remains in the end no clear cut winner.

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#### EXHIBIT 1 HOMEOWNERS

#### DEVELOPMENT OF EXPECTED CATASTROPHE INCURRED LOSS RATIO

(1) Average Earned AIY* for 12 month period ending 3/31/2001	135.88
(2) Factor to Adjust AIY @ 01/01/2003	1.046
(3) Average AIY Trended to 01/01/2003 (1) x (2)	142.13
<ul> <li>(4) Total Dollar Catastrophe Provision Per AlY including all LAE</li> <li>(Refer to the Dev. of Total Catastrophe Provision Exhibit)</li> </ul>	0.431
(5) Expected Catastrophe Losses (3) x (4)	\$61.26
(6) Average Earned Premium @CRL	<b>\$4</b> 43.87
(7) Factor to Adjust Premium for Premium Trend @ 01/01/2003	1.046
(8) Trended Average Earned Premium @CRL (6) x (7)	\$464.29
(9) Expected Catastrophe Loss Ratio including all LAE (5) / (8)	13.20%

\*1 AIY = \$1000 Of Coverage in Force for One Year

#### HOMEOWNERS COUNTRYWIDE DEVELOPMENT OF CATASTROPHE TREND FACTOR

(1)	(2)	(3)	(4)	(5)
	AMOUNT OF	CATASTROPHE	CATASTROPHE	FITTED
CALENDAR	INSURANCE	INCURRED	RATIO	CATASTROPHE
YEAR	YEARS	LOSS	(3) / (2)	RATIO
1971	50,744,591	5,574,000	0.11	0.155
1972	56,809,992	5,357,000	0.094	0.168
1973	63,630,027	8,119,000	0.128	0.182
1974	71,301,809	23,660,000	0.332	0.196
1975	79,935,311	18,550,000	0.232	0.209
1976	92,593,646	9,278,000	0.1	0.223
1977	109,629,993	11,545,000	0.105	0.237
1978	140,793,253	29,102,000	0.207	0.25
1979	172,171,716	67,836,000	0.394	0.264
1980	205,704,018	56,214,000	0.273	0.278
1981	229,742,921	37,883,000	0.165	0.291
1982	244,770,419	74,005,000	0.302	0.305
1983	259,520,483	91,019,000	0.351	0.319
1984	282,063,918	107,694,000	0.382	0.332
1985	309,884,767	116,237,000	0.375	0.346
1986	352,952,506	95,634,000	0.271	0.36
1987	400,596,851	75,712,000	0.189	0.373
1988	447,064,515	121,665,000	0.272	0.387
1989	503,736,622	184,044,000	0.365	0.401
1990	551,875,055	299,840,000	0.543	0.414
1991	604,545,778	328,134,000	0.543	0.428
1992	628,498,039	357,020,000	0.568	0.442
1993	643,057,601	312,072,000	0.485	0.456
1994	673,490,999	394,674,000	0.586	0.469
1995	709,520,629	405,451,000	0.571	0.483
1996	743,945,331	513,895,000	0.691	0.497
1997	783,663,555	195,818,000	0.25	0.51
1998	831,623,953	328,613,000	0.395	0.524
1999	878,902,781	385,679,000	0.439	0.538
2000	927,355,116	566,488,000	0.611	0.551

1)	Projected Catastrophe Ratio	0.585
2)	Average Catastrophe Ratio	0.344
3)	Catastrophe Trend Factor	1.701

## NON-CATASTROPHE WIND PLUS NON-MODELED CATASTROPHES

	(1)	(2) <b>1990-2000</b>	(3)	(4)	(5) (4) x (6)	(6) (3)/(5)
	1990-2000 AIY	Damage ratio	2000 AIY	(2) x (3)	Adj. Dam Ratio	Adjustment
1	1,459,116,130	0.66	167,735,984	111,360,643	0.62	
2	625,160,130	1.22	73,452,055	89,944,077	1.14	
3	299,750,783	2.03	36,862,828	74,758,372	1.88	
4	968,763,429	0.59	109,989,815	64,731,746	0.55	
5	1,768,915,559	0.37	191,130,811	71,461,447	0.35	
6	278,441,837	0.28	28,216,696	7,898,130	0.26	
7	322,105,688	0.44	43,943,005	19,175,022	0.41	
8	307,439,130	0.37	39,331,209	14,450,301	0.34	
9	1,443,547,377	0.60	158,041,453	94,466,352	0.56	
10	415,847,509	2.65	67,147,524	177,723,848	2.46	
11	43,338,576	0.28	5,551,336	1,561,510	0.26	
Countrywide	7,932,426,148	0.734	921,402,716	727,531,450	0.79	0.93

Scrambled							Ratio with
State	Year	AIY	Ratio	Normalized	Difference	Load	Excess Load
7	1997	4932842	0.13	0.35	-0.22	-1105963	0.46
2	1992	1558165	0.13	0.35	-0.22	-338129	0.46
19	1990	4968539	0.18	0.35	-0.17	-854218	0.46
19	1995	6103028	0.18	0.35	-0.17	-1013489	0.46
1	1995	47046433	0.20	0.35	-0.15	-7132006	0.46
19	1993	5512493	0.20	0.35	-0.15	-819112	0.46
6	1995	6222733	0.21	0.35	-0.14	-884108	0.46
12	1991	21348083	0.22	0.35	-0.13	-2861658	0.46
1	1992	39866439	0.22	0.35	-0.13	-5273210	0.46
6	1990	17708641	0.22	0.35	-0.13	-2244416	0.46
19	1996	6446360	0.22	0.35	-0.13	-805847	0.46
2	1993	1555988	0.23	0.35	-0.12	-194307	0.46
19	1997	6768754	0.24	0.35	-0.11	-752187	0.46
12	1998	26544315	0.24	0.35	-0.11	-2893222	0.46
19	1999	7309175	0.24	0.35	-0.11	-770019	0.46
6	1993	21492188	0.25	0.35	-0.10	-2236552	0.46
6	1992	20173868	0.25	0.35	-0.10	-1922780	0.46
3	1992	5222934	0.26	0.35	-0.09	-471473	0.46
19	1994	5750330	0.27	0.35	-0.08	-487845	0.46
19	1992	5397392	0.29	0.35	-0.06	-340511	0.46
1	1991	38340227	0.31	0.35	-0.04	-1667870	0.46
7	1992	4171362	0.31	0.35	-0.04	-164660	0.46
6	1990	5365445	0.31	0.35	-0.04	-199001	0.46
6	1993	5859889	0.32	0.35	-0.03	-169550	0.46
6	1992	5719858	0.33	0.35	-0.02	-108512	0.46
6	1991	551 <del>9</del> 497	0.34	0.35	-0.01	-47540	0.46
6	1994	5901932	0.34	0.35	-0.01	-35195	0.46
1	1998	54028023	0.35	0.35	0.00	-221306	0.46
3	1991	5025826	0.36	0.36	0.00	0	0.47
3	1999	7300808	0.36	0.36	0.00	0	0.48
12	1995	23459255	0.37	0.37	0.00	0	0.48
1	1994	43867236	0.38	0.38	0.00	0	0.49
2	1995	10422946	0.40	0.40	0.00	0	0.51
2	1996	1748661	0.40	0.40	0.00	0	0.51
1	1993	41086429	0.40	0.40	0.00	0	0.52
19	1991	5207609	0.42	0.42	0.00	0	0.53
12	1997	25333505	0.43	0.43	0.00	0	0.54
2	1990	1369293	0.44	0.44	0.00	0	0.55
6	1994	23166192	0.46	0.46	0.00	0	0.57
12	1992	21804382	0.47	0.47	0.00	0	0.58
12	1990	19740580	0.47	0.47	0.00	0	0.58

#### WIND+NON-MODELED CATASTROPHE DAMAGE RATIOS CALCULATION OF EXCESS LOAD

0.48

0.49

0.00

0.00

0

0

0.59

0.60

4442279

6011216

0.48

0.49

1990

1999

3

7

State	Year	AlY	Ratio	Normalized	<b>Difference</b>	Load	Excess Load
7	1998	5459104	0.50	0.50	0.00	0	0.61
2	1994	9659257	0.52	0.52	0.00	0	0.64
6	1991	19287517	0.53	0.53	0.00	0	0.64
1	1999	55360869	0.53	0.53	0.00	0	0.64
6	1996	6543222	0.54	0.54	0.00	0	0.65
6	1995	25501750	0.54	0.54	0.00	0	0.65
1	1997	52321296	0.55	0.55	0.00	0	0.66
2	1995	1655078	0.57	0.57	0.00	0	0.68
12	1999	27636612	0.58	0.58	0.00	0	0.69
12	1993	22146895	0.59	0.59	0.00	0	0.70
2	1990	8596674	0.59	0.59	0.00	0	0.70
2	1998	12701378	0.60	0.60	0.00	0	0.71
6	1996	28761106	0.61	0.61	0.00	0	0.72
7	1990	4083888	0.62	0.62	0.00	0	0.73
1	1990	34421881	0.64	0.64	0.00	0	0.75
2	1999	2224422	0.66	0.66	0.00	0	0.77
2	1991	9124509	0.68	0.68	0.00	0	0.79
12	1994	22671807	0.70	0.70	0.00	0	0.82
1	1996	49718593	0.74	0.74	0.00	0	0.86
6	1997	30502724	0.76	0.76	0.00	0	0.87
2	1992	9038422	0.77	0.77	0.00	0	0.89
2	1993	9178447	0.79	0.79	0.00	0	0.91
7	1993	3993066	0.81	0.81	0.00	0	0.92
2	1997	12162994	0.81	0.81	0.00	0	0.92
7	1991	4326154	0.83	0.83	0.00	0	0.95
6	1998	31253404	0.87	0.87	0.00	0	0.98
3	1997	6474537	0.90	0.90	0.00	0	1.01
3	1995	5867127	0.92	0.92	0.00	0	1.03
12	1996	24394643	0.92	0.92	0.00	0	1.04
2	1997	1839770	0.95	0.95	0.00	0	1.06
6	1997	6853448	1.08	0.95	0.13	868074	1.06
7	1994	4099556	1.16	0.95	0.21	868622	1.06
2	1991	1521504	1.16	0.95	0.21	323906	1.06
3	1994	5506161	1.17	0.95	0.22	1199413	1.06
7	1995	4282047	1.21	0.95	0.26	1106249	1.06
7	1996	4565126	1.30	0.95	0.35	1582846	1.06
3	1993	5258085	1.31	0,95	0.36	1898605	1.06
6	1999	32900006	1.41	0.95	0.46	15220088	1.06
19	1998	7099487	1.43	0.95	0.48	3399160	1.06
6	1999	7355554	1.74	0.95	0.79	5802451	1.06
3	1998	6946682	2.15	0.95	1.20	8309594	1.06
2	1999	13029501	2.16	0.95	1.21	15829750	1.06
2	1998	1982210	2.21	0.95	1.26	2488907	1.06
2	1994	1581060	3.39	0.95	2.44	3854807	1.06
2	1996	11328705	3.49	0.95	2.54	28789905	1.06
3	1996	6226123	5.19	0.95	4.24	26405747	1.06
6	1998	7116595	9.86	0.95	8.91	63430190	1.06
Totals		1291380146			0.11	145363632	

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#### Credibility weighting by State grouping States1,2,3,4,5,6 Non-Modeled Catatrophes

		1	2	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>			
	1990	0.29	0.86	0.00	1.11	0.59	0.43			
	1991	0.41	0.72	1.32	1.02	0.25	0.43			
	1992	0.18	0.61	0.16	0.18	0.36	0.01			
	1993	0.03	0.19	0.09	0.93	0.90	0.32			
	1994	0.76	0.09	1.12	0.82	0.69	1.82			
	1995	0.56	1.69	0.23	0.89	0.18	0.70			
	1996	5.65	0.93	1.57	1.15	0.24	0.60			
	1997	0.87	0.37	0.07	0.23	0.12	0.81			
	1998	0.07	0.27	0.45	1.60	1.26	1.33			
	1999	3.06	0.46	0.12	0.04	0.21	0.96	Regional	Variance of	
	2000	2.00	5.21	0.14	0.96	0.45	0.15	Mean	Means	
	Artihmetic m	n 1.26	1.04	0.48	0.81	0.48	0.69	0.79	0.098	
								Average Proces	s Variance	
Process variance		2.971	2.111	0.328	0.225	0.126	0.281	1.007		
Estimated Process v	ariance	1.989	1.559	0.667	0.616	0.566	0.644			
Total variance	1.012									
Estimated VHM	0.052									
(1) Cred estimate		0.207	0.249	0.437	0 457	0 478	0 446			
(2) Damage ratio esti	imate	0.89	0.85	0.66	0.407	0.470	0.440	SUM		
(3) 2000 AIY		3153771	9386777	2389888	7501237	15807745	7830024	46069442		
(4) (2)*(3)		2805442	8007591	1566336	6003659	10142149	5834552	34359729		
							0004002	0 746	Implied 2000 region	al damage rotio
Balanced estimates		0.82	0.79	0.61	0.74	0.59	0.69	0.69	Chosen regional da	mage ratio

1/13/2003Exhibitssent9-3.xlsExhibit 5

Credibility weighting by State grouping
1,2,3,4,5,6
Non-modeled Catastrophes and Non-Hurricane Wind

		1	2	3	4	<u>5</u>	6			
	1990	1.10	1.42	0.89	1.90	1.02	0.86			
	1991	1.41	1.71	2.82	1.59	0.68	0.86			
	1992	1.13	1.34	0.97	0.64	0.73	0.34			
	1993	0.74	0.74	0.74	1.39	1.33	0.76			
	1994	1.55	0.39	1.80	1.20	1.01	2.11			
	1995	1.17	2.02	0.85	1.47	0.61	1.05			
	1996	6.40	1.39	2.17	1.61	0.54	1.07			
	1997	1.34	0.89	0.74	0.88	0.49	1.27			
	1998	0.55	0.83	1.20	2.37	1.86	2.28			
	1999	3.67	0.92	0.69	0.71	0.64	1.32			
	2000	2.58	5.78	0.67	1.36	0.96	0.57			
	Arth. Mean	1.97	1.58	1.23	1.37	0.90	1.14	Grand Mean:	1.37	
								Variance of means:	0.14	
Process variance		2.94	2.15	0.52	0.26	0.17	0.36	Average Process Var	1.07	
Estimated Process var	iance	2.00	2.00	2.00	2.00	2.00	2.00			
Total variance	1.1026									
Estimated VHM	0.0881									
(1) Cred estimate		0.3259	0.3259	0.3259	0.3259	0.3259	0.3259			
(2) Damage ratio estim	nate	1.56	1.44	1.32	1.37	1.21	1.29		Totals	
(3) 2000 AIY		3,153,771	9,386,777	2,389,888	7,501,237	15,807,745	7,830,024		46,069,442	
(4) (2)*(3)		4,924,742	13,485,689	3,157,599	10,263,966	19,177,172	10,106,926		61,116,094	
									1.3266	Implied 2000 regional da
Balanced estimates		1.34	1.23	1.14	1.18	1.04	1.11		1.1400	Chosen regional damag

311

amage ratio ge ratio

0.859 Balancing adjustment

#### COUNTYWIDE NON-MODELED CATASTROPHE RELATIVITIES

	CALENDAR	State 1	State 2	State 3	State 4	State 5	State 6	State 7	State 8	State 9	State 10	State 11	State 12	State 13
	YEAR													
	1981	0.17	0.27	0.01	0.23	0.63	0.52	1.04	4.53	0.14	0.41	0.22	0.67	0.10
	1982	0.60	0.78	7.99	0.00	0.79	1.69	0.41	5.41	1.29	0.56	0.03	0.77	0.74
	1983	0.31	1.10	1.75	0.02	0.32	0.26	0.58	1.31	0.40	2.05	-0.01	0.60	2.73
	1984	1.37	1.70	0.42	0.11	1.48	0.55	0.70	1.95	0.85	0.68	0.03	0.22	0.80
	1985	0.12	1.17	0.30	0.00	0.40	0.26	0.15	2.82	0.74	0.74	0.02	0.33	0.45
	1986	0.00	0.20	0.18	0.20	0.07	0.31	3.50	1.63	4.75	0.97	0.50	0.01	0.13
	1987	0.22	0.08	1.07	1.47	0.74	1.03	1.25	6.22	1.13	1.72	0.15	1.16	0.12
	1988	0.75	0.29	-0.45	0.04	0.61	1.47	2.51	0.30	0.22	1.44	0.02	0.42	0.06
	1989	0.43	0.85	0.01	0.17	0.38	2.19	0.29	0.36	0.31	3.00	0.02	0.54	0.00
	1990	0.00	0.92	0.00	0.18	0.76	0.61	0.47	1.94	0.34	1.36	0.04	0.11	0.04
	1991	0.01	0.43	0.01	0.29	0.26	0.87	1.68	8.27	0.20	1.24	0.03	0.01	0.55
	1992	0.16	0.50	0.02	0.20	0.13	0.84	0.05	17.13	0.03	0.84	-0.01	0.02	0.07
	1993	0.28	1.70	-0.03	0.03	0.47	1.16	0.12	6.49	1.95	0.36	0.07	0.35	0.00
	1994	0.78	1.02	0.00	0.00	0.23	0.45	4.82	2.96	1.22	0.14	0.15	0.71	0.12
	1995	0.00	0.26	0.00	0.12	0.08	0.27	0.71	2.88	0.99	2.50	0.34	0.12	0.28
	1996	0.25	0.33	0.00	0.18	0.81	4.52	0.38	1.73	6.91	1.31	0.03	0.95	0.36
	1997	0.05	0.47	0.00	0.13	1.56	2.23	3.21	0.72	2.55	1.43	-0.03	0.46	1.84
	1998	0.20	3.16	0.00	0.01	0.51	1.01	5.15	2.98	4.74	0.69	4.20	-0.05	1.63
	1999	-0.01	0.48	0.00	0.00	0.73	4.34	0.98	5.05	0.20	1.04	0.01	0.18	2.44
	2000	0.01	0.74	0.00	0.01	1.71	1.94	0.53	-0.15	1.97	8.53	0.12	0.42	0.51
Arithmetic mean		0.28	0.82	0.56	0.17	0.63	1.33	1.43	3.73	1.55	1.55	0.30	0.40	0.65
Weighted mean		0.26	0.90	0.19	0.12	0.75	1.68	1.59	4.01	1.91	2.00	0.35	0.40	0.69
	Max	1.37	3.16	7.99	1.47	1.71	4.52	5.15	17.13	6.91	8.53	4.20	1.16	2.73
	St Dev	0.35	0.72	1.81	0.32	0.47	1.24	1.57	3.90	1.87	1.79	0.93	0.34	0.83
	CV	1.24	0.87	3.21	1.90	0.75	0.93	1.10	1.05	1.21	1.16	3.13	0.84	1.28
	Linear Trend	-0.02	0.02	-0.15	-0.01	0.00	0.11	0.10	0.05	0.12	0.01	0.05	-0.02	0.03
	R-Squared	0.12	0.02	0.20	0.02	0.00	0.26	0.12	0.00	0.13	0.00	0.10	0.08	0.05
Correlation of Damage		0.14	0.32	-0.24	0.08	0.26	0.40	0.14	0.47	0.33	0.37	-0.04	0.28	-0.08
Ratios to Adjusted CW														
Process variance		0.12	0.52	3.27	0.10	0.23	1.53	2.45	15.25	3.49	3.22	0.86	0.11	0.70

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E.A.	6		

#### Region 1 Non-modeled Catastrophe Relativities (Adjusted to regional 2000 AIY distribution)

	1	2	3	4	5	6	7	8	9			
1981	3.044	2,110	3.271	0.275	0.519	1.059	1.272	0.547	0.213			
1982	0 161	0.426	4.293	1.347	0.881	1.764	0.829	0.238	0.771			
1983	1 301	0 649	1.238	0.453	0.399	0.293	0.354	0.230	3.057			
1984	0.633	0.671	3 923	0.811	0.214	0.529	1.423	0.784	0.770			
1985	0.033	0.234	3.149	1.148	2.294	0.397	0.620	0.623	0.705			
1986	0 220	8.671	1.208	11,792	0.420	0.758	0.170	0.020	0.332			
1987	1 664	1 980	1.503	1.795	0.933	1.642	1.170	0.260	0.168			
1988	0.016	5.905	0.286	0.528	0.279	3.460	1.446	0.146	0.153			
1989	0.425	0.778	0.571	0.845	0.156	5.884	1.020	1.002	0.009			
1990	0.464	1.050	1.282	0.756	0.905	1.359	1.678	0.218	0.091			
1991	0.607	4.280	2.401	0.522	0.126	2.227	0.669	1.262	1.409			
1992	0 472	0.214	1.061	0.126	1.636	3.825	0.603	1.302	0.316			
1993	0.257	0.229	1.992	3.697	1.370	2.202	0.898	0.177	0.007			
1994	0.200	10.870	3.221	2.761	1.373	1.008	0.525	0.137	0.265			
1995	0.006	2,776	5.405	3,900	0.823	1.050	0.301	0.002	1.109			
1996	0.351	0.296	1.162	5.388	0.672	3.528	0.632	0.114	0.284			
1997	1 388	2.092	-0.119	1.660	0.585	1.454	1.015	0.266	1.199			
1998	10.984	2.323	0.371	2.140	0.089	0.457	0.229	1.442	0.736			
1999	2.345	0.673	0.326	0.134	0.559	2.972	0.500	0.084	1.674			
2000	1 587	0.429	0.014	1.595	0.544	1.569	1,386	1.325	0.415			
Arth. Mean	1.308	2.333	1.828	2.084	0.739	1.872	0.837	0.509	0.685	Grand Mean:	1.355	
										Variance of means:	0.320	
Process variance	5.884	8.799	2.472	7.199	0.321	2.053	0.200	0.244	0.541	Average Process Var	3.079	
Estimated Process variance	4.223	4.223	4.223	4.223	4.223	4.223	4.223	4.223	4.223			
Total variance 3.244 Estimated VHM 0.320												
(1) Cred estimate	0.635	0.635	0.635	0.635	0.635	0.635	0.635	0.455	0.455			
(2)Relativity estimate	1.325	1.976	1.655	1.818	0.963	1.684	1.026	0.970	1.050		Totals	
(3) 2000 AIY	7639139	2693808	6656491	7677641	28965458	13675577	58042460	7548625	34836785		167,735,984	
(4) (2)*(3)*Chosen Regional	4397677	2312986	4787313	6064115	12123511	10002277	25867396	3181945	15896752		84,633,973	
Damage Ratio											0.505	Implied 2000 reg
Balanced estimates	0.496	0.739	0.619	0.680	0.360	0.630	0.384	0.363	0.393		0.434 0.861	Chosen regional Balancing adjustm

#### Sample of Proposed Non-modeled Cat loading calculation

		CW Damage		
	Damage	Ratio	Relativity	Capped
<u>Year</u>	Ratio	(reweighted)	to CW	<b>Relativities</b>
1981	I	1	Ľ	I
1	1	1	1	I
1990	6.728	0.634	10.619	6.250
1991	3.639	0.582	6.250	6.250
1992	0.970	0.721	1.346	1.346
1993	0.634	0.531	1.195	1.195
1994	2.008	0.680	2.954	2.954
1995	0.117	0.675	0.173	0.173
1996	0.762	0.712	1.070	1.070
1997	0.824	0.257	3.206	3.206
1998	0.296	0.397	0.745	0.745
1999	0.297	0.443	0.670	0.670
2000	0.205	0.610	0.336	0.336
(1) arithmetic mean			2.650	2.394
(2) standard deviation			2.527	
(3) max relativity			10.619	
(4) relativity cap:(1)+3*(	(2)		10.232	
(5) process variance				3.68
(6) credibility				0.901
(7) credibility weighted	relativity			2.290
(8) implied 2000 losses				19,794,656
(9) implied 2000 1 sd lo	SS			37,976,702
(10) rebalanced, to 1.0,	relativity			2.645
(11) balanced damage	ratio			1.367

#### NOTES:

(4) Three standard deviations (calculated from the unadjusted numbers) above the arithmetic mean

(5) The process variance is the unweighted variance of the adjusted 20 year relativities. The average across states of this number is the process variance used in the credibility formula

(6) Credibility is 20/(20+K); K is the ratio of the above process variance and the VHP(not shown)

(7) (1)\*(6)+(1-(6))\*1

(8) is (7)\*selected CW damage ratio\*State 2000AIY

(9) is sqrt((5))\*(8)

(10) adjusts individual state indicated relativities for the difference between the weighted (by AIY) CW relativity and 1. This adjustment by state is done in proportion to (9)

11) The balanced damage ratio is (10)\*the selected CW damage ratio

#### Exhibit 10

#### **COMPARISON OF METHODS**

			Relativity	Relativity
STATE	Agg-to-agg	Trended	Regional	<b>Countrywide</b>
1	1.984	2.522	1.71	2.184
2	1.872	2.555	1.60	1.861
3	1.683	2.337	2.20	2.114
4	1.133	1.524	1.30	1.367
5	1.073	1.578	1.43	1.384
6	1.008	1.57	1.35	1.073
7	0.900	0.908	0.47	0.502
8	0.868	1.994	1.60	1.024
9	0.819	0.98	0.60	0.889
10	0.720	1.024	0.78	0.816
11	0.698	0.963	0.62	0.888
12	0.693	0.865	1.05	0.801
13	0.689	0.743	0.58	0.755
14	0.642	0.795	1.15	0.859
15	0.614	0.783	1.03	0.798
16	0.567	0.7	0.53	0.671
17	0.539	0.668	0.60	0.718
18	0.525	0.83	0.52	0.602
19	0.515	0.98	0.56	0.659
20	0.449	0.549	0.91	0.578
21	0.422	0.516	0.52	0.557
22	0.405	0.397	0.30	0.450
23	0.391	0.495	0.45	0.442
24	0.356	0.505	0.43	0.534
25	0.335	0.412	0.29	0.364
26	0.296	0.413	0.35	0.471
27	0.296	0.359	0.40	0.395
28	0.284	0.288	0.27	0.261
29	0.269	0.426	0.40	0.382
30	0.239	0.271	0.32	0.320
31	0.236	0.384	0.38	0.309
32	0.236	0.274	0.34	0.291
33	0.226	0.308	0.30	0.186
34	0.210	0.359	0.20	0.147
35	0.202	0.247	0.23	0.232
36	0.201	0.208	0.25	0.212
37	0.189	0.256	0.38	0.249
38	0.184	0.24	0.28	0.331
39	0.173	0.252	0.24	0.261
40	0 164	0 199	0.16	0.261
41	0 158	0.136	0.15	0 113
42	0 144	0 165	0.14	0.173
43	0 141	0.171	0.21	0.176
45	0.120	0 197	0.28	0.298
45	0.099	0.133	0.17	0 147
46	0.090	0.368	0.085	0 187
47	0.058	0.069	0.15	0 116
48	0.030	0.051	0.08	0.099
49	0.033	0.042	0.08	0.098

#### SENSITIVITY: CHANGE IN INDICATED DAMAGE RATIO BETWEEN 1999 AND 2000

			<b>CW Relativity</b>
State	Trended	AGG/AGG	Method
1	-2.4%	-9.0%	2.2%
2	-1.5%	-9.0%	-3.5%
3	-1.4%	-7.3%	-4.0%
4	-1.4%	-6.4%	-4.3%
5	-1.4%	-10.6%	-3.1%
6	-1.3%	-7.1%	-2.6%
7	-1.3%	-10.9%	-12.0%
8	-1.2%	-9.8%	-2.9%
9	-1.2%	-5.9%	-4.0%
10	-1.1%	-7.4%	-4.0%
11	-1.1%	-6.7%	-3.7%
12	-1.0%	-8.0%	-3.8%
13	-0.9%	-7.4%	-3.9%
14	-0.7%	-7.1%	-3.3%
15	-0.6%	-7.1%	-2.9%
16	-0.5%	-6.8%	-3.4%
17	-0.4%	-6.5%	-2.6%
18	-0.1%	-5.2%	-2.8%
19	0.0%	-6.4%	-1.6%
20	0.0%	-4.8%	-2.3%
21	0.4%	-4.3%	-2.3%
22	0.5%	-5.0%	2.8%
23	0.8%	-3.6%	-1.9%
24	1.2%	-3.3%	-1.8%
25	1.3%	-2.9%	-2.0%
26	1.4%	-4.0%	-1.3%
27	2.2%	-3.9%	1.0%
28	2.8%	-2.0%	-0.4%
29	3.0%	-0.5%	-0.4%
30	3.6%	0.4%	0.0%
31	3.8%	1.3%	0.6%
32	3.9%	2.4%	-0.2%
33	4.0%	3.5%	0.9%
34	4 0%	2.3%	0.8%
35	4 4%	4 9%	2.7%
36	4.5%	2.8%	1.6%
37	5.3%	7.5%	0.7%
38	5.6%	3.6%	2.2%
39	5.7%	4.5%	2.2%
40	5.7%	1.7%	1.4%
41	6.0%	1.9%	0.7%
42	61%	2.2%	7.5%
43	7.5%	5.3%	3.2%
44	9.6%	7.2%	4.6%
45	12.2%	21.2%	9.7%
46	16.4%	34.1%	16.3%
47	16.6%	20.2%	8.7%
48	20.3%	29.0%	32.0%
49	41.5%	61.4%	8.1%
ĊW	3.9%	1.9%	0.6%

Countrywide numbers weighted by 2000 AIY's